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# A Self Organizing Map Based Postural Transition Detection System

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## 1. Introduction

A high percentage of elderly people has been continually increased in every part of the world. This results from the successes of both the advancements of medical knowledge and the high coverage of medical services which altogether make people healthier and live longer. One of the consequences of advancing years is greater frailty due to declining health and mobility, leading to increased risk of injury and fatality due to accidents, especially in the home. It can be said that 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 elderly people's self-confidence and motivation, affecting their ability to function independently and result in decreased activity, isolation and further functional decline. In addition, the cost of caring for elderly people after a fall is substantial, although estimates vary. Some suggest that fall-related injuries account for 6% of all medical expenditures in the USA (Stevens, 2006). 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. The normal changes of aging, like poor eyesight or poor hearing, can make elderly people more likely to fall. Illnesses and physical conditions can affect their strength and balance. Poor lighting or throw rugs in their home can make them more likely to trip or slip. The side effects of some medicines can upset elderly people's balance and make them fall. Medicines for depression, sleep problems and high blood pressure often cause falls. Some medicines for diabetes and heart conditions can also make them unsteady on their feet.

As a way to observe the activities of elderly people in order to prevent and/or alert when they fall, an EKG (Electrocardiogram) sensor, a pulse sensor and a blood pressure sensor are also employed. It is expected that if some measuring parameters are changed, they might result in a severe fall and unconsciousness of elderly people. To function correctly, these sensors must be firmly attached to the body of wearers by a well-trained medical staff. The sensors may cause uncomfortable for wearers and make them lack of self-confidence to live by their own. In addition, from the technical point of view, these sensors consume a high percentage of battery power if they are operated continuously or at the high sampling frequency. The aim

of our research as a whole is to minimize the fall risk effecting parameters which should be sampled from the movement of wearers. This also leads to minimizing the number of sensors to implement the monitoring and alert system.

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; Riley, 2008).

This chapter is aimed to present the details of an adaptive postural transition detection system which operates by use of a wearer's knee movement. The system is developed in order to make a decision if a wearer has the transition types of either sit-to-stand (Si-St) or stand-to-sit (St-Si) which are believed to be a fall-risk in elderly people. The output from the system can be used to trigger an additional sensor to operate in order to make further measurement and judgement. Within the system, the Kohonen self organizing map (KSOM or SOM) neuron network was employed to perform an adaptive analyzer and classification functions which made the system applicable to wearers with different ages and motion conditions. In the next section, the literature survey of related research work on the topic of PT detection is described.

## 2. Literature survey

The PT detection by use of a single 3-axis accelerometer attached to the chest is presented in (Barralon, 2005). To automate the identification processes for sitting and standing postures and pave the way to implement an automatic fall detection system, (Nyan, 2006) reports the developed system for measuring the time of Si-St and St-Si transitions and their duration. In the developed system, a miniature gyroscope attached to the chest and a portable data logger placed on the waist are employed. The comparison between two groups of elderly people subjects (with high and low fall-risk) shows that the computed parameters are significantly correlated with the fall risk as determined by the record of falls during the previous year. Moreover, the parameters are correlated to the balance and gait disorders, visual disorders, and cognitive and depressive disorders. A 2-axis accelerometer is used for motion detection of body movement in (Yang, 2007). A dedicated body movement algorithm embedded in the microcontroller is developed to actively recognize three still postures (sitting, standing, and lying), four postural transitions (sit-stand transitions and lie-sit transitions) and locomotion (walking) in a home environment. The proposed algorithm relies on using the slope mapping technique. The experimental result shows that the detection correctnesses of Si-St and St-Si are 92.2 and 95.6%, respectively. In (Bidargaddi, 2007), a wavelet-based algorithm for detecting and calculating the durations of Si-St and St-Si transitions is developed and reported. The algorithm processes the signal vector magnitude of the measured acceleration signal. Later, (Najafi, 2008) proposes an approach to utilize the pattern of the vertical accelerometer to detect a PT, recognize the interval of PT and finally classify the transition types. The classification process is based on the time-frequency analysis. This is performed by considering that a gravitational acceleration has a lower frequency component as compared with a translational (linear) acceleration, and that a velocity does not have a DC component.

Accelerometers and magnetometers are used to study the activity of person (Fleury, 2009). The signal from these sensors are analyzed by a wavelet-based pattern recognition algorithm

in order to detect the postural transitions. This is fairly similar approach to the one previously presented in (Bidargaddi, 2007). Results of an experiment are also given to show a mean classification rate of 70% for this approach. In contrast to the previously proposed approaches, a Hidden Markov Model (HMM) processing framework for stochastic identification of body postures and physical contexts is proposed in (Quwaider, 2009). The key idea relies on collecting and wireless transmitting data from multi-modal sensor attached to a human subject's body segments. The data is processed by using HMM in order to identify the subject's instantaneous physical context. It is claimed that the conducted experiments show that a technique can achieve high detection match rates for all posture transitions. Unfortunately, no comparative result is presented in the publication. Recently, it is studied in (Dijkstra, 2010) whether gait and postures can accurately be detected with a single small body-fixed device. The study is focused on a group of patients with mild to moderate Parkinson's disease (PD). It is concluded that the triaxial monitor system is a practical and valuable tool for objective, continuous evaluation of walking and posture transitions in patients with mild to moderate PD. Unfortunately, it is concluded that detection of sitting and standing requires further fine-tuning.

From our point of view, there are several drawbacks of the previously proposed system. That is to say the differences in the collected data among different persons, or even within the same person but different time, which are very common are not taken into account. The proposed postural transition detection systems are all in a class of a pre-programmed system with the threshold for warning or alert resulted from limited samples. This is in contrast to our proposed system that relies on utilizing SOM to make it adaptable to a particular wearer. The movement nature of the wearer is used for system training and, in turn, used to report the transition types of the wearer. The details of our proposed system are given in the next sections.

3. Method

In this section, an introduction to SOM which is our main tool is given. Then, it is followed by the details of our proposed system which consists of the wireless sensor network based system and the developed computer software to communicate with the wireless sensor network.

3.1 A brief introduction to SOM

In general, SOM is one of the most prominent artificial neural network models adhering to the unsupervised learning paradigm (Kohonen, 1990). It has been employed to solve problems in a wide variety of application domains. For the applications in engineering domain, it was elaborately surveyed and reported in (Kohonen, 2002). Generally speaking, the SOM model consists of a number of neural processing elements (PE). Each of the PE,  $i$ , is assigned an  $n$ -dimensional weight vector  $m_i$  where  $n$  is the dimension of an input data. During the learning stage, the iteration  $t$  starts with the selection of one input data  $p(t)$ .  $p(t)$  is presented to SOM and each PE determines its activation by means of the distance between  $p(t)$  and its own weight vector. The PE with the lowest activation is referred to as the winner,  $m_c$ , or the best matching unit (BMU) at the learning iteration  $t$ , i.e.:

$$m_c(t) = \min_i \| p(t) - m_i(t) \| . \tag{1}$$

The euclidean distance (ED) is one of the most popular way to measure the distance between  $p(t)$  and a PE's weight vector  $m_i(t)$ . It is defined by the following equation:

$$d(p(t), m_i(t)) = \sqrt{(p(t)_1 - m_i(t)_1)^2 + (p(t)_2 - m_i(t)_2)^2 + \dots + (p(t)_n - m_i(t)_n)^2} \quad (2)$$

Finally, the weight vector of the winner PE as well as the weight vectors of selected PEs in the vicinity of the winner are adapted. This adaptation is implemented as a gradual reduction of the component-wise difference between the input data and weight vector of the PE, i.e.:

$$m_i(t+1) = m_i(t) + \alpha(t) \cdot h_{ci}(t) \cdot [p(t) - m_i(t)]. \quad (3)$$

Geometrically speaking, the weight vector of PEs of the adapted units are moved a bit towards the input data. The amount of weight vector movement is guided by a learning rate,  $\alpha$ , decreasing with time. The number of PEs that are affected by this adaptation is determined by a neighborhood function,  $h_{ci}$  which also decreases with time. This movement makes the distance between these PEs decrease and, thus, the weight vector of the PEs become more similar to the input data. The respective PE is more likely to be a winner at future presentations of this input data. The consequence of adapting not only the winner alone but also a number of PEs in the neighborhood of the winner leads to a spatial clustering of similar input patterns in neighboring parts of the SOM. Thus, similarities between input data that are presented in the  $n$ -dimensional input space are mirrored within the two-dimensional output space of SOM or SOM map. The learning stage is terminated after the final SOM map is labelled with some known conditions.

The classification stage is very similar to the learning stage with some exceptions. That is to say there is no need to perform adaptation to the winner PE and its neighbours of the SOM map with respect to the input data. Instead, the label of the winner PE corresponding to the input data is returned and used for further interpretation; i.e. if the input data is mapped to the PE whose label is either Si-St or St-Si transitions.

### 3.2 The wireless sensor network based system

To be successfully employable to the main target of the proposed detection system which are elderly people, several criteria must be considered (Rajendran, 2008). One of the most important criteria is that the system must be the least obtrusive. In addition, the system should be as small as possible to ease attachment to the body of elderly people and to avoid eye catching by others. It must require the least cable connection. Also, the power consumption of the overall system must also be kept minimum in order to lengthen the battery operating time. To fulfill these requirements, the wireless sensor network (WSN) based system was selected from our initial design stage. During the course of design and experimentation, a WSN based data acquisition system was developed to be the least obtrusive manner to gather knee movement data from elderly people. During the learning stage, the gathered data is used for training SOM and activity types labeling to its resulting map on a semi-automatic basis. Later during the normal operation mode (classification stage), the sampled data is automatically gathered and mapped to the appropriate PE. The label of the mapped PE which is either Si-St or St-Si transition is then returned. The overall roles of the developed WSN are shown in Fig. 1.

The developed WSN system was based on the MSP430 family of microcontrollers from Texas Instruments Inc (Texas Instruments Inc., 2008). The eZ430-RF2500 development tool, both hardware and software, was selected as it consists of all required components to accelerate



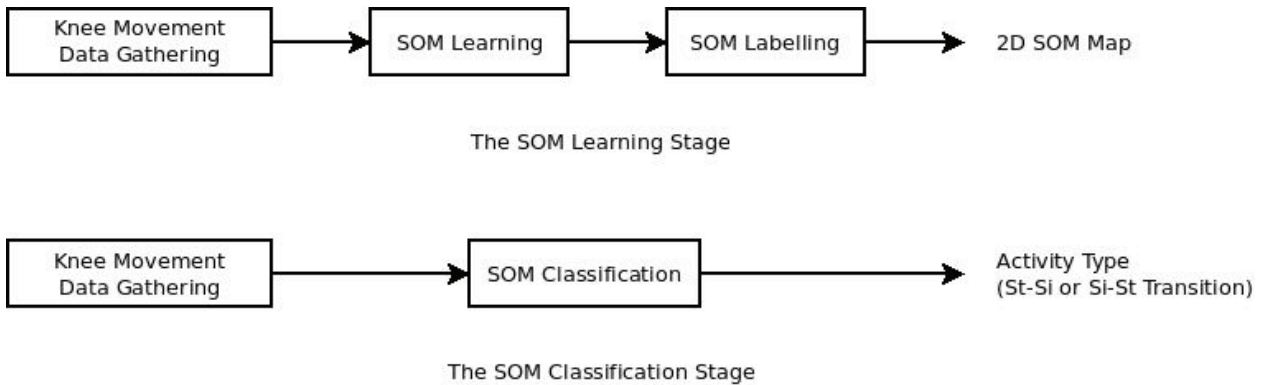


Fig. 1. The overall roles of proposed system.

the WSN design and implementation process. Fig. 2 illustrates the proposed system during the SOM learning and classification stages. The hardware part of the tool integrates the MSP430F2204 microcontroller (which combines 16-MIPS performance with a 200-ksps 10-bit Analog-to-Digital Converter (ADC)) with the CC2500 multi-channel RF transceiver chip. The overall size of the system is about half of the thumb size as clearly be shown in the top-left part of Fig. 3(a). A pair of eZ430-RF2500 were used with two different versions of software to operate as an end device and an access point modes. The main role of an end device during the learning stage is to sample the knee movement data via an external sensor (will be detailed shortly), pack the sampled data into a communication protocol, and transfer the protocol to an access point via a wireless data communication. An access point which is connected to a personal computer is responsible for receiving incoming protocol from one or many end devices and transforming and transferring the packet to a personal computer via a USB port. The upper left and right parts in Fig. 3(a) illustrates an eZ430-RF2500 module and an access point (an eZ430-RF2500 module with an RS-232 to USB protocol converter module), respectively. The middle part of the figure is the prototype of an end device with an external sensor. Fig. 3(b) illustrates the attachment of an end device to our volunteer’s knee by use of a Tubigrip.

In contrast to the previously proposed PT detection systems which rely on using an

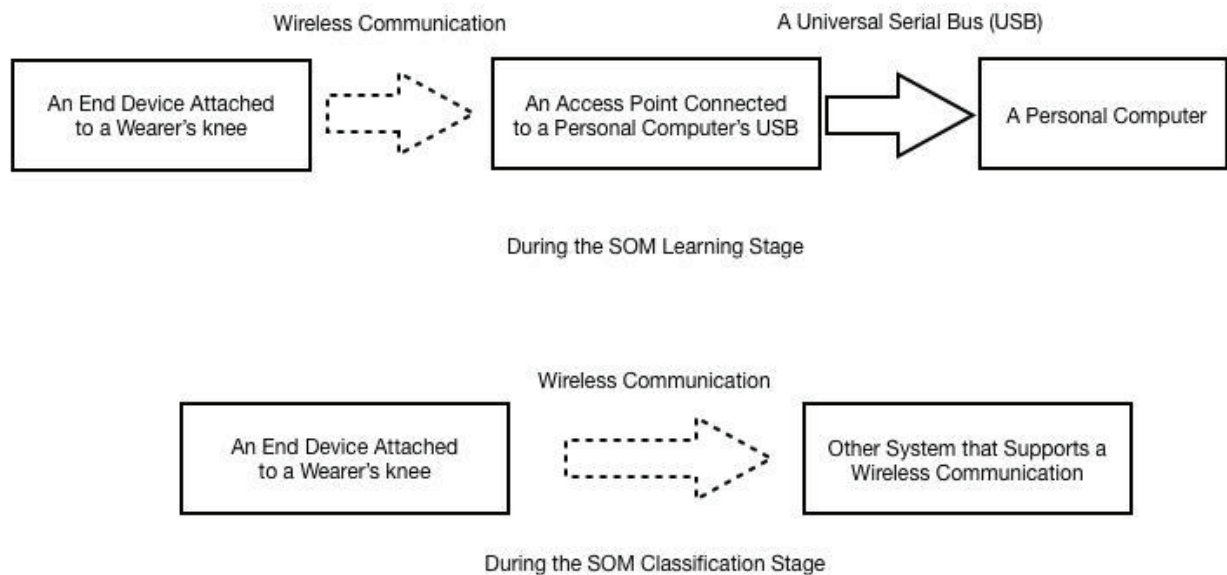
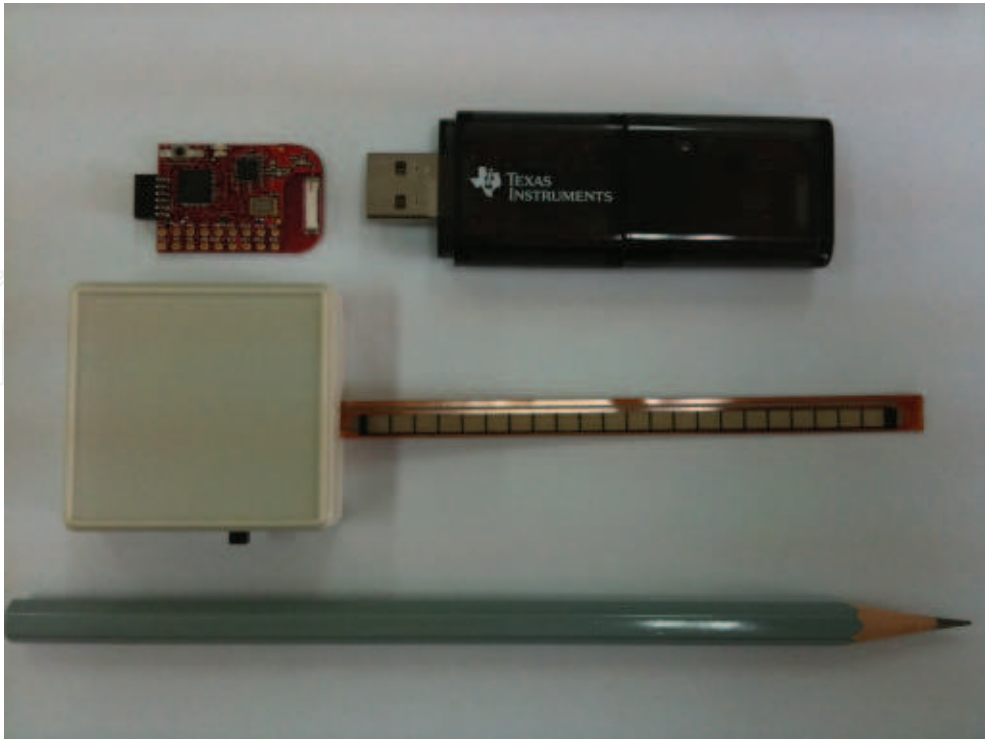


Fig. 2. The architecture of the proposed WSN system.



(a)



(b)

Fig. 3. (a) An eZ430-RF2500 module (top-left), an access point (top-right), the prototype of an end device with an external sensor (middle), (b) The attachment of the end device with our volunteer's knee by use of a Tubigrip

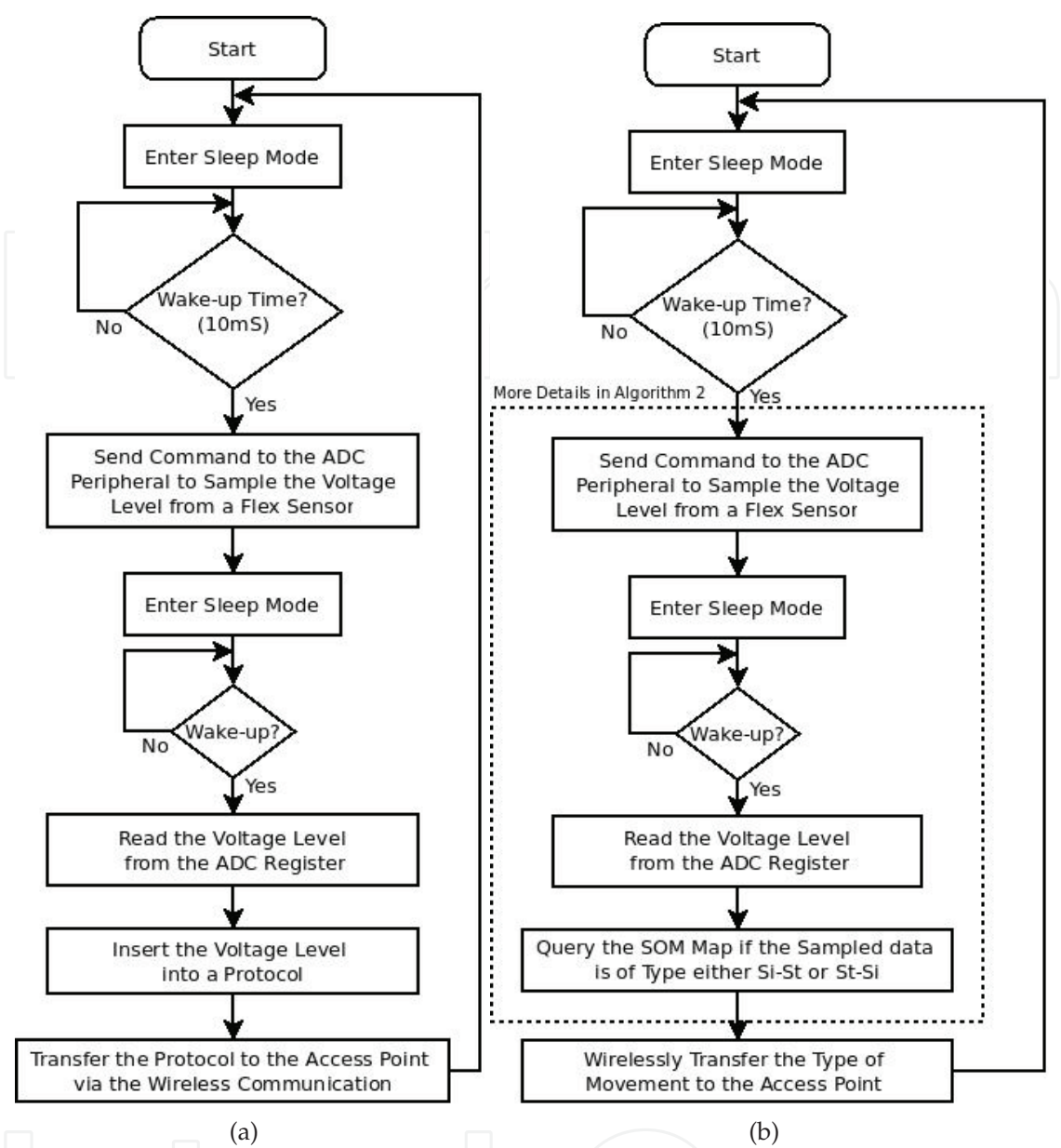


Fig. 4. Flowcharts of (a) an end device operations during the data gathering/transmitting stage, (b) an end device operations during the normal operation stage

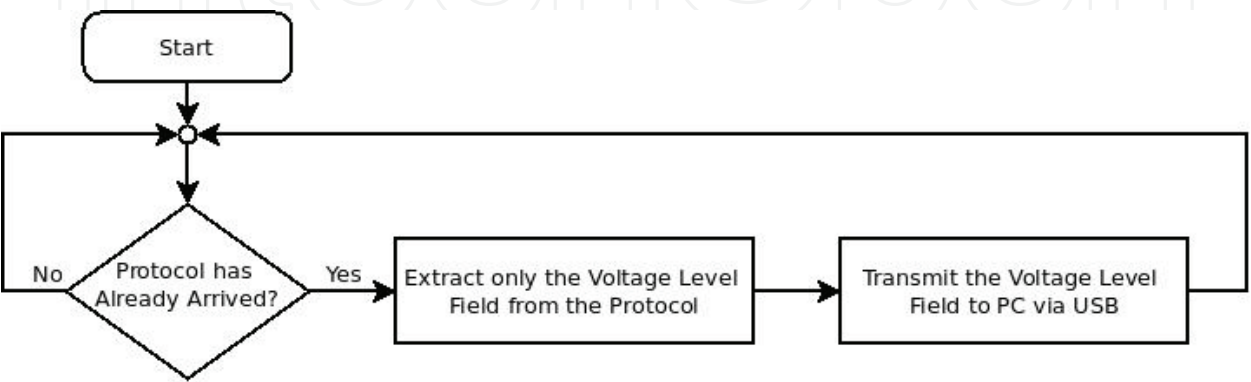


Fig. 5. Flowchart of an access point.



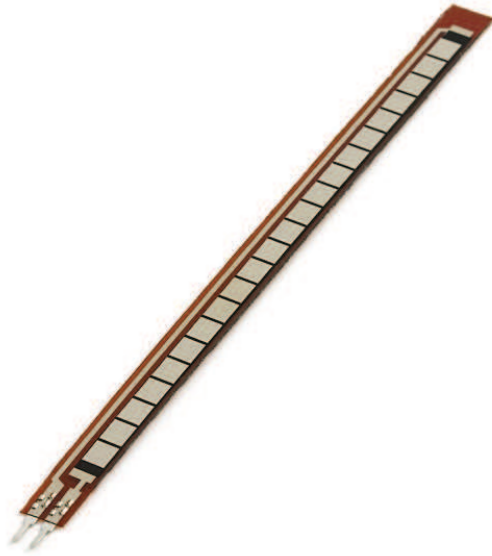


Fig. 6. The flex sensor: the sensor used to measure a knee movement variable in our proposed system. Image from: [www.sparkfun.com](http://www.sparkfun.com)

accelerometer or other active sensors (i.e. tilt sensors and/or gyroscopes), our system makes use of a flex sensor. The sensor is a tiny bendable strip, with the dimension of about  $3/8''$  wide by 5" long, which is shown in Fig. 6. It is a passive resistive device that can be used to detect bending or flexing. Previously, the sensor has been found used in many applications which are: to detect collision on mobile robots and to construct virtual reality (VR) gloves and VR suits. In addition, some physics applications and experiments have also exploited this sensor to measure/detect bending. The resistance of the sensor decreases in proportion to the amount it is bent in either direction. As it is a passive device, it consumes no electric current during operation. This makes it very attractive for an application that requires a long battery operating time like this application. In our proposed system, only a simple voltage divider circuit is required to interface between the MSP430F2204 microcontroller and the flex sensor. The voltage divider consists of a single extra resistor to connect between the positive terminal of a power supply and one terminal of the flex sensor. The other terminal of the sensor is connected to the ground of the power supply. The connection point between the resistor and the sensor is served as an input to an analog-to-digital pin of the MSP430F2204 microcontroller.

It is worth noting at this point that there are two different roles of an end device which are clearly illustrated in Fig. 1. That is to say during SOM learning stage, it serves as a system to gather knee movement data and wirelessly transmit to an access point. The transferred data is used for training SOM on a personal computer in order to produce the most appropriate map; i.e. the map whose quantization error is the minimum. This is operated on an offline and semi-automatic basis and on a personal computer. In the normal operation stage, the role of the end device is changed to sample the knee movement and query the map to make a final decision if the movement is of type St-Si or Si-St transition. This means that there is no need to use an access point anymore. The resulting decision is, in turn, wirelessly sent to caretakers or other system in order to alert caretakers to pay more attention to the wearer or to activate the other system to further measure additional movement parameters. Alternatively, the activation can be used to initiate the video system to capture motion patterns of the



Fig. 7. The screenshot of the application running on a personal computer.

wearer. There are wide variety of applications of the resulting decision from our proposed PT detection system. The flowcharts showing the operational steps of an end device in these two stages are illustrated in Fig. 4. In addition, the flowchart of an access point previously detailed is also presented in the same figure. It is noticeable that an end device spends most of its operational time in waiting for wake-up loop; i.e. sleep mode of operation. It is our intention to design an end device to behave in this way as it lengthens the battery life cycle. This comes from the fact that the microcontroller of an end device consumes the least power in the sleep mode.

In the next section, we describe the details of a personal computer based application software responsible for making communication with an access point, providing assistance for activity types labeling and invoking the backend SOM toolbox to perform the learning stage.

3.3 The developed computer software

During a SOM learning stage, running on a personal computer is a Microsoft Windows based application to communicate with an access point via a universal serial bus (USB). The application was developed in-house by use of the Microsoft Visual Basic 6.0. The screenshot of the application is illustrated in Fig. 7. The signals currently shown on the screen of the application are captured while the wearer of the end device was repeatedly performing Si-St and St-Si transitions (with short periods of sitting and standing). Along with showing the plot of the incoming signals, the application also shows the time series of the incoming raw data. These are partially shown in the listbox on the right side of the application window.

Followings are the roles of the application software:

- Retrieve the data packets from an access point, extract the knee movement signals and store in a personal computer on a real-time basis,
- Provide a user interface tool to assist an application user to locate and mark the beginning and end of each type of knee movement to the signals,
- Preprocess the signals and perform the SOM learning stage in order to come up with the final SOM map.

At this point, it is expected that it became clear to readers for the first role of the application. Let's give more details for the second role of the application which results in generation

the thin horizontal colour bar embedded at the topmost of the signal display screen. It is observable from Fig. 7 that there are three different colours in the colour bar for an individual Si-St and St-Si transitions which are light blue, black and dark blue. These colours represent three different activities which are: Si-St and St-Si transition, respectively. The application was developed to provide a mechanism to respond to the mouse click event from an application user. Typically, an application user clicks the mouse in order to place vertical lines at different location on the signal display screen. The vertical lines are used to cluster signals resulting from the same activity types together and separate the signals resulting from different activity types. Having finished placing the vertical lines, the next step is to assign the activity type to all the signals between each pair of the vertical lines. It is noted that the above steps are required to perform manually. This could inevitably result in incorrect labeling signal and/or misplacing activity separation lines even with very careful placement of the vertical lines. However, we developed an additional algorithm to make correction to these (will be presented in Section 4) and have found from the experiment that this does not degrade the overall outcome PT detection results.

Since during the experiment a single end device was used, given the incoming raw data represented by the following set:

$$S = \{K_0, K_1, K_2, K_3, \dots, K_{n-1}\}. \quad (4)$$

The second and third roles of the application resulted in producing the following set of data to be ready for the SOM learning stage:

$$\{K, \delta K, a\} = \{(K_0, K_1 - K_0, a_0), \dots, (K_i, K_{i+1} - K_i, a_i), \dots, (K_{n-2}, K_{n-1} - K_{n-2}, a_{n-1})\}, \quad (5)$$

whose member consists of the signal value  $K_i$ , the slope between the consecutive pair of signals  $K_{i+1}$  and  $K_i$  and the activity type  $a_i$ . The activity types are classified into jogging, sitting, standing, walking, walking downstairs, walking upstairs, sit-to-stand and stand-to-sit and numbered between 1 to 8, respectively. The sample period of the end device was fixed to be 10 mS. It can be seen that only the second field of data was calculated by the application. The third data is resulted from the second role of the application described earlier. The first and second fields of data are then normalized to have a mean of zero and a standard deviation (SD) of one to be ready for the SOM learning stage. As a backend tool to perform the SOM learning and labeling stages, the application relies on using a SOMPAK toolkit (Kohonen, 1996).

In the next section, we present the routine to be performed during the SOM learning stage, the details of the algorithm to increase the correctness of the PT classification and the experimental results.

#### 4. Experimental results

In order to perform the SOM learning stage with the knee movement data captured by the system detailed in the previous section, the procedures to capture data was developed. Followings are the activities that need performing by a wearer during the data capturing stage:

- Perform a normal walk,
- Perform a normal jogging,
- Perform a normal walking up and down stairs,
- Perform a sit to stand and sit transition

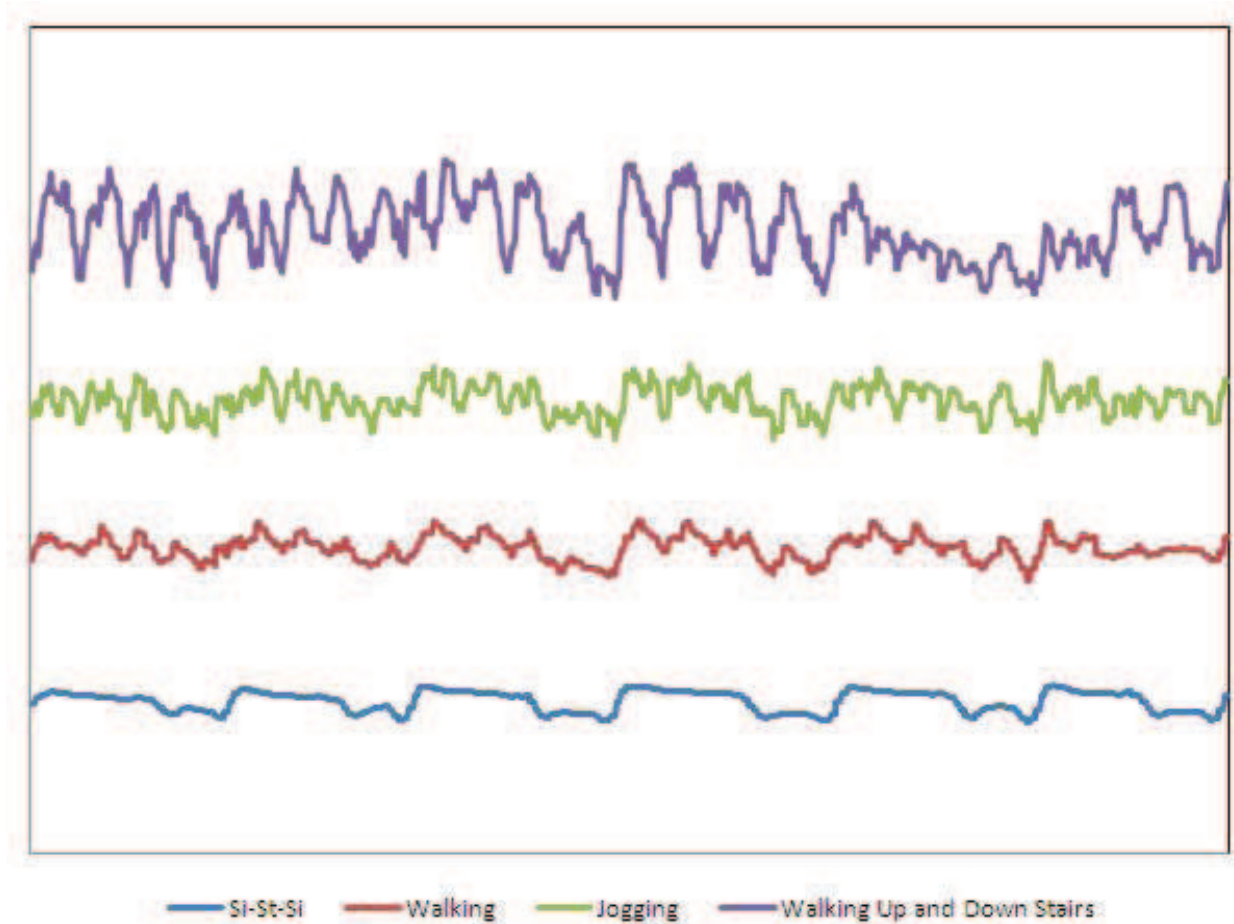


Fig. 8. The plot of the knee movement data from all captured activities in the same graph.

Each activity is equally captured and wirelessly transferred from the end device to a computer via the access point for a period of 10 seconds. This is equivalent to the number of 1,000 sampled data per activity as the sample period is 10 mS. It is noted that while performing these procedures, a wearer needs to be closely monitored by our staff. This is done in order to prevent the wearer to perform incorrect activities apart from the activity to be captured. This reduces capturing unwanted activities which may result in increasing the incorrect activity labeling. Having finished data capturing stage, the captured data are manually labelled utilizing the features of the computer application and ready for use in the SOM learning stage. Fig. 8 illustrates the plots of all activities with the aim to show that different activities result in dissimilar raw data pattern. It is noted that the signal levels should not be considered in this case.

With respect to our experimentations, the SOM learning stage which gave rise to the best quality map, measured by a quantization error (QE), consisted of two phases with the neural processing elements of  $14 \times 20$ . In the first phase, the learning coefficient  $\lambda(t)$  was set to decrease from 1.0 to 0 in 100,000 iterations, while the radius of the neighbourhoods was reduced from 15 at the beginning to 1 at the end of the learning stage. In the second phase,  $\lambda(t)$  was set to decrease from 0.125 to 0 in 10,000 steps, while the radius of the neighborhood was reduced from 3 to 1. The map were labelled with only 2 knee movement types which are: Si-St and St-Si transitions whose number is 7 and 8, respectively. Fig. 9 depicts (a) the resulting SOM map, (b) the SOM map projection on the normalized knee movement



data only, and (c) the SOM map projection on the normalized delta of knee movement data only. These maps were reproduced by use of a Neural Networks Tool (Nenet) from [koti.mbnet.fi/phodju/nenet/Nenet/General.html](http://koti.mbnet.fi/phodju/nenet/Nenet/General.html).

It is observable from the resulting map that some PEs were labelled with both knee movement types. This can be explained that Si-St and St-Si transitions have shared some common knee movement parameters. This could also be resulted from incorrectly manual labeling of activity types during using the application software by our staff. In order to avoid making difficulties to the labeling stage, we developed an addition algorithm, Algorithm 1, to take into account the popularity of being matched for all PEs. That is to say, in stead of keeping only the activity type label, each PE needs to have an additional register set, a popular register set or *PS* in the algorithm, to keep track of the number of times it is matched by activity types during the SOM labeling stage. For example, at the end of learning stage after applying this addition algorithm, it is found that the registers of the PE at position (1, 14) of Fig. 9 have the following values: [0,0,0,0,0,0,0,2670,1330]. This means that this PE is more popular to the activity type 7 (Si-St transition) compared to the activity type 8 (St-Si transition). During the classification stage, if a knee movement parameter,  $K$ , and its delta,  $\delta K$ , counterpart is mapped to this PE, it is reasonable to conclude that the knee movement is of type Si-St transition.

```

input : SOM: the already trained SOM map,  $\{K, \delta K\}$  : Data set for training
output: The labelled SOM map with embedded popular set; PS, in all PEs

foreach member indices  $(i, j)$  of SOM do
|    $PS_{(i,j)} \leftarrow [0,0,0,0,0,0,0,0,0]$ 
end

foreach member  $m$  of  $\{K, \delta K\}$  do
|    $a \leftarrow$  the activity type of  $\{K, \delta K\}_m$  ;
|    $(r, c) \leftarrow$  indices of the BMU with respect to  $\{K, \delta K\}_m$  ;
|    $PS_{(r,c)}[a] \leftarrow PS_{(r,c)}[a] + 1$  ;
end

```

**Algorithm 1:** An algorithm for SOM map labeling with taking into account the popularity of being matched of all PEs.

```

input : The labelled SOM map with embedded PS; a set of 10 samples of  $\{K, \delta K\}$ 
output: C: Classification result

 $C = 0$  ;
for  $i \leftarrow 1$  to 10 do
|    $(r, c) \leftarrow$  indices of the BMU with respect to  $\{K, \delta K\}_i$  ;
|    $a \leftarrow \arg(\max(PS_{(r,c)}))$  ;
|    $C \leftarrow C + a$  ;
end

 $C = C / 10$ 

```

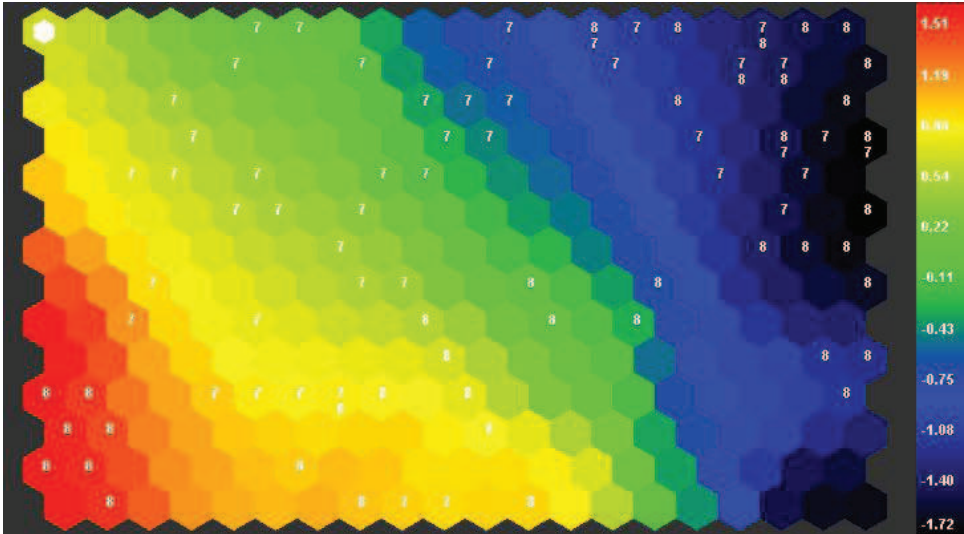
**Algorithm 2:** An algorithm for activity classification with making used of the popularity of being matched and calculating the average activity from 10 consecutive samples.

Following the previous additional algorithm for classifying a single sample, the classification error is reduced significantly. However, this does not satisfy our requirement. We then

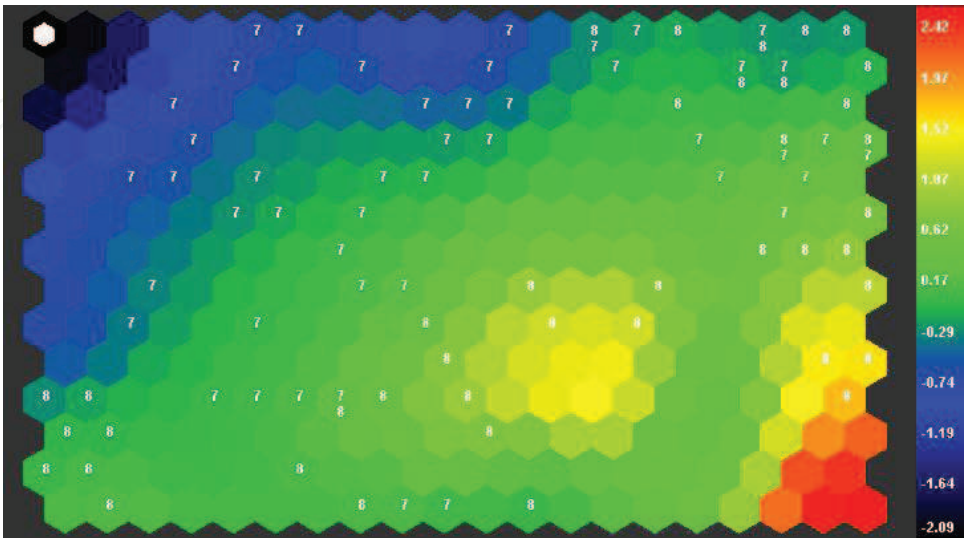




(a)



(b)



(c)

Fig. 9. (a) The result SOM map after labeling stage which is displayed by use of a Nenet-tool.

Activity Type	Percent Correctness
Si-St	100
St-Si	93.3

Table 1. The percent correctness of the verification results from testing the map with unknown activity data retrieved from the end device

further take an additional feature to the classification algorithm. This is simply done by taking the average of the classification results instead of relying on returning the activity type immediately after querying the SOM map with only a single knee movement parameter. The algorithm is detailed in Algorithm 2. We have found that by taking the average of the classification results from 10 consecutive samples of knee movement parameter (equivalent to 100 mS), it gives rise to the best result. Taking more samples results in reducing the detection sensitivity of the system without increasing the classification correctness. After integrating all proposed algorithms to the end device, we then verify whether the resulting map was capable of finding the correct movement type with respect to an unknown activity retrieved from the end device. The verification results are shown in Table 1. It can be seen that the verification results give rise to very high degree of correctness. We, therefore, ported the system to implement as a stand-alone system relied on using a knee movement data. The operations of the system has already been illustrated in Fig. 4(b).

5. Conclusion

In this chapter, we proposed another utilization of SOM as an approach to classify postural transitions from knee movement data. The details and experimental results of a SOM-based stand-alone postural transition detection system were also presented. The stand-alone system is embedded with a low-power consumption microcontroller with a multi-channel RF transceiver chip. The sensor uses for gathering knee movement data is a flex sensor whose type is a passive component. The overall system is in the category of wireless sensor network (WSN) with two different operation stages: a SOM learning and a classification stage. During the SOM learning stage, the end device subsystem samples and wirelessly transfers a knee movement data to the access point subsystem. The access point subsystem then encodes the incoming protocol and transmits only the movement data to a personal computer. The data, which are consisted of a movement data and the delta between a consecutive pair of data, are used for training SOM on an off-line and semi-automatic basis. We experimentally proved that SOM could be successfully employed in this application domain. The results, the final SOM map, show that similar movement parameters are clustered together. Also, SOM gives rise to more than 93.3 percents of correctness for making decision of stand-to-sit and sit-to-stand transition types from a knee movement parameter. With positive experimental results, we modified the software of the end device subsystem to perform the SOM classification stage. The final stand-alone system can be utilized to make the decision and alert to caretakers or another fall-risk detection system.

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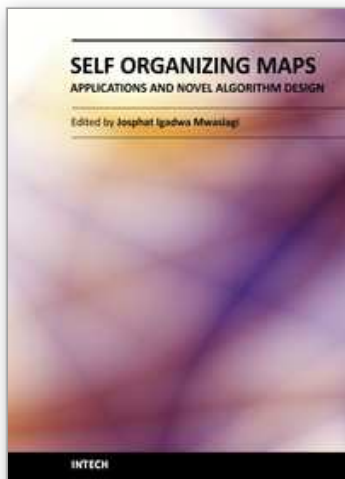
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Kohonen Self Organizing Maps (SOM) has found application in practical all fields, especially those which tend to handle high dimensional data. SOM can be used for the clustering of genes in the medical field, the study of multi-media and web based contents and in the transportation industry, just to name a few. Apart from the aforementioned areas this book also covers the study of complex data found in meteorological and remotely sensed images acquired using satellite sensing. Data management and envelopment analysis has also been covered. The application of SOM in mechanical and manufacturing engineering forms another important area of this book. The final section of this book, addresses the design and application of novel variants of SOM algorithms.

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