A Survey on Behavior Recognition Using WiFi Channel State Information

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The authors present a survey of recent advances in passive human behavior recognition in indoor areas using the CSI of commercial WiFi systems. The movement of the human body parts cause changes in the wireless signal reflections, which result in variations in the CSI. By analyzing the data streams of CSI for different activities and comparing them against stored models, human behavior can be recognized.

The work is supported in part by the Fund de Researche du Quebec-Nature et technologies (FQRNT) and FURUKAWA ELECTRIC Co., LTD.

The authors would like to thank Dr. Wei Wang of Nanjing University, China for the helpful discussions on CARM and sharing part of his code.

Digital Object Identifier: 10.1109/MCOM.2017.1700082

ABSTRACT

In this article, we present a survey of recent advances in passive human behavior recognition in indoor areas using the channel state information (CSI) of commercial WiFi systems. The movement of the human body parts cause changes in the wireless signal reflections, which result in variations in the CSI. By analyzing the data streams of CSIs for different activities and comparing them against stored models, human behavior can be recognized. This is done by extracting features from CSI data streams and using machine learning techniques to build models and classifiers. The techniques from the literature that are presented herein have great performance; however, instead of the machine learning techniques employed in these works, we propose to use deep learning techniques such as long-short term memory (LSTM) recurrent neural networking (RNN) and show the improved performance. We also discuss different challenges such as environment change, frame rate selection, and the multi-user scenario; and finally suggest possible directions for future work.

BACKGROUND ON TRADITIONAL ACTIVITY RECOGNITION SYSTEMS

Human activity recognition has gained tremendous attention in recent years due to numerous applications that aim to monitor the movement and behavior of humans in indoor areas. Applications include health monitoring and fall detection for elderly people [1], contextual awareness, activity recognition for energy efficiency in smart homes [2], and many other Internet of Things (IoT)-based applications [3].

In existing systems, the individual has to wear a device equipped with motion sensors such as a gyroscope and an accelerometer. The sensor data is processed locally on the wearable device or transmitted to a server for feature extraction, and then supervised learning algorithms are used for classification. This type of monitoring is known as *active* monitoring. The performance of such a system is shown to be around 90 percent for recognition of activities such as sleeping, sitting, standing, walking, and running [4].

However, always wearing a device is cumbersome and may not be possible for many passive activity recognition applications, where the person may not be carrying any sensor or wireless device. While camera-based systems can be used for passive activity recognition, the line-of-sight (LOS) requirement is a major limitation for such systems. Furthermore, the camera-based approaches have privacy issues and cannot be employed in many environments. Therefore, a passive monitoring system based on wireless signal, which does not violate the privacy of people, is desired.

Because of ubiquitous availability in indoor areas, recently, WiFi has been the focus of much research on activity recognition. Such systems consist of a WiFi access point (AP) and one or several WiFi enabled device(s) located in different parts of the environment. When a person engages in an activity, body movement affects the wireless signals and changes the multi-path profile of the system.

TECHNIQUES BASED ON WI-FI SIGNAL POWER

Received signal strength (RSS) has been used successfully for active localization of wireless devices using WiFi fingerprinting techniques as summarized in [5]. RSS has also been used as a metric for passive tracking of mobile objects [6]. When a person is located between a WiFi device and an AP, the signal is attenuated, and hence a different RSS is observed. Although RSS is very simple to use and can easily be measured, it cannot capture the real changes in the signal due to the movement of the person. This is because RSS is not a stable metric even when there is no dynamic change in the environment [7].

TECHNIQUES REQUIRING MODIFIED WIFI HARDWARE

To use some metrics other than RSS, in some systems, the WiFi system is modified so that extra information can be extracted from the signal. The WiFi universal software radio peripheral (USRP) software radio system is a modified WiFi hardware and has been used for 3D passive tracking in WiTrack [7]. The idea is to measure the Doppler shift in the orthogonal frequency-division multiplexing (OFDM) signals caused by movement of the human body using a technique called frequency modulated carrier wave (FMCW). Since the Doppler shift is related to the distance, the location of the target can be estimated. Using a similar idea to WiTrack, in WiSee [2], the USRP system is used to measure the Doppler shift in OFDM signals due to movement of the human body. The movement of the parts of the body toward the receiver causes positive Doppler shift, while moving the body parts away results in negative shift. For instance, for a gesture moving at 0.5m/s, in a 5 GHz system, the Doppler shift is

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around 17 Hz [2]. Therefore, such small Doppler shifts need to be detected in the system. In WiSee, the received signal is transformed into narrowband pulses of a few Hertz, and the WiSee receiver tracks the Doppler shift in the frequency of these pulses. After transforming the wideband 802.11 to narrowband pulses, the next steps in WiSee are as follows.

Doppler Extraction: To extract the Doppler information, WiSee computes the frequency-time Doppler profile by taking the fast Fourier transform (FFT) over samples in a window of half a second and then shifting the window by 5 ms and continuing this process. This technique is also known as short-time Fourier transform (STFT), which was used in other techniques as well [8, 9]. Since the movement of a human body generally has a speed of 0.25 m/s to 4 m/s, the Doppler shifts at 5 GHz is between 8 Hz and 134 Hz, hence only the FFT output in this frequency range is considered in WiSee.

Segmentation: The next step is to segment the STFT data to distinguish different patterns. For example, a gesture might consist of one segment with positive and negative Doppler shifts, or two or more segments, each of which has a positive and negative Doppler shift. Detecting a segment is based on the energy detection over a small duration. If the energy is 3 dB higher than the noise level, the beginning of the segment is found, and if it is less than 3 dB, the segment has ended.

Classification: The idea of classification is quite simple. Each segment has three possibilities: only positive Doppler shifts, only negative Doppler shift, and segments with both positive and negative shifts, based on which three numbers are assigned to them. Thus, each gesture is represented by a sequence of numbers. The classification task is to compare the obtained sequence with the one used during training.

WiSee also claims that the system can detect multiple moving targets and identify their activities using the idea that the reflections from each mobile target can be regarded as a signal from a wireless transmitter. Therefore, using the idea used in multiple-input multiple-output (MIMO) receivers, the reflected signals due to different people moving in the area can be separated. The problem is to find the weight matrix that, when multiplied with the Doppler energy corresponding to each segment of each antenna, maximizes the Doppler of each segment. To this end, iterative algorithms have been employed.

In contrast to techniques such as WiSee that require specialized USRP software radios, there have been several efforts to employ commercial WiFi APs without the need to modify the WiFi system. To represent the dynamic changes in the environment due to movement of the human body, recently other metrics have been employed, such as channel state information (CSI), which is described in more detail below.

WiFi Channel State Information

CSI of a WiFi System

The wireless devices in IEEE 802.11n/ac standards use MIMO systems. By using MIMO technology, it is possible to increase the diversity gain, array gain, and multiplexing gain, while reducing the co-channel interference [10]. The modulation used in IEEE 802.11 is OFDM where the bandwidth is shared among multiple orthogonal subcarriers. Due to the small bandwidth, the fading that each subcarrier faces is modeled as flat fading. Therefore, using OFDM, the small-scale fading property of the channel can be mitigated.

Let M_T denote the number of transmit antennas at the device, and M_R the number of receive antennas at the AP. The MIMO system at any time instant can be modeled as $\mathbf{y}_i = \mathbf{H}_i\mathbf{x}_i + \mathbf{n}_i$, for $i \in \{1, ..., S\}$ where S is the number of OFDM subcarriers, and $\mathbf{x}_i \in \mathbb{R}^{M_T}$ and $\mathbf{y}_i \in \mathbb{R}^{M_R}$ represent the transmit and received signal vectors for the ith subcarrier, respectively, and $\mathbf{n}_i$ is the noise vector. The channel matrix for the ith subcarrier $\mathbf{H}_i$, which consists of complex values, can be estimated by dividing the output signal with a known sequence of input also known as pilot. The channel matrix is also known as the CSI, as it shows how the input symbol is affected by the channel to reach at the receiver. In OFDM systems, each subcarrier faces a narrowband fading channel, and by obtaining the CSI for each subcarrier, there will be diversity in the observed channel dynamics. This is the main advantage of using CSI compared to RSS, in which the changes are averaged out over all the WiFi bandwidth and hence cannot capture the change at certain frequencies. In some commercial network interface cards (NICs), such as Intel NIC 5300, the CSI can be collected using the tool provided in [11].

Limitations and Errors of WiFi Systems

The amplitude of CSI is generally a reliable metric to use for feature extraction and classification, although it can change with transmission power, and transmission rate adaptation. As discussed later, by using filtering techniques, the burst noise can be reduced [9]. However, in contrast to amplitude, the phase of a WiFi system is affected by several sources of error such as carrier frequency offset (CFO) and sampling frequency offset (SFO). The CFO exists due to the difference in central frequencies (lack of synchronization) between the transmitter and receiver clocks. The CFO for a period of 50 μs of 5 GHz WiFi band can be as large as 80 kHz, leading to phase change of 8π. Therefore, the phase changes due to the movement of the body, which is generally smaller than 0.5π, is not observable from CSI phase. The other source of error, SFO, is generated by the receiver analog-to-digital converter (ADC). The SFO is also varying by subcarrier index; therefore, each subcarrier faces a different error.

Due to the unknown CFO and SFO, using the raw phase information may not be useful. However, a linear transformation is proposed in [12], such that the CFO and SFO can be removed from the calibrated phase. This process is also known as phase sanitization. In Fig. 1, the CSI amplitude, CSI phase, and sanitized CSI phase vs. the subcarrier index are plotted for a scenario where the WiFi transmitter and receiver are located in the vicinity of each other in LOS condition. As observed, the CSI amplitude is relatively stable but forms some clusters, as mentioned in [12]. The raw phase increases with subcarrier index since the SFO grows with subcarrier index, as illustrated in Fig. 1b. After phase sanitization, the

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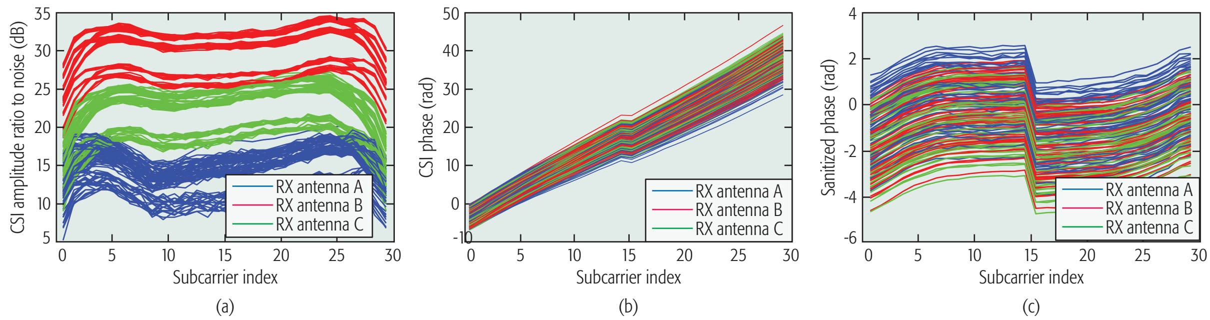

Figure 1. CSI measured in LOS condition for three antennas as a function of subcarrier index: a) amplitude of CSI; b) phase of CSI; c) sanitized phase of CSI.

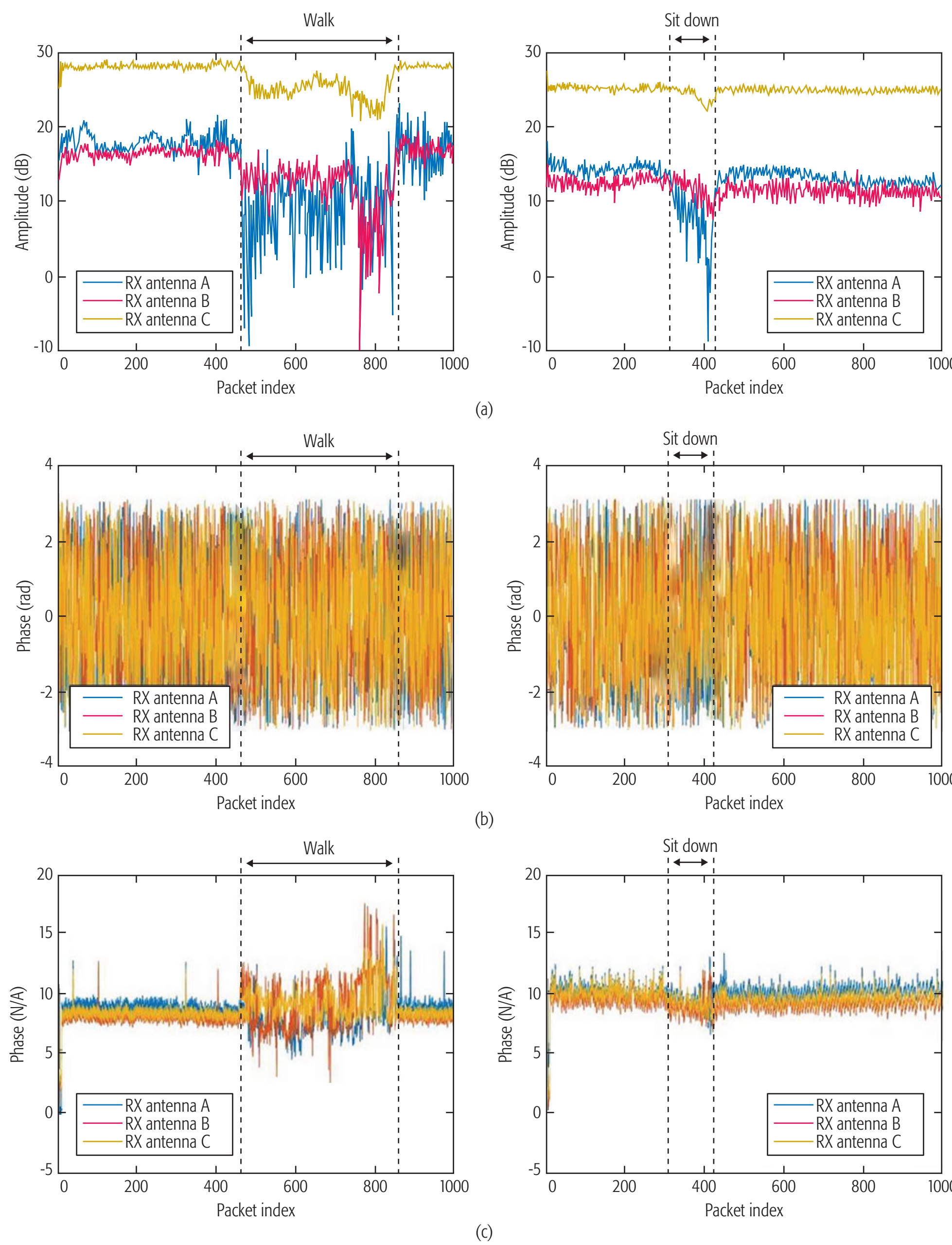

Figure 2. CSI changes under human motion: a) CSI amplitude for three antennas as a function of time; b) CSI phase for three antennas as a function of time; c) sanitized CSI phase for three antennas as a function of time.

change of phase due to SFO will be reduced as observed in Fig. 1c.

Effect of Human Motion on Wireless Channel

The movement of humans and objects change the multipath characteristic of the wireless channel and hence the estimated channel will have a different amplitude and phase. The CSI amplitude for one subcarrier and all the antennas, related to a person walking and sitting down between a WiFi transmitter and receiver, is illustrated in Fig. 2a. The person is stationary for the first 400 packets but then starts walking or sitting down. As observed, when the person is not moving, the CSI amplitudes for all antennas are relatively stable; however, when the activity starts, the CSIs start changing drastically. The walking period is longer than sitting in this experiment because when the person sits down he/she remains stationary.

The received phase, is very distorted due to the CFO and SFO, as mentioned earlier. This can be observed in Fig. 2b. However, using the phase sanitization technique, the effect of errors in phase can be eliminated. The calibrated phase can be observed in Fig. 2c.

Wi-Fi CSI-Based Behavior Recognition

In this section, we provide a summary of the techniques using commercial WiFi NICs. The general diagram of activity recognition systems using WiFi CSI is illustrated in Fig. 3.

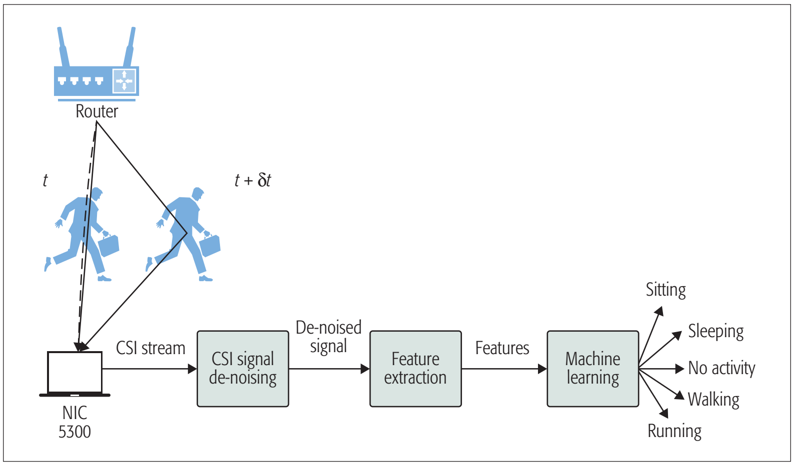

Figure 3. The scheme of common activity recognition techniques. A person is moving in the area between the router and WiFi device from time t to time $t + \delta t$.

Histogram-Based Techniques

One of these technique is E-Eyes [13], in which CSI histograms are used as fingerprints in a database. In the test phase, by comparing the histogram of the obtained CSI with the database, the closest one is found, and hence the activity can be recognized. The preprocessing steps are low-pass filtering and modulation and coding scheme (MCS) index filtering. The former is necessary to remove the high frequency noise, which may not be due to the human movement, and the latter is needed to reduce the unstable wireless channel variations. Although the performance of this technique is good and its computational cost is low, the histogram technique is sensitive to environment changes and hence may not perform well for varying environments.

CARM

Recently, other techniques have been proposed such as WiHear [3], CARM [9[, and the one proposed in [14]. In WiHear, directional antennas are used to capture CSI variations caused by the movement of mouth. The performance of WiHear is good; however, the application is only to monitor spoken words. In [14], the authors use advanced feature extraction and machine learning techniques for recognition of words typed on a keyboard. The idea is similar to the idea in CARM [9], which is described in more detail below.

CSI De-Noising: The CSI is noisy and may not show distinctive features for different activities. Therefore, it is necessary to first filter out the noise and then extract some features to be used for classification using machine learning techniques. There are different methods for filtering the noise such as Butterworth low-pass filters [9]. However, due to the existence of burst and impulse noises in CSI, which have high bandwidths, the low-pass filter cannot yield a smooth CSI stream [9].

It has been shown that there are better techniques for this purpose such as principal component analysis (PCA) de-noising [9]. PCA is a technique for dimensionality reduction of a large-dimension system using the idea that most of the information about the signal is concentrated over some of the features. In CARM, the first principal component is discarded to reduce the noise, and the next five ones are employed for feature extraction. By removing the first principal component, the information due to the dynamic reflection coming from a mobile target is not lost because it is also captured in other principal components. After PCA de-noising of CSI data, some features are extracted from it so that it can be used for classification. Feature extraction is discussed below.

Feature Extraction: One way to extract features from a signal is to transform it to another domain, such as frequency domain. The FFT, which is an efficient implementation of discrete Fourier transform (DFT), can be used for this purpose. To this end, a window size of a certain number of CSI samples is selected, and then the FFT is applied on each segment by sliding the window. This technique, also known as STFT, can detect the frequency changes of a signal over time. The STFT has been applied on radar signals for detection of the movement of torso and legs in [8]. In Fig. 4, the STFT (spectrogram) of CSI for different activities is shown for CSI data collected at 1 kHz rate. As observed in Fig. 4, activities that involve drastic movements such as walking and running show high energy in high frequencies in the spectrogram.

In [3, 9, 14], DWT is employed to extract features from CSI as a function of time. DWT provides high time resolution for activities with high frequencies and high frequency resolution for activities with low speeds. Each level of DWT represents a frequency range, where the lower levels contain higher frequency information while higher levels contain lower frequencies. The advantage of DWT over STFT as mentioned in [9] are:

- DWT can provide a nice trade-off in the time and frequency domains.

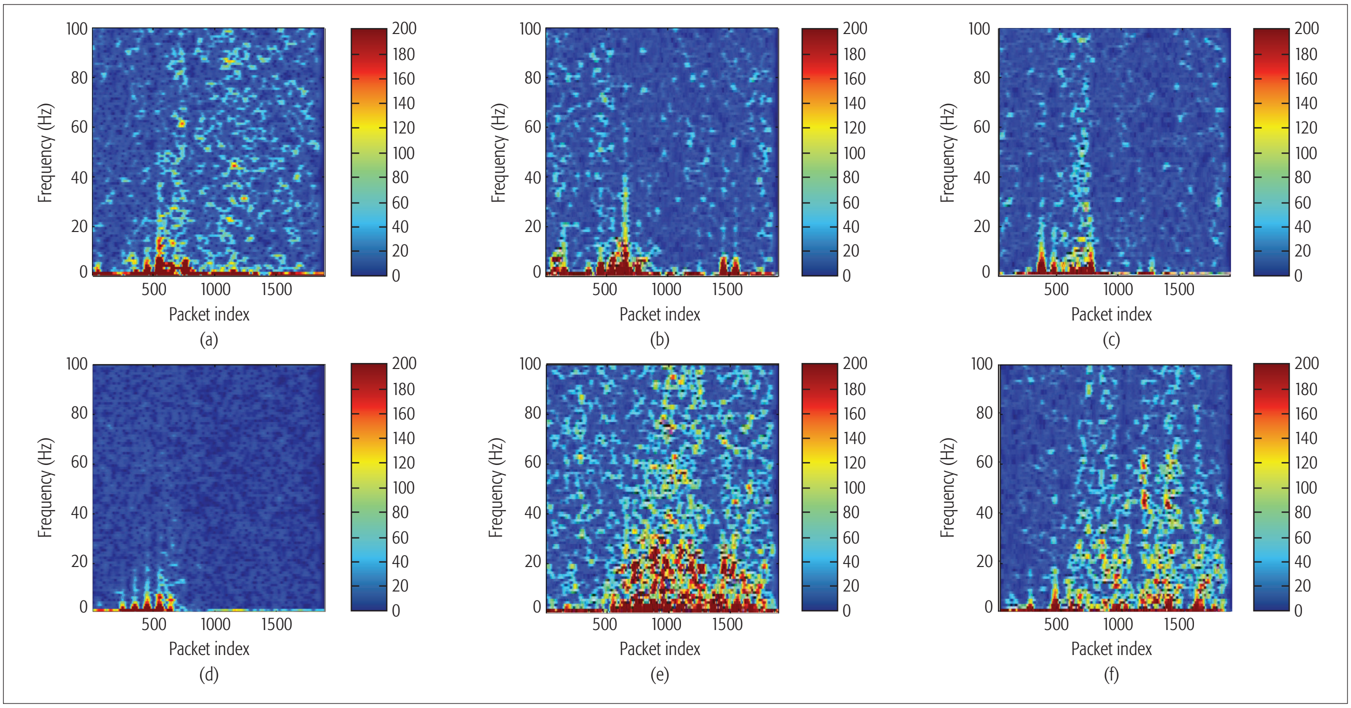

Figure 4. The spectrogram of one subcarrier's CSI amplitude for different activities: a) standing up; b) sitting down; c) lying down; d) falling; e) walking; f) running.

- DWT reduces the size of the data as well, so it becomes suitable for machine learning algorithms.

In CARM, a 12-level DWT is employed to decompose the five principal components (after removing the first principal component). Then the five values of the DWT are averaged. For every 200 ms, CARM extracts a 27-dimensional feature vector including three sets of features:

- The energy in each wavelet level, representing the intensity of movements with different speeds.
- The difference in each level between consecutive 200 ms intervals.
- The torso and leg speeds estimated using the Doppler radar technique [8].

These features are used as the input to the classification algorithm described below.

Machine Learning for Classification: Different machine learning techniques can be used for multi-class classification based on certain features that are extracted. Some of the popular classification techniques are logistic regression, support vector machines (SVMs), hidden Markov model (HMM), and deep learning. Since the activity data is in a sequence, CARM uses HMM, and it is shown that satisfactory results can be obtained.

Using Deep Learning for Behavior Recognition

The problem of activity recognition is somewhat similar to the speech recognition process, where traditionally HMM has been used for classification. However, deep recurrent neural networking (RNN) has been considered as a counterpart of HMM. Training an RNN is difficult as it suffers from the vanishing or exploding gradient problem; however, it was shown in [15] that using the long short-term memory (LSTM) extension of RNN, the best accuracy for speech recognition so far can be achieved. Therefore, we propose using LSTM for activity recognition rather than other conventional machine learning techniques, such as HMM, although feature extraction is not done similar to CARM. Using LSTM has two advantages. First, the LSTM can extract the features automatically; in other words, there is no necessity to pre-process the data. Second, LSTM can hold temporal state information of the activity, i.e., LSTM has the potential to distinguish similar activities like "Lie down" and "Fall." Since "Lie down" consists of "Sit down" and "Fall," the memory of LSTM can help in recognition of these activities.

Evaluation of Different Methods

In this section, we implement different methods as well as our proposed method and show the performance of each one.

Measurement Setup

We do the experiments in an indoor office area where the Tx and Rx are located 3 m apart in LOS condition. The Rx is equipped with a commercial Intel 5300 NIC, with sampling rate of 1 kHz. A person starts moving and doing an activity within a period of 20 s in LOS condition, while in the beginning and at the end of the time period the person remains stationary. We also record videos of activities so that we can label the data. Our dataset includes 6 persons, 6 activities, denoted as "Lie down, Fall, Walk, Run, Sit down, Stand up," and 20 trials for each one.

Evaluating Machine Learning Techniques

We apply the PCA on the CSI amplitude, and then use STFT to extract features in the frequency domain for every 100 ms. We only use the first 25 frequency components out of 128 FFT frequency bins as most of the energy of activities is in lower frequencies, and in this way, the feature vector does not become sparse.

First, we use random forest with 100 trees for classification of activities. To have a feature vector that contains enough information about an activity, the modified STFT bins are stacked together in a vector for every 2 s of activity; hence, every feature vector will be of length 1000. We also implemented other techniques such as SVM, logistic regression, and decision tree; however, random forest outperformed these techniques. The confusion matrix for random forest is shown in Table 1a and, as observed, decent performance can be obtained for some of the activities, but not for activities such as "Lie down," "Sit down," and "Stand up."

We also apply HMM on the extracted features using STFT and use the MATLAB toolbox for HMM training. Note that HMM is also used in CARM; however, DWT and the technique in [8] are used for feature extraction. The result is shown in Table 1b, and improved accuracy compared to random forest can be observed, although with higher computation time needed for training. Although the performance of HMM is good, especially for "Walk" and "Run," it sometimes misclassifies "Stand up" with "Sit down" or "Lie down."

We evaluate the performance of LSTM using Tensorflow in Python. The input feature vector is the raw CSI amplitude data, which is a 90-dimensional vector (3 antennas and 30 sub-carriers). The LSTM approach is different from conventional approaches in the sense that it does not use PCA and STFT, and can extract features from CSI directly. The number of hidden units is chosen to be 200 where we consider only one hidden layer. For numerical minimization of cross entropy, we use the stochastic gradient descent (SGD) with batch size of 200 and learning rate of 10^{-4}. Our result is shown in Table 1c, where the accuracy is over 75 percent for all activities. One of the drawbacks of using LSTM in this way is the long training time compared to HMM. However, using deep learning packages such as Tensorflow, one can also use GPUs and speed up the training. Once the LSTM is trained, the test can be done quickly.

(a) Random forest

Actual \ Predicted	Lie down	Fall	Walk	Run	Sit down	Stand up
Lie down	0.53	0.03	0.0	0.0	0.23	0.21
Fall	0.15	0.60	0.03	0.07	0.1	0.05
Walk	0.04	0.05	0.81	0.07	0.01	0.01
Run	0.01	0.03	0.05	0.88	0.01	0.01
Sit down	0.15	0.03	0.02	0.04	0.49	0.26
Stand up	0.10	0.03	0.02	0.06	0.20	0.57

(b) Hidden Markov model

Actual \ Predicted	Lie down	Fall	Walk	Run	Sit down	Stand up
Lie down	0.52	0.08	0.08	0.16	0.12	0.04
Fall	0.08	0.72	0.0	0.0	0.2	0.0
Walk	0.0	0.04	0.92	0.04	0.0	0.0
Run	0.0	0.0	0.04	0.96	0.0	0.0
Sit down	0.0	0.04	0.0	0.0	0.76	0.20
Stand up	0.16	0.04	0.0	0.0	0.28	0.52

(c) Long short-term memory

Actual \ Predicted	Lie down	Fall	Walk	Run	Sit down	Stand up
Lie down	0.95	0.01	0.01	0.01	0.00	0.02
Fall	0.01	0.94	0.05	0.00	0.00	0.00
Walk	0.00	0.01	0.93	0.04	0.01	0.01
Run	0.00	0.00	0.02	0.97	0.01	0.00
Sit down	0.03	0.01	0.05	0.02	0.81	0.07
Stand up	0.01	0.00	0.03	0.05	0.07	0.83

Table 1. Confusion matrix.

Discussions

Effect of Environment Change on Performance: The CSI characteristics are not the same for different environments and different people. There are different techniques to reduce the influence of environments [9]. For instance, after using PCA, the first component mainly includes the CSI information due to stationary objects [9]. By discarding the first principal component, the information due to the mobile target is mainly captured. Therefore, using this technique, relatively similar features can be obtained for different environments. Other techniques such as STFT and DWT represent the speed of change in the multipaths, which is related to the speed of movement of human body parts. Although the same activities in different environments result in very different CSI characteristics, due to similarity in the change of signal reflections, similar features can be obtained for different environments and people using STFT or DWT [9].

Effect of Wi-Fi Transmission Rate on Performance: In order for the CSI to show noticeable changes due to the movement, the rate of transmission should be high enough (nearly 1 kHz) to capture activities that are done quickly. We have observed severely degraded performance of classification methods when sampling rate is around 50 Hz. Increasing the frame rate increases the number of samples, and hence the computational cost increases for de-noising and feature extraction. Increasing the frame rate may also not help further after some point because human movement speed is limited in indoor areas. Therefore, by selecting a suitable sampling rate (around

There are still several challenges that need to be addressed in future work such as how to use CSI phase information in addition to the amplitude, how to make the system robust in different dynamic environments, and how to identify the behaviors of multiple users.

1 kHz), a good trade-off between the computational cost and the accuracy can be obtained.

Using CSI Phase Information: Due to errors such as CFO and SFO, the phase of WiFi CSI has rarely been used for activity recognition in the literature. However, by subtracting the phase information of neighboring antennas from one another, the CFO and SFO are omitted. The phase difference is related to the angle of arrival (AOA), although there is integer ambiguity in the number of full cycles of the received signal. The change in the target location can change the AOA and hence the phase difference. When the movement is fast and drastic, the signal will be scattered by the human body more randomly, and hence the AOA and phase difference will change faster. It might thus be helpful to use phase difference together with amplitude for feature extraction and then apply classification algorithms. However, further investigation will be left for future work due to lack of space.

Multi-User Activity Recognition: While many activity recognition techniques have been tested for a single user, the more interesting and also challenging problem is the case where multiple people are in the environment. One solution has been proposed in [2] to use the idea of MIMO receivers to separate the signals due to two distinct mobile objects. Having multiple receivers might also help in distinguishing the activities of multiple users. Some techniques for multi-speaker recognition might be applicable to the activity recognition problem. This remains an interesting open problem.

Conclusion and Future Work

In this work, a survey of recent advancements in human activity recognition systems using WiFi channel has been provided. The literature in this area shows great promise in achieving good accuracy in indoor environments. Using numerical testing, it has been observed that better accuracy can be obtained by employing deep learning techniques such as RNN LSTM rather than methods such as HMM. There are still several challenges that need to be addressed in future work such as how to use CSI phase information in addition to the amplitude, how to make the system robust in different dynamic environments, and how to identify the behaviors of multiple users.

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