

# **Development of Artificial Intelligence- based Model to Predict Esports Players' Skill Levels**

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## Abstract

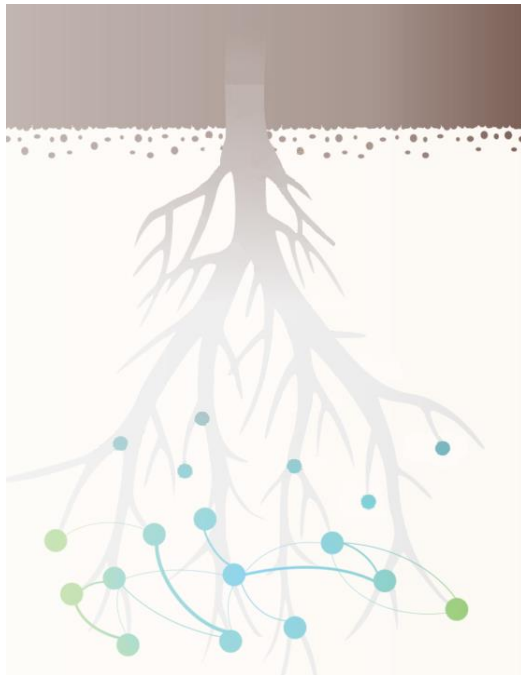
Evaluating eSports players' skills could be significantly important for game developers by enabling them to make their designed games adaptable to the players' skill levels. Moreover, an accurate and reliable method that could discover the features discriminating between low-skilled and highly-skilled players could help eSports teams design a more effective program focused on improving the extracted features. Sensor data, and in particular EEG data, have been proved to be effective in classifying the players' skill levels. However, there is currently a lack of a reliable EEG dataset in the literature. Moreover, methods using sensor data still lack sufficient accuracy due to several reasons, including inefficient data preprocessing, inefficient feature extraction, and uncertainties and inaccuracies in sensor and EEG data. Novel methods to overcome these problems are proposed in this thesis. For this purpose, a dataset containing EEG data of 18 League of Legends (LoL) players is gathered first. To the best of my knowledge, this is the first reliable EEG dataset with the highest sample size compared to the previous studies. In the next step, two novel methods are introduced to classify players' skill levels using sensor and EEG data, respectively. For the first method, a new preprocessing technique using a time window that extracts the most relevant segments of players' sensor data in LoL is developed. Symbolic Transfer Entropy (STE) is then employed to compute the STE features between sensors' data using the extracted segments. These features, which show the connectivity between body parts, are finally used to classify the players' skill levels and calculate the optimum window size. For the second method, a new brain source localisation method, called ReLORETA, is proposed to reconstruct the EEG signals inside the brain, thereby removing uncertainties that naturally exist in EEG data. The reconstructed brain signals are then used to classify the players into two skill levels. The first and second methods were applied to a secondary sensor dataset, and the primary gathered EEG dataset, respectively. The classification results demonstrated a significant improvement compared to previous methods. The most significant features in the classification of the players' skills were the connectivity features between gaze data and keyboard, mouse, and hand movement. Also, there was a significant difference in the temporal, frontal, and occipital lobes between professional and amateur players. Besides eSports players, the proposed methods in this thesis can be also applied to sports people's data to improve the training programs in sports and eSports industries.

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To test the accuracy of the proposed ReLORETA method in this thesis, real EEG data of a patient with epilepsy were used. The data were provided by the Distributed EEG Lab at the Neuroscience Health Center of Stanford University.



# CHAPTER 1

## Introduction and literature review

### OVERVIEW

In this chapter, research history and recent developments in analysing the skills and behaviour of eSports players are presented. A comprehensive literature review, the current gaps in the literature, the research questions, and objectives are set out, and the contributions that this research makes to the knowledge in the related field are discussed in this chapter as well. The structure of the thesis and a brief description of different chapters are presented at the end.

## 1.1. Research background and motivation

eSports is a type of video games in which a number of teams or players compete to win the game. In recent years, eSports has evolved into a self-sustainable industry and is still rapidly growing in many fields, including streaming, connectivity, hardware, broadcasting, and game statistics. Accordingly, eSports athletes face stricter training activities, and evaluating their performance has acquired considerable importance in recent years (Anderson et al., 2018; Kuposov et al., 2020). As a result, a large portion of research in eSports is dedicated to discovering what features set elite players apart (Huang et al., 2017; Rambusch, 2011).

The benefit of accurately assessing the players' skill levels is twofold for eSports teams as follows:

- 1- Firstly, it enables teams to better identify and recruit highly skilled players. One may argue we can use statistics for this purpose. However, statistics are not sufficiently available in many cases, especially at the junior level when the players are starting their career. Moreover, the player's statistics can be misleading because the statistics do not provide clear information about the decline in players' physical and cognitive abilities.
- 2- Secondly, it helps teams create a better training program focused on improving the distinguishing features thereby enhancing players' skills more effectively. Currently, coaches have to rely on their own knowledge to design the training program and recruit new players. This is while in one of the most recent studies (Sabtan et al., 2022), professional coaches in eSports consider the players' skill evaluation as one of the most difficult challenges in their jobs. Players of different expertise react differently to the game's events and unexpected problems, such as high network latency during eSports competitions (Liu et al., 2021; Mendoza et al., 2021). Therefore, each player needs a different training program customised to their skill levels and focused on their weak points entailing an accurate estimation of their abilities in the first place. For example, if the difference between players' skills levels could be explained based on the difference between their body parts or brain regions' function, this would help eSports teams to focus on programs that would strengthen those body parts or brain regions. An example of such application is transcranial Direct Current Stimulation (tDCS) which can be used to boost eSports players' performance (Friebs et al., 2021;

Okano et al., 2015). Fig. 1 shows how the F4 electrode according to the 10-20 setup can be used for the eSports players' brain stimulation Friehs et al. (2021). However, to implement such methods, we first need to discover the body or brain regions that function differently in players of different skill levels.

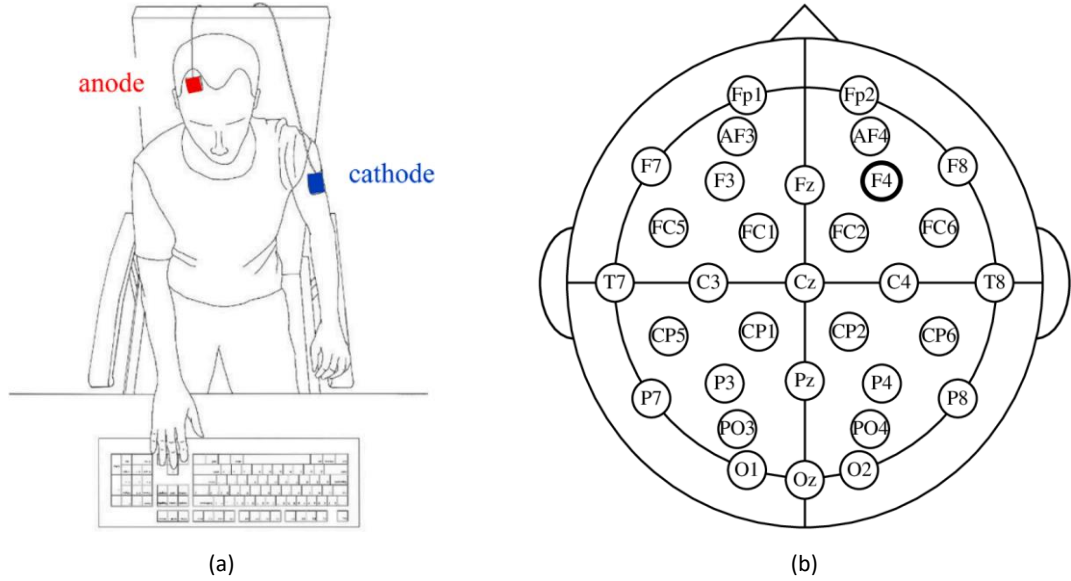


**Fig. 1.** Stimulation using the tDCS method presented in (Friehs et al., 2021). (a) tDCS electrodes positioned over the F4 electrode and the left deltoid and (b) F4 electrode's position according to the standard 10-20 placement system.

From a broader point of view, assessing players' cognitive abilities holds great significance for the progress of the gaming industry as well by enabling designers to create games adaptable to the players' skill levels, which is known as dynamic difficulty adjustment (DDA) (Baldwin et al., 2013; Guo et al., 2024; Zohaib, 2018). In the United States, the video game industry formed more than 80% of the total profit, which is around \$36 billion, obtained from all software-related industries in 2018 (Hafeez et al., 2021). Moreover, the gaming industry in 2021 was worth more than \$180 billion according to the report provided by the global games market (Hafeez et al., 2021). As a result of this rapid growth in the gaming industry, intense competition started among game developers to improve the user experience for their diverse game players population. Since players' cognitive abilities play a role in their engagement and experience during the game (Himmelstein et al., 2017; Rozendaal et al., 2009; Sharek and Wiebe, 2014), effectively improving their experience entails an accurate evaluation of these abilities first and foremost (Łupkowski and Krajewska, 2019). This evaluation can be used to enhance the game design and user experience by creating gameplays which can be adaptively updated based on to the players' skill levels (Gábana Arellano

et al., 2017; HuynhSinh et al., 2018). This can be done, for example, using a brain-computer interface (BCI) (Diya et al., 2019; Maby et al., 2012). This adaptive behaviour will make the game more engaging for the end user and can be beneficial to different applications such as game-based learning (GBL) (Abdul Jabbar and Felicia, 2015; Cheung and Ng, 2021). In particular, Lopez-Gordo et al. (2020) showed how the evaluation of players' skills could be used in Virtual Reality (VR) first-person shooter video games to anticipate players' actions and decisions before they are taken, thereby enabling the VR game to modify the virtual scenario, e. g. change environmental conditions or abort the mission, or drive the players, e. g. by suggesting options, according to the purpose of the mission. For this purpose, they used a closed-loop design as shown in Fig. 2. The VR headset collected contextual information, such as the last shot accuracy, the distance to the target, the remaining life, etc., from the game, and then this information was transferred to a remote server where a predictive model based on a two-layer Artificial Neural Network (ANN) was used to predict the accuracy of the next shot. After each prediction, the closed loop design (the dashed arrow in the figure) could be implemented to update the VR context accordingly. After training, the model could predict the "hit" and "miss" events with a mean accuracy of 74.1%.

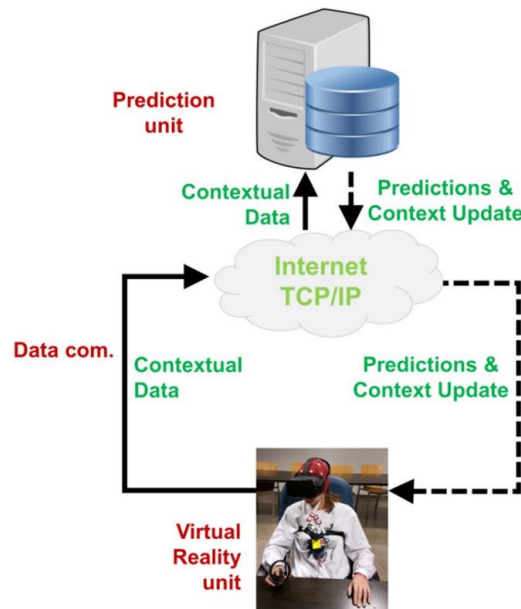


**Fig. 2.** The closed-loop design which uses the contextual information in a VR game to update the game's features (Lopez-Gordo et al., 2020)

In summary, according to what has been discussed above, the evaluation of players' skill levels holds great significance for the success of eSports teams and the improvement of video games for the following reasons:

1. These methods can be used by eSports teams to evaluate players' skill levels more accurately when recruiting new players.
2. These methods help eSports players to improve their training programs by focusing on physical and brain features that distinguish elite players from low skilled players. An example of such an application is tDCS.
3. The methods can help game designers to improve their games and the user experience using DDA.

In this thesis, new methods are proposed to improve the accuracy of eSports players' skill evaluation. The proposed methods in this thesis will also discover what physical features distinguish highly skilled players from low skilled players, and what is the difference between their different brain regions' activities during the game. To the best of my knowledge and according to the literature, this thesis is the first study investigating this issue and finding these features.

In what follows, a comprehensive literature review of the existing methods for the evaluation of eSports players' skill levels will be presented in the first step. In the next step, the gaps in the literature will be discussed. The research questions, aims and objectives will then be designed based on the identified gaps.

## 1.2. Literature Review

### 1.2.1. Introduction

Subjective evaluations, which are based on questionnaires, were among the first methods initially used for evaluating eSports players' skills and abilities (Himmelstein et al., 2017). However, these methods were gradually replaced with objective evaluation methods that provide a more efficient and reliable evaluation of players' cognitive abilities. These methods perform a comprehensive analysis of the players' data gathered during the game (Smerdov et al., 2021b). Different objective evaluation methods have been proposed in the literature that can be divided into three groups: methods using game analytics and statistics, methods employing the players' physical, biological or neural data gathered by a keyboard, mouse, or a set of sensors, and finally, a hybrid approach using a combination of the first two methods.

The methods in the first group use statistics including in-game data such as Kill-Death Ratio (KDR), Win/Loss rate, etc., alongside Artificial Intelligence (AI) or Machine Learning (ML) techniques to evaluate the player's performance and classify their skill levels (Makarov et al., 2018; Urbaniak et al., 2020). These methods, which comprise a significant portion of the existing studies, could also determine specific settings (L. Zhang et al., 2020) and boost players' and audiences' experience during the game (Katona et al., 2019).

Methods in the second category factor in players' physical and cognitive characteristics to evaluate and model their performance more efficiently. A number of these methods take into account these features by incorporating gameplay inputs such as mouse movements and keyboard dynamics as well as players' gaze or eye tracking (Bickmann et al., 2020; Khromov et al., 2019; Korotin et al., 2019). These inputs extract some features and then evaluate players' skills using the ML techniques. On the other hand, some studies take advantage of the physical features of the player, including Galvanic Skin Response (GSR), heart rate, and players' movement during the game to measure their performance and classify their skills (Smerdov et al., 2019b, 2021b). These data are typically obtained using wearable sensors mounted on a framework like a smart chair. There are also some hybrid methods using a combination of in-game and sensor data (Blom et al., 2019; Smerdov et al., 2019a). However, due to including in-game data in the simulation, these methods have lower performance than methods using only sensor data.

Electroencephalography (EEG) is another subset of this family, i. e. methods based on sensor data, that has been successfully used to evaluate eSports players' cognitive behaviour and skills. Minchev et al. (2009) used an EEG spectral analysis to identify selected moments of 'win' and 'lose' events corresponding to correct decisions and actions compared to mistakes and lethal situations. Moreover, Meneses-Claudio and Roman-Gonzalez (2018) showed that EEG signals can successfully differentiate between players called Newbie, who are starting to play video games, and Hardcore, who have game knowledge but are not professional. Similarly Melentev et al. (2020) employed EEG signals to predict whether a player is a professional eSports athlete or a casual player as well as whether the player is fresh or tired. Due to its efficiency and effectiveness in evaluating the cognitive and affective states of the players, EEG, besides other biological measures such as electromyography (EMG) (Nacke et al.,

2010), Electrocardiography (ECG) (Kneer et al., 2016), and Electrodermal Activity (EDA) (Nacke, 2013), is gaining importance in GUR also.

To better understand how the players' behavioural data gathered by sensors can significantly improve the accuracy of players' skills classification, let us consider an example of using amateur and professional players' gaze positions in Counter-Strike: Global Offensive (CS: GO) (Korotin et al., 2019). In this game, eSports players should visually check different in-game elements. Firstly, they have to track various factors in the dynamic 3D game environment, including allies, enemies, shots, positions, etc. Secondly, the player has to regularly check the different elements of the game User Interface (UI) that overlays the game 3D environment as shown in Fig. 3. The UI elements include radar, time and player panel, game event log, health and armour bar, aiming crosshair, weapon, and ammo bar. Keeping these elements in check is important. For example, the weapon and ammo panel let the player efficiently manage the ammo usage, the radar provides information about enemies and teammates' positions, etc. 15 eSports players, including 5 professional players and 10 amateur players, played the game for 10 repeated rounds while each round lasted approximately 1 minute. The players' gaze position during the game was then recorded at the frequency of 60 Hz. After completing all rounds, a *k*-means method is applied to all observed gaze positions (here *k*=9) to cluster them according to their distance from the position of UI elements shown in Fig. 3. In addition to the six UI element positions in Fig. 3, three more gaze positions at right, left, and bottom of the aiming crosshair

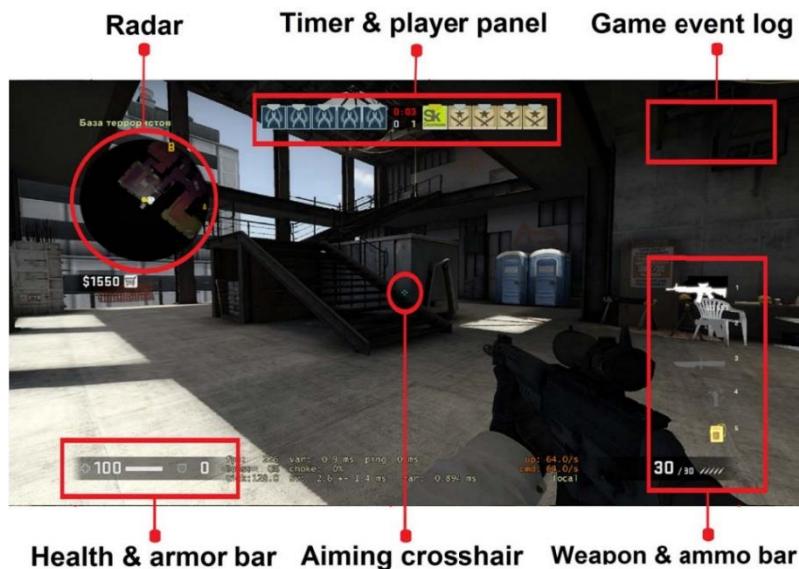


**Fig. 3.** The elements of UI in CS: GO Korotin et al. (2019).

are considered for the clustering. Fig. 4 shows the results of the clustering while each zone represents a cluster. The gaze positions for amateur and professional players have different distributions over the screen that are even detectable by the eyes. This information, which is missed if only in-game data are used for the classification, can significantly improve the classification results for amateur and professional players. However, the gaze position of the players still depends on the position of elements on the screen, which can vary in different versions of the game. This problem could be properly resolved using behavioural data such as EEG signals, which are not dependent on the game's features. For this reason, such data are utilised more widely than gaze data in analysing players' behaviour in the more popular Multiplayer Online Battle Arena (MOBA) games such as League of Legends (LoL) (Blom et al., 2019; Smerdov et al., 2021a, 2019b, 2019a).

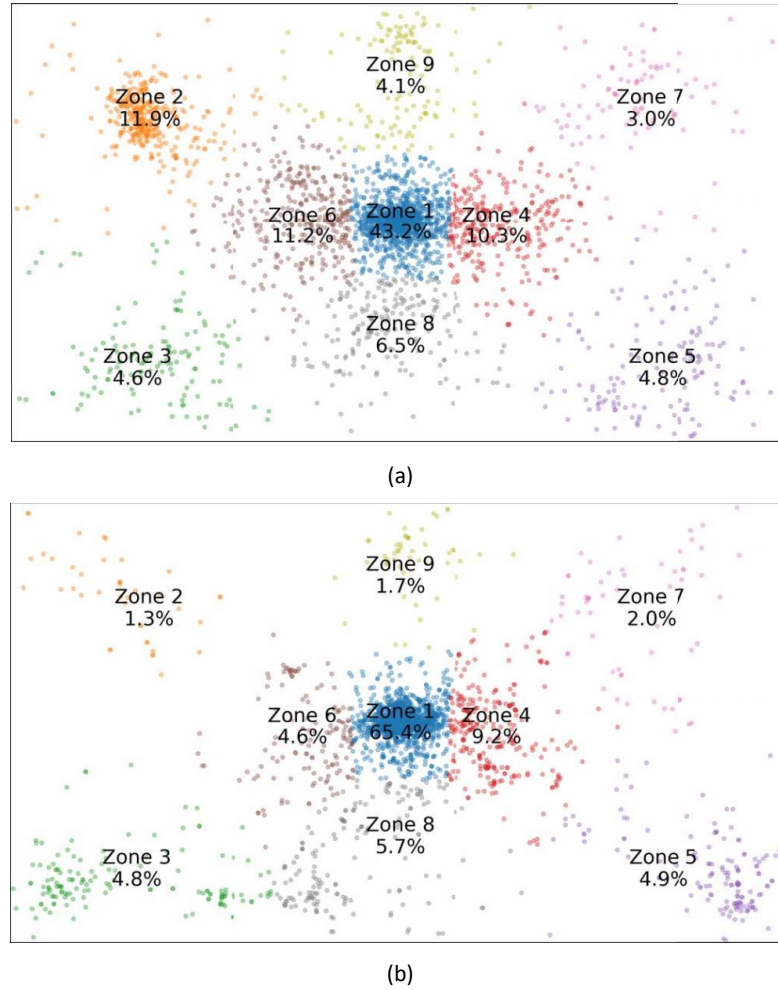


**Fig. 4.** The concentration of the player's gaze position on the different zones of the screen during 10 minutes of the CS: GO game sampled at the frequency of 60 Hz. (a) amateur players and (b) professional players (Korotin et al., 2019).

In the following sections, the methods in each category will be presented and discussed in more detail.

### **1.2.2. Subjective methods**

Subjective methods try to evaluate the relationship between the cognitive abilities of the players and the outcome of the game based on data gathered by questionnaires. Particularly, these methods try to associate the cognitive abilities of players with their personality traits such as neuroticism, extraversion, openness, agreeableness, and conscientiousness (Beres et al., 2021; Matuszewski et al., 2020; Semenova et al., 2020), or other determinants of success in elite eSports players (Fanfarelli, 2018; Himmelstein et al., 2017; Kleinman et al., 2022; Poulus et al., 2022). Author Fanfarelli (2018) carried out a thematic analysis to discover skills believed to be crucial for having an excellent performance in the eSports game Overwatch. Finally, it was concluded that the “game sense” of the player, including survival (i. e. the ability to survive in the game), prediction ability, communication ability, and thoughtfulness, besides the theme “mechanics”, which refers to the players’ ability to precisely use input devices and manipulate game mechanics, are the main skills capable of discriminating between players with varied skill levels. However, the study did not include any amateur players; it was based only on the analysis of 11 interviews with professional overwatch players. Similarly, Poulus et al. (2022) used a thematic analysis to explore elite eSports players’ perception of success determinants. For this purpose, interviews were employed to assess the elite players’ psychology when training, working in eSports teams and playing well. According to the results, elite players showed uninterrupted focus, high levels of confidence, and flow states. They also used psychological techniques to remain mindful in the presence of ‘tilt’ and regulate their emotions. Furthermore, elite eSports athletes used tactical breaks and breathing techniques to effectively cope with stress when feeling nervous. When working in teams, they helped to improve team cohesion and reported interpersonal disagreements as the biggest challenge. Himmelstein et al. (2017) interviewed five competitive LoL players to identify the cognitive abilities that enable them to achieve optimal performance in tournaments. The results proved that competitive players possess different cognitive abilities and mental skills, including adaptation to variable circumstances and staying focussed under pressure, distinguishing them from casual gamers. However, despite acknowledging the role of mechanical skills such as reflexes, speed of hand movements, and speed-

accuracy trade-off, the authors did not investigate the effect of these skills in their study and did not provide any scale for measuring the skill levels of players using the cognitive abilities reported in their results. Furthermore, the small sample size used in their study is highly likely to distort the generalisability of their results. Conducting a qualitative study with a large number of participants, Beres et al. (2021) investigated the relationship between players' personality traits and their choke and clutch performance. After interviewing 274 gamers and analysing the results, they found that trait tendencies toward public consciousness, reinvestment, approach, and avoidance coping style as well as obsessive passion orientation positively correlate with the propensity to choke. Furthermore, the propensity to clutch was found to be negatively correlated with anxiety and positively correlated with self-consciousness and players' experience in competitive gaming. However, the questionnaires in their study did not include items applicable to clutch performance and were designed to assess the players' coping style during stressful game events, raising serious doubts about the significance of their results for the propensity to clutch.

Due to the subjective nature of these methods, their results may drastically vary across different studies. For example, in one study (Matuszewski et al. 2020) consisting of 206 eSports players, a significant difference between lower rank and higher rank players in three personality traits, including extraversion, openness, and agreeableness was reported. The NEO-five-factor inventory questionnaire (McCrae and Costa, 1987) was used to measure the personality traits within the gathered sample. Fig. 5(a) depicts their results where the vertical axis shows the intensity of each measure, and the letters N, E, O, A, and C stand for neuroticism, extraversion, openness, agreeableness, and conscientiousness, respectively. On the other hand, in another study by Semenova et al. (2020) no significant difference was found between casual gamers and eSports professional players in their personality traits. In their study, they gathered a dataset from 34 participants using the IPIP-NEO big five personality traits Japanese questionnaire (Tsuji et al., 1997). Although their results showed some differences in the players' traits as depicted in Fig. 5(b), none of them was significant. What is more, their results considerably contradict the results from the former study. The drastic changes in the results across different subjective experiments can be due to several reasons such as the highly sensitive nature of these methods to the circumstances of the study including the game genre used for designing the questionnaire, the number of participants, their gender, age, etc. Moreover, self-reported information is subject to

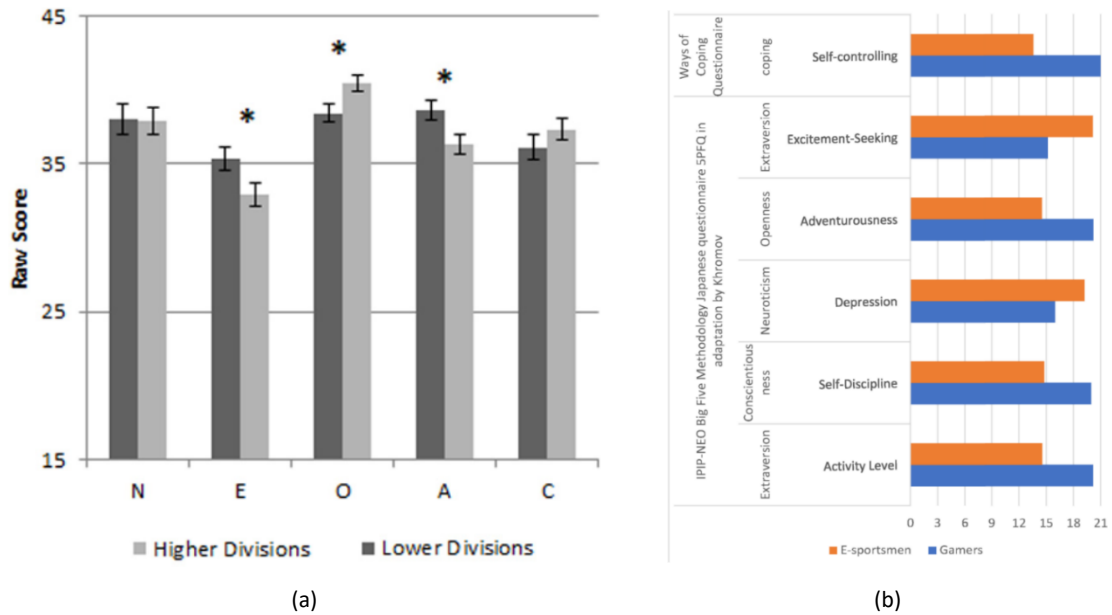


**Fig. 5.** The five personality traits measured for gamers (lower divisions) and professional eSportsmen (higher divisions) according to (a) (Matuszewski et al., 2020) and (b) (Semenova et al., 2020)

bias (Berg and Rapaport, 1954; Choi and Pak, 2004). This problem is more crucial in eSports studies, where players usually tend to provide socially desirable information by overestimating their performance and abilities (Aeschbach et al., 2023). For this reason, several studies tried to include other types of data, such as in-game and gaze data, in their simulations to alleviate the effect of bias in self-reported information and increase the validity and accuracy of results. Halim et al. (2019) tried to include the in-game data, collected from strategy game datasets, namely, StarCraft and World of Warcraft, in their analysis. For this purpose, they first categorised the in-game data into two groups using clustering methods. The participants then took the benchmark personality traits test IPIP-NEO-120, and its results were used to correlate the players' personalities with the clusters' features. Using this method, they identified two different clusters, with the personality traits neuroticism, openness, and extraversion and the personality traits conscientiousness and agreeableness falling into the first and the second cluster, respectively. They reported an average classification accuracy of 78-91% using different classifiers. Also, in another study, Kopusov et al. (2020) examined the relationship between the players' personality traits and their gaze data. Analysing 35 CS: GO players, including 7 professional and 28 amateur players, they observed a significant difference between the gaze data of the two groups. They also found that the extraversion was highly correlated with the professional players' gaze data and could

be used to characterise them. However, they did not provide any classification results using the extracted features.

Table 1 shows a summary of the studies using subjective methods. According to Table 1 and what has been discussed so far, subjective methods can barely provide an accurate model for classifying the players' skill levels and performance. This is mainly because these methods use qualitative metrics and tools such as personality traits and questionnaires to evaluate players' abilities. This problem prompted researchers to seek more reliable approaches based on objective methods capable of performing a more systematic assessment of players' skill levels.

### **1.2.3. Objective methods**

In objective methods, the analysis is performed on the data directly gathered from the players' performance during the game. As mentioned in Chapter 1, objective methods, which are the main focus of this study, can be divided into three groups: methods using in-game data, methods using sensor data, and hybrid methods using a combination of the first two approaches.

#### **1.2.3.1. Objective methods using in-game data**

These methods employ the in-game data and statistics such as kills, deaths, items, abilities learned, etc. to evaluate players' cognitive abilities and skill levels and predict the game outcome according to the players' performance. The popularity of these methods is mainly due to the increasing availability of in-game data through different sources including the publishers' websites and APIs. Since elite players are normally expected to have better in-game statistics, some research works are dedicated to proving the relationship between the in-game data and players' cognitive abilities. In one of the most recent studies, Sörman et al. (2022) investigated if there is a relationship between players' skill levels in the strategy video game Dota 2 and their decision-making ability and experience as measured by the Iowa Gambling Task (IGT). Two predictors based on 337 players' in-game data, namely, Match-Making Rating (MMR) and Medal, were used to predict the players' performance in IGT. Their results showed that in-game data related to Medal was a significant predictor of performance in IGT while MMR was borderline significant. This means that players who have better performance in the game tend to have higher decision-making abilities. They also included the Cognitive Reflection Task (CRT) in their experiment and concluded

**Table 1.** Summary of subjective methods and their results

| Study                     | Number of participants | What they measured                                                                                       | Result                                                                                                                                                                                                                                                                                                                                                                                                            |
|---------------------------|------------------------|----------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Beres et al. (2021)       | 274                    | The relationship between players' personality traits and their choke and clutch performance              | They found that trait tendencies toward public consciousness, reinvestment, approach, and avoidance coping style as well as obsessive passion orientation positively correlate with the propensity to choke. Furthermore, the propensity to clutch was found to be negatively correlated with anxiety and positively correlated with self-consciousness and players' experience in competitive gaming             |
| Matuszewski et al. (2020) | 206                    | Difference between lower rank and higher rank players in five personality traits                         | Fig. 5(a)                                                                                                                                                                                                                                                                                                                                                                                                         |
| Semenova et al. (2020)    | 34                     | Difference between casual gamers and eSports professional players in their personality traits            | No significant difference was found                                                                                                                                                                                                                                                                                                                                                                               |
| Fanfarelli (2018)         | 11                     | Discover skills believed to be crucial for having an excellent performance in the eSports game Overwatch | It was concluded that the "game sense" of the player, including survival (i. e. the ability to survive in the game), prediction ability, communication ability, and thoughtfulness, besides the theme "mechanics", which refers to the players' ability to precisely use input devices and manipulate game mechanics, are the main skills capable of discriminating between players of different expertise levels |
| Himmelstein et al. (2017) | 5                      | The cognitive abilities that enable players to achieve optimal performance in tournaments                | The results proved that competitive players possess different cognitive abilities and mental skills, including adaptation to variable circumstances and staying focussed under pressure, distinguishing them from casual gamers                                                                                                                                                                                   |
| Poulus et al. (2022)      | 7                      | Elite eSports players' perception of success determinants                                                | According to the results, elite players showed uninterrupted focus, high levels of confidence, and flow states. They also used psychological techniques to remain mindful in the presence of 'tilt' and regulate their emotions.                                                                                                                                                                                  |
| Halim et al. (2019)       | 50                     | Players' personality clusters                                                                            | They identified two different clusters, with the personality traits neuroticism, openness, and extraversion and the personality traits conscientiousness and agreeableness falling into the first and the second cluster, respectively. Results show that the gameplay can be used to predict various personality features using strategy game data                                                               |
| Koposov et al. (2020)     | 35                     | The relationship between the players' gaze data and their personality traits                             | They observed a significant difference between the gaze data of the two groups. They also found that the extraversion was highly correlated with the professional players' gaze data and could be used to characterise them                                                                                                                                                                                       |

that the relationship between MMR and CRT was positively significant. CRT is an indicator of players' cognitive ability to engage in rational and logical thinking. In another recent study, Mathonat et al. (2020) introduced a method to classify the skill shots of players in Rocket League using in-game data from 298 games where 7 features for each game were extracted for the classification. Although the proposed method obtained a mean accuracy of 73.9%, the labels in their dataset were considerably noisy, making it difficult to assess the significance of their results. Urbaniak et al. (2020) evaluated the players' skills and ranking in the game CS: GO using in-game data provided by Half-Life Television (HLTV) and the multiple-criteria decision-making-based method called Characteristic Objects Methods (COMET). After predicting the rankings of the top 40 players, Spearman's correlation coefficient between their results and the real ranking of players was equal to 0.5304, which is disappointingly low for a prediction system. Spearman's correlation coefficient is a measure of the strength and direction of the relationship between two variables which can range between -1 and +1. A Spearman's correlation value of +1, -1, and 0 indicate a perfect positive relationship, a perfect negative relationship, and no relationship between two variables, respectively. In another study, Makarov et al. (2018) used in-game statistics to predict the players' rankings and the winning team in the Dota 2 and CS: GO games, respectively. They reported 90% accuracy in predicting the players' ranking in the Dota game. However, their model achieved a low accuracy of approximately 60% in predicting the winning team in CS: GO. Clark et al. (2020) demonstrated how an Adjusted Plus-Minus (APM) model developed with Bayesian hierarchical regression could be used to evaluate the players' performance and predict the outcome of the Dota 2 game. In particular, they investigated how 'gold' could be used as a predictor for the team's performance, and then used a Bayesian APM model to estimate the players' contribution to the team's gold differential. Their model obtained 66% accuracy using a dataset containing in-game data from 2356 games. However, they mentioned that the prediction accuracy could drop to 60% using a smaller dataset of 150 games. Katona et al. (2019) used in-game data from approximately 10000 games, including 5000 professional and 5000 semi-professional games, to predict which of the 10 players of either competing team will die within 5 seconds. Using deep learning for the prediction, their model achieved average precision and recall values of 0.377 and 0.725, respectively, on the test data. This means, on average, the model was able to predict 72.5% of players who died within 5 seconds after the prediction, but

only 37.7% of players whom the model predicted would die within 5 seconds indeed died. Analysing in-game data of LoL offered by the game API, Hitar-Garcia et al. (2022) tried to find the connection between players' skills and the winning probability of the team. For this purpose, they built new features based on the players' skills in different tasks, such as handling a champion or beating another player. Despite their novelty in employing new features, their proposed method for predicting the winning team achieved an accuracy of 70%. Similarly, Jadowski and Cunningham (2022) used in-game data to build a predictive model for rating teams and players' performance in LoL. Their model achieved even lower accuracy than the previous study by predicting only 67% of 306 games correctly, and they concluded that substantially more data and contextual information would be required to attain a higher degree of accuracy. Maymin (2021) analysed a large dataset containing in-game data from approximately 150000 LoL games to find if there is a relationship between players' skills and the win probability of the team. In addition to the initial features provided by the game API, they extracted extra features such as Ward maps, Heat maps, vision, abilities, and time management to reinforce their analysis. They found that all features had a significant relationship with the team's win probability except for the abilities. However, they did not propose any method for predicting the winning team. Kleinman et al. (2021) used the last hitting feature of LoL to compare the self-regulatory processes of expert, non-expert, and novice players and found that they were significantly different in the forethought phase.

The research works concerning the application of in-game data are not limited to recent studies. Deja and Myslak (2015) tested the hypothesis that it is possible to predict team performance in LoL using in-game topological data such as the area of a polygon where vertices are the players' positions and their dispersion. Using data from 5199542 games and 7 extracted features for each game, their method achieved a mean accuracy of approximately 80%. According to their results, higher rank players demonstrated similar cognitive abilities, and they found that the probability of winning increases along with the dispersion of team members. However, due to the nature of data used in their model, their results are considerably sensitive to the gameplay and barely could be generalised to other games. A similar approach was adopted by Ravari et al. (2017) to predict the match outcomes in the game Destiny. The dataset containing performance data of 9000 players was used in their study to predict the outcomes of both win-loss individual and ranking games. They achieved an average

classification accuracy of 83% with a minimum accuracy of 68% in some matches. They also found the most important in-game features for the evaluation of the players' skills were Score Per Life (SPL), Kills Deaths Assists (KDA), and KDR.

Table 2 shows a summary of the methods using in-game data. Although in-game data provide convenient means for evaluating players' skills and performance, they could rarely reach an accuracy greater than 80%. Moreover, the in-game data are highly dependent on the gameplay, and it is difficult to generalise their results to other game genres.

#### **1.2.3.2. Objective methods using sensor data**

Instead of using data that are dependent on the gameplay, the methods in this category factor in data directly gathered from the players to analyse their behaviour. The elimination of the intermediary steps in gathering the players' data enabled these methods to enhance the accuracy of the players' skills evaluation significantly, and methods in this category generally provide higher accuracy than methods in the previous category. Objective methods that use sensor and biological data can be divided into three categories as follows: methods using players' gaze data, methods using keyboard and mouse data, and methods using data gathered by sensors. There are also a few research works using a combination of gaze, keyboard, and mouse data (Khromov et al., 2019; Korotin et al., 2019). These studies are not presented in a separate section and are assessed in the sections related to keyboard & mouse and gaze data. In the following sections, a review of the methods in each category is presented.

##### **1.2.3.2.1. Gaze data**

Methods that employ players' gaze data aim to find whether the difference between players' gaze positions or duration during the game is significant. Korotin et al. (2019) assessed the amateur and professional players' gaze behaviour in CS: GO. Analysing 15 players' gaze data, they observed a significant difference in the players' gaze positions based on their expertise. Their work result is shown in Fig. 4. However, they did not classify the players' skill levels using the gathered data and did not provide any numerical measures for the differences observed in their study. Similarly, Khromov et al. (2019) presented a comparative study of professional and amateur players in CS: GO using their keyboard, mouse, and gaze data. The gaze behaviour of 28 players

**Table 2.** Summary of subjective methods and their results

| <b>Study</b>                   | <b>Number of samples or subjects</b>                             | <b>What they measured</b>                                                                                                                                                 | <b>Result</b>                                                                                                                                                                                                                                        |
|--------------------------------|------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Sörman et al. (2022)           | 337 players' in-game data                                        | Relationship between players' skill levels in the strategy video game Dota 2 and their decision-making ability and experience as measured by the Iowa Gambling Task (IGT) | Their results showed that in-game data related to Medal was a significant predictor of performance in IGT while MMR was borderline significant                                                                                                       |
| Mathonat et al. (2020)         | 298 games' data                                                  | Classifying the skill shots of players in Rocket League                                                                                                                   | The proposed method obtained a mean accuracy of 73.9%                                                                                                                                                                                                |
| Urbaniak et al. (2020)         | 40 players' in-game data                                         | Players' ranking in the game CS: GO                                                                                                                                       | Spearman's correlation coefficient between their results and the real ranking of players was equal to 0.5304                                                                                                                                         |
| Makarov et al. (2018)          | 5000 records for the Dota 2 game, and 162 games' data for CS: GO | Predicting the players' rankings and the winning team in the Dota 2 and CS: GO games, respectively                                                                        | They reported accuracies of 90% and 60% in predicting the players' ranking in the Dota 2 game and the winning team in CS: GO game, respectively.                                                                                                     |
| Clark et al. (2020)            | 2356 games' data                                                 | Predicting the outcome of the Dota 2 game                                                                                                                                 | Their model achieved 66% accuracy                                                                                                                                                                                                                    |
| Katona et al. (2019)           | 10000 games' data                                                | Predict which of the 10 players of either competing team will die within 5 seconds                                                                                        | Their model achieved 0.377 precision with 0.725 recall on test data                                                                                                                                                                                  |
| Hitar-Garcia et al. (2022)     | 7583 games' data                                                 | The relationship between players' skills and the winning probability of the team                                                                                          | Their proposed method for predicting the winning team achieved an accuracy of 70%.                                                                                                                                                                   |
| Jadowski and Cunningham (2022) | 1188 games' data                                                 | A predictive model for rating teams and players' performance in LoL                                                                                                       | Their model achieved 67% accuracy                                                                                                                                                                                                                    |
| Maymin (2021)                  | 150000 games' data                                               | Relationship between players' skills and the win probability of the team                                                                                                  | They extracted extra features such as Ward maps, Heat maps, vision, abilities, and time management to reinforce their analysis. They found that all features had a significant relationship with the team's win probability except for the abilities |
| Kleinman et al. (2021)         | 30 players' data                                                 | The self-regulatory processes of expert, non-expert, and novice players                                                                                                   | They found that the players were significantly different in the forethought phase                                                                                                                                                                    |
| Deja and Myslak (2015)         | 5199542 games' data                                              | The hypothesis that it is possible to predict team performance in LoL using in-game topological data                                                                      | Their method achieved a mean accuracy of approximately 80%                                                                                                                                                                                           |
| Ravari et al. (2017)           | 9000 players' performance data                                   | Predict the match outcomes in the game Destiny using the players' performance data                                                                                        | They achieved an average classification accuracy of 83% with a minimum accuracy of 68% in some matches                                                                                                                                               |

including 24 amateur and 4 professional players were analysed while the amateur players were divided into three groups, namely, low-skill amateur, newbie, and highly-skill amateur. Fig. 6 shows the players' gaze heatmaps. By increasing the players' skill levels, the gaze heatmap becomes more concentrated on the centre. Mann-Whitney test also confirmed their findings by showing a significant difference in the gaze

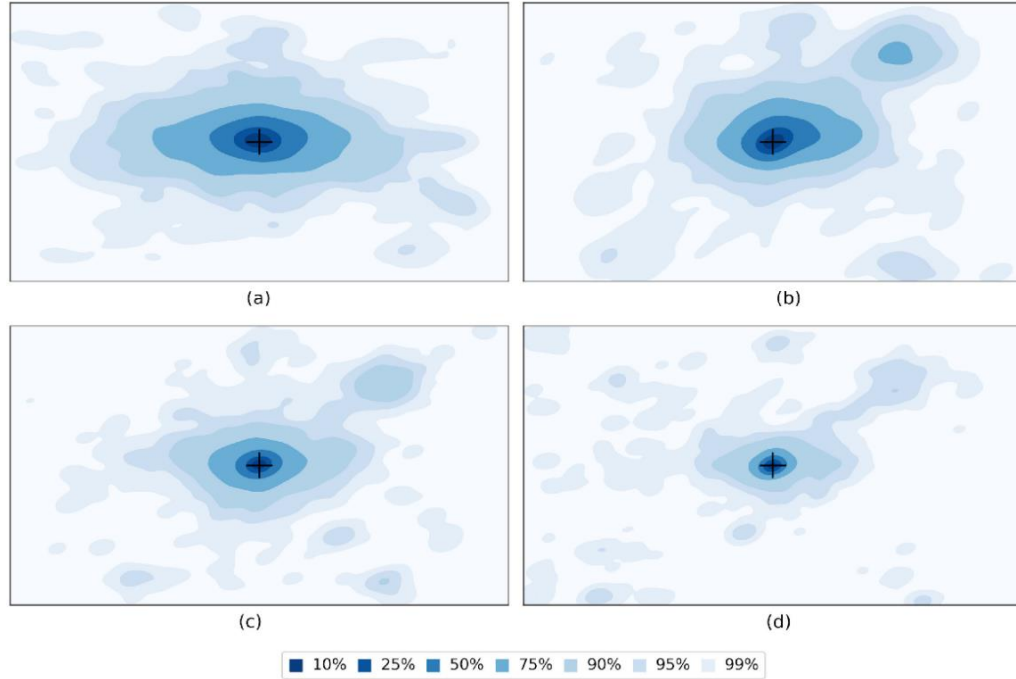


**Fig. 6.** Gaze heatmaps for players of different skill levels in CS:GO according to Khromov et al. (2019). Different coloured regions show the probability of the gaze being inside it. (a) newbies, (b) low skilled amateur player, (c) highly skilled amateur players, and (d) professional players.

behaviour between professional and amateur players. In order to classify the players, they were split into two classes, amateur and professional. An accuracy of 90% for the binary classification problem was reported which was achieved using a mix of gaze, keyboard, and mouse data. Velichkovsky et al. (2019) also analysed players' distribution of visual fixation for CS: GO. For this purpose, an experiment was designed using data of 21 players with 3 different skill levels including 10 newbies who had played the game less than 700 hours, 7 amateur players who had played the game more than 700 hours, and 4 professional players with an experience of more than 10000 hours of playing. They did not report a significant difference in the mean visual fixation duration between players. However, a significant difference in the standard deviation of fixation duration among players was reported. The results showed that players who had higher skill levels also had higher standard deviations. Therefore, their

results conform to the outcome of two previously mentioned studies that higher skilled players tend to concentrate their gaze on some specific locations on the screen longer. However, they did not provide any information about the players' gaze location. Jeong et al. (2022) presented an analysis of players' gaze behaviour in the StarCraft game. For this purpose, seven expert and nine low skilled players played StarCraft at three difficulty levels while their gaze data was being gathered. According to their observations, the expert players' gaze position covered a significantly larger horizontal interval compared to low-skilled players. Moreover, it was observed that the expert players' intensity, number, and velocity of saccades were significantly higher than those of low-skilled players.

Gaze-based methods for the evaluation of players' skills are more applicable to the games in which the players need to focus on some specific items and panels on the screen, and they proved ineffective for other genres of games. For example, Bickmann et al. (2020) investigated if there was a significant relationship between the gaze behaviour of players in FIFA 19 and their skill levels. Gaze data were recorded from 21 FIFA 19 players, including 11 professional and 10 non-professional players. After analysing the gaze behaviour of players in the nine regions of the screen, they reported no significant difference in the number and duration of the fixations. Although the fixation location for the two groups of players was significantly different, they concluded that gaze behaviour could not be a decisive factor in the evaluation of the players' performance. A summary of methods using Gaze data is presented in Table 3.

#### *1.2.3.2.2. Keyboard & mouse data*

Keyboard and mouse data have proved to be effective in differentiating between players with varied cognitive abilities and skills. Korotin et al. (2019) reported an analysis of mouse and keyboard usage by amateur and professional athletes in CS: GO. In particular, the specific periods when the player held down the left mouse button (MOUSE1) while moving forward with the W key, as well as the times when the player used the A and D keys to move left and right, were taken into account. They reported a significant difference between professional and amateur players in mouse and keyboard usage as shown in Fig. 7.

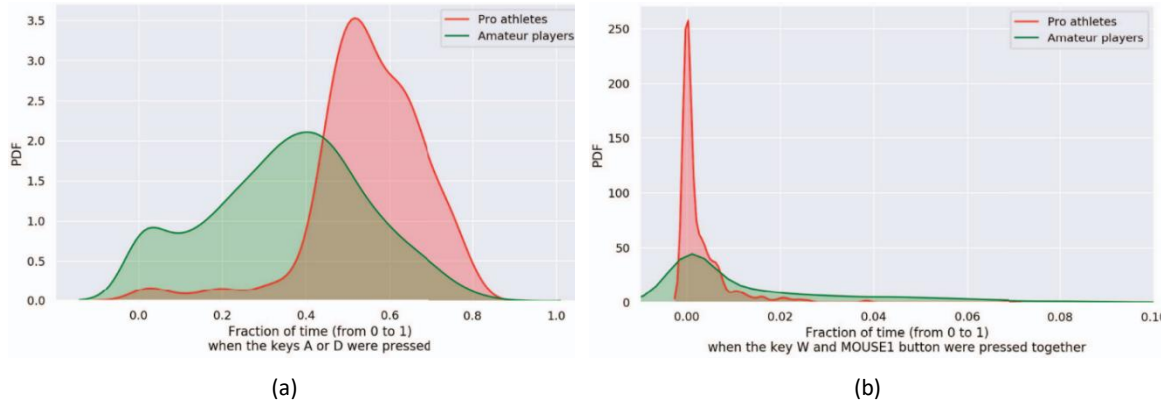


**Fig. 7.** (a) Keyboard and (b) mouse data usage of amateur and professional players in CS:GO Korotin et al. (2019).

**Table 3.** Summary of objective methods using gaze data

| Study                      | Number of participants | What they measured                                                                       | Result                                                                                                                                                                                                                                                                                                                                                |
|----------------------------|------------------------|------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Korotin et al. (2019)      | 15                     | The amateur and professional players' gaze behaviour in CS: GO                           | A significant difference in the players' gaze positions based on their expertise was reported. Their work result is shown in Fig. 4. They did not classify players skill levels.                                                                                                                                                                      |
| Khromov et al. (2019)      | 28                     | Difference in the professional and amateur players' gaze behaviour                       | Fig. 6 shows the players' gaze heatmaps. By increasing the players' skill levels, the gaze heatmap becomes more concentrated on the centre. Mann-Whitney test also confirmed their findings by showing a significant difference between the gaze behaviour of professional and amateur players. They reported a binary classification accuracy of 90% |
| Velichkovsky et al. (2019) | 21                     | Players' distribution of visual fixation for CS: GO                                      | They did not report a significant difference in the mean visual fixation duration between players. However, a significant difference in the standard deviation of fixation duration among players was reported.                                                                                                                                       |
| Jeong et al. (2022)        | 16                     | Difference in the gaze behaviour of low skilled and expert players in the StarCraft game | According to their observations, the expert players' gaze position covered a significantly larger horizontal interval compared to that of low-skilled players.                                                                                                                                                                                        |
| Bickmann et al. (2020)     | 21                     | Relationship between the gaze behaviour of players in FIFA 19 and their skill levels     | They reported no significant difference in the number and duration of the fixations. Although the fixation location for the two groups of players was significantly different, they concluded that gaze behaviour could not be a decisive factor in the evaluation of the players' performance                                                        |

Khromov et al. (2019) conducted a similar study and investigated the relationship between players' keyboard & mouse, as well as gaze data and their skill levels. They first gathered 900 samples from 4 professional and 24 amateur players during the game, from which 9 features per sample were used for the classification. Finally, they achieved a 90% classification accuracy using the extracted features and found that the most important features were related to the keyboard, gaze, and mouse, respectively. Fig. 8 shows the importance of the nine features used for classifying the players' skill levels in their study.

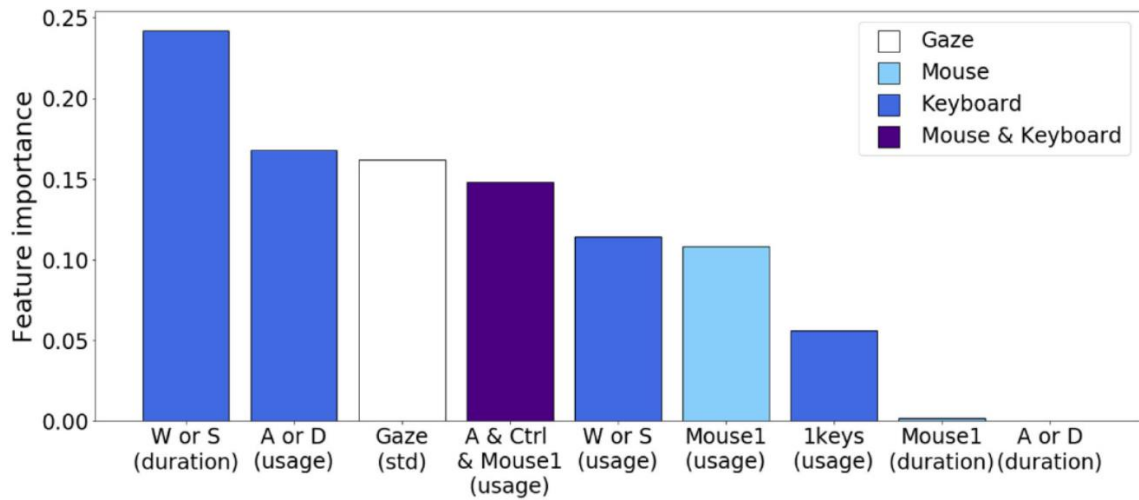


**Fig. 8.** Importance of gaze, keyboard, and mouse features in classifying the players of different skill levels in CS:GO (Khromov et al., 2019). The word “usage” and “duration” denote the mean time and the continuous time interval when the specific keys or mouse buttons were pressed, respectively.

In a study by Pluss et al. (2022), the researchers explored whether the Mobalytics Proving Ground Assessment (MPGA) could distinguish between low skilled and highly skilled players in LoL. MPGA is an online tool designed to evaluate LoL players' proficiency in using a mouse and keyboard to respond to visual stimuli by clicking on randomly appearing targets. To achieve this, they collected 40 LoL players' keyboard and mouse data, comprising 20 low skilled and 20 highly-skilled players. After comparing each group's top scores, they identified 17 variables that differed between the two groups. The researchers concluded that the MPGA is effective in distinguishing between low skilled and highly-skilled LoL players. Buckley et al. (2013) collected mouse and keyboard data from 34 participants to predict their skill levels in the Red Eclipse game. They classified the players into four skill categories and, using features extracted from 60 seconds of gameplay, achieved a classification accuracy of 76%. Although they did not calculate the results of a binary classification, they achieved

accuracy was satisfactory for a four-class problem. Lange et al. (2022) invited 22 CS: GO players including 11 hardcore, 4 professional, and 7 casual players to gather their mouse and keyboard data while playing the game. In the next step, a proposed recursive feature selection was used to identify the top 10 most important features for characterising the players. After analysing the selected features, they discovered that the same features could characterise the differences between amateur and professional players as well as the differences among amateur players of varying skill levels. However, they also found that the same features could not be used to classify professional players of different skill levels. Despite their attempts to balance the dataset with a comparable number of professional and amateur players, they did not use the features to classify the players due to the impact of imbalance and insufficient training data.

Contrary to the majority of research works surveyed here, there are also few studies reporting contradictory results. For example, Toth et al. (2019) analysed the keyboard Colour-World Stroop test data of 129 CS: GO players, including 12 novice players with rankings from silver 1 to silver elite master, 26 intermediate players with rankings from gold nova 1 to master guardian 2, and 60 elite players with rankings from master guardian elite to the global elite, to investigate if there was a relationship between the results of the test and the players' skill levels. Similar to MPGA, the Stroop test is designed to assess players' ability to work with the keyboard using their response to the coloured words popping up on the screen. Contrary to their hypothesis, the Stroop test did not discover a significant difference among players of varying expertise. However, they found that when considering the response time and accuracy simultaneously, elite players demonstrated a significantly better performance than players with lower skill levels. The results could be affected by the nature of the Stroop test which needs the participants to have good skills in differentiating between colours in addition to their abilities in working with keyboards. A summary of methods using Keyboard and mouse data is presented in Table 4.

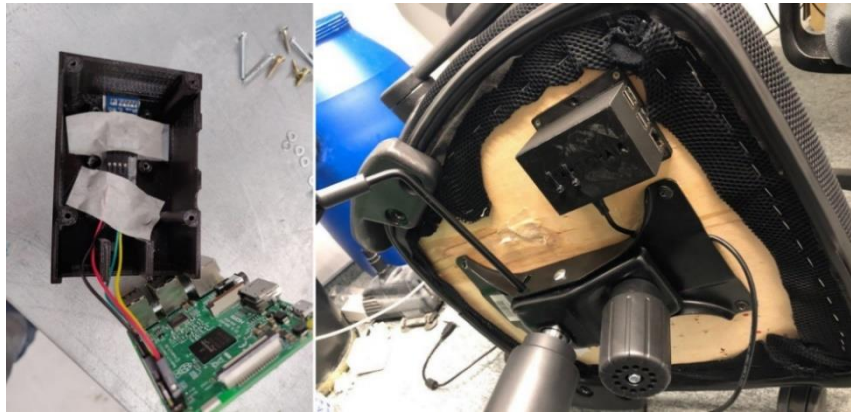
**Table 4.** Summary of objective methods using keyboard and mouse data

| Study                 | Number of participants | What they measured                                                                                                                                    | Result                                                                                                                                                                                                                                                                                                            |
|-----------------------|------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Korotin et al. (2019) | 15                     | Mouse and keyboard usage by amateur and professional athletes in CS: GO                                                                               | They reported a significant difference between professional and amateur players in mouse and keyboard usage as shown in Fig. 7                                                                                                                                                                                    |
| Khromov et al. (2019) | 28                     | The relationship between players' keyboard & mouse, as well as gaze data and their skill levels                                                       | They achieved a 90% classification accuracy using the extracted features and found that the most important features were related to the keyboard, gaze, and mouse, respectively                                                                                                                                   |
| Pluss et al. (2022)   | 40                     | LoL players' proficiency in using a mouse and keyboard to respond to visual stimuli by clicking on randomly appearing targets (MPGA assessment)       | They found 17 variables between the two groups which were significantly different and concluded that the MPGA is effective in distinguishing between low skilled and highly-skilled LoL players                                                                                                                   |
| Buckley et al. (2013) | 36                     | Players' skills in the Red Eclipse game                                                                                                               | They divided the players into four skill classes, Using the features which were extracted from 60 second segments of the game, they reported an accuracy of 76%                                                                                                                                                   |
| Lange et al. (2022)   | 22                     | The top 10 most important features for characterising the players                                                                                     | They discovered that the same features could characterise the differences between amateur and professional players as well as the differences among amateur players of varying skill levels. They also found that the same features could not be used to classify professional players of different skill levels. |
| Toth et al. (2019)    | 129                    | CS: GO players' ability to work with the keyboard using their response to the coloured words popping up on the screen (Colour-World Stroop test data) | The Stroop test did not discover a significant difference among players of varying expertise. However, they found that when considering the response time and accuracy simultaneously, elite players demonstrated a significantly better performance than players with lower skill levels                         |

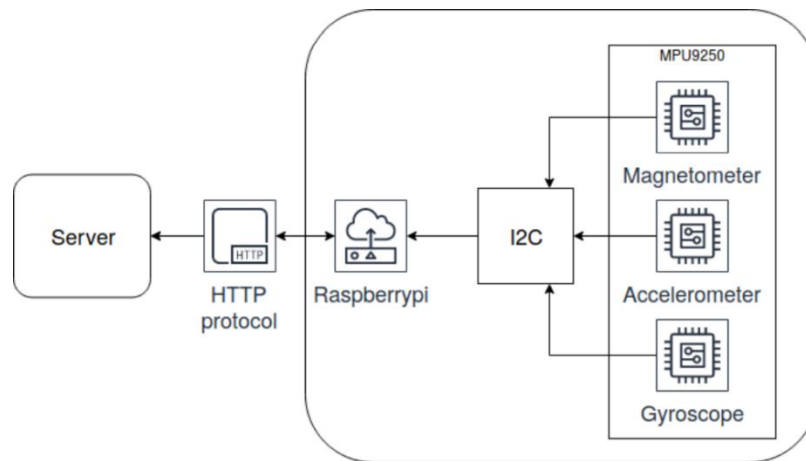
#### 1.2.3.2.3. Sensor data

Despite their advantages, the keyboard & mouse data are still dependent on the gameplay up to some extent. This problem could be alleviated using sensor data directly gathered from the players. Orun and Seker (2012) presented one of the first studies using sensor data for analysing players' cognitive behaviour. For this purpose,

they first recorded two players' GSRs during the different game events. The collected data, along with the reactions of players in various game events, were then input into a classifier to predict the player's identity. The trained model achieved an accuracy of 87%. Despite this high accuracy, the study's small sample size made it challenging to extend the results to larger samples. Additionally, their model requires the reactions data during the game, making it sensitive to the gameplay. Smerdov et al. (2019b) evaluated the players' skill levels using their body movements during the CS: GO game. 19 players, including 10 amateur and 9 professional players were invited to play CS: GO. The players' movement data were then collected using a smart chair as shown in Fig. 9. They split each player's collected data into 3-minute sessions. This resulted in 154 samples which were used for classifying players' skill levels. Their method achieved 86% accuracy by applying the Support Vector Machine (SVM)



(a)



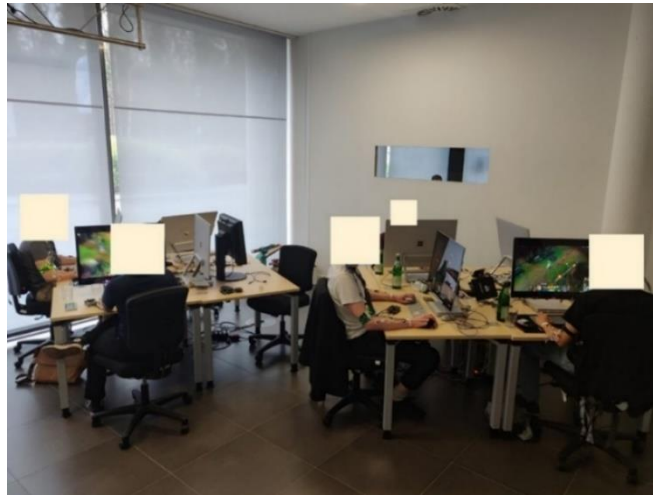
(b)

**Fig. 9.** (a) Smart chair used for gathering the players' movement data and (b) block diagram of the platform Smerdov et al. (2019b).

classifier. Smerdov et al. (2021b) conducted a similar study to see whether including more types of sensor data could increase the accuracy of the predictive model. However, they analysed LoL players in their study. They collected sensor data from one professional and one amateur team in LoL. Each team consisted of 5 players and completed 11 matches in three days. Each match was then split into up to five sessions of 3-minute length. This resulted in 540 samples, which were finally used to classify players' skill levels. The features used for the classification included GSR, heart rate, electromyography data describing the players' muscles' intensity, mouse clicks and keyboard stroke frequencies, pupil diameter, gaze data, face temperature, and 3 more features related to the players' movements. Fig. 10 and Fig. 11 show the game interface, the data collection process, and the extracted features for different players projected on their first two principal components using the t-SNE method



(a)



(b)

**Fig. 10.** (a) LoL game interface and (b) data collection process

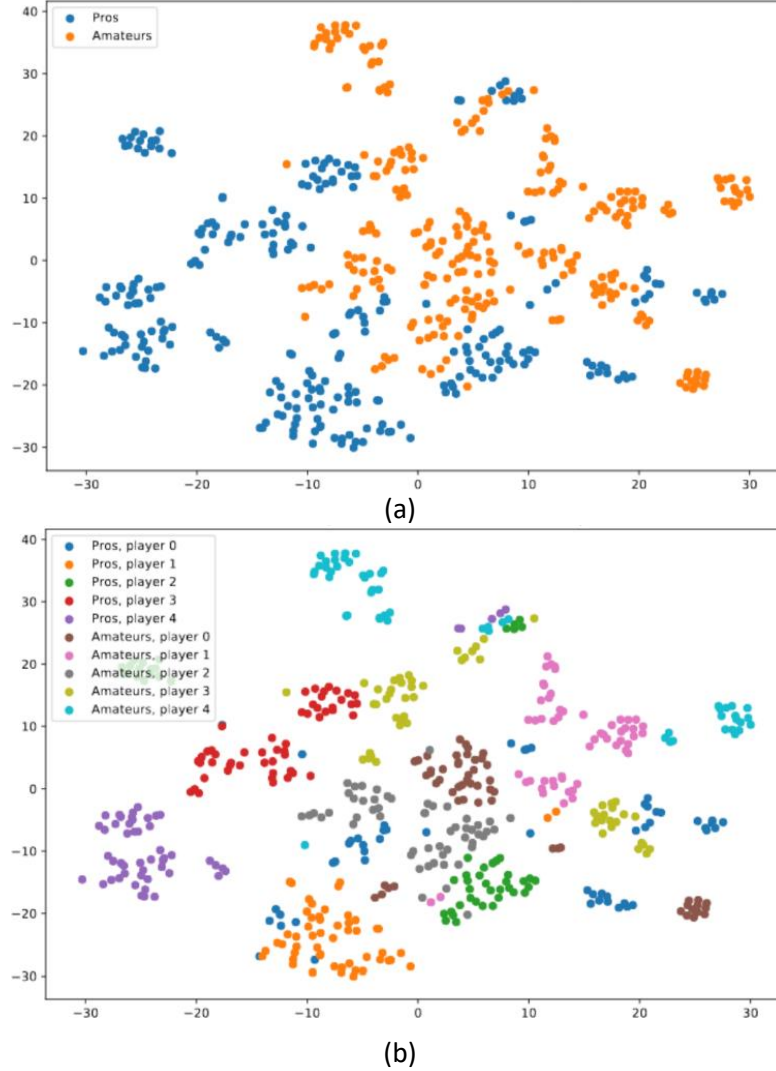


**Fig. 11.** Sensor features projected on their first two components based on (a) players' skill and (b) the players' ID.

(Maaten, 2014), respectively. Finally, they could differentiate between professional and amateur players with 86% accuracy using the extracted features and the SVM classifier. Although they gathered the players' EEG data, they did not use them in their simulations. This is while Smerdov et al. (2021a) used the same data and showed that EEG features are the most important features in evaluating the players' skills compared to other sensor features. Fig. 12 shows the importance of features based on their coefficients in the logistic regression model. IMU and SpO2 denote features related to the inertial measurement unit and pulse oximeter that measure the players' movements and blood oxygen levels, respectively. As can be seen, six out of the first seven features are related to EEG (See (Smerdov et al., 2021a) for the full description of all features).

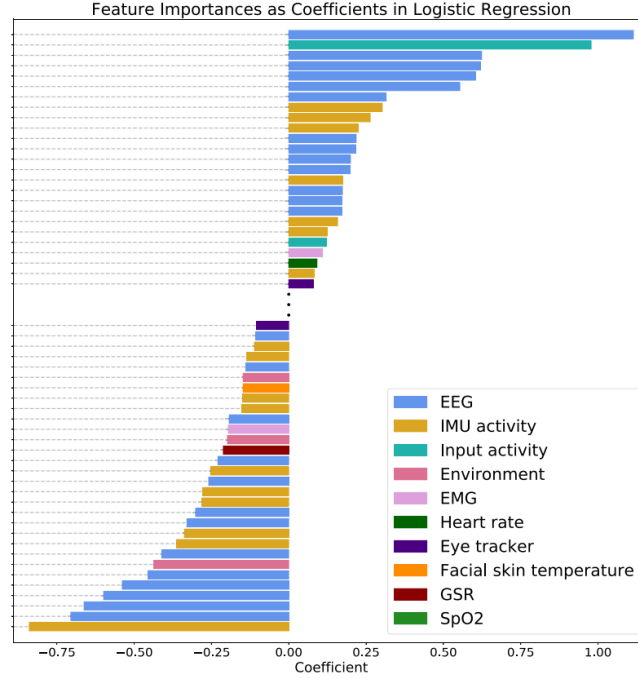


**Fig. 12.** Features' importance based on coefficients in logistic regression model Smerdov et al. (2021a)

Several studies have explored the relationship between players' skill levels and their EEG data. In a study by Melentev et al. (2020), 40 CS: GO players' EEG data, including 20 professional and 20 amateur players were collected and used to predict the players' level of tiredness and skill levels. Using features extracted by FFT, they trained two classifiers to predict if the player is amateur or professional and if the player is tired or fresh, respectively. They achieved accuracies of 92% and 87% using the first and second classifiers, respectively. Using the continuous wavelet transform, Minchev et al. (2009) performed an experiment to find the relationship between moments of "win" and "lose" and players' EEG spectra. 10 players' EEG signals were decomposed into five frequency bands, namely,  $\delta$  (1-4 Hz),  $\theta$  (4-7 Hz),  $\alpha$  (8-13 Hz),  $\beta$  (13-30 Hz), and  $\gamma$  (30-45 Hz). Their results showed an overall decrease in the alpha band for "loss" and an overall increase in the alpha band for "win" events. However, for the same events, they observed the opposite behaviour in the theta band. A similar study was conducted by Meneses-Claudio and Roman-Gonzalez (2018) to find the relationship between Dota 1 players' level of expertise and their EEG signals. To achieve this aim, two players' EEG data, including one hardcore and one newbie, were gathered. Finally, they reported a significant difference in F7 and P3 channels' EEG signals in the players of varying skill levels. The methods using sensor data have been summarised in Table 5.

**Table 5.** Summary of objective methods using sensor data

| Study                                     | Number of participants | What they measured                                                                                        | Result                                                                                                                                                                                                                                                              |
|-------------------------------------------|------------------------|-----------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Orun and Seker (2012)                     | 2                      | Difference between players GSR and reactions                                                              | The trained model achieved an accuracy of 87% in classifying the players' data.                                                                                                                                                                                     |
| Smerdov et al. (2019b)                    | 19                     | Players' skill levels                                                                                     | The trained model classified the players' data with 86% accuracy                                                                                                                                                                                                    |
| Smerdov et al. (2021a)                    | 10                     | Feature importance in evaluating players' skill levels and whether a player will win the future encounter | They reported that EEG features were the most important features in evaluating the players' skills compared to other sensor features. The trained model predicted whether a player would lose the encounter occurring in 10 s in 88.3% of cases with 73.5% accuracy |
| Smerdov et al. (2021b)                    | 10                     | Players skill levels                                                                                      | The trained model classified the players' data with 86% accuracy                                                                                                                                                                                                    |
| Melentev et al. (2020)                    | 40                     | Players' skills and level of tiredness                                                                    | They reported average accuracies of 92% and 87% for the first and second classifications respectively                                                                                                                                                               |
| Minchev et al. (2009)                     | 10                     | The relationship between moments of "win" and "lose" and players' EEG spectra                             | They results showed an overall increase in the alpha band for "win" events and an overall decrease in the alpha band for "loss". However, for the same events, they observed the opposite behaviour in the theta band                                               |
| Meneses-Claudio and Roman-Gonzalez (2018) | 2                      | The relationship between Dota 1 players' level of expertise and their EEG signals                         | They reported a significant difference in F7 and P3 channels' EEG signals in the players of varying skill levels.                                                                                                                                                   |

### 1.2.3.3. Hybrid methods

Hybrid methods avoid restricting the designed model to any data type and employ a combination of all data for prediction. Blom et al. (2019) collected wearable sensor, keyboard & mouse, and in-game data of 11 LoL teams participating in a single best-of-two round-robin pool while each team consisted of eight players. Regarding wearable sensors, they collected data related to the heart rate, GSR, and movement of players,

including a 3-axis accelerometer and a gyroscope measurement. Using the gathered data, they reported a relationship between players' stress level and their in-game and sensor data. However, they did not provide any statistical measures to support their results.

Smerdov et al. (2019a) used a combination of in-game and sensor data to classify 19 LoL players into two groups, namely, professional and amateur. For this purpose, they gathered the players' movement data using a set of sensors including an accelerator, a magnetometer, and a gyroscope. The game API was used to gather the in-game data from which only KDR was used in their simulations. They used eight features including the movement data, KDR, players' age, and gender for the classification and reported a maximum accuracy of 78%. As can be seen, methods in this category tend to have lower accuracy than methods using only sensor data. Also, by utilising the in-game data, they become dependent on the gameplay, which is not a favourable feature. Moreover, several studies have already achieved a higher accuracy of approximately 86% in the prediction of the LoL players' skill levels using only sensor data (Smerdov et al., 2021b, 2019b). Therefore, the existing evidence strongly suggests that not only a combination of the in-game and sensor data does not increase the accuracy but also probably degrades the performance of the predictive model and makes it more dependent on the game's features. For this reason, a few methods used a combination of in-game and sensor data as surveyed in this section.

#### **1.2.4.Applications**

The application of predictive models in GUR started early. (Buckley et al., 2013) was one of the first studies showing how a predictive model could be used for DDA, in which the game adjusts the difficulty level according to players' abilities. For this purpose, they used in-game data such as KDR as well as keyboard and mouse data to predict the players' skills in the first-person shooter Red Eclipse game. All data were gathered from a time window with a size of 5-180 seconds before the prediction point. Considering the small window size used for the data collection, the game could be continuously updated using the outcome of the predictive model. In one study, Lopez-Gordo et al. (2020) set out a first-person shooter VR game which could be adaptively updated using the players' skills predicted by an ANN. Their proposed system is shown in Fig. 2 and described in the first chapter. (Katona et al., 2019) investigated how predictor systems could be utilised to enhance the commentators and audience

experience during Dota 2 matches. For this purpose, they used in-game data from approximately 10000 games, including 5000 professional and 5000 semi-professional games, to predict which of the 10 players of either competing team would die within 5 seconds. Using deep learning for the prediction, their model achieved 0.377 precision with 0.725 recall on test data. Their model could be used for the real-time predictions of kills in Dota 2, thereby giving spectators enough time to move their attention to these key events. Analysing the gaze behaviour of 12 players in the game Call of Duty 4: Modern Warfare, Almeida et al. (2016) discovered the areas of the map that were most explored by the players to help the game designers provide a more efficient experience for the players. Loria and Marconi (2020) proposed an algorithm to predict players' preferences using their in-game behaviour in the game Play&Go. For this purpose, they assumed that the players' activity level could be an indicator of how much they appreciated a specific preference offered by the game. However, only for 51% of the participants, the algorithm could successfully learn the players' preferences. Using in-game data and choosing inefficient features to explain the players' behaviour were some of the reasons for their model's low performance. Tabacof et al. (2021) investigated if an adaptive gaming setup could improve the game experience of players with Spinal Cord Injury (SCI). After analysing data from seven participants with cervical SCI, they observed a significant difference in the players' social connectedness, which is negatively correlated with time since the injury. Nagle et al. (2016) showed how difficulty adaptation in a first-person shooter game could significantly improve the players' experience. For this purpose, they first derived a linear regression model to relate the big five personality traits with enjoyment and gameplay duration in the four difficulty levels. The regression model was then used to choose a difficulty level that could maximise enjoyment and gameplay duration based on the players' personality traits. They reported a significant difference in the players' enjoyment and gameplay duration after applying their model to the game. Soler-Dominguez and Gonzalez (2022) proposed a new research topic to evaluate the cognitive abilities of players using their EEG signals and then create a customised training program for the players based on their cognitive abilities. For this purpose, they proposed to create a Neurofeedback Training (NFT) environment in which the players are presented with an adaptive training program based on their psycho-cognitive abilities evaluated using a predictive model. However, they did not provide any implementation of such an NFT environment.

Balanced matchmaking also proved to be one of the major factors in enhancing the players' engagement and providing an optimal game experience (Baldwin et al., 2013). Without an efficient matchmaking system, players with lower skill levels may end up facing professional players, resulting in an unsatisfactory experience for both sides. For this reason, Marcin et al. (2019) used in-game data to include the engagement factor in the matchmaking process. For this purpose, they first defined a 'churn' objective function according to the in-game data such as kill and then introduced a method to find the optimal matchmaking by maximising the churn function. In another study, Urbaniak et al. (2020) introduced a method for predicting the players' ranking in CS: GO using the HLTV database. However, their model's accuracy was not satisfactory as discussed in section 1.2.3.1.

### **1.2.5. Summary and research gaps**

According to Table 1, studies using subjective methods do not provide accurate quantitative measures in evaluating the eSports players' skill levels. This is mainly because these methods evaluate players' abilities using qualitative metrics such as personality traits.

Among objective methods, the methods using in-game data comparatively have lower accuracy and ignore the players' biological characteristics which play a crucial role during stressful major competitions and particular game situations e.g., 'clutch' in CS: GO discipline. 'To clutch' refers to the phenomenon of athletes under pressure or 'in the clutch' to summon strength, concentration, and whatever else necessary to succeed and change the outcome of the game, usually in the last minutes of a game. Finding the correct in-game data which could predict the players' cognitive abilities and performance is not straightforward or even possible. Some research works tried to address this problem using a combination of in-game data and questionnaires (Halim et al., 2019). However, due to the utilisation of subjective techniques, the accuracy of these methods is unsatisfactory and highly dependent on the dataset and gameplay. This problem makes them less effective for practical applications such as adaptive games, where the game needs to be updated according to the player's features, including their skill levels, to enhance their experience and engagement. Furthermore, this drawback renders these methods largely obsolete for creating efficient training programs for boosting players' skills since such programs entail precise evaluation of players' skill levels and abilities.

The use of in-game data causes another major problem which is the low robustness of the resulting ML models. These models explore the underlying relationship between the in-game variables and some target variables indicating the skill levels of the players. When the rules and features of the game change, the previous model used to predict the relationship between inputs and outputs might not be valid anymore. This is because the in-game variables used to fit the model may drastically change by changing the game's features. Consequently, the model's performance will be highly dependent on a large training dataset containing a wide range of in-game variables. In practice, obtaining such a comprehensive dataset is difficult or even impossible, limiting the extrapolation power of the trained model. Furthermore, given the fast pace of updates in the games' versions and quick development of eSports games, the in-game variables used for training might not be valid for the new versions of the game. Therefore, a large connection between in-game features and the model's accuracy can significantly affect the model's durability. This further demonstrates the advantage of using real-world biological data collected from sensors as they are less sensitive to the changes in the game features and mechanics.

The methods using sensor data have been able to partly surmount the problems mentioned above. However, there is not currently any established procedure for gathering and preprocessing players' sensor data such as keyboard dynamics, eye tracking, etc. This issue could give rise to two problems. Firstly, the comparison between different methods without a unanimous data acquisition system is not as reliable as when their data gathering procedures are the same. The lack of a systematic data gathering and preprocessing may result in including irrelevant data in simulations thereby degrading the performance of the predictive model.

The existing methods also fail to provide a clear answer to more complex questions. Questions like "What features distinguish highly skilled players from low skilled players?" or "What is the difference in body and brain function between professional and amateur players?" are not properly addressed in these methods.

The main motivation of this research is to propose more accurate methods for the evaluation and classification of eSports players' skill levels while mitigating the problems of the previous methods mentioned above. To this end, several research questions and objectives are designed that will be described in the next sections.

### 1.3. Research questions

According to what has been said so far, the main research questions that this project is trying to answer are as follows:

1. How can we gather and preprocess the most important parts of eSports players' sensor data to increase the accuracy of their skill level evaluation?
2. Which features can be extracted from the gathered data to predict eSports players' skill levels more accurately?
3. What is the difference in body and brain regions' function between highly skilled and low skilled eSports players?
4. What AI-based model or algorithm can be used to predict eSports players' skills levels using the extracted features?

The first research question is designed to address the first problem, i.e., the lack of an established method to find the most relevant segments of eSports players' biological data. The second and third research questions are to find the features distinguishing players of different skill levels. The fourth research question aims to find an AI-based model or algorithm comprising different stages, including data preprocessing, feature extraction, feature selection, and classification, to predict eSports players' skill levels more accurately.

### 1.4. Research aims

Overall, this research aims to enhance the performance of systems and applications reliant on the evaluation of eSports players, including eSports teams, eSports games, balanced matchmaking, etc. The research aims in this thesis can be summarised as follows:

1. Improving the accuracy in evaluating the players' skill levels
2. Providing a method for eSports teams to better identify and recruit new players, especially at the junior level where the players' statistics are not sufficiently available
3. Helping eSports teams to create a more effective training program focused on the features that distinguish highly skilled players from low skilled players.
4. Helping game designers enhance the quality of the games and the user experience by creating games adaptable to players' skill levels

## 1.5. Research objectives

Based on the research questions and aims discussed in the previous sections, the main research objectives that this project is trying to achieve can be summarised as follows:

1. To propose a new data acquisition technique capable of considering the most influential parts of eSports players' sensor data.
2. To present a new feature extraction technique which can produce more robust and accurate results in comparison with the existing methods.
3. To discover the difference in body and brain regions' function between highly skilled and low skilled eSports players
4. To propose an AI-based method or algorithm to classify eSports players' skill levels more accurately.

## 1.6. Contribution to the knowledge

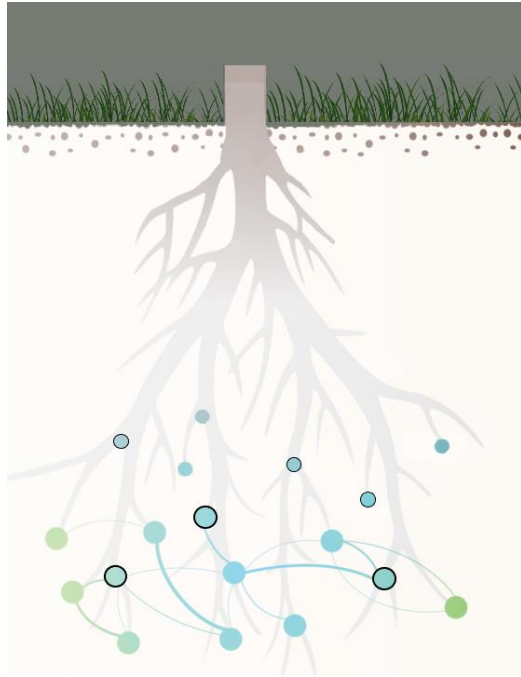
According to the research questions and objectives, this project will make the following contributions to the knowledge:

1. Proposing a novel data acquisition and preprocessing technique
2. Currently, there is a lack of reliable datasets for evaluating eSports players' performance. To the best of my knowledge, the acquired dataset in this project will be the first EEG dataset for evaluating eSports players' skills.
3. Providing a systematic study of eSports players' brain activity during the game for the first time to discover the differences in brain activity between players of different skill levels.
4. Presenting a new feature extraction technique capable of finding features that distinguish highly-skilled players from low-skilled players.
5. Presenting a new algorithm to classify players' skill levels, which is not dependent on the game settings and features. The proposed method could be applied to athletes' data in other sports, such as soccer, basketball, etc.
6. Providing a comparison of different classification techniques for evaluating eSports players' performance.
7. This thesis also presents a novel and robust brain source localization method, called ReLORETA, which is capable of reconstructing the EEG source signals inside the brain without having access to an accurate head

model or magnetic resonance image (MRI) for simulation Noroozi et al. (2022)

## 1.7. The thesis's structure

In chapter 1, the research background and a comprehensive literature review have been presented, and the research questions, research aims, and objectives have been discussed. As this project utilises EEG data, the prerequisite materials about EEG and related topics are presented in chapter 2. These materials are crucial to understanding the proposed methodology which is presented in chapter 3. The reader can skip chapter 2 and only study the summary section to gain the required information if they are familiar with the EEG method. However, to fully understand the proposed methodology in chapter 3, it is necessary to study the entire chapter 2. The results and discussion are finally presented in Chapter 4 and 5, respectively.



# CHAPTER 2

## Prerequisite materials and methods

### OVERVIEW

This chapter includes the required information about the EEG method and related topics such as brain source localisation (BSL) methods which are used to reconstruct the EEG signals inside the brain. A novel BSL method is also proposed in this chapter to deal with the problems of the existing BSL techniques. The chapter summary and required information for the proposed methodology in chapter 3 are presented at the end.

## 2.1. Introduction

Understanding the proposed methodology in this thesis entails general knowledge of the EEG method and how it works. In this chapter, different topics related to EEG data will be introduced and discussed in detail. The reader can also skip to the summary section to gain the required information if they are already familiar with EEG.

EEG has the advantages of accessibility and low cost. The inherently high temporal resolution of EEG allows precise measurement of the moment-by-moment dynamics of brain electrical activity. However, EEG data are sensitive to noise and other uncertainties such as the head conductivity and may produce misleading results if not preprocessed well. Moreover, EEG data are captured on the surface of the brain and do not provide accurate information about the regions inside the brain where they originated from. For this reason, the use of brain source localisation (BSL) techniques has gained ground in recent years. These methods are capable of reconstructing the EEG signals inside the brain, referred to as source signals, before reaching the brain's surface. These methods are also able to find the exact brain regions involved in producing the source signals, which is referred to as brain source localisation. These features enable these methods to provide an accurate image of brain regions' activities during different tasks, including playing games, which is the case in this thesis. The generated brain images, i. e. source signals, can then be used to compare and classify players of different skill levels. However, existing BSL methods lack sufficient accuracy and require exact data about the EEG setup and participants, including the electrode positions, head conductivity, etc, which is not practical in most cases. In this chapter, a new BSL technique will be proposed to overcome these problems.

In what follows, the basics of the EEG method and data will be presented first. In the next step, the current BSL methods and their disadvantages will be discussed. A new BSL method will then be proposed to overcome the problems of the existing methods. The source signals generated by the novel BSL method presented in this chapter will be employed in the proposed methodology in chapter 3 to reconstruct the eSports players' brain source signals.

## 2.2. EEG

### 2.2.1. Scientific basis

The brain is a significant part of the human body consisting of millions of neurons, which play an important role in controlling the body's behaviour and reactions in

response to internal/external motor/sensory stimuli. Neurons in the nervous system communicate with each other and other types of cells in the body, particularly muscles, by sending and receiving electrical signals. EEG is a technique that records these electrical activities using a set of sensors (electrodes) placed on the scalp. For this reason, brain signals are sometimes referred to as EEG signals, or simply EEG, in the literature (Louis et al., 2016).

The neural activity recorded by EEG represents the summation of the potentials, known as excitatory and inhibitory postsynaptic potentials, produced by relatively large groups of neurons firing synchronously. The majority of EEG signals are thought to be primarily generated in the cerebral cortex by so-called cortical pyramidal neurons that are oriented perpendicularly to the brain's surface. The summated electrical activity of neurons can be represented as a field with positive and negative poles, which is known as a dipole. The dipole vector, or direction of energy flow, is parallel to the orientation of the pyramidal cells generating the activity.

There are interactions between cortical neurons (i. e. neurons near the surface of the brain) and between cortical and subcortical neurons (i. e. far from the brain surface, or alternatively, inside the brain) lying in structures such as the thalamus. Any sinusoidal rhythmic activity seen on the EEG is thought to represent oscillatory communications between the cortex and deeper, subcortical structures. These communication loops occur when the cortex is at rest or is not performing any specific task. Once the cortex has a task to perform, the electrical activity of the cortex desynchronises, and lower amplitude, faster electrical rhythms take predominance until the cortex completes its task and returns to a resting state (Louis et al., 2016). The most well-known example of this is the Post Dominant Rhythm (PDR), which is an oscillatory, 8.5- to 12-Hz rhythm seen in the posterior head regions during relaxed wakefulness with eyes closed. The PDR attenuates when eyes open because eye opening starts a stream of visual input that activates the visual cortex at the back of the head. With activation, the visual cortex desynchronises and transiently disrupts communication with the thalamus in order to process the new visual information. This desynchronisation results in the transient disappearance of the PDR. In the following section, basic information about the brain's structure, which is crucial in understanding the EEG data, is presented.

### **2.2.2. Brain lobes**

The outermost layer of the brain that gives the brain its characteristic wrinkly appearance is known as the cerebral cortex. The cerebral cortex could be divided into

two hemispheres connected by a thick bundle of nerve fibres called the corpus callosum. Each of the hemispheres is divided into four lobes, namely, frontal, parietal, temporal, and occipital as shown in Fig. 13 (“Parts of the Brain,” 2022).

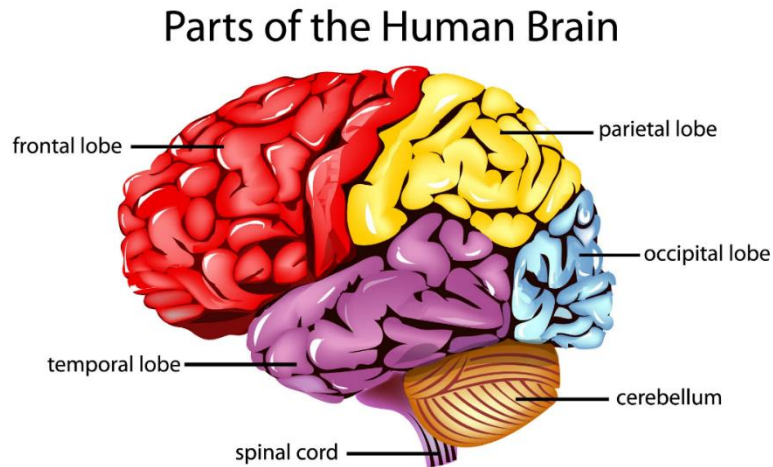


**Fig. 13.** The brain lobes (“Parts of the Brain,” 2022)

Although brain functions rely on many regions across the entire brain working together, it is well established that each lobe could be associated with certain functions. Fig. 14 briefly describes the functions that each part of the brain is believed to be responsible for (“Lobes of the brain,” 2016).

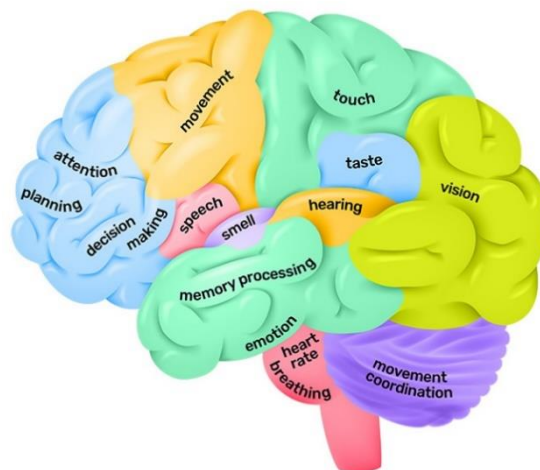


**Fig. 14.** The functions associated with different parts of the brain (“Lobes of the brain,” 2016)

#### 2.2.2.1. *Bumps and grooves of the brain*

In humans, the brain lobes consist of several bumps and grooves (or fissures) known as gyrus and sulcus, respectively. The brain’s folding shape, and the resulting gyri and

sulci, increase its surface area and enable more cerebral cortex matter to fit inside the skull. Fig. 15 shows the brain's folding, including gyri and sulci ("Lobes of the brain," 2016; Wikipedia, 2007).

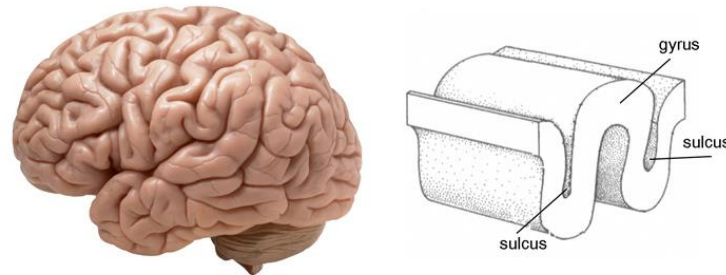


**Fig. 15.** The brain's gyrus (bump) and sulcus (groove) ("Lobes of the brain," 2016; Wikipedia, 2007)

#### 2.2.2.2. *Frontal lobe*

The frontal lobe is the largest lobe of the brain comprising almost one-third of the hemispheric surface. It is separated from the parietal lobe by a space called the central sulcus, and from the temporal lobe by the lateral sulcus. The frontal lobe is associated with higher executive functions, including planning, emotional regulation, reasoning, problem solving, and movement (Collins and Koechlin, 2012; "Lobes of the brain," 2016). The frontal lobe includes the motor cortex which is believed to be responsible for planning and coordinating movements. It also contains the prefrontal cortex, which is responsible for initiating higher-level cognitive functioning, and Broca's Area, which is essential for language production (Collins and Koechlin, 2012; "Parts of the Brain," 2022)

#### 2.2.2.3. *Parietal lobe*

The parietal lobe is positioned above the occipital lobe and behind the frontal lobe. It is separated from the frontal lobe by the central sulcus. The parietal lobe is responsible for integrating sensory information, including spatial sense and navigation (proprioception), touch, temperature, pressure and pain. The parietal lobe helps us to build a coherent picture of the world around us by integrating information from the body's senses. This allows us to perceive our bodies through somatosensory information (e.g., through touch, pressure, and temperature). It can also help with visuospatial processing, reading, and number representations (mathematics). The somatosensory cortex is another part of the parietal lobe that receives and processes sensory information and integrates them into a representational map of the body. This enables the brain to pinpoint the exact area of the body where sensation is felt and to

perceive the weight of objects, shape, and texture (Berlucchi and Vallar, 2018; “Lobes of the brain,” 2016).

#### 2.2.2.4. *Temporal lobe*

As the name suggests, the temporal lobe is located near the temples of the head and separated from the frontal lobe by the lateral fissure. This lobe is associated with different functions, including understanding, recognising language, memory acquisition, perception, face recognition, object recognition, and auditory information processing. The primary auditory cortex is a part of this lobe that receives auditory information from the ears and processes it so we understand what we’re hearing (e.g. words, laughing, and crying). Certain regions in the temporal lobe process complex visual information, including faces and scenes. The left temporal lobe is the most dominant in people and is responsible for language, learning, memorising, forming words, and remembering verbal information. The left lobe also contains a vital language centre known as Wernicke’s area, which is essential for language development. The hippocampus, a region of the brain important for memory, learning and emotions, lies in the medial temporal lobe (i. e. the part of the temporal lobe which is closer to the middle of the brain). Also, the right temporal lobe is believed to be associated with learning and memorising non-verbal information and determining facial expressions (“Lobes of the brain,” 2016; “Parts of the Brain,” 2022; Patel et al., 2023).

#### 2.2.2.5. *Occipital lobe*

The occipital lobe is located at the back of the brain behind the temporal and parietal lobes and is the major visual processing centre in the brain. It receives sensory information from the eyes’ retinas and then encodes it into different visual data. The occipital lobe’s functions include assessing the size, depth, and distance, object and facial recognition, determining colour information, and mapping the visual world. The primary visual cortex, also known as V1, lies in the occipital lobe. This cortex receives visual information from the eye’s retinas and relays it to several secondary visual processing areas to interpret depth, distance, location, colour, and the identity of the objects in the field of vision (“Lobes of the brain,” 2016; “Parts of the Brain,” 2022; Rehman and Al Khalili, 2023).

#### 2.2.2.6. *Brodmann’s areas*

Brodmann’s areas of the cortex are a system that divides the cerebral cortex into 52 regions based on cytoarchitectonic (cell size, spacing or packing density, and lamination) differences. The regions were identified in 1909 by German Neurologist,

Korbinian Brodmann and are still very widely used as a standardised nomenclature. Brodmann classified brain regions based on the fact that the human cortex is composed of six cellular layers. He realised that the density and architecture of these layers vary from region to region, and these patterns are visible under a light microscope (Gaillard, n.d.). Brodmann's areas are typically shown on a map of the brain surface, but each region is continued through the depth of the cerebral cortex. Although Brodmann believed these regions apply to all mammals, some of them are only present in non-human primates. Some regions have also been subsequently subdivided. Fig. 16 illustrates Brodmann's areas of the human brain ("Brodmann areas," n.d.). There are other brain maps that divide the brain based on the functions of different regions or their gyral and sulcal anatomy. Although Brodmann's areas are not defined based on the regions' functions, in some cases, the boundary identified by Brodmann is also a functional boundary. For instance, Brodmann's area 17 contains the primary visual cortex. Brodmann's area 18 is considered to be a higher-order visual cortex. Brodmann's areas 3, 1, and 2 are associated with Somatosensory functions, with part of area 3 being recognised as the primary somatosensory cortex. Brodmann's areas 41 and 42 are believed to be involved in audition (hearing). Also, Brodmann's area 4 is associated with the primary motor cortex (the output for motor commands), while the premotor cortex (where the decision to move likely arises) is found in Brodmann's area 6 (Jacobs, 2011). Table 6 shows 82 brain regions used in simulations, including the Brodmann's areas (abbreviated as BA) in both hemispheres, their respective MNI ("CoordinateSystems - Brainstorm," n.d.) coordinates, the anatomical or functional regions that correspond to each area, and other anatomical regions, which were used in simulations but did not correspond to any Brodmann's area.

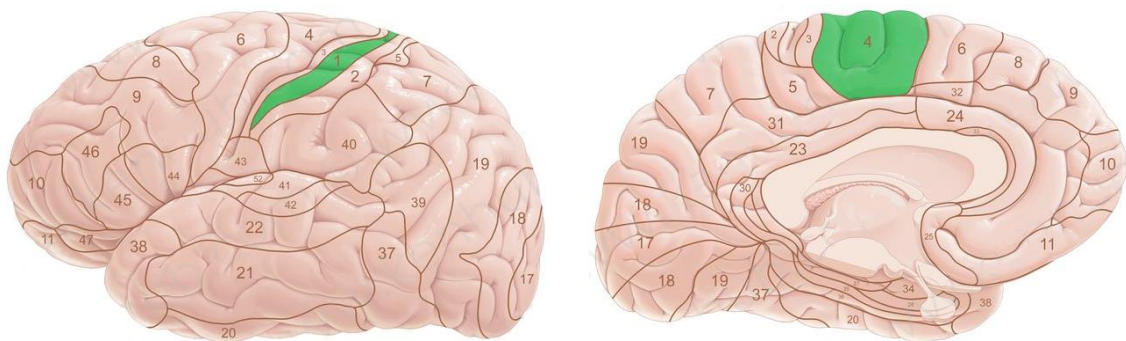


**Fig. 16.** Brodmann's areas of the human brain

**Table 6.** The list of 82 brain regions used in simulations and their respective MNI coordinates.

| BA | Region name                                                       | MNI coordinates | BA    | Region name                               | MNI coordinates |
|----|-------------------------------------------------------------------|-----------------|-------|-------------------------------------------|-----------------|
| 1  | Right postcentral gyrus                                           | [41, -27, 47]   | 31    | Left posterior cingulate cortex           | [-8, -49, 38]   |
| 1  | Left postcentral gyrus                                            | [-40, -27, 47]  | 32    | Right pregenual anterior cingulate cortex | [6, 33, 16]     |
| 4  | Right precentral gyrus                                            | [38, -18, 45]   | 32    | Left pregenual anterior cingulate cortex  | [-5, 39, 20]    |
| 4  | Left precentral gyrus                                             | [-36, -19, 48]  | 34    | Right dorsal entorhinal cortex            | [31, 3, -15]    |
| 5  | Right superior parietal lobule (somatosensory association cortex) | [15, -33, 48]   | 34    | Left dorsal entorhinal cortex             | [-28, 3, -17]   |
| 5  | Left superior parietal lobule (somatosensory association cortex)  | [-14, -33, 48]  | 36    | Right para hippocampal gyrus              | [26, -19, -25]  |
| 6  | Right supplementary motor cortex                                  | [28, -1, 51]    | 36    | Left para hippocampal gyrus               | [-26, -20, -22] |
| 6  | Left supplementary motor cortex                                   | [-28, -2, 52]   | 37    | Right fusiform gyrus                      | [47, -51, -14]  |
| 7  | Right superior parietal lobule (visuo-motor coordination)         | [23, -60, 61]   | 37    | Left fusiform gyrus                       | [-47, -52, -12] |
| 7  | Left superior parietal lobule (visuo-motor coordination)          | [-18, -61, 55]  | 38    | Right temporal pole                       | [40, 11, -30]   |
| 8  | Right frontal eye fields                                          | [22, 26, 45]    | 38    | Left temporal pole                        | [-43, 13, -30]  |
| 8  | Left frontal eye fields                                           | [-23, 24, 44]   | 39    | Right angular gyrus                       | [46, -59, 31]   |
| 9  | Right dorsolateral prefrontal cortex                              | [35, 39, 31]    | 39    | Left angular gyrus                        | [-46, -60, 33]  |
| 9  | Left dorsolateral prefrontal cortex                               | [-39, 34, 37]   | 40    | Right supramarginal gyrus                 | [51, -33, 34]   |
| 10 | Right anterior prefrontal cortex                                  | [23, 55, 7]     | 40    | Left supramarginal gyrus                  | [-53, -32, 33]  |
| 10 | Left anterior prefrontal cortex                                   | [-23, 55, 4]    | 41&42 | Right primary auditory cortex             | [50, -21, 7]    |
| 11 | Right Orbitofrontal area                                          | [12, 37, -19]   | 41&42 | Left primary auditory cortex              | [-52, -19, 7]   |
| 11 | Left Orbitofrontal area                                           | [-11, 38, -19]  | 44    | Right broca and inferior frontal gyrus    | [49, 12, 17]    |
| 13 | Right posterior insular cortex                                    | [44, 4, 0]      | 44    | Left broca and inferior frontal gyrus     | [-48, 13, 17]   |
| 13 | Left posterior insular cortex                                     | [-42, 4, -1]    | 45    | Right broca and inferior frontal gyrus    | [46, 26, 7]     |
| 17 | Right primary visual cortex                                       | [11, -78, 9]    | 45    | Left broca and inferior frontal gyrus     | [-47, 27, 6]    |
| 17 | Left primary visual cortex                                        | [-11, -81, 7]   | 46    | Right middle frontal gyrus                | [43, 38, 12]    |
| 18 | Right lateral occipital lobe                                      | [29, -92, 2]    | 46    | Left middle frontal gyrus                 | [-46, 38, 8]    |
| 18 | Left lateral occipital lobe                                       | [-19, -92, 2]   | 47    | Right pars orbitalis                      | [38, 30, -12]   |
| 19 | Right cuneus                                                      | [44, -75, 5]    | 47    | Left pars orbitalis                       | [-40, 31, -13]  |
| 19 | Left cuneus                                                       | [-45, -75, 11]  | --    | Right caudate                             | [14, 13, 11]    |
| 20 | Right inferior temporal gyrus                                     | [48, -17, -31]  | --    | Left caudate                              | [-11, 13, 10]   |
| 20 | Left inferior temporal gyrus                                      | [-47, -14, -34] | --    | Right putamen                             | [25, 3, -1]     |
| 21 | Right middle temporal gyrus                                       | [60, -27, -9]   | --    | Left putamen                              | [-26, 3, -1]    |
| 21 | Left middle temporal gyrus                                        | [-59, -25, -13] | --    | Right thalamus                            | [10, -19, 6]    |
| 22 | Right superior temporal gyrus                                     | [54, -19, 1]    | --    | Left thalamus                             | [-9, -17, 6]    |
| 22 | Left superior temporal gyrus                                      | [-57, -20, 1]   | --    | Right globus pallidus                     | [19, 0, -2]     |
| 23 | Right posterior cingulate cortex                                  | [9, -45, 24]    | --    | Left globus pallidus                      | [-20, 0, -2]    |
| 23 | Left posterior cingulate cortex                                   | [-10, -45, 24]  | --    | Right nucleus accumbens                   | [10, 10, -12]   |
| 24 | Right anterior cingulate cortex                                   | [5, 5, 31]      | --    | Left nucleus accumbens                    | [-11, 9, -11]   |
| 24 | Left anterior cingulate cortex                                    | [-5, 1, 32]     | --    | Right amygdala                            | [21, -1, -22]   |
| 25 | Right subgenual area                                              | [7, 17, -14]    | --    | Left amygdala                             | [-24, 0, -21]   |
| 25 | Left subgenual area                                               | [-5, 17, -13]   | --    | Right hippocampus                         | [28, -22, -14]  |
| 30 | Right dysgranular retrosplenial cortex                            | [12, -45, 8]    | --    | Left hippocampus                          | [-29, -19, -15] |
| 30 | Left dysgranular retrosplenial cortex                             | [-12, -43, 8]   | --    | Right hypothalamus                        | [3, -1, -11]    |
| 31 | Right posterior cingulate cortex                                  | [8, -48, 39]    | --    | Left hypothalamus                         | [-4, -2, -11]   |

### 2.2.3. EEG electrodes

EEG signals are recorded by placing electrodes on the scalp with a conductive gel or paste. The scalp area is usually cleaned before recording to reduce impedance due to dead skin cells. Electrodes can be placed on the scalp individually, where each of which is attached to a wire. EEG headsets, caps, or nets with embedded electrodes are

other methods to record EEG signals. These methods are particularly common when high-density arrays of electrodes are needed. Fig. 17 Shows different EEG recording devices.

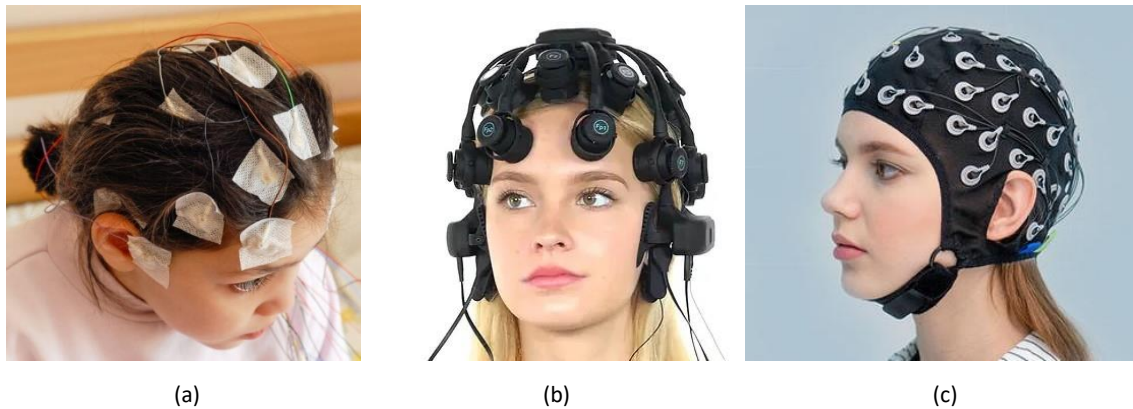


**Fig. 17.** Different EEG devices. (a) Individual electrodes (seermedical, 2020), (b) EEG headset (“EEG 20 Channels - EEG headset with dry electrodes,” n.d.), and (c) EEG cap (“Pro - 32-channel EEG cap by Wuhan Greentek | MedicalExpo,” n.d.)

The electrode locations on the scalp can be arranged according to different standard placement systems, including 10-20, 10-10, and 10-5 systems (Jurcak et al., 2007). The 10-20 system was first presented by Klem et al. (1999) to standardise the EEG placement on the scalp. The system uses the relationship between electrode locations and the underlying area of the cerebral cortex whilst ensuring that all brain regions are covered (“The 10-20 System for EEG,” n.d.). The numbers “10” and “20” represent the distances between adjacent electrodes, which is either 10% or 20% of the total front-back distance or right-left distance of the skull. The total distance is calculated between the following anatomical locations on the scalp: nasion and inion (front-back direction) and the two preauricular points (right-left direction) as shown in Fig. 18. The placement of the electrodes can be determined along the front-back and right-left directions with the pre-specified proportions as follows: the distance between the anatomical landmarks and the first electrode in each direction is 10% of the total distance in the same direction. The distance between other electrodes in each direction is 20% of the total distance in the same direction. For example, the Fp1 electrode is placed at 10% of the total back-front distance from the nasion, and the Fz electrode is placed at 20% of the total back-front distance from Fp1.

Electrodes are traditionally labelled using one or more letters and a number (e. g. Fp1). The letter of each electrode’s label represents the brain region that the electrode covers. From front to back, the electrodes are labelled as follows: Fp (pre-frontal or

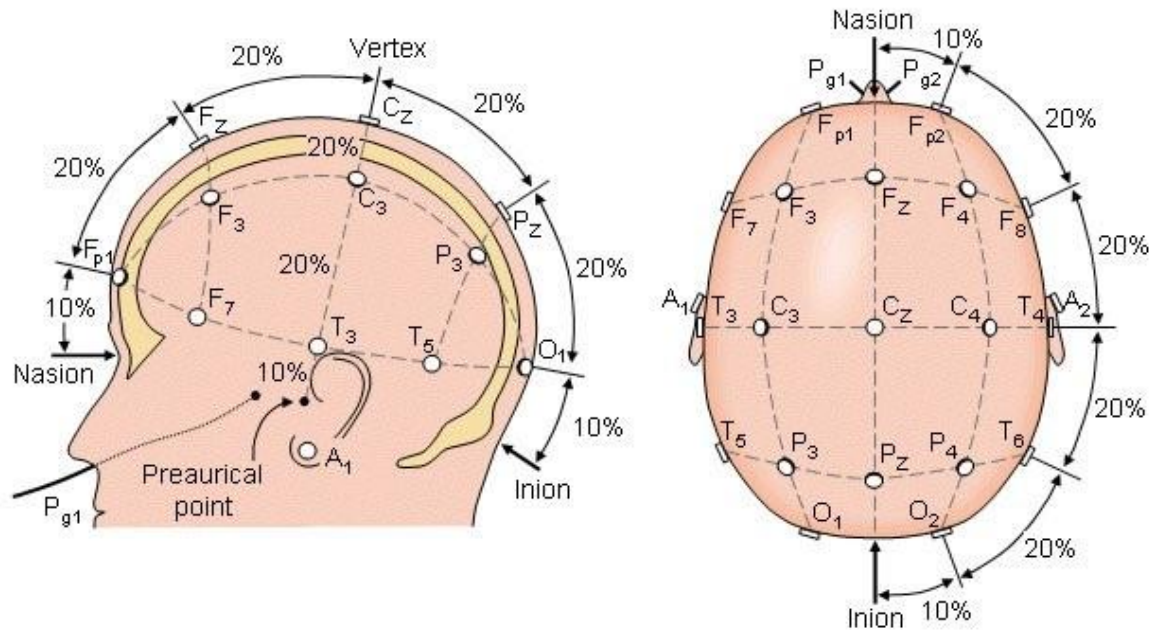


**Fig. 18.** The 10-20 EEG electrode placement systems Shriram et al. (2012).

frontal pole), F (frontal), C (central line of the brain), T (temporal), P (parietal), and O (occipital). In higher density systems, such as 10-10 and 10-5 systems, additional electrodes are placed between the 10-20 system electrodes. The labels of the additional electrodes are then a combination of multiple letters ordered from front to back. Letters M and A are also sometimes used to refer to the mastoids or earlobes, respectively.

The number of the electrode labels shows the distance between each electrode and the electrode placed on the midline of the brain. Electrodes lying on the midline of the brain are labelled with a 'z', which stands for zero. As we move away from the midline, the electrode numbers increase. Electrodes on the left and right hemispheres are labelled with odd and even numbers, respectively. Fig. 19 shows the 10-20 system layout with the corresponding brain lobes.

The 10-10 system (10% system) and 10-5 system (5% system) are two other EEG placement methods that provide a higher resolution compared to the 10-20 system. These systems, which are extensions of the original 10-20 system, use additional electrodes between the existing electrodes of the 10-20 system. This results in a higher density measurement. Fig. 20 shows a layout of the 10-10 systems and the corresponding brain lobes.

# The 10-20 System

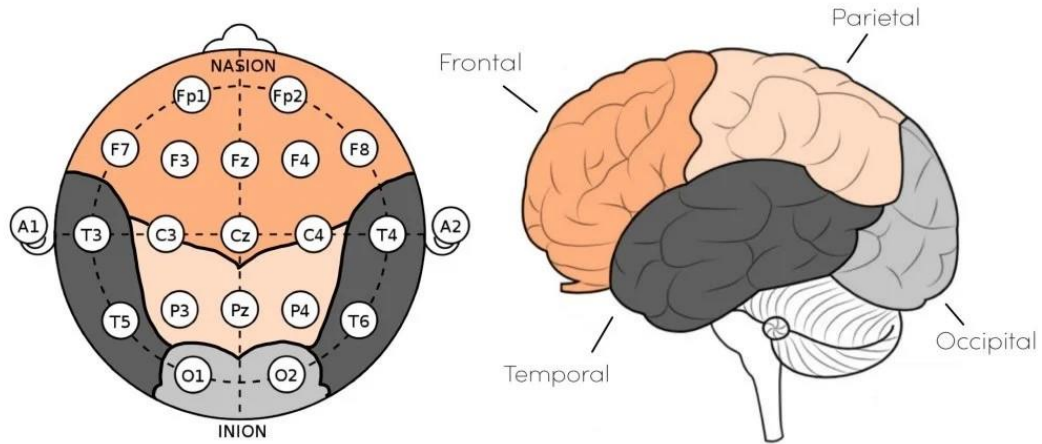


**Fig. 19.** The electrode layout of the 10-20 system (left) and corresponding brain regions (right) ("The 10-20 System for EEG," n.d., pp. 10–20)

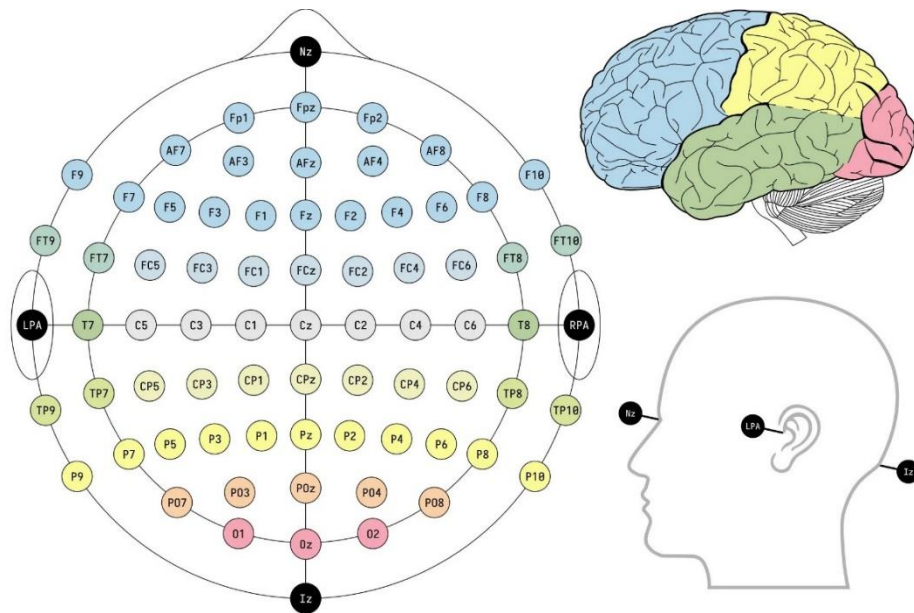


**Fig. 20.** The 10-10 system and the corresponding brain lobes ("The 10-20 System for EEG," n.d., pp. 10-).

The positioning of electrodes on the scalp, also referred to as montage, could be done using two methods: referential and bipolar. In the referential method, each electrode records the potential difference between itself and a single reference electrode which is placed on either of ear lobes. The electrodes on the left and right hemispheres use the left and right ear lobe electrodes as the reference, respectively.

On the other hand, in the bipolar method, the potential differences are recorded between electrode pairs, for example, between Fp2 and F4, or F4 and C4 (Kumar and Bhuvaneswari, 2012).

The use of the EEG electrode placement system ensures the repeatability and reproducibility of the experiment results. Of course, this entails that electrodes are placed correctly on the desired locations on the scalp. Therefore, it is important to choose a headset with the right size and to check if the Cz and reference electrodes are placed correctly.

#### 2.2.4. EEG signal characteristics

EEG signal amplitude is small and measured in microvolts ( $\mu V$ ). In the frequency domain, EEG signals could be decomposed into five bands, namely  $\delta$  (0.5 Hz–4 Hz),  $\theta$  (4 Hz–8 Hz),  $\alpha$  (8 Hz–13 Hz),  $\beta$  (13 Hz–30 Hz), and  $\gamma$  (greater than 30 Hz). The decomposition of EEG signals into different frequency bands could be achieved using different methods, including Fast Fourier Transform (FFT) (Nussbaumer, 1981) and Wavelet Transform. FFT decomposes a signal into sinusoids, but wavelet decomposition uses an underlying wavelet function for decomposition. Examples of EEG signals in the five frequency bands are also shown in Fig. 21 (Abhang et al., 2016a).

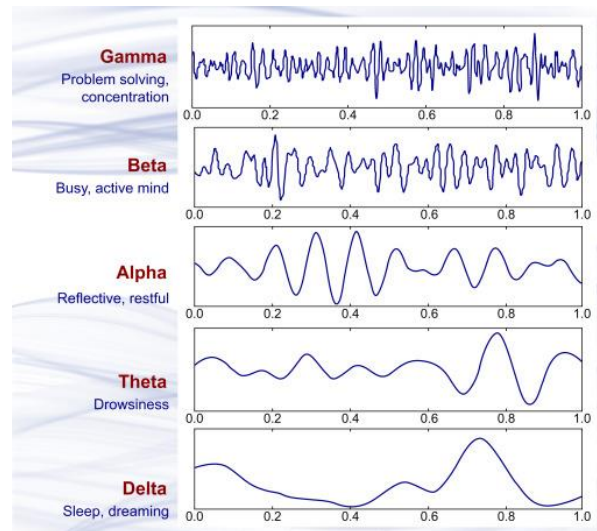


**Fig. 21.** EEG signals with dominant frequencies belonging to delta, theta, alpha, beta, and gamma bands

##### 2.2.4.1. Delta frequency band

Delta waves have the highest amplitude among all frequency bands and are the slowest recorded brain waves in human beings. They are often dominant waves in

infants and young children and are associated with the deepest levels of relaxation and restorative, healing sleep. Delta waves are located in the frontal regions of the brain in adults and posterior regions of the brain in children. However, they are produced in the thalamus as well. Physiologically, these waves are abnormal for adults who are awake and salient during their slow-wave sleep. In babies, delta waves may also occur during specific continuous attention tasks. They are found in all stages of sleep, especially in stages 3 and 4. Stage 3 sleep is believed to have less than 50% delta wave activity, while stage 4 sleep has more than 50% delta wave activity. Delta waves are prominently seen in patients with learning problems, brain injuries, inability to think, and severe ADHD. Suppressing these waves could lead to poor sleep and an inability to rejuvenate the body and revitalise the brain. Adequate production of delta waves improves restorative/deep sleep, immune system, and natural healing, and helps us feel completely rejuvenated (Abhang et al., 2016b).

#### *2.2.4.2. Theta frequency band*

Theta band reflects the state between wakefulness and sleep and is related to the subconscious mind. It is rarely seen in awake adults but is perfectly normal in young children up to 13 years old. In older children and adults, it usually appears during meditation or in hypnotic, drowsy, and sleeping states (of course not during the deepest stages of sleep). Theta waves are also dominant during focus, prayer, and spiritual awareness and are associated with activity from the limbic system and hippocampal regions (Mari-Acevedo et al., 2019). The hippocampus generates some of the largest EEG signals among all brain structures, which is due to the high density of its neural layers. Sometimes, there are dominant regular waves with frequencies of 4–10 Hz in EEG signals, often continuing for many seconds. This EEG pattern is known as the hippocampal theta rhythm. Theta waves originating in the midfrontal cortex are specifically related to cognitive behaviour. Alterations in these signals are believed to play a role in multiple psychiatric and neurodevelopmental disorders (McLoughlin et al., 2022).

#### *2.2.4.3. Alpha frequency band*

Alpha waves are observed in all age groups and are usually seen in adults mostly over the posterior (occipital) portions of the head during wakefulness, but they may also be found in the central (parietal) or temporal regions. They are believed to be produced by the white matter of the brain. These waves are more dominant when the subject is resting with the eyes closed. Alpha waves act as a bridge between conscious and

subconscious minds and are associated with the production of serotonin, a neurotransmitter that increases satisfaction, happiness and optimism. Introverts tend to show fewer alpha waves, and for this reason, these waves have been linked to extroversion (introverts show less), as well as creativity (alpha waves are observed in more creative subjects when listening and reaching a solution for creative problems), and mental work. When producing alpha waves, we tend to experience good moods and calmness (Kumar and Bhuvaneshwari, 2012).

#### *2.2.4.4. Beta frequency band*

Beta waves are observed in the conscious states, such as talking, decision making, and problem solving, and are produced in both hemispheres of the frontal and parietal lobes. They are associated with the production of cortisol, a hormone that regulates many vital functions throughout the body, including metabolism and the immune response (Kumar and Bhuvaneshwari, 2012). It also plays a crucial role in helping the body respond to stress. Having the right amount of beta waves allows us to focus. Having too much beta waves causes stress, anxiety, high arousal, and an inability to relax, while its suppression can lead to Attention Deficit Hyperactivity Disorder (ADHD), daydreaming, depression, and poor cognition. These waves could be divided into three groups: low beta waves (13–15 Hz), mid-range beta waves (15–20 Hz), and high beta waves (20–30 Hz). The first group, known as “beta one” waves, are associated mostly with quiet, focused, introverted concentration. The second group, known as “beta two” waves, are associated with increases in performance, energy, and anxiety. The third and last group is known as “beta three” waves and is associated with significant stress and anxiety, paranoia, high arousal, and high energy (Abhang et al., 2016b).

#### *2.2.4.5. Gamma frequency band*

A gamma wave is the fastest brain activity and the only frequency group found in every part of the brain. Due to small amplitude and high contamination by muscle artefacts and noise, gamma waves are not widely studied as compared to other slower brain waves. Dominant gamma activity in temporal regions of the brain is associated with memory processes. Some studies reported that gamma activity plays a role in working memory, attention, and long-term memory processes. Gamma activity is also associated with psychiatric disorders such as epilepsy, Alzheimer’s disease, hallucination, and schizophrenia (Malik and Amin, 2017). A well-regulated and efficient gamma activity improves memory, whereas a gamma deficiency creates learning disabilities.

Table 7 summarises different EEG frequency bands discussed above and their characteristics.

**Table 7.** Characteristics of five EEG frequency bands Abhang et al. (2016a)

| Frequency band name | Frequency          | Brain state                                  | Neurotransmitter (Hormone)                                                | Location                                                    |
|---------------------|--------------------|----------------------------------------------|---------------------------------------------------------------------------|-------------------------------------------------------------|
| $\delta$            | 0.5 Hz–4 Hz        | Deep rest, dreamless sleep                   | Human growth hormone, Melatonin                                           | Frontal regions in adults and posterior regions in children |
| $\theta$            | 4 Hz–8 Hz          | Deeply relaxed                               | Serotonin, Acetylcholine, Anti-cortisol, Endorphins, Human growth hormone | Thalamic regions                                            |
| $\alpha$            | 8 Hz–13 Hz         | Daydream, calm, resting with the eyes closed | Serotonin, Endorphins, Acetylcholine                                      | Posterior regions                                           |
| $\beta$             | 13 Hz–30 Hz        | Active thinking, concentration               | Adrenaline, Cortisol, Norepinephrine, Dopamine                            | Frontal and parietal                                        |
| $\gamma$            | Greater than 30 Hz | Conscious perception, Hyper alertness        | Serotonin, Endorphins                                                     | All regions, especially frontal, temporal, and parietal     |

### 2.2.5. EEG signal artefacts

The low amplitude of EEG signals (microvolts) makes them highly sensitive to contamination from unwanted sources of interference. Artefacts are undesired signals recorded by the EEG device but not generated by the brain. As some artefacts may look like true epileptiform abnormalities or seizures, knowing the true EEG signal waveform is important in distinguishing artefacts from the brain waves. Artefacts are mainly divided into two groups: physiological artefacts and non-psychological artefacts. The psychological artefacts originate from the body (electrophysiological sources other than the brain). The non-physiological artefacts, on the other hand, originate from the environment and external sources outside the body (“Common physiological EEG artefacts,” n.d.). The main psychological artefacts include ocular activity, muscle activity, cardiac activity, perspiration, and respiration. The main non-psychological artefacts include electrode pop, cable movement, incorrect reference placement, AC electrical and electromagnetic interference, and body movements.

### 2.2.5.1. Psychological artefacts

#### 2.2.5.1.1. Ocular activity

It is well established that eyes can be modelled by magnetic dipoles. This makes them capable of distorting the surrounding electric field when they move. The amplitude of the distortion caused by this artefact, which is known as the EOG (Electrooculogram) signal, can be around 100-200 microvolts, i. e. one order of magnitude larger than the EEG signal. This artefact could be generated by blinking, lateral movement, and eye movements, and its amplitude is almost proportional to the angle of gaze. Blinking produces a sudden high amplitude fluctuation on the EEG signals in the frontal area electrodes, which is more apparent in those electrodes closer to the eyes. Lateral movements of the eye also affect the frontal regions but are more dominant in the regions closer to the temples of the brain. This artefact can be confused with low frequency EEG signals in delta and theta bands. Fig. 22 and Fig. 23 show examples of blinking and lateral eye movement artefacts as well as the electrodes and regions of the brain where these artefacts are more dominant ("Common physiological EEG artefacts," n.d.). From Fig. 22, it can be seen that high amplitude voltage peaks resulting from blinking mainly affected frontal electrodes, including F7, Fpz, and F8. In the frequency domain, low frequency bands, including delta and theta bands, have been more affected by this artefact and have a high power amplitude. In Fig. 23, the effect of lateral eye movement can be seen in F7 and F8 electrodes with quick changes in amplitude in different directions, which is due to the dipole created by the eye. This artefact is also called a phase reversal artefact, as it may mimic a change of phase. In the frequency domain, low frequency bands, inducing delta and theta bands, have higher power amplitude as a result of the lateral eye movement.

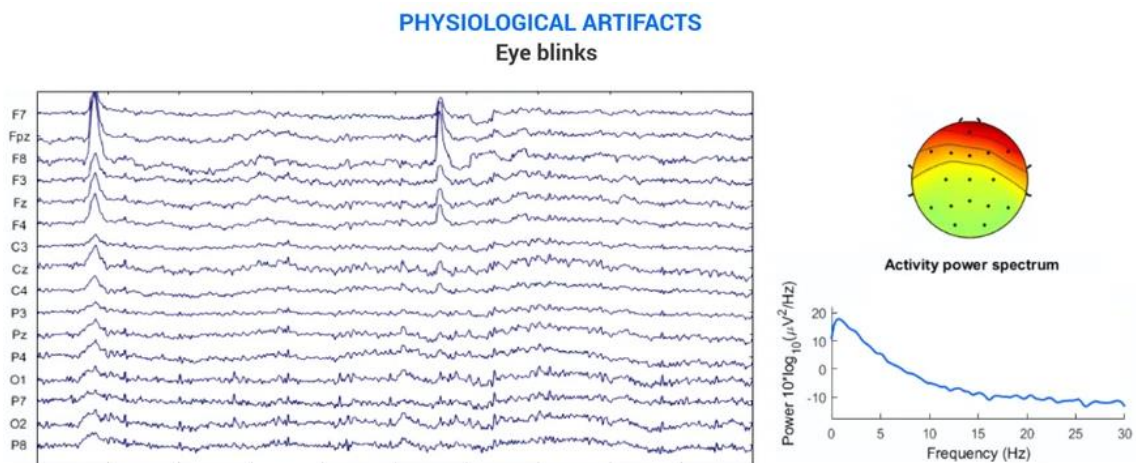


Fig. 22. The blinking artefact (picture adapted from ("Common physiological EEG artefacts," n.d.))

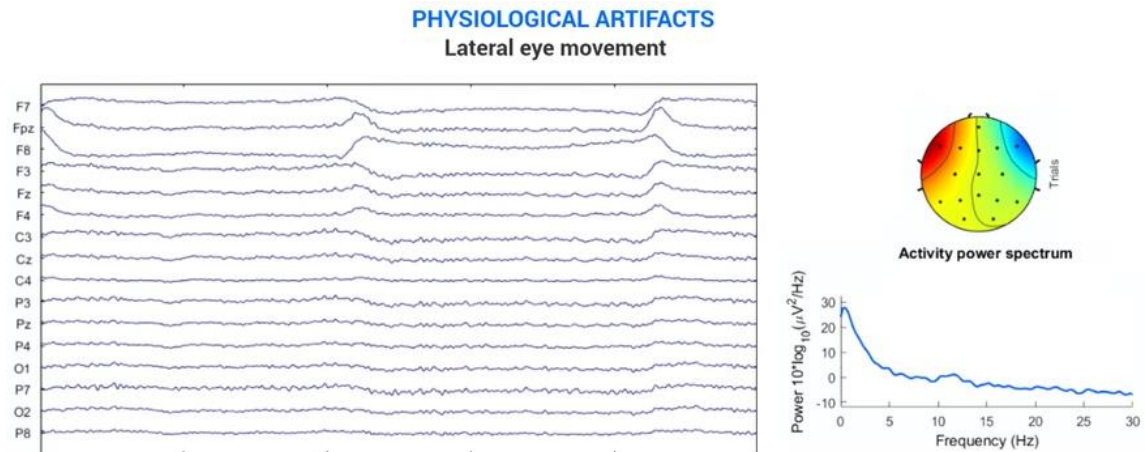


**Fig. 23.** Lateral eye movement artefact (picture adapted from ("Common physiological EEG artefacts," n.d.)).

#### 2.2.5.1.2. Muscle activity

Muscles can produce electrical activity if they are contracted. The resulting signal, which is called Electromyography (EMG), can distort the recorded EEG signals. These high-frequency artefacts can be observed by the naked eye and may be caused by different muscle activities, including clenching the jaw, swallowing, tension in neck and shoulder muscles, chewing, sucking, talking, sniffing, frowning, grimacing, and hiccupping. In the time domain, this artefact manifests as a high frequency signal that overlaps the EEG signal. The amplitude of the artefact is directly proportional to the strength of the muscle activity. In the frequency domain, the effect of this artefact is in the form of overlapping signals in high frequencies, such as beta and gamma EEG bands ("Common physiological EEG artefacts," n.d.). Fig. 24 shows a muscle activity artefact resulting from jaw clenching in the time and frequency domain. The jaw clenching is observable in the C3 electrode in the time domain and causes EEG signals to have a higher power in high frequencies, including beta and gamma bands.

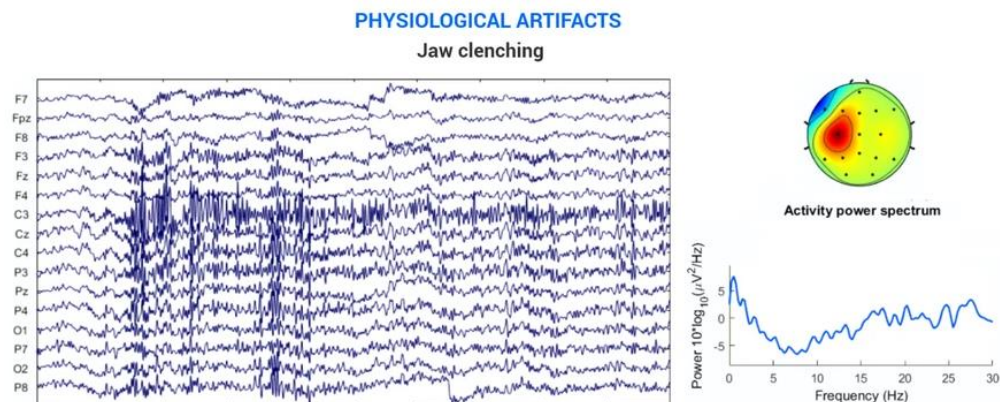


**Fig. 24.** Jaw clenching artefact (picture adapted from ("Common physiological EEG artefacts," n.d.)).

#### 2.2.5.1.3. Cardiac activity

Cardiac activities are electrical activities generated by the heart. The resulting signal is called Electrocardiogram (ECG). This artefact is also known as the pulse artefact. Although ECG has a low amplitude on the scalp, sometimes, depending on the participant's body shape and the placement of the electrode, we see a rhythmic distortion in the EEG signals, which is caused by the pulse artefact. This artefact can be detected as a rhythmic pattern, corresponding to the heartbeats, that overlaps the EEG signal. However, it is not easy to detect the cardiac activity in the frequency domain, as the frequency components of the ECG overlap EEG band frequencies. Fig. 25 shows the cardiac activity in EEG signals (Correa et al., 2007).

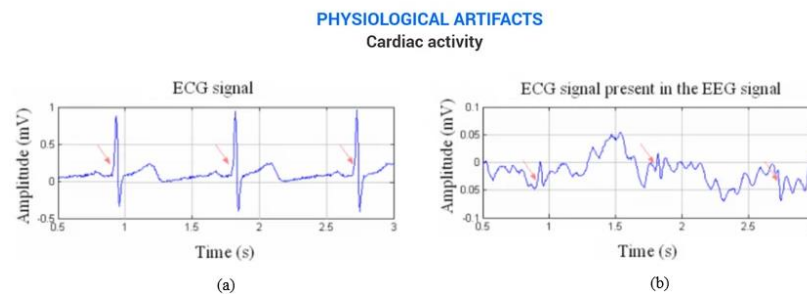


**Fig. 25.** The cardiac activity. (a) the ECG signal and (b) the ECG signal present in the EEG signal Correa et al. (2007).

#### 2.2.5.1.4. Perspiration

Perspiration is caused by sweat glands of the skin and can affect the electrical baseline of the electrodes. Intense perspiration could even create short circuits between electrodes. This artefact can be observed as slow waves overlapping the EEG signals in the time domain and low frequency waves overlapping the delta and theta frequency bands in the frequency domain. Fig. 26 shows the perspiration artefact in the time and frequency domains ("Common physiological EEG artefacts," n.d.).

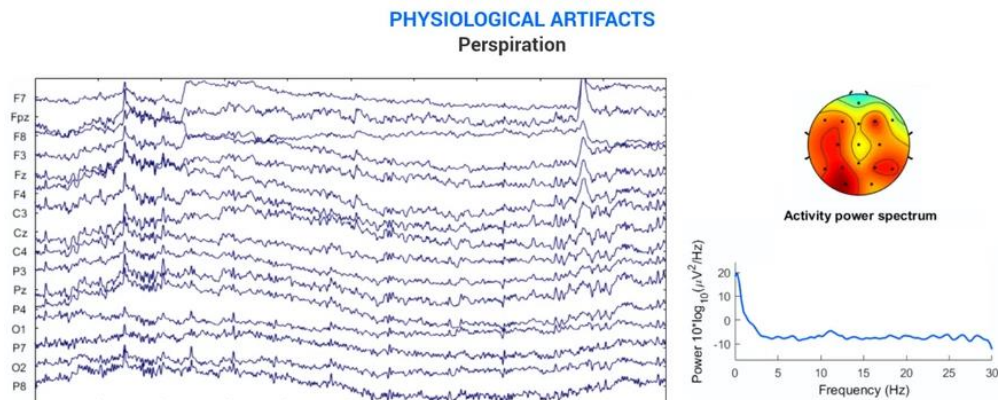


**Fig. 26.** The perspiration artefact in the time and frequency domains (picture adapted from ("Common physiological EEG artefacts," n.d.)).

#### 2.2.5.1.5. Respiration

Respiration causes the chest and head to move when inhaling and exhaling. This movement can affect the contact between the electrodes and the scalp, especially if the participant is lying on the bed. Therefore, this artefact is more common in resting state EEG Signals (rsEEG) recording. In the time domain, respiration may be observed as slow waves synchronised with breathing that overlap the recorded EEG signals. In the frequency domain, it will be in the form of low frequency artefact overlapping delta and theta bands. Fig. 27 shows an example of the respiration artefact.

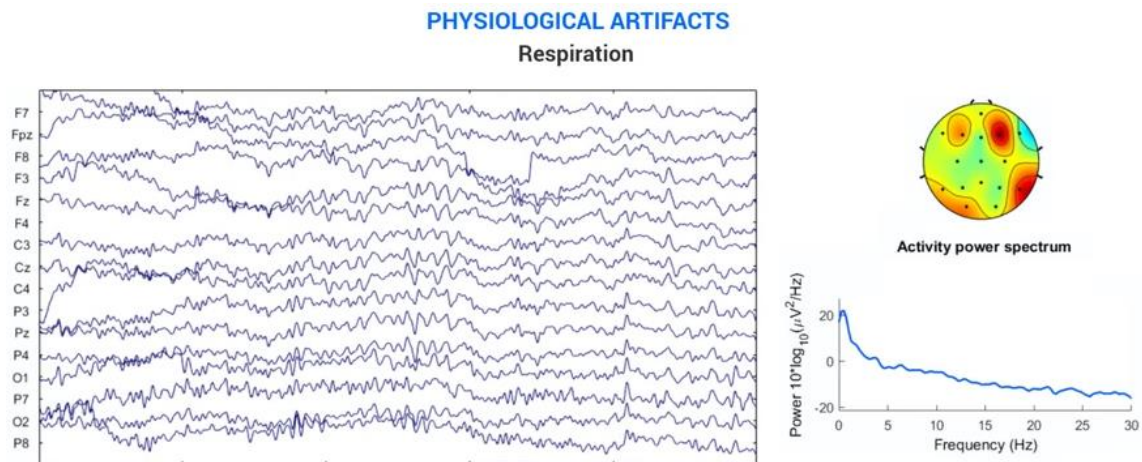


**Fig. 27.** The respiration artefact in the time and frequency domains (picture adapted from ("Common physiological EEG artefacts," n.d.)

#### 2.2.5.2. Non-psychological/technical artefacts

##### 2.2.5.2.1. Electrode cap

Temporary disruptions in the contact between EEG electrodes and the scalp can distort the recorded EEG signals. This is mainly due to variations in the contact potential between the electrodes and the scalp. In the time domain, this artefact will appear as abrupt and high amplitude distortions in the recorded EEG signals that are concentrated in a single electrode. However, it is not easy to associate this artefact with any specific change in the frequency domain due to the wide range of possible distortions. Fig. 28 shows the distortion in the F3 electrode caused by touching the electrode ("Common physiological EEG artefacts," n.d.).

##### 2.2.5.2.2. Cable movement

This artefact is caused by the movement of the cables connecting the electrodes and the amplification system. This movement can in turn cause changes in the electromagnetic fields and distort the recorded EEG signals. It may also affect the

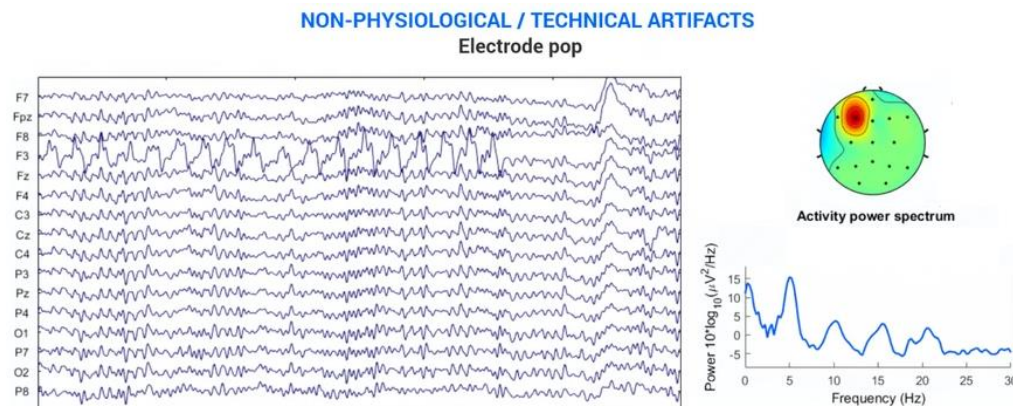


**Fig. 28.** The electrode pop artefact in the recorded EEG signals (picture adapted from (“Common physiological EEG artefacts,” n.d.)).

contact between electrodes and the scalp. Due to its nature, this artefact is very dependent on the type of movement both in time and frequency domains. If the movement is rhythmic, the artefact will be observed as distortions overlapping the recorded EEG signals in the time domain and with the same rhythm of the cable movement. Some peaks that are irrelevant to EEG signals will also appear in the frequency domain. Fig. 29 shows EEG signals collected with a Bitbrain versatile 16 channel device and filtered between 0.5 and 30 Hz (“Common physiological EEG artefacts,” n.d.). In this figure, the cable movement distortion appeared in the Cz and Pz electrodes. Some unusual frequencies can also be observed in the Pz electrode and the frequency domain.

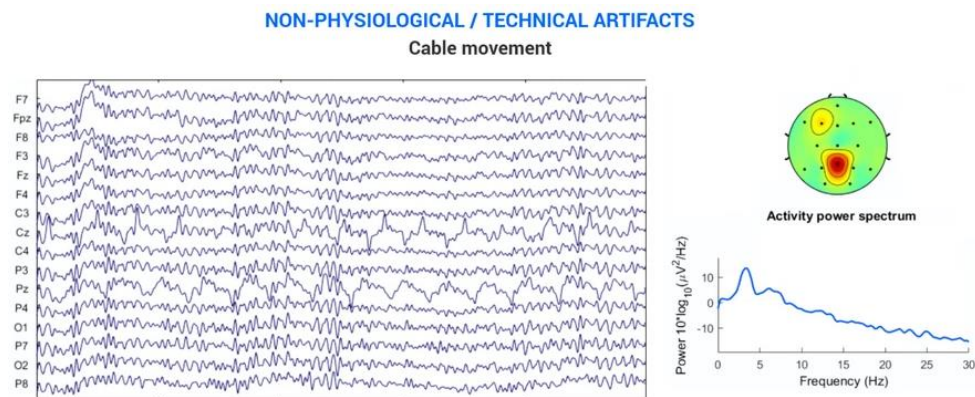


**Fig. 29.** Cable movement artefact in recorded EEG signals (picture adapted from (“Common physiological EEG artefacts,” n.d.)).

### 2.2.5.2.3. Incorrect reference placement

If the reference electrode is not placed in the correct location or there is bad contact between the reference electrode and the scalp, the recorded signals will not be EEG

signals. This artefact causes abrupt high-amplitude changes in all channels (electrodes) and high power in all channels in the frequency domain. If the reference electrode is placed properly, EEG signals recorded by all channels will slowly converge to actual EEG signals. Fig. 30 shows an example of this artefact (“Common physiological EEG artefacts,” n.d.).

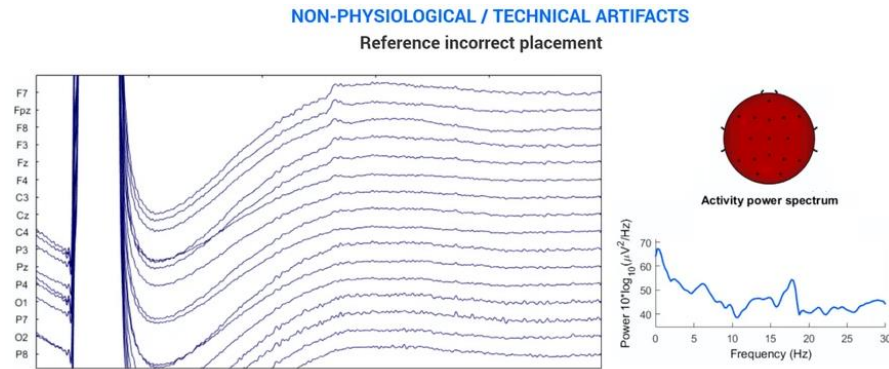


**Fig. 30.** EEG artefact due to incorrect reference electrode placement (picture adapted from (“Common physiological EEG artefacts,” n.d.))

#### 2.2.5.2.4. AC electrical and electromagnetic interferences

The recorded EEG signals can be distorted by the surrounding magnetic fields produced by AC power sources and wires if the wire shielding is insufficient. This artefact will appear as a high frequency noise (50 or 60 Hz) continuously overlapping the EEG signals in the time domain. In the frequency domain, a big spike will appear around 50 or 60 Hz, depending on the applied AC frequency standard. Fig. 31 shows an example of this artefact in the EEG signals recorded in Spain. A high amplitude peak appeared around 50 Hz, which is the standard powerline frequency in Spain.

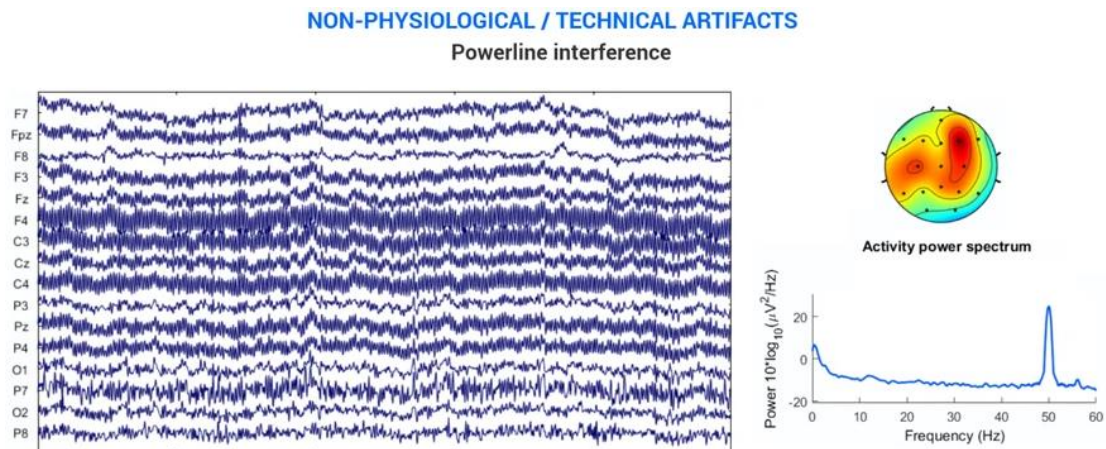


**Fig. 31.** The AC line artefact in the recorded EEG signals. EEG signals were recorded in Spain and the powerline frequency is 50 Hz (picture adapted from (“Common physiological EEG artefacts,” n.d.)).

#### 2.2.5.2.5. Body movements

When moving the body, the contact between EEG electrodes and the scalp can be affected. This can in turn distort the recorded EEG signals. This artefact can be generated by any body movement, including head and arm movements, walking, and running. In the time domain, this artefact manifests in the form of slow waves with a rhythm corresponding to the rhythm of the movement. In the frequency domain, the effect of the body movement will appear in lower frequencies and overlaps the power of the signals in the delta and theta bands, as shown in Fig. 32.

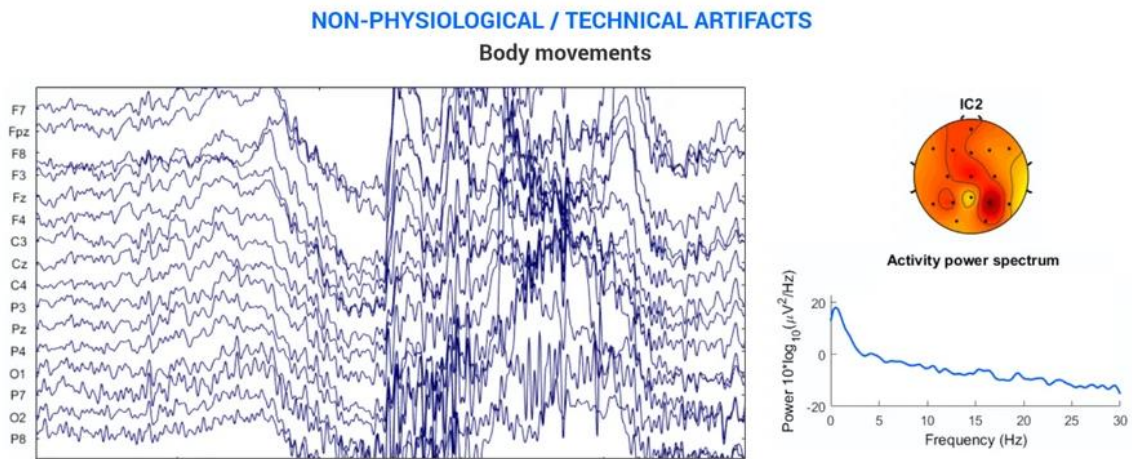


**Fig. 32.** The body movement artefact (picture adapted from ("Common physiological EEG artefacts," n.d.)).

### 2.3. BSL methods

As discussed in the introduction, despite their advantages, EEG signals recorded from scalp sensors have poor spatial resolution due to the so-called "volume conduction effect" which refers to the distortion of the brain electrical activity by the brain conductivity while reaching the surface of the brain. This becomes more important if we notice that the electrical activity produced by a single source inside the brain is recorded at several electrodes on the scalp. Therefore, the recorded signal at each electrode and its distortion level are the aggregate of brain signals coming from multiple sources inside the brain and their corresponding distortions. This aggregate distortion effect can significantly impact the quality of the recorded EEG signals. For this reason, it is more efficient to calculate and use the electrical activity inside the brain instead of the distorted copy of these activities recorded on the scalp. BSL techniques have been developed to address this problem by mathematically calculating the neuroanatomical source of an EEG signal inside the brain while suppressing interfering signals from

neighboring regions thereby improving the SNR value. Exact low-resolution electromagnetic tomography (eLORETA) is one of the most accurate and widely used BSL techniques (Pascual-Marqui, 2007). However, to accurately calculate the electrical activity inside the brain, eLORETA requires precise knowledge of the true head model obtained through magnetic resonance imaging (MRI) or computerised tomography (CT) imaging (Asadzadeh et al., 2020; Vorwerk et al., 2019). Alternative approaches including using pre-determined head models such as Colin 27 (Holmes et al., 1998), ICBM152 (Mazziotta et al., 1995) and New York Head (Huang et al., 2016) are also vulnerable to inaccuracies related to discrepancies between true and predetermined head model anatomy, electrode positioning, and variable tissue conductivities.

To overcome the problem mentioned above, a new robust version of the eLORETA method, called ReLORETA, was developed, which is capable of predicting the source of EEG signals inside the brain even if an accurate head model or MRI image of the subject is not available for simulation (Noroozi et al., 2022). This is specifically important in studies with many participants (such as the experiment in this thesis), as taking MRI images of all participants is not practical or even possible. The proposed ReLORETA method is described in the next section.

### **2.3.1. Proposed ReLORETA method**

#### **2.3.1.1. Introduction**

eLORETA is a widely used BSL method to reconstruct the EEG signals inside the brain before reaching the brain surface and to find the brain regions where the EEG signals originated from (Iwai et al., 2021; Pascual-Marqui, 2007). The reconstructed source signals resulting from this process, which is called EEG inverse problem, then are utilised to enhance mental or neurological disorders diagnosis and treatment, including depression (Y. Zhang et al., 2020), epilepsy (Rajaei et al., 2020), and schizophrenia (Masyshev et al., 2021). eLORETA is a precise method in reconstructing the signals for a focal source (Halder et al., 2019) compared to other methods such as low-resolution electromagnetic tomography (LORETA) (Pascual-Marqui et al., 1994), standardised LORETA (sLORETA) (Pascual-Marqui, 2002), minimum norm estimation (MNE) (RD., 1999), and weighted MNE (WMNE) (RD., 1999). eLORETA also suppresses less significant sources better than its predecessor the sLORETA method thereby resulting in less noisy results (Jatoi et al., 2014; Pascual-Marqui, 2002).

Electrical activities inside the brain can be discretised into a number of dipoles spread over cortex. To solve the EEG inverse problem we need to calculate the scalp potential values generated by dipoles inside the brain which is known as the forward problem (Asadzadeh et al., 2020). For this purpose, we need to simulate the human subject's head and generate a head model which can be used to solve the EEG inverse problem. The accuracy of the inverse solution depends on the accuracy of the simulated head model used in the forward problem (Asadzadeh et al., 2020; Steinsträter et al., 2010; Vorwerk et al., 2019). Generating an accurate head model requires MRI or CT systems, which are expensive and require high computational complexity to accurately simulate the correct head geometry. This issue can be extremely challenging for experiments and studies using many participants, as gathering all participants' MRIs is expensive, and in most cases not possible. For example, gathering EEG datasets for the applications such as diagnosis of mental disorders (Masyshev et al., 2021), emotion recognition (Becker et al., 2020), etc. Alternatively, we can use the head models which are created based on the real head geometry such as ICBM152 (Mazziotta et al., 1995), colin27 (Holmes et al., 1998), and New York head (Huang et al., 2016). The head's electrical properties are also considered in these models by including them in the lead field matrix containing aggregate potential values gathered by EEG electrodes from dipole sources inside the brain.

BSL methods' performance may drastically deteriorate by even a small error between the simulated and true lead field matrices (Fickling et al., 2020; Steinsträter et al., 2010; Zagorchev et al., 2021). What is more, the true lead field matrix is usually unavailable in practice. In real-world settings, most assumptions about the simulated head model, dipoles inside the brain, and the electrode locations may no longer be valid. There is usually a substantial difference between the real head geometries and the simulated model used to solve the inverse problem, which is referred to as geometry uncertainty in this thesis. Moreover, there is usually some error in simulating the electrode positions and tissues' conductivities. The difference in the number of dipoles and their locations between the inverse and forward models, referred to as the discretisation uncertainty in this thesis, can also impact the results (Hossein Hosseini et al., 2018). "Inverse" and "Forward" models in this thesis refer to the head models used for solving the EEG inverse problem and simulating EEG signals, respectively. Other unknown factors may also impact the results and calculations. As a result, it is likely to

have a mismatch between the simulated lead field matrix which is generated by the simulated forward head model and the real lead field matrix. This problem, which is referred to as forward model uncertainties, can impact the BSL method's performance, it is of vital importance to develop a model capable of dealing with this mismatch.

The impact of the forward model uncertainties on the BSL methods have been investigated by different studies. The studied uncertainties include tissues' conductivity (Stenroos and Hauk, 2013; Vorwerk et al., 2019; Wang and Ren, 2013), head geometry (Akalin Acar and Makeig, 2013; Steinsträter et al., 2010), and error in electrode placement (Akalin Acar and Makeig, 2013; Wang and Gotman, 2001). Vorwerk et al. (2019) found that skin and skull conductivities errors have a significant impact on the BSL method's accuracy. They used a single-dipole source and a head model consisting of five compartments, namely, white matter, grey matter, skull, skin, and cerebrospinal fluid (CSF) which was constructed using T2-weighted and T1-weighted MRIs. They simulated the sources in the somatosensory cortex. However, they did not constrain the source space in the inverse model to the grey matter and constructed it in the intracranial space which contains both grey and white matters. They found that errors in grey and white matters' conductivities could have negligible effect on the BSL method. However, it was found that it could have a strong effect on the reconstructed source's strength and orientation. Similarly, they found that CSF conductivity had a negligible impact on the reconstructed source (Vorwerk et al., 2019). Steinsträter et al. (2010) assessed the forward model uncertainties' effect and reported that the head model conductivity and geometry could generate up to 22 mm and 37 mm localisation error, respectively. They used a three-layer head model, including brain, skull, and scalp, which was derived from an MRI dataset, and a simulated three-layer isotropic spherical head model for the forward and inverse problem, respectively. In another study by Akalin Acar and Makeig (2013), the researchers reported that error in the simulated head conductivity could cause up to 31 mm error in localization. They also observed a significant relationship between the localization error and the head geometry. The effect of electrode placement errors was also examined in their research by tilting the EEG electrodes 5 degrees to the left. Their results showed that the shift in electrode positions caused localisation errors of up to 12 mm.

Several methods have been proposed in the literature to address the problems mentioned above. This includes beamformer-based techniques (Gross and Ioannides, 1999; Sekihara et al., 2002, 2001; Vorobyov et al., 2003), Bayesian approaches

(Koulouri et al., 2016; Rimpiläinen et al., 2019), and conductivity fitting (Akalin Acar et al., 2016; Huang et al., 2007). Gross and Ioannides (1999) applied a diagonal loading (DL) technique to the MEG data. The DL method is able to decrease the localisation error to some extent. However, it is not clear how to determine the optimal DL factor based on the extent of error in the lead field matrix (Vorobyov et al., 2003). Sekihara et al. (2002, 2001) showed that eigenspace-based beamformers could reduce the localisation error sensitivity to the errors in the simulated head model. However, their method is prone to the so-called “subspace swaps” problem (Vorobyov et al., 2003). The robust minimum variance beamformer (RMVB) (Hossein Hosseini et al., 2018) include the lead field matrix error into the beamforming spatial-filter weights calculations. The calculated weights are then utilised to reconstruct the source signals inside the brain. Despite its novelty, the RMVB method only considers the conductivity and discretisation uncertainties. Moreover, the dipoles orientation in the inverse model is fixed in their study, a condition which is likely to be violated in real-world settings. Chrapka et al. (2019) reformulated the RMVB method to include free dipole orientations. However, their method still lacks sufficient accuracy.

Bayesian approximation error (BAE) is capable of dealing with different types of errors and uncertainties in the forward model. The BAE method can mitigate the impact of head geometries on the source localisation error (Koulouri et al., 2016). Error in conductivity can also be factored in using the BAE approach (Rimpiläinen et al., 2019). However, it was observed that BAE method becomes unstable when the SNR value drops to 20 dB (Rimpiläinen et al., 2019). Conductivity fitting techniques can also factor in the error in conductivity to reduce the localisation error. In these methods, the correct conductivity value is determined while calculating the source localtion simultaneously (Akalin Acar et al., 2016). However, both Bayesian and conductivity fitting approaches still lack reliability and accuracy in practical settings when multiple head model errors could be present.

A novel BSL method, called ReLORETA, is proposed in this section, which is capable of accurately reconstructing the brain signals even in the presence of different errors in the simulated head model and does not need any prior information such as electrode positions, head geometries, conductivities, etc. In contrast to the previous studies discussed above that need to set some hyperparameters such as the DL factor to solve the EEG inverse problem, in this section it is assumed no information about the subject head is available. The lead field matrix will then be iteratively updated while

solving the EEG inverse problem. The ReLORETA method can be employed to solve any problem involving the reconstruction of EEG source signals inside the brain. However, in this thesis, it is first applied to simulated focal sources including single-dipole sources and sources with extended activities referred to as “extended sources”. To test ReLORETA’s reliability, it will also be applied to real EEG data from an epilepsy patient. In the proposed methodology, which is presented in the next chapter, ReLORETA is utilized to reconstruct LoL players’ EEG source signals inside the brain. The reconstructed brain signals are finally used to classify the players’ skill levels.

In what follows, the eLORETA method will be briefly described first, and the proposed ReLORETA algorithm will then be introduced. Finally, it is described how ReLORETA can be applied to eSports players’ EEG signals to evaluate their skill levels. The results of the proposed method will be presented in the next chapter.

### 2.3.1.2. eLORETA

Assume  $M$  EEG electrodes gather the electrical activities on the scalp at the  $n^{th}$  time points, and the gathered EEG data are then stored in the vector  $\mathbf{x}(n) \in \mathbb{R}^{M \times 1}$ . It can be shown that the following equation could describe the relation between the gathered EEG data  $\mathbf{x}(n)$  and the source signals inside the brain (Pascual-Marqui, 2007, 2002):

$$\mathbf{x}(n) = \mathbf{H}\mathbf{y}(n) + \boldsymbol{\eta}(n) \quad (1)$$

where  $\mathbf{H} \in \mathbb{R}^{M \times (3 \times K)}$  is the lead field matrix containing the electrical potentials at  $K$  dipoles inside the brain which can be written as

$$\mathbf{H} = [\mathbf{H}_1, \mathbf{H}_2, \mathbf{H}_3, \dots, \mathbf{H}_K] \quad (2)$$

where  $\mathbf{H}_i \in \mathbb{R}^{M \times 3}$ ,  $i \in \{1, 2, \dots, K\}$ , and  $\boldsymbol{\eta}(n)$  shows the background neural activities or noise. The brain source signals are stored in the vector  $\mathbf{y}(n) \in \mathbb{R}^{(3 \times K) \times 1}$ . If the gathered EEG data on the scalp, i. e.  $\mathbf{x}(n)$ , are given, the EEG inverse problem can then be translated into finding the source signals stored in  $\mathbf{y}(n)$  which satisfies (1).

It can be shown that  $\mathbf{y}(n)$  can be calculated from the following equation using the regularised weighted minimum norm method (Pascual-Marqui, 2007, 2002)

$$\min_{\mathbf{y}(n)} (S_{el}(n) + \alpha \mathbf{y}(n)^T \mathbf{W} \mathbf{y}(n)) \quad (3a)$$

$$S_{el}(n) = \|\mathbf{x}(n) - \tilde{\mathbf{x}}_{el}(n)\|^2 \quad (3b)$$

$$\tilde{\mathbf{x}}_{el}(n) = \mathbf{H}\mathbf{y}(n) \quad (3c)$$

In this equation,  $\mathbf{W} \in \mathbb{R}^{(3 \times K) \times (3 \times K)}$  is a symmetric weight matrix,  $\tilde{\mathbf{x}}_{el}$  contains the reconstructed EEG signals by eLORETA, and  $\alpha \geq 0$  is the regularisation parameter

(Pascual-Marqui, 2007, 2002).  $S_{el}(n)$  is a metric showing how well eLORETA has reconstructed the EEG signals. The eLORETA total reconstruction error for  $N$  time points can then be given as

$$E_{eloreta} = \sum_{n=1}^N S_{el}(n) \quad (4)$$

It has been proved that this problem's solution is linear as follows

$$\mathbf{y}(n) = \mathbf{T}\mathbf{x}(n) \quad (5)$$

where the matrix  $\mathbf{T}$  is given by

$$\mathbf{T} = \mathbf{W}^{-1}\mathbf{H}^T(\mathbf{H}\mathbf{W}^{-1}\mathbf{H}^T + \alpha\mathbf{L})^+ \quad (6)$$

where  $\mathbf{L}$  is the centering matrix also known as the average reference operator. The superscript “+” denotes the Moore-Penrose pseudoinverse (Pascual-Marqui, 2002).

The weight matrix  $\mathbf{W}$  is block-diagonal in the eLORETA method. This means all matrix elements values are zero except for the diagonal sub-blocks denoted by  $\mathbf{W}_i \in \mathbb{R}^{3 \times 3}$ ,  $i \in (1, 2, \dots, K)$ . The following equation can be used to compute the current density at the  $i^{th}$  voxel:

$$\mathbf{y}_i(n) = \mathbf{W}_i^{-1}\mathbf{H}_i^T(\mathbf{H}\mathbf{W}^{-1}\mathbf{H}^T + \alpha\mathbf{L})^+\mathbf{x}(n) \quad (7)$$

where  $\mathbf{H}_i$  shows the value of the lead field matrix related to the  $i^{th}$  voxel, aka dipole, according to (2). The following set of equations can then be used to compute the optimum  $\mathbf{W}_i$  matrices:

$$\mathbf{W}_i = [\mathbf{H}_i^T(\mathbf{H}\mathbf{W}^{-1}\mathbf{H}^T + \alpha\mathbf{L})^+\mathbf{H}_i]^{1/2}. \quad (8)$$

To solve (8), the block-diagonal weight matrix  $\mathbf{W}$  should be computed. The following iterative algorithm can be used for this purpose (Pascual-Marqui, 2007):

**Step 1:** Initialise  $\mathbf{W}$  to the identity matrix using the given regularisation parameter  $\alpha \geq 0$  and an averaged reference lead field  $\mathbf{H}$

**Step 2:** use the symmetric square root matrix in (8) to calculate  $\mathbf{W}_i$ .

**Step 3:** Continue Step 2 until  $\mathbf{W}$  converges, i.e., the difference in the value of the calculated  $\mathbf{W}$  in two consecutive iterations drops below a threshold.

eLORETA is defined as the EEG inverse problem's solution given by (7) and the weight values satisfying (8).

### 2.3.1.3. ReLORETA

If the employed lead field matrix is accurate, eLORETA can generate zero localisation error for single-dipole sources. However, the correct precise lead field matrix is usually unknown in practice. Therefore, achieving accurate results may not be possible. The error function in (3) will not converge if the lead field matrix is not precise, thereby increasing the localization error.

To deal with the problem mentioned above, the ReLORETA method assumes that the real correct lead field matrix  $\tilde{\mathbf{H}}$  can be calculated using the current imprecise lead field matrix  $\mathbf{H}$  as follows

$$\tilde{\mathbf{H}} = \mathbf{R}\mathbf{H} \quad (9)$$

In this equation,  $\mathbf{R} \in \mathbb{R}^{M \times M}$  is called the transformation matrix. ReLORETA's goal is to compute the optimum  $\mathbf{R}$  and the lead field matrix  $\tilde{\mathbf{H}}$  such that the objective function in (3) converges properly. If we substitute (9) into (3), the transformation matrix  $\mathbf{R}$  and the source signals  $\mathbf{y}$  can be simultaneously computed using the following optimisation problem

$$\min_{\mathbf{R}} (\min_{\mathbf{y}(n)} (S_{rel}(n) + \alpha \mathbf{y}(n)^T \mathbf{W} \mathbf{y}(n))) \quad (10a)$$

$$S_{rel}(n) = \|\mathbf{x}(n) - \tilde{\mathbf{x}}_{rel}(n)\|^2 \quad (10b)$$

$$\tilde{\mathbf{x}}_{rel}(n) = \tilde{\mathbf{H}}\mathbf{y}(n) \quad (10c)$$

$\tilde{\mathbf{x}}_{rel}(n)$  in this equation contains ReLORETA's reconstructed EEG signals. Equation (3) and the eLORETA method can be used to solve the inner optimisation problem in (10a). However, it is not straightforward to find a closed form solution for the outer optimisation problem. To simultaneously find the optimum  $\mathbf{R}$  and  $\mathbf{y}(n)$  the following iterative algorithm is proposed in the ReLORETA method: in the first iteration, the existing lead field matrix is assumed to be the correct lead field matrix that minimises (10a) (i. e.  $\tilde{\mathbf{H}} = \mathbf{H}$ ). eLORETA is used to solve the inner optimisation problem according to (3), and  $\mathbf{H}$  is then replaced with  $\tilde{\mathbf{H}}$  from (9). To calculate the optimum  $\mathbf{R}$  using the outer optimisation problem, the computed  $\mathbf{y}(n)$  and  $\mathbf{W}$  are then input into (10) as follows

$$\min_{\mathbf{R}} (S_{rel}(n) + \alpha \mathbf{y}(n)^T \mathbf{W} \mathbf{y}(n)) \quad (11)$$

The second term in (11) is constant as  $\mathbf{y}(n)$  and  $\mathbf{W}$  are calculated by the inner optimization problem. The optimization problem in (11) can be reformulated using the EEG signals at  $N$  time points as

$$\min_{\mathbf{R}} E_{reloreta} \quad (12a)$$

$$E_{reloreta} = \sum_{n=1}^N S_{rel}(n) \quad (12b)$$

where  $E_{reloreta}$  is ReLORETA's reconstruction error. In both optimisation problems, *i.e.* (3) and (11), the error function (10a) should converge to the same value if the initial assumption is correct (*i.e.*  $\tilde{\mathbf{H}} = \mathbf{H}$ ). If this does not happen, the lead field matrix is recalculated using (9). All the previous steps are then run again using the new lead field matrix. We continue this iterative process until the algorithm converges. In the equations in this section, eLORETA<sup>*j*</sup> shows the eLORETA method in the  $j^{th}$  iteration which is used to solve (3). Similarly, ReLORETA,  $E_{reloreta}$ , and  $E_{eloreta}$  in the  $j^{th}$  iteration are shown by ReLORETA<sup>*j*</sup>,  $E_{reloreta}^j$ , and  $E_{eloreta}^j$ , respectively.

ReLORETA's convergence entails convergence of (3) and (11) to the same value. This in turn requires the first terms in these equations, *i. e.*  $S_{el}(n)$  and  $S_{rel}(n)$  converge to an equal value. This is because the second terms in both error functions are the same. Therefore, when the difference between  $E_{reloreta}^j$  and  $E_{eloreta}^j$  converges to zero, we can conclude that the algorithm has converged properly. In the next section, it is discussed how the Levenberg-Marquardt (LM) optimisation can be employed to solve (12).

#### 2.3.1.3.1. LM optimisation

The LM algorithm has been widely used to find a solution to nonlinear least-squares problems (Noroozi et al., 2013, 2012; Rubio, 2021). The LM algorithm is capable of converging to the correct minimum despite starting at an initial value which is far from the correct minimum point (Rubio, 2021).

For the optimization problem in (12), the optimum transformation matrix  $\mathbf{R}$  can be calculated using the matrix form of the LM algorithm as follows

$$\mathbf{R}^{j+1} = \mathbf{R}^j - (\mathbf{C} + \lambda \mathbf{I})^{-1} \mathbf{D} \quad (13)$$

where  $\mathbf{I}$ ,  $\mathbf{D}$ , and  $\mathbf{C}$  show the identity matrix,  $E_{reloreta}$  derivative with respect to  $\mathbf{R}$ , and the Hessian matrix, respectively.  $j$  shows the number of iterations, and  $\lambda$  represents the algorithm's learning rate.

To find  $\mathbf{D}$ , (10c) and (12b) can be first reformulated into the matrix form as follows

$$\tilde{\mathbf{X}}_{rel} = \tilde{\mathbf{H}}\mathbf{Y} = \mathbf{R}\mathbf{H}\mathbf{Y} \quad (14a)$$

$$E_{reloreta} = \|\mathbf{X}_{diff}\|_F^2 \quad (14b)$$

$$\mathbf{X}_{diff} = \mathbf{X} - \tilde{\mathbf{X}}_{rel} \quad (14c)$$

where  $\|\cdot\|_F$  is the Forbenius norm. Reconstructed source signals inside the brain, simulated or real EEG signals, and ReLORETA's reconstructed EEG signals are stored in the  $\mathbf{Y}$ ,  $\mathbf{X}$ , and  $\tilde{\mathbf{X}}_{rel}$  matrices, respectively as follows

$$\mathbf{X} = [\mathbf{x}(1), \mathbf{x}(2), \mathbf{x}(3), \dots, \mathbf{x}(N)] \quad (15a)$$

$$\tilde{\mathbf{X}}_{rel} = [\tilde{\mathbf{x}}_{rel}(1), \tilde{\mathbf{x}}_{rel}(2), \tilde{\mathbf{x}}_{rel}(3), \dots, \tilde{\mathbf{x}}_{rel}(N)] \quad (15b)$$

$$\mathbf{Y} = [\mathbf{y}(1), \mathbf{y}(2), \mathbf{y}(3), \dots, \mathbf{y}(N)] \quad (15c)$$

To compute  $\mathbf{D}$  the scala derivative function (*i.e.*  $E_{reloreta}$ ) with respect to a matrix (*i.e.*  $\mathbf{R}$ ) should be computed, which obeys the chain rule as follows

$$\mathbf{D} = \frac{\partial E_{reloreta}}{\partial \mathbf{R}} = \left( \frac{\partial E_{reloreta}}{\partial \mathbf{X}_{diff}} \right) \left( \frac{\partial \mathbf{X}_{diff}}{\partial \mathbf{R}} \right) \quad (16)$$

The matrix algebra then will give

$$\frac{\partial E_{reloreta}}{\partial \mathbf{X}_{diff}} = 2\mathbf{X}_{diff} \quad (17a)$$

$$\frac{\partial \mathbf{X}_{diff}}{\partial \mathbf{R}} = -(\mathbf{H}\mathbf{Y})^T \quad (17b)$$

The derivative matrix  $\mathbf{D}$  can be calculated by substituting (17a) and (17b) into (16) and then using (14a), which results in the following equation:

$$\mathbf{D} = 2(\mathbf{R}\mathbf{H}\mathbf{Y} - \mathbf{X})(\mathbf{H}\mathbf{Y})^T \quad (18)$$

To compute the Hessian matrix, (10c) can be reformulated to fit the equation of a single layer neural network's output as follows

$$\tilde{\mathbf{x}}_{rel}(n) = f(\mathbf{R}\mathbf{z}(n)) \quad (19)$$

$\mathbf{z}(n)$  is given by

$$\mathbf{z}(n) = \mathbf{H}\mathbf{y}(n) \quad (20)$$

and  $f$  is a linear activation function such that

$$f(\mathbf{R}\mathbf{z}(n)) = \mathbf{R}\mathbf{z}(n). \quad (21)$$

Bishop (1992) proposed a method which can be used to calculate the Hessian matrix as follows

$$\mathbf{C} = f''(\tilde{\mathbf{x}}_{rel}(n)) \frac{\partial S_{rel}(n)}{\partial \tilde{\mathbf{x}}_{rel}(n)} + (f'(\tilde{\mathbf{x}}_{rel}(n)))^2 \frac{\partial^2 S_{rel}(n)}{\partial \tilde{\mathbf{x}}_{rel}(n)^2} \quad (22)$$

where  $f'$  and  $f''$  show the second and first derivatives of  $f$ . Since  $f$  is linear, then  $f' = 1$  and  $f'' = 0$ . If we substitute these values in (22), the Hessian matrix is then given by

$$\mathbf{C} = \mathbf{I} \quad (23)$$

#### 2.3.1.3.2. Proposed algorithm

In each iteration, the transformation matrix  $\mathbf{R}$  is updated using (13), (18), and (23). To calculate the source signals, i.e., the  $\mathbf{Y}$  matrix, the calculated matrix can then be fed input into the eLORETA<sup>j</sup>. This procedure continues until the algorithm converges to a global minimum. To set a threshold to stop the algorithm, the differential reconstruction error (DRE) for iteration  $j$  can be defined as

$$DRE^j = \|E_{reloreta}^j - E_{eloreta}^j\| \quad (24)$$

The algorithm's convergence then requires that  $DRE^j$  or the difference between two consecutive  $DRE$  values falls below a threshold  $\varepsilon$ .  $DRE$  in iteration  $j$  can also be normalised to make the threshold value independent of the measurements unit as follows

$$NDRE^j = \frac{\|DRE^j - DRE^{j-1}\|}{\max(DRE) - \min(DRE)}, \quad j \geq 2 \quad (25)$$

where

$$DRE = [DRE^1, DRE^2, \dots, DRE^j] \quad (26)$$

and  $NDRE^j$  is the normalised  $DRE^j$ . Finally, the algorithm converges when  $NDRE^j \leq \varepsilon$ . Fig. 33 shows the proposed ReLORETA algorithm which can be summarised as follows:

**Step 1:** The matrices  $\mathbf{R}$ ,  $\mathbf{H}$ , are initialised and  $\varepsilon$  is set.

**Step 2:** Given simulated or real EEG signals stored in matrix  $\mathbf{X}$  and the lead field matrix, the source signals  $\mathbf{Y}$  are reconstructed using eLORETA<sup>j</sup>.

**Step 3:** The transformation matrix  $\mathbf{R}$  is updated using (13), (18), and (23).

**Step 4:**  $NDRE$  is calculated using (24) and (25). The algorithm is terminated if  $NDRE^j \leq \varepsilon$ , else go to the next step.

**Step 5:** The lead field matrix is updated using (9), and  $\mathbf{H}$  is replaced with  $\tilde{\mathbf{H}}$ , and the algorithm goes step 2.

The algorithm stops after the predefined threshold is achieved.  $\mathbf{Y}$  can then be used as the reconstructed source signals.

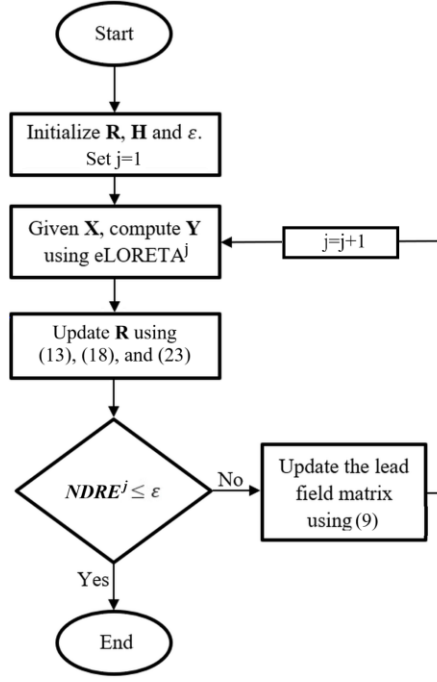


**Fig. 33.** Flowchart of the proposed ReLORETA algorithm

#### 2.3.1.3.3. ReLORETA convergence proof

In the proposed algorithm, a proof by contradiction method was used, which can be described as follows: according to the proposed algorithm, (3) and (11), objective functions for the inner and outer optimisations in (10) can be written as follows:

$$O_{el} = \|\mathbf{x}(n) - \mathbf{H}\mathbf{y}(n)\|^2 + \alpha \mathbf{y}(n)^T \mathbf{W} \mathbf{y}(n) \quad (27a)$$

$$O_{rel} = \|\mathbf{x}(n) - \tilde{\mathbf{H}}\mathbf{y}(n)\|^2 + \alpha \mathbf{y}(n)^T \mathbf{W} \mathbf{y}(n) \quad (27b)$$

where  $O_{el}$  and  $O_{rel}$  are the inner and outer (or eLORETA and ReLORETA) objective functions respectively. In the proposed algorithm, in the first step, it was assumed that the existing lead field matrix is the true lead field matrix that can minimise the inner objective function, i. e.  $O_{el}$ . If this assumption is true, then because  $O_{el}$  and  $O_{rel}$  are only different in the employed lead field matrices, the outer objective function  $O_{rel}$  is only minimised when  $\tilde{\mathbf{H}} = \mathbf{H}$  that will, in turn, result in  $O_{rel} = O_{el}$ . So, under this assumption, after optimizing  $O_{rel}$  with respect to  $\mathbf{R}$ , the resulting lead field matrix  $\tilde{\mathbf{H}}$  should converge to  $\mathbf{H}$ , and consequently,  $O_{rel}$  should converge to  $O_{el}$ . If this does not

happen, then our initial assumption was not valid, and we need to update the lead field matrix.

In each iteration, it is first assumed that the updated lead field matrix from the previous iteration  $\mathbf{H}^{j-1}$  is the true lead field matrix, and the source amplitudes matrix  $\mathbf{Y}$  is computed using  $\mathbf{H}^{j-1}$  by eLORETA<sup>j</sup>. The reconstruction error  $E_{eloreta}^j$  is then calculated using  $\mathbf{H}^{j-1}$  and  $\mathbf{Y}$ . In the next step, in the current iteration  $j$ , the lead field matrix is updated, and the updated lead field matrix  $\mathbf{H}^j$  together with source amplitudes matrix  $\mathbf{Y}$  are used to calculate ReLORETA<sup>j</sup> reconstruction error, i. e.  $E_{reloreta}^j$ . Therefore,  $O_{el}$  and  $O_{rel}$  in each iteration can be rewritten as follows:

$$O_{el}^j = \|\mathbf{x}(n) - \mathbf{H}^{j-1}\mathbf{y}(n)\|^2 + \alpha\mathbf{y}(n)^T\mathbf{W}\mathbf{y}(n) \quad (28a)$$

$$O_{rel}^j = \|\mathbf{x}(n) - \mathbf{H}^j\mathbf{y}(n)\|^2 + \alpha\mathbf{y}(n)^T\mathbf{W}\mathbf{y}(n) \quad (28b)$$

and reconstruction errors of eLORETA<sup>j</sup> and ReLORETA<sup>j</sup> in each iteration can be written as (please also see (4) (12b))

$$E_{eloreta}^j = \sum_{n=1}^N \|\mathbf{x}(n) - \mathbf{H}^{j-1}\mathbf{y}(n)\|^2 \quad (29a)$$

$$E_{reloreta}^j = \sum_{n=1}^N \|\mathbf{x}(n) - \mathbf{H}^j\mathbf{y}(n)\|^2 \quad (29b)$$

If our initial assumption is true, then as explained, the currently updated lead field matrix converges to the previous iteration's lead field matrix, i. e.  $\mathbf{H}^j \cong \mathbf{H}^{j-1}$ . Furthermore, since EEG measurements  $\mathbf{x}(n)$  and source amplitudes  $\mathbf{y}(n)$  for both  $E_{eloreta}^j$  and  $E_{reloreta}^j$  are equal, if the lead field matrix converges to its final value ( $\mathbf{H}^j \cong \mathbf{H}^{j-1}$ ), then both reconstruction errors converge to the same value, and this is not dependent on the value of alpha.

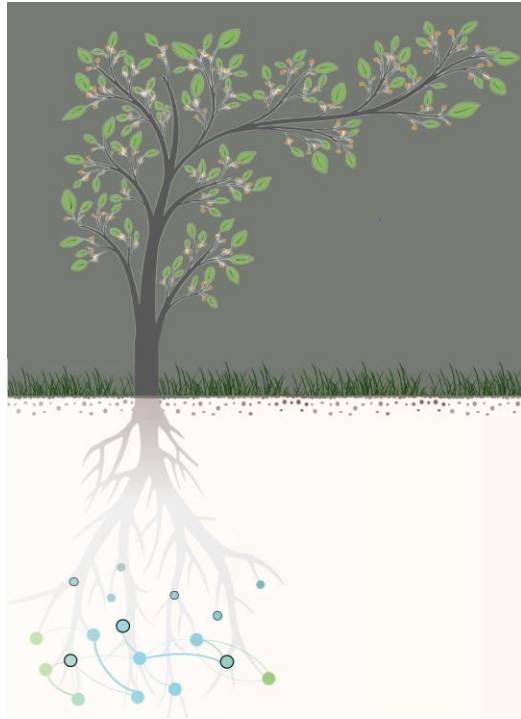
## 2.4. Summary

In this chapter, the basics of the EEG and BSL were discussed and a new BSL technique called ReLORETA was developed to deal with the problems of the existing methods. The following is a summary of what was discussed in this chapter:

- 1- EEG is a method to gather the brain electrical activity on the surface of the brain using a number of electrodes, aka channels.
- 2- The EEG electrode placement on the scalp is based on international standards, some of which include 10-20, 10-10, and 10-5 systems. Each EEG electrode has a standard name which is shown in Fig. 19 and Fig. 20.

- 3- EEG signal amplitude is small and measured in microvolts ( $\mu V$ ). In the frequency domain, EEG signals could be decomposed into five bands, namely  $\delta$  (0.5 Hz–4 Hz),  $\theta$  (4 Hz–8 Hz),  $\alpha$  (8 Hz–13 Hz),  $\beta$  (13 Hz–30 Hz), and  $\gamma$  (greater than 30 Hz)
- 4- Despite their advantages, EEG signals can be easily distorted by noise and other artefacts, including eye movements, body movement, cardiac activity, etc. For this reason, EEG data should be preprocessed before being used in simulations.
- 5- EEG data can be also distorted by other factors such as brain electrical conductivity before reaching the brain's surface. In contrast to noise and artefacts, this error cannot be removed using preprocessing methods, making EEG signals prone to producing misleading results.
- 6- Moreover, EEG data are captured on the surface of the brain and do not provide accurate information about the regions inside the brain where they originated from.
- 7- To overcome the problems mentioned above, reconstructing the brain signals inside the brain before reaching the brain's surface is of interest.
- 8- BSL methods are used to reconstruct the brain signals inside the brain, referred to as source signals, before reaching the brain's surface, thereby providing an accurate image of brain regions' activities during different tasks, including playing games.
- 9- Current BSL methods, such as eLORETA, have low accuracy and need exact knowledge of the electrode locations, the head's conductivity, and the head's geometry, which is not practical in real-world settings.
- 10- The proposed BSL method in this chapter, called ReLORETA, is capable of accurately reconstructing the source signals inside the brain without the need for data which are required by other BSL methods mentioned above. This makes the proposed method ideal for real-world applications where access to such information is impractical.
- 11- ReLORETA will be used in the proposed methodology in this thesis to reconstruct eSports players' brain signals (i. e. brain images) which will be used to classify the players' skill levels.

In the next chapter, the proposed methodology to address the research questions will be described in detail.



# CHAPTER 3

## Methodology

### OVERVIEW

In this chapter, the proposed methodology to address the research questions mentioned in the first chapter is presented. For this purpose, two new methods are developed to evaluate LoL players' skill levels using two datasets, including one secondary dataset and one primary dataset gathered by the author, respectively. The evaluation metrics and a summary of the chapter are presented at the end.

### 3.1. Introduction

In the previous chapters, the disadvantages of the existing methods were discussed, and the project requirements were presented. To address the research questions, two methods were developed by the author, which will be presented in this chapter.

For the first proposed method, a novel machine learning algorithm was developed to classify LoL players' skill levels using a secondary dataset provided by Smerdov et al. (2021a), which contained sensor data from 10 LoL players' body parts. For the second proposed method, in the first step, a primary dataset, containing EEG data of 18 LoL players, was gathered by the author of this thesis. In the next step, the ReLORETA method developed in the previous chapter was utilised to reconstruct the players' brain signals using the gathered EEG signals. The reconstructed brain signals by ReLORETA were then used to classify the players' skill levels.

The second proposed method in this chapter requires knowledge of EEG data and BSL methods. Therefore, the reader needs to study chapter 2 before diving into the methodology. The rest of the chapter is organised as follows: the datasets used in simulations are described in section 3.2. The proposed methods are then presented and discussed in detail in section 3.3. The evaluation metrics and a summary of the chapter are presented in section 3.4 and 3.5, respectively.

### 3.2. Datasets

#### 3.2.1. Secondary dataset

To assess the performance of the first proposed method in this thesis, a secondary dataset presented by Smerdov et al. (2021a, 2021b) was used. This dataset was collected from 10 LoL players including 5 amateur and 5 professional players whose information and experience are shown in Table 8. Each team played 11 matches over 3 experimental days versus real opponents from the internet or bots. In each match, 3 types of data were collected from in-game logs, sensors and surveys from team members. Therefore, 110 data gathering sessions were carried out in total (55 sessions for amateur players and 55 sessions for professional players).

##### 3.2.1.1. Sensor data

The experimental testbed shown in Fig. 34 was used to gather thirteen types of sensor data as follows:

**Table 8.** Players' statistics and information

| Team          | Played id | Hours played | Best rank | Current rank | Rank percentile | Dominant hand |
|---------------|-----------|--------------|-----------|--------------|-----------------|---------------|
| Amateurs      | 0         | 336          | Gold      | Gold         | 34%             | Right         |
|               | 1         | 1200         | Gold      | Gold         | 34%             | Right         |
|               | 2         | 1000         | Platinum  | Platinum     | 9.66%           | Right         |
|               | 3         | 400          | No rank   | No rank      | 100%            | Right         |
|               | 4         | 415          | Gold      | Gold         | 34%             | Right         |
| Professionals | 0         | 5000         | Diamond   | Diamond      | 2.07%           | Left          |
|               | 1         | 6000         | Diamond   | Diamond      | 2.07%           | Right         |
|               | 2         | 5000         | Diamond   | Diamond      | 2.07%           | Right         |
|               | 3         | 10000        | Master    | Master       | 0.09%           | Right         |
|               | 4         | 7000         | Diamond   | Diamond      | 2.07%           | Right         |

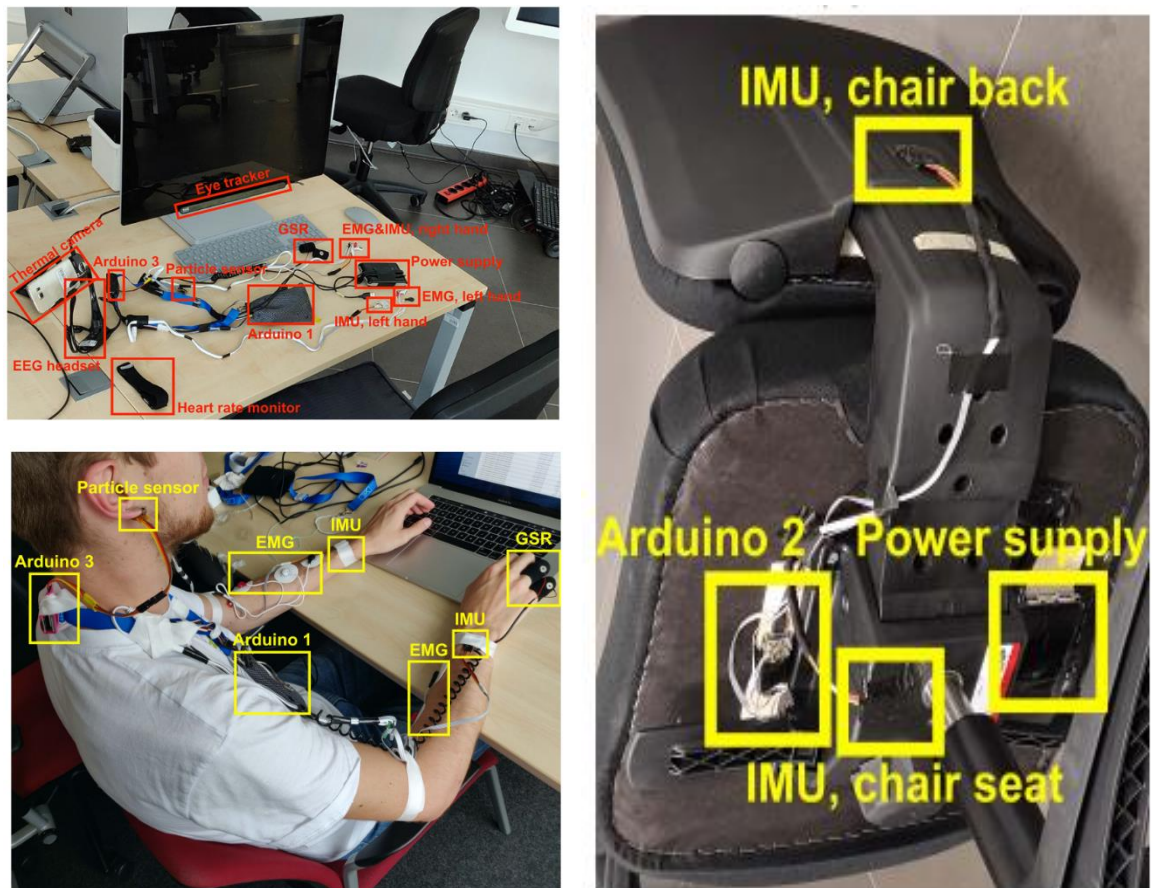


**Fig. 34.** The experimental settings to gather the sensor data by Smerdov et al. (2021b).

- 1) **Electromyography (EMG):** These data were gathered using a Grove EMG Sensor v1.1. This sensor measures the intensity of the muscle activity and shows it as an output voltage. For this purpose, it uses three electrodes, including ground, plus, and minus electrodes placed on the forearm to measure the voltage, which can be interpreted as the muscle intensity.
- 2) **Galvanic skin response (GSR):** These data were gathered using a Grove GSR Sensor v1.2. This sensor has two electrodes placed on two fingers on the participants' right hand. The sensor's output is a voltage from which the participant's skin resistance could be inferred. Due to more sweat, the skin resistance is usually lower in the arousal state. Therefore, these data can also be used as the participant's stress indicator.
- 3) **Hand movement:** An inertial measurement unit (IMU) consisting of a Bosch BNO0553 sensor was used to record linear acceleration, gravity, angular velocity, and Euler angles of players' hands.
- 4) **Chair movement:** Two IMUs were placed under the chair seat and on the chair back to record the chair movement as shown in Fig. 34. The sensors' models and the recorded data types were the same as hand movement.
- 5) **Environmental data:** A Bosch BME280 sensor was installed in the gaming room to measure the relative humidity and temperature.
- 6) **Carbon dioxide:** A CO2 MH-Z19B sensor was used to measure the carbon dioxide concentration in ppm.
- 7) **Gaze data:** The gaze data were gathered using a Tobii 4C eye tracker device installed under the monitor. The eye tracker data indicate which information (and the related location) on the game screen players gaze at more frequently. To synchronise the information obtained with eye trackers, a screen with a 1920x1080 resolution was used for all matches, and players calibrated the eye trackers before each experimental day.
- 8) **EEG:** EEG data were gathered using an Emotiv Insight headset.
- 9) **Keyboard data:** These data were collected using a keyboard logger which was a Python script running on the gamer's PC.
- 10) **Mouse data:** Similar to keyboard data, these data were collected using a mouse logger program written in Python running on the gamer's PC.
- 11) **Facial skin temperature:** These data were gathered using an infrared camera Flir One, directed at players' faces.

12) **Heart rate:** The players' heart rates were recorded using a Polar OH1 armband.

13) **Blood oxygen level:** A Maxim MAX30102 pulse-oximeter sensor was positioned on the players' right earlobe to measure their blood oxygen level.

Three Arduino boards were used to collect data from each player. EMG and GSR sensors were connected to analogue ports on the Arduino 1. Two IMUs on both hands were also connected to Arduino 1 but via I2C protocol. Arduino 2 gathered data from two IMUs located on the chair. Arduino 3 collected the signal from the particle sensor via I2C protocol. Arduino 4 was used to collect environmental data. It received data from the humidity sensor via I2C protocol and from the CO2 sensor via UART. Arduino boards were powered with standard 5.0V 10000 mAh batteries. The experimental setting and sensor network architecture are shown in Fig. 34. and Fig. 35, respectively.

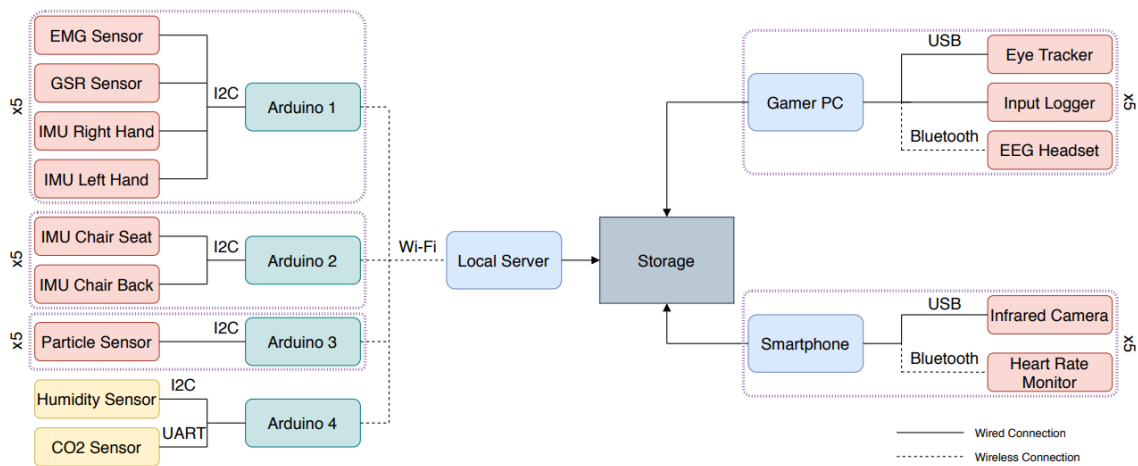


**Fig. 35.** The sensor network architecture used to gather the players' data Smerdov et al. (2021b).

### 3.2.1.2. In-game data

The in-game data, which were collected using the Riot API (Riot Games, 2021), contain information about the game statistics and events as follows:

- 1) **Champion kill:** This event shows the killer, the victim, the assistants, as well as the location and the timestamp.
- 2) **Building kill:** The gathered data specifies the type and the location of the building destroyed, the players who participated, and the timestamp.
- 3) **Skill level up:** This entry shows the champion's skill that players chose to upgrade.
- 4) **Ward placed, ward kill:** These events data show the ward type, the timestamp, and the involved player.

- 5) **Item purchased, item destroyed:** These event data give information about the purchased item, the timestamp, and the involved player.

### 3.2.1.3. Survey

Each player passed a short survey after each match to report the mental load in the game on a scale from 1 to 5 and the level of disturbance and obtrusiveness of the sensing system. They were also asked to estimate their own performance as well as their teammates' performance on a scale from 1 to 5. The average mental load in the games played versus bots was only 1.2. However, this number was considerably higher in matches against real players. The average mental load in this case was about 3.39.

Fig. 36(a) shows the distribution of responses on players' performance evaluated by themselves and other team members. The distribution of responses about the mental load in matches against real opponents is shown in Fig. 36(b). Clearly, amateurs' mental load is significantly higher than for professionals, even considering the match-making algorithm used in the experiment to pair each participant with players of the same skill level.

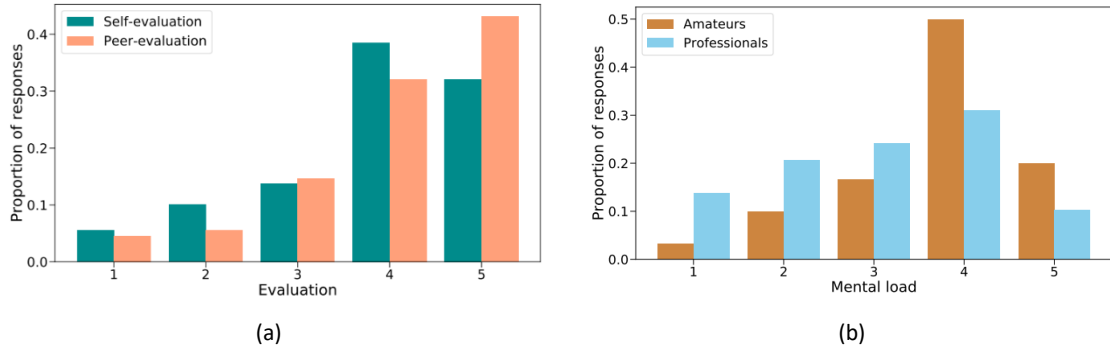


**Fig. 36.** The distribution of responses on (a) the players' performance and (b) the players' mental load in the games played versus real opponents.

### 3.2.2. Primary dataset

To the best of my knowledge, there is currently a lack of reliable EEG datasets of eSports players. The secondary dataset introduced in the previous section is the only available EEG dataset for the evaluation of eSports players' skills. Although this dataset contains EEG signals of eSports players, nearly 70% of the data are distorted and cannot be used for simulation (Smerdov et al., 2021b).

To overcome this problem, an experiment was carried out to gather EEG data of 18 LoL players, including nine highly skilled and nine low skilled players. The players were Staffordshire University students recruited from the university eSports communities with

the aid of students and lecturers who circulated the experiment's information among the students. The EEG data were gathered using an EMOTIV 14-channel EEG device shown in Fig. 37(a). The channels (electrodes) were placed on players' scalps according to the 10-10 EEG placement system shown in Fig. 37(b). The electrodes with bold dark circles in this figure were used for gathering players' EEG data. The participants were aged between 18 and 36 years old from which 15 participants were male and three were female. Also, two participants were left-handed, and the rest were right-handed. All data-gathering sessions were held between 2 and 5 pm over six days at the eSports hub of Staffordshire University. All players were given an information sheet before consenting to participate in the experiment.

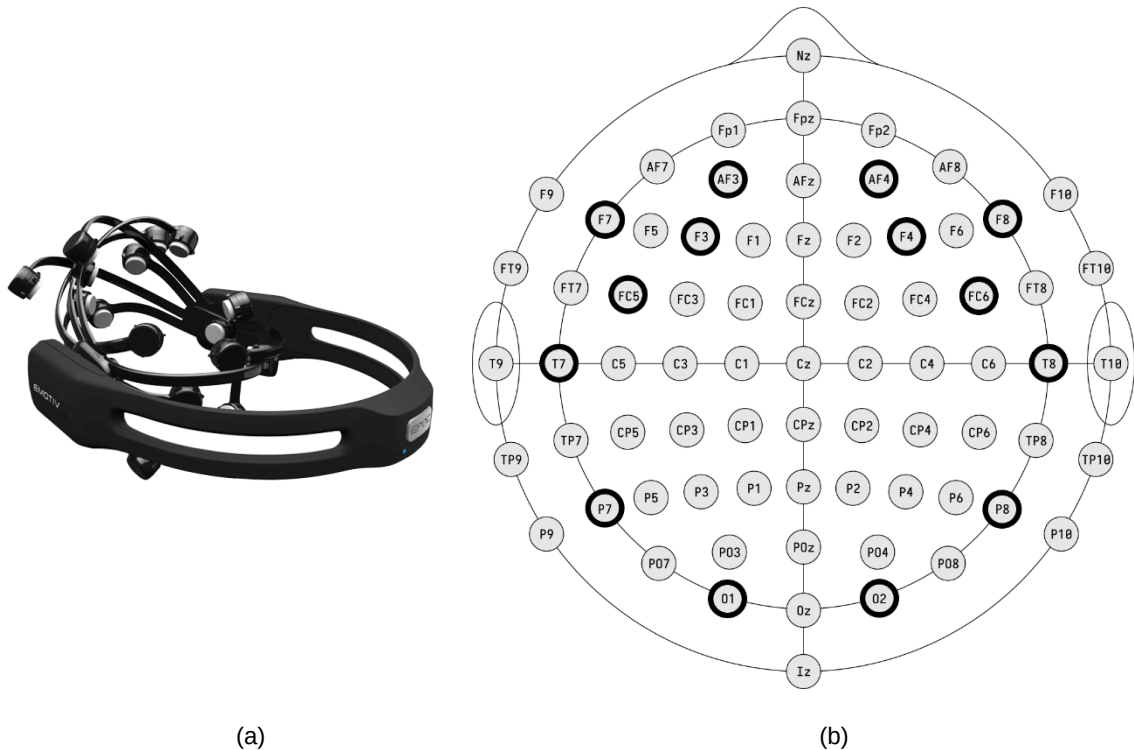


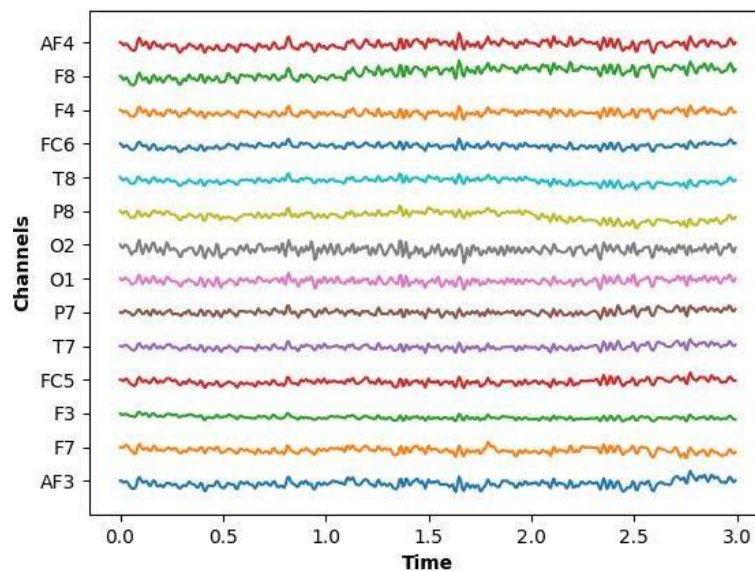
**Fig. 37.** (a) An EMOTIV EPOC 14-channel EEG device and (b) the 10-10 system used to place electrodes (channels) on participants' head. The electrodes with bold circles are used to gather data.

Before starting the experiment, the participants filled out a questionnaire in which they gave some information about their experience in the game, including their ranking and how long they had been playing the game. This information was initially used to group them into two classes, highly skilled and low skilled. After grouping the players, all players in the low skilled class had an experience lower than one year, and all players in the highly skilled players had an experience higher than two years. The

players' skill levels were further confirmed by observing their playing skills during the experiment. The players played between 10 and 30 minutes of LoL either against bots or other players while wearing the headset connected to a laptop using a dongle. The data were finally recorded and saved on the laptop. Fig. 38(a) and Fig. 38(b) show the experiment settings and one of the participants' gathered EEG data, respectively.



(a)



(b)

**Fig. 38.** The experiment settings for gathering the EEG data of LoL players.

### 3.3. Proposed methods

#### 3.3.1. Method 1: Body parts sensor data

As mentioned previously, sensor data have proved to be effective in classifying the players' skill levels. In the literature, different sensor data have been utilised for this purpose, which include gaze data (Khromov et al., 2019), keyboard and mouse data (Lange et al., 2022), EEG (Melentev et al., 2020), galvanic skin response (GSR) (Smerdov et al., 2021b), skin resistance (SR) (Smerdov et al., 2021b), heart rate (Blom et al., 2019), electromyography (EMG) (Smerdov et al., 2021b), pupil diameter (Smerdov et al., 2021b), face temperature (Smerdov et al., 2021b), and movement data of players collected using a magnetometer, accelerometer, and gyroscope (Smerdov et al., 2021b, 2021a). Methods using sensor data are not sensitive to the game's settings thereby providing better generalisation. However, these methods fail to provide sufficient information about players' biological and cognitive features. The majority of studies in this category utilise sensor data collected from only one body part (Blom et al., 2019; Khromov et al., 2019; Lange et al., 2022; Melentev et al., 2020). A few studies have additionally employed multiple sensor data (Smerdov et al., 2021b, 2021a, 2019b). However, these studies neglect the connectivity between body parts. This is while this feature could discriminate between players of varied skill levels in both sports and eSports. For example, good connectivity between strides and breathing is proved to be one of the most important features in professional runners (Pisk, 2017).

The main contributions of the first proposed method in this thesis can be summarised as follows: developing an accurate ML algorithm to find the features decisive in distinguishing professional players from amateur players is the first contribution of the proposed method. To my knowledge, this thesis is the first research work investigating this issue. The selected features are then used to enhance classify players' skill levels more accurately. Secondly, this method utilises symbolic transfer entropy (STE) (Staniek and Lehnertz, 2008) to extract connectivity features between sensors' data which are collected from different parts of the body such as hands and eyes. Although STE has been applied to other applications involving sensor data of the same type such as EEG data (Margarette Sanchez et al., 2022; Ravan et al., 2023), this thesis is the first study evaluating eSports players' skill by applying STE to different sensor data, thereby including the connectivity between body parts as input features in the ML model. Thirdly, a novel feature selection procedure is proposed, which is based on a

recently developed method called consensus nested cross-validation (CN-CV) (Parvande et al., 2020) and the minimum redundancy maximum relevance (mRMR) method (Peng et al., 2005).

The secondary dataset, introduced in section 3.2.1, is used to evaluate the proposed method. As some data in the dataset were distorted or were irrelevant to the players skills, only used 12 the most useful sensor data shown in Table 9 are used in the simulations.

### 3.3.1.1. STE

STE is a robust and efficient metric to calculate the information flow in dynamic systems. This method uses a so-called symbolisation method to measure the information flow strength and direction between time series which are collected from devices such as different sensors. The value calculated by STE is a directed measure. A large STE value from  $x$  to  $y$  shows that the  $x$  previous values could help estimate the current  $y$  values, whereas a small STE value indicates that the current  $y$  value is not dependent on the past  $x$  values.

**Table 9.** The list of sensor data used in simulations.

| Sensor data                | Symbol | Description                                                                                         |
|----------------------------|--------|-----------------------------------------------------------------------------------------------------|
| Left hand movements        | LHM    | hand movements data collected by two inertial measurement units (IMU) on the left and right hands   |
| Right hand movements       | RHM    |                                                                                                     |
| Chair movements            | CM     | Chair movements data collected by an IMU sensor installed on the bottom of the chair                |
| Gaze position              | GP     | The gaze position data collected by the eye tracker                                                 |
| Pupil diameter             | PD     | The pupil diameter data collected by the eye tracker                                                |
| Electrodermal activity     | EA     | The electrodermal activity data which are presented in Ohms.                                        |
| Left hand muscle activity  | LHMA   | Data about the left hand's muscle activity measured in voltage using an EMG sensor.                 |
| Right hand muscle activity | RHMA   | Data about the right hand's muscle activity measured in voltage using an EMG sensor.                |
| Heart rate                 | HR     | Pulse data captured by the heart rate monitor installed on the arm and measured in beats per minute |
| Keyboard activity          | KA     | Keyboard activity data presented as the number of buttons pressed in the last 5 seconds.            |
| Mouse activity 1           | MA1    | The distance passed by mouse in the last 5 seconds                                                  |
| Mouse activity 2           | MA2    | The number of mouse clicks in the last 5 seconds                                                    |

Assume that two time series  $X = (x_1, x_2, \dots, x_N)$  and  $Y = (y_1, y_2, \dots, y_N)$  are given, where  $x_i$  and  $y_i$  are the  $i^{th}$  samples measured from two sensors. STE calculates the information flow between  $X$  and  $Y$  by symbolising their amplitudes. To achieve this aim,  $m$  amplitudes  $X_i = \{x_i; x_{i+d}; \dots; x_{i+(m-1)d}\}$  for each  $i$  are organised as  $X_i^a = \{x_{i+(k_{i1}-1)d} < x_{i+(k_{i2}-1)d} < \dots < x_{i+(k_{im}-1)d}\}$  in an ascending order, where  $m$  is called the embedding dimension showing the length of the comparing segments, and  $d$  shows the time delay.  $X_i^a$ , where  $k_{ij}$ ,  $j = 1, 2, \dots, m$  show the indices of the elements of  $X_i^a$ , is then used to produce a symbol sequence  $\hat{X}_i = \{k_{i1}; k_{i2}; \dots; k_{im}\}$ . The following equation can then be used to calculate STE features from the two symbol sequences,  $\hat{X}_i$  and  $\hat{Y}_i$  (Stanek and Lehnertz, 2008)

$$T_{Y,X}^S = \sum p(\hat{X}_{i+t}, \hat{X}_i, \hat{Y}_i) \log_2 \left( \frac{p(\hat{X}_{i+t} | \hat{X}_i, \hat{Y}_i)}{p(\hat{X}_{i+t} | \hat{X}_i)} \right) \quad (1)$$

In this study, STE is used to measure the directed information flow from the sensor  $i$  to the sensor  $j$ , where  $i, j \in \{1, 2, \dots, 12\}$ .

### 3.3.1.2. Proposed ML algorithm

#### 3.3.1.2.1. Data preprocessing

Since many parts of the collected sensor signals contain no or negligible information, a significant noise level will enter the calculations if the entire collected signal is used. The moment the players react to a game event is one of the best times to capture the players' data. For instance, players' skill in working with keyboards is more discernible when they react to the game's events. Otherwise, there is not a noticeable difference in players' keyboard data at other times. In LoL, the game events when players make major decisions include Death, Kill, and Assist events. These events are referred to as "moments of interest" (Mol) in this thesis. Mol for the LoL game are provided by Riot Games and can be collected using Riot API (Riot Games, 2021). Fig. 39 depicts Mol on one of the professional players' heart rate data.

Whether the sensor data before or after each event should be used is a question that cannot be answered using only signal processing techniques and needs to be dealt with from a broader point of view by considering the psychological complications. For this purpose, we first need to know which parts of the data represent the players' decision-making process. To answer this question, the appraisal theory, whose Bayesian representation (Ong et al., 2019) is shown in Fig. 40(a), was employed. According to this theory, the players' emotions before taking action are effective in their

decision-making process, and the outcome of their actions contains information about their cognitive abilities. Accordingly, this thesis proposes a procedure for gathering sensor data before, after, and at the moments of interest. This is done by extracting the sensor data within a time window with a length of  $2t_d$ , where the time window's centre is placed at Mol. Only the extracted data segments inside are then used to compute the STE features between sensors' time series, and the data outside the time window is discarded.  $t_d$  is a hyperparameter showing the delay in extracting the sensor data before and after Mol and should be set using a trial and error approach. Fig. 40(b) shows the proposed data extraction procedure.

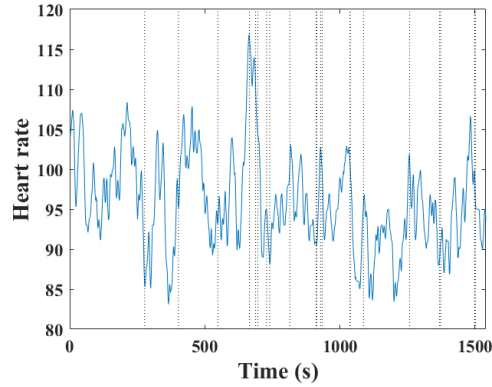


**Fig. 39.** Moments of interest (dotted lines) and heart rate data (blue solid line) of one of professional players.

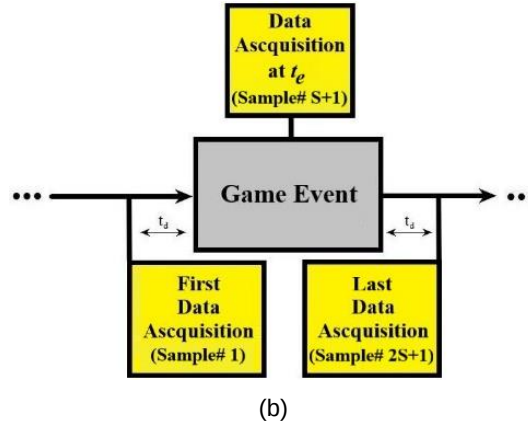
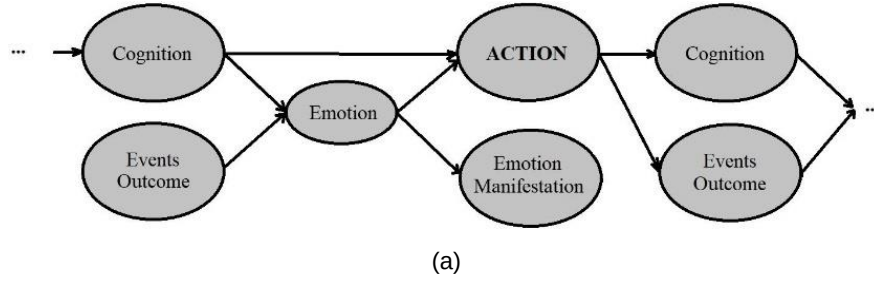


**Fig. 40.** (a) The Bayesian representation of the appraisal theory and (b) the proposed corresponding data acquisition technique to gather data on, before, and after moments of interest.

Assume  $T$  and  $t_e, e = 1, 2, \dots, N$  are the sampling rate and Mol, respectively. At each  $t_e$ , the extracted data for a player playing a match from sensors  $i$  and  $j$  using the  $2t_d$  time window can be shown using two sequences with  $2S + 1$  samples each as

$$X_i^e = (x_{t_e-ST}, \dots, x_{t_e-2T}, x_{t_e-T}, x_{t_e}, x_{t_e+T}, x_{t_e+2T}, \dots, x_{t_e+ST}) \quad (2a)$$

$$Y_j^e = (Y_{t_e-ST}, \dots, Y_{t_e-2T}, Y_{t_e-T}, Y_{t_e}, Y_{t_e+T}, Y_{t_e+2T}, \dots, Y_{t_e+ST}) \quad (2b)$$

where  $t_d = ST$ . In this study, the rate of sampling is equal to one second, i. e.,  $T = 1$ . If there are  $N$  Mol in the game, the extracted data for sensors  $i$  and  $j$  at all Mol can then be stored in two sequences as follows:

$$X_i = (X_i^1, X_i^2, \dots, X_i^e, \dots, X_i^N) \quad (3a)$$

$$Y_j = (Y_j^1, Y_j^2, \dots, Y_j^e, \dots, Y_j^N) \quad (3b)$$

$X_i$  and  $Y_j$  sequences are finally used to compute the STE feature values between sensors  $i$  and  $j$ .

#### 3.3.1.2.2. Feature extraction

(1) and data sequences in (3a) and (3b) can be used to calculate the STE feature  $S_{ij}$  between sensors  $i$  and  $j$ . Given 12 sensors used in simulations, the total STE features is  $N_c = 12 \times 12 = 144$  for each player in each match. For the matches whose number of events was large, the event sequence data was broken into  $K_s$  subsequences containing data extracted from 4-10 events. The STE features were then calculated between the subsequences. This procedure generated  $K_s$  samples for that match where the length of samples was  $N_c$ .

#### 3.3.1.2.3. Feature selection

The previous stage results in a large number of features, which does not meet the final objective of extracting a limited number of the most distinguishing features. A large number of input features in classification can also cause the overfitting problem. To overcome this problem, the  $N_r$  most important features out of all  $N_c$  features are selected. These features are finally used to classify the players' data.

Many feature selection methods, such as the mRMR technique (Peng et al., 2005) have been proposed in the literature. These methods rank features based on their importance. However, how many of the ranked features should be used for classification is a challenge which is not addressed in these methods and remains unanswered. This problem is more important for the problem in this thesis, as one of this research's objective is to determine the exact number of optimum features. To

deal with this problem, the following procedure was applied to select a set of features using the mRMR and CN-CV methods:

- Step 1:** Split the training data into  $K_{train}$  folds.
- Step 2:** Remove one of the folds, and merge the remaining  $K_{all} - 1$  folds merged a fold called the outer training fold  $K_{o_i}$  ( $i = 1, 2, 3, \dots, K_{train}$ ).
- Step 3:** Split the outer training fold  $K_{o_i}$  into  $L$  inner fold.
- Step 4:** To find the  $N_i$  ( $i = 1, 2, 3, \dots, K_{train}$ ) most important features, for each outer fold  $K_{o_i}$ , apply the mRMR feature selection to each of the inner folds  $l$  ( $l = 1, 2, \dots, L$ )
- Step 5:** For each outer fold  $K_{o_i}$ , select features with the highest frequencies among all its inner folds
- Step 6:** Repeat all the steps 1-5 until all  $K_{train}$  folds are removed once.
- Step 7:** Select the  $N_r$  most frequent features among all the  $K_{o_i}$  outer folds as the final consensus features.

The CN-CV method selects the features without training a classifier in contrast to its previous version the nested cross-validation (NCV). Also, fewer irrelevant features are selected using CN-CV compared to the NCV method (Parvande et al., 2020). Moreover, CN-CV does not require a precise  $N_i$  in Step 4 in the algorithms mentioned above. If irrelevant features are selected while setting  $N_i$ , the algorithm automatically remove them while selecting the consensus features.

#### 3.3.1.2.4. Classification and evaluation

In this step, the  $N_r$  selected features were used to train the ML model, and the model was tested on an unseen dataset. To calculate the model's performance, a  $K_{all}$ -fold Cross Validation (CV) method was used. In the CV method, one of the folds is put aside to test the model, and the remaining  $K_{all} - 1$  folds are used to select features and train the model. This iterative process continues until all folds are used to test the model once. Three classifiers, namely, Random Forest (RF), SVM, and K-Nearest Neighbors (KNN) were used for prediction. These classifiers were selected specifically to provide a better comparison with the previous studies which employed the same classifiers and dataset (Smerdov et al., 2021b).

#### 3.3.1.2.5. The most distinguishing features

Two methods were used to find the most important features in classifying eSports players' skill levels: in the first technique, the consensus features were selected by applying the proposed feature selection procedure to the entire dataset. In the second

technique, the features resulting from of the  $K_{all}$ -fold CV described in the previous section were used to find the consensus features. For this purpose,  $N_{r_1}, N_{r_1}, N_{r_1}, \dots, N_{r_{K_{all}}}$  features were selected first using the  $K_{all}$ -fold CV when the 1<sup>st</sup>, 2<sup>nd</sup>, 3<sup>rd</sup>, ..., and  $K_{all}$ th fold was used for testing, respectively. The intersection of all  $K_{all}$  feature was then used to find the most distinguishing features follows:

$$S = \cap_{j=1}^{K_{all}} S_j \quad (4)$$

Where the set  $S$  contains features that were present in all  $K_{all}$  CV iterations. The set  $S_j$  contains  $N_{r_j}$  features which were selected in the  $j$ th iteration of the  $K_{all}$ -fold CV ( $j = 1, 2, 3, \dots, K_{all}$ ).

The CN-CV procedure is based on the features's frequency and does not rank them. To rank the features, the mRMR method was finally applied to the consensus features obtained from the methods mentioned above. If the main goal is to select the most discriminating features without evaluating the model, the first method can be used. This is because if this method is used, no data will be left for testing and evaluation. However, the model can still be tested on another dataset. The second method can be applied when we need to find the most important features and evaluate the model's performance simultaneously.

#### 3.3.1.2.6. Setting $t_d$

The following 8-step procedure was implemented to set  $t_d$ :

**Step 1:** Calculate STE features by setting  $t_d = 1$ . Break the dataset into  $K_{all}$  folds. These folds should be the same folds used to evaluate the model as described in section 3.3.1.2.4.

**Step 2:** Remove one of the folds and merge the remaining folds. Split the merged folds into 80% training data and 20% validation data.

**Step 3:** Find the consensus features by applying the proposed feature selection technique to 80% training data, and then use the consensus features to train the classifiers.

**Step 4:** Compute the model's performance on the 20% validation data.

**Step 5:** Increment  $t_d$  by one and repeat Steps 1-4 until  $t_d = 10$ .

**Step 6:** Select  $t_d$  producing the best performance on the validation data.

**Step 7:** Repeat Steps 1-6 until all  $K_{all}$  folds are removed once. This process will generate  $K_{all}$  values for  $t_d$ .

**Step 8:** Average out computed  $t_d$  values over all  $K_{all}$  folds.

The average  $t_d$  is then used to calculate STE features which are finally to select consensus features and classify the players' data.

Fig. 41 depicts the proposed algorithm's flowchart.

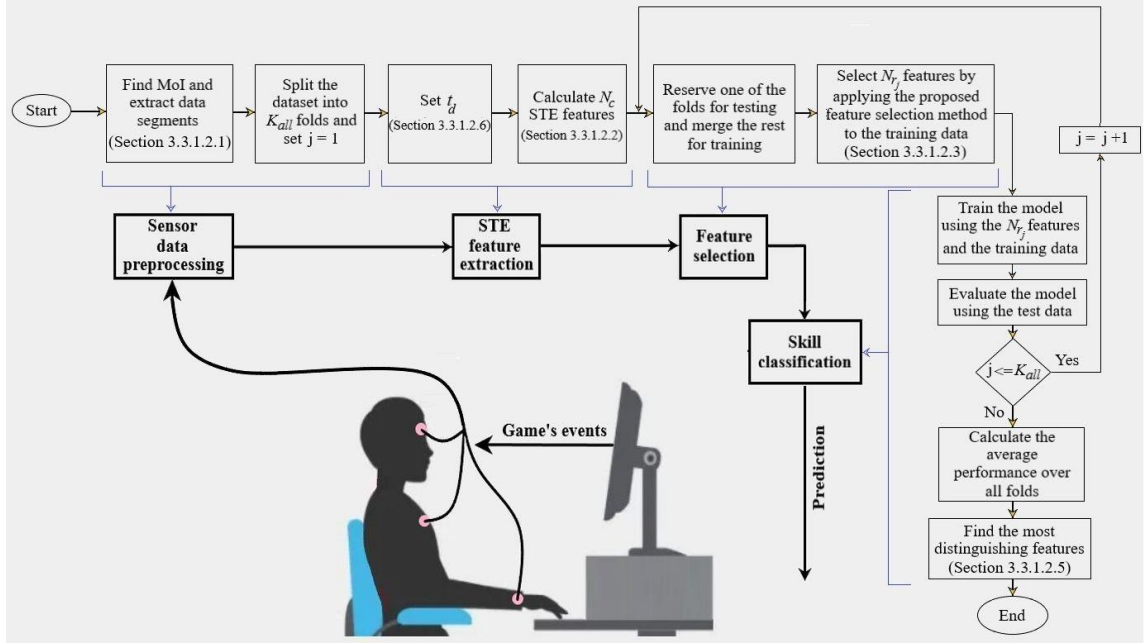


**Fig. 41.** Flowchart of the proposed algorithm (method 1).

### 3.3.2. Method 2: Deep learning algorithm (DLA) using EEG

In this section, a novel DLA method is presented to predict eSports players' skill levels using the gathered primary EEG dataset introduced in section 3.2.2. The proposed method employs ReLORETA to reconstruct the source signals inside the brain and utilises the reconstructed source signals instead of the original EEG data to classify players' skills. The proposed DLA method consists of the following steps: EEG data preprocessing, data augmentation, feature extraction, classification, model evaluation, and feature ranking.

In the following sections, each step will be described in detail.

#### 3.3.2.1. EEG data preprocessing

The EEGLAB MATLAB toolbox (Delorme and Makeig, 2004) and the following eight-step procedure were used for the offline EEG data preprocessing:

- 1) 60 Hz electrical artefact was removed
- 2) Slow drifts were removed using a 0.1 Hz high-pass filter

- 3) Bad epochs including flatline, bursts, and unrecoverable time windows were removed
- 4) Bad electrodes were rejected by thresholding the spatial correlations between the channels, i.e. electrodes
- 5) The rejected electrodes were interpolated using the surrounding electrodes
- 6) The data were re-referenced to the common average
- 7) The residual artefacts were removed using wavelet-enhanced independent component analysis (wICA) (Castellanos and Makarov, 2006)
- 8) The data were finally normalised.

To increase the data quality and avoid imbalance in the dataset, only 7 minutes of each participant's data were used in simulations, which were extracted from the cleanest parts of data despite recording between 10-30 minutes of EEG data for each player initially.

### 3.3.2.2. Feature extraction and classification

For the feature extraction stage, the brain was divided into 41 brain regions in each hemisphere resulting in 82 regions in total as shown in Table 6. The following 6-step feature selection procedure was then implemented:

**Step 1:** Employ ReLORETA to reconstruct the source signals in the 82 regions.

**Step 2:** Decompose the source signals into five frequency bands:  $\delta$  (1 Hz–3 Hz),  $\theta$  (4 Hz–7 Hz),  $\alpha$  (8 Hz–12 Hz),  $\beta$  (13 Hz–30 Hz), and  $\gamma$  (31 Hz–50 Hz).

**Step 3:** Use STE as a robust EC technique to measure the directed connectivity from the  $i^{\text{th}}$  region to the  $j^{\text{th}}$  region ( $i, j \in \{1, 2, \dots, 82\}$ ) at each frequency band. This results in  $82 \times 82 \times 5$  STE images representing the connectivity between brain regions at 5 frequency bands for each one-minute segment

**Step 4:** Classify players' skill levels using a 3D Convolutional Neural Network (3D-CNN) classifier shown in Fig. 42 and the STE images from the previous step.

**Step 5:** Vectorise the STE images and create an STE dataset with rows of size  $82 \times 82 \times 5$ .

**Step 6:** Use STE dataset in Step 5 and an RF classifier to classify players' skill levels again.

The reason the players' skill levels were further classified using an RF classifier was to rank the most important STE features in distinguishing highly skilled players from low skilled players.

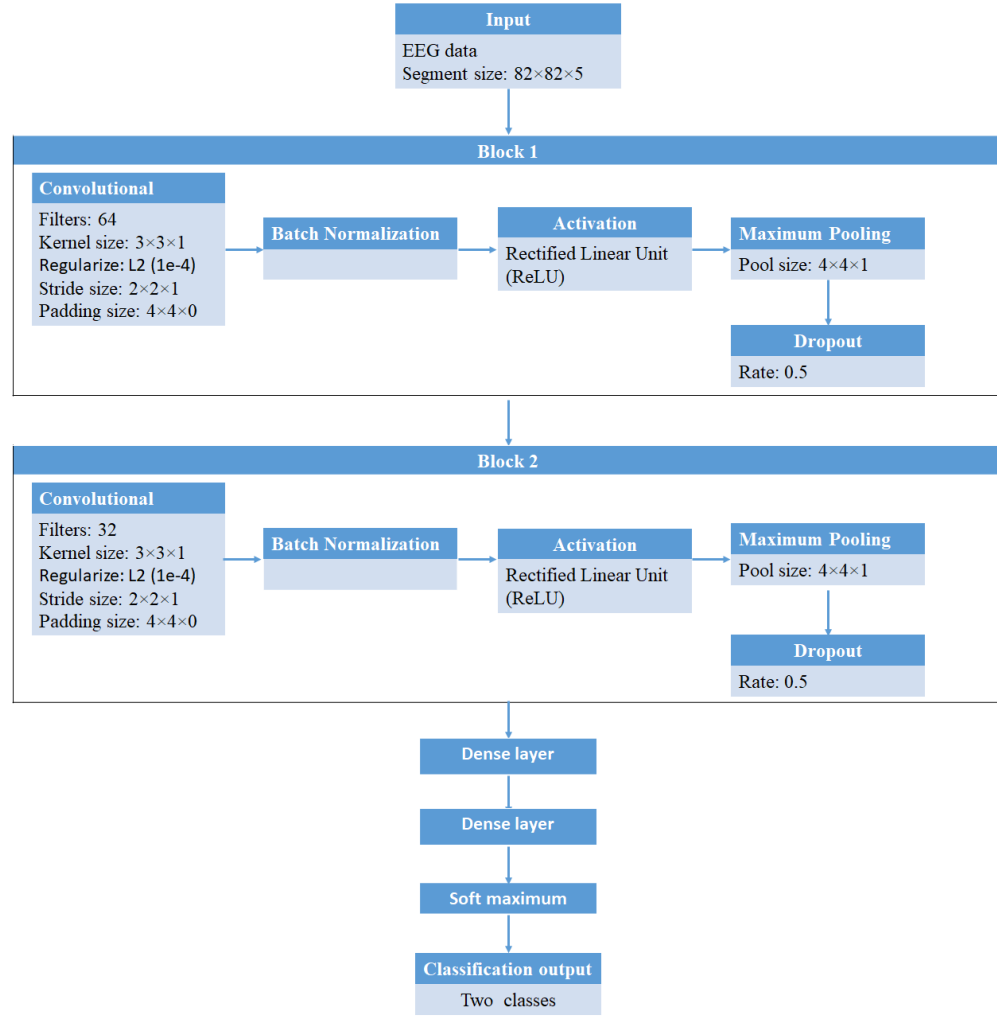


**Fig. 42.** The architecture of the proposed 3D-CNN classifier

### 3.3.2.3. Data augmentation

To increase the sample size, the preprocessed EEG signals were broken into  $K$ -second segments. To determine  $K$ , the following procedure was implemented:

**Step 1:** Split the data into training and test datasets.

**Step 2:** Apply a five-fold CV to the training dataset. For this purpose, the training dataset was split into five folds. In each iteration, four folds were used for training and one of the folds was used for validation.

**Step 3:** For each iteration, increase the segment size from 1 second to 60 seconds in 1-second increments, train the model on the training data, and evaluate the model's accuracy on the validation dataset. Select the segment size giving the highest validation accuracy as the optimum segment size for that validation fold.

**Step 4:** Repeat Step 3 for all validation folds. Calculate the final optimum segment size by averaging all optimum segment sizes calculated for all validation folds.

After implementing the proposed data augmentation technique, the optimum segment size was set to nine seconds. This resulted in nearly 46 nine-second segments for each participant and a total of  $18 \times 46 = 828$  segments for all participants from which 414 segments belong to the professional players and 414 segments belong to amateur players.

#### **3.3.2.4. Model evaluation**

To evaluate the model, two methods were employed. In the first method, a five-fold cross validation method was used, for which the training and test datasets comprised 80% and 20% of data, respectively. However, to further evaluate the model's accuracy and prevent the leakage of information between training and test datasets, a Leave-One-Subject-Out CV (LOSO-CV) method was used, in which, at each iteration, one player's data were used for testing while other players' data were used for training the classifier. In each iteration of the CV and LOSO-CV, the model was trained on the whole training data after setting the segment size.

#### **3.3.2.5. 3D-CNN structure**

Convolutional neural networks are a specific class of multi-layered neural networks, which require less image pre-processing. The main building layers of CNN are convolution, pooling, dropout, dense (fully connected), softmax, and classification layers. Convolution, pooling, and dropout layers are involved in extracting deep features, while dense, softmax, and classification layers do the classification. The convolution layer, which is the main layer of CNN, includes filters (kernels) that are moved along the image in a fixed step called stride. Convolutions of filter and image are evaluated to obtain output feature maps. Zero padding helps to preserve the features at the edge of the input image and control the size of the output feature map. The activation function adds non-linearity to CNN to improve the outputs' fit and therefore accuracy. The pooling layer reduces the size of the feature maps, which results in reducing the number of parameters to learn, thereby reducing the computational load. The dense layer that is followed by the pooling layer, is the layer with a set of neurons that are fully connected to one another. The dense Layer is used to transform the 3D image into 1D image and gives scores to the deep features that were derived from the previous layers. The softmax layer is used as the final activation function to allocate a probability distribution to the feature scores that are used to predict the output class.

Finally, the classification layer assigns the class of the input image. In addition, a CNN uses a batch normalisation layer to normalise all the feature maps hence aiding regularisation and preventing overfitting. A dropout layer can also be used to deactivate the contribution of a portion of the CNN's neurons to reduce overfitting.

As no standard models were available for this application, a CNN model with two convolution layers, two pooling layers, two dense layers, and one output layer was developed. The developed model uses a rectified linear unit (Relu) as an activation function to add non-linearity, a max-pooling layer to reduce the dimension of the feature map, a dropout layer with a probability of 0.5, and batch normalisation layers to reduce overfitting. The adaptive moment estimation (Adam) optimiser is used with the decay rates of the gradient and squared gradient moving averages of 0.9 and 0.4, respectively, with an initial learning rate of  $1e-4$  and a batch size of 16. All the parameters were set empirically based on the grid search shown in Table 10 and kept constant for all experiments.

**Table 10.** The grid search used for setting the hyperparameters of the CNN

| Hyperparameter                | Searched values                                  | Selected value           |
|-------------------------------|--------------------------------------------------|--------------------------|
| Learning rate                 | $1e-1, 5e-1, 1e-2, 5e-2, 1e-3, 5e-3, 1e-4, 5e-4$ | <b><math>1e-4</math></b> |
| Batch size                    | 1, 4, 8, 16, 32, 64, 128                         | <b>16</b>                |
| Number of epochs              | 5, 10, 15, 20, 25, 55, 75, 100, 500              | <b>10</b>                |
| Number of filters             | 3, 5, 10, 16, 32, 64, 100, 128, 200              | <b>128 and 64</b>        |
| Optimiser                     | SGD, Adam, RMSprop, Adadelata, Ftrl              | <b>Adam</b>              |
| Squared gradient decay factor | 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9      | <b>0.4</b>               |

### 3.3.2.6. RF and feature ranking

The RF classifier was formed of 100 trees in which the Gini index was utilised to calculate each split's quality. The number of features to consider when looking for the best split was set to the square root of the total number of features. All nodes were expanded until all leaves were pure or they contained fewer than 2 samples.

To rank the features, the same procedure, proposed in 3.3.1.2.3 and 3.3.1.2.5, was implemented. However, the RF feature importance was used instead of the mRMR method.

## 3.4. Evaluation metrics

To assess the performance of the predictive models, in the first step, true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) were counted for each classification problem. TP, TN, FP, and FN were then used to calculate

several key metrics, including accuracy, specificity, sensitivity, precision, and the F1 score.

Metrics such as receiver operating characteristics (ROC) and area under the curve (AUC) are not used in evaluating the classification performance in this thesis. This is mainly because these metrics measure the performance of a classifier over all possible classification thresholds (i. e. the cutoff point for deciding whether a given input is classified into the positive or negative class). However, in this thesis, decisions are only made using a threshold set to 0.5 and there is not a practical justification for using any other threshold. ROC is mainly useful for medical applications where the threshold may vary according to the consequences of false positives and false negatives (Florkowski, 2008). As the proposed methods require optimisation for a specific threshold, the use of metrics like precision, sensitivity, or accuracy at that threshold is more practical and informative than ROC. Moreover, metrics such as AUC, while useful, are abstract metrics and difficult to understand for someone with no prior knowledge. Therefore, another reason not to include ROC and AUC was to remove confusion and improve interpretation and communication with stakeholders who may not be familiar with these metrics.

In the following section, it will be first explained how TP, TN, FP, and FN were defined for the proposed methods, and then each evaluation metric will be described and formulated based on TP, TN, FP, and FN.

#### **3.4.1. True Positive (TP)**

A true positive occurs when a model correctly predicts the positive class. In other words, it represents the instances where the model's prediction matches the actual positive outcome. The positive class or outcome in this thesis is defined as highly skilled players.

#### **3.4.2. True Negative (TN)**

A true negative occurs when a model correctly predicts the negative class. This means the model has accurately identified an instance that does not belong to the positive class. The negative class or outcome in this thesis is defined as low skilled players.

### 3.4.3. False Positives (FP)

A false positive occurs when the model incorrectly classifies a negative instance as positive. This type of error is also known as a Type I error. In this thesis, a false positive means classifying a low skilled player as a highly skilled player.

### 3.4.4. False Negatives (FN)

False negatives are instances where the model incorrectly classifies a positive instance as negative, also known as a Type II error. In this thesis, a false negative means classifying a highly skilled player as a low skilled player.

### 3.4.5. Accuracy

Accuracy is one of the most intuitive metrics for model evaluation, representing the proportion of correctly classified instances (both positive and negative) out of the total instances. It is calculated as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

Accuracy provides a general measure of the model's performance but can be misleading in cases of class imbalance.

### 3.4.6. Specificity

Specificity, also known as the true negative rate or selectivity, measures the proportion of actual negatives that are correctly identified as such. It is defined as:

$$Specificity = \frac{TN}{TN+FP} \quad (6)$$

Specificity is crucial in contexts where the cost of false positives is high. For instance, for an eSports team, a low specificity could result in low skilled players being wrongly classified as highly skilled players, leading to inadvertently recruiting players with low skills. A high specificity means that most of the low skilled players are identified by the model. However, a high specificity does not guarantee that the model may not have classified many highly skilled players as low skilled players as well. To make sure this error has not happened, we need to calculate other metrics such as sensitivity.

### 3.4.7. Sensitivity (Recall)

Sensitivity, also referred to as recall or the true positive rate, measures the proportion of actual positives that are correctly identified by the model. It is calculated as:

$$Sensitivity = \frac{TP}{TP+FN} \quad (7)$$

Sensitivity is particularly important in scenarios where it is critical to identify all positive cases. A high sensitivity ensures that most highly skilled players are identified by the model, minimizing the risk of inadvertently missing out on the opportunity to recruit highly skilled players. However, a high sensitivity does not guarantee that the model may not have classified many low skilled players as highly skilled players as well. To make sure this error has not happened, we need to calculate other metrics such as precision.

#### 3.4.8. Precision

Precision, also known as the positive predictive value, is the proportion of positive predictions that are actually correct. It is given by:

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

Precision is important when the cost of false positives is high. For example, in this thesis, a high precision rate means that most of the players identified as highly skilled are indeed highly skilled.

#### 3.4.9. F1 Score

The F1 score is the harmonic mean of precision and recall. It provides a single metric that balances the two, especially useful when there is an uneven class distribution. The formula for the F1 score is:

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

The F1 score ranges from 0 to 1, where 1 indicates perfect precision and recall, and 0 indicates the worst performance.

### 3.5. Summary and discussion

A novel methodology was proposed in this chapter to address the research questions. For the first research question, a new data-gathering technique based on the well-known appraisal theory Ong et al. (2019) was developed to capture the most important parts of the players' data. Moreover, an 8-step preprocessing technique was proposed in the second method to ensure the quality of the gathered data. To address the second and third research question, two methods based on the STE feature

extraction and the ReLORETA method were proposed. Two algorithms based on the features extracted in the previous step were then developed to address the fourth research question.

The following is a summary of what was discussed in this chapter:

- 1- Two novel methods are proposed in this chapter to classify the players' skill levels using body parts' sensor data and EEG data, respectively.
- 2- The first method is applied to a secondary dataset provided by Smerdov et al. (2021a, 2021b). The second method is applied to a primary dataset gathered by the author.
- 3- The first dataset contains sensor data, such as heart rate, body temperature, hand and body movement data, etc, gathered from sensors installed on LoL players' body parts.
- 4- The second dataset contains 18 LoL players' EEG signals gathered using an Emotiv EEG headset with 14 electrodes placed on LoL players' heads while playing the game. The players were Staffordshire University students recruited from the university eSports communities. The experiment information was circulated among the students with the help of students and lecturers. The players played 10-30 minutes of LoL either against bots or other players while the headset was recording their EEG data.
- 5- The first proposed method could be summarised as follows: the moments when game events happened, called Mol, were identified. The sensor data were gathered at and around Mol with a time window of  $t_d$ . The gathered data were put in a sequence which was then split into 3 and 2 sub sequences for professional and amateur players, respectively. The STE features were calculated between sensors using corresponding data sequences. The extracted features were then used to classify players' skill levels and find the optimum  $t_d$ . The evaluation metrics were calculated for each model in the end.
- 6- The second proposed method could be summarized as follows: players' EEG data was split into multiple segments. For each segment, the source signals were calculated at 82 brain regions using ReLORETA and were then decomposed into five frequency bands. The STE features were calculated between source signals of different brain regions resulting in  $82 \times 82 \times 5$  STE images representing the connectivity between 82 brain regions at 5 frequency bands. The STE images were then fed to a CNN model to classify the players' skill levels. The STE

images were also vectorised and fed to a random forest model to find the most important features.

- 7- Five metrics, including accuracy, sensitivity, specificity, precision, and F1 score are used in this thesis to evaluate the classification performance.

In the next chapter, the proposed methods will be applied to the secondary and primary datasets and the results will be reported.



# CHAPTER 4

## Results

### OVERVIEW

This chapter presents the results of the proposed methods. As discussed in the previous chapter, the first method is applied to a secondary dataset containing sensor data of 10 LoL players, including five amateur players and five professional players. The primary dataset described in the previous chapter was used to evaluate the second method. Besides evaluating the proposed methods' performance, the results also provide deep insight into which parts of the body and brain distinguish professional players from amateur players.

## 4.1. Introduction

In this chapter, the results of the proposed methodology, including ReLORETA, the first and the second proposed methods are presented.

As discussed in the previous chapters, ReLORETA is a BSL technique to reconstruct the EEG signals inside the brain before reaching the brain's surface. To test the performance of ReLORETA, EEG signals originating from different regions of the brain were simulated. The simulated EEG signals were then fed to ReLORETA to estimate the corresponding source signals inside the brain and localise their location. To ensure ReLORETA's reliability, we further tested it using real EEG signals gathered at the Distributed EEG Lab at the Neuroscience Health Center of Stanford University to localize the source of seizure in an epilepsy patient.

The first method and second methods were applied to the secondary and primary datasets, respectively, and the evaluation metrics were calculated. The features distinguishing highly skilled players from low skilled players were extracted using both methods. In the first method, the extracted features were presented based on the connectivity between body parts. However, the extracted features in the second method represent the connectivity between brain regions.

The rest of the chapter is organised as follows: in the next section, ReLORETA's results in the localisation of simulated and real source signals are presented. The first and second methods' results in evaluating the players' skill levels are presented in sections 4.3 and 4.4, respectively. A summary of the chapter will finally be presented at the end of the chapter in section 4.5. The reader can skip section 4.2 and go to section 4.3 to observe the classification results.

## 4.2. ReLORETA's results

### 4.2.1. Simulated sources

#### 4.2.1.1. Simulation settings

Two scenarios were implemented to evaluate ReLORETA's performance in a real-world situation. In the first scenario, referred to as the worst-case scenario, ReLORETA was applied to focal sources simulated in different brain regions while simultaneously including different errors in the head geometry, electrodes locations, conductivity, and discretisation. Fig. 43(a) and Fig. 43(b) show the two head models with different geometries which were used to generate the EEG signals and solve the EEG inverse

problem, respectively. As can be seen, the New York head model was used to produce the simulated EEG signals, while the Colin27 head model was utilised to solve the EEG inverse problem.



**Fig. 43.** The head models which were used in simulations: (a) the New York head model to generate EEG signals and (b) the Colin27 head model to solve the EEG inverse problem

The segmentation data by Huang et al. (2016) were employed to create the forward head model. For this purpose, the MATLAB FieldTrip toolbox (Oostenveld et al., 2010) was used to create a hexahedral mesh for six tissues, namely, gray and white matter, skull, CSF, skin, and air. The constructed tissues and their corresponding conductivities were then input to the FieldTrip-SimBio pipeline (Vorwerk et al., 2018) to generate the forward head model. The electrode locations were fitted to the head surface, and then dipole sources were spread within the brain's grey matter uniformly. The dipoles orientations were perpendicular to the cortex surface. The FieldTrip toolbox was finally used to compute the lead field matrix using the finite element method (FEM).

To generate the inverse head model, the Colin27 MRI was split into three tissues, namely, skull, scalp, and brain. Three meshes were then created at the tissues' borders using points (or vertices) which were connected triangularly. 1000, 2000, and 3000 vertices were used for the scalp, skull, and brain respectively. FieldTrip then used the generated meshes and their conductivities to create the inverse head model and the electrodes were fitted to the head's surface. Finally, the lead field matrix was computed using the symmetric boundary element method (BEM) method implemented by the OpenMEEG software (Gramfort et al., 2010). A 3D transformation comprising translation, rotation, and scaling (Sarkar et al., 2005) was used to co-register the forward and inverse head models.

The EEG signals were produced using the Simulating Event-Related EEG Activity (SEREEGA) package (Krol et al., 2018) for 20 electrodes which were placed on the head based on the 10-20 placement system (Jurcak et al., 2007). To simulate the electrode misplacement, the electrodes' locations were slightly modified in the forward

model by tilting the EEG set up 5 degrees to the left. To simulate the source discretisation, the forward model was generated using a 2 mm grid, while a coarse 10 mm grid was employed to create the inverse model. The conductivities of the forward model's layers were set to 0.8 S/m, 0.4 S/m, 2.2 S/m, 0.0290 S/m, 0.25 S/m, and 2.5e-14 S/m for the grey and white matter, CSF, skull, skin, and air layers, respectively. However, the inverse model's conductivities were set to 0.33 S/m, 0.0041 S/m, and 0.33 S/m for scalp, the skull, and the brain respectively. All conductivities were extracted from the conductivity ratio and values for the real human reported by McCann et al. (2019).

Different noise levels with SNR values of 5 dB and 20 dB, were used to generate the EEG signals in all cases. The following equation was used to calculate SNR in dB according to (Chrapka et al., 2019):

$$SNR = 10\log_{10}\left(\frac{\text{tr}(CR_s)}{\text{tr}(CR_n)}\right) \quad (1)$$

where “tr” represents the trace of a matrix,  $CR_n \in \mathbb{R}^{M \times M}$  is the background noise covariance matrix of EEG, and  $CR_s \in \mathbb{R}^{M \times M}$  is the covariance matrix of scalp ERP signal.

In all simulations, the FieldTrip's default value, i. e. 0.5, was used to set the regularisation parameter  $\alpha$  (section 4.2.3 provides further details). The following three-step process was used to set  $\varepsilon$ : 20 EEG signals from 20 brain sources which were uniformly spread within the brain's gray matter, were produced in the first step. The hyperparameter  $\alpha$  was then set to 0.05 and ReLORETA was applied to all 20 sources and ran for 60 iterations. (25) was used to calculate the  $NDRE$  values in each iteration. Finally, it was observed that the ReLORETA localization error converged to a final value when  $NDRE^j$  fell below a specific threshold referred to as  $NDRE_{cutoff}$ . So,  $\varepsilon$  was finally set to  $NDRE_{cutoff}$ . The same procedure was used to set  $\varepsilon$  to 0.005 for both single-dipole and extended sources. The normalised reconstruction error (NRE) was additionally calculated for each simulation to better demonstrate the relationship between the reconstruction error of EEG signals and the accuracy of localisation as follows

$$NRE = \frac{\|\tilde{\mathbf{x}} - \mathbf{x}\|}{\|\tilde{\mathbf{x}}\|} \quad (2)$$

where  $\tilde{\mathbf{X}}$  shows eLORETA's or ReLORETA's reconstructed EEG signals, and  $\mathbf{X}$  contains the measure real EEG signals.

The lead field matrix was initially calculated based on the inverse head model for which the 10-20 electrode placement system was used. The transformation matrix  $\mathbf{R}$  was also initialised to the identity matrix. Localisation errors for single-dipole brain sources were computed using the Euclidean distance between the reconstructed and the real source positions. To calculate the extended sources localization error, the distance between the predicted source's center and the real source's center was calculated.

#### 4.2.1.2. Worst-case scenario

##### 4.2.1.2.1. Simulated single-dipole sources

To calculate ReLORETA's accuracy in reconstructing single dipole sources, 60 sources were simulated in different brain regions. The source depth was calculated using its distance from the closest EEG electrode on the head. Two simulated EEG signals with SNR values of 5 dB and corresponding topographic distributions for a superficial source (*i.e.*, close to the cortex surface) and a deeper source at MNI coordinates of [50, -20, -12] mm and [-24, -14, -20] mm are shown in Fig. 44(a) and Fig. 44(b), respectively. The simulated sources' coordinates are situated in the right

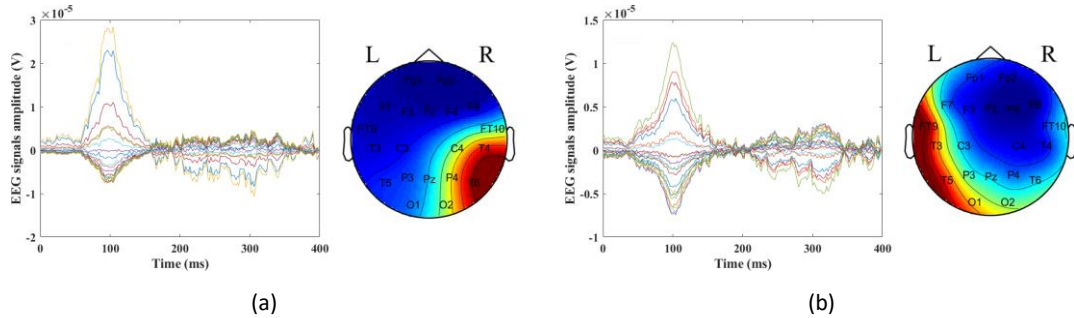


**Fig. 44.** Generated EEG signals and corresponding topographic distributions for two single-dipole sources located at (a) the MNI coordinates of [50, -20, -12] mm and (b) the MNI coordinates of [-24, -14, -20] mm, which correspond to the right Brodmann area 21 (middle temporal gyrus) and the left hippocampus, respectively

middle temporal gyrus, which is believed to be Brodmann area 21 and the left hippocampus, for the superficial and deep sources, respectively. Fig. 45 and Fig. 46 illustrate the corresponding localisation results obtained by applying eLOREATA and ReLORETA respectively. Table 11 also shows the predicted source locations, the corresponding localisation errors, and *NRE* values. As can be seen, for both

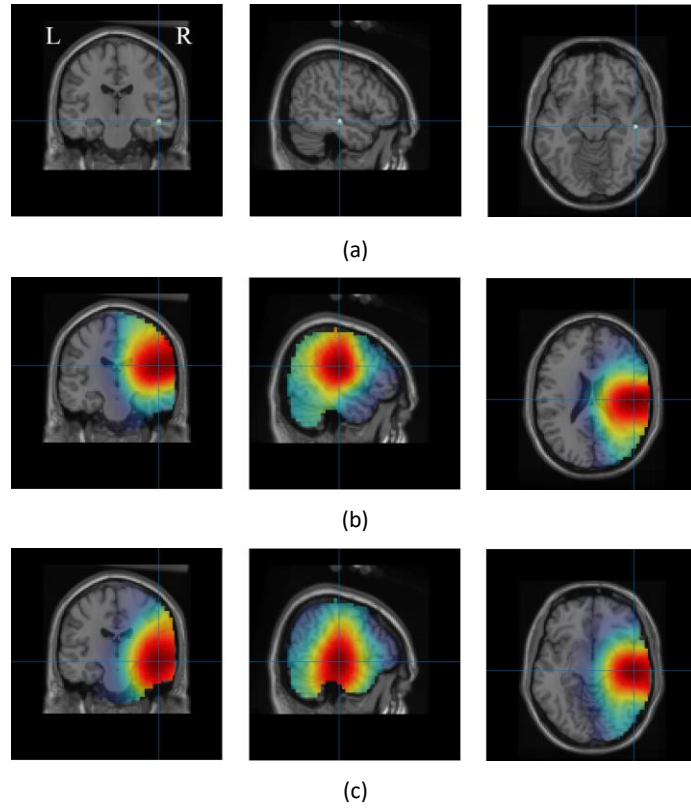


**Fig. 45.** (a) simulated source's real location and localisation outputs of (b) eLORETA and (c) ReLORETA, for the EEG singlas shown in Fig. 44(a).

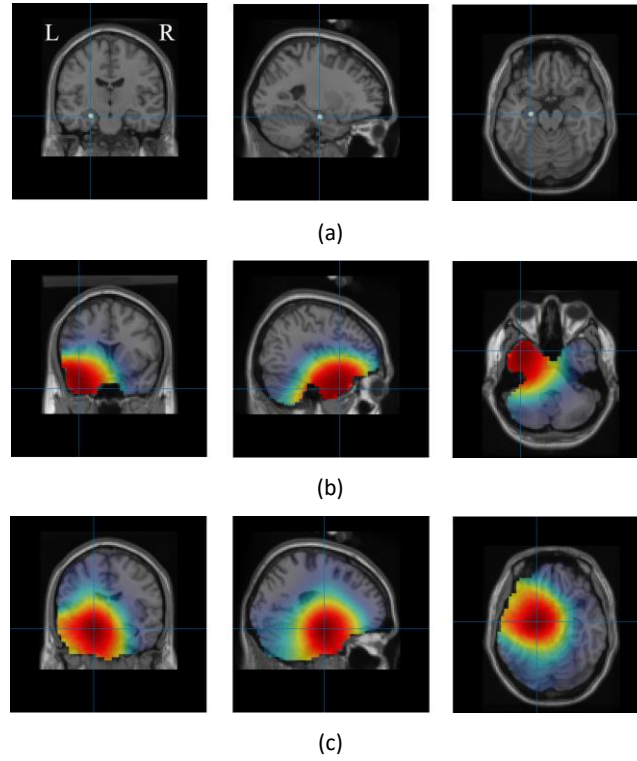


**Fig. 46.** (a) simulated source's real location and localisation outputs of (b) eLORETA and (c) ReLORETA, for the EEG data shown in Fig. 44(b).

**Table 11.** Source localisation errors for simulated single-dipole sources shown in Fig. 45 and Fig. 46

| Source area            | Source location (mm) | eLORETA estimated location (mm) | eLORETA estimation error (mm) | ReLORETA estimated location (mm) | ReLORETA estimation error (mm) | eLORETA NRE | ReLORETA NRE |
|------------------------|----------------------|---------------------------------|-------------------------------|----------------------------------|--------------------------------|-------------|--------------|
| Right Brodmann area 21 | [50 -20 -12]         | [50 -20 20]                     | 32                            | [50 -20 -10]                     | 2                              | 0.18        | 0.11         |
| Left Hippocampus       | [-24 -14 -20]        | [-40 10 -40]                    | 35.09                         | [-20 -10 -20]                    | 5.65                           | 0.21        | 0.05         |

superficial and deep source locations, ReLORETA demonstrates a considerably better accuracy than eLORETA. As a result, ReLORETA's *NRE* value is smaller than that of eLORETA, which is due to the reconstruction error minimisation described in (12).

To better compare eLORETA and ReLORETA accuracies, the overall localisation errors and corresponding *NRE* values for all 60 simulated sources are shown in the box plot in Fig. 47 for multiple noise levels. The horizontal line in the centre for each plot shows the median. The 25<sup>th</sup> and 75<sup>th</sup> percentiles are indicated by the bottom and top edge lines, respectively. The upper and lower whiskers are extended to the farthest data points which are not counted as outliers. The mean value of each plot is shown using the "o" symbol. According to the results, ReLORETA considerably boosts the source localisation overall accuracy. Also, ReLORETA's overall *NRE* value is less than that of eLORETA. Both methods demonstrated similar performance in dealing with different noise levels as both methods' accuracies slightly dropped for high noise levels. However, even in the worst case, ReLORETA's localisation error still remained below 13 mm.

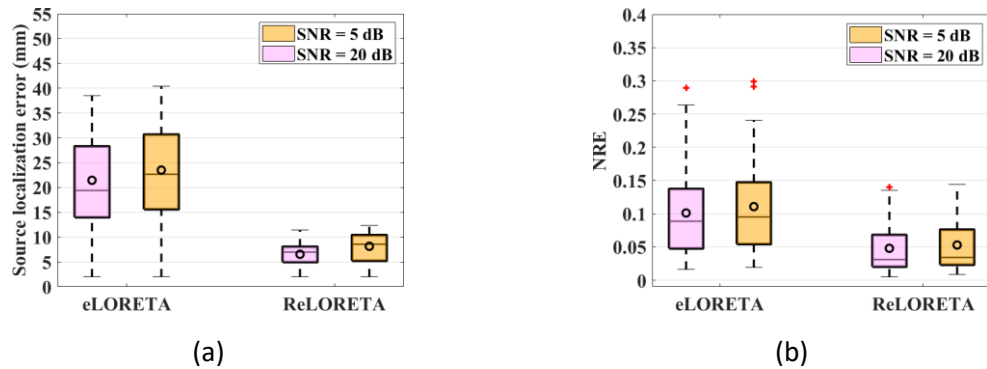


**Fig. 47.** Box plots of (a) overall localisation errors and (b) overall *NRE* values for simulated single-dipole sources.

#### 4.2.1.2.2. Simulated extended sources

To evaluate extended source localisation errors, 60 extended sources were simulated at the same coordinates as the coordinates of the single-dipole sources with each source consisting of 33 dipoles. The EEG signals simulated for two extended

sources are shown in Fig. 48(a) and Fig. 48(b). The sources centre's coordinates were the same as those of the two simulated single-dipole sources, which were right middle temporal gyrus in Brodmann area 21 and left hippocampus, respectively.

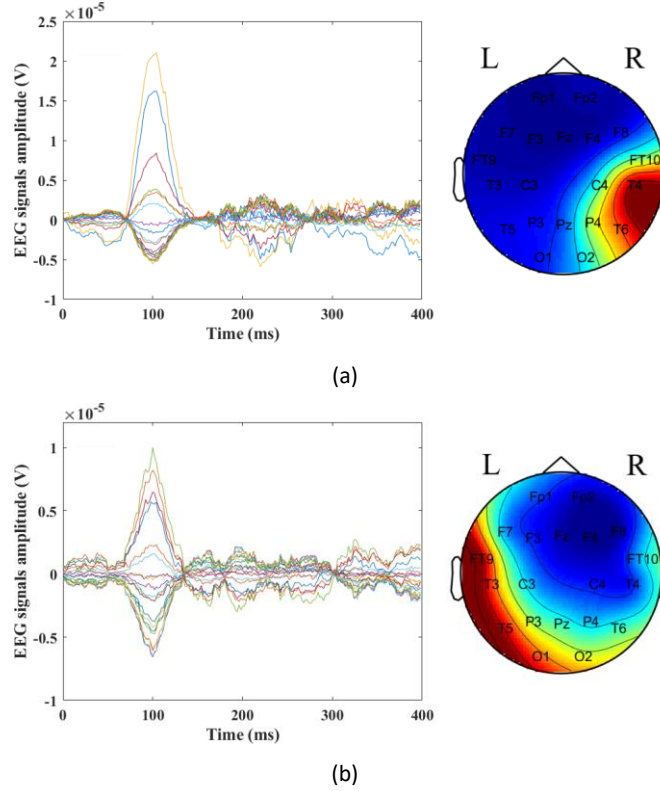


**Fig. 48.** Simulated EEG signals and the corresponding topographic distributions for two extended sources located at (a) the MNI coordinates of [50, -20, -12] mm and (b) the MNI coordinates of [-24, -14, -20] mm, which corresponde to right Brodmann area 21 (middle temporal gyrus) and the left hippocampus, respectively.

Fig. 49 and Fig. 50 and Table 12 present the localisation errors and the related *NRE* values. ReLORETA is still substantially more precise than the eLORETA for both simulated sources. The overall localisation errors and *NRE* values for all 60 extended sources are also depicted in box plots in Fig. 51. Although both methods's performance slightly decreased compared to single-dipole sources, ReLORETA's accuracy is still stable with mean errors of 6 mm and 8 mm for low and high noise levels, respectively. ReLORETA's mean *NRE* value is smaller than that of eLORETA as expected.

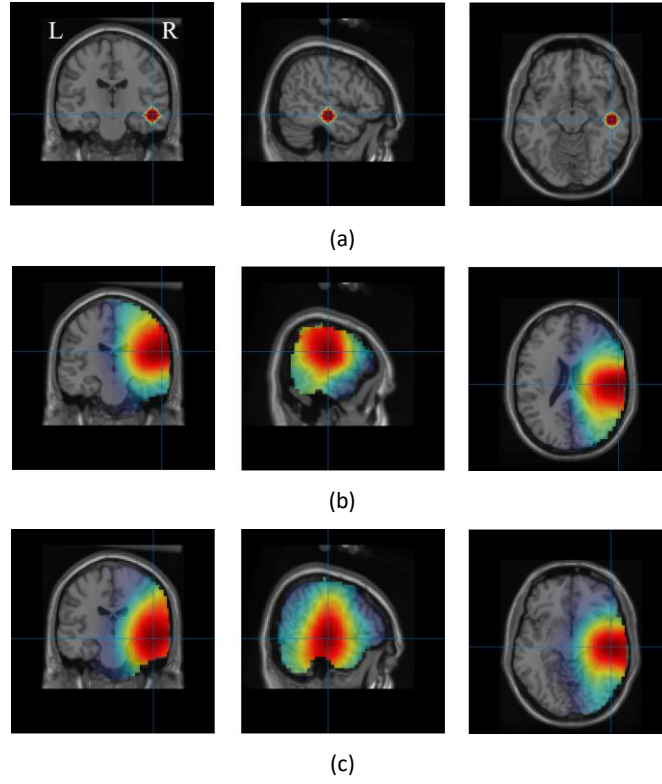


**Fig. 49.** (a) simulated source's real location and localisation results of (b) eLORETA and (c) ReLORETA for the EEG data shown in Fig. 48(a).

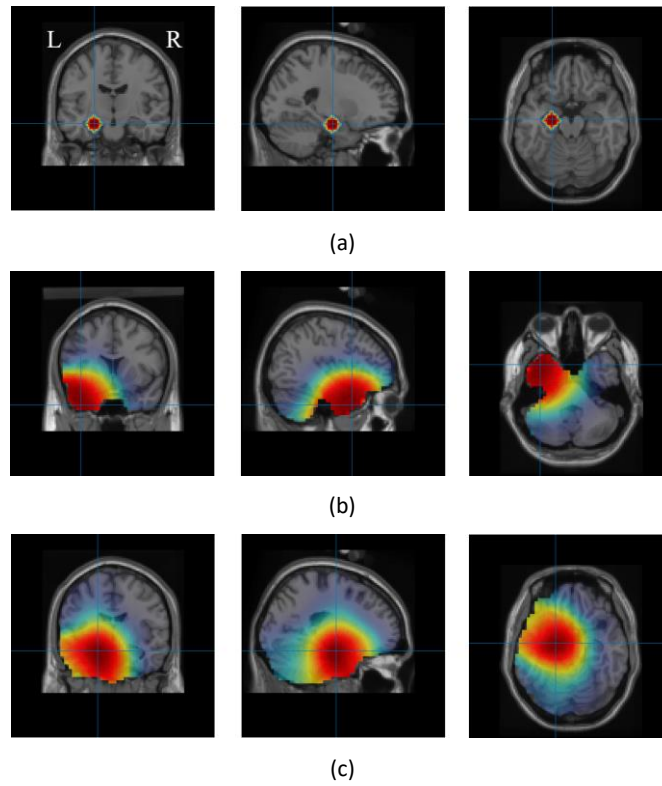


**Fig. 50.** (a) simulated source's real location and localisation results of (b) eLORETA and (c) ReLORETA, for the EEG data shown in Fig. 48(b).

**Table 12.** Source localisation errors for simulated extended sources shown in Fig. 49 and Fig. 50

| Source area            | Source location (mm) | eLORETA estimated location (mm) | eLORETA estimation error (mm) | ReLORETA estimated location (mm) | ReLORETA estimation error (mm) | eLORETA NRE | ReLORETA NRE |
|------------------------|----------------------|---------------------------------|-------------------------------|----------------------------------|--------------------------------|-------------|--------------|
| Right Brodmann area 21 | [50 -20 -12]         | [60 -20 20]                     | 33.52                         | [50 -20 -10]                     | 2                              | 0.13        | 0.042        |
| Left Hippocampus       | [-24 -14 -20]        | [-40 10 -40]                    | 35.09                         | [-30 -20 0]                      | 5.65                           | 0.105       | 0.017        |

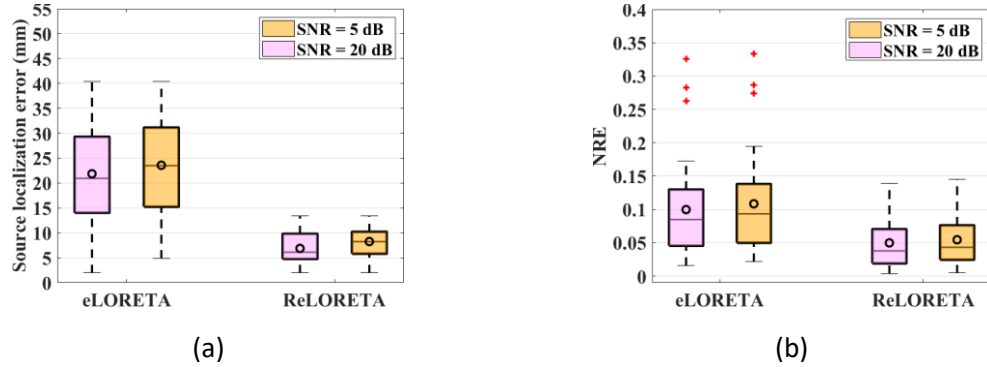


**Fig. 51.** Box plots of (a) overall source localisation errors and (b) overall NRE for simulated extended sources.

#### 4.2.1.3. Individual uncertainties scenario

In the discussed worst-case scenario, it was assumed that no information about the subject was available, including no available MRI. However, subjects' MRIs may be available for some localisation problems. Accordingly, in the second scenario in this thesis, the subject's MRI was assumed to be available, and the inverse and forward models' geometries were the same. For this purpose, the New York head model, which consists of six-shell, was applied to the forward problem. For the inverse solution, a three-shell and a six-shell New York head model were utilised to reconstruct sources. The same method, which was used for the worst-case scenario, was used to create the three-shell inverse model.

Initially, three errors, including errors in conductivity and the discretisation error as well electrode misplacement were simultaneously considered. For this purpose, the conductivities of the gray and white matter, CSF, skull, skin, and air were set to 0.8, 0.4, 2.2, 0.0290, 0.25, and  $2.5 \times 10^{-14}$  S/m for the forward model, and 0.276, 0.126, 1.65, 0.01, 0.465, and  $2.5 \times 10^{-14}$  S/m, for the six-shell inverse model, respectively. For the three-shell inverse model, the conductivities of the scalp, skull, and brain were set to 0.465, 0.01, and 0.126 S/m, respectively. the EEG set up in the forward model was tilted by 5 degrees to the left and used a 2 mm and 10 mm grid for the forward and inverse source spaces, respectively. For the second, third, and fourth simulations, each

source of uncertainty was simulated individually while other uncertainty sources in the forward model were removed. For this purpose, in each simulation, the forward model was distorted with only one uncertainty as follows: for the second simulation, it was assumed that there was no mismatch in electrode positions and a 10 mm grid was used for both forward and inverse source spaces. However, the conductivities of the inverse and forward models were set to different values. For the forward problem, the conductivities of the gray and white matters, CSF, skull, skin, and air were set to 0.8, 0.4, 2.2, 0.0290, 0.25, and  $2.5 \times 10^{-14}$  S/m, respectively, while for the six-shell inverse model these conductivities were set to 0.276, 0.126, 1.65, 0.01, 0.465, and  $2.5 \times 10^{-14}$  S/m, respectively according to Huang et al. (2013). For the three-shell inverse model, the conductivities of the scalp, skull, and brain were set to 0.465, 0.01, and 0.126 S/m, respectively. For the third simulation, it was assumed that the conductivities of the forward and inverse models were the same, and for the six-shell models, the conductivities of the gray and white matters, CSF, skull, skin, and air were set to 0.276, 0.126, 1.65, 0.01, 0.465, and  $2.5 \times 10^{-14}$  S/m, respectively. Also, for the three-shell inverse model, the conductivities of the scalp, skull, and brain were set to 0.465, 0.01, and 0.126 S/m, respectively. A 10 mm grid was used for both forward and inverse source spaces, but the EEG set up in the forward model was tilted by 5 degrees to the left. Finally, in the fourth simulation, the conductivities of the forward and inverse models were set similar to the third simulation, and the electrode positions in both models were also identically set according to the 10/20 electrode placement system. In this simulation, a 2 mm grid was used for the forward source space while a coarser grid of 10 mm was used for the inverse model. All other simulation settings and hyperparameters were set similarly to the worst-case scenario discussed in section

#### *4.2.1.3.1. Simulated single-dipole sources*

60 single-dipole sources were simulated at the same location as the worst-case scenario. When using the 10 mm grid in the forward model, the dipoles that were closest to the dipoles in the 2 mm grid were selected, for which the single-dipole sources in the worst-case scenario were simulated. Fig. 52 and Fig. 53 show the results of source localisation for eLORETA and ReLORETA where the results were broken down based on the simulated uncertainty in the forward model. The overall errors of both methods decreased in comparison with the worst-case scenario, and ReLORETA gives considerably better results in all cases. Although the average performance of eLORETA is less than 15 mm in single-uncertainty cases (Fig. 53), its

performance fluctuates considerably, making it unreliable for a real-world application where robustness is important.

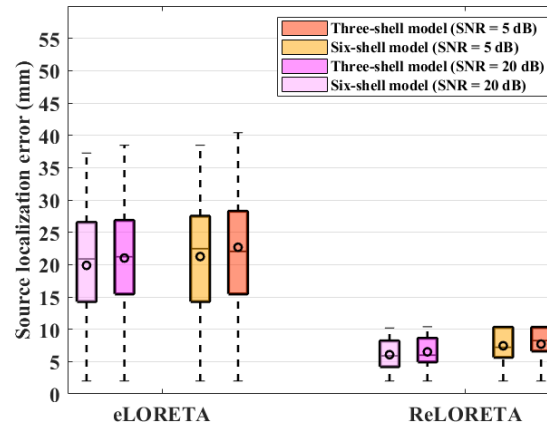


**Fig. 52.** The localisation results of eLORETA and ReLORETA for single-dipole sources when using a six-shell New York head model as the forward model, and a three-shell and a six-shell New York head model for the source localisation. The three remaining uncertainties including conductivity and discretisation uncertainties as well as error in electrode positions were considered in the forward model.

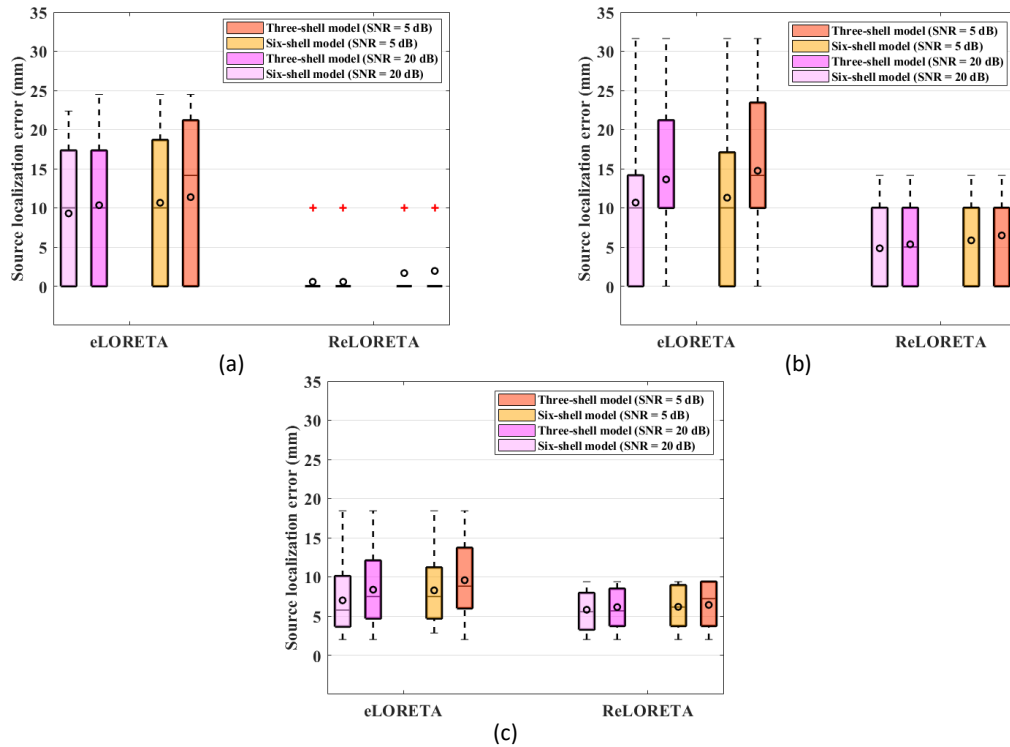


**Fig. 53.** The localisation results of eLORETA and ReLORETA for single-dipole sources when only (a) the conductivity uncertainty (b) the errors in electrodes co-registration and (c) difference in the resolutions of the forward and inverse source spaces (discretisation uncertainty) were considered individually. A six-shell New York head model was used as the forward model, and a three-shell and a six-shell New York head model were used for the source localisation

#### 4.2.1.3.2. Simulated extended sources

As for extended sources, 60 sources were simulated at the same location as dipole sources. For the second and third simulations related to the conductivity uncertainty and error in electrode positions, 10 dipoles were spread around the central dipole while for the fourth simulation the number of dipoles was 36. This is because the forward source space in the second and third simulations was a 10 mm grid and it was not possible to consider more dipoles. However, the total moment of dipoles in all cases was set to be the same. All simulation settings were similar to the single-dipole sources. The localisation results for extended sources in the second scenario can be found in Fig. 54 and Fig. 55. As it can be seen, the accuracies of both methods did not change considerably compared with single-dipole source results. The results are still more accurate than the worst-case scenario and ReLORETA provides the best results in all simulations. Except for the discretisation uncertainty in which the average accuracies of both methods are close, the accuracy of ReLORETA is considerably higher than eLORETA in all other simulations.

Overall, the use of the three-shell model for the inverse solution only negligibly degraded both methods' performance in the second scenario for single-dipole and extended sources. However, the resulting errors are still smaller than the worst-case scenario when the head geometries were different in forward and inverse models.

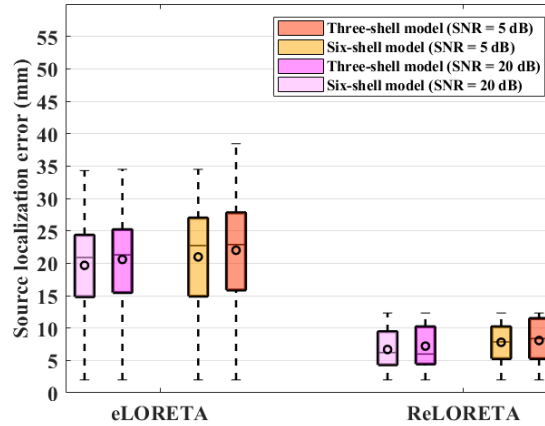


**Fig. 54.** The localisation results of eLORETA and ReLORETA for extended sources when using a six-shell New York head model as the forward model, and a three-shell and a six-shell New York head model for the source localisation. The three remaining uncertainties including conductivity and discretisation uncertainties as well as error in electrode positions were considered in the forward model.

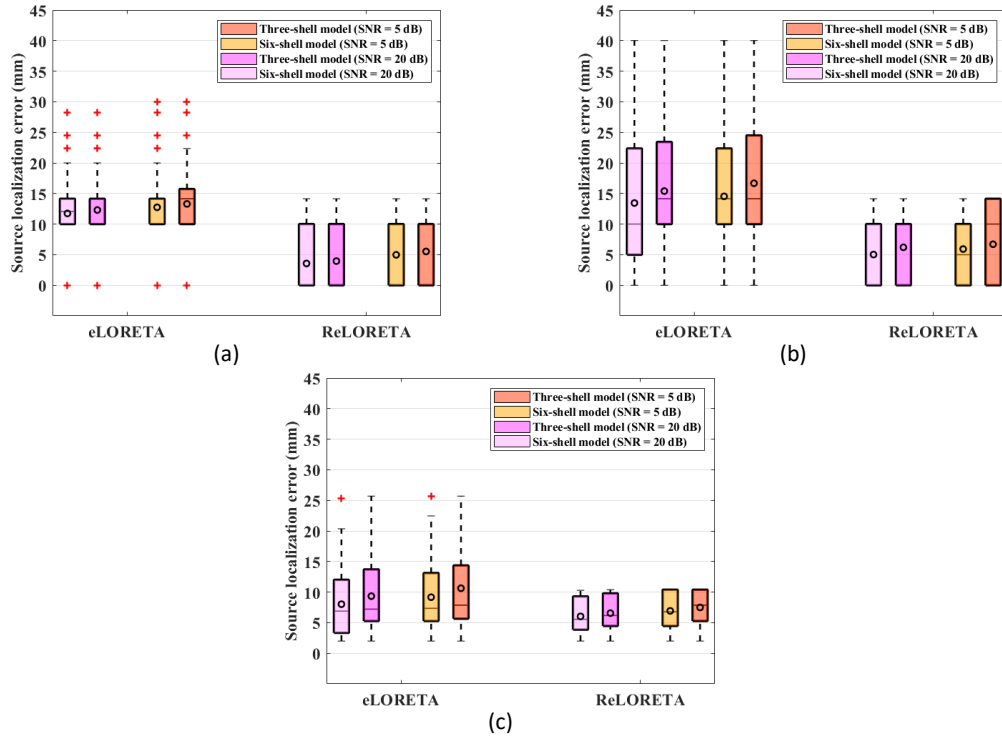


**Fig. 55.** The localisation results of eLORETA and ReLORETA for extended sources when only (a) the conductivity uncertainty (b) the errors in electrodes co-registration and (c) difference in the resolutions of the forward and inverse source spaces (discretisation uncertainty) were considered individually. A six-shell New York head model was used as the forward model, and a three-shell and a six-shell New York head model were used for the source localisation

The following can be concluded for single-dipole and extended sources from the figures in the second scenario: in all localisation problems, it was observed that ReLORETA was substantially more precise than eLORETA. When the three-shell model was used, both methods' accuracies slightly dropped. However, eLORETA was impacted more than ReLORETA. When implementing the three errors simultaneously in the first simulation, it was observed that both methods' overall errors dropped compared to the worst-case scenario. In other simulations, for single-dipole sources, electrodes misplacement, conductivity error, and discretisation error had the highest impacts on eLORETA by generating mean error values of 12 mm, 11 mm, and 8 mm, respectively. eLORETA's maximum error values were 32 mm, 24 mm, and 18 mm respectively. When applying the same uncertainties to the extended source cases using eLORETA, it was observed that it generated mean error values of 15 mm, 13 mm, and 9 mm, and maximum error values of 40 mm, 30 mm, and 26 mm, respectively. After applying ReLORETA to single-dipole sources, the discretisation error, electrodes misplacement, and conductivity error had the biggest impacts on the localisation error by generating mean error values of 7 mm, 6 mm, and 2 mm respectively. ReLORETA's maximum

error in these cases were 9 mm, 14 mm, and 10 mm, respectively. The same head model errors generated mean error values of 7 mm, 6 mm, and 5 mm, and maximum error values of 11 mm, 14 mm, and 14 mm, respectively for extended sources. To measure the sensitivity to the electrode misplacement, electrodes were randomly displaced. It was then observed that the generated errors in this case was considerably smaller than when the EEG electrodes were tilted.

#### 4.2.2. Real EEG data

ReLORETA was also applied to reconstruct the source signals in a patient with epilepsy, the results of which are presented in this section. The EEG data were collected from the same 20 channels as those used for the simulated sources in sections 4.2.1.2 and 4.2.1.3 at the Distributed EEG Lab at the Neuroscience Health Center of Stanford University. The same inverse model was also employed whose scalp, skull, and brain conductivities were set to 0.33 S/m, 0.0041 S/m, and 0.33 S/m, respectively.  $\alpha$  and  $\varepsilon$  were also set to 0.05 and 0.005, respectively. The source real location was close to the boundary of the amygdala and hippocampus regions, and its centre was located at the MNI coordinates of [-20 -5 -20] mm approximately. The seizure location was captured using depth electrodes. In particular, the depth electrodes were implanted in the patient's left and right amygdala and hippocampus brain regions. However, it is practically not possible to capture the source exact location with zero error. This is because such an accuracy entail implanting a large number of electrodes, which is not possible in real-world settings.

The real EEG signals together with the topographic distribution are shown in Fig. 56. The localisation results of eLORETA and ReLORETA and related *NRE* values are also shown in Fig. 57 and Table 13. Both methods' *NRE* and error values are nearly in the same range predicted in the extended sources simulations, *i.e.*, Fig. 51, with error values of 41.53 mm and 20.61 mm, and *NRE* value of 0.360 and 0.077 for eLORETA and ReLORETA, respectively. This could indicate that the most important head model errors were successfully considered in the forward model which was used in simulations since both methods' *NRE* and accuracy values conform to the simulations. Moreover, ReLORETA demonstrated a better performance than eLORETA, which highlights the proposed algorithm's robustness in real-world applications.

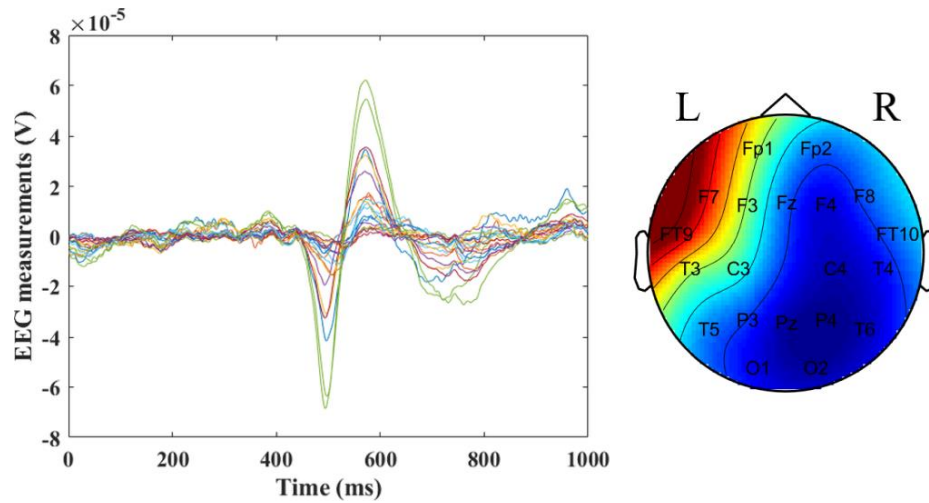


**Fig. 56.** Superimposed real EEG signals from an actual patient based on the 20 electrodes used for source localisation and the related topographic distribution. Each trace has been averaged over 13 measurements (epileptiform discharges).

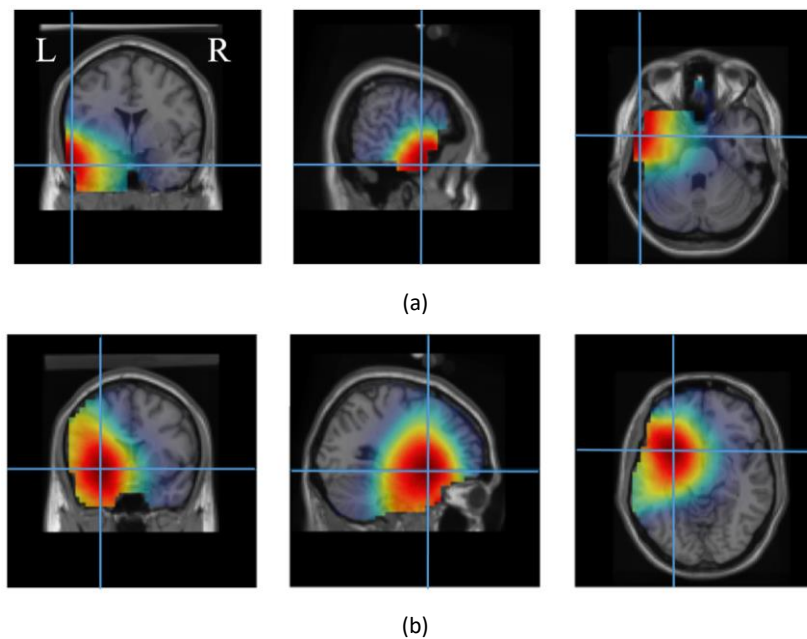


**Fig. 57.** Source localisation results for the real EEG measurements depicted in Fig. 56. The actual source location is around the left amygdala-hippocampal junction centered at MNI coordinates of [-20 -5 -20] approximately. (a) eLORETA output and (b) ReLORETA output.

**Table 13.** Source localisation error for real EEG data shown in Fig. 56

| Approximate source location (mm)                   | eLORETA estimated location (mm)                      | eLORETA estimation error (mm) | ReLORETA estimated location (mm) | ReLORETA estimation error (mm) | eLORETA NRE | ReLORETA NRE |
|----------------------------------------------------|------------------------------------------------------|-------------------------------|----------------------------------|--------------------------------|-------------|--------------|
| [-20 -5 -20]<br>Left Amygdala-Hippocampal Junction | [-60 0 -30]<br>Left Temporal Pole (Brodmann area 38) | 41.53                         | [-30 10 -10]<br>Anterior Insula  | 20.61                          | 0.360       | 0.077        |

### 4.2.3. Noise sensitivity and tuning the regularisation parameter

Fig. 58 shows the results of eLORETA and ReLORETA for different levels of noise averaged over 60 sources. All simulations are carried out using the same simulation settings as the worst-case scenario, and the value of alpha was set to 0.05. It is worth mentioning that using a 5 dB noise the generated EEG signals looked more like real EEG signals and even slightly noisier. The real data of the patient with epilepsy have also an SNR value of 5 dB approximately according to the definition of SNR in (27). By using lower levels of SNR, the resulting ERP signals are completely buried under noise and cannot be observed; something that seems not to be the case with typical EEG data used for brain source localisation. However, the proposed algorithm was examined using lower levels of SNR as well, as shown in Fig. 58. As can be seen, both methods are nearly insensitive to noise. Moreover, they perform similarly in dealing with different levels of noise. This can be due to the fact that, ReLORETA uses the source amplitudes calculated by eLORETA for the localisation of the source after the final iteration and the convergence of the algorithm.

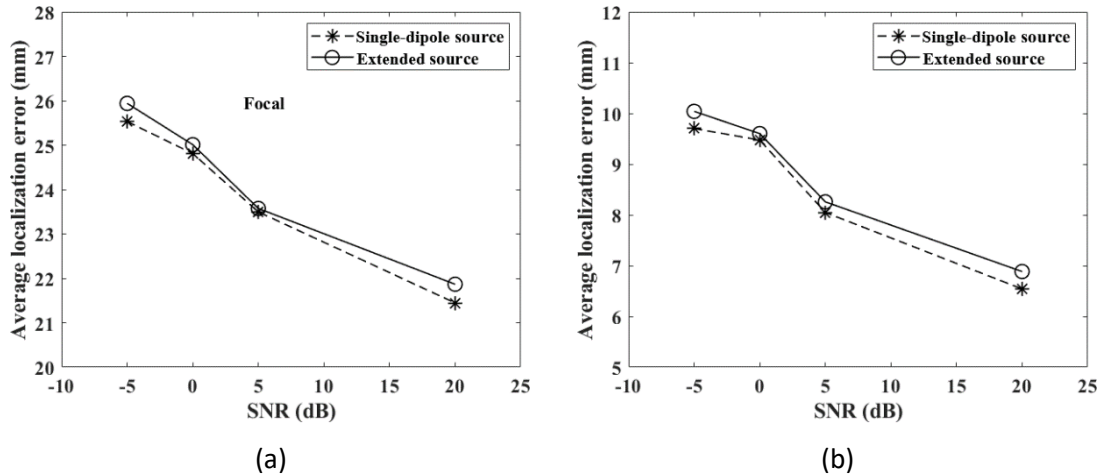


**Fig. 58.** Average error of (a) eLORETA and (b) ReLORETA for single-dipole and extended sources for different levels of noise. The results are averaged over 60 sources.

Regarding the regularisation parameter, different values were used for alpha. For the values between 0.02 and 0.9, considerable changes in results did not happen; the accuracy of eLORETA slightly fluctuated by changing the value of alpha, but the accuracy of ReLORETA remained unchanged. Although the threshold value (i. e. epsilon) changes by changing alpha, the final results of localisation are not affected. It was observed that epsilon is directly proportional to alpha. This means that by increasing alpha the threshold increases too. Furthermore, by using an alpha greater

than 0.02, both eLORETA and ReLORETA became nearly insensitive to noise. In contrast, for values lower than 0.02 both algorithms become more sensitive to noise. Accordingly, in new simulations, alpha was set slightly higher to 0.05 which is FieldTrip's default value as well.

Generally, as long as the employed lead field matrix is not correct, decreasing the EEG signals reconstruction error by any method cannot improve the localisation accuracy, and it can be proved as follows: assume that  $\mathbf{Y}$  and  $\tilde{\mathbf{H}}$  are the true source amplitudes and the true lead field matrix respectively that minimise the reconstruction error according to the equation (3) in the previous chapter. Now, assume that we use the distorted lead field matrix  $\mathbf{H}$  and find the source amplitudes  $\mathbf{Y}_1$  that minimise the reconstruction error roughly to the same extent as what  $\mathbf{Y}$  and  $\tilde{\mathbf{H}}$  do, for example, only by tuning alpha. As the measured EEG signals for both cases are the same, then this entails that the following equation is true:

$$\tilde{\mathbf{H}}\mathbf{Y} \cong \mathbf{H}\mathbf{Y}_1 \quad (3)$$

This equation will hold in the following two conditions:

$$1) \mathbf{Y} \neq \mathbf{Y}_1, \tilde{\mathbf{H}} \neq \mathbf{H}$$

This means that the calculated source amplitudes are not the true source amplitudes. Accordingly, if we use these source amplitudes, then the resulting localisation will not be accurate ((Here the symbol  $\neq$  means that two matrices are not even roughly the same)

$$2) \mathbf{Y} = \mathbf{Y}_1, \tilde{\mathbf{H}} = \mathbf{H}$$

If  $\mathbf{Y} = \mathbf{Y}_1$ , then according to (3) we have  $\tilde{\mathbf{H}} = \mathbf{H}$  (or  $\tilde{\mathbf{H}} \cong \mathbf{H}$ ). This means that the employed lead field matrix should be roughly the true lead field matrix which is against our initial assumption that the employed lead field matrix is not the true lead field matrix.

The right side in (3) depends on  $\mathbf{Y}_1$  and  $\mathbf{H}$ , but tuning alpha can only change  $\mathbf{Y}_1$  and has no effects on the lead field matrix  $\mathbf{H}$ . This is while in real-world problems both lead field matrix and source amplitudes are initially distorted and need to be updated, and this is exactly what ReLORETA is doing. By updating the lead field matrix, both  $\mathbf{H}$  and  $\mathbf{Y}_1$  will be updated and the right side in (3) can be tuned properly. Moreover, this is not dependent on the value of alpha. For any chosen alpha, we only need to update the lead field matrix and source amplitudes, and this will be enough to achieve a solution for (S1).

#### 4.2.4. Reconstruction of EEG signals

Fig. 59 shows the reconstructed EEG signals of the electrode F7 by eLORETA and ReLORETA for the real epilepsy data discussed in section 4.2.2. ReLORETA reconstructs the signal with a minimum error ( $E_{reloreta}^{1/2} = 9.47e - 5 \text{ V}$ ), while the reconstructed signal by eLORETA has a considerable difference from the real measurements ( $E_{eloreta}^{1/2} = 3.31e - 4 \text{ V}$ ).

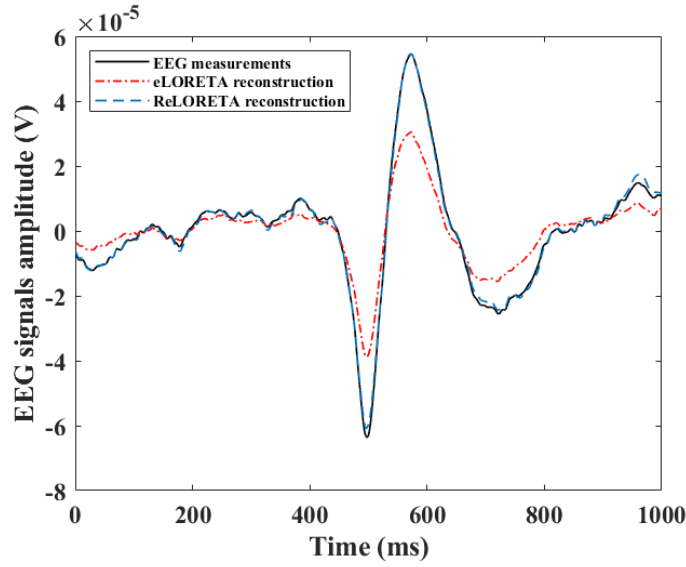


**Fig. 59.** Reconstructed EEG signals of the electrode F7 by eLORETA and ReLORETA for the real epilepsy data discussed in section 4.2.2.

#### 4.2.5. Convergence of ReLORETA

Fig. 60 illustrates the  $NRE$  values of eLORETA<sup>j</sup> and ReLORETA<sup>j</sup> for the real EEG source localisation of the patient with epilepsy shown in Fig. 56. As can be seen, both reconstruction errors converged to an equal value. It is worth mentioning that ReLORETA converged in less than 60 iterations in all simulations. However, using the cutoff value defined by equation (25) in the previous chapter, the average number of iterations needed for convergence was 25.

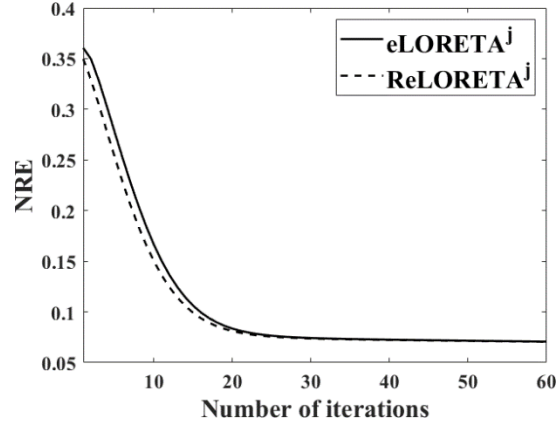


**Fig. 60.** The convergence of  $eLORETA^j$  and  $ReLORETA^j$  for the real EEG localisation of the patient with epilepsy based on the NRE measure.

#### 4.2.6. Effect off number of samples

To assess the performance of eLORETA and ReLORETA with a small number of samples, 10 ms EEG signals with a 1000 Hz sampling frequency for 60 singe-dipole were generated, and sources were extended at the same locations as the worst-case and second scenarios. Fig. 61 shows the localisation results for eLORETA and ReLORETA. The number of samples has nearly no systematic effect on the localisation results, and the accuracy of both methods even slightly decreased in this case.

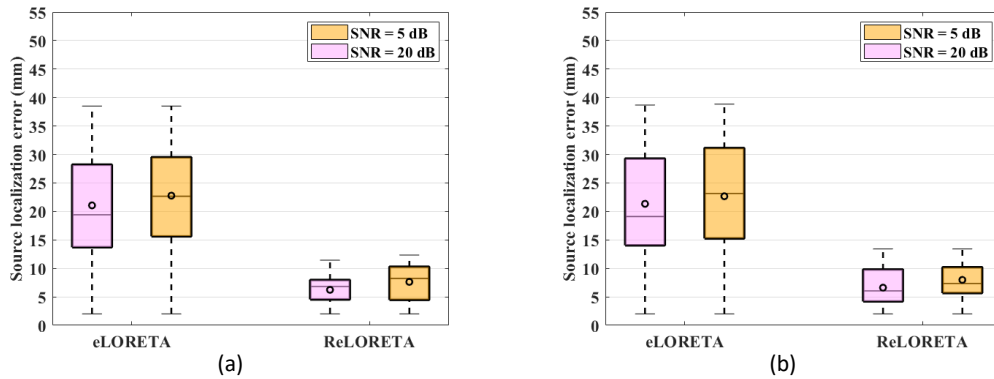


**Fig. 61.** The localisation results of the worst-case scenario using 10 ms EEG signals for (a) single-dipole sources and (b) extended sources.

#### 4.2.7. EEG signals reconstruction error

Fig. 62 and Fig. 63 show the  $NRE$  of eLORETA and ReLORETA for the second scenario, respectively. Overall, the ReLORETA average reconstruction error is lower than eLORETA. This is because for updating the lead field matrix in the proposed iterative algorithm, ReLORETA minimises the reconstruction error according to equation (12) in the previous chapter.

#### 4.2.8. Regularisation effect

To examine the results sensitivity to the regularisation hyperparameter  $\alpha$ , the value of alpha was incremented from 0.1 to 0.9 by a constant value, and then for each value, eLORETA's and ReLORETA's localisation error for the problem in Fig. 50 were calculated. Fig. 64 depicts the results. Alpha values have no effect on the localisation error, and ReLORETA performs considerably better than eLORETA regardless of the alpha value. However, the dotted line shows that if we set  $\alpha = 0.05$ , eLORETA achieves the same EEG signal reconstruction error as that of ReLORETA using  $\alpha = 0.58$ , but ReLORETA's localisation error is still substantially lower than eLORETA's error. This is mainly due to the errors in the head model used by eLORETA for localisation. Therefore, as long as the lead field matrix is not correct, the localisation error cannot be improved by decreasing the EEG reconstruction error regardless of the method used for this purpose, including tuning  $\alpha$ . The results also demonstrate that by applying ReLORETA, the lead field matrix converges to its correct values regardless of the value of alpha.

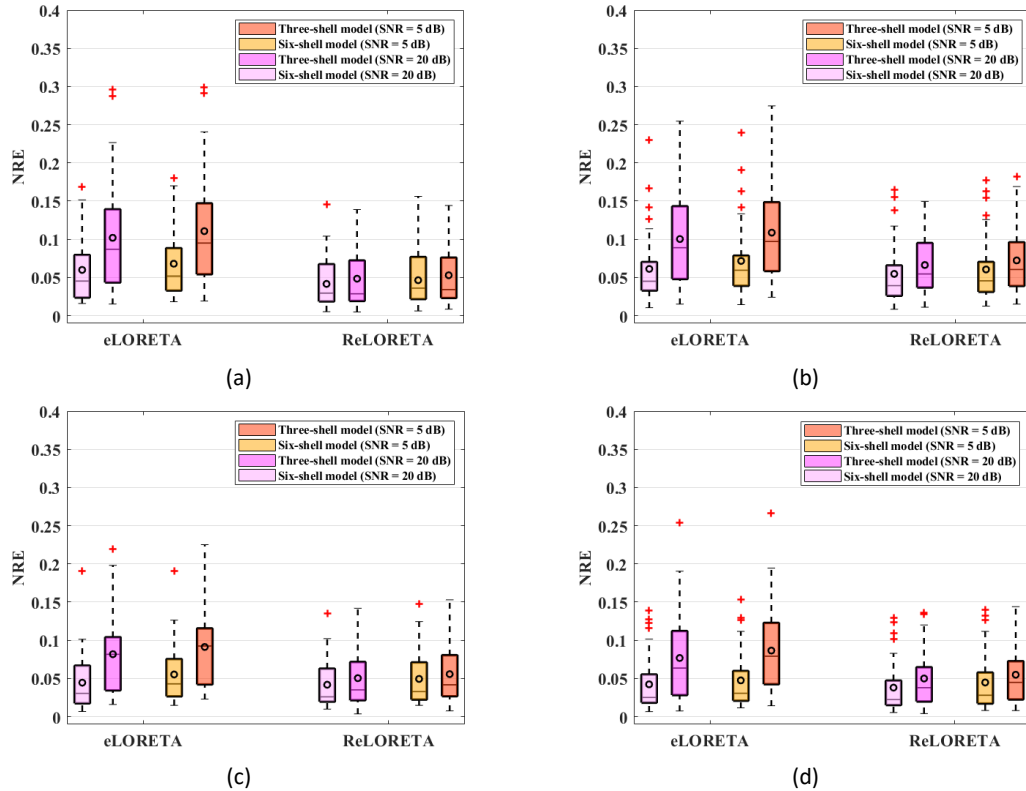


**Fig. 62.** NRE of eLORETA and ReLORETA in the second scenario for single-dipole sources when (a) all uncertainties (Fig. 52), (b) the conductivity uncertainty (Fig. 53(a)), (c) the electrode co-registration uncertainty (Fig. 53(b)), and (d) the discretisation uncertainty (Fig. 53 (c)) was included in the simulations.

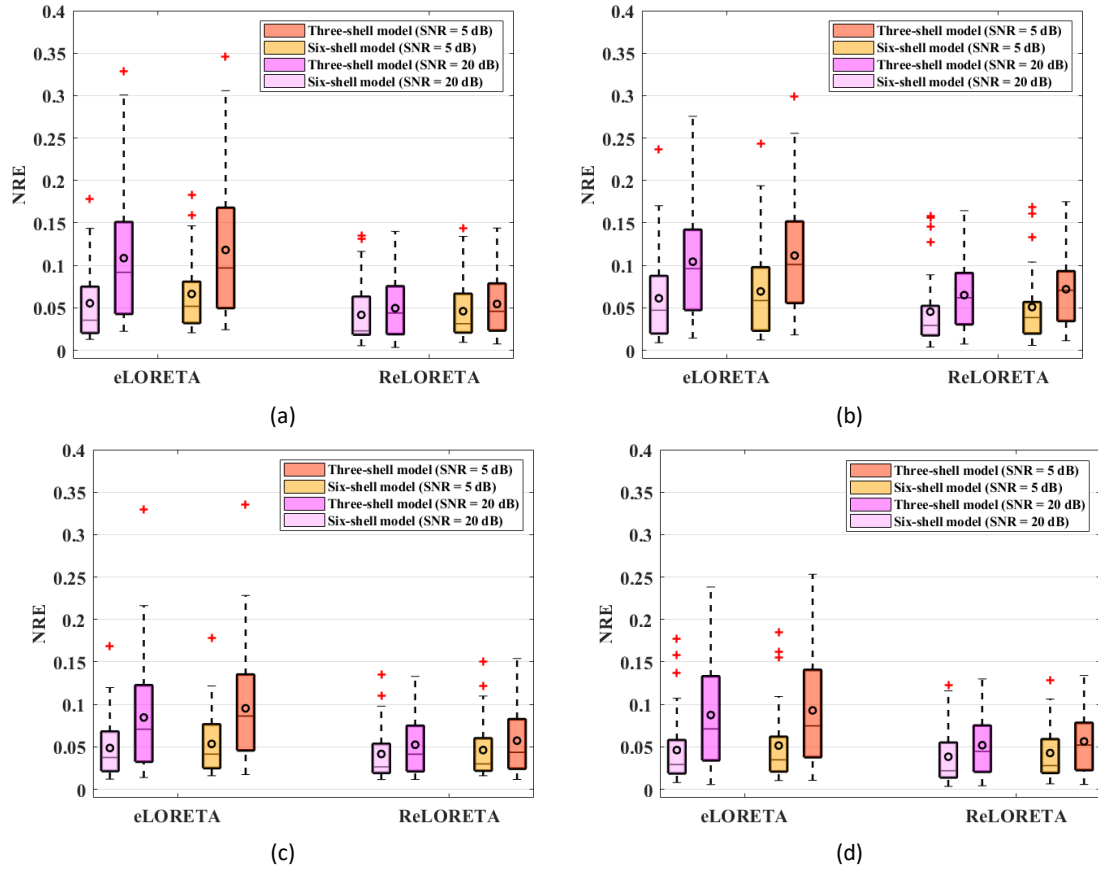


**Fig. 63.** NRE of eLORETA and ReLORETA in the second scenario for extended sources when (a) all uncertainties (Fig. 54), (b) the conductivity uncertainty (Fig. 55(a)), (c) the electrode co-registration uncertainty (Fig. 55 (b)), and (d) the discretisation uncertainty (Fig. 55 (c)) was included in the simulations.

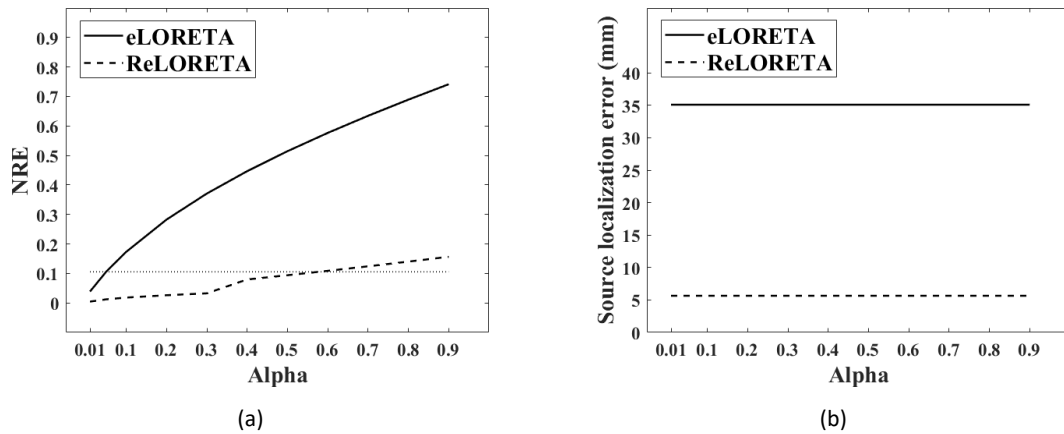


**Fig. 64.** (a) NRE values and (b) localisation accuracies for the source localisation problem shown in Fig. 50 using different values of  $\alpha$ . The horizontal dotted line shows the NRE values of eLORETA and ReLORETA using  $\alpha = 0.05$  and  $\alpha = 0.58$ , respectively.

MATLAB R2020a was used for all simulations in this section, which was run on a laptop with 8 GB of RAM and an Intel Core i7-8565U 1.80 GHz processor. In all simulations, ReLORETA successfully converged in fewer than 60 iterations and mainly in fewer than 25 iterations. Each iteration took a mean running time of 2 seconds to finish. Therefore, the algorithm converged in 50 seconds on average.

### 4.3. First proposed method's results

The section presents the first proposed method's results in the classification of eSports players' skill levels.

To implement the first method, in the first step, game events in each game were extracted using Riot API (Riot Games, 2021) and put in a sequence. In each game, the event sequences were split into two and three subsequences (i.e.  $K_s = 2$  and  $K_s = 3$ ) for amateur and professional players, respectively, due to the number of events being higher for professional players than amateur players. Therefore, for amateur and professional players, each game produced 2 and 3 vectors of length 144, respectively. Since each amateur and professional player played 11 games and 5 players played each match, this procedure approximately generated up to 110 and 165 vectors of length 144 for amateur and professional players, respectively. However, only 110 vectors (i.e. rows) were used for both classes of players to remove the imbalance from the training data. Table 14 shows a summary of the data used in simulations.

**Table 14.** Summary of the data used in simulations

| Players' class | Number of subsequence (i. e. sample) for each game's event ( $K_s$ ) | Number of the games played | Number of players | Total number of subsequence (i. e. samples) | The number of samples used in simulations |
|----------------|----------------------------------------------------------------------|----------------------------|-------------------|---------------------------------------------|-------------------------------------------|
| Professional   | 2                                                                    | 11                         | 5                 | 110                                         | 110                                       |
| Amateur        | 3                                                                    | 11                         | 5                 | 165                                         | 110                                       |

#### 4.3.1. The most distinguishing features

The top 8 STE features selected by the proposed feature selection method are shown in Table 15. The connectivity between the eye sensor data and other data, such as keyboard, mouse, and hand activities are present in most of the selected features. Therefore, according to the results, the connectivity between eyes and hand activities could be a distinguishing factor in elite players compared to low skilled players. The STE feature calculated between between left hand and right hand activities, and

between keyboard and mouse activities are also among the selected features. These results suggest that the connectivity between left and right hands, which work with keyboard and mouse, respectively, is different in professional players compared to amateur players.

**Table 15.** Top 8 STE features selected for classification

| <b>Feature number</b> | <b>Selected connectivity (STE) feature between sensors</b> |
|-----------------------|------------------------------------------------------------|
| <b>1</b>              | GP to KA                                                   |
| <b>2</b>              | GP to MA2                                                  |
| <b>3</b>              | GP to LHMA                                                 |
| <b>4</b>              | GP to RHMA                                                 |
| <b>5</b>              | LHMA to RHMA                                               |
| <b>6</b>              | KA to MA2                                                  |
| <b>7</b>              | MA2 to KA                                                  |
| <b>8</b>              | RHMA to LHMA                                               |

LHMA and RHMA, which are hand activity features, should not be mistaken with LHM and RHM, which are hand movement features. The LHMA and RHMA indicate the tension of the muscle while players are reacting to the game events, but the LHM and RHM features indicate the hand movements of the players in their reactions to the game events. The STE features calculated between the gaze position and hand muscle activities are among the top features, whereas hand movements are not present in any features. Therefore, the results suggest that the reaction time, which is the time lapse between the moment an event is observed by the player (gaze data) and the moment the player reacts to it (hand movements), is a more significant factor than how the players react to the game events using their hands. This fact can also be seen in the mouse activity feature. The number of mouse clicks is present in features 2, 6, and 7, whereas the distance which the mouse has passed is absent in all selected STE features. Therefore, the players' reactions' speed is a more distinguishing feature than how they react. Most players may know how they should react in a specific game event. However, swiftly applying that knowledge in a short moment is a more decisive factor according to the selected features.

Fig. 65 shows the projection of all samples onto their first two principal components, PC1 and PC2. In this figure, the principal components were normalised and the outliers were removed and for a better visualisation. According to the figure, the principle components separate the two classes very well.

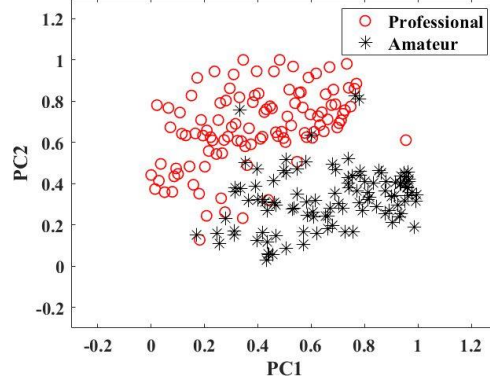


Fig. 65. The dataset projected onto the first two principal components, PC1 and PC2

### 4.3.2. Classification results

The mean accuracy values of all classifiers including SVM, RF, and K- KNN in predicting the players' skill levels using different  $t_d$  are shown in Fig. 66. To evaluate different game events' impact on the ML model's performance, only one game event' sensor data, including kill, death, and assist, were individually used for classification. The best performance from the previous studies, which was achieved by the SVM classifier, is depicted using the dashed horizontal line (Smerdov et al., 2021b).

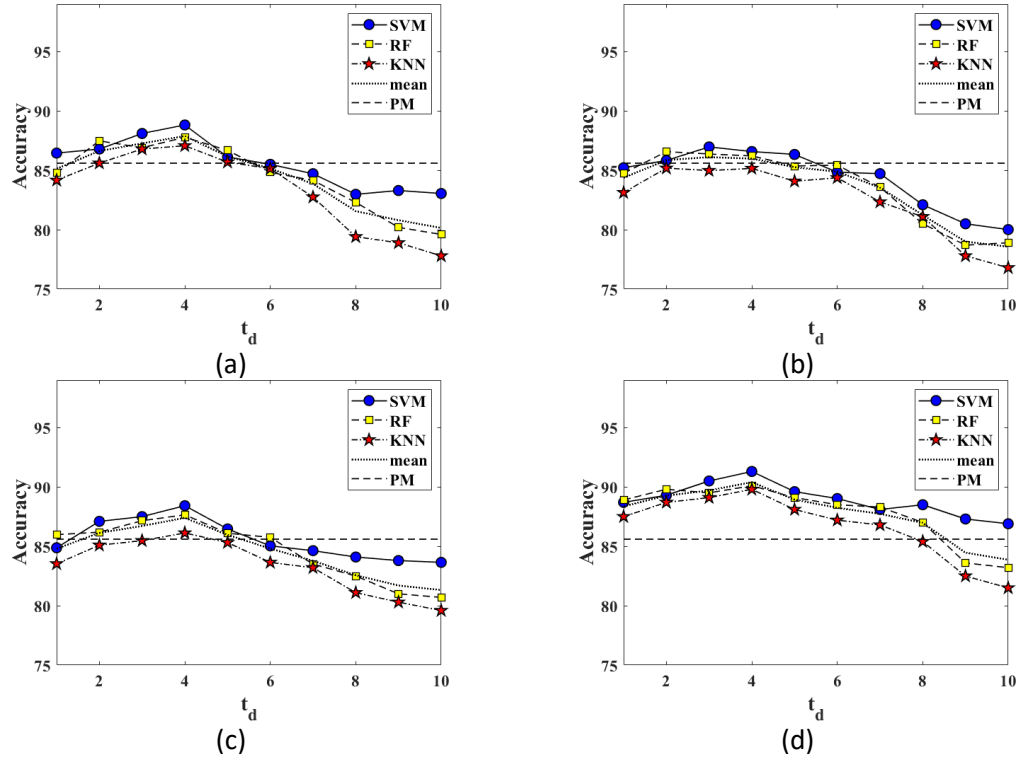


Fig. 66. The proposed method accuracy using SVM, RF, and KNN as well as the mean accuracy values of all classifiers with different  $t_d$  values when (a) only kill data, (b) only death data, (c) only assist data, and (d) all events' data were used for classification. The dotted and the horizontal dashed lines show the mean classification accuracy and the previous method's (PM) best classification accuracy Smerdov et al. (2021b), respectively

When all events' sensor data are included in classification, the proposed ML method demonstrated a significantly better accuracy than the previous study. The best classification accuracies using only kill data, death data, assist data, and all events' data were achieved using  $t_d$  values of 4, 3, 4, and 4, respectively. Except for the death data, when each event's data and the related optimum  $t_d$  value were individually used for classification, all trained models still showed better performance than the previous method. However, compared to the case when all events' data were included, their accuracies slightly dropped, which could be mainly due to fewer number of samples used for training.

The models' accuracies started to decrease at lower  $t_d$  values (*i. e.*,  $t_d = 3$ ) using only death data (Fig. 66(b)). If we assume that by increasing  $t_d$  noisier sensor signals with lower SNR values enter the dataset, this early decrease in the models' accuracies may suggest that the models' outputs are distorted more easily by noise in this case compared to when all events' data were included. However, this needs further investigation to be proved. The overall accuracies using all events' data suggest that, on average, 5 seconds before and after each event, the quality of data start to decrease, thereby degrading the models' performance. Moreover, the classifiers' performance does not rise and fall symmetrically using  $t_d$  values that are smaller and greater than 4. The decline in the models' accuracy with  $t_d > 4$  happens faster than its rise when  $t_d < 4$ . This behaviour may suggest that the collected data have better quality at moments closer to the events.

The classification accuracies using kill and assist data are close and show nearly the same pattern on the graph (Fig. 66(a) and (c)). This effect could be due to the nearly equal number of kill and assist events in the games, and the fact that players' EEG data around these events show similar patterns. The overall accuracy also is more similar to the classification accuracy using only kill or assist data than using the death data (Fig. 66(a), (c), and (d)). This may suggest that that kill and assist events data contain more information than death events about the players' skills.

Table 16 shows the classification performance, including sensitivity (highly skilled players' prediction rate), specificity (low skilled players' prediction rate), overall accuracy (the correctly predicted cases over the sum of all cases), precision (correctly predicted cases of highly skilled players over the sum of all correctly predicted cases), and F1 score (the harmonic mean of precision and sensitivity), for different classifiers and events' data using the optimum  $t_d$ . The results are calculated using a five-fold

cross-validation over 50 runs. Using all events' data, the SVM classifier demonstrates the best performance with a mean accuracy value of 91.3%. closely followed by the RF and KNN classifiers with mean accuracies of 90.1% and 89.8%, respectively. All classifiers' mean performance is relatively close which indicates the robustness and accuracy of the proposed method.

**Table 16.** The classification results using different game events' data

| Classifier | Event data | $t_d$ | Accuracy | Sensitivity | Specificity | Precision | F1_score |
|------------|------------|-------|----------|-------------|-------------|-----------|----------|
| SVM        | Kill       | 4     | 88.6±2.8 | 83.6±6.1    | 93.6±2.2    | 93.0±2.1  | 87.9±3.3 |
| RF         |            |       | 87.7±1.7 | 83.7±7.8    | 91.8±6.8    | 92.6±5.2  | 87.1±2.4 |
| KNN        |            |       | 87.2±3.4 | 82.7±7.8    | 91.8±6.0    | 91.6±5.7  | 86.5±3.3 |
| SVM        | Death      | 3     | 86.8±2.2 | 82.7±4.4    | 90.0±4.0    | 90.3±3.7  | 86.2±2.4 |
| RF         |            |       | 86.3±1.4 | 81.8±4.7    | 90.9±6.6    | 91.0±5.8  | 85.7±1.1 |
| KNN        |            |       | 85.0±3.4 | 80.9±6.0    | 89.0±4.6    | 88.3±4.3  | 84.2±3.6 |
| SVM        | Assist     | 4     | 88.2±3.9 | 85.4±6.0    | 90.9±3.9    | 90.4±4.1  | 87.7±4.2 |
| RF         |            |       | 87.6±1.1 | 81.8±3.7    | 93.6±4.1    | 93.5±3.8  | 86.9±1.2 |
| KNN        |            |       | 85.9±3.0 | 82.7±5.3    | 89.0±3.6    | 88.4±3.5  | 85.3±3.2 |
| SVM        | All events | 4     | 91.3±2.6 | 89.0±4.4    | 93.6±3.6    | 93.5±3.7  | 91.1±2.8 |
| RF         |            |       | 90.1±2.3 | 84.5±3.6    | 95.4±3.9    | 95.2±4.9  | 89.4±2.2 |
| KNN        |            |       | 89.5±3.6 | 87.2±3.4    | 91.8±5.3    | 91.6±5.2  | 89.3±3.7 |

To further evaluate the proposed method's robustness in classifying unseen test data, the models' performance was calculated using the LOSO-CV method. In this evaluation method, one player's data is used to test the model at each iteration, while other players' data are used for training. Table 17 shows the evaluation metrics calculated using all events' data. Although all models' performance slightly decreased, their accuracy values are still considerably higher than the previous method.

**Table 17.** The classification results using LOSO-CV when all events data were used

| Classifier | Accuracy  | Sensitivity | Specificity | Precision | F1_score  |
|------------|-----------|-------------|-------------|-----------|-----------|
| SVM        | 88.6%±2.4 | 84.5±2.2    | 92.7%±4.6   | 92.3%±4.8 | 88.1%±2.3 |
| RF         | 86.2%±3.8 | 81.8±4.9    | 90.9%±2.8   | 89.9%±3.4 | 85.6%±4.2 |
| KNN        | 83.1%±4.6 | 80.9%±3.4   | 85.4%±6.2   | 85.1%±5.7 | 82.8%±4.4 |

#### 4.4. Second proposed method's results

In this section, the results of the DLA described in 3.3.2 are presented. For this purpose, the performance of DLA was evaluated using a 5-fold CV in terms of sensitivity (highly skilled players' prediction rate), specificity (low skilled players' prediction rate), overall accuracy (the correctly predicted cases over the sum of all cases), precision (correctly predicted cases of highly skilled players over the sum of all correctly predicted cases), and F1 score (the harmonic mean of precision and sensitivity).

Table 18 shows the results. As can be seen, DLA could classify highly skilled players and low skilled players with 92.2% and 87.1% accuracies using the CNN and RF classifiers, respectively. To further assess the generalizability of the proposed DLA to new test data, its performance was evaluated using the LOSO-CV method. Expectedly, the performance of DLA decreased slightly. However, it remained in an acceptable range, with an overall accuracy of 89.1% and 82.7% for the CNN and RF classifiers, respectively. Table 19 shows the top ten most important features selected using the feature ranking method described in section 3.3.2.6. These features are also illustrated in Fig. 67 and Fig. 68.

**Table 18.** Mean±standard deviation of the DLA classification accuracy

| Validation method | Classifier | Sensitivity | Specificity | Accuracy | Precision | F1 score |
|-------------------|------------|-------------|-------------|----------|-----------|----------|
| Five-fold CV      | CNN        | 87.9±3.8    | 96.4±1.2    | 92.2±1.6 | 95.6±1.3  | 91.7±1.9 |
|                   | RF         | 82.6±4.7    | 91.5±3.6    | 87.1±2.7 | 90.9±3.6  | 86.4±2.9 |
| LOSO-CV           | CNN        | 82.6±6.7    | 95.7±2.7    | 89.1±4.8 | 95.0±3.3  | 88.3±4.7 |
|                   | RF         | 78.7±3.1    | 86.7±3.6    | 82.7±2.9 | 85.6±3.7  | 82.0±3.1 |

**Table 19.** Top ten most discriminating features in classification of players' skill levels. The abbreviations: T: Temporal lobe, O: Occipital lobe, F: Frontal lobe, P: Parietal lobe

| Features | Region 1                                                             | Region 2                                                              | Frequency band |
|----------|----------------------------------------------------------------------|-----------------------------------------------------------------------|----------------|
| 1        | Left inferior temporal gyrus (ITG)<br>T                              | Right anterior prefrontal cortex (APrFC)<br>F                         | $\beta$        |
| 2        | Left middle temporal gyrus (MTG)<br>T                                | Right orbitofrontal area (OrF)<br>F                                   | $\beta$        |
| 3        | Right orbitofrontal area (OrF)<br>F                                  | Left temporal pole (TP)<br>T                                          | $\beta$        |
| 4        | Right cuneus (Cun)<br>O                                              | Right inferior temporal gyrus (ITG)<br>T                              | $\gamma$       |
| 5        | Right lateral occipital lobe (LOL)<br>O                              | Right superior parietal lobule (visuo-motor coordination) (SPLV)<br>P | $\alpha$       |
| 6        | Left superior parietal lobule (visuo-motor coordination) (SPLV)<br>P | Left dorsolateral prefrontal cortex (DPrFC)<br>F                      | $\beta$        |
| 7        | Right lateral occipital lobe (LOL)<br>O                              | Right temporal pole (TP)<br>T                                         | $\alpha$       |
| 8        | Right primary auditory cortex (PAC)<br>T                             | Right orbitofrontal area (OrF)<br>F                                   | $\gamma$       |
| 9        | Right lateral occipital lobe (LOL)<br>O                              | Left middle temporal gyrus (MTG)<br>T                                 | $\beta$        |
| 10       | Left caudate (Cau)<br>O                                              | Right superior parietal lobule (visuo-motor coordination) (SPLV)<br>P | $\gamma$       |

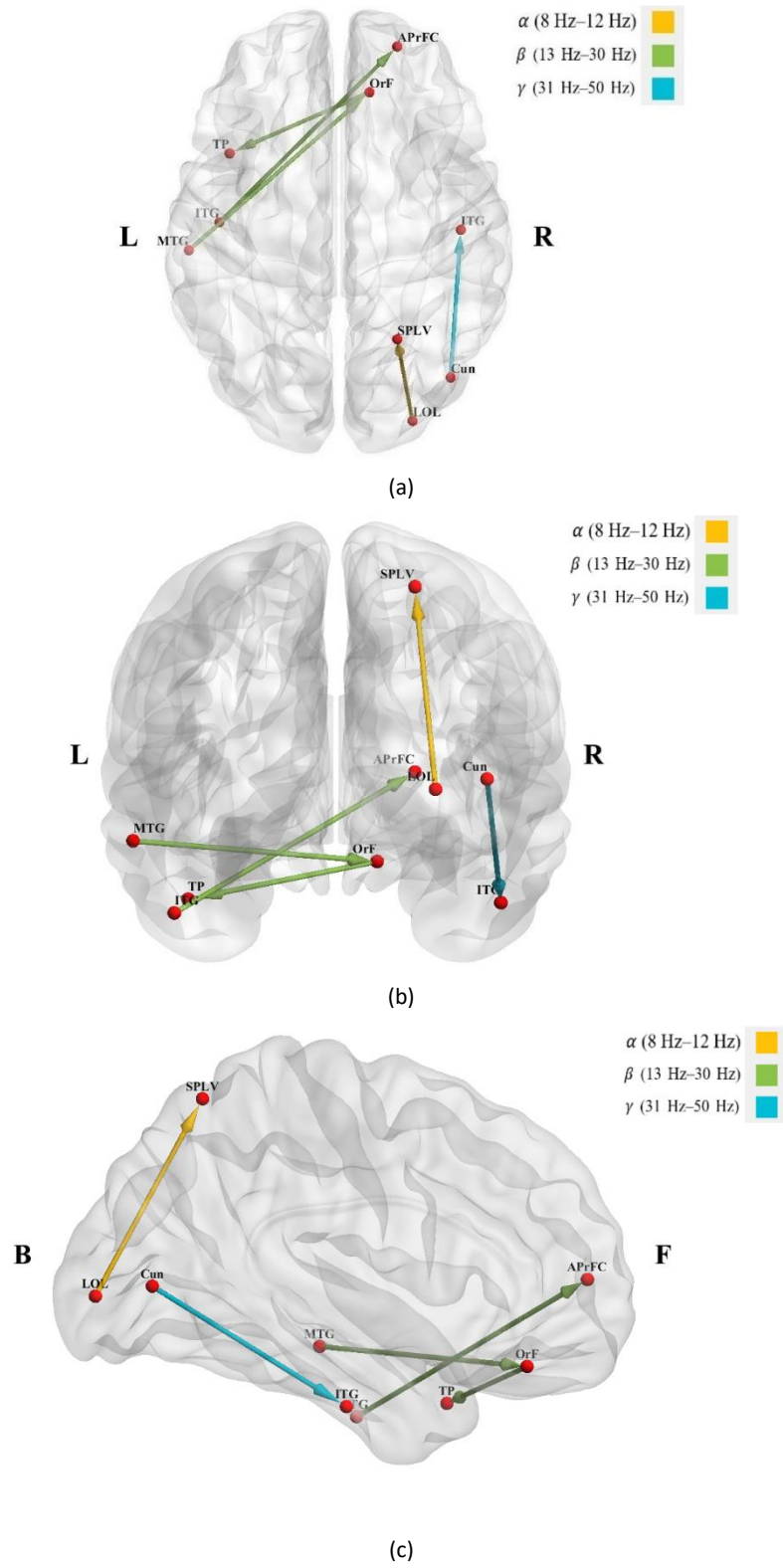


**Fig. 67.** The first five features (features 1-5) in Table 13. (a) Axial view, (b) coronal view, and (c) sagittal view. The abbreviations are as follows: R: Right, L: Left, B: Back, F: Front

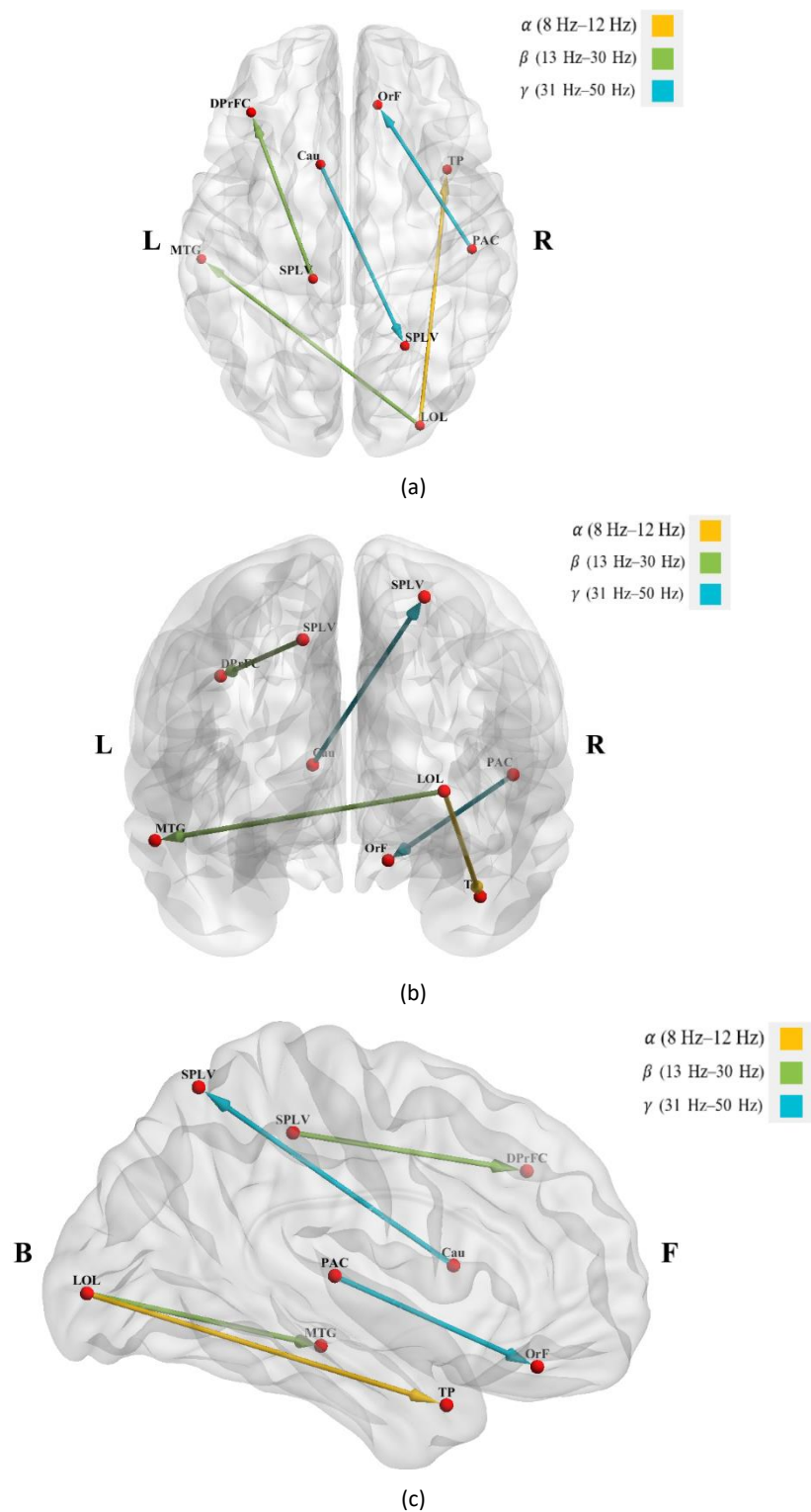


**Fig. 68.** The second five features (features 6-10) in Table 13. (a) Axial view, (b) coronal view, and (c) sagittal view. The abbreviations are as follows: R: Right, L: Left, B: Back, F: Front

In all cases, the sensitivity, i. e. the highly skilled players' prediction rate, is lower than specificity, the low skilled prediction rate. According to the evaluation metrics discussed in 3.4, this means that both classifiers predict amateur players more accurately than professional players.

According to Table 19, temporal, frontal, and occipital lobes are the three main lobes distinguishing professional players from amateur players by appearing in 7, 5, and 5 features in the table, respectively. The parietal lobe is the next dominant lobe by appearing 3 times in different features. The first three connectivity features only include temporal and frontal lobes underscoring the importance of these lobes in the classification. Also, the beta frequency band has the highest frequency among all features by being present in 5 features, followed by gamma and alpha frequency bands with frequencies of 3 and 2, respectively.

## 4.5. Summary and discussion

According to the results presented in this chapter, the proposed methods successfully classified eSports players' skill levels and achieved high accuracy. The following is a summary of the results discussed above:

- 1- ReLORETA, which is a BSL method, was tested using simulated and real EEG signals to reconstruct the source signals inside the brain. In all cases, ReLORETA performed better than the previous BSL method eLORETA even when the EEG setup and simulation settings such as electrode positions, conductivity and geometry of the head were unknown.
- 2- The first method successfully classified the players' skill levels using their body parts sensor data such as heart rate, body and hand movement, eye movement, etc. The classification resulted in 91.3% and 88.6% accuracy using a five-fold and LOSO CV evaluation, respectively.
- 3- According to the first method's results, the connectivity between the eye tracker sensor and other sensors, including mouse, keyboard, and hand activities were among the most important features in discriminating between highly skilled and low skilled players.
- 4- The second proposed method also achieved high accuracy in classifying the players' skill levels using their EEG data by producing 92.2% and 89.1% accuracy using a five-fold and LOSO CV, respectively.

- 5- The second proposed method's results show that temporal, frontal, and occipital lobes are the most important regions in distinguishing professional players from amateur players. The results also showed that the temporal and frontal lobes were the only lobes in the top three most important features. Also, the beta band was the most important frequency band with the highest occurrence among other frequency bands.

The extracted features in this chapter provide a solid answer to the question which eluded researchers for a long time. These features shed light on physical features that could be the main reason some players outperform their peers in eSports. However, delving deeper into the results needs a thorough discussion which will be presented in the next chapter.



# CHAPTER 5

## Discussion

### OVERVIEW

This chapter provides a comprehensive discussion of the results presented in chapter 4. This includes the results of ReLORETA, first and second proposed methods. The limitations of the proposed methodology and the topics emerging from this thesis that could be used for future work are also discussed in this chapter.

## 5.1. Introduction

In the previous chapter, the results of the proposed methods were presented. However, the results were not discussed in detail. In this chapter, a more comprehensive discussion of the results is presented. For this purpose, the results of ReLORETA, the first and second methods will be discussed and compared with previous studies. It will also be discussed how the proposed methods could answer the research questions objectives.

In what follows, ReLORETA's results will be discussed in section 5.2. The discussion of the first and second methods' will also be presented in sections 5.3 and 5.4, respectively. In section 5.5, it will be discussed how the proposed methods achieved the research objectives and then some emerging topics will be discussed for future work.

## 5.2. ReLORETA

ReLORETA's localisation results were presented in the previous chapter in which different errors were included in the forward model. To evaluate the performance of ReLORETA, a worst-case scenario was simulated. In this scenario, different errors including the conductivity error, error in the electrodes' locations, as well as the geometry and discretization errors, were present simultaneously. The results showed that ReLORETA can provide substantially better performance than eLORETA in all cases including reconstruction of single-dipole and extended sources. In the second scenario, multiple errors were simulated both individually and simultaneously while the forward and inverse models' geometries were the same. This can happen in real world applications when the subject's MRI is given. The New York head model consisting of six layers was used to produce EEG signals, and a simplified New York head model with three layers as well as complete six-shell New York head model were used to solve the EEG inverse problem. ReLORETA in this scenario still showed a substantially better performance than eLORETA. When considering different errors individually, ReLORETA showed superior results compared to the previous studies (Akalin Acar et al., 2016; Chrapka et al., 2019; Hossein Hosseini et al., 2018; Rimpiläinen et al., 2019). Both methods' accuracy only negligibly dropped when using the model with three layers compared to the six-shell model. However, eLORETA was

impacted more than ReLORETA. These results confirm the previous studies (Vorwerk et al., 2019) in which it was reported that conductivities of grey and white matters, and CSF have a insignificant impact on the localisation error. However, both methods' error in the second scenario decreased compared with the first worst-case scenario confirming the previous studies' results (Akalin Acar and Makeig, 2013; Steinsträter et al., 2010) which reported an increase in the error of localisation due to error in the head model's geometry. This also proves that a simulated head model based on the subject's MRI can considerably enhance the localisation accuracy. Error in electrodes placement may seriously impact the localisation. According to the results, for both eLORETA and ReLORETA, electrode misplacement was one of the major sources of error, which conform to the findings reported by Akalin Acar and Makeig (2013). The real EEG signals collected from an epilepsy patient was also used to reconstruct the source signals inside the patient's brain. Both methods in this case mirrored the performance achieved on the simulated data while ReLORETA produces a better accuracy than eLORETA. ReLORETA's ability to provide reasonable accuracy and robustness with a low number of electrodes may be of great significance in practical settings where utilizing a sufficient number of electrodes is not possible.

### 5.3. First proposed method

It has been proved that sensor data are effective in assessing eSports players' skill. However, there is currently a lack of an unanimous procedure for preprocessing the collected sensor data. In this thesis, a new method was proposed to deal with this problem, which utilises the appraisal theory. The connectivity between sensors was also included into the trained model by using the STE features as the model's input. To the best of my knowledge, this thesis is the first study using the STE features calculated between sensors, which are installed on different body parts, for classification of eSports players.

The proposed method demonstrated a better performance after being applied to sensor data of LoL players compare to the previous methods. The STE features between the eye data and other sensor data, such as mouse, keyboard, and hand activities, were among the most important features discriminating between professional players and amateur players. This may suggest that the connectivity between eyes and hands is a decisive feature in professional players distinguishing them from amateur players. Therefore, the simulations confirm other studies' outputs (Khromov et al.,

2019; Korotin et al., 2019) which observed a significant relationship between players' gaze data and their performance. However, more fundamental tests might need to be run on players to evaluate this ability outside the context of specific games. One of the most important features in classifying players' skills was the connectivity between keyboard and mouse movements according to the results. Therefore, the connectivity between players' hands working with the keyboard and mouse could be a dominant factor impacting the players' performance. Smerdov et al. (2021a) reported that the distance passed by the mouse and the mouse clicks could determine the outcome of the players' next encounter. They utilised the same dataset as this study in their simulations. However, according to the first method's results in this thesis, the distance passed by the mouse is not among the selected features. They also reported the heart rate as a important feature, but simulations in the first proposed method in this thesis do not suggest that the players' heart rate may have a significant impact on the models' performance. Smerdov et al. (2021b) presented a similar experiment where 11 sensor data were used to classify players into two skill level classes and reported a classification accuracy of 85.6% at the end. However, in both studies discussed above, the gaze position was not reported as one of the most distinguishing features. In a study by Smerdov et al. (2021b), the researchers even reported an insignificant correlation between the gaze data of the players who had the same skill level. This could be due to the fact that in their study, the gaze position is used individually without assessing its connectivity with other data. Since players' gaze position may be considerably different based on the players' role and gameplay, the correlation between their gaze data could be low. In contrast, according to the proposed method's results in this thesis, the gaze position proved to be an important feature when its connectivity with other sensor data is considered.

The significant improvement observed in the proposed ML model compared to the previous findings confirms the proposed approach's reliability. The proposed ML algorithm and the data preprocessing procedure are not dependent on the game platform or the type of the sensor. Future work could focus on applying the proposed method to other applications using other types of sensors to further investigate its robustness.

## 5.4. Second proposed method

For the second method, the decrease in the LOSO-CV results compared to CV results was noticeable, which could be partly because of the leakage of information between training and test datasets when applying the CV method. However, this effect is completely removed when using the LOSO-CV method and the prediction accuracy remains high, nevertheless. The CNN accuracy using the LOSO-CV method is still significantly higher than in previous studies (Smerdov et al., 2021b, 2021a). However, an accurate comparison of the second proposed method in this thesis with previous studies would only be possible if the same dataset were used in both methods.

The three main involved lobes in Table 19, i.e. temporal, frontal, and occipital lobes are responsible for processing sensory input and emotion, movements and cognitive functions, and visual processing, respectively. This could mean professional players have a better connectivity between their observation and movement. For example, this could indicate a lower time between the perception of game events and reaction to those events for professional players. The next dominant lobe in Table 19, i.e. the parietal lobe, is mostly associated with sensory perception and integration, including the management of taste, hearing, sight, touch, and smell. Since the parietal lobe interacts with the occipital lobe in visual perception and processing, this could further indicate a faster reaction time in professional players from the moment they perceive game events to the moment they react. Moreover, the parietal lobe mostly appeared in connection with the occipital lobe (features 5, 6, and 10), which confirms the results of other studies showing an interaction between these lobes (Rehman and Al Khalili, 2023). The most important feature (feature 1) includes the left inferior temporal gyrus and right anterior prefrontal cortex. The first region is known to contribute to visual processing while the second region is known to subserve higher cognitive functions such as task management and planning.

According to the results, it can be concluded that the main feature distinguishing professional players from amateur players is the connectivity between their perception of events and cognitive abilities such as decision-making. In other words, to improve their skills, the players need to improve their reaction time to game events, which, in turn, entails improving their skills in working with keyboard and mouse. These results confirm the outcome of the first method, where the most important features were found

to be the connectivity between the gaze position and mouse, keyboard and hand muscle movements.

## 5.5. Research questions

The proposed methods in this thesis successfully addressed the research questions and achieved the research objectives. To better understand the outcomes, the research questions are presented here and then answered according to the results and proposed methodology as follows.

### 5.5.1. First research question

The following is the first research question laid out in chapter 1:  
“How can we gather and preprocess the most important parts of eSports players’ sensor data to increase the accuracy of their skill level evaluation?”

The first proposed method in chapter 3, presented a novel method to gather the most important parts of players’ sensor data by introducing a variant time window which could be optimised while training the predictive model. Moreover, a novel 8-step procedure was developed in the second proposed method for EEG data preprocessing. The data gathering and data preprocessing methods were tested using secondary and primary datasets, respectively. The results showed a noticeable improvement in accuracy compared to previous studies and proved the reliability and robustness of the proposed approach.

### 5.5.2. Second research question

The second research question was as follows:  
“Which features can be extracted from the gathered data to predict eSports players’ skill levels more accurately?”

In answer to this question, two novel feature extraction methods based on the STE and ReLORETA methods were proposed. To the best of the author’s knowledge, STE was never applied to the sensor data in the previous studies. The ReLORETA method was developed by the author specifically to address the second question. Therefore answer to this question according to the proposed methodology and results can be summarised as follows: Connectivity values between body parts’ sensor data and brain regions’ EEG data are the features that could be extracted from the gathered data to predict eSports players’ skill levels more accurately. The first and second proposed methods were tested using the secondary and primary datasets, respectively. The

results show that the predictive model trained using the extracted features are capable of predicting the players' skill levels more accurately compared to the previous studies.

### **5.5.3. Third research question**

The second research question was as follows:

“What is the difference in body and brain regions' function between highly skilled and low skilled eSports players?”

To answer this question, the most important features differentiating professional players from amateur players were extracted in both proposed methods. In the first method, it was observed that connectivity between eyes and other body parts, including hand movements, were the most important features in classifying eSports players of different skill levels. In the second proposed method, the results showed that the temporal and frontal lobes activities were among the top three most important features discriminating between highly skilled and low skilled players.

### **5.5.4. Fourth research question**

The fourth research question was formulated as follows:

“What AI-based model or algorithm can be used to predict eSports players' skill levels using the extracted features?”

Two novel AI-based algorithms were proposed to deal with this question. Both methods included different steps, such as feature extraction, feature selection, classification and evaluation. The first method relies on machine learning models, including SVM, RF, and KNN classifiers. The second method utilises a CNN model to predict the player's skills. The results show that both methods are capable of classifying the players' skill levels successfully with high accuracy.

## **5.6. Conclusion and future work**

The lack of a reliable EEG dataset has been a major obstacle in studies investigating the behaviour of eSports players using their brain signals. The gathered dataset in this study makes a significant contribution to addressing this problem. To the best of our knowledge, the best EEG dataset provided in previous studies was presented in Smerdov et al. (2021a). However, according to the authors, their recorded EEG data were mostly distorted by noise and other factors and are not reliable. In terms of the

number of subjects, this study significantly outperforms their dataset by including 18 subjects' EEG data compared to 10 subjects presented by them.

In the first method presented in this thesis, the lack of a reliable data gathering technique was successfully addressed by introducing an algorithm incorporating the appraisal theory. The method delivered a higher accuracy compared to previous studies using the same dataset (Smerdov et al., 2021b, 2021a). This method also presented an innovative method to extract features distinguishing professional players from amateur players. To the best of our knowledge, this is the first study investigating this issue. According to our results, the connectivity between players' gaze data and mouse, keyboard, and hand movements are among the most important features setting professional players apart.

The second method proposed in this thesis covers a broader range of applications. A problem in the analysis of EEG data, which is the uncertainties and inaccuracies of the gathered data due to different factors, including the head conductivity, errors in the electrode placement, and other unknown factors, was addressed first. For this purpose, a brain source localisation method, called ReLORETA, was proposed to reconstruct the EEG signals inside the brain. The second proposed method was based on the ReLORETA technique and used the reconstructed brain signals to classify players' skill levels. Besides the high accuracy of the proposed method, it resulted in discovering the underlying brain regions whose activities may be the main contributors to professional players' better performance. According to our results, the temporal, frontal, and occipital lobes are the main regions whose activities are significantly different in professional players compared to amateur players. Also, the inferior temporal gyrus, anterior prefrontal cortex, middle temporal gyrus, orbitofrontal area, and temporal pole were among the most dominant brain regions discriminating between professional and amateur players.

Despite having the highest number of subjects compared to many of the previous studies, the dataset size could still be regarded as one of the limitations of this study. A data augmentation method was proposed to mitigate the effect of this limitation by breaking down each player's data into several segments. However, this could still cause information leakage between the training and test datasets. To prevent this problem, both methods were evaluated using the LOSO-CV technique, which caused a decline in both proposed models' performance. However, both models' accuracy remained high and better than the previous methods. Another limitation of the first

method proposed in this thesis is access to the game events' statistics, including the exact time they happened during the game. While this was possible to achieve for the LoL game, many other eSports do not boast such a sophisticated API to obtain this information. One way to overcome this problem could be recording the game events manually in such games, which will be an arduous and time-consuming task. Since the deep learning and machine learning models training stage is time-consuming, the proposed models are not suitable for any real-time applications that need an immediate response.

The results of this research together with the tDCS method can be used to boost eSports players' performance (Friebs et al., 2021; Okano et al., 2015). However, currently, there is a lack of sufficient evidence for choosing the correct electrode positions and the brain regions that need to be stimulated. This problem could be addressed using the result of this research which finds the brain regions involved in distinguishing highly skilled players from low skilled players. Moreover, as Nijholt et al. (2009) concluded, practically, using a large number of EEG electrodes for building a peripheral device for neuro-feedback games is not viable. For this reason, several studies tried to assess the effect of using a smaller number of electrodes (Nijholt et al., 2008). However, the results were not satisfactory; they could reduce the number of electrodes to six but at the cost of reducing the performance to a low value of 70%. Therefore, a more efficient algorithm, capable of using a small number of electrodes while keeping the performance in an acceptable range, is of interest. Identifying the most important brain regions involved in players' cognitive activities could alleviate this problem (Nijholt et al., 2008). In this regard, this research holds great significance for designing neuro-feedback games and applying DDA by providing a thorough study of players' brain activity.

The methods proposed in this thesis are not limited to eSports players and could be applied to other applications, such as the performance evaluation of athletes. The ReLORETA method proved a significant contribution to studies involving EEG data analysis and has been welcomed by researchers globally. At the time of writing this thesis, ReLORETA has been successfully applied to other applications, including the diagnosis of mental disorders using EEG data.

Effects of uncertainties such as demographics, left-handedness and right-handedness, latency between players' reactions and the gathered data, for example, the heart rate data, and headset (i.e. whether players perform differently with and

without the headset and whether this could affect the results) were not investigated in this thesis and could be a subject for future work. Although the proposed method in this thesis achieved high accuracy by applying ReLORETA to the gathered EEG data, whether ReLORETA is universally better compared to other BSL methods is not guaranteed. Therefore, the effect of ReLORETA in other applications could be the subject of future studies.

Future work may also focus on improving the accuracy of the proposed methods using a larger dataset or other data augmentation techniques. Applying the proposed methods to other fields, such as sports, medicine, geography, agriculture, etc, could be another focus area for researchers interested in this study. For example, the first and second proposed methods in this thesis could be used to discover the physical features and brain regions that distinguish professional or highly skilled players in a specific game or sport. A training program then can be put in place to improve those features, especially for novice players. However, the effect and reliability of such applications need to be investigated and could be the subject of future studies.

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