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Monitoring Daily Life Activities of the Elderly using Data Mining, Cloud and Web Services*

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Abstract

Currently, the number of elderly people worldwide has substantially increased. The elderly living alone are prone to accidents such as falls, which sometimes lead to fatalities without timely notifications and help. This research applies sensors in smartphone, data mining, web services and cloud computing techniques. We have developed an Android application for a smartphone to detect daily activities of the elderly. Smartphone communicates with the cloud computing through web services. The cloud integrates with data mining to classify activities done by the elderly. In addition, we have developed the Android application for a tablet computer to monitor the daily activities done by the elderly, including lying, sitting, standing, walking, running, fall, and any changes occurring in their routines. This can help to perceive the risk as well as the daily activities of the elderly and find a solution for a timely assistance. Furthermore, it also helps a caregiver or family members to monitor the elderly's activities when they need to go out of their homes.

Keywords: Activity classification, cloud computing, daily life activities, sensor fusion

Introduction

At present, medical technologies and public health services have developed so rapidly that the elderly population worldwide has increased. The elderly population from 1980 to 2015 increased by 12.23 %. In the future, the number of the elderly is likely to increase more and more, and by the year 2050 it may increase by 21.15 % [1]. As a result, more countries are fast becoming ageing societies. When people are getting old, they are likely to get ill, isolated and depressed, or prone to accidents. That may lead the elderly people who live alone to disability or fatality when they do not receive a timely help or caregivers do not get the proper notifications; therefore, we should better understand how the elderly spend their daily life activities, such as lying, sitting, standing, walking and running, and be prepared to find health-related services to support them. This research applies a few technologies such as smartphone sensors to detect daily life activities of the elderly [2,3]. Our smartphone application communicates with a cloud server through web service technologies [4,5] in order to classify activities done by the elderly by using some well-known data mining techniques [6-9]. We use a tablet computer to monitor the elderly's daily activities in real time. If the system detects any unusual activity such as a fall or unusually long-time activity, it will report and notify family members or a caregiver so that they can provide assistance in a timely manner.

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Materials and methods

System's overview

We develop the system to monitor daily life activities of the elderly by using a smartphone and tablet computer. Cloud computing is the new computing paradigm that can provide dynamically scalable and virtualized resources as a service with pay-as-you-go manner, especially a platform as a service (PaaS) [10]. Therefore, we decide to use the PaaS cloud environment for our system in order to reduce an implementation effort and development cost. The conceptual architecture of the activity monitoring is illustrated in **Figure 1**. It is divided into 3 parts including Elderly, Cloud Server, and Caregiver's Activity Monitoring of the Elderly for Assistance Provision. The details are given as follows.

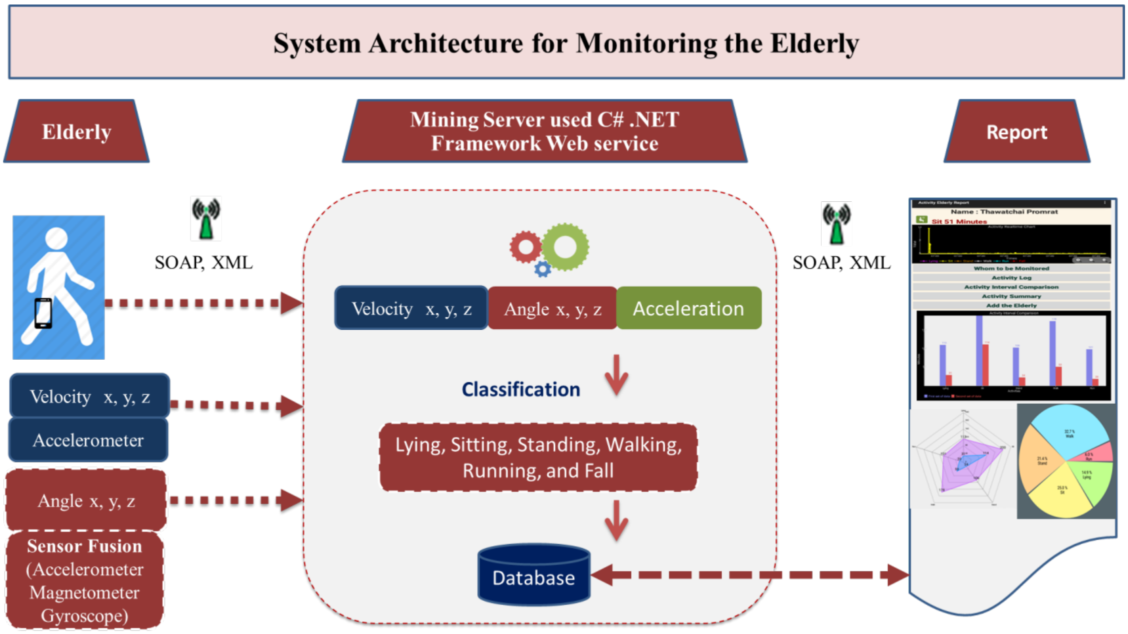


Figure 1 Conceptual architecture of the activity monitoring.

Elderly consists of the elderly, internet 3G - 4G or Wi-Fi, and Samsung Galaxy S3 smartphone attached to the elderly's thigh to measure and detect the activities. We develop an application to measure and detect the activities of the elderly, and it is installed in the smartphone to send raw data to the cloud server. The raw data consist of the values X, Y, and Z, which are obtained from the accelerometer sensor, as well as angles X, Y, and Z, which are obtained from the combined sensors of accelerometer, magnetometer and gyroscope. The smartphone application communicates with the cloud server via web service XML-based SOAP (Simple Object Access Protocol).

Cloud server consists of Windows Server Operating System, Internet Information Service (IIS), C# .NET Framework and the data mining model to classify the activities of the elderly. The Cloud Server is divided into 3 functional parts as given below.

1) Classify activities done by the elderly such as lying, sitting, standing, walking, running, and fall.

2) Analyze the changes occurring in their routines.

3) Provide information about the activities of the elderly by generating reports on the tablet computer.

Caregiver's activity monitoring of the elderly for assistance provision is a prototype application for caregiver and family members. They can use a tablet computer or smartphone to monitor the daily life activities of the elderly and can view reports of the elderly's routines. Moreover, they can compare the activities at each period of time, and the system will notify the caregiver or family members about an unusual activity of the elderly such as changes in their routines, falling, and an unusual long activity.

We have developed both the Android smartphone application for measuring and detecting activities of the elderly and the application that sent raw data to cloud in order to classify the elderly's activities. We also have developed the Android application for a tablet computer to monitor daily life activities of the elderly. We have utilized Visual studio and JDK7 to develop the Android application. The application communicated with the cloud server by using the web service KSoap 2 API. The web service functions are listed in **Table 1**.

Table 1 Functions of web services.

Function name	Method	Details
Classification	POST	Send data from sensor to cloud for activity classification
Real-time Activities	GET	Get activity report from cloud and show in real time on tablet computer
Activities Logs	GET	Get logs of unusual activities from cloud and show on tablet computer
Summary Report Activities	GET	Get data summary from cloud and show pie chart on tablet computer
Activities Summary Comparison	GET	Get data summary from cloud to show on both radar chart and bar chart on tablet computer
Change in Routine	GET	Get information change in routine from cloud to show line chart on tablet computer
Select Elderly	GET	Select the elderly for monitoring
Add Elderly	POST	Add the elderly to list

Steps used in data mining for system monitoring daily life activities of the elderly

Figure 2 shows the steps which are used in data mining of the activity monitoring system, which includes Human Activities Measurement, Human Activities Classification, Human Activities Analysis, and Unusual Human Activities. The details of each step are given as follows.

Figure 2 Steps of an abnormal human activity detection method.

Human activities measurement

We have applied the smartphone's sensors such as accelerometer, magnetometer and gyroscope. The developed application sends both the values X, Y, and Z from the accelerometer sensor and angles X, Y, and Z from the combined sensors of accelerometer, magnetometer and gyroscope of the activities which are done by the elderly to the cloud server in order to classify the activities [11-13]. However, the gyroscope has an angular speed whose value needs to be changed to a common vector before being combined to the other sensors.

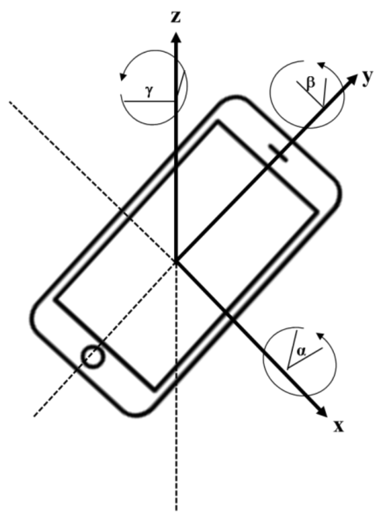


Figure 3 Coordinate system used by the Sensor Event API of the Android OS with the angles for which the gyroscope measures the angular speeds [14].

Figure 3 shows the operation of the gyroscope sensor in the Android smartphone, of which the Z-axis is called gamma (γ); the Y-axis is called beta (β), and the X-axis is called alpha (α). The 3 axis values which are obtained from the gyroscope sensor are kept in the 3×3 matrix as shown in Eq. (1) and subsequently are used in the matrix multiplications as done in Eq. (2).

$$R_x = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\alpha & \sin\alpha \\ 0 & -\sin\alpha & \cos\alpha \end{bmatrix} \tag{1}$$

$$R_y = \begin{bmatrix} \cos\beta & 0 & \sin\beta \\ 0 & 1 & 0 \\ -\sin\beta & 0 & \cos\beta \end{bmatrix}$$

$$R_z = \begin{bmatrix} \cos\gamma & \sin\gamma & 0 \\ -\sin\gamma & \cos\gamma & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R = R_z R_x R_y \tag{2}$$

$$R = \begin{bmatrix} \cos\gamma\cos\beta - \sin\alpha\sin\beta\sin\gamma & \sin\gamma\cos\alpha & \cos\gamma\sin\beta + \sin\gamma\sin\alpha\cos\beta \\ -\cos\beta\sin\gamma - \sin\alpha\sin\beta\cos\gamma & -\cos\gamma\sin\alpha & \cos\gamma\sin\alpha\cos\beta - \sin\gamma\sin\beta \\ -\cos\alpha\sin\beta & -\sin\alpha & \cos\alpha\cos\beta \end{bmatrix}$$

Eq. (3) is used to calculate the size of the acceleration vector (or sometimes called Euclidean distance or length), where i is the current value which is obtained from the accelerometer while i-1 is from the previous accelerometer value. The value is to be used as one of attributes used in training a classification model. The complementary filter is the sensor data fusion which is used to get an accurate angle [15]. Each sensor has different advantages and disadvantages. For example, the Z-axis accelerometer has a gravity force. On the other hand, the gyroscope does not have the gravity force, but it has the value drifted when it is working, which causes inaccurate values over time. **Figure 4** illustrates the values obtained from the accelerometer and magnetometer sensors which are combined together because the information is a common vector. After that the information is filtered with a low-pass filter to reduce noises. The gyroscope data are an angular speed whose value needs to be changed to a common vector. Thereafter the data are integrated, and then the information is filtered with a high-pass filter to reduce noises. Finally, we combine the information which is obtained from the low-pass filter and high-pass filter to get the more correct angle.

$$A = \sqrt{(\Delta X)^2 + (\Delta Y)^2 + (\Delta Z)^2} \tag{3}$$

$\Delta X = X_i - X_{i-1}$

$\Delta \mathrm{Y} = Y_i - Y_{i-1}$

$\Delta \mathrm{Z} = Z_i - Z_{i-1}$

A = Size of the acceleration vector (m/s^2)

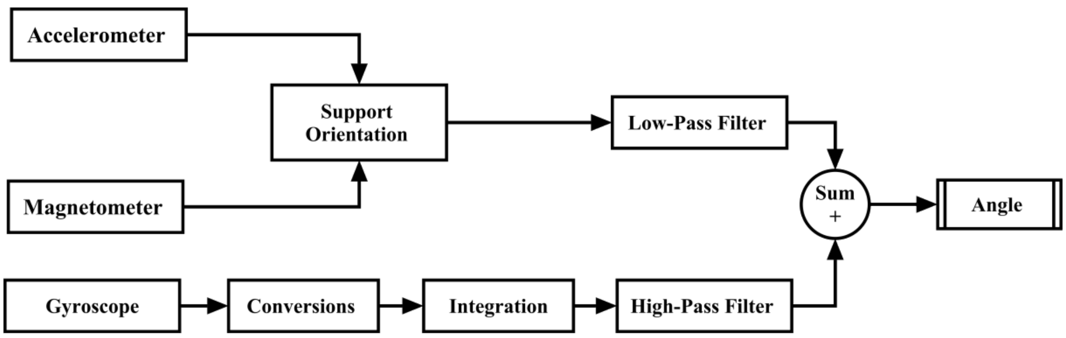


Figure 4 Sensor data fusion with a complementary filter.

Human activities classification

Figure 5 shows our process which uses data mining techniques to classify activities. First, we collect data from 25 elderly volunteers (10 men and 15 women). The elderly aged between 60 and 84 years old. The average age is 65.98 years (SD = 6.3) and the mean body mass index (BMI) is 21.30 (SD = 3.30). Data collection is done by attaching the Samsung Galaxy S3 smartphone to the elderly's thighs. Data of each activity are collected from each elderly person every 0.2 second for 30 seconds long. Thus the raw data of each activity are 5 * 30 * 25 = 3,750 frames, and the total raw data are 5 * 30 * 25 * 6 = 22,500 frames. We develop 3 sets of data, and each set has 22,500 frames in order to establish the activity classification model, and we select the best data set which provides the most accuracy. The first data set is from the 3 accelerometer axes, X, Y, and Z as well as the size of the acceleration vector. The values of the second data set are the angle values, X, Y, and Z, which are obtained from the sensors' fusion of accelerometer, magnetometer and gyroscope as well as the size of the acceleration vector. The third data set, however, uses the first data set, second data set, and the size of the acceleration vector. In each data set the activities are identified as a specific class, i.e., lying, sitting, standing, walking, running and fall, so that they can be used for training and testing our model. In this research, we use Weka to train the 3 sets of data, and we compare them to the classifiers provided by Weka [16], including multi-layer perceptron (MLP), naïve Bayes, support vector machine (SVM) and k-nearest neighbor (KNN), and we test the performance of the models using a 10-fold cross-validation in order to select the optimal classifier. After that we use the program which is developed with the C# .NET to classify the activities [17,18].

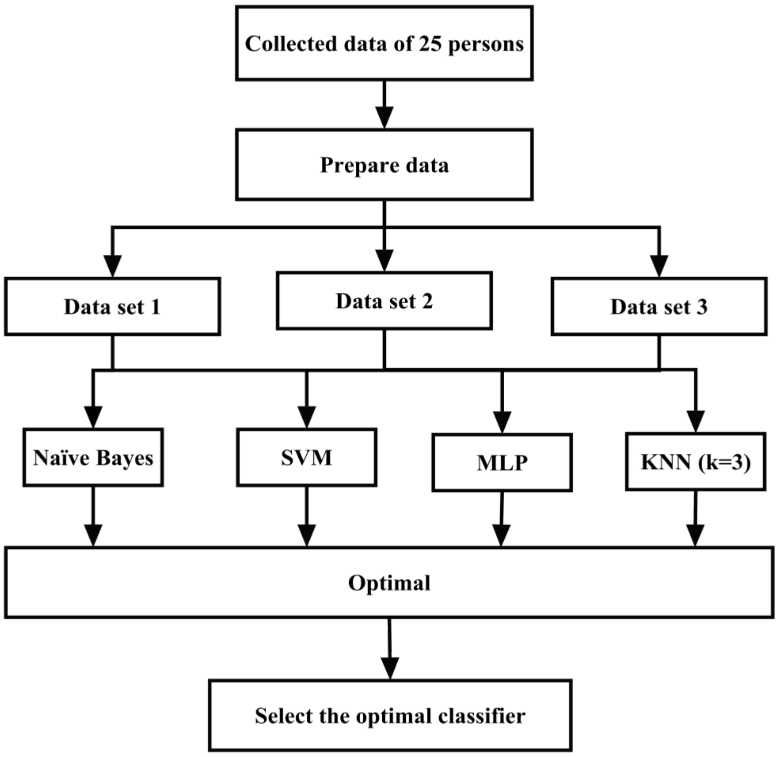


Figure 5 Process of data mining used to classify activities.

Human activities analysis

This step is to detect and display the output of the unusual activity which has changed from the routines. According to the study on advantages and disadvantages of data mining techniques, consisting of classification, clustering, and statistical methods, these techniques are the main approaches which are used to detect anomalies. Clustering and statistical based techniques can be unsupervised, and there is no need for training and labeling steps. However, their effectiveness depends on assumptions of a data distribution. We need to detect the changes in the activity routine, such as lying and sitting. We use the data which are obtained from the classification of the activities in the database. We collect the data for 14 days from the elderly with 3 h each day because it is limited by the smartphone battery. We use a statistical detection technique because "an anomaly is an observation which is suspected of being partially or wholly irrelevant because it is not generated by the stochastic model assumed" [19,20]. Every 10 min of the 3 h collected data are assigned to a segment and analyzed with the statistical based technique in order to find the changes in the routine. We count the number of frames in the database of the lying and sitting activities on the current day and also count the number of frames on the previous day. Then, we use the statistical methods in Eq. (4) to test whether or not the data are presented in the normal range of 95 % confidence level or from the standard -2 to 2 Z-score values as shown in **Figure 6**. If the Z scores are beyond -2 to 2, the system would notify the caregiver about the change in the routine. We find the number of previous days to identify the suitable day for detecting changes in the routine, and in our experiment the past 9 days are used [21-23].

$$Z = \frac{X - \mu}{\sigma} \tag{4}$$

Variable X is a number of frames of a current day.
Variable μ is average number of frames of at least past 9 days.
Variable σ is standard deviation of the number of frames of at least past 9 days.

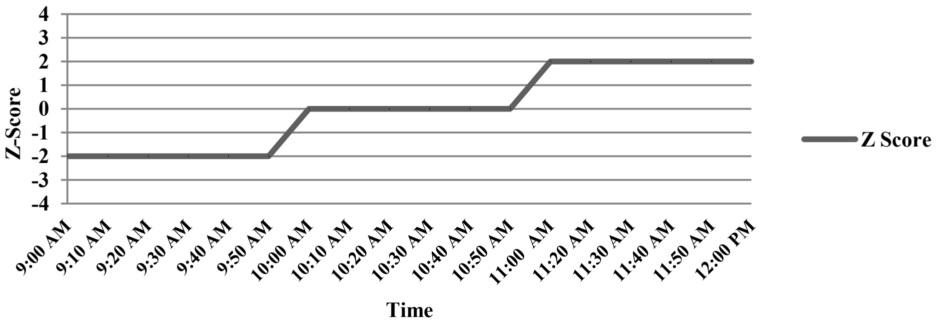
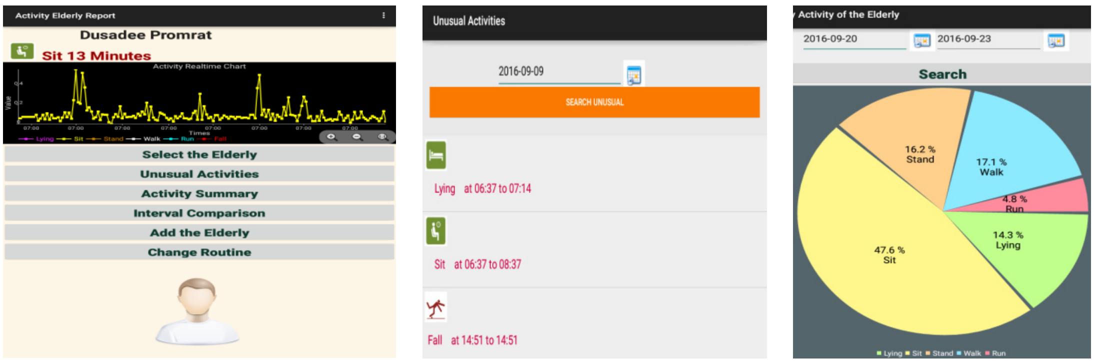


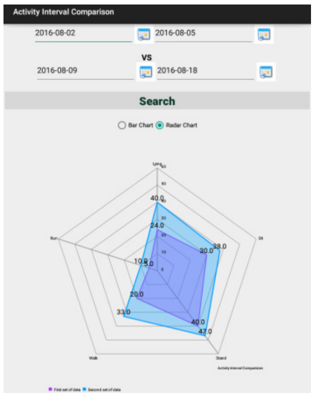
Figure 6 Example of normal distribution ranges within 95 % confidence level.

Results and discussion

We have developed the application which is used to monitor daily life activities of the elderly via the tablet computer, having interfaces as illustrated in **Figure 7**.



(a) (b) (c)



(d) (e)

Figure 7 (a) The first screen of the Android application. Besides the name, the real-time activity report consists of photo, texts and line chart. (b) the fall and activities which have been done continuously for a long time. (c) a summary of activities at different selected times. (d) and (e) are screen display comparisons of the elderly's activities in each period of time frame. This can be displayed with bar charts and radar graphs.

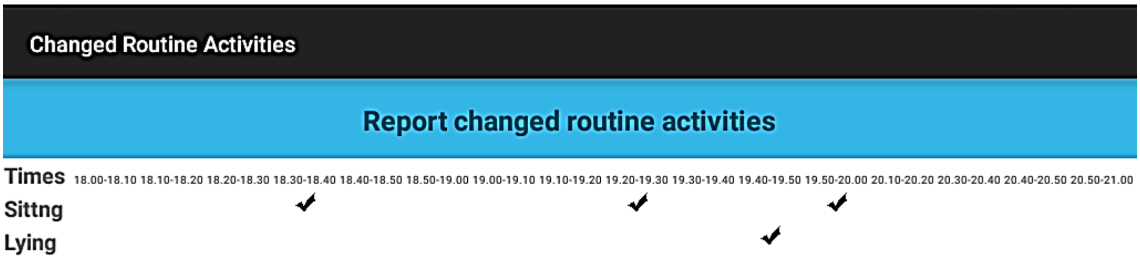


Figure 8 Screen display of the changed activities of sitting routine.

In our experiment for the detection of any changes in the routines, we collect the activity data from another 10 elderly volunteers, such as lying and sitting for 14 days, and seek the number of days that can detect changes in the routine. The result shows that the changes in the routine beyond the normal range of 95 % confidence level can be detected on day 9 or later, which is suitable for detecting the changes. **Figure 8** shows the changed routine activities for sitting and lying from 1800 to 2100 h. It shows that the changes in sitting routine occur at 18.30 - 18.40, 19.20 - 19.30, 19.50 - 20.00, and in lying at 19.40 - 19.50 when the Z-score values go beyond −2 to 2 range. For the sitting, the changes could mean more sitting or less sitting, depending on the sign of the Z-score value. A positive Z-score indicates more sitting than usual, while the negative Z-score indicates the change from sitting to the other activities. Therefore, when there is any change, the caregiver or family members could look up the activities of the past days for more detailed comparisons, as could be done in **Figures 7(d)** and **(e)**.

For the activity classification experiment, we found that on average the neural network (multi-layer perceptron: MLP) was the best classifier, and particularly for the Data Set 3, which consists of 3 accelerometer axes, X, Y, and Z, and angle values, X, Y, and Z as well as the size of the acceleration vector, it had the highest precision of 99.50 %, recall of 99.50 %, and accuracy of 99.52 % as shown in **Table 2**.

Table 2 Percentage of correct activity classifications of different algorithms.

Algorithms	Data Set 1			Data Set 2			Data Set 3		
	Precision (%)	Recall (%)	Accuracy (%)	Precision (%)	Recall (%)	Accuracy (%)	Precision (%)	Recall (%)	Accuracy (%)
MLP	96.90	96.90	96.91	98.50	98.50	98.46	99.50	99.50	99.52
KNN (k = 3)	97.00	97.00	96.98	98.50	98.50	98.46	98.50	98.50	98.67
Naive Bayes	94.30	93.70	93.72	95.90	95.90	95.88	96.10	95.90	96.85
SVM	95.10	94.70	94.73	93.20	92.90	92.85	95.90	95.60	95.60

Figure 9 shows the size of the acceleration vector of each activity, in the Y axis, which is one of the attributes used in the activity classification. For activities of lying, sitting, and standing the size of the acceleration vector is about zero since these activities have very little body movement. The activities of walking, running, and fall involve far more body movement, and thus the size of the acceleration vector is more than zero, with around 1 - 6 for walking and noticeably higher for running. Fall has the size around 10 - 20, with an abrupt spike.

For the system usability and acceptance, we gave 15 elderly volunteers to do activities. The elderly aged between 60 to 82 years old and were 4 men and 11 women. The average age was 63.7 years (SD = 5.5), and the average body mass index (BMI) was 23.18 (SD = 3.35). Thereafter we asked 3 voluntary nurses to evaluate our system. The score was based on the 5-point scale (1 = the least, 5 = the most). The evaluation scores of the real-time activities, usefulness, satisfaction and convenience with the system were 4.8, 4.8, 4.6, and 4.7, respectively. Our system received high marks on all 4 aspects.

For the experiment of changes in the routine activities, we had collected data for 14 days with 10 elderly volunteers. Examples of the 3 elderly are given as follows. Elderly volunteer no. 1 was male and 72 years old (BMI = 17.18). We collected data with the elderly at 6:30 - 9:30 a.m. He did not change his routine activities, and we found that he spent majority of his time by sitting and watching TV and sat leisurely in the morning as usual, as shown in **Figure 10(a)**. Elderly volunteer no. 2 was female and 77 years old (BMI = 23.11). We collected data with the elderly at 1:00 - 4:00 p.m. She did not change her routine activities, and we found that she spent her majority of time by sitting and lying to relax in the afternoon as shown in **Figure 10(b)**. Elderly volunteer no. 3 was male and 60 years old (BMI = 20.95). We collected data with the elderly at 6:00 - 9:00 p.m. He had changed his routine activities to sitting and lying at the particular times as shown in **Figure 10(c)**, when the Z-score went beyond the -2 to 2 range. For instance, at 6:30 - 6:40 p.m. the large positive Z-score indicated that there was more sitting than the usual; however, at 8:20 - 8:30 p.m. the somewhat large negative Z-score indicated that there was the change from the usual lying to the other activities. We had confirmed the activities with the elderly and found that depending on the weather conditions he spent the time sitting in front of TV or walking outside in that evening.

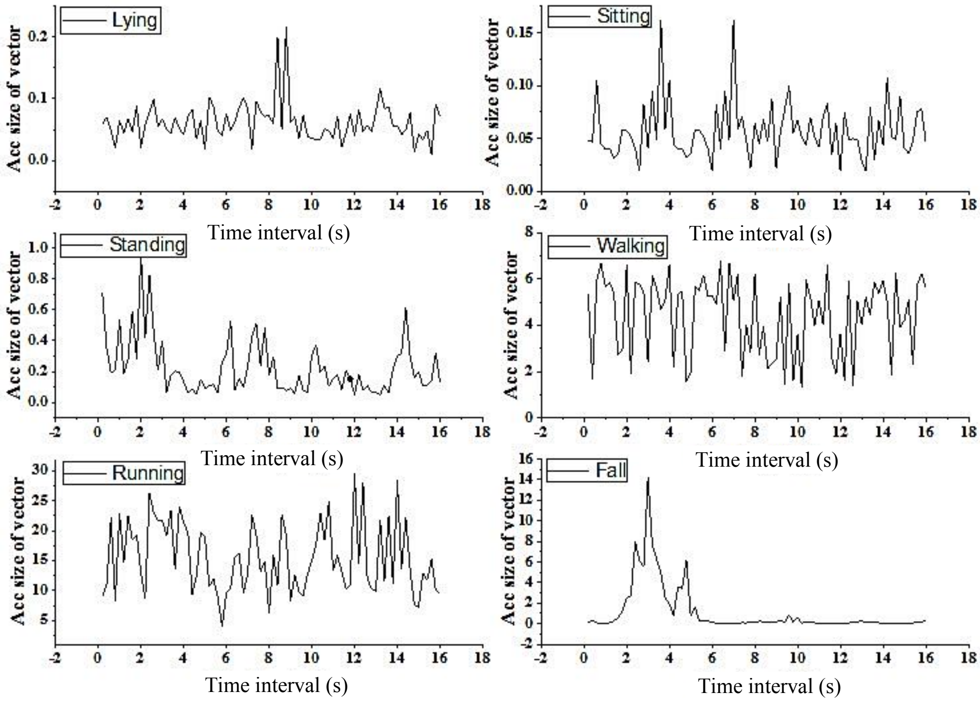
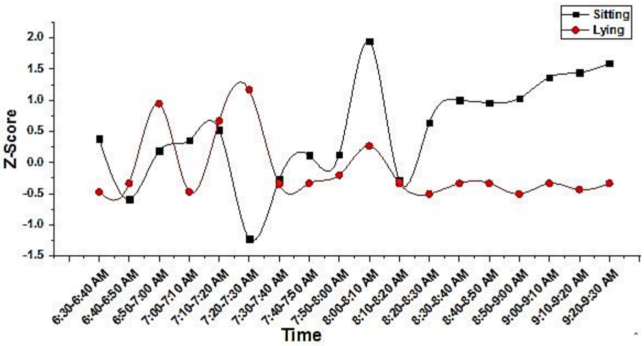
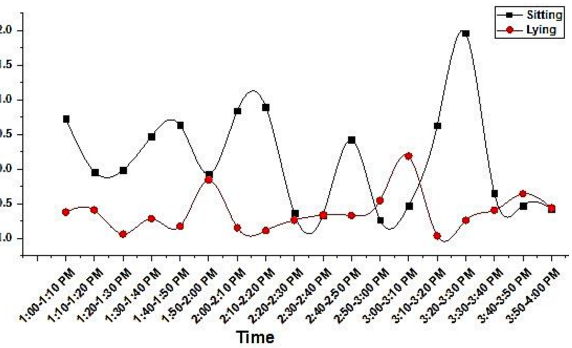


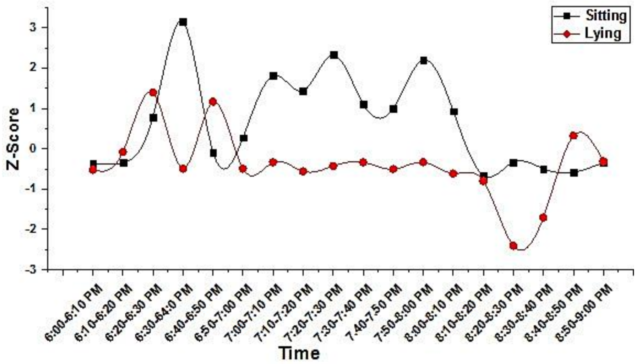
Figure 9 Example of the line chart of the size of the acceleration vector of each activity.



(a)



(b)



(c)

Figure 10 Example of the line chart of the (a) activity of the elderly volunteer no. 1, (b) activity of the elderly volunteer no. 2 and (c) changed activity of the elderly volunteer no. 3.

Conclusions and future work

In this research, we have applied the advancement of the sensor technologies in smartphone, data mining, cloud computing, and web services in order to detect and monitor daily life activities of the elderly via the tablet computer. Moreover, without the need to be at home, our application facilitates the caregiver or family members to regularly monitor the elderly. When there is a possible risk or issue in daily living, the solutions and timely assistance could be served to the elderly.

In the future, it is possible to apply the combination of sensors with smartwatch to detect other interesting activities besides the activities of daily living, such as drinking water, brushing teeth and eating. In addition, sensor technologies may be integrated further with smart home in order to fully detect the daily life activities of the elderly so that needed services could be provided to improve the quality of life.

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