KNOWLEDGE BASED SYSTEM FRAMEWORK OF SOM AND CBR TECHNIQUES USING MOTION CAPTURE TECHNOLOGY IN ELDERLY FALLING RISK FOR PHYSIOTHERAPIST ASSESSMENT AND SUPPORT

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ABSTRACT

Nobody can avoid becoming old and all of us will be faced with accidents and illnesses during our life time. Many surveys have reported that during everyone's life time; a person will have at least two bad falls possibly causing severe problems later on in life with 72.4% affecting the Musculo Skeletal System and 90% of these relate to three issues: gait, balance and mobility. Consequently, physiotherapists will be needed to diagnose elderly patients as currently 11% of Thailand population is aged over 59 years and the percentage will increase to 22% by 2045. Unfortunately, the number of medical experts is not sufficient for the increasing numbers of elderly population and this could have serious consequences in the near future.

Keywords— *Decision support system, Knowledge based system, Self-Organizing Map, Case Based Reasoning, Motion capture technology, Elderly falling risk*

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This paper outlines a Knowledge Based System to diagnose falling patterns in elderly people using Motion Capture Technology.

The idea is to integrate with appropriate procedure self-organizing map, case based reasoning and motion capture to provide a decision support system. The diagnosis information derived from the process of KBS will support the physiotherapist to determine serious falling risks in the elderly and recommend guidelines for medical treatment.

I. INTRODUCTION

According to the United Nations online database, the elderly population (≥60 years) is currently 11% and this is expected to increase to 22% by 2045 (United Nations, 2009). In particularly in the Far East, including Thailand, it is increasing at a much faster pace than the developed countries in the West. Thailand is ranked the 68th in the world elderly population ranking. The National Survey (micro data by the National Statistics Office of Thailand as shown in Fig. 1) in 2001, indicates the amount of elderly people, over 59 years, is 5,969,000 (9.4% of population). In 2007, this had increased to 7,020,000 (10.7% of population). Thus, the elderly population is evidently increasing within the recent ten years. While people are getting older, they cannot avoid illnesses such as acute condition, accidents and general ailments, etc. Fig. 2 show a recent survey of the elderly population in Thailand which indicated that most of the elders are struggling with the Musculo Skeletal System problems. In Maharaj Nakorn Chiang Mai Hospital, Chiang Mai, Thailand, there are many geriatric patients who have an invalid musculo skeletal system (Tongsawad, 1998). They have difficulty in moving their bodies as a healthy person would and have to come for treatment for their disorders. Most of the accidents in geriatric patients are falling and knocking and this accelerates the geriatric patient’s risk of breaking a skeletal bone (Tunmukkayakul, 1983).

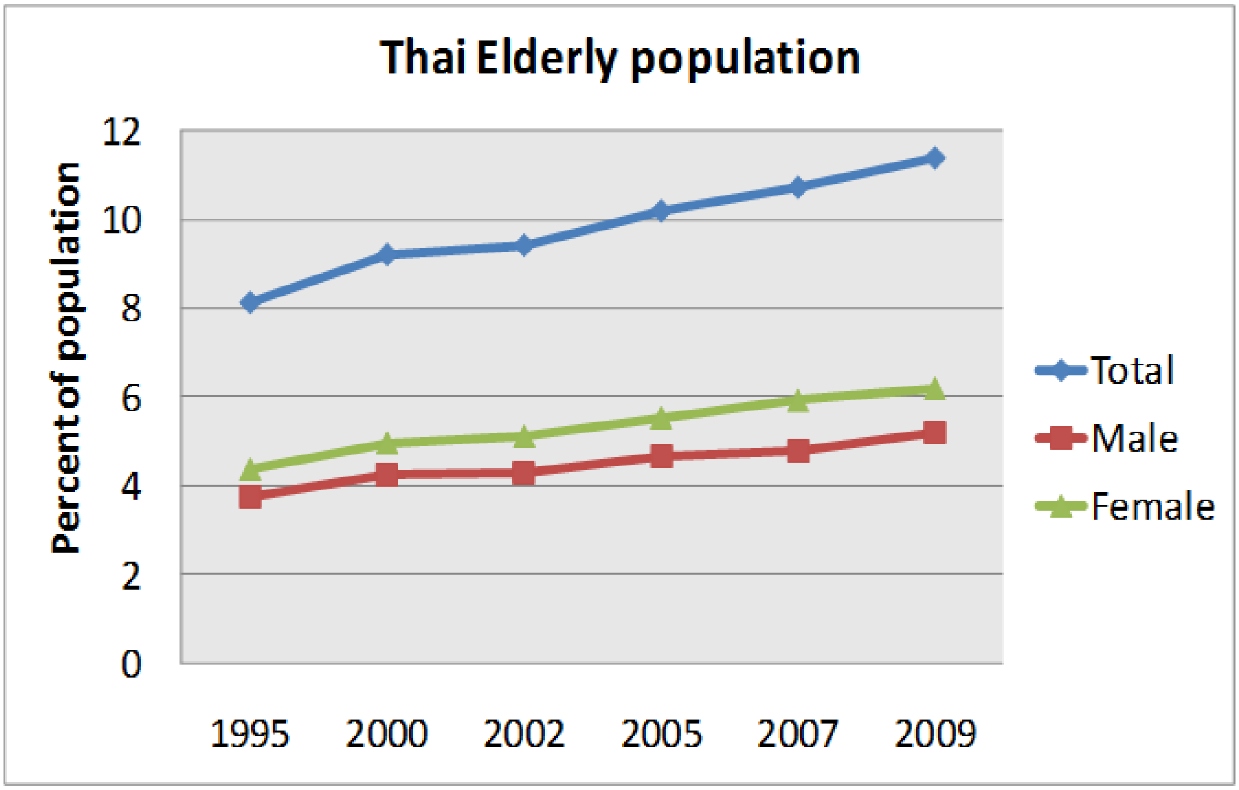

Fig. 1. The 2007 elderly people in Thailand survey

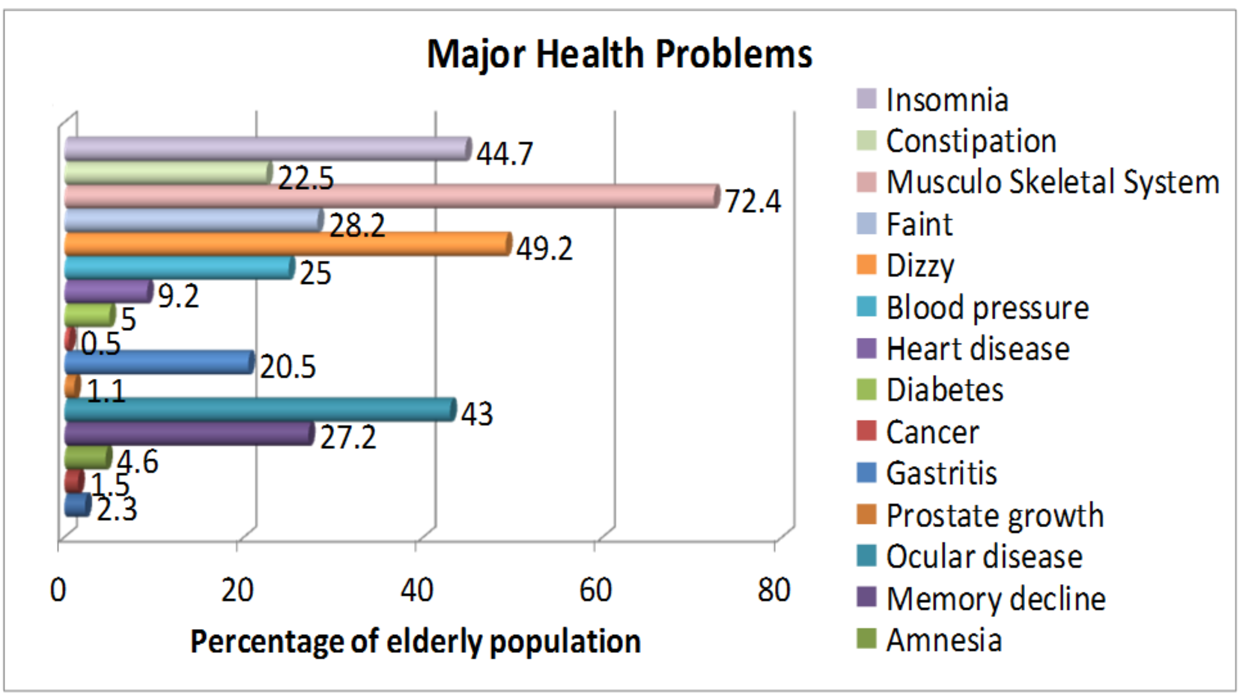

Fig. 2. Major health problems of Thai elderly people

Falls and fall-related injuries are among the "most serious and common medical problems experienced by elders" (Hayes, 1996). During everyone's life; a person will have at least two bad falls possibly causing severe problems later on in life. Additionally, approximately one-third of community-dwelling elders and approximately 43% of institutionalized elders have trouble due to falling each year (Welsh, 2006). The main cause of falls and fall-related injuries is tripping. This is a major contributor to hip fractures in elderly people. Also, the walking velocity is one of the many variables that have been associated with falls by elders. The elder who walks slowly has a significantly higher risk of falling (Bath and Morgan, 1999) and hip fracture (Dargent-Molina, 1996) and 90% of these relate to three issues: gait, balance and mobility. In other cases, they are affected by acute disease and adverse medication (Tideiksaar, 2005).

As a result of the evident sickness, physiotherapists are needed to diagnose elderly patients and the number of medical experts is not sufficient for the currently increasing numbers of elderly population and could have serious consequences in the future. The role of physiotherapy in the treatment of conditions and injuries that affect the bones and joints of elderly people is now recognised. In particular, physiotherapists are often required to help patients who are recovering from orthopedic surgery. Nowadays, visual analysis of human motion is one of the most active research topics in computer vision. To aid both the elderly and physiotherapists, a number of researchers have developed visual analysis systems of human motion which are concerned with the detection, tracking and recognition of people's movements. Understanding of human behaviours from image sequences has been included in this work, and Artificial Intelligence (AI) techniques are necessary in this domain, e.g. Decision Support System (DSS), Clustering, Self-Organizing Map, and Case Based Reasoning (CBR) to support physiotherapists etc.

Normally, the physiotherapist can understand the nature of the injuries caused by the falls and provide the necessary physical therapy and rehabilitation programme for their clients with common problems. However, in case of complex problems, they cannot always provide relevant treatment and physiotherapy to improve the quality of life of the elderly population. Therefore, there is a need for a measurement tool to help them assess the characteristic of problems or injuries. The data clustering technique, such as Self-Organizing Map, can support the physiotherapist to identify the features of falling in elderly people (Rueangsirarak, Atkins, Sharp, Chakpitak, & Meksamoot, 2011).

In practice, the doctors, who are the medical experts, diagnose their patients by their own heuristic reasoning. In terms of computing, each medical reasoning procedure is regarded as an independent knowledge problem solving matter; in which some useful results were recorded in databases (Yang, 1990). Using the database and other reasoning procedures can update their characteristics including their weight coefficient which will be used as a basis of a Knowledge Based System (KBS). The Knowledge Based System will be used in the updated characteristics as the solution to solve a new similar problem using the application of Case Based Reasoning (Aamodt, 1994).

This paper explains and discusses the necessity of a KBS to classify and diagnose falling patterns in elderly people; using Self-Organizing Map, Case Based Reasoning and Motion Capture technology, for supporting the physiotherapists.

II. THEORETICAL BACKGROUND-FALLS

A. Risk Assessment Tool

The most frequent health incident in the elderly occurs with the Musculo Skeletal System, and is caused by falling. Consequently, in order to prevent senior citizens from bad falls, an evaluation of risk level of falling is required.

There are numbers of fall risk assessment tools available with a reasonable amount of evidence to support their use. Perell (2001) had reviewed a fall risk assessment tool from a number of studies and distinguished two different tools namely Functional Assessment Tool (FAT) and Nursing Assessment Tool (NAT). Selection of the appropriate tool depends on particular purpose and situation. NAT is suitable for acute care settings which are caused by a variety of illnesses and medication changes whereas FAT is appropriate for outpatient settings caused by mobility and balance. The author also asserted that a universal precaution for falls was worthwhile for extended care setting categorized for nursing homes and rehabilitation units. The specific assessment tool chosen might vary depending on the setting and professionals responsible for completing the assessment forms. This means that there is no single tool that can be recommended for implement action in all setting or all subpopulations within each setting (Scott, 2006).

B. Risk Assessment Matrix

Previous work by Rueangsirarak and Pothongsunun (2009) created a new tool to assess falling risks which proposed applying heuristics rather than a standard rule. Generally fall risk management has been developed by using best practice guidelines and adopting assessment of risk factors to provide information for preventative intervention. The process of fall risk management by an expert is to diagnose their patients with their own heuristic solving technique. Each medical reasoning procedure is regarded as an independent knowledge problem solving situation. As a result, a Risk Assessment Matrix (RAM) was created and used as the screening tool as shown in Fig. 3. This enables an elderly peoples' fall screening test to be constructed by capturing the experts' heuristic knowledge using Common Knowledge Acquisition and Design System (CommonKADS) model suite (Schreiber, n.d.). The CommonKADS as well as mining the expert knowledge also consists of constructing different aspect models of human knowledge. CommonKADS's assessment template for falling risk assessment in this study focuses on two issues. Firstly, *possibility/likelihood* refers to biomechanics such as physical gait parameters etc. Secondly, *seriousness/ consequent* concerns daily living activities. Each case considered through heuristic criteria based on RAM will be disseminated to the physiotherapists.

>60%	>50%	>50%	>75%	>75%	>90%	>30%	<10%	<10%	<25°	<25°	>30°	>30°	> 70% of (BSW/2)	> 70% of (BSW/2)	H (3)	(h,l) = 3	(h,m) = 6	(h,h) = 9
41% - 60%	36% - 50%	26% - 50%	61% - 75%	61% - 75%	51% - 90%	16% - 30%	11% - 30%	11% - 30%	26° - 30°	26° - 30°	21° - 30°	21° - 30°	30% - 70% of (BSW/2)	30% - 70% of (BSW/2)	M (2)	(m,l) = 2	(m,m) = 4	(m,h) = 6
<40%	<35%	<25%	<60%	<60%	<50%	<15%	>30%	>30%	31° - 40°	31° - 40°	0° - 20°	0° - 20°	< 30% of (BSW/2)	< 30% of (BSW/2)	L (1)	(l,l) = 1	(l,m) = 2	(l,h) = 3
Base support length	Base support width	Cadence	Stride length (L)	Stride length (R)	Step width	Double support phase	Swing phase (L)	Swing phase (R)	Hip flexion (L)	Hip flexion (R)	Knee flexion (L)	Knee flexion (R)	Centre of Gravity (L)	Centre of Gravity (R)		L (1)	M (2)	H (3)
Possibility/Likelihood (Biomechanics)														Seriousness/Consequent (Behavior)	Percentage of walking	<10%	10%-50%	>50%
															Type of work	Officer	Deliverer	Heavy carrier
															Type of exercise	Stretch	Aerobic Exercise	Sport

Fig. 3. Risk Assessment Matrix (Rueangsirarak, Atkins, Sharp, Chakpitak, & Meksamoot, 2011).

Fig. 3 is classified into two main groups: a likelihood factor and a severity factor. This matrix was applied to the outpatient setting, in order to diagnose elderly falling patterns and consists of nine possible pairs of risk. Heuristic matrix of categories (l,l); (m,l) or (l,m); (l,h) or (m,m) or (h,l) can be resolved without the need for expert diagnosis. However (m,h) or (h,m); and (h,h) needs to be referred to an expert for analysis and treatment recommendation.

Although fall risk management is not a new concept, the construction of a heuristic assessment tool is novel, especially for fall risk assessment and treatment in the elderly. This paper focuses on the fall risk assessment of elderly people who are determined as outpatients by using a Knowledge Based System screening tool.

III. CASE REVIEW-RELATED WORK

A. Self-Organizing Map

The technique used to classify the characteristics of data is Clustering. Clustering is a type of data mining (DM) technique with an unsupervised learning approach. When the clustering is performed, the supporting information helps in the DM process. The intention is to use unsupervised learning and therefore it is not required to know the number of clusters and an attributes in advance (Free Books Online, 2005).

One well known clustering technique is Self-Organizing Map (SOM), which has been proposed by Kohonen (1990) in the early 1980's. It is an extremely popular artificial neural network model based on unsupervised learning. SOM models are mostly used for visualization of nonlinear relation of multi-dimensional data. The multi-dimensional data is drawn onto map units, which form the plane of a two-dimensional lattice. SOM will cluster similar data patterns together in the output space while preserving the topology of input space. The network architecture of SOM consists of two layers; input layer and output layer. The input layer is connected to each vector of the dataset (training vector) and the output layer forms a two-dimensional array of nodes (see Fig. 4). The output space often results in the reduction of the dimensionality of the input space which is not shown in Fig. 4.

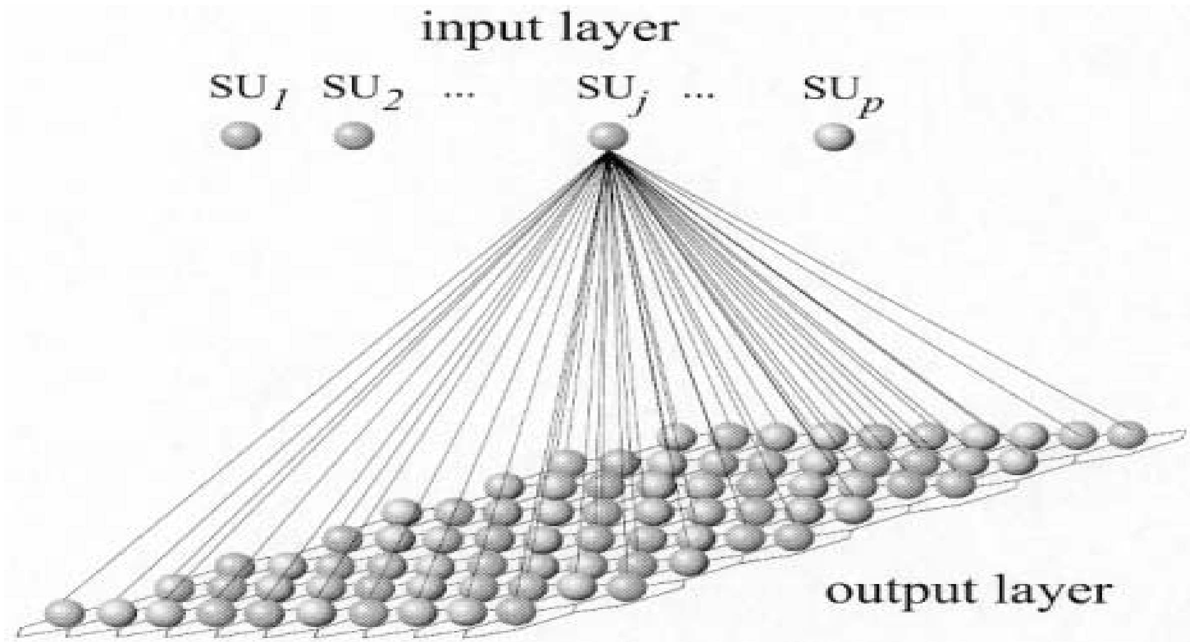

Fig. 4. A two-dimensional Self-Organizing Map (Giraudel, & Lek, 2001).

The SOM training process is briefly summarized as an algorithm by Mehotra, Mohan, and Ranka (1997) as follows:

Step 1: Select output layer network topology; initialize current neighborhood distance, *D(0)*, to a positive value

Step 2: Initialize weights from inputs to outputs to small random values

Step 3: Let $t = 1$

Step 4: While computational bounds are not exceeded, do:

1) Select an input sample i_l to the network

2) Compute the distance of i_l from weight vectors (w_j) associated with each output node by using the Euclidean distance equation.

$$\sum_{k=1}^{n} (i_{l,k} - w_{j,k}(t))^2 \tag{1}$$

3) Select output node j^* that has weight vector with minimum value from step 2)

4) Update weights to all nodes within a topological distance given by $D(t)$ from j^*, using the weight update rule:

$$w_j(t+1)=w_j(t)+\eta(t)(i_l-w_j(t))$$

(2)

5) Increment *t*

Step 5: End While.

In this algorithm, *D(t)* is the neighborhood function, *t* is the iteration step, *i* is the input vector node, *w* is the weight of the output node, and *η(t)* is a learning rate which ranges in (0, 1). Learning rate generally decreases with time (t):

$$0<\eta(t)\leq\eta(t-1)\leq 1$$

(3)

The most widely used SOM for data analysis has appeared in many areas. Previous study by Rueangsirarak, Atkins, Sharp, Chakpitak, and Meksamoot (2011) developed the decision support system to diagnose falling risk in Thai elderly. Based on the validation of SOM in this research, the rate of correct classification of risk of falling is well over 80%. In elderly people whose data derived from the cluster appears higher than moderate/high risk (> (m, h)), as mentioned in Section II, this group of patients needs to be referred to an expert for a detailed medical analysis and appropriated treatment schemes. Case based reasoning provides a beneficial decision support system to store and retrieve knowledge from an expert to provide solutions for the future.

B. Case Based Reasoning

Case Based Reasoning (CBR) was originated by Schank and Abelson (1977). In their proposed work, the general knowledge of past events was recorded in the brain memory in order to predict the upcoming event in the near future. Schank, later, explained that memory of past events and their pattern was related to problem solving and learning. These memories were called memory organization packets (MOPs) (Schank, 1982). In the 1980s, Schank and his group at Yale University proposed the cognitive model for CBR which became the basis case memory model for influential CBR systems, and which was implemented on the first CBR system, called CYPUS, by Janet Kolodner (Kolodner, 1983). Later CBR systems integrated both approaches: heuristic classification and machine learning. Although CBR has a relatively short history compared to other decision support technologies, its mechanism and easiness in implementation have helped it to become a popular tool (Watson and Marir, 1994).

Basically CBR is the process of solving new problems based on the solutions of similar past problems. Previous problems are stored as previous cases in a database, referred to as case base, and consisting of three elements: the problem or situation description, the solution to the problem, and its outcome, normally elicited from experts. In problem space, some features of the case are indexed in order to speed up the retrieval process. The indexing is normally predictive, abstract and concrete enough to be used and recognised in the future use of the case base.

The CBR has four formalised processes: Retrieve, Reuse, Revise, Retain (known as the 4Rs). A problem query is specified by a user and entered into the system. The system retrieves the most similar case, or cases, to the query. In some circumstances, the retrieved solution is not appropriate enough to be a new solution. It then needs to be adapted by applying a rule or formula to take into account the difference between retrieved and new solution. It reuses the stored information and knowledge in the case base to solve the problem. In cases where the problem does not match the new solution, it must be revised by the expert, and retained in the case base to be used for future problem solving.

To retrieve a previous case which is most similar to the new problem from the case base, the CBR uses the Nearest Neighbor Retrieval (NNR) to measure the similarity between a target case and a source case using the following equation.

$$\text{Similarity}(T, S) = \sum_{i=1}^{n} f(T_i, S_i) \times w_i \tag{4}$$

Where T is the target case, S is the source case, n is the number of attributes in each case, I is an individual attribute from 1 to n, f is a similarity function for the attribute i in case T and S, and w is the important weighting of attribute i. This equation represents the sum of similarity of the target case to source case for all attributes. The NNR is a simple technique which has the lowest sensitive to a missing case feature (Watson, 1997). Although the NNR has a weakness about its retrieval speed, it is still recommended as a primarily technique for CBR.

C. Motion Analysis in Biomechanics

Three-dimensional motion capture or biomechanical evaluation has fast become an indispensable tool in the medical assessment of the neuromuscular and musculoskeletal systems. It has been proposed that these opto-electronic motion analysis systems are one of the most accurate means of measuring human motion (Gibbs, 2008). Gait analysis has now advanced to a point where it is used routinely in many centres as a component of patient management. These have improved the human motion analysis beyond basic description and towards prominent roles in surgical decision making, rehabilitation, pros- thetics, orthotics, ergonomics, and athletic performance. The basis of motion capture is the electronic tracking of markers, either passive or active, placed over defined bony landmarks on the body (see Fig. 5).

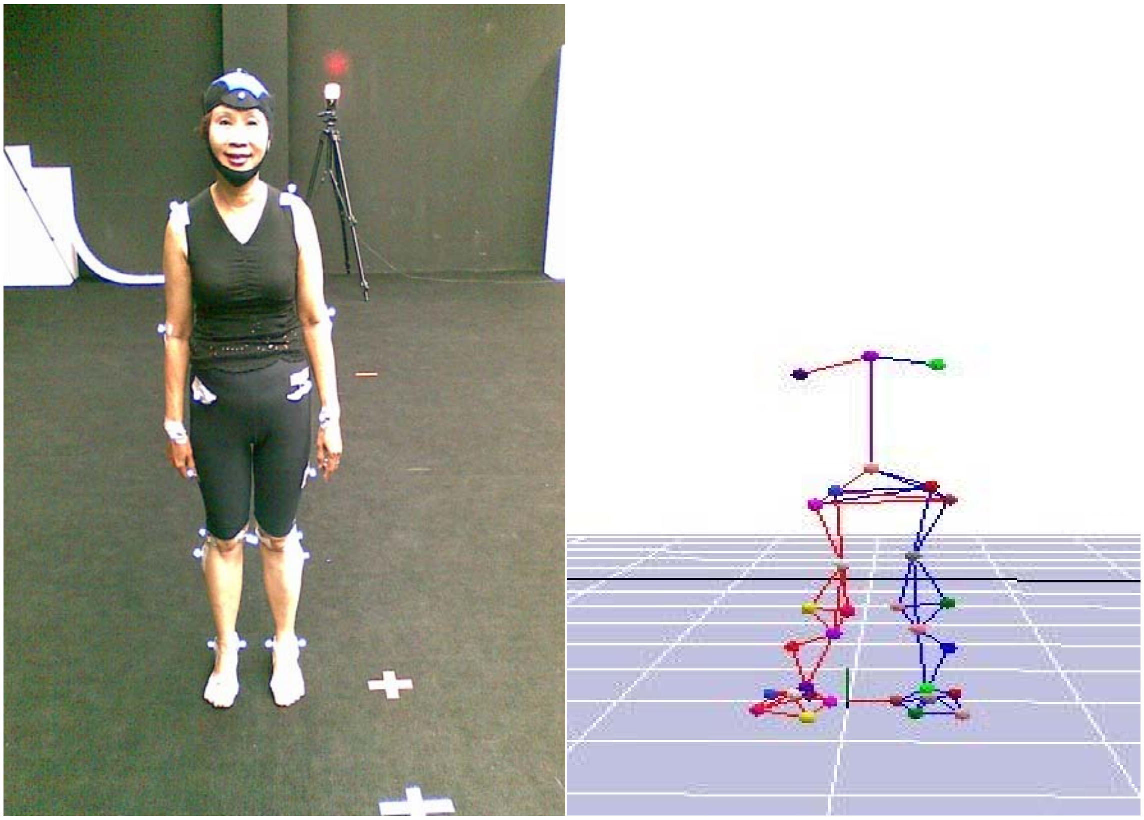

Fig. 5. Marker System (a) a participant was installed the markers (b) a simulation of marker set on the computer screen

Mathematical algorithms are applied to the gait data to generate 3D joint angles. The resulting series of gait graphs for an elderly person are compared to an age-related normal person. Analysis of these graphs reveals information that is not easily visible to the eye, for example, the rate of motion at the knee, which is critical for foot clearance during the swing phase of gait movement. Importantly, the analysis of all the graphical information can reveal compensatory motion occurring in different planes which is extremely difficult to determine by eye alone.

The Motion analysis is widely used in sport science. A detailed understanding of the biomechanics of human motion in sports generally requires the service of a multiple camera three-dimensional motion analysis system to film, capture, track, digitize and analyze motion over time (Ferdinands, 2010). The objective of this application is to obtain raw positional data of segment point (marker) that can be filtered and used to calculate various kinematic derivable variables. These variables are applied to quantify and experimentally validate descriptions of sport techniques, and also to provide biomechanical explanations of the motion patterns observed in sports, to improve the quality and clarity of coaching instruction.

Beside the standard methodology for using a motion analysis system, such as defining the capture volume, completing calibrations and developing appropriate marker systems, which are a preliminary method; there are other procedures that need to be completed for biomechanical analysis. Firstly, the motion analysis positional data is exported to numeric computational software. Secondly, the cut-off frequency needs to calculate and smooth the data using an algorithm with appropriate filters. Then, the full range of kinematic is calculated, automatically, by defined algorithms. Finally, the inverse dynamic is calculated and exported to numeric computational software, in order to perform a kinetic analysis. The motion analysis is applied not only to evaluate on individual performance, but also to suggest methods of optimizing technique for enhanced performance and injury risk reduction, such as fall risk assessment.

D. Application of Integrated Systems

System integration is successfully used in many domains and is also common in the commercial arena and there are an extensive number of studies documented in the literature. Temi (2009) presents the combination techniques of Learning Classifier Systems with Self-Organizing Map to develop the intrusion detection system. ESMPD is an expert systems for assisting mapping from performance space to design space using rough sets theory and self-organizing map (Chu, 2010).

There has been an explosion of interest in integrated applications in the health and medical domains. Basara (2008) developed a system to project the distributions of disease in communities based on an investigation of SOM and geographic information systems. Zhang (2009) conducted a monitoring and surveillance system by using SOM as tool to recognize patterns of epidemiology data and Google Maps Services techniques of WebEpi to present. Obal (2005) proposed an integrated framework for healthcare information systems by exploring a large system of systems using system dynamics. WEALTHY is a comfortable health monitoring system based on a textile wearable interface implemented by integrating advanced signal processing techniques and modern telecommunication systems to monitor individuals affected by cardiovascular diseases (Paradiso, Loriga and Taccini, 2005).

The literature reviewed above shows that a combination or more than one technique could enhance the performance of human work. Consequently, an application of motion analysis, self-organizing map and case based reasoning can be combined to provide the best practice in a medical domain.

IV. OUR KNOWLEDGE BASED SYSTEM

A. Application Framework

The procedure of a knowledge based system (KBS) called Screening System, to diagnose the falling risk in elderly people, using Motion Capture technology is proposed.

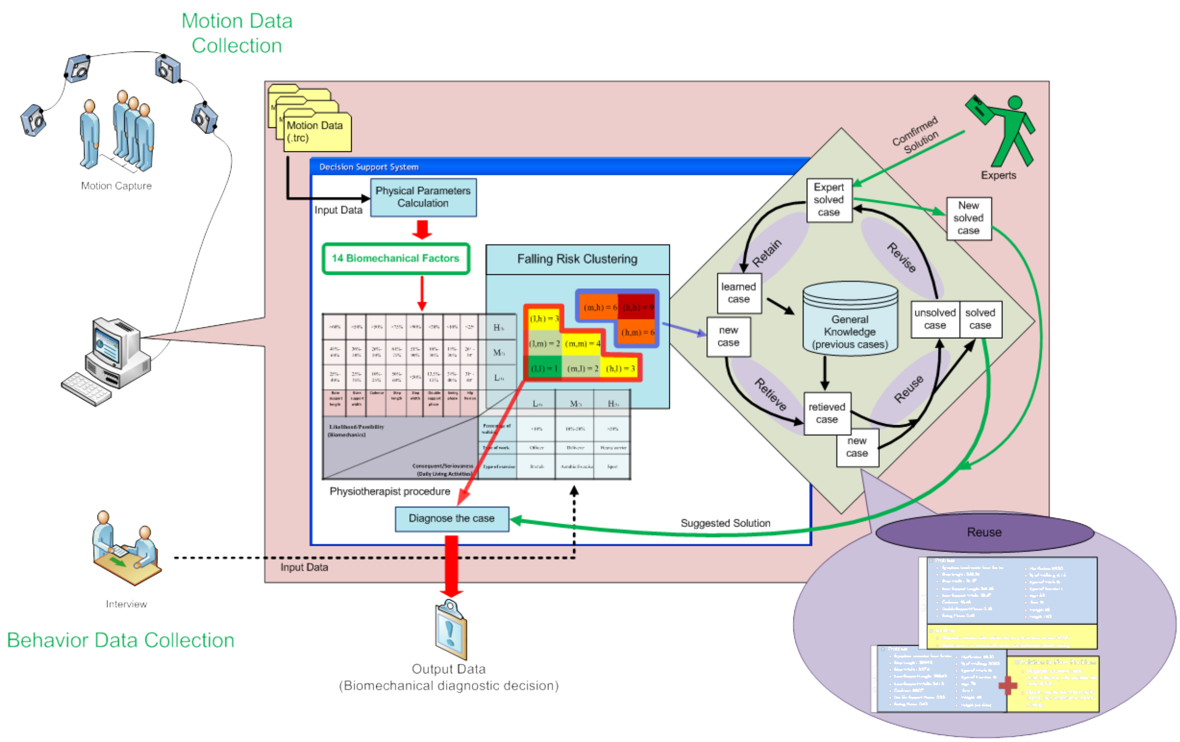

Fig. 6. Falling risk screening system framework.

This screening system investigates the design of the decision support system which applies case based reasoning and self-organizing map techniques. Procedures of combination techniques within the proposed framework are explained in C, D, and E, respectively.

B. Knowledge Source

Our integrated system makes use of three main knowledge sources: (i) the motion data collected from the elderly sample population, (ii) the risk levels extracted from RAM, and (iii) the knowledge elicited from three experts in the orthopedic domain (see Fig. 7).

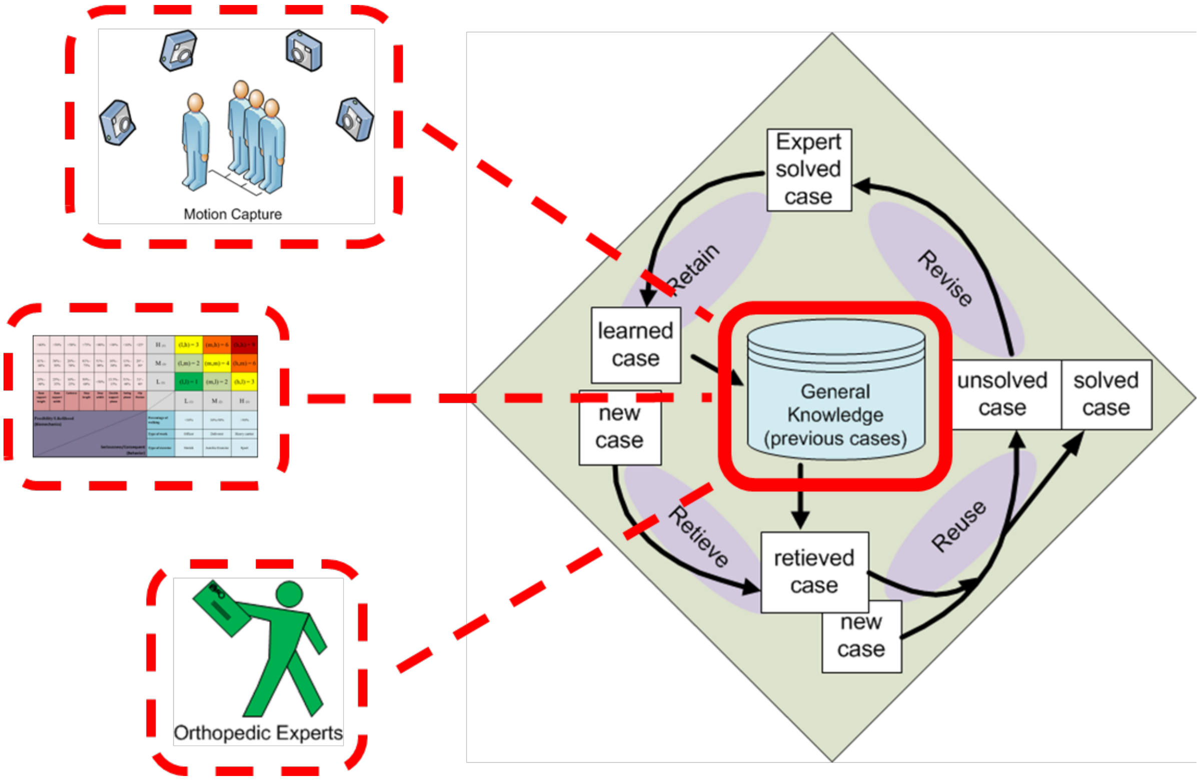

Fig. 7. Three main knowledge sources used in the proposed system.

C. Data Collection

Firstly all the motion data will be collected from the participants by using a Motion Analysis System (Motion Analysis, 2011). These participants are elderly people who are more than 60 years old. The participants agreed to wear a motion capture suite and install a marker set on their body as show in Fig. 5. They were then asked to walk naturally along to capture the volume of the motion capture system. This motion capture system will generate positional data of each elderly person in the form of a three-dimensional coordinate system (x,y,z). The positional data will cut-off the noise within itself in order to prepare the data for biomechanical calculation which is input data for the fall risk clustering process. Then, the positional data is imported from the motion capture system into the screening system which can calculate the biomechanical parameter of RAM as outlined in Fig. 3.

The second step of the proposed system is to gather the participant's daily living activities (behavioral data). The data collection from returned questionnaires was analyzed, summarized and stored in a screening system in order to acquire the behavioral parameter of the elderly as a parameter of RAM. Then, both biomechanical and behavioral parameters will be used as input data for clustering procedure in order to classify a falling risk.

D. Falling Risk Clustering

The screening system, which is running as a front end, will feed the parameters of RAM into SOM to classify all elderly data into a group of similarity which is called a cluster. The number of clusters varies depending on the characteristic of input data. Then the SOM will return the clustering result back to the screening system. If an elderly person's data is stated on a cluster which has falling risk between low and moderate level, the screening system will finalize the diagnostic result for the individual. These groups of clusters can be diagnosed easily by physiotherapists following recommended procedures. However, certain elderly people's data determined from the cluster as having a falling risk higher than *moderate/high* (>(m,h)) will be exported as input data for CBR analysis. These groups of clusters are referred to as an extreme case of risk.

E. Physiotherapist Assessment based on Expert Knowledge

The final step adopted in a CBR approach is to analyze the extreme cases selected from clustering. The extreme cases from the high risk of falling cluster are imported as input data to the CBR—back end system—by feeding from the screening system. This input data will be identified as new incoming problems for CBR. The CBR will retrieve a previous case which is the most similar to the new problem from the database called Case Base. This database includes a set of cases; each case captures the features associated with each problem case and its treatment recommendation. Rueangsirarak, Atkins, Sharp, Chakpitak, and Meksamoot (2011) proposed that the problem case should include four important components: (i) symptom name, (ii) motion features such as step length and width, base support length and width, cadence, and support and swing phases, flexion and walking patterns, (iii) activity types namely type of work and exercise level, and (iv) patient's profile including age, gender, weight and height. Furthermore, the treatment, which is elicited from the experts, should provide the physiotherapist with a diagnosis and a set of exercises to be carried out by the patients with their help. A typical description of a case and a new case is shown in Fig. 8. The previous solution from the similar case will be mapped to a new problem, in order to solve it. If the adapted solution matches with the new problem is referred to as a solved case which has feature correlation >80%, this solution will be appear as a diagnostic result. If the adapted solution does not match with the new problem it is referred to as unsolved case and it will be revised by the expert doctor. This expert solved solution will also appear as a diagnostic result and will be stored in the case base as a new previous case in order to reuse it next time.

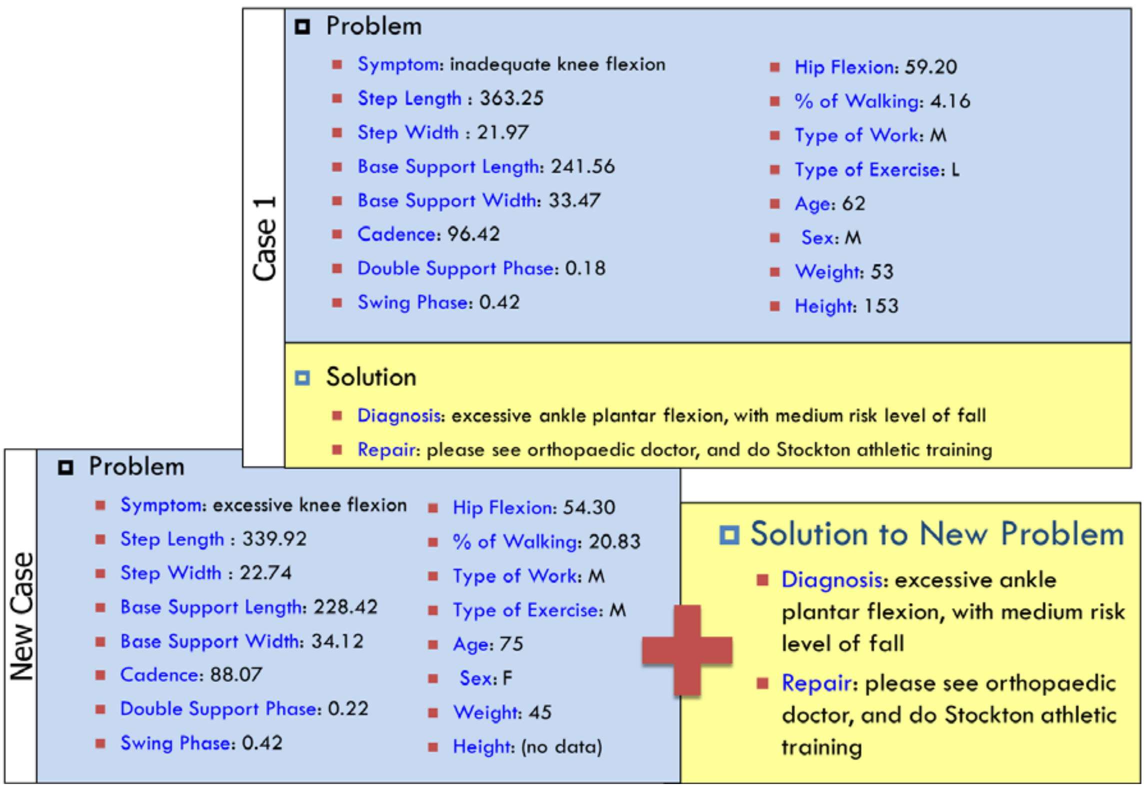

Fig. 8. Case adaptation (Rueangsirarak, Atkins, Sharp, Chakpitak, & Meksamoot, 2011).

The motivation of this system is to combine all the diagnostic processes together in one system. The diagnostic results both from extreme and non-extreme clusters will be used as a supported procedure treatment system for the physiotherapist. This will help the physiotherapists to make a diagnostic decision from knowledge provided by the expert doctor.

V. CONCLUSION

This paper reviews the situation of the elderly population and their health incident problems. The main health problems which occur with elderly people are Musculo Skeletal System problem that are related with gait, balance and mobility. These problems are affected by falling and in order to prevent the elder from falling a fall risk management system is needed. The fall risk assessment will be used by physiotherapists. Unfortunately, the number of medical experts is not sufficient with the increasing number of ageing population. Therefore, this proposed framework of a falling risk screening system was designed to help the physiotherapist to make a diagnostic decision from knowledge provided by a medical expert. The idea is to combine KBS technique and motion capture together as a decision support system. This DSS will be created by the application of case based reasoning and self-organizing map technique. This system includes all the diagnostic processes to be together in one system. The diagnosis information derived from the process of screening system will provide the result to the physiotherapist to determine serious falling risks the elderly are likely to have and recommend guidelines for medical treatment for them. The screening system will also shorten the health check-up duration as the patients will not have to wait in long queues in the hospital for falling risk analysis and the system can also be used to provide learning physiotherapists.

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