Reactive and Proactive Anomaly Detection in Crowd Management Using Hierarchical Temporal Memory

Amna Bamaqa, Mohamed Sedky, and Benhur Bakhtiari Bastaki

Abstract—**An effective crowd management system offers immediate reactive or proactive handling of potential hot spots, including overcrowded situations and suspicious movements, which mitigate or avoids severe incidents and fatalities. The crowd management domain generates spatial and temporal resolution that demands diverse sophisticated mechanisms to measure, extract and process the data to produce a meaningful abstraction. Crowd management includes modelling the movements of a crowd to project effective mechanisms that support quick emersion from a dangerous and fatal situation. Internet of Things (IoT) technologies, machine learning techniques and communication methods can be used to sense the crowd characteristic /density and offer early detection of such events or even better prediction of potential accidents to inform the management authorities. Different machine learning methods have been applied for crowd management; however, the rapid advancement in deep hierarchical models that learns from a continuous stream of data has not been fully investigated in this context. For example, Hierarchical Temporal Memory (HTM) has shown powerful capabilities for application domains that require online learning and modelling temporal information. This paper proposes a new HTM-based framework for anomaly detection in a crowd management system. The proposed framework offers two functions: (1) reactive detection of crowd anomalies and (2) proactive detection of anomalies by predicting potential anomalies before taking place. The empirical evaluation proves that HTM achieved 94.22%, which outperforms k-Nearest Neighbor Global Anomaly Score (kNN-GAS) by 18.12%, Independent Component Analysis-Local Outlier Probability (ICA-LoOP) by 18.17%, and Singular Value Decomposition Influence Outlier (SVD-IO) by 18.12%, in crowd multiple anomaly detection. Moreover, it demonstrates the ability of the proposed *alerting* framework in predicting potential crowd anomalies. For this purpose, a simulated crowd dataset was created using MassMotion crowd simulation tool.**

Index Terms—**Alert framework, crowd management, hierarchical temporal memory, reactive anomaly detection, proactive anomaly detection, spatiotemporal data.**

I. Introduction

A crowd is a large gathering of people, which can be either for a predefined purpose e.g. sports or pilgrimage events or spontaneous e.g. random gathering by chance or incidence such as casual crowd. Crowd density defines the number of people per unit of area at a specific time period [1].

By large, crowds are influenced by a diversity of physical and socio-psychological aspects which arise different crowd behaviours and result in different considerations of normal or abnormal behaviours [2], [3]. External and internal factors determine crowd characteristics. The external factors include the environment e.g. indoor and outdoor, areas e.g. entrances, intersections, narrow paths and size scale e.g. macro or micro [4]. As an illustration, some crowd management studies focus on the macro-level of crowd characteristics such as crowd flow rather than individuals' characteristics i.e. micro level, such as their locations and speeds [4]. In contrast, the internal factors are related to the demographic characteristics of pedestrians e.g. cultures, gender, and age and the purpose e.g. the type of gait is different in shopping than public transport places. All these pedestrians' characteristics make the crowd analysis a challenging task due to the unexpected behaviours such as stampede or overcrowding.

Overcrowding might happen daily at many locations such as transport hubs, shopping centeres, and in large events such as sports stadia, pilgrimage places e.g. Hajj or Kumbh Mela, and concert venues [5]. The consequences of overcrowding can be catastrophic and cause a state of chaos. This can trigger panic as individuals sense a loss of control, which may result in disastrous crowd turbulence. Basic crowd management strategies can avoid the majority of crowd disasters by avoiding the buildup of particularly dense crowds and slowing their rate of movement.

Overcrowding without proper crowd management could lead to hazardous situations such as stampede or congestions. These hazardous situations can have side effects on revenue and insurance, which, may cost the organisers extra money, and may affect their reputation severely. For example, the absence of crowd management in pilgrimage events at main intersections results in excessive congestion, which can threaten people's life [6]. Moreover, urban crowd management becomes a major area of interest within the field of crowd management due to the increase of population in urban areas [7]. Therefore, crowd management is not only needed for large events, but it is also critical in daily activities to ensure people's smooth movement and safety.

In recent years, the crowd management domain has progressed with the use of state-of-the-art technologies including IoT communications and machine learning, which have made the crowd management more intelligent, sustainable, faster, and effective [8]. These technologies have given a whole new paradigm and a set of applications, which covers most of our daily life activities, particularly smart systems (e.g., such as smart cities, homes and transport). Besides, smart crowd management (SCM) applications can provide more insights about crowd behaviour and its size [9]. This ability is facilitated by interactions among technologies

Manuscript received October 9, 2020; revised April 12, 2021.

Amna Bamaqa is with Staffordshire University, College Road, ST4 2DE Stoke-on-Trent, UK, and Taibah University, Medina, Saudi Arabia (e-mail: amnabereks.bamaqa@research.staffs.ac.uk).

Mohamed Sedky and Benhur Bakhtiari Bastaki are with Staffordshire University, College Road, ST4 2DE Stoke-on-Trent, UK (e-mail: m.h.sedky@staffs.ac.uk, b.b.bastaki@staffs.ac.uk).

doi: 10.18178/ijmlc.2022.12.1.1072

to sense, collect, transmit, analyse data, and infer semantic content and valuable information based on classification, density estimation, prediction and detecting anomalies.

Numerous empirical studies have examined pedestrian dynamics, and several models have been developed using various methods including field, simulation and experimental [10]. Understanding the dynamics of crowds and patterns of the crowd's behaviour contribute to decision making in artificial intelligence applications, where critical/unwanted situations can be predicted/avoided. The application of Machine Learning (ML) and Deep Learning (DL) techniques to crowd data opens a new approach to understand and manage the crowd's behaviours. The crowd management models that use ML and DL techniques can apply sophisticated pattern recognition, anomaly detection and history-based prediction by exploring correlation in data. In order to add intelligence and leverage the learning ability of a crowd management system, it is necessary to gain access to large volumes of crowd datasets. Therefore, the crowd dataset plays a key role in training, testing, and validation of crowd management systems as their performance is usually affected by the features of selected crowd dataset e.g. changeable densities and speeds [11].

The literature on crowd management has highlighted two main types of crowd data, which are *real* or *synthetic* datasets [12]. Real crowd datasets are either generated manually or by automatic techniques such as video analytic technologies, radio-frequency devices, location-based or mobile sensing. For instance, static or dynamic installation of cameras is often used to collect real crowd data in surveillance applications [13]. However, there are common issues with real crowd datasets, including cost, time, sufficiency, and availability. Other challenges include adhering to ethical issues in emergency cases. These challenges in real crowd datasets result in a lag between the actual empirical research in the crowd analysis field and the theoretical development [14]. Hence, recognizing these limitations of real datasets have motivated the use of simulation tools to generate representative datasets based on the required crowd scenarios.

Prediction and anomaly detection are two of the fundamental ML techniques in the crowd management domain. Crowd management applications seek to identify anomalies in the early stages, which requires the ability to recognise subtle developments in patterns and provide early warning signs. Current methods fail to reach the full potential of anomaly detection and prediction, which demands further exploration of other potential intelligent techniques that can yield promising results [15]. Although there is a relatively large body of literature on crowd management; however, more investigations are required for building adaptive early detection techniques in an online fashion (i.e., learning from continuous data streams). In a natural environment, survival depends on the ability to recognise, interpret and anticipate sensory inputs and their temporal sequences. Hierarchical Temporal Memory (HTM), a new bio-inspired approach for deep learning, is a sequence memory for prediction based upon the knowledge of cortical neurons. HTM draws insight from computational science to include a set of concepts that are important for prediction such as feedback, attention, alerting, time and context as part of the learning process, all of which play a role in how the human brain functions [16].

Reactive crowd management methods provide insights about current crowd behaviour. However, there are certain scenarios in which the ability to predict how crowds will behave is more important than merely recognising how they act e.g. to avoid collisions, provide early warnings or to identify abnormal events [17]. Essentially, the importance of being able to predict how crowds might behave lies in the ability to provide enough response time and advance warning of potential dangers before they occur. The potential crowd disasters can be mitigated (or even avoided) by employing proper crowd management techniques that can *proactively* detect potential problems promptly with coordinated readiness of the relevant authorities to take actions. This triggers the following question: is it conceivable that we could develop a proactive approach that entails anticipating anomalous occurrences rather than relying on the conventional reactive means of merely detecting problems as they occur? Therefore, the focus of this paper is to propose an online reactive and proactive (alerting framework that predicts anomalies) anomaly detection frameworks for crowd management based on the bioinspired HTM. The proposed reactive and proactive (alerting) frameworks aim to use online crowd streaming data to mitigate or avoid anomalies by detecting them as early as possible.

The remainder of this paper is organised as follows: Section II reviews the literature on existing crowd management solutions while paying more attention to crowd anomaly detection and prediction techniques. Section III details the proposed reactive and proactive (alerting) anomaly detection framework using HTM. Then Section IV demonstrates the experimental evaluation of the proposed reactive and proactive anomaly detection solution. Finally, Section V concludes the work done and describes some potential future research directions.

II. Related Work

A. Knowledge of the Crowd

Pedestrians' interactions in a crowd do not adhere to previously agreed on rules or regulations; rather, their movements are governed by self-organisation motion that results in particular spatiotemporal patterns [1]. Crowd behaviour is complex and difficult to represent by a universal rule due to the psychological factors of pedestrians and external factors such as the variety of environmental layouts that influence them [14]. Pedestrians' behaviours rely on demographic and geographic characteristics of people e.g. cultures, gender and age and the environment e.g. geometric layout. Thus, the crowd could happen in any place and any time after reaching specific numbers of pedestrians or after reaching specific speeds or specific forms in an identified area. From the other side, each pedestrian has a desired speed and direction (i.e. vector) and able to move in two dimensions, which is different from vehicular movement. In addition, the width of ways is well-defined in vehicular facilities, whereas it changes over time regarding to flow states in pedestrian movement [18].

Crowd types can be classified based on the *crowd form*, the *moving state*, or *how the crowd is handled/treated*. In terms of the crowd form, the crowd may be classified as either structured or unstructured [19]. The structured crowd usually reflects a homogenous shape because it has a common goal; for example, following the prevailing direction in a planned path as in Hajj event. On the contrary, unstructured crowd reflects a heterogeneous form; for example, random movements in different directions as what happens in aggressive crowds. In terms of moving state, a crowd can be classified as static (a.k.a. stationary); for example, setting in stadiums or standing in music festivals, whereas crowd dynamics need more space for moving such as running in a marathon race. Furthermore, in the treatment of crowd dynamics, two approaches were followed by either looking at the group as one entity (holistic-based) or by dealing with individuals (object-based). In crowd literature, different properties that characterise the crowd motion have been identified, and spatiotemporal features are considered as descriptive power for different tasks such as anomaly detection [19], [20].

Therefore, crowd characteristics are essential to capture the details of crowd movement patterns. Besides, there are different standards for defining normal behaviour characteristics for different types of crowd. Resulting from different characteristics and pedestrians' interaction, crowd movements can be classified to *normal* and *abnormal*/*anomaly*. Normal crowd means that the pedestrians follow regular movement patterns whereas anomaly considers a vital rise in density or multidirectional movements as examples of irregular patterns. It is possible to model normal patterns in various ways based on the discrepancies between normal and abnormal behaviours. When a behaviour diverges from patterns that are considered to be normal, this can be classified as an abnormal behaviour [21].

B. Crowd Modelling and Anomaly Detection

Crowd models can be built either from extracted information (manually or automatically) from a crowd scene and/or the pre-knowledge base, i.e. by experts [20], [22]. Robust crowd models can estimate precise features of crowd behaviour and help in crowd analysis. For example, in crowd behaviour analysis, crowd modelling techniques are classified into several categories that assumed the input data are visual, such as, motion-based techniques, appearance-based techniques, deep learning techniques, social force model and simulation modelling [3].

Over the past decade, crowd management research has focused on the use of diverse visual crowd analysis techniques using computer vision [23]. These computer vision-based techniques have three phases, which are image acquisition, feature extraction and crowd modelling, aiming to estimate density [24], detect and track trajectory [25] and analyse targeted object [22]. Additionally, image processing-based approach that uses automated CCTVs has been adopted for crowd monitoring [5], [13]. On the other hand, recently, a data-driven decision approach opens a new analysis framework of urban anomaly analysis that includes unexpected crowds [21]. This approach automatically detects or predicts anomalies by exploiting big data and machine learning algorithms [21].

Anomaly is something subjective or context dependent; for example, while some people consider it perfectly normal to walk from A to B, others could classify this case as an anomaly. Therefore, there is no consensus regarding the definition of an anomaly in practical conditions. Anomaly is an observation that arouses suspicion due to the extent to which it deviates from other observations [26]. Anomaly detection has been applied for fraud detection, patient monitoring to detect the abnormal situation in medical applications, industrial damage detection, and other domains [27].

Anomaly detection techniques are classified into supervised, semi-supervised and unsupervised. In supervised anomaly detection, a fully labelled dataset, including normal and abnormal cases (anomalies), needs to be available. While in semi-supervised anomaly detection, the training data only represents normal cases. However, unsupervised anomaly detection techniques do not require labelled data. Detecting anomalies in dynamic problems, e.g. behaviour changing over time, is challenging due to the lack of labelled data for training; therefore, the unsupervised learning techniques are widely used [15], [27]. The majority of the available anomaly detection solutions are only suitable for resolving specific domain problems, therefore, they might not be generalised to other domains [28]. Anomaly detection has been extensively researched [28]; however, there are peculiarities for the crowd anomalies as the crowd behaviour is highly complex, as there is a close relationship with socio-psychological and physical elements. Besides, analysing crowded scenes can be problematic because of the need to identify and categorise specific crowd behaviours that may not occur frequently and can be easily missed. This leads to the fact that there are few examples of behaviours in crowd scenarios that need to be learned [19].

Based on the degree of interest, it is possible to classify the empirical research concerning anomaly detection into one of two categories: local anomaly detection and global anomaly detection [29]. When detecting local anomalies, it is important to identify any individual's behaviour that is out of step with those immediately surrounding them. Local anomaly detection is concerned with identifying the location where anomaly events occur. When detecting global anomalies, it is essential to identify a group's behaviour that is out of step with the norm. As such, global anomalies involve events that affect public safety, including fires, disasters and explosions from which individuals need to be able to escape. Consequently, the dynamics of the crowd change entirely, and the purpose of global anomaly detection is to identify whether the conditions in a given crowd are normal or abnormal. For both types, various methods have been devised [19].

Crowd anomaly detection models adopted in visual-based and physics-based of crowd dynamics analysis [19], [30]. Moreover, Crowd anomaly detection solutions can be classified based on the main groups of inputs, including video anomaly detection analysis, spatiotemporal feature-based and dynamic pattern based [21]. The remainder of this section classifies machine learning (ML) techniques used in crowd analysis for anomaly detection and prediction into statistically-based and biologically-inspired techniques.

In terms of statistical ML methods, Zhou *et al.* [31] proposed an unsupervised Support Vector Machine (SVM) algorithm with Higher-Order Singular Value Decomposition (HOSVD) to measure the crowd density. SVM was used to classify different levels of crowd densities. Additionally, Wu *et al.* [32] proposed the application of SVM to estimate crowd density through texture analysis to deal with the crowd density regression problem. Nevertheless, SVM is not the best choice for large datasets, and its performance degrades with noisy data, which makes it challenging in crowd management scenarios. Wang *et al.* [33] introduced a crowd management system that uses an unsupervised machine learning technique, Hierarchical Bayesian Models (HBMs), to model different behaviours in crowded scenes. Their proposed model summarises the human's interactions in a complicated scene and detects the anomalies by connecting three Hierarchical Bayesian models. However, HBMs usually have a high computational cost, and they need extensive pre-planning as these models are usually complex. Andersson *et al.* [34] estimated crowd behaviour using Hidden Markov Model (HMM) for behaviour recognition. Feng *et al.* utilised Gaussian Mixture Model (GMM) to detect abnormal events from videos, in an unsupervised form [35]. However, GMM is computationally expensive.

Numerous attempts have been made by leveraging variants of bio-inspired algorithms to improve crowd management techniques. Chrysostomou *et al.* [36] proposed a multi-camera system for dynamic crowd analysis. They used bio-inspired optimisation algorithms: Artificial Bee Colony (ABC) to determine the number of required cameras and Artificial Spiders to indicate their positions in a crowded area. The main goal was to minimise the number of cameras that cover a crowded area and maximise the coverage area to reduce the number of security guards in the building. Abdelghany *et al.* [37] have proposed an evacuation system for large-scale crowd facilities. They have used a genetic algorithm (GA) and a microscopic pedestrian simulation to simulate their system. The main task for GA is to find an optimal evacuation plan for crowd safety. However, GA's computational time to converge could be significant.

A Neural Network (NN) has been used to classify crowd behaviour in a dynamic crowd management system [38]. Additionally, a Convolutional Neural Network (CNN) has been adopted to estimate crowd densities in [39]. A deep attribute-embedding graph ranking method has been used for crowd video retrieval in [40]. The HTM theory and its implementation, the Cortical Learning Algorithms (CLAs) have the ability to conceptually and perceptually mimic neocortex learning in the brain [16]. HTM relies on online learning and deals with streaming data; it has shown promising results in anomaly detection and prediction applications. HTM can detect both highly subtle anomalies that a human operator may not notice besides anomalies in noisy data [41]. HTM has been used in different applications for detecting anomalies such as in smart homes [42] and in vital signs for ambient assisted living [43].

By reviewing crowd management literature, it is apparent that most of the crowd prediction and anomaly detection models use offline models that fail to capture the dynamic features of streaming crowd movements data. Moreover, they do not offer proactive detection of anomalies. Therefore, this article makes use of the Hierarchical Temporal Memory (HTM) to create frameworks for reactive and proactive detection of online crowd streams.

III. Reactive and Proactive Anomaly Detection Frameworks Using HTM

This section starts by giving a quick overview of HTM. Then, it demonstrates the HTM-based reactive and proactive frameworks for the early detection of crowd anomalies.

A. Hierarchical Temporal Memory (HTM)

The neocortex performs complex tasks, such as visual pattern recognition and spoken language. Jeffrey Hawkins and Sandra Blakeslee [16] had introduced a new bio-inspired machine intelligence known as Hierarchical Temporal Memory (HTM), which reflects how the neocortex works. HTM aims to provide a theoretical framework for understanding the neocortex by capturing its structural and algorithmic properties. Like the human brain, HTM is a memory-based system, including its memorisation and learning capabilities; however, HTM works in a statistical realm. More importantly, HTM cannot understand what the patterns mean. Instead, it simply seeks patterns that are likely to be replicated and learned; then, it can infer by matching new input with previously learned patterns to distinguish between normal and abnormal patterns [44].

The HTM elements involve cells, columns, layers, regions and hierarchy. It includes billions of brain cells that are called neurons, connected in columns (usually called mini-columns), to form layers and regions. This structure is similar in all parts of the neocortex; thus, all neurons in each region perform the same functionality and common process.

The main learning principles of HTM include hierarchy, regions, Spare Distribution Representation (SDR) and time. In the case of crowd management, the HTM's hierarchical design includes regions to store temporal information in a hierarchal way to memorise temporal sequences of crowd movement patterns. Each region consists of a set of layers, and it has a given functionality; for example, there are regions that are responsible for hearing, vision, language and other. Moreover, SDR is a binary coding technique where the number of active cells (1's) is much smaller than the number of inactive cells (0's), and the semantic meaning is represented across the set (distributed) of active cells. The SDRs have designated features including the implicit semantic meaning of the representation (high overlapping of SDRs for similar inputs) and their resistance to noise (reliable classification can be achieved with 50% noise) [45], [46]. SDR is a representational scheme of sequential information, and the input and output of data flow in the HTM model are in SDR format. HTM is a time-based continuous learning algorithm that can update itself over time as new input streaming data is received [44].

The HTM algorithm represents the part of the world that it is exposed to by memorising patterns. Learning happens by determining spatial patterns (a group of events occurring together), memorising them. Then the temporal memory (a chain of events taken place in the same order) identifies the sequences of spatial patterns and expect the future states. Data flows down and up the hierarchy to disambiguate between different possible patterns [44].

HTM models are universal, which means that the same learning principle can be applied to a variety of applications that have data flowing over time. The application of HTM for anomaly detection and prediction has shown promising results [41], [47]. HTM has been applied in disease diagnosis [48], pattern recognition (signed polish words) [49], image processing (license plate recognition) [50]. Moreover, HTM also has been used in geospatial tracking applications (modelling the movements of objects) that detect anomalies in travel patterns [51]. This article employs a similar approach to geospatial tracking applications to accommodate crowd management requirements.

B. *Reactive Crowd anomaly Detection*

In crowd management systems, it is crucial to figure out the travel patterns by measuring the crowd spatiotemporal properties focusing on density, speed and heading. The main crowd pedestrian spatiotemporal characteristics are [12]:

1) The pedestrian localisation positioning (latitude, longitude), and the number of participants (density), which represent the *spatial* data.
2) The movement includes speed (change of location with time), and acceleration (change of speed with time), which represent the *temporal* data.
3) The direction/ heading includes the change in location and speed over time, which represent locations of the object moving over time (an example of *spatiotemporal* data).

The remainder of this section details the main components of the proposed framework for detecting anomalies in crowds using the HTM model, as shown in Fig. 1.

1) *Data preparation*

The data preparation phase involves two steps, namely the generation of a crowd dataset and preprocessing the generated dataset. This article uses MassMotion simulator [52] to generate the synthetic crowd dataset for the required crowd scenario. The chosen scenario and context, including the types of anomalies, are adopted from the findings of previous studies [53], [54]. High densities and people walking in the opposite direction are two examples of crowd anomalies.

The MassMotion can simulate tens of thousands of pedestrian movements in 2D or 3D and can export the generated data in different formats e.g. CSV. As shown in Fig. 2, the main features of the generated dataset, based on a sampling rate of one second, are the Frame number, Agent ID, position (X, Y, and Z), Time, Speed, and Heading. The Speed feature refers to the distance (in meter) that pedestrians cover in a unit of time (each second). The Heading represents the direction of the agent in degrees. The generated dataset represents individual pedestrians (agents); however, we are interested in the crowd itself e.g. how many pedestrians in a specific area at any point in time. Therefore, the data preprocessing step focuses on performing aggregated statistical calculations to compute the average values of the most important features, such as Speed and Heading.

Additionally, the data preprocessing phase calculates new features such as Agent Count, Density, level of Crowdedness, and Severity Level, as shown in Fig. 3. The Heading column has been modified by converting negative Heading to be positive by adding 360 degrees to the original heading value. The Agent Count represents the number of pedestrians in a predefined area at a fixed sampling rate (once per second). The Density feature represents the number of pedestrians in a predefined area per second divided by the area, where the area is 100 m^2.

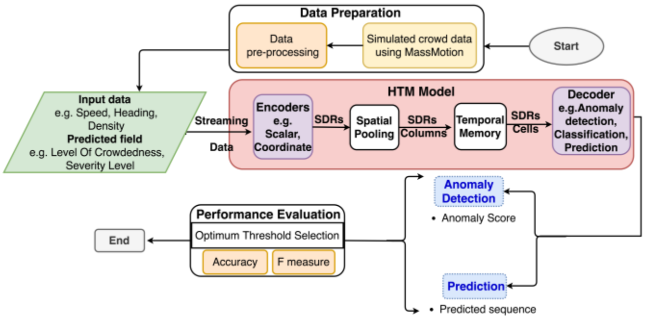

Fig. 1. Workflow of proposed framework.

#Frame	AgentID	X	Y	Z	Time	Speed	Heading
12	1001	1.31227	0	-13.6187	00:00:02	0.387138	-114.571
13	1001	1.27599	0	-13.4902	00:00:02	0.667857	-28.2484
14	1001	1.24054	0	-13.3113	00:00:02	0.911904	-11.2062
15	1001	1.2017	0	-13.093	00:00:03	1.10867	-10.0886
16	1001	1.1733	0	-12.8428	00:00:03	1.25912	-6.47645
17	1001	1.14576	0	-12.5674	00:00:03	1.38362	-5.71187
18	1001	1.13036	0	-12.2723	00:00:03	1.47775	-2.98602
19	1001	1.12948	0	-11.962	00:00:03	1.55128	-0.16171
20	1001	1.12912	0	-11.639	00:00:04	1.61523	-0.06514
21	1001	1.11526	0	-11.307	00:00:04	1.66131	-2.39076
22	1001	1.09854	0	-10.967	00:00:04	1.70219	-2.81529
23	1001	1.08453	0	-10.6204	00:00:04	1.73447	-2.3147
24	1001	1.08381	0	-10.2692	00:00:04	1.75565	-0.11662

Fig. 3. Generated data using MassMotion.

Time	Speed	Heading	AgentCount	Density	LevelOfCrowdedness	Severity_Level
00:05:36	1.1432	89.1222	81	0.81	1	0
00:05:37	1.1476	89.5976	83	0.83	1	0
00:05:38	1.1466	89.4905	86	0.86	1	0
00:05:39	1.1521	89.2123	88	0.88	1	0
00:05:40	1.1499	89.2521	88	0.88	1	0
00:05:41	1.1406	89.5428	90	0.9	1	0
00:05:42	1.1492	89.9155	91	0.91	1	0
00:05:43	1.1419	89.7962	90	0.9	1	0
00:05:44	1.1503	88.7938	92	0.92	1	0
00:05:45	1.1566	88.6091	91	0.91	1	0

Fig. 3. Preprocessed data.

TABLE I: LEVEL OF CROWDEDNESS

Density Person /m^2	Crowd behaviour state		Level of crowdedness
Less than 1.79	Normal cases	Free walk	1
Between 1.79 and 2		Non-contact	2
Between 2 and 3.99		Average	3
Between 4 and 4.99	Abnormal cases	Contact	4
5 and above		Critical	5

Furthermore, the data preprocessing phase involved creating a new column, Level of Crowdedness, to identify anomalies in crowded places. This column is as ground truth (i.e. labels) for the data representing anomalies definition in the representative scenario. Table I: level of crowdedness shows the different levels of crowdedness. Besides, the Severity Level of pedestrian streams has also been estimated based on the Density and Heading to get an entire picture of the serious crowd situations, as shown in Table II. Four severity levels have been identified, where level Zero means no risk and three means it is very critical because the situation includes high density and reverse direction. The Level of Crowdedness and Severity Level may assist in devising proactive anomaly detection and prediction towards efficient crowd management.

TABLE II: SEVERITY LEVEL

Density Person /m ^{2}	Heading (Degree)	State	Severity level
0	0	No high density, no opposite direction	0
0	1	No high density, opposite direction	1
1	0	High density, no opposite direction	2
1	1	High density, opposite direction	3

2) HTM model

Cortical Learning Algorithm (CLA) is the practical implementation of several parts of the theoretical HTM model. CLA is structured in columns and cells that have the flexibility to represent feedforward (from sensors) and context (from another region) input simultaneously, which can be used to learn the sequence of crowd movement patterns. In the CLA algorithm, SDRs of encoded data are the input, while a collection of active, inactive or predictive cells are the output.

The CLA algorithm works on a set of data structures, and two stages in the learning process Spatial Pooler (SP) and Temporal Memory (TM) to represent encoded data semantically and achieve some level of spatial and temporal pattern matching. An anomaly detection or a classification algorithm can handle the output from the TM in order to detect or predict anomalies [44]. The CLA algorithm contains four main components which are encoders, spatial pooling and temporal memory, and decoder, which are outlined in the HTM model components of Fig. 1. Workflow of Proposed Framework. A summary of these components is described as follows:

1) The CLA model receives a stream of different types of sensory data that comes from lower levels (sensory region). In this article, these sensory data are the simulated crowd dataset with features, including Speed, Heading, and Density. Then, the encoder (e.g., scalar or coordinate) encodes the input data into the equivalent SDR which is then forwarded to the spatial pooler.
2) The SDRs resulting from the encoders (feedforward input) are fed into the SP to learn spatial features of each input and find a stable representation of spatial patterns. The output from the SP is a sparse vector, which represents the set of active columns.
3) The TM receives the SDRs output of active columns from the SP to learn their transition over time and form predicted sequences based on the temporal context of each input.
4) Finally, the output from TM acts as the input to the anomaly detection or the classification algorithm in order to detect or predict anomalies.

NuPIC[1] provides several types of encoders, such as scalar and coordinate, and decoders, such as CLA classifiers for prediction. The output of the CLA anomaly detection is an Anomaly Score (AS), which is estimated by comparing the CLA's predictions against the actual new data points that continuously arrive over time. The AS value is in the range between zero and one, where zero means no anomaly was detected, while one indicates an anomaly. However, the CLA classifier produces a probability distribution for the predicted field based on the number of required steps in the future.

In case of crowd prediction, sequences often involve contextual dependencies covering multi-time steps. Prediction models require to dynamically determine how much to memorise of the temporal context from the history to make a better prediction, which is called high-order predictions. HTM natively supports temporal sequences, and is able to perform high-order predictions, learn an order as efficiently as possible [55]. In addition, the sequences of data streams frequently overlap and have branches. Therefore, a particular temporal context could have various possible outcomes in the future. HTM can make multiple predictions simultaneously in the future [55]. For example, for a given time step, the CLA classifier uses the output of the TM (active cells), and information from the encoder (the predicted field (PF), the bucket index of PF, and the record number) to map an association of SDR at time t. SDRs have a massive capacity that enables them to classify multiple predictions simultaneously based on its mathematical properties e.g. overlapping, union, matching, compression, with a low chance of collisions [45], [46].

The following subsection describes the alerting framework, which enables proactive detection of crowd anomalies.

C. Alerting Framework for Proactive Anomaly Detection

Most of the existing anomaly detection models detect anomalies after they do happen; however, for crowd management, the early detection of anomalies can help in avoiding several critical situations such as collisions. An alerting mechanism [56] can be used to trigger a warning in the run-up to a target event to bring about a phasic change in alertness. The warning effectively causes a switch from a resting state to a new state in which preparations are made in readiness to alert anomalies and respond to an anticipated sign. Therefore, the proposed alerting framework can predict potential anomalies (e.g., high density, opposite movements). To do so, the proposed crowd alerting framework integrates prediction and anomaly detection modules to achieve fast response and early detection, as shown in Fig. 4.

The altering framework predicts crowd anomalies. As shown in Fig. 4, the CLA prediction model receives the input sensor data, such as Speed and Heading, as well as the Severity Level to predict the potential level of severity (multiclass classification, PSL [0, 1, 2, 3]). The CLA prediction model can predict multistep ahead of severity level (e.g., predicted severity level minutes or hours ahead). Then, the output from the CLA prediction model (predicted severity level) besides the original input features become the input to train the CLA anomaly detection model so that it can identify anomalies. The crowd prediction task is a multivariate multistep sequence prediction task, as it involves multivariate inputs (e.g. Speed, Heading and/or Severity Level) and it aims to predict a sequence of severity levels (e.g. sequence size is 60). Therefore, the alerting framework is designed to

[1] https://github.com/numenta/nupic/

identify anomalies that may happen multistep ahead. Once potential anomalies got identified, an early alarm is sent to operators to perform the proper actions that can enable them to avoid or mitigate potential crowd problems.

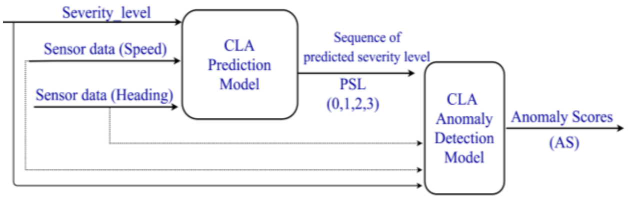

Fig. 4. Alerting framework for predicting anomalies.

The outcome from the alerting framework classifies the anomalies into three categories, namely *warning*, *cautions*, and *advisories*. A warning alert necessitates an immediate response, whereas a caution requires rapid response and an advisory is intended to inform about a marginal condition with no need to respond. As an illustration, if there is an abnormal change in crowd patterns, where the crowd severity level is changed from one (normal densities with opposite direction) to three (critical density with opposite direction), then there is a need for immediate action rather than just an advisory.

IV. Experimental Evaluation

A. Experimental Setup

This section describes the crowd scenarios used in the experiments, the CLA parameters and the performance metrics.

1) Crowd scenario

The conducted experiments consider two types of crowd scenarios: (1) *Uni-directional with a single anomaly*, and (2) *Uni-directional with multiple anomalies*. The first crowd scenario, Uni-directional with a single anomaly, simulates the crowd flow in a single direction; the anomaly is represented by the density level, where low density is considered as normal, while high density is considered as an anomaly. The low density means that there is a maximum of four pedestrians per square meter at any point in time, while high density means there are more than four pedestrians per square meter at any time. Fig. 5 exhibits the unidirectional scenario with a single anomaly behaviour, where the anomaly is represented by high-density values (higher than four).

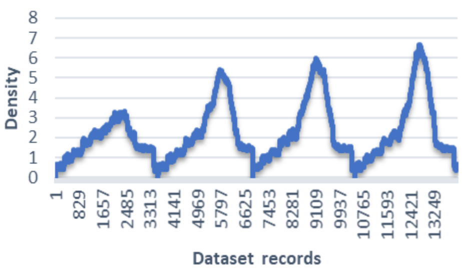

Fig. 5. Single anomaly (high density).

The second scenario, unidirectional with multiple anomalies, exhibits two anomalies resulting from the high density and agents walking in the opposite direction (Heading), as shown in Fig. 6.

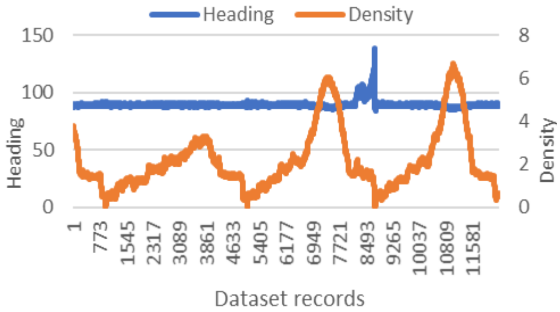

Fig. 6. Multiple anomalies (high density, opposite direction).

2) CLA parameters and implementation platform

The implementation of the experiments is conducted using the open-source Python-based NuPIC, which is recognised as the state-of-the-art implementation of the HTM learning algorithm. The CLA model requires a thorough selection of various hyperparameters to guarantee the best possible performance. These hyperparameters are related to encoders, spatial pooler, and temporal memory. The CLA parameters are initially generated using a medium-size swarm[2]. Then, the output from the swarming process is manually tuned to optimise the SP and TM related parameters. The conducted experiments use scalar and coordinate encoders. In the following experiments, the coordinate encoder uses Heading and Speed instead of x and y; and uses Density instead of radius to encode the spatiotemporal data. The Level of Crowdedness is the predicted field, and the learning phase is enabled until a certain amount, then, stopping the learning phase, and the inference phase is applied.

3) Performance metrics

Both accuracy and f_measure are used to evaluate the performance of the anomaly detection algorithms. The accuracy is estimated as follows:

$$Accuracy = \frac{TP + TN}{P + N}$$

where *TP* is referred to a true positive, and *TN* is the true negative. Additionally, the f_measure is estimated based on recall and precision as follows:

$$F\_measure = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

where recall represents the ratio of accurately identified positive examples as a proportion of the total number of positive examples, and the precision is the ratio of accurately identified positive examples as a proportion of the total number of positive predictions.

B. Experiments

This section demonstrates the experiments for the reactive and proactive detection of crowd anomalies.

1) Reactive experiments

Two different experiments were conducted for two types of anomalies (single anomaly and multiple anomalies). The performance of CLA (using both scalar and coordinate

[2] http://nupic.docs.numenta.org/stable/guides/swarming/index.html

encoders) is evaluated against other anomaly detection methods namely, k-Nearest Neighbor Global Anomaly Score (kNN-GAS), the Independent Component Analysis-Local Outlier Probability (ICA-LoOP) and also the Singular Value Decomposition Influence Outlier (SVD-IO).

a) Uni-directional scenario (single anomaly)

This experiment is based on a dataset representing single crowd anomaly (high densities, as previously shown in Fig. 5, and the data consists of 14068 records. Fig. 7 shows the performance of CLA using scalar and coordinate encoders against kNN-GAS, ICA-LoOP and SVD-IO. Looking at Fig. 7, it is apparent that both versions (scalar and coordinate) of the CLA model significantly outperform the counterparts for detecting single anomaly (high density). Furthermore, using coordinate encoder improves the performance of the CLA model as opposed to using the scalar encoder. The coordinate encoder managed to improve the CLA anomaly detection over scalar encoder by around 7 % (F_measure of 99.08% in case of the coordinate encoder as opposed to 92.26% for the scalar encoder).

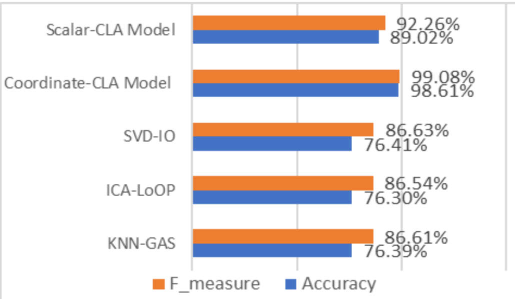

Fig. 7. Reactive detection of anomalies using uni-directional scenario with a single anomaly.

b) Uni-directional Scenario (Multiple anomaly)

This experiment aims to investigate the performance of the CLA compared to other anomaly detection algorithms for crowd anomaly detection based on a dataset with two types of anomalies (i.e., high densities, bi-directional flow with normal density). This dataset consists of 12337 records. Fig. 8 confirms the same results found in Fig. 7, where the CLA (using scalar or coordinate encoders) significantly outperform the other anomaly detection counterparts.

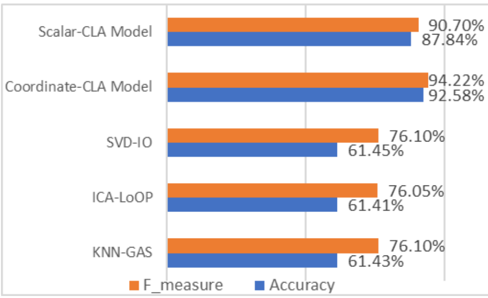

Fig. 8. Reactive detection of anomalies using uni-directional scenario with multiple anomalies.

It can be concluded that, from the two previous experiments, CLA model outperforms KNN-GAS, ICA-LoOP and SVD-IO in detecting anomalies in the unidirectional scenario with both single and multiple anomalies. In addition, using the coordinate encoder, for encoding Heading, Speed and Density inputs, boosts the F_measure results to 99.08% and 94.22% in case of single and multiple anomalies, respectively.

2) Predicting anomalies using the alerting framework

This experiment aims to evaluate the performance of the proposed alerting framework for the proactive detection of crowd anomalies using scalar and coordinate encoders. For predicting the Severity Level, the scalar encoder uses Speed and Severity Level as input features, and outputs the Predicted Severity Level (PSL). For anomaly detection, the input features in case of the scalar encoder are Speed and PSL, while the coordinate encoder uses Speed, Heading and PSL features. The output from the alerting framework is early anomaly scores in the range between zero and one. Therefore, we have used a threshold to distinguish normal from abnormal cases of the predicted severity level. The altering framework considers the predicted severity level as an anomaly if it is greater than the prespecified threshold (0.5).

Fig. 9 summarises the performance of the alerting framework using both the scalar and coordinate encoders. It is interesting to see the ability of the altering framework to proactively predict potential anomalies, with an F_measure of 92.30% for the scalar encoder and 94.66% for the coordinate encoder. Finally, it is notable that the coordinate encoder slightly outperforms scalar encoder for detecting anomalies in crowd dataset.

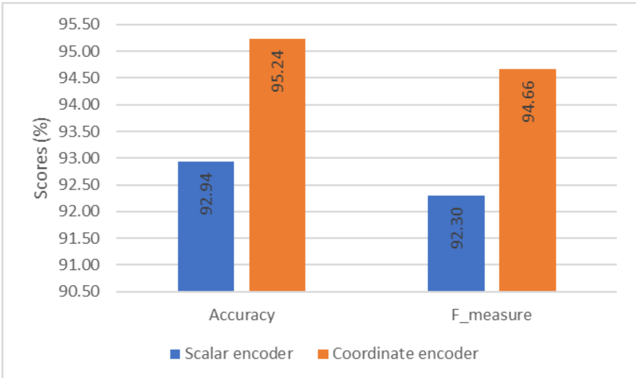

Fig. 9. Proactive detection (predicting) of anomalies using the alerting framework.

V. Conclusion and Future Work

This article investigated the adoption of HTM-based model for the reactive and proactive detection of crowd anomalies to mitigate or avoid any potential accidents. Due to the limitations associated with real crowd datasets, this article presents a new synthetic crowd dataset generated using the MassMotion simulator. The generated dataset reflects two crowd scenarios involving both single and multiple anomalies. The article proposes a novel HTM-based reactive crowd anomaly detection framework. Then, it proposes a novel alerting framework for the proactive detection of crowd anomalies. The altering framework consists of two separate modules for prediction and anomaly detection. The prediction model predicts the crowd severity level for the upcoming 60 seconds. Then, the anomaly detection model makes use of the predicted severity level to predict crowd anomalies. The reactive approach for anomaly detection showed significant improvement of CLA over kNN-GAS, ICA-LoOP and SVD-IO in detecting anomalies. Moreover, the coordinate encoder outperforms the scalar encoder for the CLA-based experiments. Finally, the proposed alerting framework managed to predict potential crowd anomalies with an F_measure of 94.66% and 92.30% using coordinate and scalar encoders, respectively.

As a future work, we will focus on improving the prediction accuracy of the crowd prediction model by paying more attention to crowd anomalies.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Amna designed the proposed framework, organised the experimentational steps and prepared the manuscript. Mohamed participated in design and evaluation of the proposed framework and help in reviewing the manuscript. Benhur is also contributed in experimentational and testing steps of the proposed framework. All authors approved the final version of manuscript.

Acknowledgment

Amna acknowledges the Ministry of Education in Saudi Arabia for funding and supporting her PhD project.

References

[1] D. Helbing and A. Johansson, "Pedestrian, crowd, and evacuation dynamics," *Encycl. Complex. Syst. Sci.*, pp. 6476–6495, 2013.

[2] R. Challenger, C. W. Clegg, and M. A. Robinson, *Understanding Crowd Behaviours: Supporting Evidence*, vol. 11, no. 2, 2009.

[3] M. S. Zitouni, A. Sluzek, and H. Bhaskar, "Visual analysis of socio-cognitive crowd behaviors for surveillance: A survey and categorization of trends and methods," *Eng. Appl. Artif. Intell.*, vol. 82, pp. 294–312, 2019.

[4] M. S. Zitouni, H. Bhaskar, J. Dias, and M. E. Al-Mualla, "Advances and trends in visual crowd analysis: A systematic survey and evaluation of crowd modelling techniques," *Neurocomputing*, vol. 186, no. January, pp. 139–159, 2016.

[5] B. Yogameena and C. Nagananthini, "Computer vision based crowd disaster avoidance system: A survey," *Int. J. Disaster Risk Reduct.*, vol. 22, pp. 95–129, 2017.

[6] Q. A. Ahmed and Z. A. Memish, "Hajj 2016: Required vaccinations, crowd control, novel wearable tech and the Zika threat," *Travel Med. Infect. Dis.*, vol. 14, no. 5, pp. 429–432, 2016.

[7] G. Cardone, A. Cirri, A. Corradi, L. Foschini, R. Ianniello, and R. Montanari, "Crowdsensing in Urban areas for city-scale mass gathering management: Geofencing and activity recognition," *IEEE Sens. J.*, vol. 14, no. 12, pp. 4185–4195, 2014.

[8] T. Franke, P. Lukowicz, and U. Blanke, "Smart crowds in smart cities: Real life, city scale deployments of a smartphone based participatory crowd management platform," *J. Internet Serv. Appl.*, vol. 6, no. 1, pp. 1–19, Aug. 2015.

[9] F. Botta, H. S. Moat, and T. Preis, "Quantifying crowd size with mobile phone and Twitter data," *R. Soc. Open Sci.*, vol. 2, no. 5, May 2015.

[10] D. Roggen, M. Wirz, G. Tröster, and D. Helbing, *Recognition of Crowd Behavior from Mobile Sensors with Pattern Analysis and Graph Clustering Methods*, pp. 1–24, 2011.

[11] H. Assem and D. O 'sullivan, "RCMC: Recognizing crowd-mobility patterns in cities based on location based social networks data," *ACM Trans. Intell. Syst. Technol. Artic. ACM Trans. Intell. Syst. Technol.*, vol. 8, no. 70, 2017.

[12] A. Draghici and M. Van Steen, "A survey of techniques for automatically sensing the behavior of a crowd," *ACM Comput. Surv.*, vol. 51, no. 1, pp. 1–40, 2018.

[13] S. A. M. Saleh, S. A. Suandi, and H. Ibrahim, "Recent survey on crowd density estimation and counting for visual surveillance," *Eng. Appl. Artif. Intell.*, vol. 41, pp. 103–114, 2015.

[14] M. Haghani and M. Sarvi, "Crowd behaviour and motion: Empirical methods," *Transp. Res. Part B Methodol.*, vol. 107, pp. 253–294, 2018.

[15] R. Chalapathy and S. Chawla, "Deep learning for anomaly detection: A survey," 2019.

[16] J. Hawkins and S. Blakeslee, *On Intelligence: How a New Understanding of the Brain Will Lead to the Creation of Truly Intelligent Machines*, Macmillan, 2005.

[17] N. Bisagno, B. Zhang, and N. Conci, "Group LSTM: Group trajectory prediction in crowded scenarios," *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11131, pp. 213–225, 2019.

[18] L. D. Vanumu, K. R. Rao, and G. Tiwari, "Fundamental diagrams of pedestrian flow characteristics: A review," *Eur. Transp. Res. Rev.*, vol. 9, no. 4, 2017.

[19] T. Li, H. Chang, M. Wang, B. B. Ni, R. C. Hong, and S. C. Yan, "Crowded scene analysis: A survey," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 25, no. 3, pp. 367–386, 2015.

[20] B. Zhan, D. N. Monekosso, P. Remagnino, S. A. Velastin, and L. Q. Xu, "Crowd analysis: A survey," *Mach. Vis. Appl.*, vol. 19, no. 5–6, pp. 345–357, 2008.

[21] M. Zhang, T. Li, Y. Yu, Y. Li, P. Hui, and Y. Zheng, "Urban anomaly analytics: Description, detection and prediction," *IEEE Trans. Big Data*, p. 1, 2020.

[22] M. Irfan, L. Marcenaro, and L. Tokarchuk, "Crowd analysis using visual and non-visual sensors, a survey," in *Proc. 2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, 2016, pp. 1249–1254.

[23] J. C. S. J. Junior, S. R. Musse, and C. R. Jung, "Crowd analysis using computer vision techniques. A survey," *IEEE Signal Process. Mag.*, vol. 27, no. 5, pp. 66–77, 2010.

[24] A. F. Gad, A. M. Hamad, and K. M. Amin, "Crowd density estimation using multiple features categories and multiple regression models," in *Proc. ICCES 2017 12th Int. Conf. Comput. Eng. Syst.*, 2018.

[25] A. Brunetti, D. Buongiorno, G. F. Trotta, and V. Bevilacqua, "Computer vision and deep learning techniques for pedestrian detection and tracking: A survey," *Neurocomputing*, vol. 300, pp. 17–33, 2018.

[26] D. M. Hawkins, "A single outlier in normal samples," *Identification of Outliers*, Springer Netherlands, pp. 27–41, 1980.

[27] M. Goldstein and S. Uchida, "A comparative evaluation of unsupervised anomaly detection algorithms for multivariate data," *PLoS One*, vol. 11, no. 4, 2016.

[28] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection: A survey," *ACM Ref. Format*, vol. 41, no. 15, 2009.

[29] Y. Cong, J. Yuan, and J. Liu, "Abnormal event detection in crowded scenes using sparse representation," *Pattern Recognit.*, vol. 46, no. 7, pp. 1851–1864, 2013.

[30] V. J. Kok, M. K. Lim, and C. S. Chan, "Crowd behavior analysis: A review where physics meets biology," *Neurocomputing*, vol. 177, pp. 342–362, 2016.

[31] B. Zhou, F. Zhang, and L. Peng, "Higher-order SVD analysis for crowd density estimation," *Comput. Vis. Image Underst.*, vol. 116, no. 9, pp. 1014–1021, 2012.

[32] X. Wu, G. Liang, K. K. Lee, and Y. Xu, "Crowd Density Estimation Using Texture Analysis and Learning," in *Proc. 2006 IEEE Int. Conf. Robot. Biomimetics*, 2006. , pp. 214–219

[33] X. Wang, X. Ma, and W. E. L. Grimson, "Unsupervised activity perception in crowded and complicated scenes using hierarchical bayesian models," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 3, pp. 539–555, Mar. 2009.

[34] M. Andersson, J. Rydell, and J. Ahlberg, "Estimation of crowd behavior using sensor networks and sensor fusion," in *Proc. FUSION'09. 12th Int. Conf.*, 2009, pp. 396–403.

[35] Y. Feng, Y. Yuan, and X. Lu, "Learning deep event models for crowd anomaly detection," *Neurocomputing*, vol. 219, pp. 548–556, 2017.

[36] D. Chrysostomou, G. C. Sirakoulis, and A. Gasteratos, "A bio-inspired multi-camera system for dynamic crowd analysis," *Pattern Recognit. Lett.*, vol. 44, pp. 141–151, 2014.

[37] A. Abdelghany, K. Abdelghany, H. Mahmassani, and W. Alhalabi, "Modeling framework for optimal evacuation of large-scale crowded pedestrian facilities," *Eur. J. Oper. Res.*, vol. 237, no. 3, pp. 1105–1118, 2014.

[38] M. Szczodrak, J. Kotus, K. Kopaczewski, K. Lopatka, A. Czyzewski, and H. Krawczyk, "Behavior analysis and dynamic crowd management in video surveillance system," in *Proc. Int. Work. Database Expert Syst. Appl. DEXA*, 2011, pp. 371–375.

[39] M. Fu, P. Xu, X. Li, Q. Liu, M. Ye, and C. Zhu, "Fast crowd density estimation with convolutional neural networks," *Eng. Appl. Artif. Intell.*, vol. 43, pp. 81–88, 2015.

[40] Y. Zhang *et al.*, "Crowd video retrieval via deep attribute-embedding graph ranking," in *Proc. 2016 IEEE Int. Conf. Multimed. Expo*, 2016, no. 1945788X, pp. 2–7.
[41] J. Hawkins, "The science of anomaly detection," *Numenta, Inc.*, pp. 1–18, 2014.
[42] N. O. Alshammari, *Anomaly Detection Using Hierarchical Temporal Memory in Smart Homes Nasser Owaid Alshammari List of Publications*, March 2018.
[43] B. B. Bastaki, *Application of Hierarchical Temporal Memory to Anomaly Detection of Vital Signs for Ambient Assisted Living*, 2019.
[44] D. Hawkins, J. Ahmad, and S. Dubinsky, "Hierarchical Temporal Memory including HTM cortical learning algorithms," Whitepaper Numenta Inc, vol. 202, no. 2, p. 68, 2010.
[45] S. Ahmad and J. Hawkins, *Properties of Sparse Distributed Representations and their Application to Hierarchical Temporal Memory*, Mar. 2015.
[46] S. Purdy, *Encoding Data for HTM Systems*, 2016.
[47] Y. Cui, C. Surpur, S. Ahmad, and J. Hawkins, "A comparative study of HTM and other neural network models for online sequence learning with streaming data," in *Proc. the International Joint Conference on Neural Networks*, 2016, vol. 2016-Octob, pp. 1530–1538.
[48] Y. Fu, X. Guo, Y. Xie, D. Zhang, and H. Li, "Disease diagnosis supported by hierarchical temporal memory," in *Proc. 2015 IEEE 12th Int. Conf. Ubiquitous Intell. Comput.*, 2016, pp. 863–870.
[49] T. Kapuscinski and M. Wysocki, *Using Hierarchical Temporal Memory for Recognition of Signed Polish Words*, Springer, Berlin, Heidelberg, pp. 355–362, 2009.
[50] Y. A. Bolotova, A. A. Druki, and V. G. Spitsyn, "License plate recognition with hierarchical temporal memory model," in *Proc. 2014 9th Int. Forum Strateg. Technol.*, 2014, pp. 136–139.
[51] Numenta, *Geospatial Tracking Learning the Patterns in Movement and Detecting Anomalies*, 2014.
[52] Oasys software | Oasys. [Online]. Available: https://www.oasys-software.com/
[53] R. A. Smith, "Density, velocity and flow relationships for closely packed crowds," *Saf. Sci.*, vol. 18, no. 4, pp. 321–327, 1995.
[54] A. M. Ibrahim, I. Venkat, K. G. Subramanian, A. T. Khader, and P. D. Wilde, "Intelligent Evacuation management systems," *ACM Trans. Intell. Syst. Technol.*, vol. 7, no. 3, pp. 1–27, 2016.
[55] Y. Cui, S. Ahmad, and J. Hawkins, "Continuous online sequence learning with an unsupervised neural network model," *Neural Comput.*, vol. 28, no. 11, pp. 2474–2504, 2016.
[56] S. E. Petersen and M. I. Posner, "The attention system of the human brain: 20 years after," *Annu. Rev. Neurosci.*, vol. 35, no. 1, pp. 73–89, Jul. 2012.

Amna Bamaqa is currently a PhD student at the School of Computing and Digital Technologies, Staffordshire University, Stoke-on-Trent, UK. She holds the MSc in software engineering from the University of Leicester, UK, and a BSc (Hons) in computer science and engineering from Taibah University, KSA. She worked as a teaching assistant at the Department of Computer Science and Information at Taibah University. Her research interests include software engineering, artificial intelligence, machine learning and data mining.

Mohamed Sedky is an associate professor in Staffordshire University. After he received his BEng(Hons) in electro-physics and communications in Alexandria University, Egypt, in 1996, He founded SKM communication systems. From 1998 to 2003, he was an assistant lecturer in the Department of Electronics and Communications, at the Arab Academy for Science and Technology (AAST), Egypt. He finished his MSc degree in communications and electronics from the AAST in 2002. He joined Staffordshire University in 2003 as a lecturer. In 2009, he gained a PhD from Staffordshire University, researching the application of physics-based image formation models to change detection in the context of workplace video surveillance. He has led the Artificial Intelligence (AI) & Internet of Things (IoT) research group in Staffordshire University to conduct research in the development of artificial intelligent techniques and simulation tools for different Internet of things applications, robotic, and more recently applying his work in forensic science towards the detection and classification of microplastics.

Benhur Bakhtiari Bastaki received the BSc (Hons) in computing science, MSc in computer science and the PhD degree in computing science in 2007, 2010 and 2019 respectively. In his PhD, he researched the application of Hierarchical Temporal Memory to Anomaly Detection of Vital Signs for Ambient Assisted Living. Since 2012, he has been with the Staffordshire University, UK, where he is currently a lecturer in applied software engineering at the School of Digital, Technologies and Arts. He also has more than 3 years of industrial experience as a software developer for the insurance software Warehouse. His research interests are ambient intelligence (AmI), machine learning (ML), ubiquitous sensing, contextual information, data mining (DM) and assisted living.