Human Activity Recognition using the Data From Inertial Measurement Units

Aman Mishra

Department Of Computer Science, National Institute of Technology, Ichchhanath Surat - Dumas Rd, Gujarat 395007

Dr. Chetan Singh Thakur

Department Of Electronic Systems Engineering, Indian Institute of Science, Bangalore, CV Raman Rd, Bengaluru, Karnataka 560012

Table of Contents

Human Activity Recognition using the Data From Inertial Measurement Units

Aman Mishra

Department Of Computer Science, National Institute of Technology, Ichchhanath Surat - Dumas Rd, Gujarat 395007

Dr. Chetan Singh Thakur

Department Of Electronic Systems Engineering, Indian Institute of Science, Bangalore, CV Raman Rd, Bengaluru, Karnataka 560012

Abstract

Inertial measurement units namely IMU sensors are widely used to gain data regarding human activities. These sensors provide us with the data regarding the motion of the body in the form of different sensor readings like accelerometer, gyroscope, magnetometer and may be more. This data is utilized in applications like determining direction in GPS system, head motion in AR/VR systems and even in medical applications to detect Parkinson's disease by observing strange body motion of the affected person. This paper employs the use of raw data collected from 6 degree of freedom IMU sensor that comprises of accelerometer and gyroscope in order to predict certain human activities. There are in total 12 different physical human activities taken into account here. The raw data has been taken from University of California's machine learning repository. Information regarding the raw data and experiment conditions can be acquired from their website. Feature extraction makes use of both frequency domain as well as time domain techniques over the given sampled raw data. While frequency domain features have been extracted from the spectrogram of raw data; time domain features include parameters like variance, kurtosis, skewedness, mean etc. Datasets having different number of features have been created and tests have been conducted on each of them separately. In order to overcome the problem of scarcity of data, data augmentation technique of down-sampling by local averaging and shuffling have been utilized. The generated datasets have been tested rigorously on a machine learning algorithms named support vector machines with a one vs rest approach. The results comprising of the training and test accuracy along with the confusion matrix have been provided.

Keywords or phrases:time domain, frequency domain, gyroscopes, accelerometers, physical activities, data augmentation

Abbreviations

The following abbreviations mentioned in table below have been used in this paper:

Abbreviations

STFT	Short Term Fourier Transform
HAR	Human Activity Recognition
IMU	Inertial Measurement Unit
SVM	Support Vector Machine

1 INTRODUCTION

1.1 Background/Rationale

Rapid leads and growth in the field of microelectronic devices has led to the development of wearable sensors that can provide us information regarding the motion of human body. These IMU sensors provide us a variety of information in the form of accelerometer, gyroscope and magnetometer readings. It is due to this large amount of data that we have become capable of using data-driven machine learning and deep learning models in accordance with the problem statement. This data can help us in determining various human activities like walking, sitting, lying etc. as well as detect abnormalities in motion as compared to a healthy person. The sensor-based approach can be used in areas where we cannot use the cameras as they pose a threat to human privacy. Moreover, the computational and storage costs incurred by image processing tasks are quite high as compared to wearable IMU's.

Studies [1] and [2] have clearly shown that deep learning models are able to classify easily human activities ranging from walking , running , climbing upstairs or downstairs , sitting and many others but at the same time there are also studies [2] suggesting that activities like sitting, standing, lying down that produce a relatively stationary data are difficult to distinguish amongst each other. Thus, a proper feature extraction approach forms an important part for our deep learning or machine learning algorithms to provide us with promising results.

1.2 Objectives of the Research

Following is the major objective of the project:

- To get state of the art accuracy for HAR using the data from a 6 degree of freedom IMU having accelerometer and gyroscope.

1.3 Scope

The task of HAR can help change the way our healthcare system works. Ageing population forms a major part of our society. To keep them in check under the cameras all the time is not a feasible option and also a violation of privacy. For instance, if an elderly person falls while bathing then the cameras are of no use and at that time this sensor-based system can help in getting the required medical assistance. Also, this system can help people having disabilities, mental as well as physical. Parkinsons Disease is one of the medical ailments where this sensor based HAR can be utilized. Parkinsons Disease is a progressive nervous system disorder that affects movement. Symptoms start gradually, sometimes starting with a barely noticeable tremor in just one hand. Tremors are common, but the disorder also commonly causes stiffness or slowing of movement. These strange motion patterns can be detected using this sensor based system prematurely.

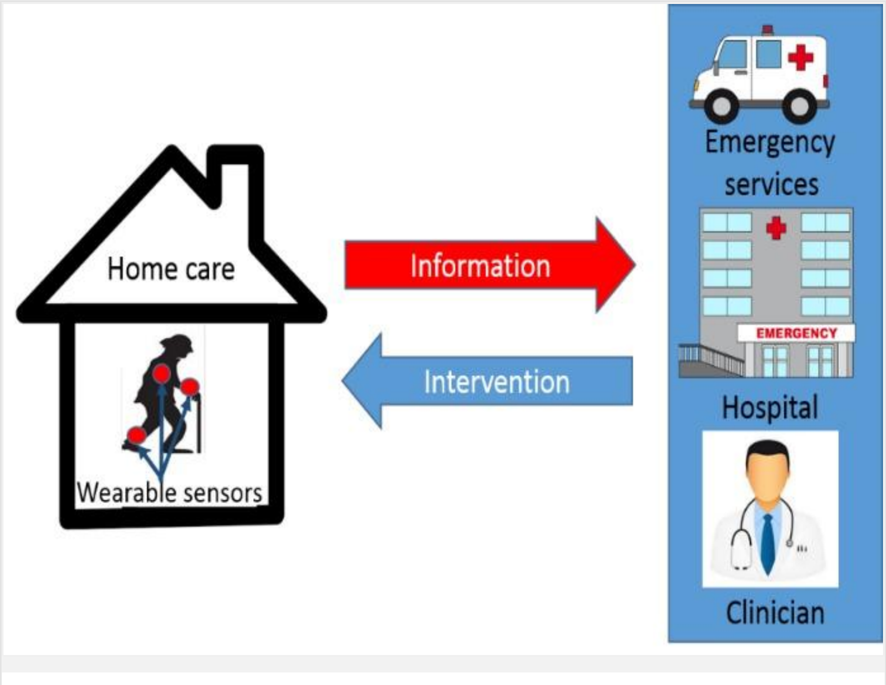

Fig 1 Elderly Health Monitoring System

Along, with all this nowadays there are various fitness apps that have been seamlessly integrated with various mobile sensors and collect the data and do the required mathematical analysis to provide us with various body assessment parameters [3] . It may be the distance you ran today or the count of your push ups or distance you covered while cycling. In [4] , a data analysis tool called SwimMaster was developed with the capability of identifying the swimming style, swimming stroke counter, body balance and rotation. Inertial sensors were mounted on the swimmers' upper arm, the lower back and the right wrist for data collection purposes. The sensor based systems have now become an integral part of sport sector where they are widely used to analyze an athlete's fitness. Thus, it is quite evident that development in this area holds a great future.

2 LITERATURE REVIEW

There are in particular two major problems that come in the way when designing HAR based sensor systems. These have been discussed in the next two sections in detail.

2.1 Sensor Placement

A major concern regarding HAR is the placement of sensor on human body since we get different data according to the placement of the sensor and henceforth our machine learning or deep learning model will depend on sensor placement. Along with the placement of sensor, it is also necessary that the sensor is firmly confined to its position. Displacement or vibration of sensor from desired location may incur noise that tend to affect the accuracy of our machine learning model. Fig. 3 denotes the various positions where IMU can be placed on body.

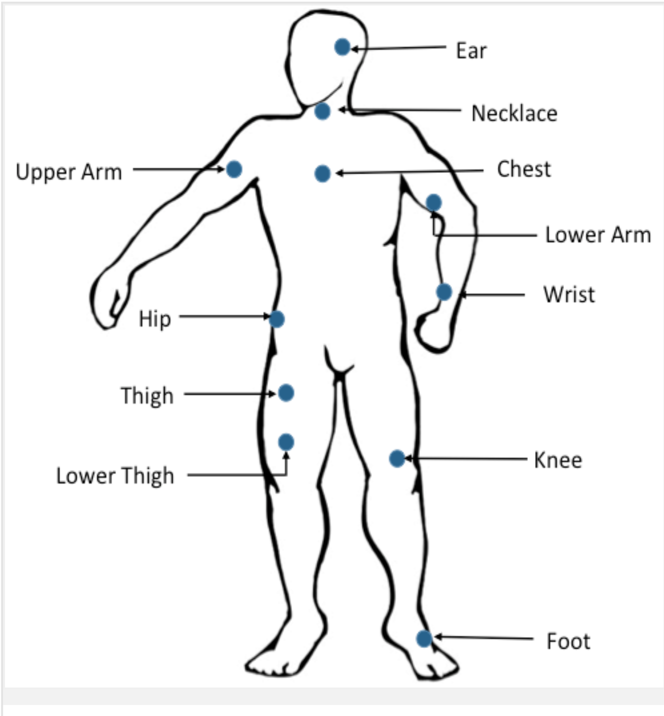

Fig 2 Different locations where sensor can be placed [5]

Various studies have been conducted regarding sensor placements for HAR. But all this majorly boils down to the activities that we are trying to classify. The following table taken from [5] gives us an idea about the placement of accelerometers only for basic human activities classification.

Table 1 Review of studies on placement of accelerometers

Ref.	Sensor Placement	Detected Activities	Accuracy %
[6]	Waist	Walking,Falling	90.8
[7]	Waist	Falling,Walking,Sitting,Standing,Lying	98.9
[8]	Wrist	Walking,Running,Scrubbing,Standing,PC work,Vacuuming,Brushing Teeth	95
[9]	Thigh,Necklace,Wrists	Typing,Watching TV,Drinking,Stairs Ascent and Descent	91.5
[10]	Wrist,Chest	Lying,Sitting,Walking,Rowing,Cycling	83.3
[11]	Wrist,Chest,Hip	Sitting,Running,Walking,Standing,Lying,Crawling	92.13
[12]	Lower Back	Lying,Sitting,Standing,Working on PC,Walking,Running,Cycling	93
[13]	Thigh, Waist	Sitting,Lying,Standing,Walking Speed	100
[14]	Thigh,Trunk	Sitting,Standing,Lying,Moving	92.25
[15]	Trunks,Shanks	14 daily living activities	-

It is quite obvious that making use of multiple sensors placed at different position for classification tends to give much higher accuracy rates but still it becomes cumbersome for the person concerned. Moreover, it also poses a problem regarding privacy. Efforts are continuously being made to integrate these sensors into clothing but still there are issues regarding unwanted noise incurred due to sensor displacement relative to human body. With the advent of rapid development in mobile technology it has now become possible to collect data regarding human activity from inertial sensors present in mobile devices. Recently, many systems have been proposed to recognize daily human activities using data acquired from mobile phones [2] [16] . Also, wrist watches are now also being considered as a source of data for HAR.

2.2 Data Pre-Processing

Data pre-processing forms an important part of any machine learning problem. Rather then feeding large amount of raw data to a machine learning algorithm and increase its computational complexity to detect the hidden pattern; it is necessary that we feed to it the data that does makes sense. The process of feature extraction involves the reduction of large amount of raw data to a collection of fixed small feature vectors such that these vectors can represent the information that the raw data holds. Feature vectors corresponding to different labels tend to hold a distinctiveness that our machine learning model can detect and hence make accurate classifications for different classes. Following table shows various parameters taken into consideration in different studies.

Table 2 Some widely used features as discussed in [17]

Type	Features	Applications
Time-Domain	Mean,variance, standard deviation,root mean square ,zero crossing rate,derivative,peak counts	HAR,speech recognition
Frequency-Domain	Discrete fast fourier transforms coefficient,spectral energy	HAR
Time frequency domain	Wavelet coefficients	Blink detection

Multiple approaches have been employed in this paper. These include:

1. Taking least and greatest values from spectral data obtained from STFT of the raw data [17] .

2. Taking the above mentioned spectral data along with the time domain features mentioned in [5] to generate the featadsfure vector.

3. Making use of only time domain features mentioned in [5] to generate feature vector.

After feature extraction comes data augmentation.In [18] , a sizeable number of data augmentation methods for time series data are mentioned and implemented. These include as said in [17] :

(1) Rotations: To cater for multiple sensor placement scenarios which represent the same label, controlled data rotation may offer generalization ability of such unseen data. An example of such a scenario is when a sensor is placed upside down compared to its normal position during collection of training data.

(2) Permutation: This is a method to perturb the temporal location of with-in window events. To perturb the location of data in a single window, the data are first sliced into N same length segments. The segments are then randomly permutated to create a new window.

(3) Time-warping: Is another approach used to perturb the temporal location of data. This is done by smoothly distorting the time intervals between samples. This is like time scale modification (TSM) whereby the window can be compressed by reducing the time interval of samples or extended by increasing on the time interval between samples.

(4) Scaling: This approach involves changing the magnitude of the data in a window by applying a random scalar.

(5) Magnitude-warping: Involves changing the magnitude of each sample by convolving the data window with a smooth curve varying around one.

(6) Jittering: Involves including additive sensor noise.

Here in this paper we make use of the data-augmentation technique as described in [17] which comprise of local averaging by down sampling followed by shuffling. The details regarding data augmentation and feature extraction have been covered in the next section.

3 METHODOLOGY

3.1 About the data

The raw data has been collected from University Of California's online machine learning repository [19] . The data comprises of the raw accelerometer and gyroscope readings of 12 different human activities. These activities are :

1. Walking (W)

2. Walking–Upstairs (WU)

3. Walking – Downstairs (WD)

4. Sitting (SI)

5. Standing (ST)

6. Laying (LA)

7. Stand to Sit (STSI)

8. Sit to Stand (SIST)

9. Sit to Lie (SILA)

10. Lie to Sit (LASI)

11. Stand to Lie (STLA)

12. Lie to Stand (LAST)

The raw feature data comes from the accelerometer and gyroscope 3-axial raw signals tAcc-XYZ and tGyro-XYZ (t denotes time). These time domain signals were captured at a constant rate of 50 Hz. Then they were filtered using a median filter and a 3rd order low pass Butterworth filter with a corner frequency of 20 Hz to remove noise. The details of the experiment involving data collection can be found at University Of California’s online machine learning repository.

From this raw data, we have prepared three different datasets using the three feature extraction approaches as mentioned earlier. Results comprising of all the three datasets have been presented separately.

3.2 Feature Extraction And Data Augmentation

Here we have made dataset using three different approaches. Each one of them is explained separately.

3.2.1 Frequency Domain features only

This makes use of the approach described in [17] . Fig. 4 shows the process to be followed . In order to generate the spectral data we make use of the STFT. Mathematically, it is:

$$STFT\{k[n]\}(m,\omega) = \sum_{n=-\infty}^{\infty} k[n]W[n-m]e^{-j\omega n} \quad (1)$$

Here the window function used is Hann window since it removes the noise at the ends of each window. It is important to note that consecutive windows are 50% overlapped with each other so as to generate continuous spectrogram features. The number of datapoints taken in each block is 512 with a sampling frequency of 50 Hz. The spectrogram can now be obtained by squaring each of the resulting STFT terms. The spectral data of each of the 3 dimension is then combined and sorted in accordance of its magnitude. Then from this, we select S least and L greatest values. This process is done for both accelerometer and gyroscope readings and in the end we get a feature vector having 2*(S + L) features. Here S and L are selected at random. In this paper we have tried with 3 different values with S being equal to L. They are 15,25 and 50.

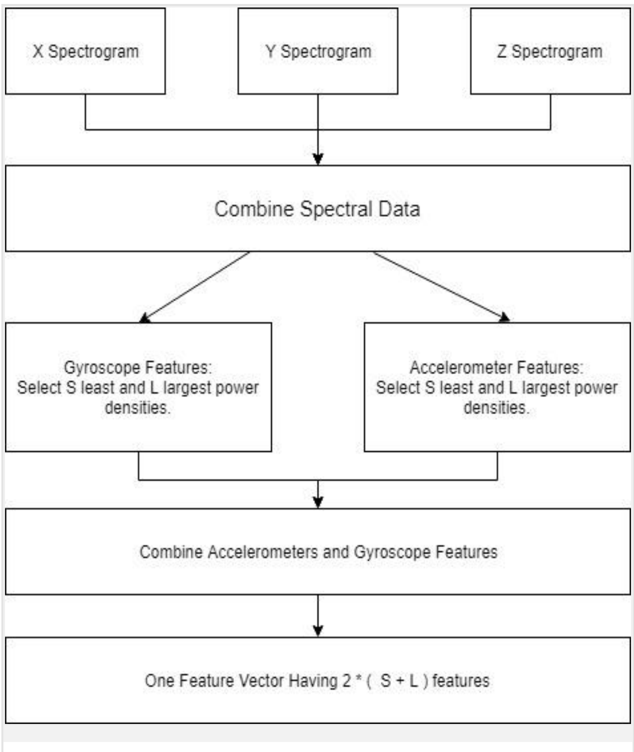

Fig 3 Feature Extraction process [17]

From the spectrogram raw information we can generate features using convolution [1] but this process adds a larger latency in real time systems as compared to least and largest values selection approach. By carefully setting S and L we can still obtain good results without having to add latency in the system.

After feature extraction, the data is augmented using the process described in [17] . Fig. 5 gives the overview of the process. For each of the 12 different classes, the spectral data is taken and then is locally averaged by a sliding window of size 4. This downsampled data is combined with the spectral features and then shuffled to form set 2. On set 2 another local averaging is done with a window size of 2 and the locally averaged data is again combined to form set 3. It is important to note that since we are doing averaging of our dataset on each step of the augmentation process, our dataset tends to shift towards mean and hence the chances of overfitting the dataset by out machine learning model is greatly reduced. Moreover, the issue of small dataset is also resolved.

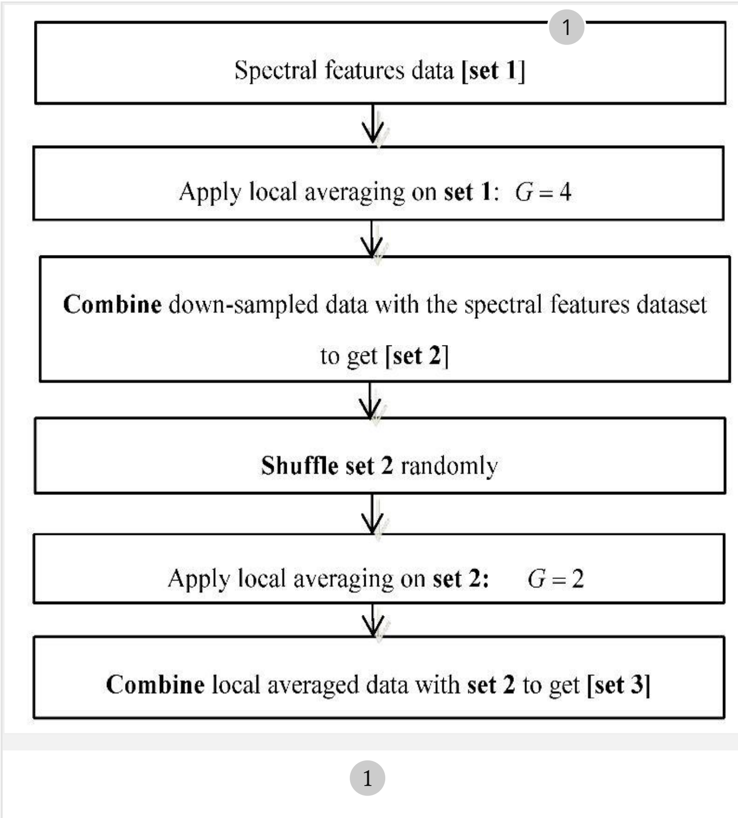

Fig 4 Overview of Data Augmentation [17]

Following the above process, 3 datasets having 60(S = L = 15), 100(S = L = 25) and 200(S = L = 50) features respectively were prepared.

3.2.2 Time And Frequency Domain features

Here we prepare the dataset using the same process as described in section 3.2.1 but we also include some time domain features along with the spectral features as said in [5] for each of the sliding window .These include :

1. Mean
2. Variance
3. Root Mean Square
4. Range
5. Skewness
6. Median
7. Kurtosis
8. Peak to Peak
9. Interquartile Range
10. Crest Factor

Since there are in total 6 different components (3 of gyroscope and 3 of accelerometer) and 10 different parameters, therfore a total of 60 new features get added. Here, we prepared the dataset comprising of 60 frequency domain features and 60 time domain features and hence a 120 feature dataset.

3.2.3 Time Domain Features only

Here we prepare the dataset just by taking certain time domain parameters for each of the sliding window without taking the spectral features as mentioned in section 3.2.1 . Here the following time domain parameters are taken:

1. Mean
2. Variance
3. Median
4. Peak to Peak
5. Root Mean Square

Using these parameters, a 30 feature time domain dataset is prepared.

4 RESULTS

The different datasets prepared in section 3.2 is classified using One Vs Rest approach with an SVM with both linear and R.B.F. (Radial Basis Function) kernel . The train-test accuracies along with the confusion matrix have been presented in this paper. The train-test split is 90 : 10 .

Linear Kernel Equation:

$$k(x_i, x_j) = x_i . x_j \tag{2}$$

Gaussian Radial Basis Function Equation:

$$k(x_i, x_j) = exp(-\gamma || \; x_i \; - \; x_j \; ||^2) \; , \; \gamma > 0 \tag{3}$$

4.1 Frequency domain Features

4.1.1 60 Feature Dataset

- **Linear Kernel**

Train Accuracy = 80.9 %

Test Accuracy = 78.7 %

Table 3 Confusion Matrix

	W	WU	WD	SI	ST	LA	STSI	SIST	SILA	LASI	STLA	LAST
W	79	6	1	0	0	0	0	0	0	0	0	0
WU	7	40	3	0	0	0	1	0	0	0	0	0
WD	3	2	45	0	0	0	0	0	0	0	0	0
SI	0	0	0	65	21	6	0	0	0	0	0	0
ST	0	0	0	7	124	2	0	0	0	0	0	0
LA	0	0	0	27	30	46	0	0	0	0	0	0
STSI	0	2	0	0	0	0	13	1	0	0	0	0
SIST	0	0	0	0	0	0	1	7	0	0	0	0
SILA	0	0	0	0	0	0	0	0	9	1	0	0
LASI	0	0	0	0	0	0	0	0	0	16	0	0
STLA	0	0	0	0	0	0	1	0	2	0	16	3
LAST	0	0	0	0	0	0	0	0	1	0	1	18

- **RBF Kernel**

Train Accuracy = 79.0 %

Test Accuracy = 74.7 %

Table 4 Confusion Matrix

	W	WU	WD	SI	ST	LA	STSI	SIST	SILA	LASI	STLA	LAST
W	82	2	2	0	0	0	0	0	0	0	0	0
WU	5	41	3	0	0	0	0	2	0	0	0	0
WD	3	1	46	0	0	0	0	0	0	0	0	0
SI	0	0	0	47	39	6	0	0	0	0	0	0
ST	0	0	0	4	129	0	0	0	0	0	0	0
LA	0	0	0	28	49	26	0	0	0	0	0	0
STSI	0	1	0	0	0	0	14	1	0	0	0	0
SIST	0	1	0	0	0	0	0	7	0	0	0	0
SILA	0	0	0	0	0	0	0	0	10	0	0	0

LASI	0	0	0	0	0	0	0	0	0	15	1	0
STLA	0	0	0	0	0	0	0	0	1	0	20	1
LAST	0	0	2	0	0	0	0	0	1	0	0	17

4.1.2 100 Feature Dataset

- **Linear Kernel**

Train Accuracy = 82.5 %

Test Accuracy = 77.1 %

Table 5 Confusion Matrix

	W	WU	WD	SI	ST	LA	STSI	SIST	SILA	LAST	STLA	LAST
W	145	15	9	0	0	0	0	0	0	0	0	0
WU	6	100	1	0	0	0	1	0	0	0	0	0
WD	6	7	85	0	0	0	0	0	0	0	0	0
SI	0	0	0	111	59	10	0	0	0	0	0	0
ST	0	0	0	21	200	9	0	0	0	0	0	0
LA	0	0	0	46	58	99	0	0	0	0	0	0
STSI	0	4	0	0	0	1	30	0	0	0	0	0
SIST	1	0	0	0	0	0	0	31	0	0	0	0
SILA	0	0	0	0	0	0	0	0	36	1	1	1
LASI	0	0	0	0	0	0	1	0	1	33	1	0
STLA	0	0	0	0	0	0	1	0	3	3	41	3
LAST	0	0	0	0	0	0	0	0	1	2	5	25

- **RBF Kernel**

Train Accuracy = 79.4 %

Test Accuracy = 75.0 %

Table 6 Confusion Matrix

	W	WU	WD	SI	ST	LA	STSI	SIST	SILAt	LASI	STLA	LAST
W	158	8	3	0	0	0	0	0	0	0	0	0
WU	5	99	3	0	0	0	1	0	0	0	0	0
WD	2	2	94	0	0	0	0	0	0	0	0	0
SI	0	0	0	81	82	17	0	0	0	0	0	0
ST	0	0	1	13	208	8	0	0	0	0	0	0
LA	0	0	0	43	85	75	0	0	0	0	0	0
STSI	0	1	3	1	0	0	30	0	0	0	0	0
SIST	1	1	0	0	0	0	0	30	0	0	0	0
SILA	0	0	2	0	0	0	0	0	33	1	0	3
LASI	0	0	1	0	0	0	0	0	4	29	0	2
STLA	0	0	2	0	0	0	1	0	1	2	45	0
LAST	0	0	0	0	0	0	0	0	1	1	2	29

4.1.3 200 Feature Dataset

- **Linear Kernel**

Train Accuracy = 86.4 %

Test Accuracy = 82.2 %

Table 7 Confusion Matrix

	W	WU	WD	SI	ST	LA	STSI	SIST	SILA	LASI	STLA	LAST
W	189	6	1	0	0	0	0	0	0	0	0	0
WU	5	109	1	0	0	0	0	0	0	0	0	0
WD	4	6	97	0	0	0	0	0	0	0	0	0
SI	0	0	0	112	52	10	0	0	0	0	0	0
ST	0	0	0	7	210	8	0	0	0	0	0	0
LA	0	0	0	44	51	112	0	0	0	0	0	0

STSI	0	4	1	0	0	0	26	0	0	0	0	0
SIST	0	0	0	0	0	0	1	17	0	0	0	0
SILA	0	0	0	0	0	0	0	0	30	0	3	1
LASI	0	0	0	0	0	0	1	0	1	28	0	0
STLA	0	0	0	0	0	0	3	0	1	0	35	0
LAST	0	0	0	0	0	0	0	0	3	1	0	34

- **RBF Kernel**

Train Accuracy = 86.4 %

Test Accuracy = 80.3 %

Table 8 Confusion Matrix

	W	WU	WD	SI	ST	LA	STSI	SIST	SILA	LASI	STLA	LAST
W	194	1	1	0	0	0	0	0	0	0	0	0
WU	6	104	5	0	0	0	0	0	0	0	0	0
WD	0	4	103	0	0	0	0	0	0	0	0	0
SI	0	0	2	113	47	12	0	0	0	0	0	0
ST	1	0	1	13	203	7	0	0	0	0	0	0
LA	0	0	1	47	46	113	0	0	0	0	0	0
STSI	0	1	1	0	0	0	29	0	0	0	0	0
SIST	1	0	0	0	0	0	1	16	0	0	0	0
SILA	0	0	7	0	0	0	0	0	26	0	0	0
LASI	0	0	1	0	0	0	0	1	4	24	0	0
STLA	0	0	6	0	0	0	2	0	0	1	30	0
LAST	0	0	8	0	0	0	0	0	2	4	3	21

4.2 Frequency And Time Domain Features

4.2.1 120 Feature Dataset

- **Linear Kernel**

Train Accuracy = 99.9 %

Test Accuracy = 99.2 %

Table 9 Confusion Matrix

	W	WU	WD	SI	ST	LA	STSI	SIST	SILA	LASI	STLA	LAST
W	99	0	0	0	0	0	0	0	0	0	0	0
WU	0	64	0	0	0	0	0	0	0	0	0	0
WD	0	0	53	0	0	0	0	0	0	0	0	0
SI	0	0	0	95	0	0	0	0	0	0	0	0
ST	0	0	0	2	105	0	0	0	0	0	0	0
LA	0	0	0	0	0	103	0	0	0	0	0	0
STSI	0	0	0	0	0	0	11	0	0	0	0	0
SIST	0	0	0	0	0	0	0	11	0	0	0	0
SILA	0	0	0	0	0	0	0	0	19	0	0	0
LASI	0	0	0	0	0	0	0	0	0	10	0	0
STLA	0	0	0	0	0	0	0	0	0	0	22	0
LAST	0	0	0	0	0	0	0	0	0	0	0	13

- **RBF Kernel**

Train Accuracy = 100 %

Test Accuracy = 98.1 %

Table 10 Confusion Matrix

	W	WU	WD	SI	ST	LA	STSI	SIST	SILA	LASI	STLA	LAST
W	98	0	1	0	0	0	0	0	0	0	0	0
WU	0	64	0	0	0	0	0	0	0	0	0	0
WD	0	0	53	0	0	0	0	0	0	0	0	0
SI	0	0	0	94	0	1	0	0	0	0	0	0
ST	0	0	0	2	104	1	0	0	0	0	0	0
LA	0	0	0	0	0	103	0	0	0	0	0	0
STSI	0	0	0	0	0	1	10	0	0	0	0	0
SIST	0	0	0	0	0	0	0	11	0	0	0	0
SILA	0	0	0	0	0	0	0	0	18	0	1	0
LASI	0	0	0	0	0	1	0	0	0	9	0	0
STLA	0	0	0	0	0	3	0	0	0	0	19	0
LAST	0	0	0	0	0	0	0	0	0	0	0	13

4.3 Time Domain Features

4.3.1 30 Feature Dataset

- **RBF Kernel**

Train Accuracy = 99.1 %

Test Accuracy = 96.1 %

Table 11 Confusion Matrix

	W	WU	WD	SI	ST	LA	STSI	SIST	SILA	LASI	STLA	LAST
W	43	0	2	0	0	0	0	0	0	0	0	0
WU	0	30	0	0	0	0	0	0	0	0	0	0
WD	1	0	22	0	0	0	0	0	0	0	0	0
SI	0	0	0	42	3	0	0	0	0	0	0	0
ST	0	0	0	0	62	0	0	0	0	0	0	0
LA	0	0	0	0	0	50	0	0	0	0	0	0
STSI	0	0	0	0	0	0	9	0	0	0	0	0

SIST	0	0	0	0	0	0	0	8	0	0	0	0
SILA	0	0	0	0	0	0	0	0	8	0	2	0
LASI	0	0	0	0	0	0	0	0	0	10	0	3
STLA	0	0	0	0	0	0	0	0	0	0	9	0
LAST	0	0	0	0	0	0	0	0	0	1	0	3

- **Linear Kernel**

Train Accuracy = 99.6 %

Test Accuracy = 93.8 %

Table 12 Confusion Matrix

	W	WU	WD	SI	ST	LA	STSI	SIST	SILA	LASI	STLA	LAST
W	44	0	1	0	0	0	0	0	0	0	0	0
WU	1	29	0	0	0	0	0	0	0	0	0	0
WD	1	0	22	0	0	0	0	0	0	0	0	0
SI	0	0	0	42	3	0	0	0	0	0	0	0
ST	0	0	0	5	57	0	0	0	0	0	0	0
LA	0	0	0	0	0	50	0	0	0	0	0	0
STSI	0	0	0	0	0	0	9	0	0	0	0	0
SIST	0	0	0	0	0	0	0	8	0	0	0	0
SILA	0	0	0	0	0	0	0	0	8	0	2	5
LASI	0	0	0	0	0	0	0	0	0	8	0	0
STLA	0	0	0	0	0	0	0	0	1	0	8	0
LAST	0	0	0	0	0	0	0	0	0	0	0	4

5 CONCLUSION AND RECOMMENDATIONS

Through this project, we learned the role of different types of feature extraction techniques for HAR. From the confusion matrices, it is quite evident that the combination of frequency and time domain parameters as a feature vector produces much better results than taking either time domain or frequency domain parameters alone. It is also quite clear that classification accuracies can be deceptive as there might exist certain classes that might have been classified with very low accuracies. This factor can be seen in the case of classifying dataset having spectral features only. The confusion matrix shows that classes 4 (Sitting) and 5 (Standing) are getting misclassified majorly as compared to other classes. When considering only the time domain parameters, from the confusion matrix it can be seen that class 12(Lie To Stand) is getting misclassified and has accuracy less then 50% for its classification.

This project can be further extended by making use of other features in the frequency domain rather then taking the spectral features only. Also, multiple sensors can be employed for the data collection rather then using a single sensor as used here. Along, with taking different features we can also make use of deep learning models like RNN which are widely used with continuos time series data

ACKNOWLEDGEMENTS

To start with, I would like to express my sincere gratitude to my guide **Dr. Chetan Singh Thakur** for his excellent guidance, care, patience and providing me with an excellent atmosphere for doing research. I also would like to extend my gratitude to all the Phd. and M.Tech. students especially **Mr. Abhishek Nair** (Phd. student) and **Mr. Sarthak Gupta** (M.Tech second year) for helping me through the various problems I faced during the project as well as giving me an insight on how the higher end research work goes on in IISc.

I am extremely grateful to the **Indian Academy of Sciences** for providing me with an opportunity to work as a fellow in one of the best institutions of our country and making my summer an experience of lifetime.

References

1. Ravì, D.; Wong, C.; Lo, B.; Yang, G.-Z. A deep learning approach to on-node sensor data analytics for mobileor wearable devices. IEEE J. Biomed. Health Inform. 2017, 21, 56–64.
2. Ronao, C.A.; Cho, S.-B. Human activity recognition with smartphone sensors using deep learning neuralnetworks. Expert Syst. Appl. 2016, 59, 235–244.
3. Bruno, B.; Mastrogiovanni, F.; Sgorbissa, A. Wearable inertial sensors: Applications, challenges, and publictest benches. IEEE Robot. Autom. Mag. 2015, 22, 116–124.
4. Bächlin, M.; Förster, K.; Tröster, G. SwimMaster: A wearable assistant for swimmer. In Proceedings of the11th International Conference on Ubiquitous Computing, Orlando, FL, USA, 30 September–3 October 2009;pp. 215–224.
5. Attal F., Mohammed S., Dedabrishvili M., Chamroukhi F., Oukhellou L. Physical human activity recognition using wearable sensors. Sensors.Physical Human Activity Recognition UsingWearable Sensors,
6. Karantonis, D.M.; Narayanan, M.R.; Mathie, M.; Lovell, N.H.; Celler, B.G. Implementation of a real-timehuman movement classifier using a triaxial accelerometer for ambulatory monitoring. IEEE Trans. Inf.Technol. Biomed. 2006, 10, 156–167.
7. Mathie, M.; Celler, B.G.; Lovell, N.H.; Coster, A. Classification of basic daily movements using a triaxialaccelerometer. Med. Biol. Eng. Comput. 2004, 42, 679–687.
8. Yang, J.-Y.; Wang, J.-S.; Chen, Y.-P. Using acceleration measurements for activity recognition: An effectivelearning algorithm for constructing neural classifiers. Pattern Recog. Lett. 2008, 29, 2213–2220.
9. Pirttikangas, S.; Fujinami, K.; Nakajima, T. Feature Selection and Activity Recognition from WearableSensors. In Ubiquitous Computing Systems; Springer: Berlin, Germany, 2006; pp. 516–527.
10. Parkka, J.; Ermes, M.; Korpipaa, P.; Mantyjarvi, J.; Peltola, J.; Korhonen, I. Activity classification usingrealistic data from wearable sensors. IEEE Trans. Inf. Technol. Biomed. 2006, 10, 119–128.
11. Olguın, D.O.; Pentland, A.S. Human activity recognition: Accuracy across common locations for wearablesensors. In Proceedings of 2006 10th IEEE International Symposium on Wearable Computers, Montreux,Switzerland, 11–14 October 2006.
12. Bonomi, A.G.; Goris, A.; Yin, B.; Westerterp, K.R. Detection of type, duration, and intensity of

physicalactivity using an accelerometer. Med. Sci. Sports Exerc. 2009, 41, 1770–1777.

13. Yeoh, W.-S.; Pek, I.; Yong, Y.-H.; Chen, X.; Waluyo, A.B. Ambulatory monitoring of human posture andwalking speed using wearable accelerometer sensors. In Proceedings of the Engineering in Medicineand Biology Society, 2008 EMBS 30th Annual International Conference of the IEEE, Vancouver, BC, USA,20–25 August 2008; pp. 5184–5187.
14. Lyons, G.; Culhane, K.; Hilton, D.; Grace, P.; Lyons, D. A description of an accelerometer-based mobilitymonitoring technique. Med. Eng. Phys. 2005, 27, 497–504.
15. Salarian, A.; Russmann, H.; Vingerhoets, F.J.; Burkhard, P.R.; Aminian, K. Ambulatory monitoring ofphysical activities in patients with Parkinson's disease. IEEE Trans. Biomed. Eng. 2007, 54, 2296–2299.
16. Bayat, A.; Pomplun, M.; Tran, D.A. A Study on Human Activity Recognition Using Accelerometer Datafrom Smartphones. Proced. Comput. Sci. 2014, 34, 450–457.
17. Odongo S. E.; Dong Seog Han,Feature Representation and Data Augmentation forHuman Activity Classification Based on WearableIMU Sensor Data Using a Deep LSTMNeural Network
18. Um, T.T.; Pfister, F.M.J.; Pichler, D.; Endo, S.; Lang, M.; Hirche, S.; Fietzek, U.; Kuli´c, D. Data Augmentationof Wearable Sensor Data for Parkinson’s Disease Monitoring using Convolutional Neural Networks.In Proceedings of the 19th ACM International Conference on Multimodal Interaction, Glasgow, UK,13–17 November 2017.
19. http://archive.ics.uci.edu/ml/datasets/Smartphone-Based+Recognition+of+Human+Activities+and+Postural+Transitions

Source

1. Fig 2: Odongo S. E.; Dong Seog Han,Feature Representation and Data Augmentation for Human Activity Classification Based on Wearable IMU Sensor Data Using a Deep LSTM Neural Network
2. Fig 3: Odongo S. E.; Dong Seog Han,Feature Representation and Data Augmentation for Human Activity Classification Based on Wearable IMU Sensor Data Using a Deep LSTM Neural Network
3. Fig 4: Odongo S. E.; Dong Seog Han,Feature Representation and Data Augmentation for Human Activity Classification Based on Wearable IMU Sensor Data Using a Deep LSTM Neural Network