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Recognition of Arm & Elbow Exercises using Smartphone's Accelerometer

Tahir Javed [1,2], Muhammad Arshad Awan[1], Tahir Hussain[2]

[1] *Department of Computer Science, Allama Iqbal Open University, Islamabad, Pakistan*
[2] *Department of Computing, Iqra University, Islamabad, Pakistan*

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***Corresponding Author:**
tahircs@gmail.com
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ABSTRACT

Human activity recognition using Smartphone's sensors is a growing area now a day. This study is concerned with health monitoring and typically recognized arm and elbow exercise activities with the help of Smartphone's accelerometer. The recognized arm and elbow exercises are: Bicep Curl, Active Pronator, Active Supinator, Assisted Biceps, Isometric Biceps and Isometric Triceps. The data were collected by placing Smartphone at two positions, i.e. "at wrist" and "in hand", using supervised approach. Twenty (20) volunteers (ten male and ten female) were engaged for the experiment. Each participant performed these activities approximately 20 minutes and total dataset includes around 400 minutes time. Various algorithms based on literature were used for the recognition of defined activities. Results show that Smartphone's accelerometer can be used for the recognition of arm & elbow exercises, which can further be extended for the application of stroke and injured patients.

I. INTRODUCTION

A number of studies have been conducted to recognize the activities of daily living i.e. walking, running, sitting, laying, walking upstairs and downstairs etc. [1], [2] & [3] using different sensors. Smartphone's accelerometers were being used in sports [4] & [5] and healthcare activities [6] & [7]. In such studies we did not find the activities of Arm & Elbow exercises. The concept for chosen these specific activities was taken from sports injury clinic website [8]. The activities performed are: Bicep Curl, Active Pronator, Active Supinator, Assisted Biceps, Isometric Biceps and Isometric Triceps. These exercises can be performed independently and play vital role in rehabilitation of stroke patients and injured personals, in case of arm or elbow injuries. The proposed activity recognition application is the first stage and an application for stroke patients and sports injured patients, can be developed on later stages.

Healthcare is a major application area for activity recognition, especially using Smartphone's sensors. Human Activity Recognition (HAR) and its application's focus is on bringing improvement in human life by using such modern technologies and inventions. HAR can bring change in the field of; caring children, senior citizens, and chronic patients [9], sports training, sports injury recovery and help in sports decisions [10], recovery of stroke patients and recovery in sports injury. In this paper, we worked on arm & elbow exercises, considering a new direction in the field of HAR in general and especially for sport's injury patients. Accelerometer based activity recognition is not novel, bi-axial accelerometer for the identification of twenty common activities was used; i.e. running, sitting, sleeping, walking, cooking, working on computer etc. [11].

This paper contains five sections; section 1 is about the introduction of the work, the section 2 is on related works already done in the area. Section 3 is on the methodology. Its sub-sections are; 3.1 Data collection, 3.2 Filtering, 3.3 Labeling, 3.4 and classification. The sub-section of classification is on results and discussion. Section 4is comprised of conclusion and future work. References are given in section 5.

II. RELATED WORK

Numbers of human activities were being recognized with diverse algorithms, by different researchers. The studies analyzed the HAR results, using single sensor like accelerometer or combination of different sensors i.e. accelerometer, gyroscope, proximity etc.[12]. The problems examined in the studies were minimum utilization of energy and memory. Now a day's memory is not a big issue, even in portable devices. However minimum energy consumption in sensors, is still a major research area. In these circumstances accelerometer is a very good choice in human activity recognition. [13].

Another option for sensing human activity signals, is wearable sensors [14]. However in wearable sensing there are lot of issues i.e. privacy, difficulty in wearing sensors for patients on different parts of body and expensive sensing circuits etc. The Smartphone's sensor based research resolved most of these issues. The second issue raised, can also be avoided after using Smartphone, as we didn't need to wear out anything on body. As Smartphone with sensors is most common device, so the third issue is automatically resolved. We can also use smartphone for recognition in; behavioral biometrics, control based video analysis, security and surveillance, and interactive applications.

Another study on activity recognition using inertial sensors was conducted and presented by [15]. The authors focused healthcare, wellbeing and sports applications. They elaborated six challenges for future research i.e. human behavior, sensor inaccuracy, sensor placement, resource constraints, usability and privacy. They also discussed applications regarding rehabilitation. The presented researchers explore the different activities and disabilities with different disease patients. Reference 10 published their work on sports applications using wearable sensing. They used body worn sensor for recognition of actor's physical activities regarding sports. As per their results the system is reliable, practical and can be employed for healthcare. They recognize eight different activities using twenty diverse subjects.

Smartphone based human activity recognition system for able-bodied and stroke patients recovery was presented by [2]. They applied their technique on 15 able-bodied participants and 15 stroke patients. The subjects participated in research wore a BlackBerry Z10 smartphone on their waist to collect accelerometer and gyroscope based data. The raw data from both the sensors was evaluated using decision tree and five features were derived. The performance of classifier was measured using sensitivity, specificity and F-scores. In normal situations the classifier performed well for both the areas.

III. PROPOSED METHODOLOGY

This study aims is to develop a methodology for recognition of arm and elbow exercise activities. The general procedure is presented in figure-3. The raw data was collected using Samsung Galaxy S-4 Smartphone's accelerometer sensor. Then, filter raw data for classification using "Class conditional probabilities" filter. After that data was labeled and then classifiers were trained and tested. The further details of all these steps are given in next sub-sections.

A. Data Collection

Data collection is a process of gathering relevant information for decision making. For collection of data, an android based Smartphone application was developed; that collects tri-axial accelerometer values. A group of 20 volunteers (10 male, 10 female) was taken. They wore Smartphone at their wrist or take it "in hand" and performed different arm and elbow exercises, i.e. Active Pronator Elbow Stretch, Active Supinator Elbow Stretch, Assisted Biceps, Biceps Curl, Isometric Biceps and Isometric Triceps. Data were collected using Samsung Galaxy S-4 Smartphone. Our population was youngsters with the age group of 25-35 years old. The Smartphone positions are presented in Fig-1& Fig-2

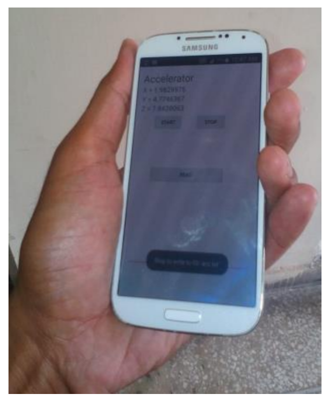

Fig.1: Data collection in hand position

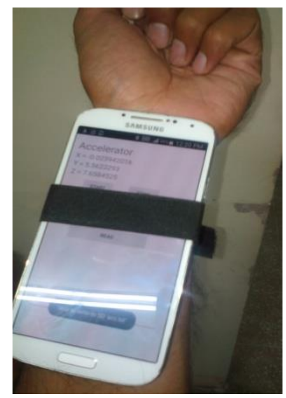

Fig.2: Data collection at wrist position

B. Labeling

Labeling means; tagging of raw data manually or automatically. In this study data labeling was performed manually. For the purpose, first data set files was converted to CSV (comma separated) format and then tagged data by adding concern activity name. The data can be labeled automatically but trained users are required for data collection. Following are the samples of activities used for recognition in Fig-4 to Fig-9.

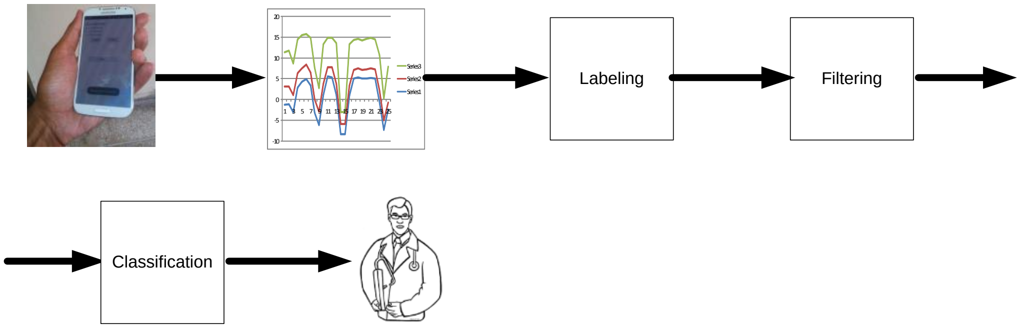

Fig.3: Proposed Human Activity Recognition System

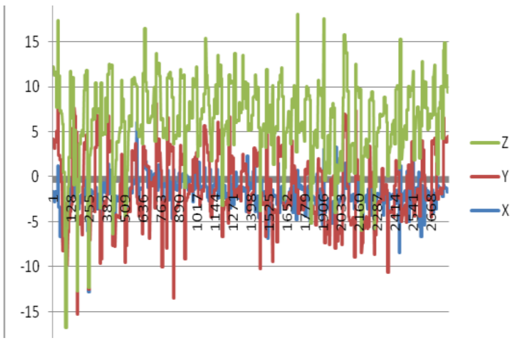

Fig.4: Assisted Biceps

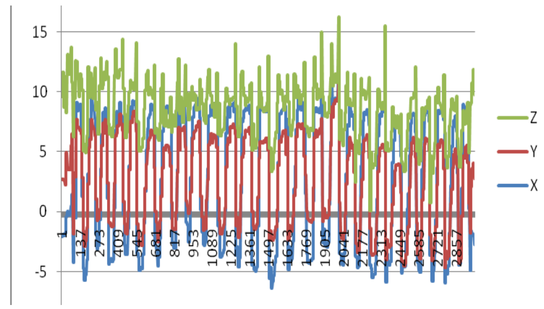

Fig.5: Active Pronator

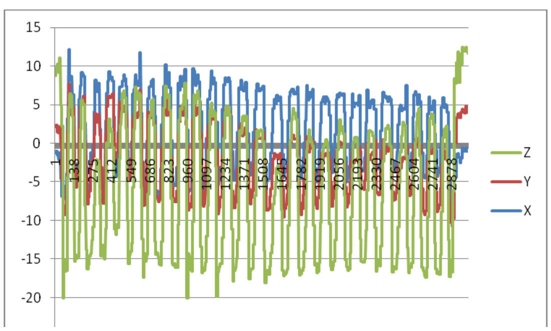

Fig.6: Active Supinator

Fig.7: Biceps Curl

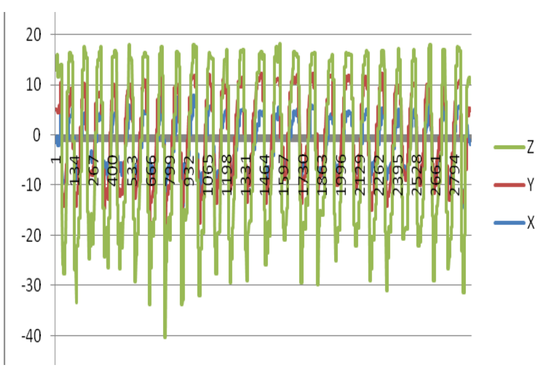

Fig.8: Isometric Biceps

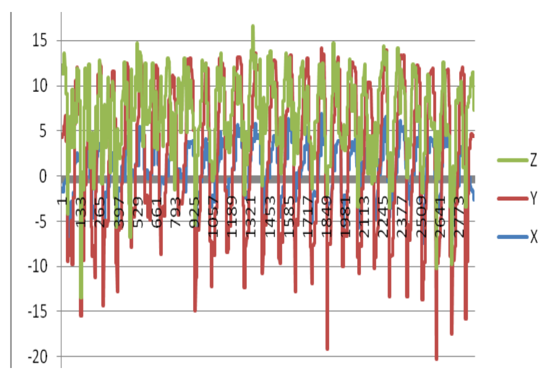

Fig.9: Isometric Triceps

C. *Filtering*

Filtering is a process of removing noise or unwanted data signals. In this study the noise, produced due to untrained users, was removed manually. The results taken after filtering were better than the results taken without filtering.

D. Classification

For classification offline approach was used and analysis was performed using Waikato Environment for Knowledge Analysis (WEKA) tool [15]. Algorithms shown in Table-1, based on literature survey were selected and analyzed.

Table-1: Algorithms used for Classification

Sr.	Algorithm	Description
1.	Multilayer Perceptron (MP)	A feed-forward artificial neural network representation that draws input as per suitable outputs is multilayer perceptron.
2.	Random Forest (RF)	A collective learning methodology for categorization that constituted by different decision trees during training phase and produces classification or predict mean of different trees separately.
3.	Logistic Model Tree (LMT)	An LMT is a classification technique, that associate supervised methodology for training and it combines learning techniques i.e. decision tree and logistic regression.
4.	Simple Logistic (SL)	It is an inverse function of logit function and this algorithm was being used for conversion of logarithm of odds into a probability.
5.	Logit Boost (LB)	This is an improving algorithm that enhances results from previous learning.

Table-2: Summary of Results for different Classifiers “At Wrist” Position

Sr.	Algorithm	Accuracy	KAPA	Precision	Recall	F-measure	ROC
1.	MP	96%	0.92	0.93	0.93	0.93	0.96
2.	RF	99.5%	0.99	0.99	0.99	0.99	1.00
3.	LMT	99.83%	0.97	0.98	0.98	0.98	0.99
4.	SL	77.2%	0.65	0.72	0.71	0.73	0.90
5.	LB	96.67%	0.90	0.92	0.91	0.91	0.99
6.	SVM	74.56%	0.60	0.66	0.63	0.62	0.89

Table-3: Summary of Results for different Classifiers “In Hand” Position

Sr.	Algorithm	Accuracy	KAPA	Precision	Recall	F-measure	ROC
1.	MP	90.82%	0.91	0.93	0.93	0.93	0.95
2.	RF	99.83%	0.99	0.99	0.99	0.99	1.0
3.	LMT	99%	0.97	0.98	0.98	0.98	0.999
4.	SL	74.8%	0.53	0.62	0.60	0.60	0.885
5.	LB	98%	0.90	0.92	0.92	0.92	0.99
6.	SVM	75%	0.56	0.66	0.63	0.63	0.886

Summaries of results for both of the positions were given in Table-2 (At Wrist) and Table-3(In Hand). The features used were accuracy, KAPA statistics, precision, recall, f-measure and ROC. The results showed that the "at wrist" position produces relatively better results but the difference at both the positions was minimal. The classifiers Random Forest, LMT and Logit Boost produce very good results. However the algorithms Simple Logistic and Support Vector Machine did not performed well for recognition of mentioned activities. Sometime SVM did not perform well, when observations are high and due to its choice of kernel (Burgess, 1998). The SL is especially useful when trying to account for potential confounding factors studies (Flom, 2017). The detail of accuracies of different classifiers was given in Table-4 and graphical comparison is available in Figure-10.

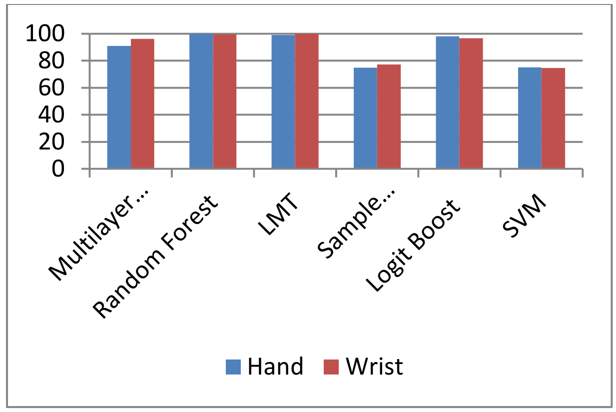

Fig.-10: Accuracies comparison of different classifiers

Table-4: Accuracies of Different Algorithms

Sr.	Algorithm	Accuracy	
		In Hand	At Wrist
1.	MP	90.82%	96.00%
2.	RF	99.83%	99.5%
3.	LMT	99.00%	99.83%
4.	SL	74.80%	77.2%
5.	LB	98.00%	96.67%
6.	SVM	75%	74.56%

IV. Conclusion & Future Work

In the proposed research arm and elbow exercise activities were recognized with the help of Smartphone's accelerometer. The recognized arm and elbow exercises were: Bicep Curl, Active Pronator, Active Supinator, Assisted Biceps, Isometric Biceps and Isometric Triceps. The data was collected by placing Smartphone at two positions, i.e. "at wrist" and "in hand", using supervised approach. These activities were performed on 20 subjects. Different classifiers were used for the recognition of defined activities. Results showed that Random Forest and LMT classifiers performed comparatively better results. However Simple logistic and Support Vector Machine did not performed well. This research can further be extended for the application of stroke and injured patients.

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