High-Resolution Image Reconstruction Array of Based on Low-Resolution Infrared Sensor

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Abstract. As the time is progressing the number of wireless devices around us is increasing, making Wi-Fi availability more and more vibrant in our surroundings. Wi-Fi sensing is becoming more and more popular as it does not raise privacy concerns in compare to a camera based approach and also our subject (human) doesn't have to be in any special environment or wear any special devices (sensors).

Our goal is to use Wi-Fi signal data obtained using commodity Wi-Fi for human activity recognition. Our method for addressing this problem involves capturing Wi-Fi signals data and using different digital signal processing techniques. First we do noise reduction of our sample data by using Hampel filter then we convert our data from frequency domain into time domain for temporal analysis. After this we use the scalogram representation and apply the above mentioned steps to all our data in terms of sub carriers. Finally we use those sub carriers in combined for one activity sample as all the sub carriers combined form up an activity so we shall use the combined signal in the form of power spectrum image as input for the neural network.

We choose Alexnet for classification of our data. Before feeding our data into pre-trained CNN for training we first divided the data into two portions first for training which is 85% secondly for validation which is 15%. It took almost 18 h on single CPU and finally achieved an accuracy of above 90%.

Keywords: Wi-Fi sensing · Human activity recognition · CSI · CNN

1 Introduction

Human activity recognition in digital signal processing has become a subject of great importance in research community especially in recent few years with the advancement of technology. These days more and more new methods are discovered and studied to achieve the goal of Human activity recognition as it has diverse range of applications in law in order, security, health, and many other fields. There have been many methods used for HAR (human activity recognition), human counting, localization, gesture recognition, human identification, respiration monitoring, heart rate monitoring which

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required some wearable sensors for the subject or cameras, which require certain conditions to work but in recent times radio frequency signals have been used for sensing purposes and performs the above mentioned tasks with the help of these radio signals. In this paper we will study the classification of human activity recognition. The reason we are motivated to use Wi-Fi/RF signals for sensing purposes is that it does not require any wearable sensors or special systems to deploy with extra cost. Cameras are not that good solution anymore as they require line of sight (LOS) with good light conditions to give a good result also it raises many privacy. There are other sensing techniques like ultrasound, radar and vision techniques but normally they are quite expensive need specialized equipment and environment sometimes while mentioned before with Wi-Fi/RF signals we don't need our subject (Human) to wear any sensors or be in a special environment rather our goal of human activity recognition can be achieved with off the shelf commodity Wi-Fi router that are easily available in markets so that the human does not need to wear sensors like gyroscope, accelerometer etc.

In this work, we have exploited Wi-Fi-CSI data for Human activity recognition we did theoretical and experimental work with CSI data in our lab to demonstrate that commodity Wi-Fi can be used for human activity recognition with very high precision. We shall use 5 sample activity classes for our research case. We will take data sample of an activity using the Wi-Fi (MIMO) along with its Orthogonal Frequency-Division Multiplexing (OFDM) making different sub carriers and later make use of different digital processing techniques to extract a refined signal that we shall use as input for our neural network to train our network for the classification of these activities. Our results from the use of neural networks indicate very high accuracy of above 90% in terms of classifying human activity. This would make it possible to use this research in remote healthcare, surveillance and more with no special environment or deployment of specialized equipment.

2 Related Work

In recent times more and more work has been carried out on activity recognition [1–3] using radio frequency signals such as Wi-Fi signals. Wi-Fi-CSI has been hot source for Wi-Fi sensing these days as it has many benefits over the traditional systems. These are few papers that presents some work on indoor localization using RF signals [4–6] localization means tracking the positon of a person or device, gesture recognition [7] this is a survey paper which describe some of the work related to gesture recognition which is important for our research as gestures are specific pattern movements of body parts that the RF signals have to capture and have a meaning to it, behavior recognition [4, 8–12] these papers are closely related to our work as our prime goal is human activity recognition with WiFi-CSI data and these paper are mostly about human behavior recognition with Wi-Fi CSI data. Our focus is on wearable-free sensing so in [4] writer exploits wireless signals for localization further more in [8] the writer uses CSI data for human identification as well as motion recognition of humans. These papers [9–12] discuss different methodologies for human activity recognition using CSI, these approaches include 'big data analytics', 'pattern based model based', 'deep learning models', 'signal processing'.

It is also important to mention that there are number of apps that rely on phase shifts so it should be accurate for this purpose we use AoA/ToF which are basically used for localization and tracking purposes. SopFi [13] gives us technique in which sampling time offsets/sampling frequency offsets are subtracted via linear regression. Wisee [14] is first uses raw data and applies Doppler phase shift to get motion data later it does recognition of gesture and hand with KNN similarly in WiAG [15] first use channel frequency ration to orientation later it uses KNN for gesture recognition.

As research in Wi-Fi sensing progressed researchers started working on human event detection in which different events experienced by humans were studied with the help of wife signals like falling down which will be referred as fall detection. Some of the work in literature related to fall detection is [16–20] this work is important for medical care in hospitals specially and in case of patients monitoring remotely with no extra wearable sensors. Some of the work related to human motion detection is [21–24]. Similarly human walking [25], Posture change [26], Sleeping [27], Key stroke [28], Intrusion detection [23, 29]. There have been work and papers on driving fatigue detecting, lane change, school violence, smoking, attack tamper, abnormal activity, all these using Wi-Fi sensing.

3 System Overview

Our working model involves capturing the CSI data from Wi-Fi signals in the indoor environment where the subject (Human) performs 5 different types of activities that are caused due to different body parts movements has effect on the channel state information in terms of the signals which are propagating form transmitter to receiver will have certain effects like amplitude attenuation, phase shift for OFDM-WiFi signals, scattering, fading, multipath effect and more so we are going to use this recorded CSI data to analyze the signal in a way it gives us information about the human activities performed. Now different signal processing techniques are used to refine a signal to ones needs that it gives some useful information for this first we shall do some pre-processing on the signal like removing the noise from the signal. In our work we shall use Hampel filter for this purpose next after noise reduction we shall do down sampling of our signal but in order to do so first we should convert our signal in to time domain so after we did these process on our given signal data we shall now apply continuous wavelet transform and get scalograms in the form of images for each sub carrier but as our data is concerned with motion and it the body movement causes each sub carrier to have some changes so all the sub carriers are important for classification hence for this reason we shall combine all the subcarriers of one sample together and generated a new image that reflect the whole signal for one complete activity. Now that we have images of each complete one activity we shall use machine learning for classification of our dataset.

We shall use deep learning and convolution neural network are a good resource to work with in this domain in our case we shall prefer to use a pre-trained neural network which means that it is a neural network which has already been trained on some or many different datasets already and has learned many things and over the time became very efficient. Some of the famous pre- trained CNN are Alexnet and google net. We shall feed our image data into these networks for classification. Using this approach has advantages over tradition camera/sensor/radar based approach as it is inexpensive because it does not require some expensive equipment rather simple Wi-Fi router form the market can capture CSI data with Wi-Fi AP also it does not need to deploy special systems as Wi-Fi is almost everywhere plus it does not require line of sight. In our work we shall use Wi-Fi CSI fingerprints for human activity. Also unlike radar systems which require high bandwidth, Wi-Fi signals use narrow bandwidth it leverages the concepts of ToF, AoA, azimuthal angle, elevation angle, look angle, phase information, channel amplitude, for signal capturing and analysis. We are going to give the working model approach in Fig. 1.

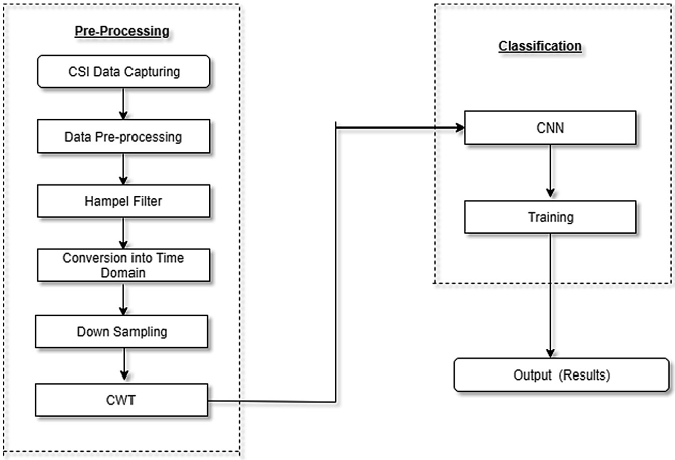

Fig. 1. Our working model approach

4 Methodology

4.1 Subcarrier Pre-processing

We shall now pre-process our signal data sample as the sub carriers have different frequencies and every sub carrier exhibit different response towards the changes in the environment in our case the changes are the body movements by human making up an activity so it is important to take all the subcarriers into account for the classification task but the problem is that it is difficult to do different analysis on the multivalued signals together so what we are going to do is take few signals for representing our analysis and perform different analysis on them and based on the better results we shall apply it to all the subcarriers so the response to every subcarrier can be taken into account. For this purpose we shall first use the subcarrier of bend knee activity as shown in Fig. 2, it is the raw sub carrier now we shall start pre-processing it with smoothing and noise reduction.

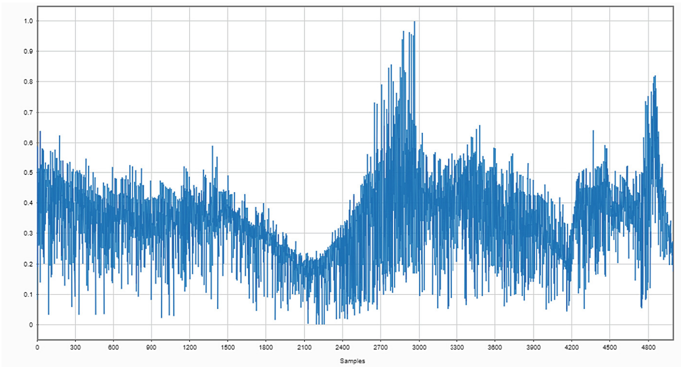

Fig. 2. One sub-carrier of bend knee activity

Noise Reduction and Smoothing

In this part, we are going to process the sub carrier signals to make the signals smooth and reduce the noise in it. Smoothing is the process that involves the reduction of extra unwanted data and makes the whole signal into an approximated signal and uses that approximation which shows only the prominent features in the signal. By using this approach we can get the prominent trends in our signal data. The whole signal is converted or reduced keeping approximation in view. The advantage of using smoothing is that it reduces the unwanted data (noise) and the sudden unrelated changes in the signal. Smoothing aligns the signal into an approximation. Now we shall use 'Hampel filter' for noise reduction and outlier removal. Hampel filter is very useful in signal processing specially in context to noise and outlier removal. It has been used before when we view literature and proved to be efficient in conditions related to movement detections like for breath detection. Hampel filter is categorized in the general class of decision filters. It works on the basis of a running window which runs over the data and at any instance if the middle value of the window is greater than the median value it would be treated as outlier and replaced with the median value this is the main mechanism behind this filter and it makes it so efficient. As for noise it could be of different patterns like it could be Gaussian noise or impulsive noise, Hample filter is good for both cases (Fig. 3).

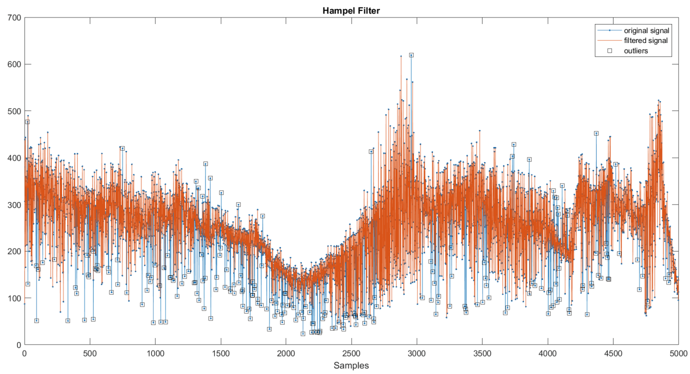

Fig. 3. Hampel filter applied on signal

Conversion into Time Domain

After using Hampel filter we want to down sample our signal but for that we first have to convert the signal into time domain for that we shall divide the total number of samples by 3.5 which is average time of the activity and the resultant will become the frequency of the signal with 0 s as starting time. Our signal after changing into time domain looks as follows. Time domain analysis describes the changes in the signal over the course of time. For conversion of frequency domain into time domain inverse flourier transform function is used. Our default CSI data recorded is in frequency domain, it is because mostly the transmitter use IFFT during modulation while on the receiver ends the signal is demodulated using FFT but sometimes we need to analyze our signal in time domain so we again convert it into time domain with IFFT and a sampling frequency (Fig. 4).

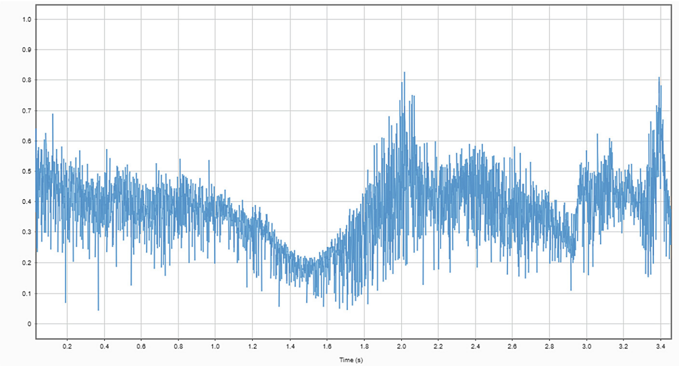

Fig. 4. Signal converted into time domain

Down Sampling

After converting the signal into time domain we shall now do down sampling of our signal. Sampling is regarded as collection of data either in signal or image form, sampling could make the recorded data as smaller (down sampling) or bigger (up sampling). Normally down sampling is done by decreasing the sampling rate this process is also called decimation. Down sampling decimates the sample frequency but the pattern remains almost same the new sample is an approximation of the original signal it has some benefits like it reduces the computation cost increasing the processing efficiency (Fig. 5).

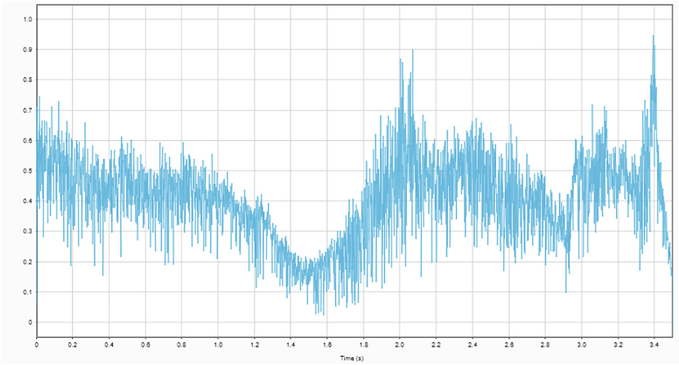

Fig. 5. Signal down sampled

4.2 Continuous Wavelet Transform

Wavelet filters are of so many different types and have so many uses. Some wavelet filters are used for noise reduction or smoothing of signal. We are going to use continuous wavelet transform what it does is that it scales the original signal into wavelets which make up the whole signal these wavelets could be small scale or big scale. In case of small scaled wavelets the oscillation is more where as in case of long scale, the oscillation would be less. One of the advantage of CWT is that it is localized in time in the wavelets are localized in time. It is quite useful for mapping the evolving properties of data related to motion. It mostly works on the basis of some mother wavelet chosen. Mother wavelets are of different types both for continuous or discrete signal analysis since are data is continuous so we can use the following mother wavelets which are for CWT: Morlet, Meyer, derivative of Gaussian, and Paul wavelets. We are going to choose Morlet wavelet as our mother wavelet as it does not require the scaling parameter and does that by itself. The final convolved result Morlet wavelets have the same time features as on in the original signal. Morelet wavelet is also more efficient in term of computation as compared to other. Below is the figure which shows both the signal after CWT and its scalogram (Fig. 6).

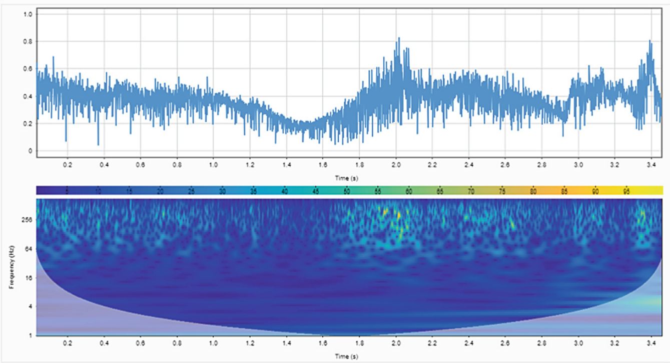

Fig. 6. Continuous wavelet transform

4.3 Using Combined Subcarriers

After applying all the mentioned signal processing techniques we finally have different form of signals including pictorial forms but the problem with using each sub carrier signal separately is that the data sample as a whole represents an activity which is the reflection of different body parts movements each movement attenuating the sub carrier differently so in order to describe the whole activity all the sub carriers should be considered in combined form as one so for this we shall combine all the sub carriers and treat them as one. After the pre-processing of the subcarriers the signals in the combined form are shown below. We are representing all the activity signals for better idea (Fig. 7).

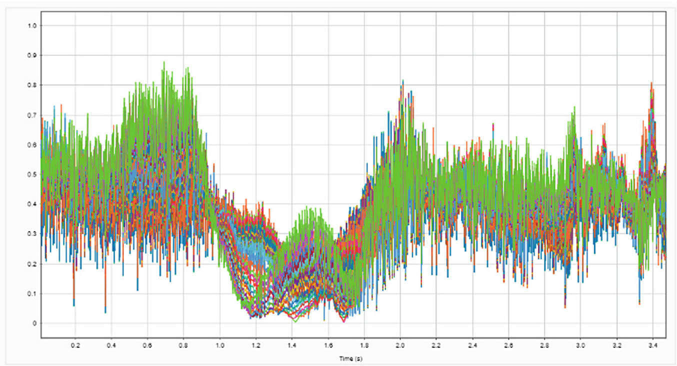

Fig. 7. Combined processed subcarriers - bend knee

As discussed above that we will consider effect of all the sub carriers together for this purpose we shall generate power spectrum of every data sample that represents one complete activity and is constituted by all the processed sub carriers combined together. Below we share the power spectrum of processed bend knee signal (Fig. 8).

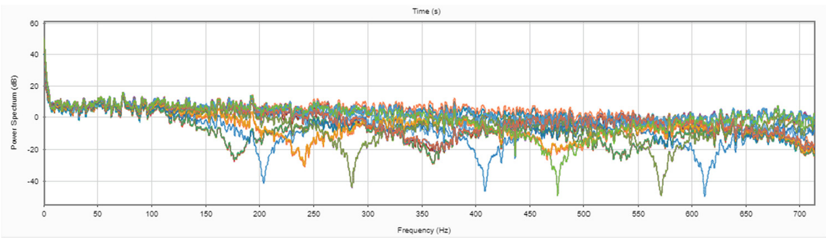

Fig. 8. Power spectrum of one data sample – bend knee

4.4 Classification Using CNN

We are going to use a deep learning neural network for classification. Convolution neural network is a type of deep learning neural network, there are many different convolution neural networks available but we are going to use transfer learning which means we are going to use an already trained network for our case i.e. human activity recognition, this classification task if performed by an already trained network like alexnet becomes more efficient and robust. Alexnet is a pre trained network that has been trained on ImageNet and has 25 layers with 24 connections further it is 8 layer deep neural network. It was trained to classify 1000 categories of data and is considered very efficient for image classification tasks. We shall input the power spectrum image of each signal making 2500 different sample images. The input size for the alexnet is $227 \times 227 \times 3$ where first two values are the size making up a 2 dimensional matrix and third value represents the color channel making it an image. There are three types of layers in alexnet CNN.

1. Convoluiton Layer
2. Max Pooling Layer
3. ReLu Layer (Rectified linear unit).

The first one that is convolution layer is focuses on searching for patterns using different kernels these kernels traverse the image and look for patterns like edges, corners etc. Second layer max pooling its main function is to do down sampling gradually it decrease the dimensionality on each iteration. Lastly Relu layer it simply converts the negative values into zero. The last three layers of Alexnet are fully connected layer, softmax, classification layer respectively. Classification layer is used to classify the dataset and give output whereas fully connected layer works a referee that it counts the score of every category and softmax changes that score into more of statistical interpretation that is probabilities.

After this we shall first load the pre trained network and change the number of class parameter which is by default 1000 in fully connected layer into 5 as in our case the number of classes we have are 5. Next we shall set the parameters to begin the training like learning rate, mini batch size, epoch etc. After that we shall start training and finally get our results and if they are not so good we can do hyper parameter tuning.

4.5 Algorithm

In our algorithm after the capturing of data the first step is the pre-processing of the raw CSI data that has noise for this we used different filters there sequence of application is as follows:

Frist we shall ***combine*** all 30 subcarriers **for** $i = 1:30$ *in one data smaple.*
Noise Reduction, now we shall apply ***Hampel Filter*** on all subcarriers.

```
We shall now convert signal into Time Domain.
We shall now down sample our signal.
Now we shall transform the signal into continuous wavelet
transform.
```

After performing all the above mentioned steps on all the subcarriers. We can not consider scalograms as they only represent the effect of one single subcarrier so we perform the following step;

```
Now we take the Power spectrum of all the subcarriers
combined.
We generated 2500 power spectrum pictures
```

Now we randomly select 15% of the above mentioned data as validation data and 85% of the data as training data and finally feed it to our pre trained convolution neural network. In our case it is Alexnet.

```
Select training and testing dataset with labels
Load pre-trained deep learning neural network, ALEXNET
Define learning rate, batch size and fully connected layers
Run training process over power spectrum with ground truth
```

After the training is complete on 85% of power spectrum data then we test the classification accuracy.

```
Classify test data with learned attributes
Output Accuracy and Confusion Matrix
end.
```

5 Evaluation

5.1 Experimental Setup

The device we are going to use for CSI data acquisition is intel NIC 5300, the transmitter we are going to use would have directional antenna with 2.4 GHz transmitting frequency and the receiver would be a 2D antenna array receiver. Now we shall transmit the OFDM signals, where it has numerous orthogonal subcarriers with different frequencies which will interact with the subject (human) at different body parts each producing some change in the signals finally the signals would be received at the 2D antenna array. Now we shall use data collected at antennas array with the phase difference data to construct our data sample which will later be used for activity recognition.

We shall set up a directional antenna with 2.4 GHz of frequency for NIC 5300 on the transmitter side and receiver would be a 4×4 2D array. The phase difference between origin antenna and first antenna was $\pi/2$ similarly the phase difference between first and second antenna is also $\pi/2$ and same is between any two consecutive antennas. To get an idea of the phase difference graphically we share the below figure.

5.2 Accuracy

As discussed in previous section after feeding the input data in our neural network which was trained on 85% data and was validated or tested on 15% which was randomly partitioned, our model after training generated a high accuracy of 94.2%. The training also generated a confusion matrix which is given below.

Table 1. Confusion matrix (A)

%	Bend knee	Left leg	Right leg	Left arm	Right arm
Bend knee	94%	1%	3%	1%	1%
Left leg	4%	96%	0%	0%	0%
Right leg	1%	2%	91%	1%	5%
Left arm	0%	6%	0%	94%	0%
Right arm	1%	1%	2%	0%	96%

As our transmitter is directional antenna and the object is just 2 m away thus reducing the noise also the movements of body cause the subcarriers to have variation in their values but if the direction of motion is same that is the direction of subcarriers is same they could be treated as one due to the fact that the difference of frequencies between these sub carriers is so small that the effect of subcarriers in one direction is almost negligible making the classification task more better as combined unidirectional subcarriers will be more prominent.

5.3 Training Process

As discussed in the previous section after all the pre-processing we generate power spectrums of our dataset and make a pictorial dataset consisting of (2500) samples with 5. We will use datagram function to load our data as mentioned 15% data is for validation purpose and rest is for training next we use a pre-defined function to resize our images as the input size for Alexnet is 227*227 after this we will load our pre-trained network which is Alexnet. By default the number of categories in Alexnet is 1000 we shall change it to 5 as we have 5 classes, this is done in the 23rd layer in number of classes. Next we shall set parameters for our training. First is initial learning rate which should be normally small as it is the start of training and it needs to look into data in details in beginning. Next we will set the mini batch size to 30, this refers to the number of images in each iteration. Now we shall set a maximum epoch since we are using transfer learning so the epoch size should not be large so we select epoch size as 15. Epoch size means the number of times the network will traverse the whole dataset. We did this training on a single CPU and it took 19 long hours to complete the training. It had 2500 iteration with 15 epochs. Below is the figure of training graph show the loss function and accuracy function graph which seems quite good (Fig. 9).

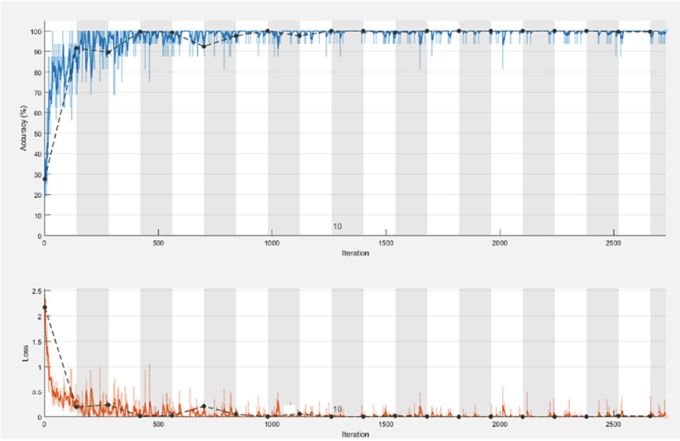

Fig. 9. Training graph

At the end of the training we achieved accuracy of 94%. We also generated confusion matrix as shown in Table 1.

5.4 Using Combined Subcarriers

The sub carrier alone do not reflect the complete activity for which they are recorded so for this reason we shall use the combined form of subcarriers that is one signal sample as a whole note that all the subcarriers are pre-processed. We used the similar method as discussed above for training our data but this time on a different image form the results it generated were not as good as the above discussed method. After training it generated an accuracy of 68%. The confusion Matrix of the above said method is shown below in Table 2.

Table 2. Confusion matrix (B)

%	Bend knee	Left leg	Right leg	Left arm	Right arm
Bend knee	68%	6%	8%	10%	8%
Left leg	7%	71%	9%	7%	6%
Right leg	7%	6%	72%	8%	7%
Left arm	4%	13%	8%	66%	9%
Right arm	9%	8%	9%	7%	67%

This difference in result is due to the fact that there is a lot of variations in the second dataset and it is highly more likely to get the neural network confused due to similar variations in different class signal hence the approach we opted first is more suitable for this task. For a better view and idea below we are sharing a comparative picture of both the signals in discussed forms. It could be noted that in the above picture the variations are very large and it's hard to see a notable pattern and even if there exist similar patterns appear up in other class data signals making it hard to differentiate but with power spectrum as it could be noted the variations are in somewhat recognizable and differentiable way making it a much better choice for classification and training of neural network (Fig. 10).

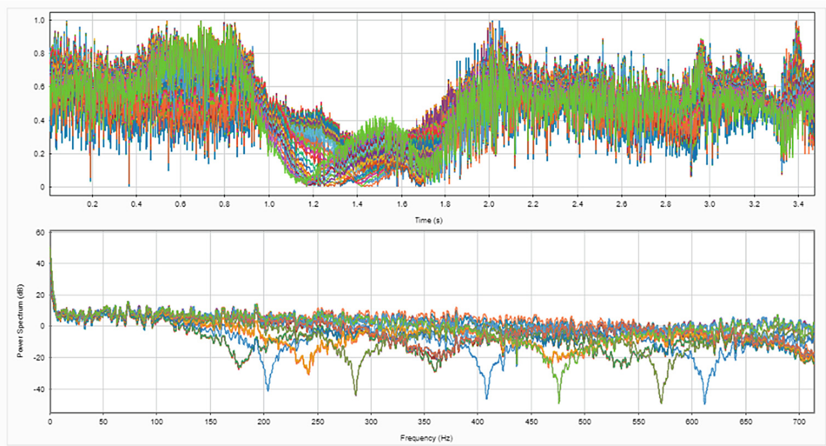

Fig. 10. Combined sub carriers with power spectrum (bend knee)

6 Conclusion

Our research suggests that human Activity Recognition with Wi-Fi is not only very efficient and cost effective method but it is the best solution considering the abundance of Wi-Fi signals around our environments. Our results successfully demonstrate that WiFi-CSI data along with phase information can successfully recognize human activities with an accuracy of more than 94% these could be very useful not only in activity recognition but in other sensing tasks, with a number of applications in healthcare, security, surveillance and much more. Our model can play an important role in many applications of Wi-Fi sensing. With our given dataset we achieved an accuracy of 94% but we want to try it on more and diverse dataset in different environments. For now our model proves to be very efficient compare to many other models we discussed in this thesis with respect to accuracy.

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