Risk Clustering for Diagnosing the Falling Risks in Elderly People Using Self-Organizing Map and Motion Capture Technology

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Abstract
A Self-Organizing Map was used to classify the risk level of falling based on the criteria of a Risk Assessment Matrix in order to assess the risk in the elderly. This screening system adopts input data collected from elderly Thai people, using Motion Capture Technology. The classification of the screening system based on the result of SOM validation in this study showed 80% accuracy which suggest that the clustering technique is adaptable and useful in falling risk management.

Keywords: Decision Support System; Motion capture technology; Elderly falling risk; Self-Organizing Map

Introduction

The National Survey (National Statistics Office of Thailand) in 2001 indicated that there were 5,969,000 elderly people who are over 59 years old (9.4% of population). In 2007, they had increased to 7,020,000 (10.7% of population). The elderly population is evidently increasing within the last ten years. According to the United Nations online database (2009), the elderly population (≥60 years) is currently 11% and it is expected to increase to 22% by 2045 [1]. While people are getting older, they cannot avoid illnesses such as acute conditions, accidents, general ailments, etc. A recent survey of the elderly population in Thailand indicated that most of the elderly are struggling with the Musculo Skeletal System problems. In Maharaj Nakorn Chiang Mai Hospital, Chiang Mai, Thailand, there are many geriatric patients who are living with an invalid musculo skeletal system [2]. They have difficulty moving their bodies as a healthy person would move and therefore need to have treatment for their disorders. Most of the accidents in geriatric patients are caused by falling. However, this effect accelerates the geriatric patient's risk in breaking a skeletal bone [3].

Falls and fall-related injuries are among the "most serious and common medical problems experienced by elders" [4]. During everyone's life; a person will have at least two bad falls possibly causing severe problems later on in life and approximately 43% of institutionalized elders have trouble with falling each year [5]. The main cause of falls and fall-related injuries is tripping and this is a major contributor to hip fractures in elderly people. Also, 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 [6] and hip fracture [7] and 90% of these falls relate to three issues: gait, balance and mobility. In other cases, they are affected by acute disease and adverse medication [8].

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 increasing current numbers of elderly population and this could have serious consequences in the future. Nowadays, visual analysis of human motion is currently an active research topic in computer vision. Human motion analysis concerns the detection, tracking and recognition of people's movements. Understanding human behaviours from image sequences involving humans has been included in the research and Artificial Intelligence (AI) techniques are necessary in this domain, e.g. Decision Support System (DSS), Clustering, and Self-Organizing Map (SOM) to support physiotherapists etc.

This paper explains and discusses the necessity of a DSS to classify the risk of falling in elderly people, using Self-Organizing Map and Motion Capture technology.

Previous study of risk assessment

Risk Assessment Matrix (RAM), by Rueangsirarak and Pothongsunun [9], was created and used as the screening tool as shown in Fig. 1. This enables an elderly fall screening test to be constructed by capturing the experts' heuristic knowledge using Common Knowledge Acquisition and Design System (CommonKADS) model suite. 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 is considered through heuristic criteria based on RAM and is disseminated to the physiotherapists to carry out appropriate treatment.

Fig. 1 is classified into two main groups: a likelihood factor and severity factor. This matrix was applied to the outpatient setting, in order to diagnose elderly falling patterns and it 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) is a result without further need for expert diagnosis. However exception case of (m, h) or (h, m); and (h, h) needs to be referred to an expert for analysis and treatment recommendation [10].

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)				
>60%	>50%	>50%	>75%	>75%	>90%	>30%	<10%	<10%	<25°	<25°	>30°	>30°	> 70% of (BSW/2)	> 70% of (BSW/2)	H (3)	(l,h) = 3	(m,h) = 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)	(l,m) = 2	(m,m) = 4	(h,m) = 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	(m,l) = 2	(h,l) = 3
Possibility/Likelihood (Biomechanics)																L (1)	M (2)	H (3)
															Percentage of walking	<10%	10%-50%	>50%
															Type of work	Officer	Deliverer	Heavy carrier
														Seriousness/Consequent (Behavior)	Type of exercise	Stretch	Aerobic Exercise	Sport

Fig. 1. Risk Assessment Matrix.

The preliminary result from the Risk Assessment Matrix is used as the data for the screening system to analyze the falling risks by the application of SOM together with motion capture technology as explained in Section III.

Case Review-Related Work

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. These opto-electronic motion analysis systems are one of the most accurate means of measuring human motion [11]. 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. 2 (a)).

Fig. 2. Marker System (a) a participant was installed with markers (b) the participant was walking during motion data collection.

Mathematical algorithms generate 3D joint angles from gait data which helps to analyze the information that is not visible to the eyes e.g. the rate of motion at the knees. Motion analysis is widely used in sport science [12]. The objective of this application is to obtain raw positional data of a 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 to smooth the data using an algorithm with appropriate filters.This allows the full range of kinematic to be 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 an individual performance, but also to suggest methods of optimizing technique for enhanced performance and injury risk reduction, such as fall risk assessment.

Self-Organizing Map (SOM)

Another technique which is 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 [13].

One well known clustering technique is Self-Organizing Map (SOM), which has been proposed by Kohonen in the early 1980's [14]. 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 on to 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. 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. 3). The output space often results in the reduction of the dimensionality of the input space which is not shown in Fig. 3.

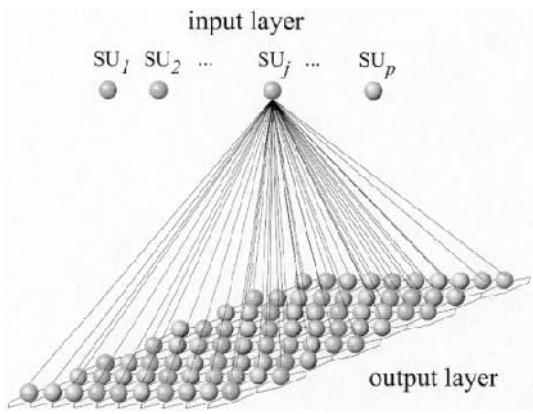

Fig. 3. A two-dimensional Self-Organizing Map [15].

The SOM training process is briefly summarized as an algorithm by Mehotra [16] 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.

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

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:

$$w_j(t+1)=w_j(t)+\eta(t)(i_l-w_j(t)) \quad (2)$$

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 $\eta(t)$ is a learning rate which ranges in (0, 1). Learning rate generally decreases with time (t):

$$0< \eta(t)\leq \eta(t-1)\leq 1 \quad (3)$$

The most widely used SOM for data analysis has appeared in many areas, for example, the medical domain [17], geographic information systems [18], Pattern recognition [19], Ecological [15], Intrusion detection [20], Expert system [21], Initialization [22], Computation [23] and Seismic [24].

Consequently, an application of motion analysis and self-organizing map can be combined to provide best practice in a medical domain.

Falling risk clustering using SOM

In this section, the procedure of a risk clustering called screening system to diagnose the falling risk in elderly people using Motion Capture technology has been proposed. This screening system investigates the design of the decision support system which applies risk assessment matrix and data clustering techniques. Procedures of combination techniques within the system, and methodologies, are explained as follows:

Firstly all the motion data were collected from the participants by using a Motion Analysis System [25]. These participants are 35 elderly people who are over 60 years old. The participants were asked to wear a motion capture suite and install a marker set on their bodies as show in Fig. 2 (a). They then were asked to walk along naturally to capture different values from the motion capture system (see Fig. 2 (b)). This motion capture system generated a positional data of each elderly person in the form of a three-dimensional coordinate system (x, y, z). The positional data cuts-off the noise within itself in order to prepare the data for biomechanical calculation which is an input data for the fall risk clustering process. Then, the positional data was imported from the motion capture system into the screening system which can calculate the biomechanical parameter of RAM as outlined in Fig. 1. This screening system was developed with Visual C# 2010 Express [26].

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

In the third step, the biomechanical and behavioral parameters were fed into the Java SOMToolbox, [27], by the screening system. The SOM toolbox is an open-source implementation in Java, which was developed at Vienna University of Technology and licensed under the Apache License, Version 2.0. Eighteen input nodes were used corresponding to the parameters of RAM. For the output nodes, the size of map is usually experiment-dependent [28]. Pölzlbauer [29] suggested that the number of output nodes should be in the range of $\sqrt{N}$ (with *N* the number of samples), in order to obtain good mapping results. However, using too few output nodes may cause the congestion of input vectors over an output node, which may make in difficult to distinguish the characteristics of the output space [28]. It is therefore better to use a large number of output nodes. In this study, a map sized *3x3* was used as output nodes, which equates to the Risk Assessment Matrix (RAM) as depicted in Fig. 1. The map is a rectangular lattice which is the default of the Java SOMToolbox.

The weighting of each connection between an input node and an output node was initialized in a random value automatically generated by the Java SOMToolbox. For the training cycle (iteration) decisions, there is no definitive stopping point [28]. The preliminary trial uses enough training cycles so that the network approach is in a stable state. In this study the recommended iteration of five times the number of input vectors as the default of the Java SOMToolbox.

Finally, the screening system classified all elderly data into a group of similarity called a cluster. The elderly person data was clustered into falling categories of risk between low-moderate and high level. The screening system then finalized the diagnostic result for the individual in order to give supported information to physiotherapist. The physiotherapist can then diagnose recommended procedures and appropriate treatment.

Experimental result

SOM presented the clusters of all the data as shown in Fig. 4. As visualization is an advantage of SOM, the group of clusters was represented for further data analysis. The *3x3* rectangular lattices were analyzed and Fig. 4 shows the result of the

clusters. SOM classified the input data into seven clusters as shown in Fig. 4 (a), which represented the amount of members in each cluster. In Fig. 4 (b), (c) and (d), SOM labeled the clusters with pie-chart representation in order to present the classification of data based on criteria of RAM [13]; highest-risk-level rule for (b), risk's weighting score shown as risk-level for (c), and risk's weighting score shown as a number for (d). Each cluster was named depend on the greatest amount of class's member contained in that group.

A performance outcome was measured in terms of the number and percentage of correct classifications and the number and percentage of misclassifications. These classifications were compared to the risk level of fall for each participant as outlined in RAM. When evaluating the results with highest-risk-level classification, Fig. 4 (b), SOM gives an 82.86% correct classification. It could perform better using a risk's weighting score and Fig. 4 (c) shows the modified classification rated at 91.42%. Table 1 portrays the SOM experiments results.

Table I: Performance result of Self-Organizing Map.

RAM Criteria	Type	#	%
Highest-risk-level	Correct classification	29	82.86
	Error	6	17.14
Risk's weighting score	Correct classification	32	91.42
	Error	3	8.58

# denotes the number of members classified in each cluster and % shows the percent of classified member in each cluster

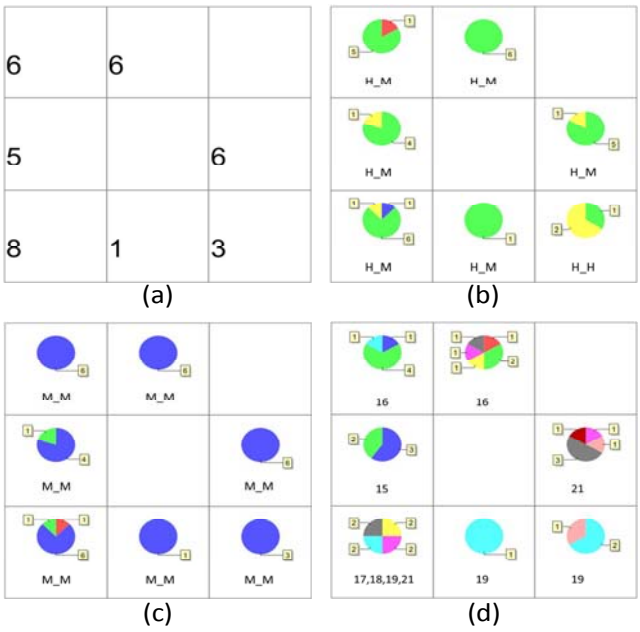

Fig. 4. Results of SOMon rectangular lattices; (a) map unit shown clusters' member; (b) pie-chart for highest-risk-level rule; (c) pie-chart for risk level of weighting score; (d) pie-chart for number of weighting score

As well as indicating the precision of classification, SOM can also present the actual position of the input data in the output map. The layout of clusters was illustrated in Fig. 5 (a). In order to measure the distance between clusters, SOM provided a visualization called U-Matrix to calculate the distance of adjacent prototype vector (closed map units) by Euclidian Distance. Fig. 5 (b) shows the U-Matrix of the falling risk cluster. The map was split into two clouds of clusters, left and right by the border and demonstrated through the lighter color in U-Matrix.

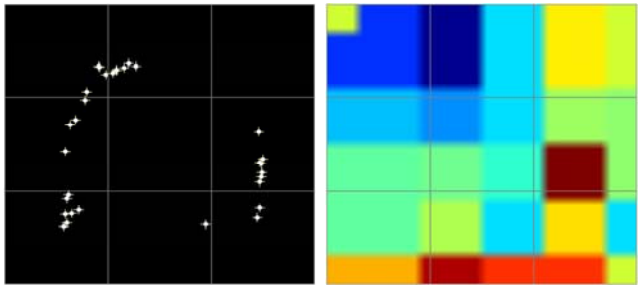

Fig. 5. (a) An exact placement of input data (b) U-Matrix for7 risk clusters.

These SOM's features can help the physiotherapist to make a better decision for diagnosing the risk of falling in elderly people especially the component plane of each input vector, which structured a density of value for each vector as shown in Fig. 6. The physiotherapist could use this component plane to analyze each risk factor in more detail such as feature extraction scheme etc.

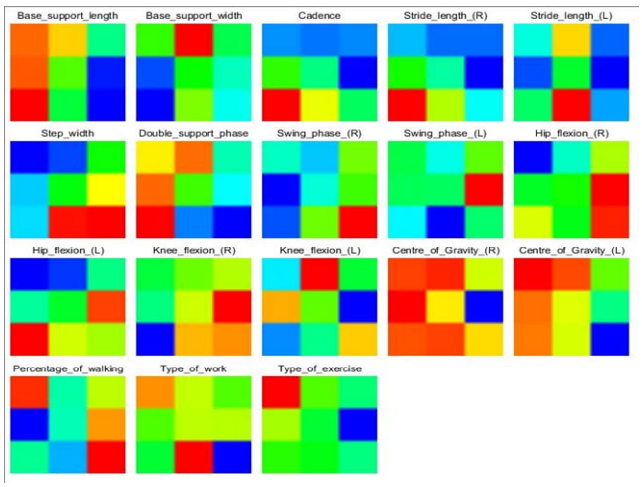

Fig. 6. SOM component plane for each input vector.

Conclusion

The Musculo Skeletal System is the main health problem of elderly people. It is related to gait, balance and mobility and is affected by falling. A new proposed framework of a falling risk screening system was designed to help physiotherapists to make an accurate diagnostic decision. The idea is to combine SOM technique and motion capture together as a decision

support system. This DSS was created by the application of a screening system with a data clustering approach. The classification derived from the screening system process provides the results to physiotherapists so that they can determine how serious the falling risk of the elderly person is likely to be, and this assists in ensuring that the patients will receive the best medical treatment. This screening system can also shorten the health check- up duration because the patients do not have to wait in long queues in the hospital for falling risk analysis.

The advantage of applying SOM together with motion capture technology in the screening system is that the user only needs the input vector to feed into the SOM. Therefore, extra information about risk-level is not required to be embedded in the unsupervised learning process. Based on the validation of SOM in this research, the rate of correct classification of risk of falling is well over 80%. Also, in the post processing, SOM visualization data also provides enhanced information to support physiotherapist's diagnosis.

However, the obstacle in using SOM as a clustering tool during the research is searching for suitable amounts of cluster and the identification of each cluster in the output space. Therefore, another clustering technique should be selected to classify the output space of SOM with a larger size map in order to avoid the congestion of input vectors.

If the cluster of elderly people shows a falling risk between low and moderate level, the result can be simply diagnosed from the knowledge of physiotherapist and appropriate treatment provided. However, in elderly people whose data derived from the cluster appears higher than moderate/high (> (m, h)), as mention in Section II, these groups of patients need 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.

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