SUPAR: Smartphone as a Ubiquitous Physical Activity Recognizer for u-healthcare Services

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Abstract— **Current generation smartphone can be seen as one of the most ubiquitous device for physical activity recognition. In this paper we proposed a physical activity recognizer to provide u-healthcare services in a cost effective manner by utilizing cloud computing infrastructure. Our model is comprised on embedded triaxial accelerometer of the smartphone to sense the body movements and a cloud server to store and process the sensory data for numerous kind of services. We compute the time and frequency domain features over the raw signals and evaluate different machine learning algorithms to identify an accurate activity recognition model for four kinds of physical activities (i.e., walking, running, cycling and hopping). During our experiments we found Support Vector Machine (SVM) algorithm outperforms for the aforementioned physical activities as compared to its counterparts. Furthermore, we also explain how smartphone application and cloud server communicate with each other.**

I. INTRODUCTION

In ubiquitous health care (u-healthcare), physical activity recognition is a well-researched topic due to its wide range of potential applications. For instance, it can provide different services to the diabetes, insomnia or obesity patients who often follow a well-defined exercise (walking, running, cycling or hoping) routine as part of their treatment. The widespread methods that have been used to assess physical activities are based on wearable devices such as wearing special shirts, bracelets or belts [1], [2], [3]. These solutions are obtrusive and have very few chances of the users to accept it for physical activity recognition.

A physical activity depends on the motion of the body and may recognize through a body mounted accelerometer sensor. To provide unobtrusive and acceptable solution, embedded triaxial accelerometer of the smartphone is viable approach to recognize the physical activities ubiquitously. The objective of smartphone accelerometer is to support advanced gaming interfaces and to enable automatic screen rotation. However, it provides an attractive platform for researchers and developer to develop different healthcare, sports, and lifestyle monitoring models and applications. Furthermore, smartphone runs a complete operating system, supports variety of data communication channels, high computation power and storage. As a result, it is possible to use smartphone to build the systems and recognize human activities for healthcare services.

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The aim of this research is to provide an alternative solution to wearable sensor devices and support healthcare applications by recognizing the physical activities. We selected Google android platform due to its open source and most competitive market [16]. We collected activity dataset of five subjects with different gender, age, height and weight by putting smartphone in the pants front pocket. Our developed smartphone application records time series signals generated by the embedded accelerometer sensor. Signals are highly fluctuated and oscillatory in nature and machine learning algorithms can not apply directly to recognize the human physical activities. In order to process the raw accelerometer signals, statistical and frequency domain features are calculated. We also investigated the performance of different algorithms to recognize the activities.

We structure our paper as follows: Section 2 outlines relevant research projects of activity recognition through accelerometer and ability of smartphone to develop different kind of health care applications. In section 3, we present proposed solution for physical activity recognition and identify a number of requirements that the system should fulfill. Section 4 describes the experimental results followed by discussion. Finally conclusions are reported in Section 5.

II. RELATED WORK

There exist several previous studies based on the motion pattern analysis of accelerometer in the healthcare domain as well as physical activity recognition. Sriram *et al.* [4] utilized a wrist mounted accelerometer to count the movement repetitions for the stroke patients and helps the clinician to track the patient's progress across different sessions. They calculated the Pearson correlation coefficient for motion analysis platform and apply this technique with video games. Lee *at el.* [5] developed an accelerometer based power reduction scheme to support guidance system for blind people. It activates the ultrasound and webcam sensors by recognizing the standing, slow and fast walking activity. They used Decision Tree classifier for classifying the activities using WEKA toolkit.

Stephen *et al.* [6] analyzed the statistical and wavelet based features for the classification of human activities using accelerometer mounted to waist, the thigh, and the ankle as well as their combinations. They reported similar levels of accuracy either time/frequency or wavelet features when accelerometer was mounted on waist. However, for both ankle and thigh mounted sensors, time/frequency domain features significantly outperformed the wavelet features. They used instance based classification algorithm nearest neighbor to

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recognize the activities. They conclude that frequency based features accurately classify physical activities.

In [7] Ravi *et al.* reported the results of their study on activity recognition using a single triaxial accelerometer worn near the pelvic region. Four features extracted from the accelerometer data were mean, standard deviation, energy, and correlation. For the classification task, they analyze the performance of base-level classifiers and meta-level classifiers using the WEKA toolkit. They achieved the average accuracy 95.675% over the two subjects through Plurality Voting classifier.

In the previous works, significant approaches have been developed by researchers, varying in the number of accelerometers, using different placements and intended outcomes. Our research focus is to recognize the physical activities ubiquitously by using smartphone accelerometer and cloud infrastructure that differs from previous study by using a commercial smartphone and cost effective solution rather than a research oriented devices. Furhtermore, we performed the experiments over the subjects recorded activities in a natural manner without fixed duration and sequence.

III. THE PROPOSED MODEL

The proposed approach for recognizing the physical activities is comprised of smartphone application, our Secured WSN-Integrated Cloud Computing for u-life care (SC^3) private cloud [8] to run the activity classifier modules, service recommender to provide healthcare services and logs repository to store human activities data. The use of cloud computing architecture helps in eliminating the time and efforts. By pooling the various IT resources into cloud infrastructure, healthcare service providers can reduce the cost and increase utilization of the resources. At first, our smartphone application records the data logs and send it to the cloud server. In this way, we avoid the bulk storage of sensor logs inside the smartphone. At the cloud server, machine learning algorithm is trained to recognize the human activities. Finally, we use these recognized physical activities to provide various kind of healthcare services. Fig. 1 shows the architecture of the proposed model.

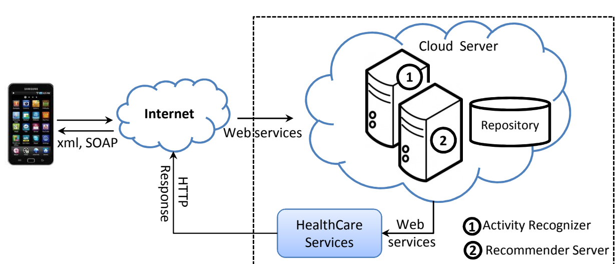

Fig. 1. Architecture of Proposed Model

A. Data Collection and Signal Processing

The smartphones used for our experiments were Samsung galaxy S and Google android operating system version gingerbread. A pilot study for two weeks, we record the activities dataset of five volunteer subjects. Four most common activities were selected as the basic activities of daily life to be recognized – walking, running, cycling, and hopping. The selection of these activities is based on the effectiveness to support healthcare applications. Each subject was requested to perform these activities in a natural manner (without fixed duration and sequence). Each subject records the activities on different days at outdoor locations through our smartphone application without researchers' supervision. Previous studies claim that 30Hz to 100Hz of frequency is suitable to classify the different physical activities [1] [2] [9]. In this study, we recorded the data over the 50Hz of frequency and it is suitable sampling rate for recognizing the defined activities. A representative set of the activities signals are shown in Fig. 2.

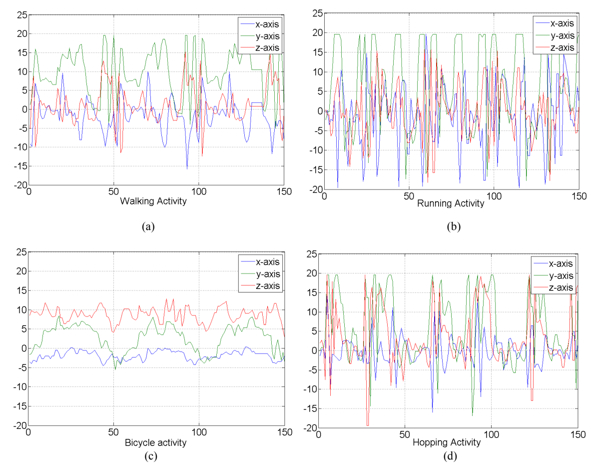

Fig. 2. A Representative Set of Activities Signals

B. Feature Extraction

Accelerometer generates time series data that is highly fluctuating and oscillatory in nature. It makes difficult to recognize the activities using the raw signals. Feature extraction is highly a domain specific technique that defines a new attribute over the raw signals to make it applicable for activity learning and recognition process. We extract the following time and frequency domain features for recognizing the activities:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{1}$$

$$\delta^2 = \frac{1}{n}\sum_{i=1}^{n} x_i - \bar{x} \tag{2}$$

$$Corr(x_i, x_j) = \frac{Cov(x_i, x_j)}{\delta_i \delta_j} \tag{3}$$

$$E = \frac{1}{n}\sum_{i=1}^{n} |FFT_i|^2 \tag{4}$$

In Equation 1, Root Mean Square (RMS) is a statistical time domain measures of the central tendency of varying quantity. Variance is a dispersion metrics to measure how spread out the data for different activities and calculated by equation 2. Correlation between axes is helpful to differentiate simple from complex movements. Energy feature represents the stress of the signal and indicates the dynamics of the motion. The selections of these features collectively have some impact on the intended activities and single feature is unable to perform best. All these features are computed for three dimension data of accelerometer with no overlapping sliding window method of size 3 seconds.

C. Cloud Server

Cloud computing can provide dynamically scalable and virtualized resources as a service with pay-as-you-go manner [10]. We utilized our private cloud computing as Infrastructure as a Service (IaaS) to provide processing power and storage space for accelerometer data. A smartphone embedded accelerometer logs are recorded and sinks to cloud through internet. It stores the data in a repository as a sensor logs. On cloud server, activity recognizer processes the raw data intelligently and recognizes the daily life activities. These activities are important source to provide different healthcare services. It consists of the following components:

1) Activity Recognizer: Activity recognition is the classification problem and the choice of machine learning classifier is critical to recognize the physical activities. We evaluated the following supervised training algorithm to classify the activities and select the most accurate from a group of following selected classifier.

Random Forest: It is ensemble group classification algorithm, which oftenly achieves the higher accuracy as compare to single learner [11]. Random forest consists of a number of independent trees. These trees are independent identically distributed random vectors. After generating a large number of trees, voting mechanism is applied to vote for the most popular class at the given input.

Decision Table: It is a popular technique in business analysis, programming and hardware design [12]. A decision table associate conditions with actions to perform complicated logic and constructed by matrix representation. Each column of the matrix represents a unique combination for making decision.

Support Vector Machine: It gained popularity due to better empirical performance and avoid over-fitting problems of the data. Many real world application tools are based on SVM such as image processing and hand written text categorization. In order to fast train the SVM, we used Sequential Minimal Optimization (SMO) method [14].

Bayesian Network: It is probabilistic directed acyclic graphical network. It encodes the conditional independence relationships between the variables and compact representation of the joint probability distribution [13]. For making inference, it calculates the probabilities of interests for the given input and place class label.

After evaluating these four classifiers, SVM performs best to classify the selected activities. Details of the recognition rate and comparison with each of them is discussed in Results and Discussion section.

2) Recommender Server: It provides different health care services to the users ranges from the general recommendation to personalized activity analytics. It may help the subject to be punctual by sending reminders for their daily walks, running, or cycling routines. On the basis of the physical activities, we are calculating the calorie consumption during a physical activity. It can recommend certain kind of food to help in finding the right meal or relate physical activity effects over daily sleep. It also maintain subject's profile that can provide different services to health practitioner's. Health-practitioners including doctors and nurses can frequently view and analyze the daily routine of patients through a web-interfaces. These u-healthcare services can be customized for different patients according to their medication requirement.

3) Database Server: Database server provides the storage services for sensor logs, recognized activities with time stamp, user profile and practitioners recommendations for individual subject (if any). It communicates with activity recognizer, recommendation server and smartphone through secured exposed web services.

4) Communication: Web services are the communication bridge between the smartphone, cloud server and other attached devices. Person's daily physical activities are recorded in repository as individual logs through web-service. To interact with the android application for providing u-healthcare services, we develop soap messages. These messages are conveyed using HTTP with XML serialization. Fig. 3 shows the XML view of the user authentication interface.


```
<?xml version="1.0" encoding="utf-8" ?>
- <DataSet xmlns="http://tempuri.org/">
  - <xs:schema id="NewDataSet" xmlns="" xmlns:xs="http://www.w3.org/2001/XMLSchema"
    - <xs:element name="NewDataSet" msdata:IsDataSet="true" msdata:UseCurrentLocale="true
      - <xs:complexType>
        - <xs:choice minOccurs="0" maxOccurs="unbounded">
          - <xs:element name="Table">
            - <xs:complexType>
              - <xs:sequence>
                  <xs:element name="UserName" type="xs:string" minOccurs="0" />
                  <xs:element name="Password" type="xs:string" minOccurs="0" />
                </xs:sequence>
              </xs:complexType>
            </xs:element>
          </xs:choice>
        </xs:complexType>
      </xs:element>
    </xs:schema>
  - <diffgr:diffgram xmlns:msdata="urn:schemas-microsoft-com:xml-msdata" xmlns:diffgr="ur
    - <NewDataSet xmlns="">
      - <Table diffgr:id="Table1" msdata:rowOrder="0">
          <UserName>Fahim</UserName>
          <Password>f32as876ash</Password>
        </Table>
      </NewDataSet>
    </diffgr:diffgram>
</DataSet>
```


Fig. 3. XML view of user-authentication

Web service contains different functions which are called by both web and android application to perform the intended actions. It is also responsible to provide ubiquitous access for any connected device (PCs, laptops, smart phones and PDAs) through web services over the internet.

IV. Results and Discussion

On the cloud server, we extract the features from the accelerometer data and apply classification algorithm to recognize the physical activities. For our experiments, we used WEKA toolkit [15] developed by the University of Waikato with default settings. We used 10-fold cross validation for all experiments. SVM outeperform as compared to other discussed classifiers.

Activities	Walking	Running	Cycling	Hopping
Walking	895	0	1	0
Running	9	339	2	0
Cycling	6	0	368	1
Hopping	3	1	0	94

TABLE I

THE CONFUSION MATRIX FOR RECOGNIZED ACTIVITIES

In Table I, the result of the SVM is presented in a confusion matrix over the 10-fold cross validation. The activities walking, running and cycling are recognized with high accuracy as compared to the hopping.

Subjets	**Walking**	**Running**	**Cycling**	**Hopping**	**Average**
Subject 1	100	94.2	97.3	87.5	94.75
Subject 2	100	100	95.8	100	98.95
Subject 3	100	98.5	100	94.7	98.3
Subject 4	100	91	97.4	100	97.1
Subject 5	100	100	97.4	100	99.35
Average					**97.69**

TABLE II

INDIVIDUAL SUBJECT ACCURACY IN %AGE OVER THE SVM

In Table II we show the individual subjects accuracy while performing the experiments by applying SVM. We achieved an average accuracy of 97.69% as depicted in Table II. The comparison results for our activity recognition results are presented in Fig. 4. It specifies the achieved accuracy associated with the activities over the evaluated algorithms.

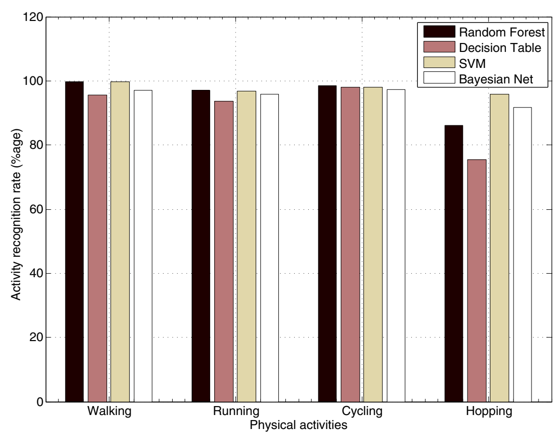

Fig. 4. Comparison of Accuracy Rate

Fig. 4 shows the high accurate results due to the extraction of powerful time and frequency domain features to distinguish between the different human physical activities. In case of walking, runnig, and cycling activities, all selected classifier recognize the activities more than 90% accurately. While confusion arises to recognize the hoping activity. Our comparison shows that SVM consistently performs as compared to counterparts.

V. CONCLUSION

In this study, we designed and developed smartphone as a ubiquitously physical activity recognizer (SUPAR) in a client-server environment. Where smartphone act as a client node to collect the acceleration data during physical activities and cloud server store the sensor logs, process the raw signals for activities and provide u-healthcare services. We extract the time and frequency domain features and classify the human physical activities by competitive SVM algorithm. Our proposed model utilized cloud computing infrastructure that offers cost effective solution and provide services for any connected device (PCs, laptops, smart phones and PDAs) through XML serialization in the form of web-services.

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