AN EXPLOITATION OF THE SELF-ORGANIZING MAP FOR HUMAN MOTION ANALYSIS

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Abstract: Falls are the most common type of home accidents among elderly people and are a major threat to their health and independence. Evaluating the risk of falling is important because it enables the provision of adapted assistance and of taking preventive measures with subjects deemed at risk of falling. Currently, the risk of falling has been evaluated by using questionnaires with their associated problems of subjectivity and limited accuracy in recall. The Kohonen Self-Organizing Map (SOM) has found applicability in a wide range of application areas. Our research as a whole has a final objective to employ the concept SOM to implement an adaptive fall risk detection and warning system. In this paper, we present the preliminary results from our research to utilize SOM to analyze the motion parameters from a miniature sensor with integrated gyroscopes and accelerometers attached to the chest of an individual. The results clearly indicate that SOM can be successfully used to cluster the activities by means of their motion parameters. This is very promising results to extend the concept to implement our final objective system.

1 INTRODUCTION

Falls are the most common type of home accidents among elderly people and are a major threat to their health and independence (Najafi, 2002). Thirty-two percent of a sample of community dwelling persons 75 years and older fell at least once a year. Among them, 24% sustained serious injuries (Tinetti, 1988) In addition, falling can dramatically change an elderly people's self-confidence and motivation, affecting their ability to function independently. Considering the growing proportion of old people (over 75) in the populations of industrial countries, falls will be one of the major problems of this important part of the population (Askham, 1990) In 2050, 16.4% of the world population and 27.6% of the European population are projected to be 65 years and above, and in 14 countries, including nine European countries, more than 10% of the total population will be 80 years or older. Most cases of falls sustained by elderly people appear to result from the cumulative effect of multiple specific disabilities. Among these, balance and gait disorders play a key role (Tinetti, 1986).

Our research has the following major goals: (1) to investigate the changes of an individual's motion parameters over a period of time, (2) to experimentally proof that SOM can be used to learn an individual's motion parameters and make the decision for an unsafe motion that could be a fall risk, and (3) to present the prototype of a SOM-based adaptive system for monitoring and warning of the fall risk motions. In this paper, we present the results that fulfil part of the second objective. We have a strong postulation that different persons have different styles of motion, different activities to perform in the daily life. In addition, it is very likely that the styles of motion and activities are likely to change over time. This calls for an automatic system that is capable of learning along with the wearer and warning if the motion parameters are out of normal conditions previously and continuously learnt by the system.

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Evaluating the risk of falling is important because it enables the provision of adapted assistance and of taking preventive measures with subjects deemed at risk of falling. The risk of falling has generally been evaluated by using questionnaires with their associated problems of subjectivity and limited accuracy in recall (Cummings, 1988). Risk of falls can also be evaluated by clinical and functional assessment including posture and gait, independence in daily life, cognition, and vision (Tinetti, 1986). However, no simple objective method is available.

A method of evaluating the characteristics of postural transition (PT) and their correlation with falling risk in elderly people is described in (Tinetti, 1988). With respect to the report, the time of sit-to-stand and stand-to-sit transitions and their duration were measured using a miniature gyroscope attached to the chest and a portable recorder placed on the waist. The comparison between two groups of elderly subjects (with high and low fall-risk) showed that the computed parameters were significantly correlated with the fall risk as determined by the record of falls during the previous year, balance and gait disorders, visual disorders, and cognitive and depressive disorders. From our point of view, the drawbacks of the proposed system are three folds. Firstly, the differences in the collected data among different persons, or even within the same person, but different time are not taken into account. Secondly, the history of falls in the part was used as an input parameter for the system. This could be an incomplete data due to the limitation of memory of the studied group. Finally, the proposed monitoring and warning system is in a class of a pre-programmed system. This is in contrast to our proposed final system that will rely on using SOM to make it adaptable. The exploitations of gyroscopes and accelerometers for monitoring and warning applications were also described in several patents (Patent, 2008). They, however, lacked the adaptability features.

Javanov et al. (Javanov, 2005) present a prototype wireless body area network (WBAN) system with unobtrusive, commercially available sensor platforms that have minimum size and weight. The prototype relies on using their proposed algorithms to monitor wearer's activity with a minimal number of accelerometers to reduce the price of future systems. The obvious difference between this prototype and our proposed one is that the prototype, itself, does not perform any adaptive feature on board at all. Its main function is only to transfer the accelerometer and electrocardiogram (ECG) data to be analyzed by the remote server.

In (Hwang, 2004), a novel algorithm and real-time ambulatory monitoring system for fall detection in elderly people were described. The system comprised of accelerometer to measure kinetic force, tilt sensor and gyroscope to estimate body posture. The BlueTooth® module was integrated to the system to send real-time data to a personal computer for data analysis and warning. The system was evaluated by attaching to the chest for fall detection on three people aged over 26 years. The experiment of four cases; forward fall, backward fall, side fall and sit-stand, was repeated ten times and the experiment in daily life activity was performed one time to each subject. The results showed that the system and the proposed algorithm could distinguish between falling and daily life activity. Moreover, the accuracy of fall detection is 96.7%. From our opinion, the system required adjustment to be suited for different persons since it lacks the feature to automatically adapt the decision making rules.

The objective of this paper is to present the experimental results of applying SOM to learn an individual's motion parameters and correctly cluster the motion parameters by means of the activities. The remaining of this paper is organized as follows. Our method is presented in Section 2, and experiments and results are detailed and analyzed in Section 3. Section 4 draws conclusions and introduces future work.

2 METHODS

2.1 Data Gathering System

As mentioned earlier that individuals are likely to have different styles of motion and different daily activities to perform. In addition, it is very likely that the styles of motion and activities change over time and age. In our research, we developed an experiment to confirm this postulation. A simple low-cost data logger was developed in-house to fulfil this purpose. The prototype of the system, illustrated in Figure 1, consists of a microcontroller (dsPIC30F2010), a couple of EEPROMs with total capacity of 256 KB (2 of AT24C1024) and a special purpose chip to serve as a voltage level converter between TTL and RS232 standards. The RS232 is used as a communication channel between a personal computer and the data logger. The Analog Devices Inc's ADIS16350 tri-axis inertial sensor (triple axes gyroscopes plus triple axes accelerometers) sensor is used to measure both angular and linear accelerations.

A Windows based application software on a personal site was specially developed to control the operations of the data logger; i.e. time stamp setting, sample time setting and data capturing for analysis. Figure 2 shows the screenshot of the results from the data logger during the period of 12:43:30 – 12:49:00. The first three columns are the time stamp of the recorded data which are arranged in the following format: the angular accelerations in the x, y and z axes and the linear accelerations in the x, y, and z axes. It is noted that the data logger was programmed to sample data every 1 second period but it is capable of immediate recording the new incoming data if and only if all parameters change more than the predefined acceptable delta which are 6 units in this case. Also, it is noted that in order to get the true value of both angular and linear accelerations the recorded values must be multiplied by 0.07326^o/s^2 and 2.522 mg, respectively.

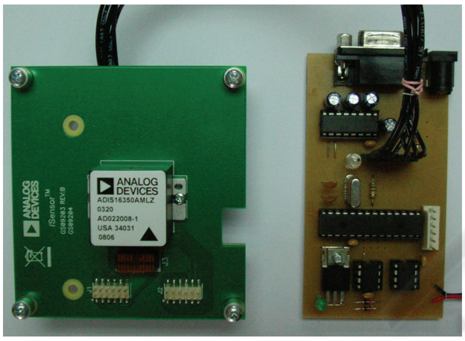
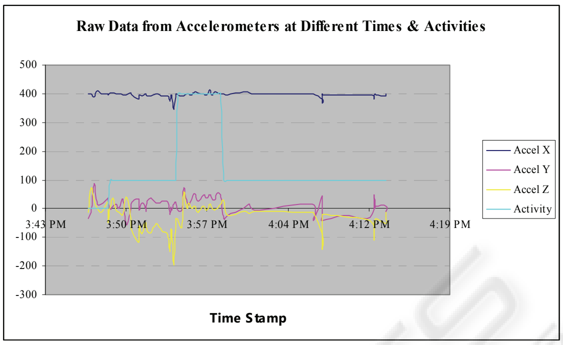


Figure 1: A photograph of the data logger system (right) and a miniature gyroscopes and accelerometers (left).

12	43	30	-0019	0026	0018	0390	0022	-0088
12	43	42	-0065	0087	0078	0398	0013	-0059
12	43	51	-0005	-0010	-0008	0397	-0011	-0042
12	43	58	0089	-0061	-0043	0396	0022	-0061
12	44	01	-0051	-0008	-0014	0395	0006	-0071
12	48	54	-0166	-0286	-0058	0386	0014	-0098
12	48	55	-0280	-0301	-0042	0365	0040	-0147
12	48	56	-0052	-0049	-0024	0338	0071	-0195
12	48	57	0149	-0057	0135	0334	0007	-0214
12	48	58	-0115	0038	-0096	0347	0034	-0197
12	48	59	-0058	0214	-0072	0356	-0059	-0156
12	49	00	-0119	0265	-0178	0379	-0026	-0118

Figure 2: The screenshot of the results obtained from the data logger during the period of 12:43:30 – 12:49:00.

Figure 3 show two snapshots of the experimental results from recording the motion, time and activity of a male volunteer of 39 years old. The legends of the activities are as follows: (0) Walking, (1) Sitting, (2) Walking Downstairs, (3) Walking Upstairs, (6) Jogging and (7) Sleeping. It is noted that during the period of our experimentations, these activity types were approximately inserted offline after the data had already been transferred to a personal computer. This was done in order not to interrupt and disturb the normal activities of our volunteers. It can be observed that there are some patterns in the graphs which have some relations with the activities. These are very promising input data for training SOM.



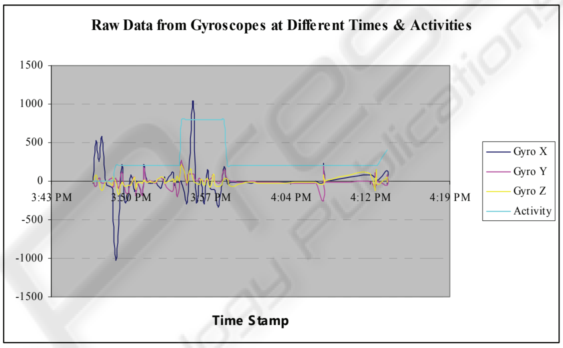


Figure 3: The snapshots of the experimental results from recording motion, time and activity of a volunteer from the accelerometers (top) and the gyroscopes (bottom).

2.2 A Brief Introduction to SOM

A 2-D map is defined by $\boldsymbol{k}$ locations or $\boldsymbol{k}$ cells arranged as a 2-D lattice. Each location contains an $\boldsymbol{n}$-dimensional model vector which comes to resemble $\boldsymbol{n}$-dimensional input (teaching) data during the unsupervised learning process, the self organization (Joutsiniemi, 1995). As a result of SOM process, the distribution of the model vectors in the $\boldsymbol{n}$-dimensional space will approximate the probability distribution of the input vectors. The topographic organization of the map will also approximate the matrix ordering relations in the input space. Thus, similar inputs project near each other onto the map. Increasing the number of locations k increases the accuracy of the approximation, which means that k should be chosen according to the computing power available. In our experiment, we chose k = 500. (a hexagonal lattice with dimensions 25 and 20).

In our experimentation, the maps were initialized, taught, and evaluated using the routines in the SOMPAK package. The learning consisted of two phases. In the first phase, the learning coefficient $\alpha(t)$ decreased from 1.0 to 0 in 100,000 steps, while the radius of the neighbourhood decreased from 15 to 1. In the second phase, $\alpha(t)$ decreased from 0.125 to 0 in 10,000 steps, while the radius of the neighborhood decreased from 3 to 1. The data retrieved from the sensors were modified to have zero mean and one standard deviation (Zachrison, 2006). This was down in order to restrain one of the input dimensions from becoming too dominant. The time stamps were not used directly for self organization process but they were instead transformed into the "*period of change*" of a consecutive pair of motion parameters. By doing this way, it made the resulting map to be in a more readable form with highly cluster groups of data.

3 RESULTS AND DISCUSSIONS

The resulting map after training process with an individual's input data of 7 dimensions, which are **the period of change, the angular accelerations and the linear accelerations in the x, y, and z axes**, is shown in Figure 4(a) (lines separating different clusters and labels within the clusters were manually inserted). In total, the data used during the learning stage consisted of 1,044 records. In order to get as general results as possible with the limited data, a leave-one-out procedure was used. This was done by taken out 10 percents of the records of the motion parameters for each activity from the training dataset and analyzed using a map trained with the parameters of the remaining records. The activities of the former set of data records were known to us but they were invisible with respect to SOM. It can be seen that the self-organization process produced the final map with different distinguishable clusters. In Figure 5(a), the clusters are grouped and the corresponding activities are labeled manually with the guidance of the data resulting from the labeling process of the SOMPAK program.

It is noted that with respect to the results after the SOMPAK labeling process, some cells in the map were labeled by many activities. Also, some cells were completely left unlabelled. For the former case, this means that some activities share common motion parameters. These activities are "walking upstairs" and "downstairs." For the latter case, such cells could be matched to a group of motion parameters which could be a fall risk. The investigation of the properties of these cells is beyond the scope of this paper.

At this point, consider the leave-one-out testing results which was performed by querying the trained SOM with an unknown motion parameters with respect to the SOM (the one which was taken out from the training dataset), the results are presented in the middle column of Table 1 (within group). It is clear that, with respect to the proposed set of motion parameters for SOM training, all activities could be correctly classified with the mean and the standard deviation of 73.45 percents and 16.08, respectively. It is noted that the hundred percents could not be achieved because some activities were matched to a group of cells of the SOM map which were previously labeled by many activities.

Table 1: The results from the leave-one-out testing procedure: within group and cross validation.

Activities	Percent Correctness	
	Within Group	Cross Validation
Walking (W)	61.54	56.24
Sitting (S)	86.67	62.00
Walking Downstairs (D)	64.29	42.85
Walking Upstairs (U)	61.54	50.00
Jogging (J)	50.00	42.71
Sleeping (SL)	100.00	87.00

Table 2: The probability of being matched of all activities after presenting to SOM with the known activity motion parameters (Use the abbreviations from Table 1).

Act	The Probabilities of Matched to Activities					
	W	S	D	U	J	SL
W	**0.62**	0.07	0.07	0.08	0.10	0.00
S	0.15	**0.87**	0.29	0.00	0.20	0.00
D	0.18	0.05	**0.64**	0.08	0.15	0.00
U	0.00	0.00	0.00	**0.62**	0.05	0.00
J	0.03	0.00	0.00	0.15	**0.50**	0.00
SL	0.03	0.02	0.00	0.08	0.00	**1.00**

The rightmost column of Table 1 presents the testing results after performing the similar testing procedures with the dataset of the motion parameters from different volunteer: the cross-validating test. It was expected prior to performing the test that the results could not be as good as the previous testing. The outcomes show that the mean of correctness is only 58.97 percents with a standard deviation of 15.19. This confirms that different persons have their own set of motion parameters. To correctly classify the activities of an individual, SOM is required to be trained with the motion parameters of the individual.

There are some interesting results if we reconsider the probability of being matched to all activities after presenting the unknown motion parameters to SOM. The results are shown in Tab. 2. Column 2 – 7 are the types of activity whose motion parameters were presented to SOM for querying and all rows are the resulting probabilities that SOM

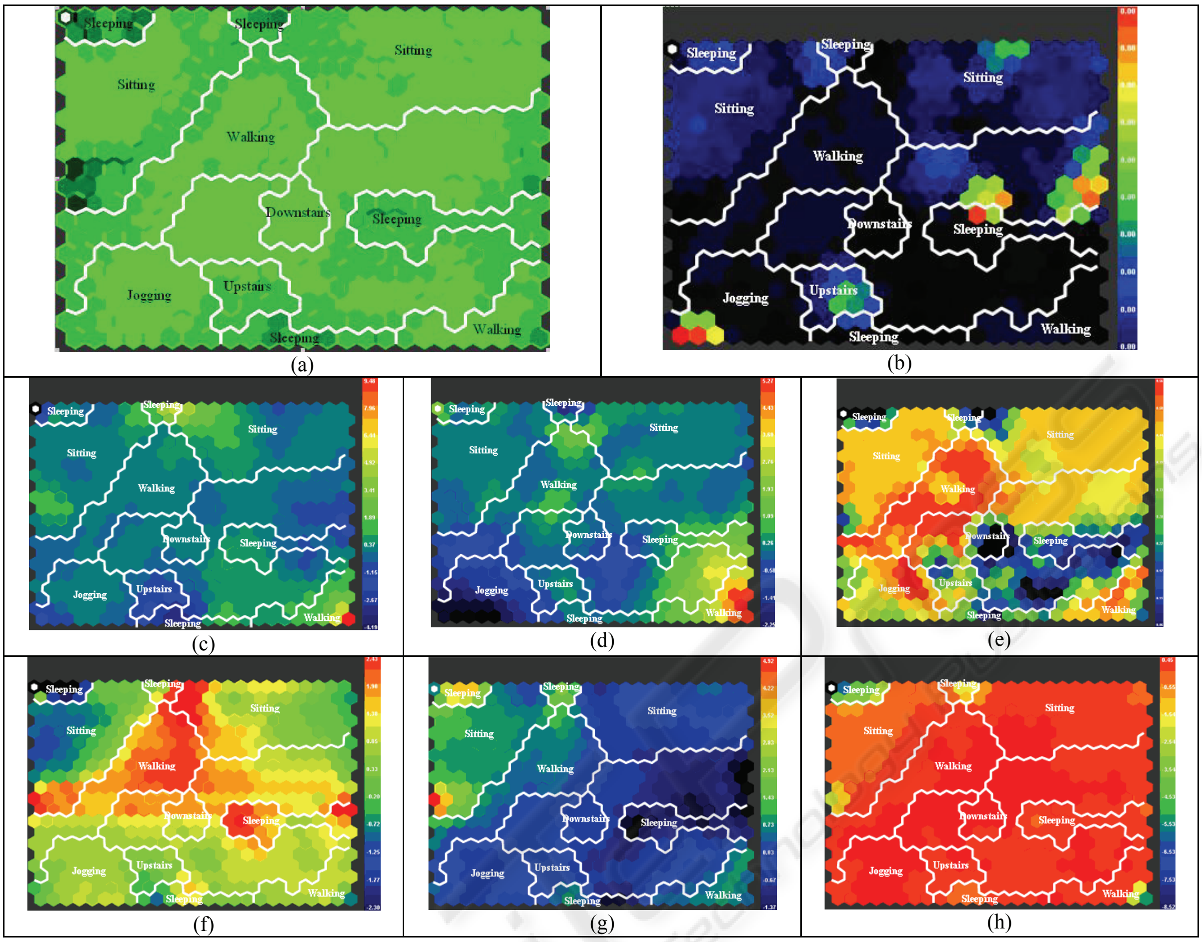


Figure 4: (a) The resulting map after clustering and labelling, the projection maps in (b) – (h) show the relationships between the activities and the training parameters: period of change, angular and linear accelerations in the x, y, and z axes.

matched those parameters to the activities. It can be seen that ("walking", "walking downstairs"), ("sitting", "walking downstairs") and ("jogging", "walking downstairs", "sitting") share some common motion parameters. It is quite clear for the first group but question could be arisen for the second and third one. This can be explained that the volunteer could be moving while sitting.

After all activities were clustered, it is now possible to analyze the relationships between different training parameters and the activities. Figure 5(b) – (h) show the projection maps with respect to individual motion parameters. Consider the map of the x and y axes of gyroscope, Figure 5(c) and (d), both maps show almost the similar clusters and the scales of the motion parameters which are reflected from their colour appearances (see the legend on the right side of the maps.) It is surprised to see that only the activity of type "walking" can make a prominent high value to the sensors in these axes. This could come from the fact that our volunteer's walking style causes a more forward movement comparing to "jogging" and "walking upstairs and downstairs". Also, the projection map of the z-axis gyroscope in Figure 5(e) which clearly shows different clusters of activities, comparing to the previous 2 maps, indicates that "walking" and "jogging" cause this sensor to output a very high level.

The maps with respect to the accelerometers shown in Figure 5(f) – (h) obviously indicate that SOM is capable of clustering "sleeping" which differs from the rest activities in the way that the motion parameters in all axes are completely changed. Also, the maps in Figure 5(f) which projects onto the x axis accelerometer clearly show the clusters of "walking." There are some variations in the motion parameters of "sitting" with respect to the accelerometers which could be interpreted that our volunteer could be moving while sitting. It is noted that these variations could not be correctly recorded during the period of our experimentations.

Lastly, consider the last projection map, the period of change, in Figure 5(b). The map reveals some interesting points in the "jogging" cluster on the bottom left part, also the "sitting", the "walking upstairs" and the "sleeping" clusters. These points can be interpreted that there were suddenly changed of the motion parameters during performing such activities. It is easy to understand these cases for "jogging" and "walking upstairs" which always cause the sudden changes of these motion parameters. For "sleeping" and "sitting", such the changes could be resulted from the immediate change of motion patterns; i.e. move backward and change to forward immediately during sitting or quickly lie before sleeping.

4 CONCLUSIONS

In this paper, we presented the results that partly fulfilled an objective of our overall research project which is intended to develop an adaptive system to detect motion parameters that are fall-risk. We experimentally proved that SOM could be trained with an individual's motion parameters: the period of change of a consecutive pair of parameters, the angular and linear accelerations in (x, y, z), resulting in clustering of similar motion parameters. Also, SOM could match between normal activities and the clusters of motion parameters on the maps with as high as 73.45 percents of correctness. However, the matching between abnormal motion parameters that could be a fall risk still needs more efforts to pursue. From the experiment results, it can be concluded that different activities of an individual have different motion parameters (period of change is also included). SOM can successfully and correctly cluster these activities in relation to the motion parameters. It is worth noting that in order to classify the activities of a person with a high degree of correctness, SOM needs to be trained with the motion parameters of that person. With positive experimental results, we expect that SOM can be utilized to make the decision for an unsafe motion that could be a fall risk in an adaptive way.

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