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Human Identification Using WIFI Signal

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***Abstract*—Prior research has shown that it is possible to identify human by examining the changes on the WiFi spectrum using WiFi signals. Wireless devices fill the air with a spectrum of invisible RF (Radio Frequency) Signals. When human start walking through this spectrum the signal propagates differently for each person as everyone's gait, body-shape, and walking style is unique and does not matches with another person. In this paper, we propose a system that uses Channel State Information (CSI) System to extract unique features of an individual's unique walking pattern. While other identification systems (e.g. fingerprint, face recognition) has certain shortcomings (e.g. intrusive, expensive, and inconvenient), the proposed system overcomes these problems. This system can uniquely identify human with an average accuracy of 78% to 97.5% by using Random Forest (RF) and 84% to 95% average accuracy by using Boosted Decision Tree (BDT) algorithm. The authors believe this system can be used in small office or smart home settings.**

Keywords—CSI, Boosted Decision Tree, Random Forest, Human Identification, WiFi Signal

I. INTRODUCTION

WiFi is a must needed component for us in our day to day life. Now a days WiFi devices is seen from home spaces to offices. All of these devices have common features. They fill the air with radio frequency signals. Identifying humans with the help of WiFi signals is possible because when human walk in between those Radio frequency signals they distract those signals and as every human has unique walking styles so they propagates those signals uniquely. By examining these with CSI (Channel State Information) every human can be identified uniquely.

In this work, the above technique has been followed. As CSI data works differently in different scenarios, we have shown that it is possible to identify human uniquely using CSI data. Moreover, machine learning approach was one of the core features in this work. We have used two different machine learning algorithms Boosted decision Tree and Random Forest for identification technique and achieved satisfactory results (e.g. 84%-95% and 78%-97.5% respectively). Human identification using other proposed systems are sometimes considered as expensive and not efficient. The objective of this system is to identify human accurately as well as in a cost effective way and also efficient.

Human identification process has been researched for many years. Previous works needed user's active participation such as inputting passwords or fingerprints [17] or using devices like cameras which may seem troublesome. Moreover, in these processes computation costs goes higher and in some cases, they are expensive too. Therefore, a passive device-free technique where users do not need to actively participate will be of importance. In recent time, WiFi techniques are being used in various research using Channel State Information because of its low deployment cost and popularity. CSI describes how a signal propagates from transmitter to receiver. It contains rich information about amplitude and phase and also sensitive to environmental variances due to the movement of various objects. Moreover, several studies has shown that human identification using CSI data can be more effective than other traditional approaches. Therefore, this work has adapted the idea and implemented a human identification technique with the help of CSI data.

The objective of this work is to implement a system which can identify human uniquely so that it can be used for security purpose. It is also shown in this paper that it is possible to implement such system with lower computational cost but higher accuracy. The rest of the paper is organized as follows. Section II describes the related works. Section III describes the overview of the proposed system. System implementation and design is described elaborately in Section IV and experimental setup is shown in Section V. Result analysis is introduced in Section VI and finally, Section VII concludes the paper.

II. RELATED WORKS

Works related to human identification is being occurred for the last decade. Most of them have been done by recording human movements through video cameras or still pictures [1] [2]. Though these approaches gave optimum results, the accuracy of these approaches depend on lighting condition and camera quality. As from better video quality or pictures they can easily examine and privacy is also a concern in the conventional procedures. Biometric techniques have given really high accuracy in identifying humans. However, many researchers has already proved that biometric can be faked [3] and there is a concern for user's discomfort while collecting biometric data. Recently, a work has been done on identifying human using WiFi signal in [5]. It was shown in [5] that human identification is possible by using wireless devices such as Intel Network Identification Card (NIC) [12]. Over the years others works have also been explored the possibilities of using WiFi signal for identification [4, 6]. All of the research indicates that

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if CSI values can obtained from the NIC cards it is possible to identify human uniquely examining the values[7][8][9]. However, all of them installed the NICs to their Laptop and they have worked on MIMO channels.

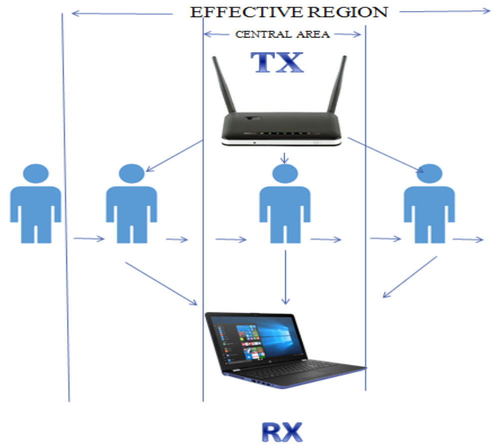

Figure 1: Operational Scenario of the Proposed System

Though we are motivated to work with WiFi signals from these works as there are no security concerns and subjects are giving their data as per their wish and these data cannot be changed, we have used Desktop PC and a SIMO channel for the experiment.

III. PROPOSED SYSTEM

We consider the scenario as in Fig. 1, where the subjects have to walk through a predefined path. Our system consists a transmitter which is a WiFI access point (AP) consisting of one antenna and a receiver which is an interface card consisting of three antennas. The transmitter continuously sends packets to the receiver and the receiver has the ability to extract CSI from the received packets. Fig. 2 shows the system architecture of our system. The system first takes human input CSI data which consists of CSI amplitudes. Then it finds the start point and end point of the effective region where the human impact affected the most. After that the system removes the ambient noise and then extracts important and appropriate statistical features from time and frequency domain that are useful for identifying human uniquely. Finally, two human identification classifiers are used differently to identify the humans uniquely and one of them is Boosted Decision Tree and the other is Random Forest.

IV. SYSTEM IMPLEMENTATION & DESIGN

In this section, we present a preview of the implementation and design of the system.

A. Overview of CSI Data

Channel State Information (CSI) describes how a signal propagates from transmitter to receiver in wireless communication. There are many subcarriers in CSI which contains amplitude values and phase information. CSI can capture the combined effects of multiple wireless phenomena like scattering, fading, power decay with distance, shadowing.

$$H(f_k)=||H(f_k)||\ e^{j<H(f_k)} \tag{1}$$

Here, $H(f_k)$ is the CSI at the subcarrier with central frequency of f_k , and $||H(f_k)||$ and $< H(f_k)$ denote its amplitude and phase [16], respectively. We have focused only on amplitude in our work.

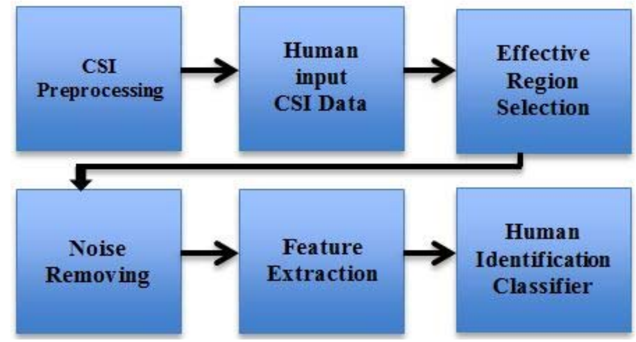

Figure 2: System Architecture

Most modern off-the-shelf WiFi devices support the IEEE 802.11n/ac standard and include multiple antennas for MIMO communications. These devices can operate 2.4GHz and 5GHz and employ OFDM at the PHY layer. The WiFi NICs continuously monitor the frequency response of the OFDM subcarriers as CSI [10]. Let X and Y be the frequency distribution of transmitted and received signals. The two signals are related by the expression below:

$$Y = H \times X + n \tag{2}$$

Here, H is the channel frequency response (CFR) and n is the noise vector [11].

Let Tx and Rx be the number of transmitting and receiving antennas. Let S is the number subcarriers of a certain channel width. Thus the total number of CSI time series is $Tx \times Rx \times S$

B. CSI Preprocessing

CSI values can be obtained from commercial off the shelf WiFi network interface cards (NICs) such as Intel 5300 [12] and Atheros 9390 [13]. For the proposed work, Intel 5300 NIC card is used as the receiver on a Desktop PC and a TP-Link Router as the transmitter. Intel 5300 NIC card has three channel width, we get 30 subcarriers information. Therefore, total number of CSI time series is $1 \times 3 \times 30$. This gives SIMO communication to minimize the computation cost but also having in mind about the accuracy of the system.

For getting CSI, CSI tool is needed to be built on Intel 5300 using a custom modified firmware. To do that, we first built and installed the modified driver on existing kernel of our Linux operating system. Then the modified firmware has been installed. The whole procedure has been done on Ubuntu Terminal. The installation processes similar to the one described in [13, 14, 15].

C. Human Input CSI Data

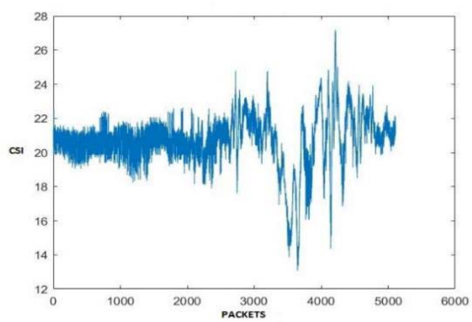

Figure 3: Human Input Signal Data for a Certain Subcarrier

To get human input data, we created a scenario shown in the Fig 1. We placed the two devices far from each other to a certain distance and also above the ground. We then asked 5 persons to walk through the path between the Tx and the Rx. We sent 1000 packets per second from the Rx to Tx by using ping command. It is worth notable that pinging must be continued throughout the whole process of taking input. The idea here is that the transmitter sends signals (i.e. packets) and receiver receives it via the antennas. When a person walks through the path between the transmitter and receiver, the signal gets obstructed because of the walking, gait and human body. A change in the signal will be found then. Because of the difference in each person's gait pattern, walking style, different person will cause different change. By carefully examining these signals, it is possible to identify human.

Each person was asked to walk between the paths 20 times. Thus, we collected 20 walking sample of a person. After that another person was asked to do the same. It is worth mentioning that this procedure was conducted in an open room where furniture and other objects were available. Other WiFi APs (Access Points) were also fully functional during the whole process. Fig 3 shows example of human input data for certain subcarrier.

D. Effective Region Selection

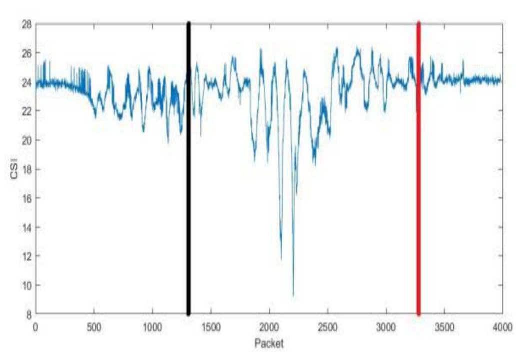

Figure 4: Start Point and End Point of Effective Region for a Certain Sub-carrier

During taking the human input data, we asked people to start walking from a certain distance to achieve some goals. First is to get the actual walking sample and the other is to get the data of effective region. Mainly, as seen in Fig 4, we are interested in the data of effective region because in this area human motion caused the most impact. Again, the effective region where Tx and Rx are connected directly is called central area. When we were taking the data from the effective region, we had some important scenarios in our mind. One is the duration of the effective region. It should neither be too long nor too short because in both cases we will miss vital information.

Another thing is finding the start point and the end point of the effective region correctly. Considering the problems above we selected the effective regions carefully. We first took a person's sample and considered values from one antenna as the effective region is same for all antennas. We then partitioned the whole sample into short frames consisting of 50 packets per sample. After than we calculated energy for each frame and also we calculated mean energy of the whole sample. For finding the start point, we then checked whether the energy of a particular frame is greater than the mean energy of the whole sample. If for a particular frame the energy is greater than the mean energy, we considered that the start point. From that we can find the packet number of the start point of the effective region. For endpoint we took half of the whole sample length and add it with the start point because from our observation in our case effective region is at least half of the whole sample. It is because of our experimental setting. It may vary for different experimental setting. Thus we selected the start point and end point of the effective region. Fig 4 shows examples of start point and end point of effective region. The black line indicated the start point and the red line indicates the end point.

E. Noise Removing

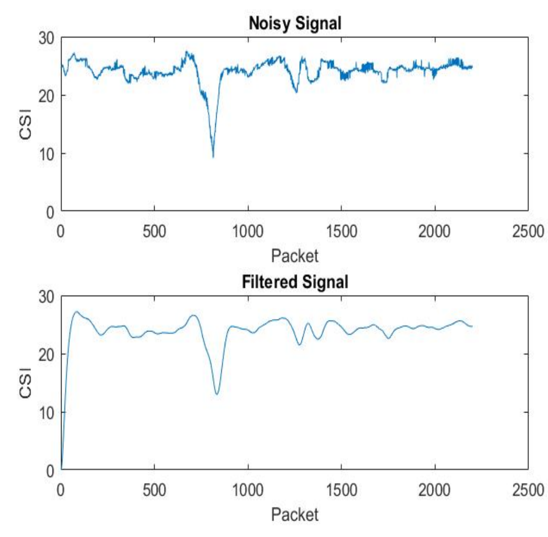

Figure 5: Noisy Signal and Signal after Applying Butterworth Filter

Noise removing is a key part of the proposed system. The CSI data gained through the interface card is noisy. Again, when there is no person walking, CSI data will capture noise. To gain more accuracy we need to remove these signals. To do that Butterworth Low Pass Filter is used. According to [8], the frequency of the variations in CSI time series caused by human walking is around 10Hz. Therefore, we have used a cutoff frequency of 10Hz. Fig 5 shows noisy signal and the same signal after removing noise with butterworth filter.

F. *Feature Extraction*

To identify human accurately and uniquely, we need to extract features which can represent each person's walking style properly. As mentioned above we have $1 \times 3 \times 30$ data stream for each packet. From a sample containing all the packets we extracted statistical features for these 90 data streams from all packets. For feature, we considered 5 time domain features - skewness, mean, maximum, kurtosis, median and 2 time domain features - energy and highest fft (fast Fourier transformation) peaks. The reason of choosing 7 features is to reduce computational cost without affecting the result. After extracting the features we fed the data to human identification classifier for identification process.

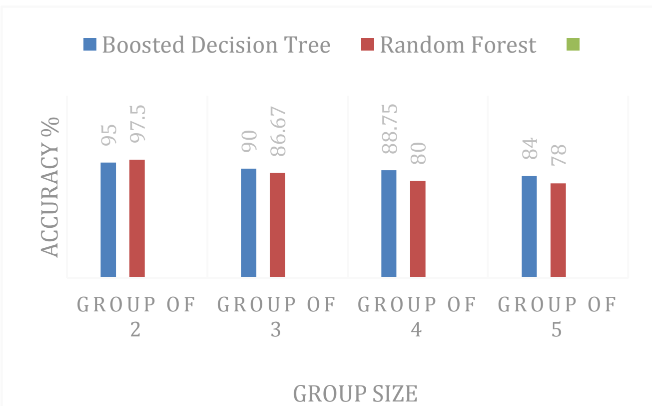

Figure 6: Impact of Different Group Size on Accuracy

TABLE 1. ACCURACY (IN %) OF THE USED CLASSIFIERS

Group Size (Number of People)	Accuracy of Boosted Decision Tree (in %)	Accuracy of Random Forest (in %)
Two (2)	95	97.5
Three (2)	90	86.67
Four (4)	88.75	80
Five (5)	84	78

TABLE 2. CHARECTERISTICS OF 5 SUBJECTS

Subjects	Gender	Height(feet)	Weight(kg)
A	Male	5'11"	90
B	Male	5'7"	80
C	Male	5'8"	75
D	Male	5'5"	55
E	Male	5'7"	78

G. *Human Identification Classifier*

For human identification we used two machine learning tree based classifiers - 1. Boosted Decision Tree 2. Random Forest.

The reason for us to choose these two classifiers lies in our approach. Our approach is in a supervised way, so we can use any supervised machine learning algorithms. But due to the non-linearity of our data sets we had to sort down our algorithms. For example, algorithm like Naive Bayes works very well in linear approach but cannot solve nonlinear problems very well and in our case also. But predictable algorithms like Decision Tree, Random Forest works well for nonlinear problems. This is why we chose above mentioned classifiers.

TABLE 3. CLASSIFICATION MATRIX FOR GROUP OF 5 (BOOSTED DECISION TREE)

	Class Predicted A	Class Predicted B	Class Predicted C	Class Predicted D	Class Predicted E
Observed A	19.0		1.0		
Observed B	1.0	15.0	2.0	2.0	
Observed C	1.0	1.0	16.0	2.0	
Observed D		1.0	3.0	16.0	
Observed E	1.0			1.0	18.0

TABLE 4. CLASSIFICATION MATRIX FOR GROUP OF 5 (RANDOM FOREST)

	Class Predicted A	Class Predicted B	Class Predicted C	Class Predicted D	Class Predicted E
Observed A	15.0	4.0	1.0		
Observed B		19.0		1.0	
Observed C	1.0	4.0	10.0	5.0	
Observed D		2.0		17.0	1.0
Observed E	1.0		1.0	1.0	17.0

V. EXPERIMENTAL SETUP

For working purpose a desktop PC with Intel Link 5300 WiFi NIC for receiving signals, Intel core-i5 processor, 4GB RAM and Ubuntu 14.0.4 is used as the Operating System. A WiFi router which is TP-LINK TL-WR740N used as the transmitter and the receiver was placed in two parallel surface and 180cm distance was maintained between them and they were both 80 cm above from the ground. The router continuously was sending 1000 packets/s to the NIC card which was in the receiving end and here CSI data was measured on ICMP packets.

VI. RESULT ANALYSIS

For this work five individuals subjected as A, B, C, D, E were selected. The height and weight of them are listed at Table 2. As mentioned earlier, 20 walking pattern samples for each individual has been collected. Therefore, all together there are 100 samples which have been fed to the two classifiers (Boosted Decision Tree and Random Forest) separately for human identification process.

As expected both classifiers gave different results. The results of the both classifier (e.g. accuracy for different group size) are shown in Table 1. When the group size is two both classifiers gave better results. But the accuracy tends to get lower when the group size began to expand because there are more people added in the comparison. For group size 2 random forest gave better result of 97.5% than boosted decision tree which is 95%. But when the group size increased, boosted decision tree gave better result than random forest. For example, for group size 5 random forest gave 78% accuracy but boosted decision tree gave 84% accuracy.

Fig.6 shows the impact of various group size in accuracy. By examining these, we can say that, in our case boosted decision tree is better than random forest as it has been able to identify human uniquely from more people. Table 3 and Table 4 shows the classification matrix of group size 5 for boosted decision tree and random forest respectively. From the tables, it is clear that boosted decision tree has identified human more correctly than random forest.

VII. CONCLUSION

In this paper, we have presented a CSI-based device free system that is able to identify Human uniquely. The system can be used basically for small office or residence. Our main focus was to implement a system which is able to identify humans in a low computation cost and high classification accuracy. We have implemented our system for an ideal indoor system. So for using this system for bigger purposes like for smart cities, big office systems we have to work in a different way or in a different approach. As we cannot have an ideal situation there because we have to work with a huge amount of space and number of subjects.

A. Future Work

The result of accuracy rate is quite satisfactory that is why we want to implement our system bigger purposes. Like for Smart city or bigger official spaces. The system has been implemented for 5 persons for some limitations like for lack of space and we have considered an ideal situation so it was not easier for us to move the Desktop PC frequently. But if we do get proper refund and working facilities then hopefully we would be able to implement our system for bigger purposes. As considering to use this system commercially, it is needed to be tested against more humans and their walking samples. Therefore, we are considering to examine the system against up to 100 or more people in future so that it can be used in smart offices and areas as well.

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