REMOTELY MONITORING ACTIVITIES OF THE ELDERS USING SMART WATCHES

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ABSTRACT

In this paper, we propose a model for using smart watches as Internet of Things (IoT). IoT can be defined as a network of physical devices, vehicles, buildings and other items which have electronics, software, sensors, and network connectivity so that these "things" can collect and exchange data. In the proposed system, the purpose is to identify daily activities such as walking, sitting, falling, etc., by using the data acquired from the sensors of a smart watch. As smart watches have the necessary hardware and sensors, the implementation such an IoT application would not cost much. Moreover, analyzing the sensor data would yield useful information. Besides it would be a user-friendly system that does not make the elderly uncomfortable. As being a watch, this device can be always on the user. The proposed system is implemented and the results of initial experiments and user experiences are promising.

Keywords – healthcare services, smart watch, classification, activity prediction, mobile computing, monitoring

1. INTRODUCTION

Smart watches are first produced as an extension to smart phones. At the first examples, they are used to display notification pushed by the mobile applications running at smart phones. The connection between smart watches and the smart phones is initially designed to utilize Bluetooth technology. Upon receiving popular demand from the customers, the smart watch producers began to add new capabilities and expand the existing ones. Nowadays, smart watches have different sensors such as accelerometer, gyroscope, magnetometer, etc. They are furnished with WiFi, GSM, and Bluetooth network cards. Their battery life, computation power, and screen resolution are developing fast. In addition to all these capabilities, the price is dropping with the increasing competition.

In this paper, we propose and develop a model for using smart watches as Internet of Things (IoT). IoT can be defined as a network of physical devices, vehicles, buildings and other items which have electronics, software, sensors, and network connectivity so that these "things" can collect and exchange data. In the proposed model, sensors embedded in the smart watches collect sensory data about the user and transfer it to a central server via a wireless connection. At the central server, the adapted artificial intelligence inference engine run on the sensory data to extract some information about the user. According to the extracted information, central server can communicate with either the user via smart watch or some predetermined responsible entity via a text message or mail.

We apply this model to monitor and predict the health condition and daily activities of elderly people. In the proposed system, we aim to identify daily activities such as walking, sitting, falling, etc., by using the data acquired from the sensors of the smart watches. Upon detecting falling, the central server communicates with the user to check if he or she is safe. Those fallings may cause dangerous injuries as well as death of the elderly people if necessary actions are not taken on time. If the user cannot reply to the central's query within a specific duration, the proposed system generates an alarm message which is sent to the family members or healthcare workers to inform the situation.

The proposed system is implemented and the initial results of the conducted experiments are promising. As smart watches have the necessary hardware and sensors, the implementation such an IoT would not cost much. Besides it will be a user friendly system that will not make the elderly uncomfortable. As being a watch, this device can be always on the user.

2. THE PROPOSED SYSTEM

The proposed system consists of a smart watch and a web service running with activity classification software. These two components are connected via wireless connection. The details of the proposed system are given in the following sections.

2.1 Smart Watch

Smart watch should have enough number and types of sensors to sense the arm movements. Furthermore, it should have the wireless communication capability to transfer the collected data to a remote server. The related sensors are accelerometer and gyroscope. In fact, a gyroscope is a tool that makes use of Earth's gravity to help decide orientation. On the other hand, an accelerometer is a tool to compute non-gravitational acceleration. When the object with an embedded accelerometer moves with any velocity, the accelerometer reacts to the vibrations coupled with such movements and it generates a voltage which can be read on any acceleration. The major distinction between these two devices is straightforward: one can detect rotation, whereas the other cannot [1]. The gyroscope is able to measure the rate of rotation around a particular axis without being affected by the world's rotation. However, the accelerometer is unable to distinguish between a movement and the acceleration provided through Earth's gravitational pull. Thus, using these two sensors readings together, one can have enough information about the direction and the speed of a movement.

Besides the sensors, smart watch should provide necessary computation power and memory capacity to read and store the sensor values. Moreover, smart watch is expected to communicate with a central server for uploading sensor data and download the predicted movement and associated reaction. The smart watch connection can be handled in two ways. In the first technique smart watch gets connected to a smart phone via Bluetooth. Then using smart phone's internet connection, smart watch can communicate with the server. In the second technique, smart watch can connect to a WIFI access point using its own network card. The first solution requires that smart watch should be close to a smart phone all the time. On the other hand second solution provides more flexibility in terms of coverage area. Therefore, we opted for a smart watch with built-in WIFI capability.

Table 1. *The specifications of Sony SmartWatch 3 SWR50 [1].*

Property	**Capacity**
CPU	Quad ARM A7, 1.2 Ghz
Main Memory	512 MB RAM
Battery power / time	420mA /up to 2 days for normal use
Water protected	IP68
Android release	Android 4.3 and onwards
Weight	45 grams
Sensors	Ambient light sensors, Accelerometer, Compass, Gyro, GPS
Connections	Bluetooth® 4.0, NFC, Micro USB, Wi-Fi

Considering the above considerations, we investigated the possible brands and opted for Sony SmartWatch 3 SWR50 for its reasonable price and embedded sensors [2]. The technical specifications of the selected smart watch are given at Table 1. The specifications of the selected watch satisfy the requirements. It has enough memory and computation power and support WIFI connectivity as well as Bluetooth.

2.2 Mobile Application, Web Service, and Classifier

Smart watches have scarce resources such as computation, battery, and memory as seen at Table 1. Therefore, mobile applications developed for this platform should take into consideration the capacity of smart watches.

In our design, we used three-tier architecture (see Figure 1). In the first tier, a mobile application runs on the smart watch. The mobile application collects the accelerometer and gyroscope readings, save them temporarily, and upload them periodically to an application server by using a web service. In the second tier, the application server receives the collected readings from the mobile application and passes them to classifier application. The classifier application executes the selected artificial intelligence algorithm to classify the movement with respect to a pre-determined classes of movements. Following the movement classification, application server can initiate several actions according to the determined rules as explained below.

Using readings of the smart watch's accelerometer and gyroscope sensors, we can predict several different movements of the arm and the body. These can be sitting down, falling down, standing up, staying still, walking, running, etc. For the scope of the work, we would like to know if the elderly person wearing the smart watch has fallen down accidentally or not. Thus, we would like to detect fall with a high accuracy. Furthermore, we would like to differentiate other moves from the fall action with a high precision.

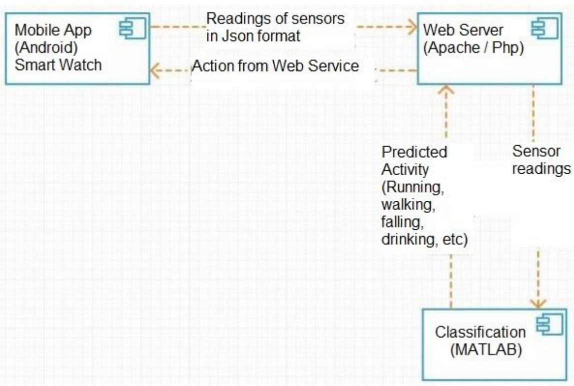

Figure 1. *The graphical representation of the proposed system.*

There are several well-known artificial intelligence methods for classification problem [3-8]. In [3], authors surveyed the classification techniques that can be used for classifying the images. In [7], another survey is done for text classification. Human action classification using video data is surveyed in [9]. In these surveys, one can find many approaches to classify objects or actions in a given context.

In general, classification is a supervised Machine Learning approach [10]. There are many different techniques to apply this approach to a classification problem. Decision trees [11], Artificial Neural Networks [10], Bayesian networks [12], k-Nearest Neighbor [13], Support Vector Machines (SVMs) [14] are some well-known techniques among others. In the proposed system, we opted for k-Nearest Neighbor (kNN) [13] due to its simplicity and high accuracy. On the other hand, others can be used as well. We used the kNN implementation available in MATLAB tool. kNN classifier requires a set of training data as well as the features that models the classified activity [15]. In this study we collected more than 600 sample sensory data for 3 different activities (falling down, sitting down, and squatting) by the help of 15 students. To obtain the training data, we used the leave-one- out method, in which only a set of data is used for testing and remaining data is used for training at each iteration. This process is repeated N times, where N is the number of the available data [15]. We used a time window of 1 second as the time frame. From that time period of accelerometer and gyroscope data, we extracted the following features: mean, min, max, and variance of the power of the sensor data, maximum value and minimum value of the data at each axis, the difference of the data at each axis, variance of the data at each axis, and entropy of the data at each axis. So a total of 19 features for each sensor (accelerometer and gyroscope) are generated and used for the classification. After obtaining the features and test and train datasets, we used kNN as the classfier [13], which is a well-known classifier used successfully in many different areas [16-17].

After classification of the activity, web service software can initiate several actions by the help of previously defined rules. Some illustrative rule examples are summarized at Table 2. Thus, user's activities are monitored and if the conditions are met then some actions can be triggered.

Table 2. *Example rules.*

Predicted Activity	**Predicate**	**Action**
Sitting	Duration >30 minutes	Send a message to smart watch for warning the user to be more active
Falling down	immediate	Send a message to smart watch for checking if the user is alright. If the user cannot reply soon call an
Walking	Duration >30 minutes	Send a message to smart watch to appreciate the user for being active
Drinking	Estimated number of glasses < 8	Send a message to smart watch for warning the user to drink water
Smoking	Estimated number of cigarettes > 1	Send a message to smart watch for warning the user to quit smoking

3. PILOT IMPLEMENTATION AND OBSERVATIONS

We have implemented proposed system as described above. The first observations and results from the implementation are summarized below.

i). The developed Android application is successfully able to collect sensor readings. One of the problematic parameter to be set is the period of readings. If the application requests frequent readings from the smart watch OS, then watch gets very slow or even gets frozen and unresponsive to user's touches. Furthermore, the amount of the collected data from two sensors gets too large in a short time to be stored in the smart watch memory. This also negatively affects smart watch operation. Therefore, we decrease the reading periods to 100 readings per second.

ii). Another issue is to upload the collected data to the web server. Since the amount of data gets bigger, the time to upload it to the sever lasts longer. If, during uploading, the connections fails or resets, we have to re-upload it which decreases the system goodput. Therefore, we split the data into small chunks and then update it.

iii). The classification software is coded using MATLAB tool. We developed the code as a web service. Since there is a continuous flow of data to the web server, classification software should run very quickly. We have not witnessed any serious delay at the prediction process provided that classification software is ready to run at the main memory of the server.

iv). To train the classification software, we have collected more than 600 sample sensory data for 3 different activities (falling down, sitting down, and squatting) by the help of 15 students. We use kNN classifier to classify the activities by using reading of two sensors. The results are given at Table 3. According these initial results, we are able to discriminate three different but very similar activities from each other with an acceptable level of accuracy. For example, for falling down activity, kNN is able to classify the sensory readings correctly about 98% of the test cases. Since sitting down and squatting is very similar to each other, kNN has not produced very good results to recognize these kinds of activities. However, sitting down and squatting activities are well differentiated from the falling activity. These initial results indicate that even with very limited number of training data and with a very simple classification technique, smart watch sensor data can be used to classify activities with a high accuracy rate.

Table 3. Confusion table for 3-activity classification.

Activity	Falling down	Sitting down	Squatting	Number of Total Activities	Accuracy
Falling down	**296**	2	5	303	97.69%
Sitting down	6	**109**	38	153	71.24%
Squatting	8	32	**112**	156	71.79%

5. CONCLUSIONS

In this work, we suggested a system to collect smart watch sensory data to predict the elderly people's activities. Smart watches have two important sensors for this reason: accelerometer and gyroscope. With this experimental study, we have demonstrated the feasibility of proposed design. A mobile application can read the outputs of the sensors in a smart watch continuously and upload them to a web service. Web service can initiate a classifier program to predict the activity. Then web service can communicate with the smart watch to warn or check the user condition.

The initial implementation provided us important experiences on system integration, mobile software development and the use of classifier. The first results are promising. We are now working on a better classifier by implementing fuzzy-neural networks. Furthermore, we plan to collect more data for various activities.

ACKNOWLEDGEMENTS: This project is supported by Atilim University as an Undergraduate Research Project (ATÜ-LAP-C-1516-04). The student members of the project group are Alkım Kulakci, Derya İgde, Orhan Sarıbal, Canberk Sepici, Adil Kutan Çingisiz, and Mehmet Serhat Özdal. We would like to extend our gratitude to all the project group student members for realizing this project.

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