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Device Free Human Activity Recognition using WiFi Channel State Information

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***Abstract*—Human Activity Recognition (HAR) is a rather broad research area. While there exist solutions based on sensors and vision-based technologies, these solutions suffer from considerable limitations. Thus in-order to mitigate or avoid these limitations, device free solutions based on radio signals like home WiFi are considered. Recently, channel state information (CSI), available in WiFi networks have been proposed for fine-grained analysis. We are able to detect the human activities like Walk, Stand, Sit, Run, etc. in a Line of Sight scenario (LOS) and a Non Line of Sight (N-LOS) scenario within an indoor environment. We propose two algorithms – one using a support vector machine (SVM) for classification and another one using a long short-term memory (LSTM) recurrent neural network. While the former uses sophisticated pre-processing and feature extraction techniques the latter processes the raw data directly (after denoising with wavelets). We show that it is possible to characterize activities and / or human body presence with high accuracy and we compare both approaches with regards to accuracy and performance.**

***Index Terms*—activity recognition, ambient assisted living, human activity recognition, channel state information (CSI), fingerprinting, localization, machine learning, neural networks, object detection, passive radar, passive (microwave) remote sensing, recurrent neural networks, remote monitoring, wireless networks**

I. Introduction

Detection or recognition of human activity is becoming increasingly important in areas such as health care of elderly and sick or otherwise impaired people. Due to demographic trends there is a tremendous increase in the elderly population and while some elderly suffer from the loss of cognitive or physical autonomy, they choose to live independently at their residence instead of living under the care of a hospital. This raises safety and security concerns. Monitoring of human activity and fall detection systems might mitigate some of the risks. Also monitoring day to day activity would give health personal a better insight into the lifestyle of their patients and it would allow them to assist them in a more informed manner to maintain good health and ensure quick recovery [1]. Human activity recognition is also a key component in context aware computing, for energy efficient smart homes, fitness tracking and many IoT based solutions [2], [3], and in the context of disaster recovery cases [4].

A lot of research has gone into the sensor-based and visual-based solutions for this purpose, but their obtrusive nature has made their use limited and cumbersome in a residential environment. Wearable sensor based solutions may not monitor the activity accurately or correctly because old people might forget to wear the device(s) or simply find it too cumbersome or inconvenient to wear it all the time. This would lead to inaccurate data. Visual based solution will only function in scenarios where the subject is in the line of sight (LOS). They also require good lighting and are intrusive as they impact the privacy of the individual. To overcome these limitations, the research community has started to investigate device-free sensing technologies. In these type of sensing technologies, radio signals such as WiFi Signals are utilized to track human motion and activities.

RF-based device free sensing have the advantage of being non-intrusive. RF-based approaches include Ultra Wide Band, Continuous Wave Radar, Zigbee, WiFi etc. Out of all the approaches WiFi based solutions are gaining more attention from the research community [5]. Basically these solutions require a WiFi Access Point and WiFi enabled devices (laptops, tablets, mobile phones etc.) at various locations in the indoor environment. WiFi set up is available easily in mostly all the indoor or residential environment today and therefore no additional set up cost is incurred. WiFi signals can travel through the wall so it is not necessary for the person to be in the line of sight (LOS). The technologies based on WiFi are based on the fact that radio signals are affected by human movement. The estimated wireless channel will have a different amplitude and phase because the movement of human and objects change the multipath characteristics of the channel.

Recently channel state information from the WiFi network interface cards (NIC) [6] has gained a lot of attention. Unlike RSSI, CSI is measured from radio links per Orthogonal Frequency Division Multiplexing (OFDM) subcarriers for each received packet [6], [7] and [8]. RSSI provides coarse grained MAC layer information whereas CSI provides a fine grained, PHY layer information such as subcarriers and amplitude/phase information for each subcarrier [6], [7] and [8]. Therefore, CSI seems to be an attractive candidate delivering sensor information to be used as an input for HAR.

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II. Related Works

A. Prior Work

The first research on WiFi based sensing was done by Paramvir et al. [9]. In this research WiFi-RSSI was used for indoor localization. Since then WiFi RSSI information has been used in localization [5], [10], and [11] for activity recognition [3], [7], [12], and for gesture recognition [13]. RSSI is a very simple metric and does not require any special hardware changes neither at the access point end nor at the mobile end. Using RSSI for activity recognition is very easy but RSSI suffers from multi-path fading, severe distortions and instability in a complex environment [6], [7] and [8]. RSSI is a coarse-grained information and it does not leverage the subcarriers of an OFDM channel [14].

Pu et al. [13] proposed a novel gesture recognition system called WiSee which leverages WiFi. This method requires modified WiFi hardware which incorporates WiFi USRP-N210 SDR (software defined radio) system. There are other systems like Wi-Vi [15] and WiTrack [16] which are built on similar platform. WiFi Track is used for 3D tracking of a user. All these systems are based on the measurement of doppler shift in Orthogonal Frequency Division Multiplexing (OFDM) signals, caused due to movement of human body.

In 2011 Halperin et al. [17] released a tool that measures WiFi channel information especially channel state information (CSI) according to 802.11n standard. This tool enables usage of CSI data for a specific Intel chip set. For an open source alternative based on Atheros chip sets, we refer to [18] and [19]. A lot of research has happened since then in the area of localization [20], [19], and human activity recognition using CSI based on commercial Wi-Fi devices. Many articles since 2014 have emerged that have used CSI for detecting human activity. Some of these articles are Wi-Hear [21], Wi-Eyes [22], CARM [3], gesture recognition [13], [6], RT-Fall [23] and WiFall [24]. Wi-Fall e.g. is a fall detection system focusing on a one-class classification (Fall) using an anomaly detection (Least Outlier Factor) based approach to retrieve the activtity's pattern segment, whereas in our work we address multiclass problems. Furthermore, in our work we use a single MIMO system rather than multiple ones (three in case of Wi-Fall). RT-Fall is another fall detection system focusing on a one-class classification exclusively and exploiting the sharp power profile decline associated with fall and fall-like activities as opposed to non-fall like activities. Our approach differs from these two as we employ different classification algorithms and compare the classification using wavelets plus SVM vs. LSTM.

B. Our Contribution

Our contribution is twofold. First, we combine Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), Power Spectral Density (PSD) and frequency of center of energy and Haart wavelet analysis to extract the lower frequency bins (Section IV) into a unique algorithm (Algorithm 1) using a support vector machine as a classifier and show that through these pre-processing techniques, we yield strong classification results. In fact, the accuracy achieved is better than in previous reported work [23] and [24], despite the fact that we classify multiple activities, see figure 6 and tables I and II for quantitative results. In addition, we define a second algorithm (Algorithm 2) using LSTM that operates directly on the raw data and uses only denoising via DWT as the underlying preprocessing technique. We compare both results, see figures 4, 5, 6, and tables I and II. We show that LSTM together with this light preprocessing is almost on a par with the more sophisticated former algorithm considering classification performance.

III. Experimental Set-Up

A. Hardware

In our experiments we use Intel WiFi Link 5300 Network Interface Card (NIC). Intel WiFi Link (IWL) 5300 supports 802.11n standard and hence makes it possible to record channel state information. There are 64 subcarriers in 20 MHz channel and 128 subcarriers in 40 MHz channel. Irrespective of the width of the channel, the subcarriers are grouped in 30 subcarrier groups. The number of indexed subcarriers that would be represented by a group is based on the width of the channel. For 20 MHz channel a subcarrier group represents 2 physical subcarriers and for 40 MHz channel a subcarrier group represents 4 physical subcarriers. Channel state information is reported in the form of 30 matrices, where each matrix represent a subcarrier group.

For our experiments we have used 2 Lenovo laptops, that are equipped with Intel WiFi Link 5300 Network Interface Card (NIC). The operating system installed on each of the Laptop is 64 Bit Ubuntu version 14.04 LTS. The kernel version is 4.2.0-42. In-order to obtain channel state information from the NIC, the existing kernel has to point to a modified wireless driver and the existing IWL 5300 firmware has to be replaced with a modified firmware as IWL 5300 firmware does not allow direct access to the NIC'S memory to read CSI. By using the modified wireless driver and modified firmware, the debug mode of IWL 5300 can be enabled. These modifications cause the NIC to report the CSI to main memory. Halperin et al. [25] proposed the 'Linux 802.11n CSI Tool" and all the instruction to modify the firmware is provided as part of the installation instruction.

B. Apartment

Data collection was conducted in the living room and hallway of an apartment depicted in figures 1 and 2. The figures indicate the position of the transmitter and receiver. All activities took place in the living room. Samples have to be collected for Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS). Note that for the Non-Line-of-Sight (NLOS) the transmitter was moved into the hallway. For the LOS scenario, the transmitter and the receiver are both placed in the living room. For the NLOS scenario, the transmitter is placed in the hallway and the receiver is left in the living room.

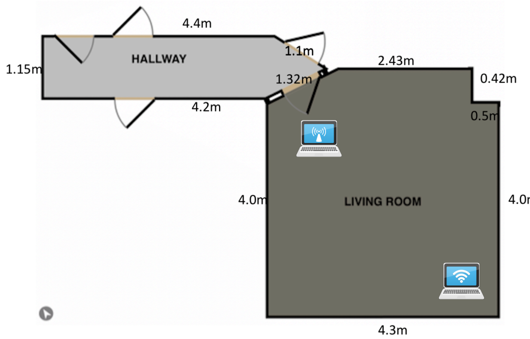


Fig. 1. Set Up For LOS Scenario

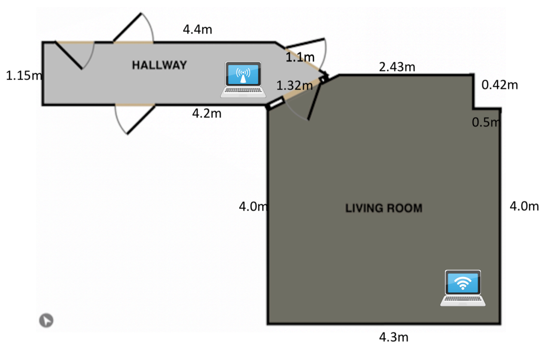


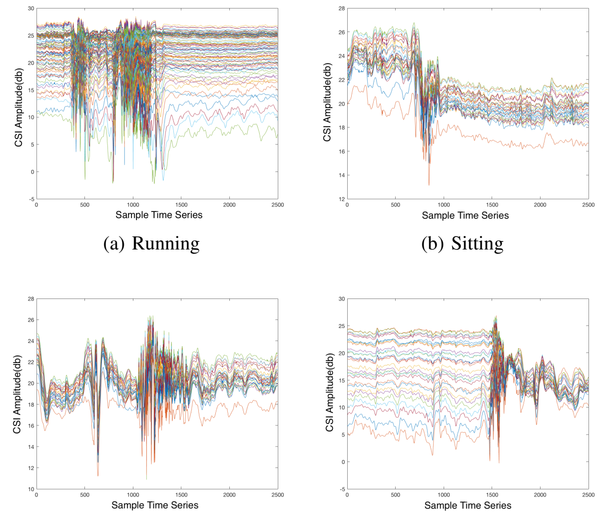
Fig. 2. Set Up For NLOS Scenario

C. Human Activities

Samples are collected for 5 activities namely “SIT”, “STAND”, “RUN”, “WALK”, “EMPTY”. We use the “Linux 802.11n CSI Tool” proposed by Halperin et al. [25] and use the tool’s injection and monitor mode set up to collect the activity samples. For sending packets we configure one laptop in the injection mode and in order to receive packets we configure the other laptop in the monitor mode. We initiate the transmission of 2500 packets with an interval of 15 millisecond between each packet transmitted and one of the activity is performed during this transmission. The packets are captured and their corresponding CSI data is logged in a file in the laptop running in monitor mode. An example for the CSI data for these activities is shown in figure 3.

IV. Algorithms

We implement two different algorithms for activity classification – the first one (Algorithm 1) is using an elaborate pre-processing and feature extraction techniques based on e.g. DWT (Wavelets), PCA etc. and performs the classification using a standard support vector machine, the second one (Algorithm 2) performs only denoising and operates otherwise directly on the data and uses a long short-term memory (LSTM) recurrent neural network. Both are described in detail below.



(a) Running (b) Sitting

(c) Walking (d) Standing

Fig. 3. CSI Data for Different Activities

A. Activity-SVM-Classification

Algorithm 1 ACTIVITY-SVM-CLASSIFICATION

Input: The time series x_τ containing raw CSI data
Output: The predicted activity label l

1: $x_\tau \leftarrow$ CSI_VALUE_EXTRACTION(x_τ)
2: $x_\tau \leftarrow$ DENOISE(x_τ)
3: $x_\tau \leftarrow$ PCA(x_τ)
4: $f \leftarrow$ FEATURE_EXTRACTION(x_τ)
5: $l \leftarrow$ SVM-CLASSIFICATION(f)

1) CSI Value Extraction: Each sample file consists of CSI values for approx. 2500 packets which are logged using one transmitter and three receivers. There exists 30 subcarrier groups between each transmitter and receiver pair. For each packet reception, CSI values are extracted into a matrix of dimension $N_T * N_R * 30$, where N_T and N_R represent the number of transmitters and receivers respectively. The CSI matrix is then flattened to yield a vector of 90 columns, which is then added to a matrix of dimension 2500 * 90. Each column forms the time series of CSI values for each of the 90 subcarrier group. Note that a CSI value is a complex number and for activity recognition, only the amplitude of the CSI value is considered (i.e. the phase is ignored).

2) Denoising: The main goal is to remove the noise, but preserve the sharp spikes caused by human activity. Discrete Wavelet transform (DWT) is a common procedure to achieve that. In DWT, a multilevel decomposition of signal is performed by passing it through a set of high pass and low pass filters at each level. The output from the high pass and low pass filters provides the detailed and approximation coefficients respectively. The first level detailed coefficient contains the information about the noise and the sharp changes caused by human activity and therefore the first level detailed co-efficient is used to calculate a threshold. This threshold is then applied to all the detailed coefficients obtained in the different levels and the signal is then reconstructed using the new detailed coefficients. For the denoise algorithm DENOISE, we use the Matlab function `wden` based on wavelet decomposition. We use "heursure", the heuristic variant of Stein's unbiased risk, soft thresholding and the `sym6` wavelet as parameters for our algorithm. `wden` performs the wavelet decomposition, applies the threshold to all the detailed coefficients and reconstructs the signal (time series of each subcarrier obtained in IV-A1).

3) PCA: As a standard feature reduction technique we apply principal components analysis [26] on the denoised subcarrier time series data x_τ. The first three components explain 70-80 percent of the variance for all the activities. As the first component contains information due to reflection from stationary objects like furniture, walls etc, only the second and the third principal component are used for the prediction of human activity in the sequel.

4) Feature Extraction: The feature extraction algorithm FEATURE_EXTRACTION makes use of spectral analysis techniques as described in the sequel.

Algorithm 1.1 FEATURE_EXTRACTION

Input: The preprocessed time series x_τ
Output: The extracted feature vector f

1: $PSD, \nu \leftarrow$ Compute Power Spectral Density PSD (and Frequency ν for Center of Energy) from x_τ
2: $m_{PSD}, m_\nu \leftarrow$ HAART WAVELET TRANSFORMATION(PSD, ν)
3: $f \leftarrow$ STATISTICAL DATA EXTRACTION(m_{PSD}, m_ν)

Different human activities lead to variations in energy and power of a signal. Power Spectral Density analysis [27] is a common technique to analyze these effects. Thus, we compute the spectral density PSD including the frequency ν for the center of energy of our time series $x(\tau)$ as follows. Let the auto correlation function $R(\tau)$ be defined as

$$R(\tau) := x(\tau) * x(-\tau),$$

then the PSD is simply the expected value of the fourier transform of the auto correlation function

$$PSD := \mathbb{E}[\widehat{R}] = \mathbb{E}\Big[\int_{-\infty}^{\infty} e^{j\omega\tau} R(\tau)\, d\tau\Big] = \mathbb{E}[|\widehat{x}|^2].$$

As the energy corresponding to human activity lies in the lower frequency bins we perform a discrete Haar 1-D wavelet transformation in HAART WAVELET TRANSFORMATION to obtain these coefficients by using the Matlab function `haart(x, level)`. We set the maximum level to which to perform the Haar transform, i.e. `level` to 5. Finally, the statistical data extraction algorithm STATISTICAL DATA EXTRACTION computes the following data:

- For each of the selected subcarrier's time series we calculate Mean, Median, Standard Deviation, Interquartile Range, Second Central Moment, Third Central Moment, Skewness, and Kurtosis.
- For each of row of the selected subcarrier's PSD matrix we calculate Mean, Max, Standard Deviation, Interquartile Range, Skewness, and Kurtosis.
- For each of row of the selected subcarrier's frequency of center of energy we calculate Mean, Max, Standard Deviation, and Interquartile Range.

5) SVM Classification: For the final multi-label classification a one-against-all [28] linear support vector machine [29] with a penalty parameter C set to 0.01 has been used.

B. Activity-LSTM-Classification

As an alternative approach (see Algorithm 2) we have used Long Short-term Memory (LSTM) networks. LSTM [30] are artificial recurrent neural networks which are suitable for processing times-series of data and relevant in our context. For the LSTM algorithm we only perform CSI VALUE EXTRACTION and DENOISE. The feature vector is a 90 dimensional vector which contains the raw CSI amplitude of each of the 90 subcarriers. The number of hidden units is 128. For minimizing the cross entropy loss, AdamOptimizer is used with a batch size of 128 and a learning rate set to 10^{-3}. The drawback of this approach is that it takes a lot of time to train the model, if the computer is not using a GPU. For example, on a MAC with a 3.3 GHz Intel core i5 processor it takes more than an hour to train the model, where as by using NVIDIA GeForce GTX 1080 Ti, the model could be trained in 9 mins approx.

Algorithm 2 ACTIVITY-LSTM-CLASSIFICATION

Input: The time series x_τ containing raw CSI data
Output: The predicted activity label l

1: $x_\tau \leftarrow$ CSI_VALUE_EXTRACTION(x_τ)
2: $x_\tau \leftarrow$ DENOISE(x_τ)
3: $l \leftarrow$ LSTM-CLASSIFICATION(x_τ)

V. EVALUATION

For each activity we collected 200 samples and analyzed them using Algorithm 1 (SVM-Classification) and Algorithm 2 (LSTM-Classification).

A. Results

Figure 4 depicts the confusion matrix obtained for the testing of activity recognition using a SVM for LOS and NLOS and figure 5 depicts the confusion matrix obtained for the testing of activity recognition using a LSTM for LOS and NLOS.

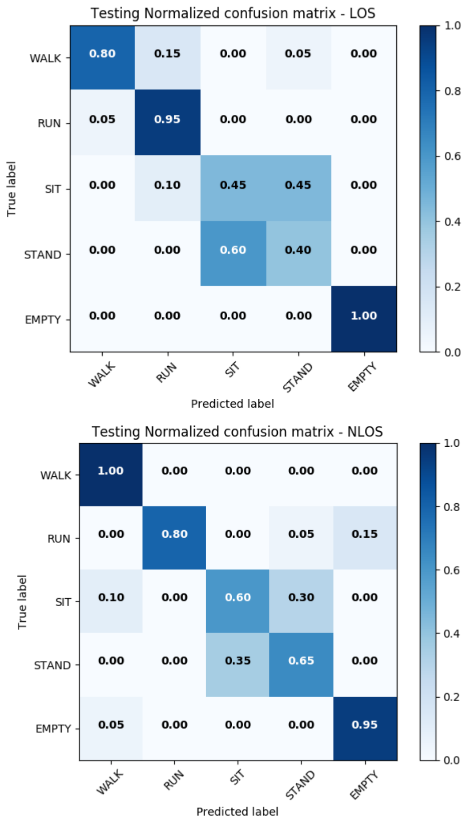


Fig. 4. Confusion Matrix SVM

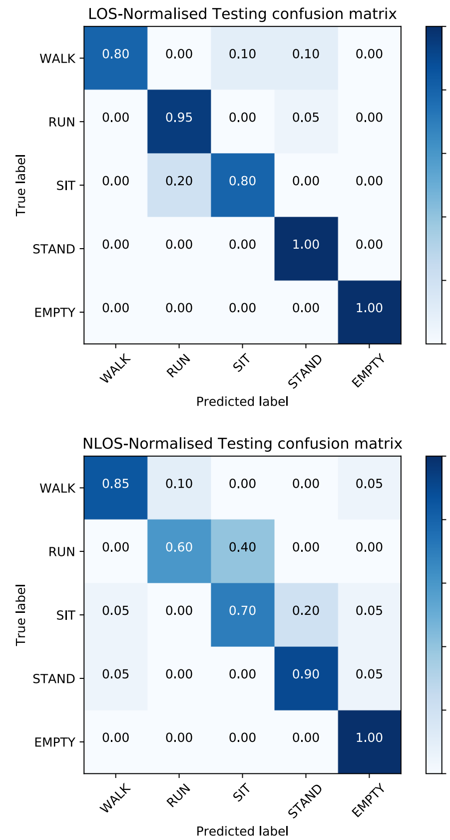


Fig. 5. Confusion Matrix LSTM

B. Interpretation

As one can infer from figure 4 and 5 both algorithms are able to detect presence (NON-EMPTY) and non-presence (EMPTY) very well. In addition, in order to compare our algorithm better to classifiers detecting moving from non-moving activities, we computed a confusion matrix by aggregating WALK and RUN and STAND and SIT, see figure 6.

Both algorithms have difficulties differentiating between similar activities, i.e. between SIT and STAND or WALK and RUN. In general, the SVM algorithm out-performs the LSTM algorithm as can be inferred from tables I and II comparing precision, recall and F-scores.

	MOV	N-MOV	EMPTY
MOV	0.975	0.025	0.00
N-MOV	0.05	0.95	0.00
EMP	0.00	0.00	1.00

(a) SVM LOS

	MOV	N-MOV	EMPTY
MOV	0.90	0.025	0.075
N-MOV	0.05	0.95	0.00
EMP	0.053	0.00	0.947

(b) SVM N-LOS

	MOV	N-MOV	EMPTY
MOV	0.875	0,125	0.00
N-MOV	0.10	0.90	0.00
EMPTY	0.00	0.00	1.00

(c) LSTM LOS

	MOV	N-MOV	EMPTY
MOV	0.775	0.225	0.00
N-MOV	0.05	0.90	0.05
EMPTY	0.00	0.00	1.00

(d) LSTM N-LOS

Fig. 6. (a), (b) Comparison of confusion matrices for a) SVM LOS, b) SVM N-LOS, c) LSTM LOS, and d) LSTM N-LOS for three activities MOV (WALK and RUN), N-MOV (SIT and STAND) and EMPTY.

TABLE I
PRECISION, RECALL AND F-SCORE FOR LOS

	Precision		Recall		F-Score	
	SVM	LSTM	SVM	LSTM	SVM	LSTM
MOV	0,95	0.90	0.98	0.88	0.96	0.89
N-MOV	0,97	0.88	0,95	0.90	0,96	0.89
EMPTY	1.00	1.00	1.00	1.00	1.00	1.00

TABLE II
PRECISION, RECALL AND F-SCORE FOR N-LOS

	Precision		Recall		F-Score	
	SVM	LSTM	SVM	LSTM	SVM	LSTM
MOV	0.92	0.94	0.90	0.78	0.91	0.85
N-MOV	0.97	0.80	0.95	0.90	0.96	0.85
EMPTY	0.86	0.90	0.95	1.00	0.90	0.95

However, given the fact, that the LSTM algorithm does not use *any* sophisticated pre-processing it is an interesting result, that the LSTM algorithm performs so well in comparison.

C. Future Work

For future work, we will combine pre-processing techniques with LSTM to further improve performance. Furthermore, we will check the stability of the trained models, i.e. whether pre-trained models can be easily transferred into a different environment (such as a different flat) – ideally with minimal or no training. Last but not least we will increase the number of activity modes, in particular to include FALL for fall detection to make our model suitable for real-life applications in the domain of ambient assisted living.

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