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An In-Depth Study of USC-HAD, its Dataset Organization and its Classifier Performance

Ahsan Memon[1], Faisal Karim Shaikh[1],Anjum Khalique Bhatti[2]

[1]*Mehran University of Engineering and Technology, Jamshoro, Pakistan*
[2]*Department of Computer Science, SZABIST Hyderabad, Pakistan*

***Abstract*—Owing to the availability of inertial measurement sensors and advancements in machine learning techniques, Human Activity Recognition has gained a widespread interest in the contemporary research community. As a result of which, many pre-prepared datasets have come into public libraries for research and analysis. We examine one such dataset, USC-HAD, and analyse it using modern machine learning algorithms. We find some discrepancies in its data organization and propose changes that that could eradicate them. In the end, we analyse them using 9 classifiers that are most widely used for the purpose of human activity recognition and present our results. Finally, we make suggestions as to which algorithms could be effectively used to analyse datasets of such nature.**

***Keywords*— human activity recognition; machine learning; USC-HAD; KNN; Decision Tree**

I. Introduction

Human Activity Recognition (HAR) has been widely studied in the research community since the 1990s. Its applications range from medical to military [1], but, the medical applications have garnered a greater interest of the researchers worldwide. The reason is simple: the world's elderly population has been on the rise since the past few decades and is expected to rise in the future too [2]. Thus, the medical care for the old population is going to become a greater challenge to surmount in the upcoming years. Taking better care of an elderly person's lifestyle includes careful monitoring of the activities that he or she performs in a day, because they are directly correlated to the kind of issues faced by oneself. Therefore, some of the research effort has been focused on the monitoring and recognition of activities via Inertial Measurement Unit (IMU) sensors, commonly available to us as Accelerometers, Gyroscopes and Magnetometers, in conjunction with machine learning techniques that make sense out of the readings. Much of the IMU sensors' use is owed to the recent advancements in the cellphone technology due to which, cellphones now come packed with IMU sensors that are almost ubiquitously used around the world. The data from these sensors is recorded for analysis [3] and uploaded to the public library for further analysis by the research community. Generally, the steps for analyzing the recorded data using Machine Learning Algorithm as highlighted by [4] are presented in Figure 1: Basic Human Activity Recognition System.

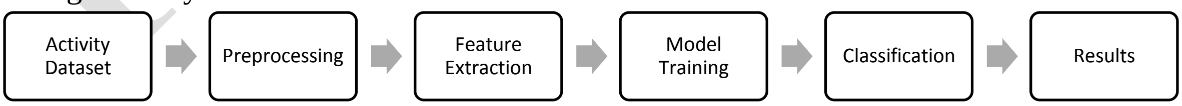

Figure 1: Basic Human Activity Recognition System

The first step in the analysis is to create a dataset using readings from sensors. The chunks of data, called "datasets" are then studied and analyzed for possible patterns that pertain to particular activities. But before that, they are preprocessed for any null values or outliers. After the completion of the cleaning process, meaningful patterns extracted from the dataset.

For example, the signal of walking from an accelerometer sensor constitutes a pattern that can be readily identified by taking the mean, median and standard deviation of all the values in the signal. These measurements are called "features" of the data. They are used to quantify the disparateness between any two signals. The activities of sitting, standing, running and jogging can also be similarly differentiated using these features. The signal identification process is however, automated via machine learning algorithms. These algorithms take in multiple instances of features of the *annotateddata:* data that has been labelled with activity name, making a bigger set of data called the "Training Set", which is then fed to the model of training that our machine learning algorithm will use. This training set contains multiple instances of activities. For example, a training set would have 10 instances of walking signals, 20 instances of sitting and so forth. We use the training set as a literal training mechanism to the machine learning algorithm. By using this set, the algorithm learns an activity's signal using its features. For example, walking signal would have a distinct set of features, such as: higher mean and lower standard deviation, etc. The algorithm is then fed a set of unknown data, which is called the "test set". This set of data is not annotated, which means it doesn't have labels of activities on it. This data is "fitted" to the machine learning algorithm which then makes predictions based on the previously learnt features. The predictions are then tested, and we finally get the measure of "accuracy" of recognition using a particular algorithm. The accuracy is a measure that tells us the percentage of correct predictions made by the algorithm. It is the ultimate measure of success factor of machine learning algorithm. Using it, we optimize the algorithms to churn better and more accurate results. It is therefore, observed, that with the passage of time, we are getting more accurate results when our smartphones try to count our steps. Similarly, the machine learning algorithms can be used to optimize the recognition efficiency of daily routine activities such as walking, standing, sitting, climbing and descending stairs. In turn, this would help us efficiently monitor activities of the elderly without physical interference fulfilling the original aim of these studies.

This study analyzes one of the most comprehensive human activity recognition datasets available publicly and meticulously dissects its features and then applies a collection of machine learning algorithms to itself, in attempt to find out the best accuracy results. The novelty of this work is the in-depth visualization of the dataset element and the analysis provided by a collection of machine learning algorithms used on it.

This paper is organized into 6 sections. Section I introduces the topic and states the problem statement. Section II presents the relevant literature to the topic in question. Section III gives out an introduction to the USC-HAD dataset, its file structure and its data organization. Section IV presents a preliminary analysis of the USC-HAD dataset that is made prior to the classifier results. Section V plots individual samples from the dataset and discusses them. Finally, Section VI puts the results forward and concludes the paper.

II. Related Work

A number of research endeavors have been recently put up in the field of human activity recognition. Most of them have derived their findings from analysis of publicly available datasets. These datasets have been collected in a variety of environments for a collection of purposes. Some of the most common occurrences are the datasets that aim to detect the scenario of "fall", where the subjects intentionally fall down to create spikes of data. Fall detection datasets are most commonly used for the elderly people who are more prone to falling off. As a result of which, after the incident, they are usually unattended for hours before someone finds out about them, often losing crucial time to frustration and poor

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medical care. Fall Detection datasets provide an insight into fall detection sensor samples, commonly left for researchers to accurately detect the incidents using machine learning. Hence, the detection mechanism is then automated, making the incidents more promptly informed to the caretakers and saving precious time of medical care.

Another aim of HAR datasets is to detect activities in general. These chunks of data are gathered with the purpose of quantifying the active time of a human being. Alternatively, they are also used to track routines. Which are most useful for physicians and scientists alike as they help monitor the schedule and help predict the future activities based on the previous inputs. One of the first HAR datasets aimed to detect general life activities is WISDM [5], developed by Kwapicz et al. It contained a total of 29 participants performing routine activities such as walking, jogging, stair climbing and more. Later, Shoaib et al. [6] followed the path and made its own dataset public. It contained similar routine activities of walking, standing, sitting etc, each activity spanning from about 3-5 minutes duration. The research community produced and analyzed a variety of datasets, some of which are available to the public. In addition to that, researchers have also introduced flavors to their measurements. For example, [5] used hilly terrain for the walking signals, whereas [6] used a smooth terrain. Similarly, some literature has used hip-mounted sensors [7] whereas, others have used sensors placed in subject's pockets [8] and some have used multiple sensor positions at the same time [9]. The variety in the sensor position, data organization and choice of sensors has resulted in a collection of challenges for the research community. However, they have also added to better efficacy of machine learning algorithms as they are not more adaptive to variety in data.

One offshoot of the variety in datasets is the device orientation. Some datasets use pocket based sensors with devices placed upside down, while others do the opposite. In general, the data gathered through IMU sensors is divided into three axes: x,y and z. These axes help determine the direction. But this direction of movement is seldom required when there is a bigger challenge of activity recognition at hand. Furthermore, the direction can also be directly extracted from a separate Global Positioning System (GPS) sensor. Hence, in order to achieve greater accuracy in activity detection, a transformation of all of the three axes is performed. Some studies analyzing in detail, the transformation of the three axes signals are [10], [11].

Ideally, after transformation of axes, the measurements in the dataset are pre-processed for better results before being fed into the machine learning algorithm. Preprocessing, therefore, plays an important role in the classification accuracy of the signals in the later stages. Some of the most widely used preprocessing techniques include the *Frequency Domain Filtering, Normalization, Windowing* and *Magnitude Transformation*.

In *frequency domain filtering*, the signal is passed through either a low pass, band pass or a high pass filter to filter out unnecessary frequency components from the data. It is known that the information in activity signals is contained between 2Hz and 15Hz [12]. Whereas, most HAR systems employ a sampling frequency of 50 Hz as shown by [13]. Therefore, according to the Nyquist rate theory, the signals should have a frequency footprint of at-least 25 Hz. The additional 10Hz and the first 2Hz of frequency can be filtered using a Butterworth filter of order n. This exercise is considered to be a part of the HAR analysis's preprocessing part.

Signal normalization is used to compensate for the high intensity signals [14]. Sometimes, the signals of varying intensity can be misread because of different intensity levels. Activities such as walking and jogging, sometimes carried with soft shoes and lightweight bodies will result in low signal amplitude. On the other hand, the same activities, if performed by someone with a higher weight, wearing slippers will result in higher intensity values of the

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accelerometer changes. In order to normalize these changes, the process of normalization can be used.

Windowing, on the other hand, is the breaking up of signals into smaller chunks, to provide for more structured training data for the classifier. Generally, the measurements in datasets are usually taken for full-length activities. For example walking of a person can last from anywhere between a few seconds to a few hours. Another example could be taken from the activity of standing. Some people can stand for hours while others only stand for a mere few seconds. Hence, to introduce some degree of standardization, we break the sensor stream of every activity into chunks of information. This technique is called windowing. In literature, the window size has been observed to vary from 2 seconds until 10 seconds in some cases. For example, [6], [15]–[20] took sample windows of 2 seconds whereas Vavoulas et al. [9] considered using a 5-second sampling window and [21] used 10-second windows. Generally, windows can also be used in three different settings. 1) Fixed-length windows, 2) event defined windows and 3) activity defined windows [18]. However, a detailed study of the three is out of the scope of this study.

A *magnitude* component is the Euclidean distance of all the points from the center of sphere. In a HAR system, it is the distance obtained by square rooting the addition of square of all axis of a sensor reading as given by the equation below.

$$magnitude_{sensor} = \sqrt{x_{sensor}^2 + y_{sensor}^2 + z_{sensor}^2}$$

A number of datasets employ magnitude as an additional feature to their datasets. The reason to this is probably because of their need to preserve direction information. Some of the observed datasets that included magnitude as an additional feature are [5], [6], [20]. Other datasets remove the separate axes completely and introduce a magnitude component instead. This technique saves up some space in the dataset but unfortunately, the user has to let go of the direction component. The studies that have used magnitude as a sole components are [15], [17], [19]. It should be noted however, that having a magnitude component has a great impact in the accurate recognition of signals. The magnitude transformation makes the signals orientation independent, which is necessary for most applications as the user is usually unconscious of the device orientation especially in real life scenarios where mobile phones are usually used for generating activity detection datasets.

The step of feature extraction of a signal comes in after the pre-processing of data. The purpose of this step is to consolidate the raw sensor readings into identities called *features*. The selection of features has a great influence on the accuracy results of the classifier used. In previous literature, it was found that the most commonly used features are the statistical figures of the data. Anguita et al. used Mean of the signal values [17], whereas Bao et al. used Power of the signal as the feature [22], Dernbach et al. made use of the standard deviation feature and [21] and Attal et al. used the interquartile range as features [18]. In other instances, various other features have been found to be used for improving accuracy of the classifier. However, the inclusion of multiple features also result in a high computational cost. Hence, the selection of a smaller set of basic features has been very prominent in the relevant literature.

Finally, after the computation of features, the resultant matrix is fed into the machine learning classifier, which then classifies and produces the predicted results. Various classifiers have been explored for the purpose. According to Morales et al. [23], the predictions of the K Nearest Neighbor algorithm have been the most accurate in human activity recognition

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datasets. Nonetheless, the use of Decision Tree, Support Vector Machines, Logistic Regression, Decision Trees and Random Forest is also found in the literature [15].
All in all, human activity detection using machine learning algorithms have been widely explored in literature. Many of the datasets have already been analyzed with the available techniques. However, some datasets are yet to be explored. Among which, lie the USC-HAD by University of Southern California.
It is the aim of this paper to elaborate and present analysis of USC-HAD, for the depth of data in this dataset is useful for the HAR research endeavors in the future.

III. An Overview of USC-HAD

USC-HAD is a dataset that was created using the front right hip sensor placement [24] and placed in the public library for further evaluation in 2012. It uses high-precision, well-calibrated, specialized hardware for the collection of data instead of the conventional cellphones that often result in inaccurate measurements. Hence, making it one of the most accurate data repositories available to us.

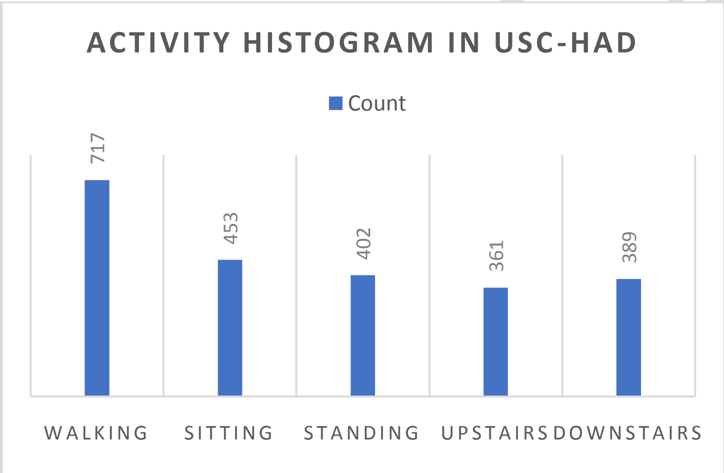

Figure 2: Activity Histogram in USC-HAD

It is a dataset commissioned to contribute to the lack of large datasets available to in the public cyberspace. It was constructed with a specialized 6-DOF node named MotionNode. The sensor was attached to a pouch on front right hip that each subject had to wear. A total of 14 subjects participated in the measurements and according to the authors each subject had to undergo a six hour long process of data gathering [7].
Another focus of the dataset was the diversity of subjects included in the trials. Four factors: Gender, Age, Height and Weight were taken into account for that purpose, and an equal mix of 7 male and 7 females were used for the trials.

TABLE I

STATISTICS OF SUBJECTS IN USC-HAD [17]summarizes the range, mean and standard deviation of three of the four factors.

TABLE I

STATISTICS OF SUBJECTS IN USC-HAD [17]

Property	Age	Height (cm)	Weight (kg)
Range	21-49	160-185	43-80
Mean	30.1	170	64.6

Standard Deviation	7.2	6.8	12.1

The data in the dataset is present in MATLAB data files, which are organized as under:
Each activity trial in the dataset is stored in a .mat file that is stored in a folder specific to every one of the 14 subjects. The following file nomenclature is used for its files:

a"m"t"n".mat

where,
"a" stands for activity
"m" stands for activity number
"t" stands for trial
"n" stands for trial number
Each .mat file contains 13 fields:

1. title: USC Human Motion Database
2. version: it is version 1.0 for this first round data collection
3. date
4. subject number
5. age
6. height
7. weight
8. activity name
9. activity number
10. trial number
11. sensor_location
12. sensor_orientation
13. sensor_readings

For sensor_readings field, it consists of 6 readings:

1. acc_x, w/ unit g (gravity)
2. acc_y, w/ unit g
3. acc_z, w/ unit g
4. gyro_x, w/ unit dps (degrees per second)
5. gyro_y, w/ unit dps
6. gyro_z, w/ unit dps

The activities that were measured in USC-HAD are described in TABLE II.

TABLE II

ACTIVITIES IN USC-HAD AND THEIR BRIEF DESCRIPTION

S.No	Activity	Description
1.	Walking Forward	The subject walks forward in a straight line
2.	Walking Left	The subject walks counter-clockwise in a full circle
3.	Walking Right	The subject walks clockwise in a full circle
4.	Walking Upstairs	The subject goes up multiple flights
5.	Walking Downstairs	The subject goes down multiple flights
6.	Running Forward	The subject runs forward in a straight line
7.	Jumping Up	The subject stays at the same position and continuously jumps up and down
8.	Sitting	The subject sits on a chair either working or resting. Fidgeting is also considered to belong to this class

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9.	Standing	The subject stands and talks to someone
10.	Sleeping	The subject sleeps or lies down on a bed
11.	Elevator Up	The subject rides in an ascending elevator
12.	Elevator Down	The subject rides in a descending elevator

IV. Preliminary Analysis of the Dataset

Upon analysis of the dataset, we was found that the dataset's organization in its nomenclature is indicative of some non-standardization. For example, there are multiple shades of walking under similar names such as walking is mentioned as walk-up, walk-right, walking-right, walk-left, walking-left and more. The names do not make particular sense at this point because they are mixed, and they could mean something else. For example, walk up could mean walk-forward or walk-upstairs.

We have compiled a list of all the activities and the possible connotations to the best of our understanding in

TABLE III: ACTIVITY INTERPRETATIONS IN USC_HAD DATASET

TABLE III: ACTIVITY INTERPRETATIONS IN USC_HAD DATASET

S.No	Interpreted Activity	Name mentioned in Dataset
1.	Running	running, run
2.	Walking	walking-forward, walk-forward,
3.	Turn clockwise	walk-right, walking-right
4.	Turn anti-clockwise	walking-left, walk-left
5.	Downstairs	walking-down, walk-downstairs, walking-downstairs
6.	Upstairs	walking-up, walk-up, walking-upstairs, walk-upstairs
7.	Sitting	sit, sitting
8.	Jumping	jump, jumping
9.	Elevator Up	elevator-up
10.	Elevator Down	elevator-down
11.	Standing	stand, standing
12.	Sleeping	sleeping

Subjectively, our analysis of the dataset raises one flag. As mentioned by the dataset creators, the subjects of the dataset used a laptop in the right hand because the sensors used were not wirelessly connected to a streaming server or a storage server. The use of a laptop in the hand might have an impact on the neutrality of measurements taken. Considering that the subjects were had to go through a six-hour-long process in the data collection phase, there is a chance that the subjects were tired of holding the laptop and the readings were somehow affected by it.

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V. Component Visualization

In this section, we plot one sample of all the activities that we consider in the forthcoming chapters. These samples give us a visual insight into the type of data that is present in the dataset. For the sake of brevity, we only take the most commonly used activities found throughout the literature, which are: Sitting, Standing, Walking, Upstairs and Downstairs. In the figures Figure 3: Accelerometer - Downstairs till Figure 12: Gyroscope - Walking, we have shown the accelerometer and gyroscope readings of the five activities that are enumerated above. Later in this paper, we analyze the same information using a variety of machine learning algorithms. The figures to the right represent a larger set of samples in the dataset whereas, similar figure on the left depict the granularity in the otherwise cluttered set.

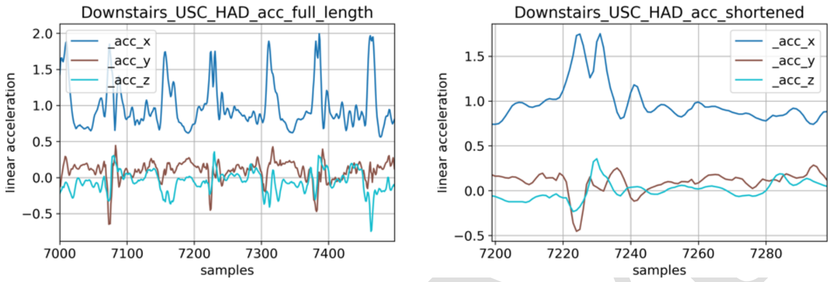

Figure 3: Accelerometer - Downstairs

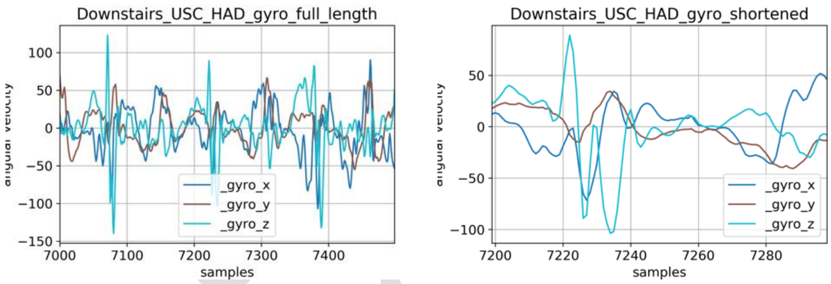

Figure 4: Gyroscope – Downstairs

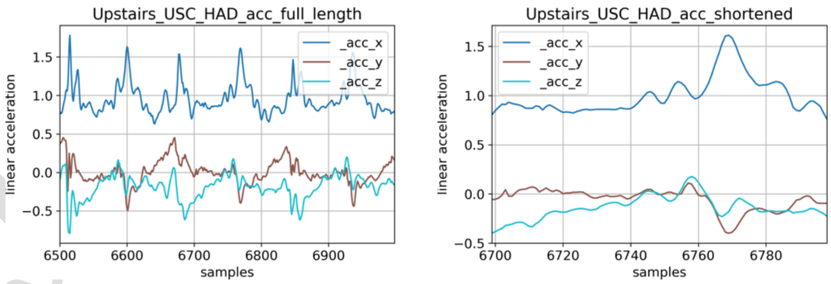

Figure 5: Accelerometer - Upstairs

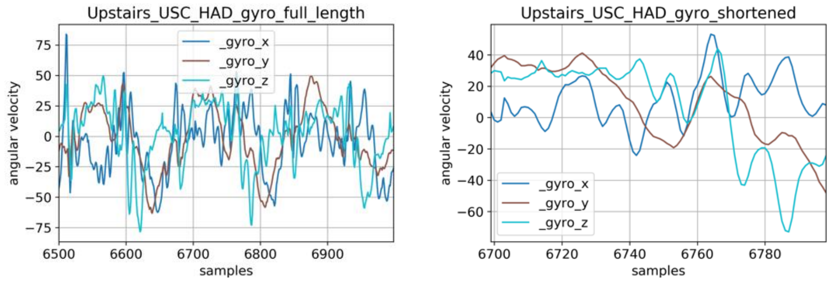

Figure 6: Gyroscope - Upstairs

The signals of Upstairs and Downstairs have been taken from amid the samples provided in the dataset. It can be observed that both the signals seem periodic in nature with similarly occurring spikes. The spikes could be taken off as the jerks that a hip position gets as one tries to climb or descend the stairs. In the case of descending, the jerk can be observed in Figure 4: Gyroscope – Downstairs to be a bit more in magnitude because of gravity working in favor of the natural mass of a person. Furthermore, the shaky nature of the downstairs signal in the accelerometer in Figure 3: Accelerometer - Downstairs more than the Figure 5: Accelerometer - Upstairs can be attributed to the jerk received by the human body when descending down the stairs. Similarly, other keen observations can also be derived using the detailed figures to the right, which show only 100 samples instead of 500 samples as seen in the images to the left.

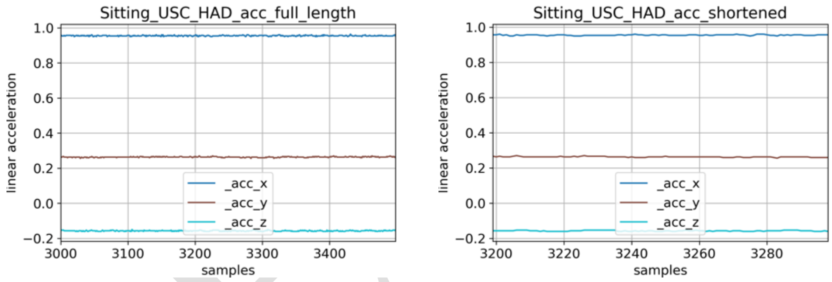

Figure 7: Accelerometer - Sitting

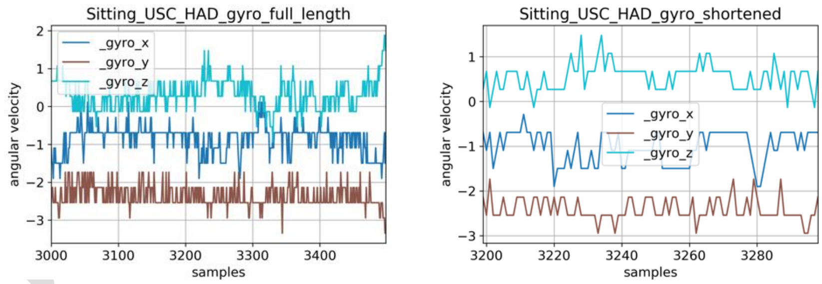

Figure 8: Gyroscope - Sitting

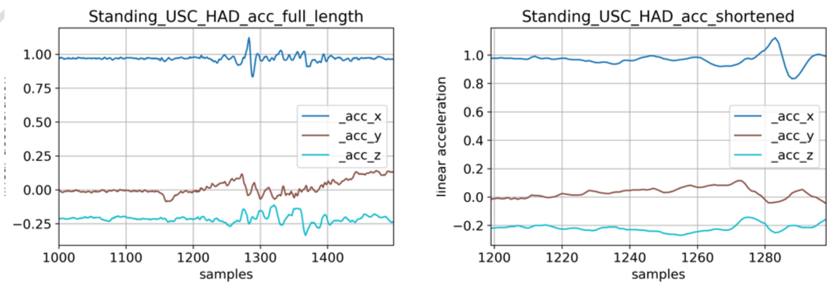

Figure 9: Accelerometer - Standing

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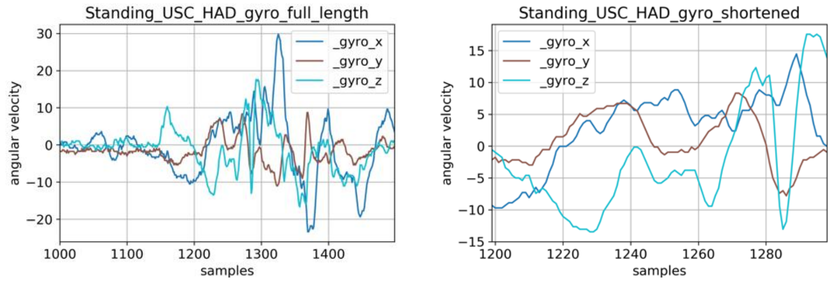

Figure 10: Gyroscope – Standing

The sitting position in Figure 7: Accelerometer - Sitting can be observed to be very steady in its operation. However, small spikes in the gyroscope can be found in Figure 8: Gyroscope - Sitting. These spikes could be resultant of the natural movements that a human body exhibits during even the steadiest of postures.

From the gyroscope measurements of Figure 10: Gyroscope – Standing, it can be observed that the spikes in the standing position are uneven compared to the spikes in the sitting position. These radiating spikes could be resultant of the inadvertent movements that we make while standing.

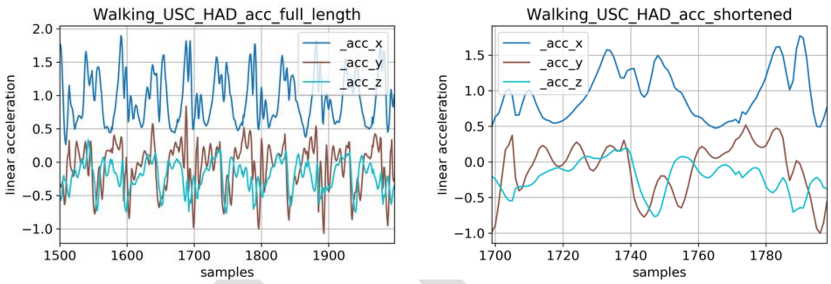

Figure 11: Accelerometer - Walking

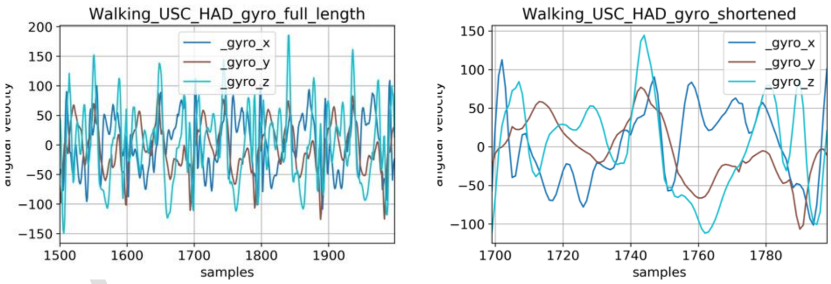

Figure 12: Gyroscope - Walking

The walk signals, as expected, show periodic movements throughout the accelerometer and gyroscope readings. These periodic movements are mostly attributed to the steps taken by the subject. However, some aberrations in the signals are also caused by the recoil from the impact of feet on the ground.

Overall, the signal samples presented in this section are indicative of close to ideal sensor readings as they do not exhibit any traits of distortions or aberrations that would be caused by using inaccurate and loosely held sensors. USC-HAD, could therefore, be considered an accurately measured dataset in that respect. However, an analysis of only one activity sample of the dataset does not necessarily speak of the rest of the samples. But, it only gives us an idea to a generic visual organization of the dataset elements. For a more comprehensive analysis of the samples, an analysis of each one of these activities can be performed analyzed if necessary.

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VI. Results and Conclusion

This section highlights the results obtained by using the following machine learning algorithms on the Dataset of USC-HAD.

1. Logistic Regression
2. SVM
3. KNN
4. Gaussian Naïve Bayes
5. Perceptron
6. Linear SVC
7. Stochastic Gradient Descent
8. Decision Tree
9. Random Forest

The activities that were considered for the algorithm were sitting, standing, downstairs, walking and upstairs. Whereas, a fixed-width sampling window of 10 seconds was used in our analysis. We used the minimal features of mean and standard deviation and used the accelerometer and gyroscope sensors for the data analysis. The resultant scatterplot obtained from the feature set obtained from USC-HAD is shown in Figure 13: Multidimensional Scatterplot of Feature Set from USC-HAD

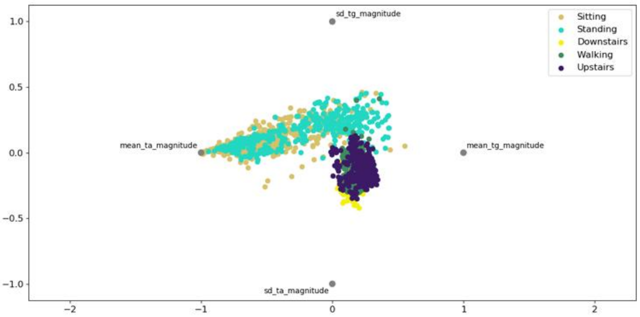

Figure 13: Multidimensional Scatterplot of Feature Set from USC-HAD

The results obtained using the classifiers are shown in Figure 14: Classifier Results for USC-HAD. It was observed that in the case of USC-HAD, the commonly used classifier, KNN, did not perform optimally. The KNN classifier gave an accuracy of 64%, which was far lesser than Random Forest's accuracy of 83%. The second best accuracy was obtained by Decision Tree, which gave out 76%. It is worth noting that Decision Tree is a widely used machine learning algorithm for HAR activities, and in this case it performed better than most other algorithms, as expected.

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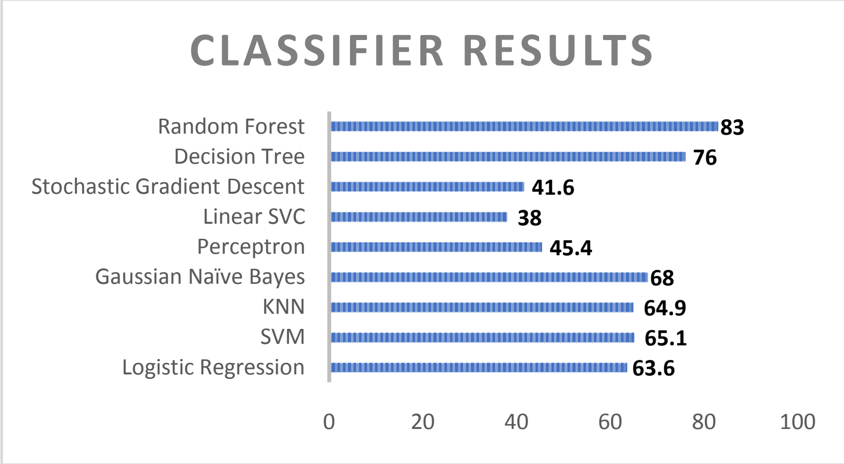

Figure 14: Classifier Results for USC-HAD

Overall, the dataset yields an accuracy of 83% using the Random Forest classification algorithm. The accuracy is fair, considering the basic set of features used in the training process. Another reason for the relatively smaller accuracy percentage could be the mix of values in the multidimensional scatter plot. As we can observe in Figure 13: Multidimensional Scatterplot of Feature Set from USC-HAD, the feature points of sitting and standing are mostly overlapping each other. The results are also reflected in the higher mixing rates in the confusion matrices presented in Figure 15: Confusion Matrices of USC-HAD over Multiple Classifiers

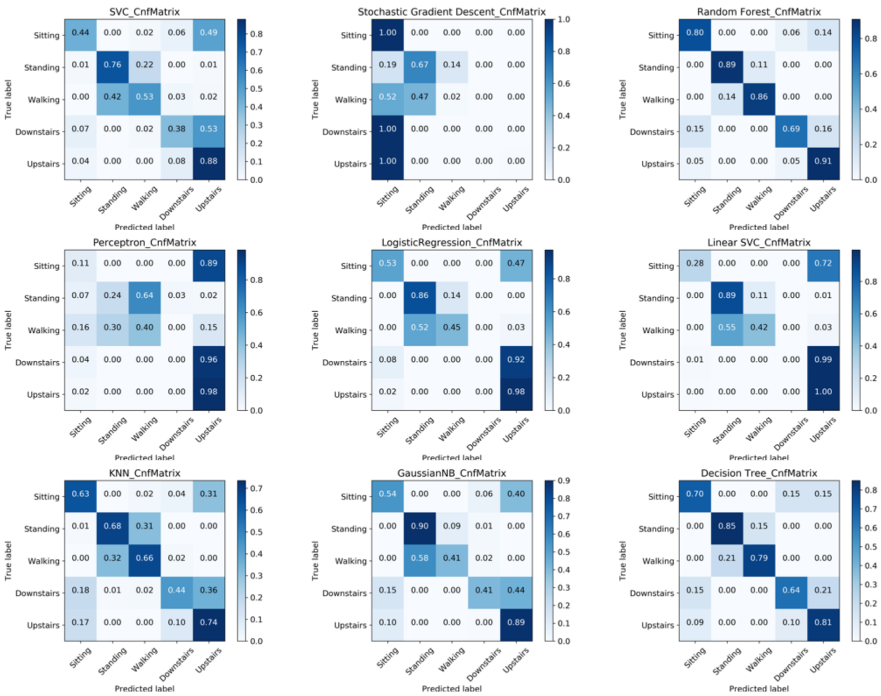

Figure 15: Confusion Matrices of USC-HAD over Multiple Classifiers

One possibility for reduced performance metrics could also be the inaccuracies generated due to the laptop that the subject had to hold during trial periods. As the authors mentioned, the trials had to go on for six-hours for each subject and there is a greater variance in age of subjects, the necessity to hold a laptop for that long could have impacted the data fidelity of data gathering. A separate study can be conducted to find out the classifier accuracy of measurements taken when the subject is holding a laptop in the hand and vice versa.

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In conclusion, this paper gives an in-depth review of the USC-HAD dataset's organization and presents an analysis obtained by injecting its values in multiple machine learning algorithms. It discusses the pitfalls that one might face when putting the dataset values in a coding language for analysis and presents solutions to overcome the data-reading challenges. The paper also presents a possible interpretation to the nomenclature that has been mixed up in some files of USC-HAD's data and provides a way-out of the naming problem. Later, it analyzes one sample from a set of commonly used activities and analyzes them in chunks of 500 and 100 samples per graph. The analysis show that the data in MATLAB files is consistent and free of the usual shaking and wobbling, which could create problems in analysis. Finally, our study produces accuracy results of nine commonly used machine learning algorithms for HAR systems. According to our results, Random forest performs most optimally and giving out an accuracy of 83% while Decision Tree trails behind on the second place with an accuracy of 76%. The results partially agree with the common observation in literature that suggest that Decision Tree and KNN perform best in HAR systems.

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