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Intelligent System for Human Context Recognition

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***Abstract*— Human-Centered computing technique aims to understand human behavior and can serve in fitness observing aging care, and numerous different spaces. Recognizing Human Context at their normal routine life is a very challenging task as behaviors vary from person to person. The current methods available for the detection of human activities are less accurate, inefficient, and are not effective to be used for recognition purposes. This study focuses on the recognition of human activities by using MPU-6050 signals, which is an efficient, cheap and relatively new method as compared to the existing practices. A total of 37 subjects were involved in this work for data acquisition and asked them to do their activities as usual while carrying the MPU-6050 sensor on their chest. Empirical Mode Decomposition (EMD) was employed for the de-noising the signals. Extensive experimentation resulted in the selection of two features, which were giving the best intra-class difference through Support Vector Machines (SVM). An accuracy of 100% was achieved using Quadratic kernel for SVM.**

Keywords— Human Context, MPU-6050, Features extraction, Empirical Mode Decomposition, Support vector machines

I. INTRODUCTION

The previous decade saw fast improvement in the internet, communications hypotheses and in some recently developing technology, for example, remote sensor systems, wearable sensing, and computation. Today is the universe of robotization and innovation, movement detecting device has become a significant instrument with the end goal of human action recognition. Human context recognition utilized to point out a person's daily routine activities gives a lot of perceptions. It gives information about a person's daily routine. Human context recognition can also be helpful in health care. Many diseases can be identified, as some abnormal context of a person can show a particular disease in its early stage like backbone pain. Human activities can be sensed by using some wearable devices or sensors that can give them activities details [1]. Analyze the data taken from sensors for context recognition. There are different approaches to place sensors on a human body, possible positions are waist, head, chest, and thigh.

In the last decade, there are many activity recognition techniques that are developed by using different wearable sensors i.e. mobile phone sensors. As they do not give good accuracy in different environments so they are not feasible for this application.

So as to see how movement detecting is appropriate for a human action acknowledgment framework, we have to know the necessities of the system. The quality of the framework ought to be:

- Easy to understand for every user
- Low approximate cost
- Exclusive
- Durable

The MPU-6050 sensors are the first motion-sensing instrument utilized for the low power, minimal effort, and elite prerequisites of smartphones, tablets and other wearable sensors. It combines the XYZ – axis of gyroscope and accelerometer on the same silicon chip.

MPU 6050 used in order to recognize the human behavior context. The sensors are placed on the chest. The subject performs different activities running, walking, sitting, standing, lying down, upstair, downstair. Classification of various classes by extracting multiscale features from the accelerometer and gyroscope signal was performed.

II. LITERATURE REVIEW

In [2], Human context recognition using a mobile phone is suggested. The method consists of a simple classification for taking better results. Sequential Forward Selection (SFS) and Sequential Floating Forward Selection (SFFS) features obtained from preprocessed data are encourage to Minimum-distance classifiers to accomplish accuracy of 90%. The classification of human activity signals records movement by utilizing midsection mounted cell phone with implanted inertial sensors in [3]. The researcher collects data from 30 subjects to use in the SVM classifier and achieves 96% accuracy.

YONATAN VAIZMAN suggested cell phones built-in sensors and smartwatch to recognize human behavior context[4]. Collect data from the extrasensory app getting data from accelerometer, gyroscope, compass, GPS, and microphone. The method utilized was multiple layer perception and achieved 83% accuracy.

In[5], five biaxial accelerometers used to gather data by placing them on different parts of the body of a subject. Entropy, correlation, and energy are features withdraw from

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preprocessing data. The tree classifier achieved 84% accuracy.

Jani Mäntyjärvi, approaches handheld devices equipped with sensors to recognize human context[6]. The method developed was collaborative context recognition for a group of handheld sensors. Dynamic weight parameters were utilized to show the reliability of context details. The system achieved 94% accuracy. Dawud Gordon uses mobile phone sensors to build a human activity recognition system [7]. KNN classifier utilized to gets 84% accuracy.

Burgos-Artizzu suggested a pair of microphones and videos for recognizing the human context[8]. The method integrates energy and agent trajectories. The dataset contains videos of the total length of 88 hours. Maximum accuracy of 70% was achieved. SEYED utilized the approach of human-centric sensing and mobile phone sensor for Human context recognition[9]. Frequency domain and heuristic as a feature are used to gets 90% accuracy by using the HMM classifier. N. D. Rodr´ıguez-et-al[10], suggest the method of ontologies and comparison between a different semantic tool that can be used for human context recognition. The system achieved 90% accuracy by using the HMM classifier. In [11], a new method of recognizing human context by wearable devices with sound recognition function. A total of 22 sounds that were linked with personal activities were used. HAAR wavelet and HMM algorithm were used to differentiate activities. 96% accuracy was achieved. D. Minnen utilized an accelerometer and sound sensor placed on the elbow and wrist to recognize the human context[12]. LDA method was used to reduce the FFT coefficient. Trained HMM by using Gaussian distribution and the system achieved 70% accuracy.

In [13], inertial sensors for real-time recognition used for human context. Works on transition aware activities and collected data from 33 activities used SVM with filtering approach.

CA Ronao [14], utilize a profound convolutional neural system for Human Activity Recognition on the crude information gets from phone sensors. It outed the other condition of expression techniques. The strategy accomplished practically ideal order on various activities and obtain 4.3% error rate.

A. M. Khan utilizes a smartphone having a built-in tri-axis accelerometer [15] to gather data from 5 activities. The feature auto-regression and signal magnitude are used in it. Piece Discriminant Analysis utilized to separate the significant non-direct segregating highlights which amplify the class fluctuation and limit the inside class change

In [16] human context recognition through the accelerometer. Collects data from different activities of a person to train classifiers. The tree classifier gives the highest accuracy of 84%.

Tomas Brezmes approaches real-time data collection from an accelerometer of the mobile phone Nokia N95 placed in the trouser pocket. by using python [17]. Developed system by using the KNN algorithm.

In [18] utilized the movement of the eye to recognize the human context. Included 4 subjects for data acquisition from eyes about 42 hours. By encoding eye movement, the SVM classifier system obtains 98% accuracy.

In [19] approaches human context by the accelerometer in the directed and undirected environment. Collected data from 12 subjects about 68 hours placed accelerometer on the hip and wrist. Artificial neural networks utilized to classify activities both regulated and solo. 89% accuracy achieved in this system.

Oscar D. Lara [20] recognize the human context in two-level scientific classification in agreement to the learning approach and the reaction time. Twenty eight systems are qualitatively judged in terms of recognition performance, energy, obtrusiveness, and flexibility, etc. Machine learning techniques were utilized to achieved 95.6 % accuracy.

In [21] tri-axial accelerometers utilized to screen human activities in an assortment of conditions. Collect data from 26 persons and each is walking, sitting and lying down. Features used in this system involves median, magnitude and averaging. Low pass filters system achieved 96% accuracy in a controlled group

III. METHODOLOGY

The methodology proposed based on the MPU-6050 signal for human context recognition is illustrated below in Fig 1. Raw data acquired from the accelerometer and gyroscope of sensor MPU-6050 preprocessed through Empirical Mode Decomposition(EMD). EMD disintegrate data into fragments called IMF (intrinsic mode function). From decomposed signals, the region of interest is obtained. Other excess details and noise are disposed of by eliminating these fragments from data. Only IMF1 was added while other IMFs are rejected. After preprocessing techniques, feature extraction is carried out from these signals. For classifying different classes, the SVM model was used.

Figure 1: System Block Diagram

A. Data Acquisition

Accelerometer and Gyroscope signals data is acquired from the MPU-6050 sensor. The sensor was clipped on the chest. A lot of trials were done to get the dataset. The dataset consists of activities record of 37 subjects, all were male between 18 to 20 years of age mostly students, volunteered to take part in this research. Every individual was told to perform 7 exercises.. Activities include Running, Stairs Up, Sleep, Walk, Standing, Sitting, and Stairs Down. The tasks were performed in different conditions but students were asked to do the activities freely.

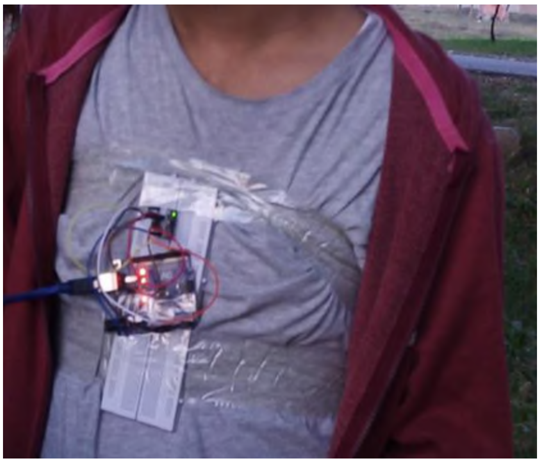

Figure 2: Sensor Placed on Chest of a Subject

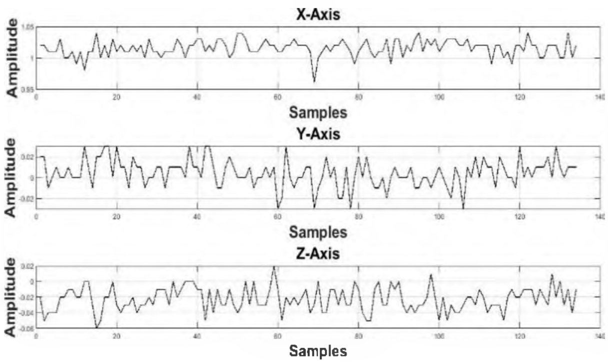

Figure 3: Raw Data of Lying Down

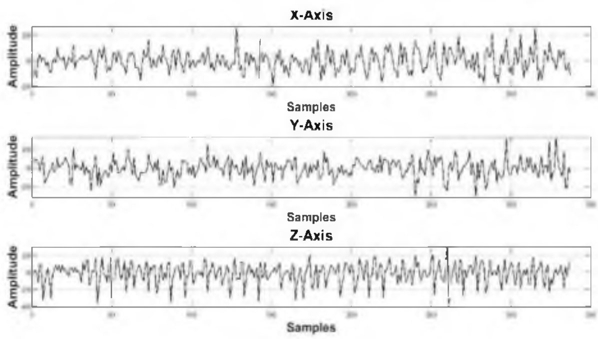

Figure 4: Raw Data of Walking

The examination of running and walking was taken on roads, grounds, corridors and in the hostel. The subjects were lying on mattresses and beds for data of sleep. For data of sitting, subjects were told to sit on chairs and on the simple surface in different styles. Data for standing collected while subjects were stands freely and gossiping. For data of stairs, subjects were moves ups and downs on stairs. All activities records are sampled at 8Hz sampling frequency. To abstain from mislabeling, subjects were approached to stop and hold up a couple of moments after an action before beginning the following movement. The data are further ready to preprocess and classify. The time-domain raw signals are shown in Figure 3,4,5.

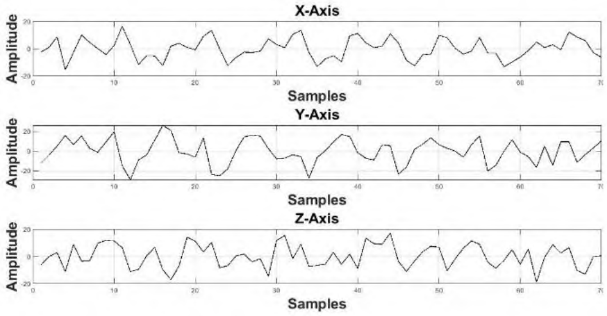

Figure 5: Raw Data of Up Stairs

TABLE I: DETAILS OF DATASET

Activity	No. of Samples
Running	**44**
Lying Down	**104**
Sitting	**115**
Walking	**90**
Stairs Up	**51**
Stairs Down	**48**
Standing	**87**

B. Preprocessing and Segmentation(EMD)

Raw data collected from subjects also get noise with them which causes hide the real information in it. So, to get a region of interest, it is necessary to remove such distortion from the signal. For this research, Empirical mode decomposition is used to discard noise and other artifacts from signals [22-24]. Raw data fed in EMD, it decomposes a signal into sub-parts having distinct amplitudes and frequencies. This is known as Intrinsic mode function [25, 26]. The first IMF has the highest amplitude and gradually starts decreasing amplitude while going to the lower IMF. The last one is the residual IMF which has no importance. As it is clear from figures 6,7,8 IMF 1 shows the denoised accelerometer and gyroscope signal while rest is noise. To make signals suitable for activity recognition

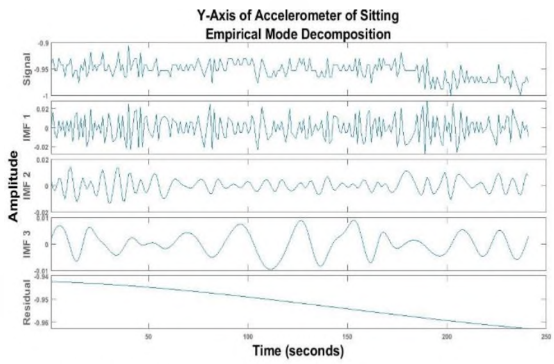

Figure 6: IMF (1-6)

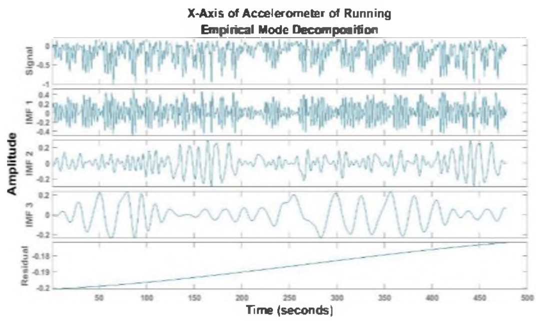

Figure 2:IMF(1-6)

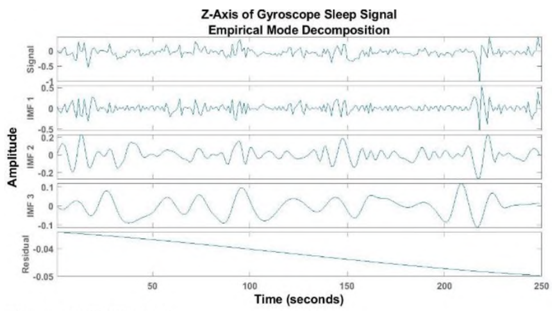

Figure 7: IMF (1-6)

new signal IMF 1 is used. The time-domain of the preprocessed signals are shown in Figure 6,7,8. The information is redundantly removed from the resultant preprocessed signal.

C. *Features Extraction*

The next step after preprocessing is feature extraction. A healthy system depends on features that can easily differentiate different classes of human activities. Through extensive experimentations we found that two features namely, standard deviation and log energy were giving the best discriminating results among various classes. The standard deviation feature is applied to the accelerometer's signals while the log of energy feature is applied to the gyroscope's signals.

D. *Classification*

The classification algorithm chosen for this research work is the support vector machine (SVM) [27]. SVM is the most accurate and widely used classifier. The main function of SVM is that it divides a signal according to a number of classes into hyperplane having N-dimensions. The boundaries of planes may be simple linear or complex. The polynomial kernel in SVM gives the best accuracy of our system.

Cross-approval, a model endorsement system for reviewing how the eventual outcomes of a factual examination (model) will summarize to an informational index. It is generally used in settings where the goal is forecast, and one needs to assess how unequivocally a judicious model will act in practice.

IV. Results and Discussions

Far-reaching experimentations were performed to achieve better identification and execution for human context recognition through MPU-6050 (accelerometer and gyroscope) signals. The raw data from MPU-6050 are preprocessed and segmented by using EMD. Feature determination is gain through assessing diverse features blends to show various exercises. For this observation skewness, mean, kurtosis, standard deviation and log energy features are used. Broad experimentation brings about assurance of the exact recognition of activities. The features which show good discrimination in different classes are shown in Table II.

The features are selected on the basis of showing the best outcomes. Table II completely shows that standard deviation and log energy are the best features which are fits on this work.

Classifiers are checked on the basis of a 10-fold. To predict the behavior of the model without training, for this purpose, cross-validation is used. In 10-fold CV, 10 numbers of groups are formed after shuffling the data set randomly. Table III shows the accuracy of different classifiers includes Trees, KNN, SVM. It is clear from Table III that SVM-Quadratic and cubic show the best classification on this dataset. The

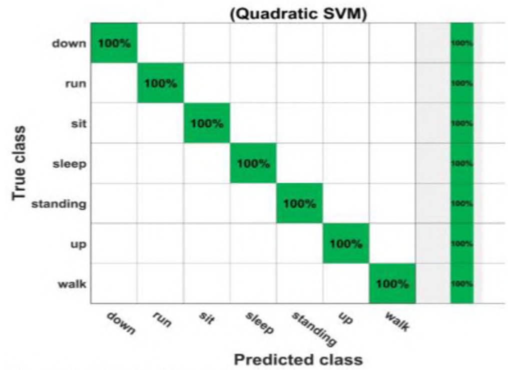

Figure 9: Class-wise true positive rate 3

TABLE II: COMBINATION OF FEATURES

Mean	Standard Deviation	Skewness	Kurtosis	Log Energy	Acc.
✓	✓	✓	✓		99.8%
	✓	✓	✓		99.6%
		✓	✓	✓	99.4%
✓				✓	98.9%
	✓		✓		99.5%
✓	✓			✓	99.8%
	✓			✓	**100%**

TABLE III: COMPARISON OF CLASSIFIERS

Classifier	Accuracy
Linear SVM	99.6%
Quadratic SVM	**100%**
Cubic SVM	**100%**
Fine KNN	94.4%
Cosine KNN	75.5%
Fine Tree	99.1%
Medium Tree	99.1%
Gaussian Naïve Bayes	99.4%
Kernel Naïve Bayes	99.4%

maximum achieved accuracy for human context recognition is 100%.

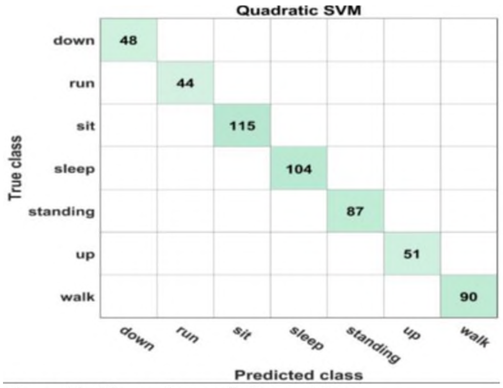

Figure 10: Class-wise confusion matrix

Fig. 10 shows the confusion matrix representation of the class wise achieved accuracy. It can be seen that out of 539 signals none of them is wrongly classified gives the accuracy of 100%.

V. Conclusion

In this exploration, a novel methodology for grouping of Human Activities are proposed. The proposed strategy conveys profound improvement when contrasted with comparative advanced mobile phone based handling techniques that utilization various sensors of phone. It can foresee human action with higher precision. Since just two features are utilized for just first IMF of MPU-6050s sign, the computational complexity of our methodology is then genuinely decreased. It is a cost friendly and easier to use system and has a comfortable application. An increase in the number of subjects in the future can result in a more accurate and reliable solution. There are a need to increase number of classes. Apart from all the limitations, it is still a more reliable and effective method which opens a doorway for its further application in the field of human motions.

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