Human Activity Recognition using, colour, RMS, Time-domain, Autocorrelation Deep Learning with better Feature Extraction

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Abstract -Finding patterns in human behaviour and providing exact information on the activity performed by a human are challenging technical and computational tasks. With improvements in human activity recognition (HAR) systems, countless applications can be created and different issues in the fields of virtual reality, health and medicine, entertainment, and security can be resolved. While HAR has been a focus of active research for more than a decade, there are still a number of issues that need to be resolved if we are to improve the system and fundamentally alter how people use smartphones. As a result, we suggest in this work a method for recognising human physical activity based on information gathered from smartphone sensors. The suggested method calls for using the three sensors found on a smartphone—the accelerometer, gyroscope, and gravity sensor—to create a classifier.

Keywords— HAR, accelerometers, gyroscopes, deep learning.

I.INTRODUCTION

Our daily lives now revolve around mobile gadgets. This is because mobile devices are becoming more complexly designed and integrated with high-quality sensors, powerful processors, ample storage, and constant communication. Consumers frequently engage with their inexpensive, pocket-sized smartphones as they go about their daily lives, which has sparked an increase in study into the information extraction from data collected by pervasive sensors in mobile devices [1]. Life logs, or the use of technology to collect and document significant portions of a user's life using mobile devices, have drawn a lot of attention recently. Using a smartphone to record daily step totals is a nice example of lifelogging.Simple physical activities like walking, running, sitting, etc. can be recorded in life diaries, as well as more involved ones like working, eating, and exercising. A wide range of study areas, including medical, augmented reality, computer-human interaction, security, and targeted advertising, can benefit from this. A lifelog can be used to gather information, provide insights into a user's lifestyle, and aid in enhancing quality of life by offering specialised advice and services.A crucial step towards resolving more complex issues will be the development of context-aware software and services using affordable consumer hardware. The gathering of activity data using various wearable sensors and the proper classification of human activity based on the acquired data are the two greatest challenges in constructing a full lifelog. Strong sensors including accelerometers, gyroscopes, GPS, magnetometers, proximity sensors, and ambient light detectors are built into mobile devices. Researchers now have the ability to easily gather sensor data with the use of minimum infrastructure thanks to cellphones.Based on the gathered data, modern machine learning algorithms can be utilised to detect and identify human behaviours. The issue of keeping a thorough record of a user's everyday activities could be resolved with the use of a straightforward smartphone. The ability to recognise human behaviour at deeper ontological levels may be pushed by developments in deep learning, feature selection techniques, and the use of a range of sensors.

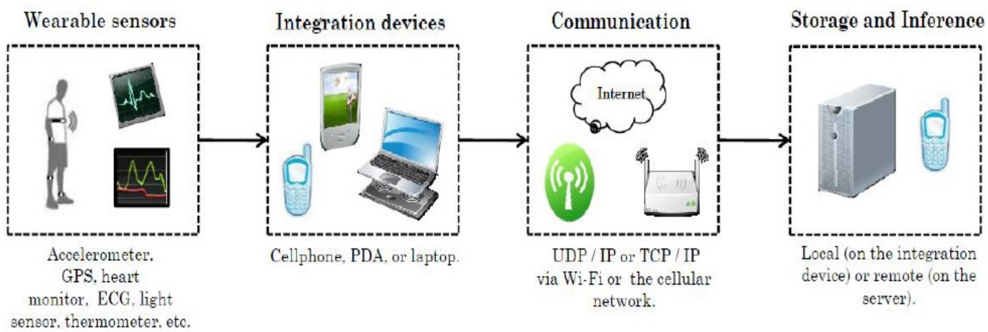

Figure 1 *: Devices to recognise Human Behaviour*

II.ACTIVITY RECOGNITION

Data acquisition is generally concerned with the gathering and storing of sensor data, whereas activity recognition is mostly concerned with the machine learning models used for predictive analytics. The typical layout of the data collecting system is shown in Figure 1. The main element of the data acquisition phase is the sensors, which monitor a number of characteristics including acceleration, position, audio, temperature, and so on. The additional components include the communication network, integration device, and remote application server. The integration device's main job is to gather and preprocess the unprocessed sensor signal. The data can also be transferred to a distant application server for real-time analysis and visualisation using networking protocols like TCP/IP or UDP.Not every data gathering system uses and implements every component. The sensors in [4] through [6] act as the device's integrated analytical processing unit. For some systems, an external wearable device that communicates with an integration device—a laptop, a phone, or another device—is necessary. The diverse applications and requirements mirror these variances in the overall design. Throughout the training and testing phases, the component for activity recognition is constructed and mainly depends on machine learning models.As explained in [11], the model must be trained using a sizable dataset of the gathered attributes. Data cleaning, feature extraction, dimensionality reduction, and feature selection are just a few of the procedures that happen throughout the training phase. The testing step is also described by the authors of [11]. Despite having a reduced dataset, this stage still processes the same amount of data. The machine's predictions are then put to the test after being evaluated for training.

III.FEATURE SELECTION

Feature selection is a fundamental concept utilised in the pipeline of machine learning. What helps to improve the model and the forecast output is the concept of selecting a set of criteria either automatically or manually. This procedure is followed since the results have a big effect on the model's correctness and build time. Since they require the model to employ information that doesn't aid in prediction, irrelevant features in the dataset may have a negative effect on training. Because irrelevant information typically acts as background noise, accuracy is frequently compromised. Less overfitting, increased accuracy, and quicker training times are benefits of feature selection. There is feature selection.We may combine all the analysis strategies identified into a single function after interactively examining a few different techniques to extract descriptive characteristics from this kind of signals. This function's task is to extract a predetermined amount of characteristics for each input signal buffer.

IV.RESULTS

This article describes a method for evaluating accelerometer signals captured by smartphones. The person wears the smartphone while engaging in six different types of physical activity. The analysis's goal is to create an algorithm that uses sensor data to automatically identify the kind of activity.

Data preparation

The data must be ready before the deep learning system can accurately predict the activities. The following four data files are produced after the data is downloaded:

1. Buffered Accelerations
2. Buffer Features
3. Recorded Accelerations by Subject

4. Trained Network

Single Acceleration Component for Particular Subjects

Access the entire "recorded" for a particular topic (such as #1–30), To get a single acceleration component for a specific subject, use a custom function. Below is a graph of subject 2's raw acceleration:

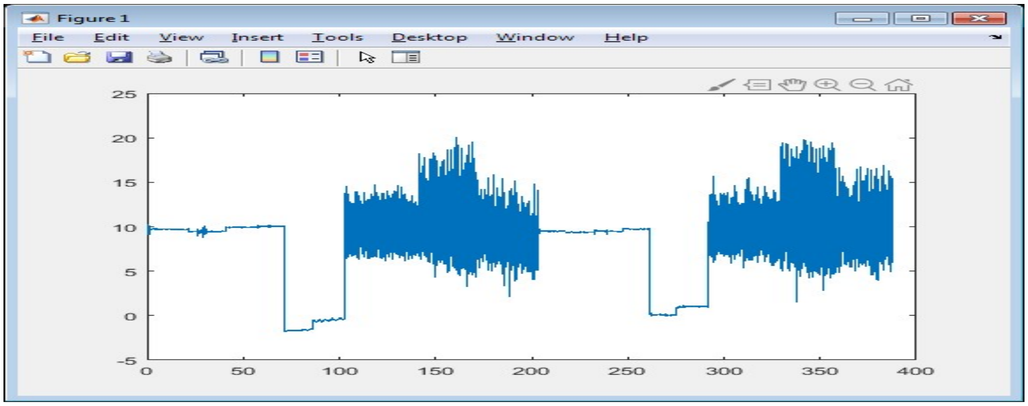

Figure 2: Raw Acc of Subject 2

Figure 2 displays the subject 2's raw acceleration over time. Between 0 and 60 seconds and 200 to 260 seconds, the subject is standing and relaxing, between 60 and 100 seconds and 260 to 300 seconds the subject is lying, between 110 and 140 seconds and 300 to 340 seconds the subject is walking, between 150 and 180 seconds and 340 to 370 seconds the subject is running, and between 180 and 200 seconds and 380 to 400 secs, the subject is running. The subject's activities can be easily predicted using the raw acceleration graph.

Colored Based Prediction

Let's look at the same data, colored according to the activity type, for a more in-depth analysis. Based on these facts:

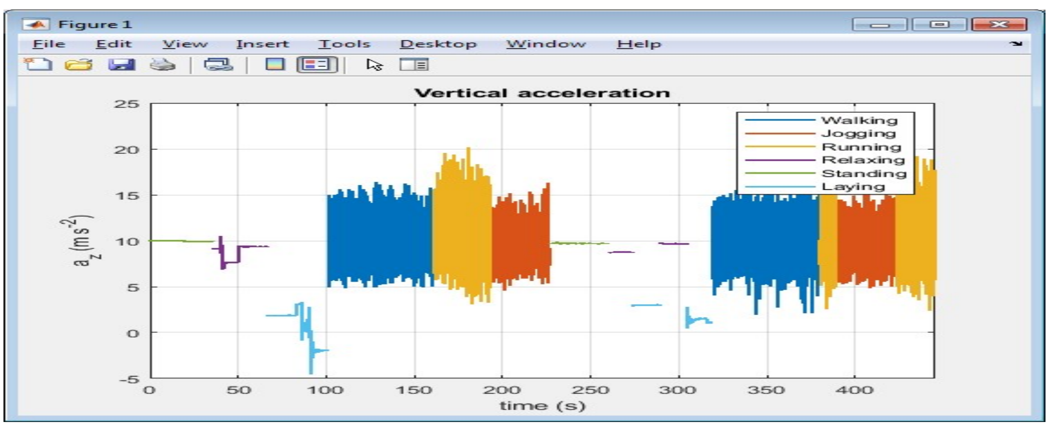

Figure 3: Colored Based Predication Subject 1

Prediction by Amplitude (mean)

The substance of the signal should be the only factor used to distinguish between the various activities. In this case, the colouring is determined by the data's known properties. A classification algorithm will be "trained" using labelled data in order to later predict the class of new data that is not labelled. Create a custom plotting method to display a signal that utilises information from unlabeled data as well. By first using a mean measure, the first sort of characterization, amplitude alone, can provide a first set of cues that make it easy to identify, for example, walking from lying, as illustrated in figure 4.

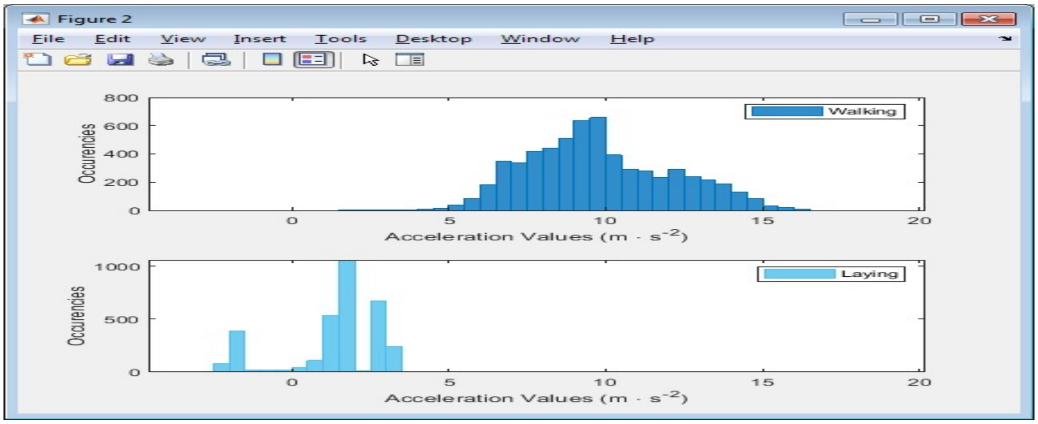

Figure 4:AccVsOccurrences (Walking and Laying)

Prediction by RMS (Root Mean Square) or standard deviation measure

Predicting standing and walking, as depicted in figure 4, is also simple. Which can assist in separating activities like walking and standing or walking and relaxing, using an RMS or standard deviation measurement.

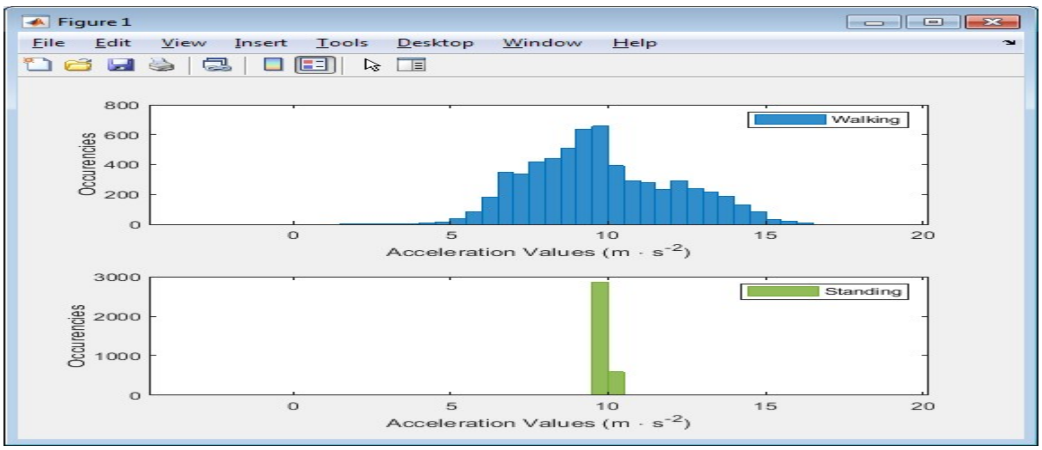

Figure 5:AccVsOccurrences (Standing and Walking)

Time-domain analysis

Our signals are caused by two basic categories of causes:

One has to do with "rapid" alterations in a short period of time brought on by the subject's bodily dynamics or movements. The second has to deal with "slow" changes that happen over time as a result of how a body is positioned in relation to the vertical gravitational field. Our categorisation of physical activities should be primarily driven by time-domain examination of the consequences of bodily motions. They are in charge of the most "rapid" (or regular) changes in our signal. In this case, the physical movement signal could be obtained by subtracting the gravitational component from the appropriate samples, which in turn allowed the gravitational component to be easily approximated.

Here, we introduce a method based on generic principles.

Digital filtering workflow

To distinguish between the faster and slower changes in the signal, digital filtering can be used:

You can design a high-pass filter, apply it to the original signal, and then remove gravity acceleration using MATLAB's Filter Design and Analysis Tool (FDA tool). Filters can be created programmatically in addition to being created interactively. In this case, the High Pass Filter function was generated automatically by the Filter Design and Analysis Tool.

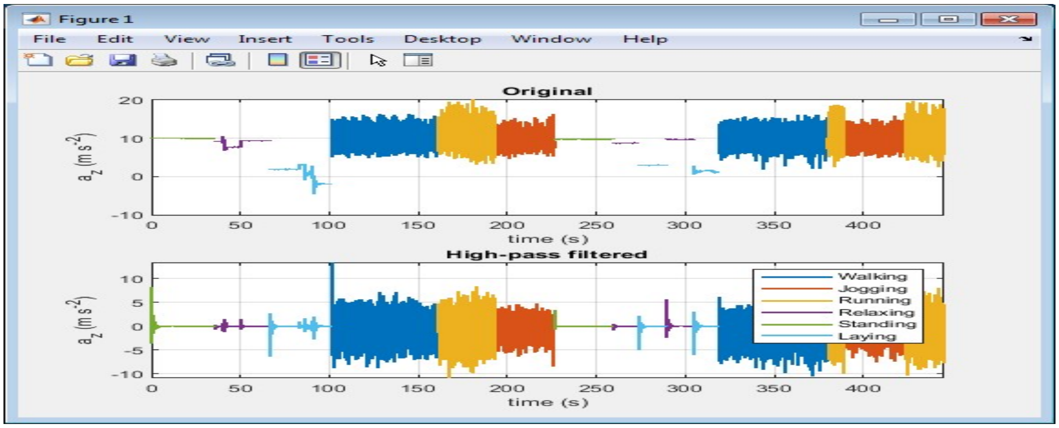

Figure 6: Filter out gravitational acceleration

You should only concentrate on one activity for subject 1: To choose the initial section of the Walking signal, we use logical indexing. You can only choose samples when walking was the activity and the time was under 250 seconds because every action happened at least once during that period. For subject 1, as seen in figure 7, which was obtained from figure 6, walking takes anything between 100 and 160 seconds.

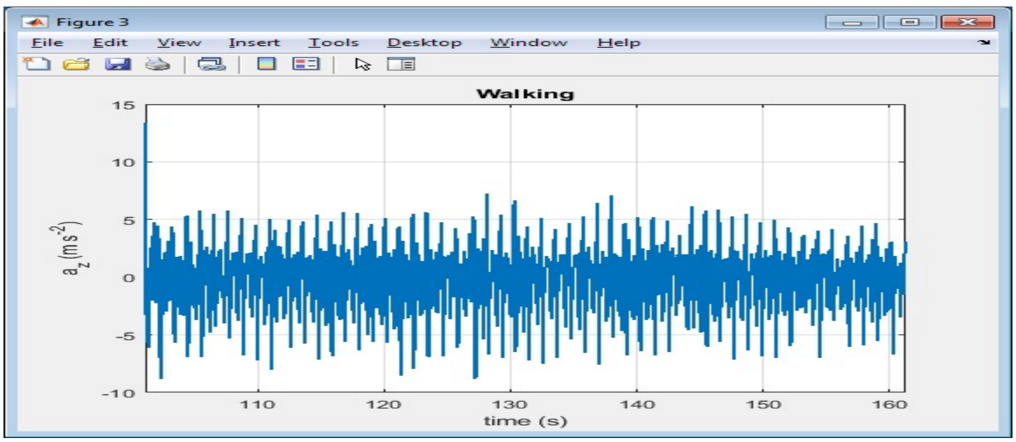

Figure 7: Extracting portion of Walking signal for subject 1.

To individual activity signal segment.With the use of interactive plot tools, we focused in on the signal and looked into it. Seeing the quasi-periodic behaviour is important. A system that displays irregular periodicity is said to have quasiperiodicity. The phrase "periodic behaviour" describes actions that repeat regularly, such as "every set time."A pattern of recurrence with a component of unpredictability that does not lend itself to precise measurement is quasiperiodic behavior.

Welch's Plot Power Spectral Density

The method known as Welch's method, after P.D. Welch, is a method for estimating spectral density. Welch's method, in contrast to Bartlett's and the conventional periodogram spectrum estimation method, sacrifices frequency resolution in favour of a cleaner estimate of power spectra.

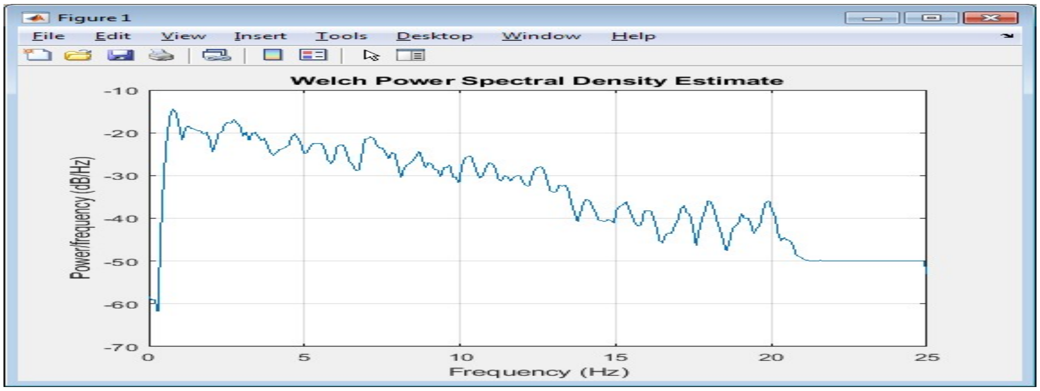

Figure 8:Welch's Plot Power Spectral Density

For topic 1, we applied Welch's Plot Power Spectral Density Comparison PSD to produce more precise forecasts for a variety of activities.

PSD of Walking for all subjects

To verify the consistency of PSD data between participants, compare the Power Spectral Density of walking signals across all subjects in the dataset.

The use of a linear amplitude scale in this helper function allows PSD peaks to visually stand out more.

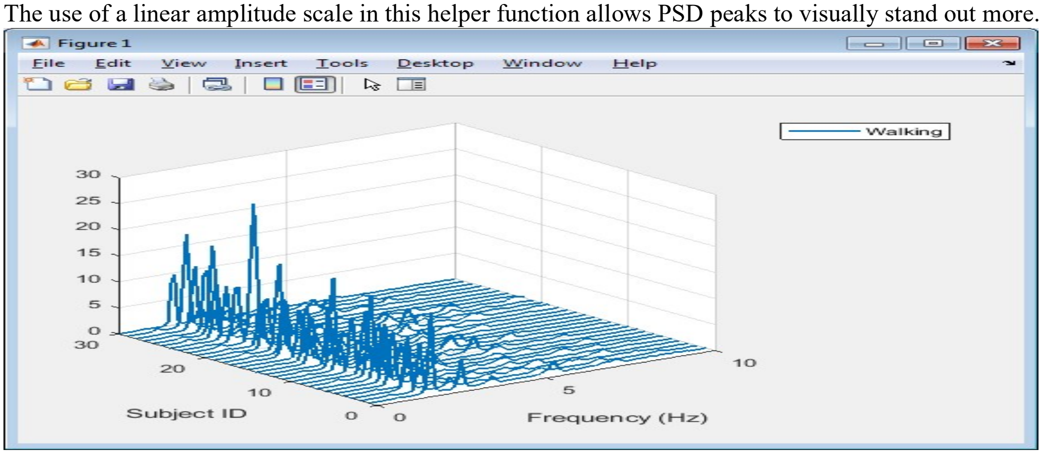

Figure 9: PSD of Walking for all subjects.

Acceleration of all subjects from 1 to 30 varies from $5m/s^2$ to $22m/s^2$ for walking.

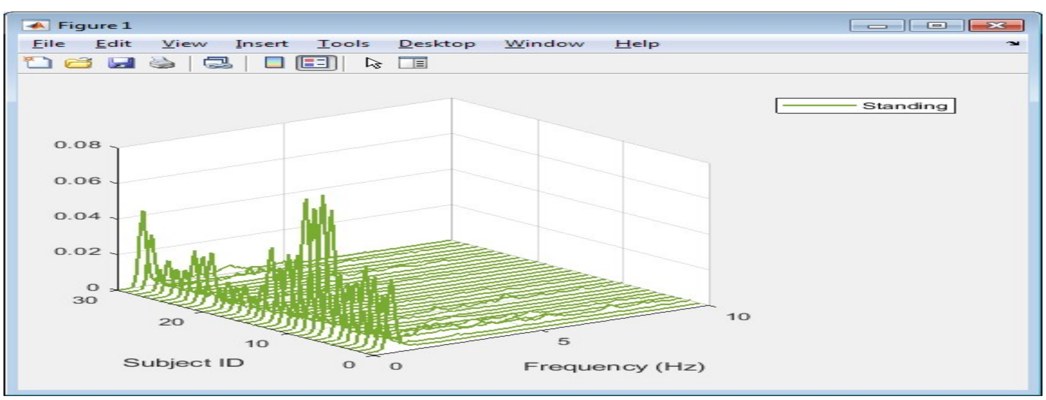

Figure 10:PSD of Standing for all subjects.

Acceleration of all subjects from 1 to 30 varies from $0.01m/s^2$ to $0.04m/s^2$ for standing.

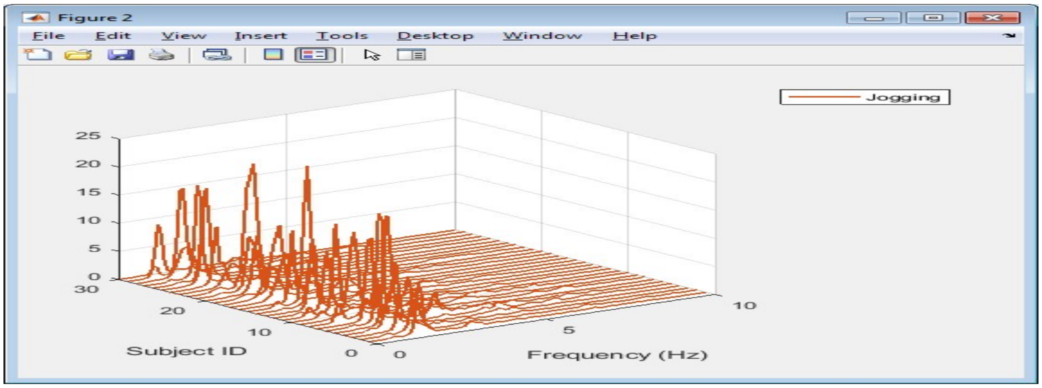

Figure 11: PSD of Joggingfor all subjects.

Acceleration of all subjects from 1 to 30 varies from 5m/s^2 to 17m/s^2 for standing

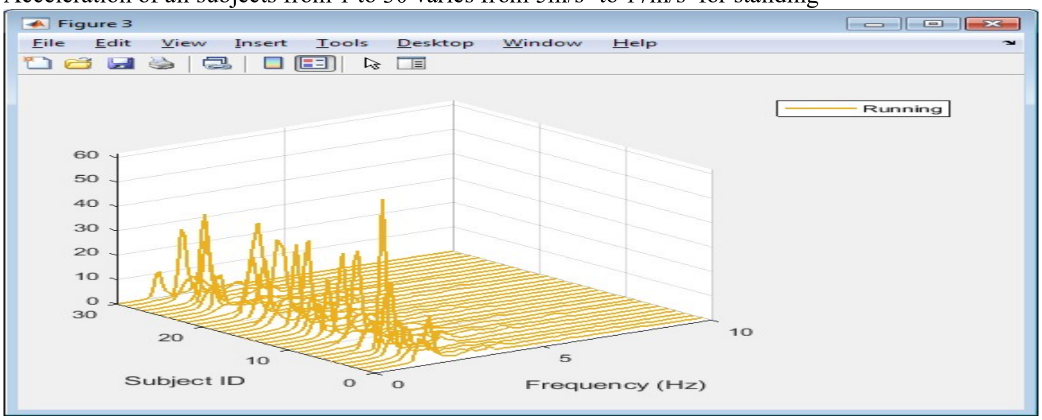

Figure 12: PSD of Running for all subjects.

Acceleration of all subjects from 1 to 30 varies from 10m/s^2 to 35m/s^2 for standing

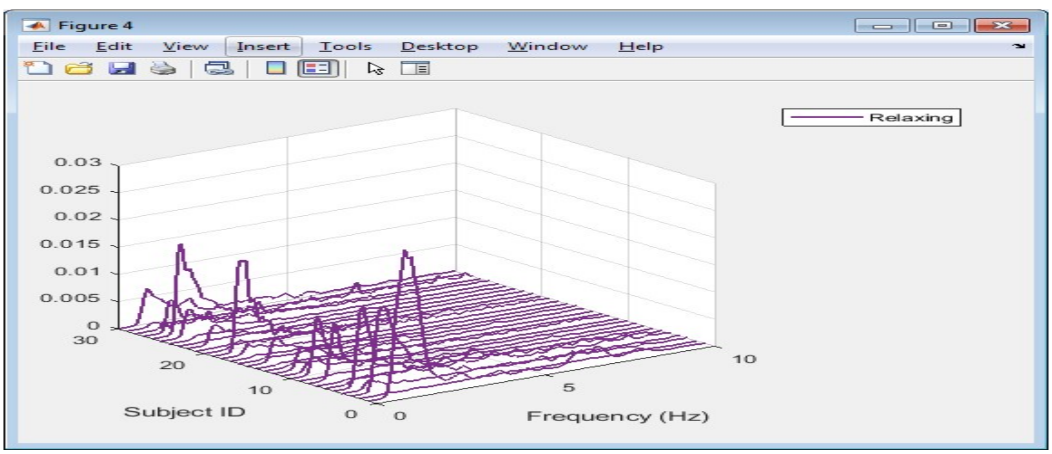

Figure 13:PSD of Relaxing for all subjects.

Acceleration of all subjects from 1 to 30 varies from 0.005m/s^2 to 0.01m/s^2 for Relaxing and from 0.02m/s^2 to 0.04m/s^2 for laying

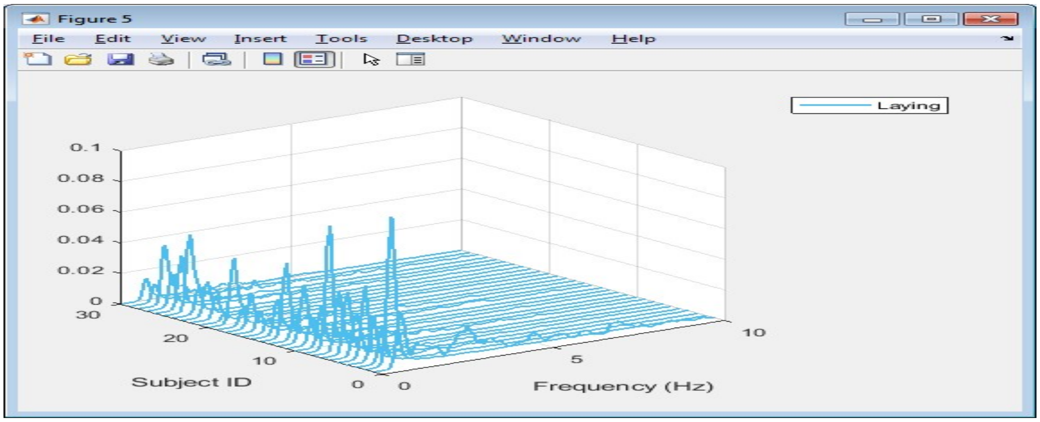

Figure 14: PSD of Laying for all subjects.

Automate peak identification

The magnitude and location of spectral peaks can be found using the Signal Processing Toolbox function locate peaks. To calculate the PSD and frequency vector's numerical values. The function p welch does not automatically plot the PSD when it receives only one or two output arguments.

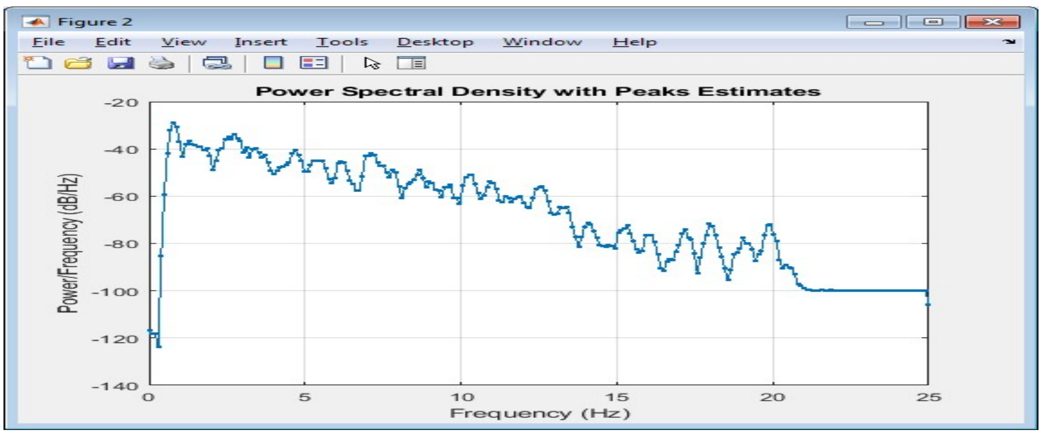

Figure 15: Automate peak identification for walking

By identifying peaks of signal, the predication accuracy will increase.

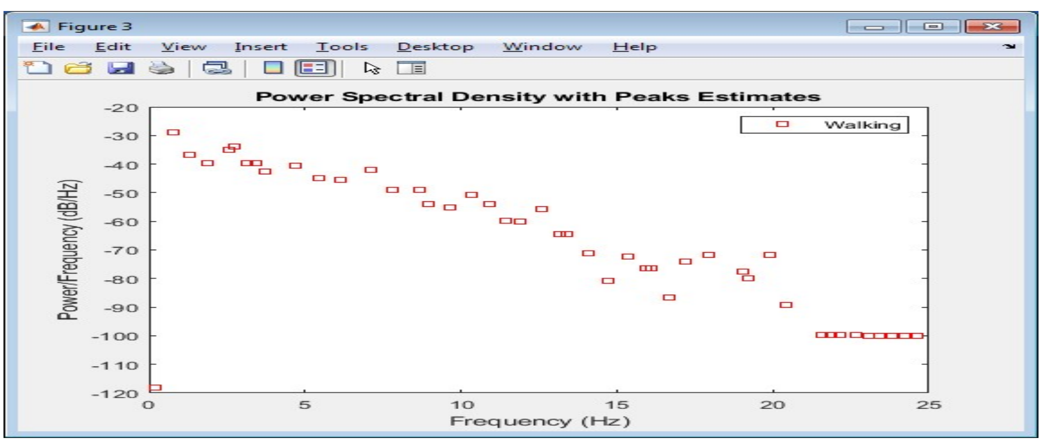

Figure 16: Peaks of walking Signal

Autocorrelation as a feature

Frequency estimation benefits from the use of autocorrelation as well. It works particularly well for estimating low-pitch fundamental frequencies because it will compute the autocorrelation using just one input.

Draw attention to the primary t=0 peak (total energy) and a few auxiliary peaks. The primary period is determined by the location of the second-highest peaks.

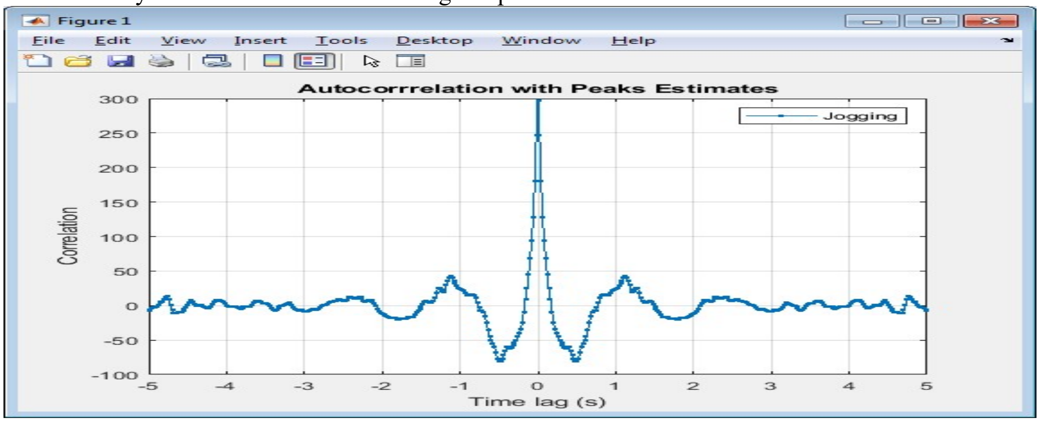

Figure 17: Peak estimation and Autocorrection of jogging

We may combine all the analysis strategies identified into a single function after interactively examining a few different techniques to extract descriptive characteristics from this kind of signals. This function's task is to extract a predetermined amount of characteristics for each input signal buffer.
Deep Learning

Using deep learning we want to predicate more accurately and for all subjects and for all activity at same time.

Figure 18: Walking Comparison

Walking values comparison is shown in figure 18. The acceleration change is shown from 5 to 15 m/s2 but avg is nearly 10m/s2 but it is varying.

Using a visual and qualitative approach, we previously evaluated the prediction function of our trained neural network.
A classification algorithm's performance would typically be evaluated quantitatively by measuring the predictions throughout the entire test dataset and comparing them to the known class values.

There are several alternative ways to visually depict the final forecast performance. We have the confusion matrix down below. The cumulative prediction results for all couplings between actual and predicted classes are compiled into the confusion matrix, which is a square matrix.

Often, it is wise to utilise a test set that is distinct from the training set. By doing this, it is made sure that the results are not skewed by the specific training dataset.

Deep learning high pass filter power spectral density with peak estimation and autocorrelation was used to increase the estimated values' accuracy.

The gathered data shows that human activity detection using a smartphone's sensors is successful, with some activities' accuracy reaching values as high as 100%. Some activities are harder to distinguish because of their similarity. Running and jogging, which are commonly confused with one another and even with walking, fit this description. Nonetheless, the suggested method also effectively detects these actions, albeit with a somewhat higher error rate. We also find that the suggested strategy is easily adaptable after testing it against two datasets.

V.CONCLUSION

We have described the basic architectural framework for developing human activity detection systems and have concentrated on design factors, such as sensor choice, intrusiveness, flexibility, etc., that are individually evaluated based on the system type being developed. The study continues by highlighting the importance of selecting important data elements and provides a quantitative analysis of the metrics for accuracy and execution time. When used on raw signal data, recurrent neural networks can achieve accuracy comparable to other classification models based on manually constructed features. The complexity or additional network layers would increase the recognition accuracy of the deep learning algorithm.

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