WiSpy: Through-Wall Movement Sensing and Person Counting Using Commodity WiFi Signals

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***Abstract*—In current era, the world is becoming more and more tetherless. A wide range of applications relies on wireless signals. In this paper, we demonstrate a system that senses movement of person behind a wall and predicts number of moving persons without instrumenting the body of target using wireless signals. This system relies on commercial off-the-shelf components and commodity WiFi signals for sensing and prediction of moving targets. In particular, we use channel state information that can incur effects induced by movement of persons. We evaluate the performance of system for a challenging scenario like 13-inch thick brick wall and our results show that system can predict up to three persons moving in a closed environment with maximum average accuracy of 96.97%.**

I. Introduction

Human nature of doing the undoable and converting fiction to reality is the sole cause of recent advancements in technology. A low-cost device that can help human beings see through the wall can revolutionize various aspects of life such as law enforcement, personal and homeland security, gaming, rescue services, healthcare and home automation to name a few. Law enforcement agencies longed for a device that could aid them in assessing the threat level that is waiting for them behind the wall for e.g. in hostage rescue missions. Prior information in such cases can help security personnel to reorganize themselves and take appropriate steps. Through-wall sensing can also be used to secure boundary wall of sensitive sites. Similarly, through-wall sensing device finds applications in natural disaster scenarios to detect people trapped under the rubble.

In this paper, we explore commodity WiFi signals to use them for through-wall sensing of person's movement and prediction of number of moving targets. WiSpy is a noninvasive and device-free system that uses WiFi signals as the illuminator of opportunity to probe the human motion in the WiFi coverage area. We leverage the PHY layer channel state information (CSI) provided by commodity WiFi radio to sense the environmental changes via their effect on wireless channel. CSI gives fine-grained channel description at the granularity of orthogonal frequency division multiplexing(OFDM) subcarriers[1]. We use collocated configuration of transceiver in which transmitter and receiver pair is placed on the same side of wall. Our hardware consists of commercial off-the-shelf components. Through-wall movement sensing and person counting concept is quite like radar principle. It is a widely-known fact that motion of an object or human induces temporal changes in reflected wireless signals[2]. WiSpy exploits movement-induced fluctuations in received signal as conveyed by CSI to distinguish moving and non-moving targets. Moreover, we further delve into movement case and predict number of moving targets by using machine learning algorithms on processed CSI data. However, reading these signatures in case of motion behind the wall is not quite easy because signal power is severely attenuated after passing through the walls [3]. There are other challenges associated with through-wall movement detection like saturation of receiver with direct reflections from the wall that make receiver unable to capture minute portion of wireless signal coming from behind the wall [4]. Selection of appropriate antenna type for maximum illumination of target area with RF waves and careful placement of sensing nodes with wall play crucial role in the performance of system. We use standard pyramidal horn antenna to direct most of the RF energy to towards desired area and place transmitter adjacent to the wall to protect receiver from strong wall reflection as discussed in §IV.

II. Related Work

Primarily, through-wall movement sensing and person counting work falls in two categories. First category uses only commercial off-the-shelf devices and commodity WiFi signals to sense movement. DeMan[5] used CSI amplitude and phase to classify moving and stationary targets in an indoor environment. But this work does not include experiments for though-wall movement detection. R-TTWD[6] is another work that extends the application of CSI to through-wall movement sensing. R-TTWD classifies only moving and stationary persons behind the wall but it does not provide any information about the number of moving targets.

Another closely related body of work is the one that does not use the commodity Wi-Fi cards, rather they rely on expensive USRP boards and custom radar equipment to tackle the problem of through-wall sensing using radio waves. Wi-Vi[4], WiTrack[7], WiTrack-2[8], and WiDeo[9] all employ the USRP or Warp boards to implement RF sensing by radio waves while still limiting themselves to WiFi radio specs. Then there are other works that do not conform to WiFi standard and are closer to traditional ultra-wideband but they aim at through-wall imaging such as [10], [11], [12]. But these

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bandwidth hungry systems need bandwidth in GHz and their implementation is very costly thus limiting their commercial use.

The rest of the paper is organized as follows. Section III reviews preliminary background concepts on CSI and in §IV interaction of RF waves with media, in particular with brick wall is discussed. Section V explains effects of through-wall person's movement and intuition behind counting the number of persons moving behind the wall. Section VI describes implementation and experimental setup, and the final results along with comparisons of machine learning algorithms on processed CSI data are given in §VII.

III. Channel State Information

Channel state information(CSI) tells how wireless signal propagates in medium and describes combined effects of phenomenon associated with wireless signals such as reflection, diffraction, fading and power decay with distance. If $\underline{\mathbf{x}}$ is the transmitted signal vector and $\underline{\mathbf{y}}$ the received signal vector, we can write

$$\underline{\mathbf{y}} = \mathbf{H}\underline{\mathbf{x}} + \underline{\mathbf{n}} \tag{1}$$

where $\underline{\mathbf{n}}$ is additive White Gaussian noise vector and $\mathbf{H}$ represents frequency response of the channel which can be estimated from $\underline{\mathbf{x}}$ and $\underline{\mathbf{y}}$. In WiFi based communication protocol, channel state information is estimated using training symbols from the preamble of packet. Firmware modifications for Intel 5300 WiFi radio enabled users to get access of PHY layer CSI [1]. This CSI extraction tool provides channel conditions on 30 OFDM subcarriers. Unlike received signal strength indicator(RSSI), CSI reveals fine-grained channel information[13]. Moreover, CSI is sampled at symbol level incurring minute changes in wireless channel.

IV. Interaction of RF Waves with Media

Radio signals experience reflection, diffraction and attenuation when they impinge upon or pass through a medium. Extent of attenuation due to medium loss is a function of material properties and frequency of the signal[3]. In our experimental setup, we used room having 13-inch thick brick wall on all sides and RF waves with 5.18GHz frequency. Although lower frequency results in smaller attenuation, we selected 5GHz WiFi band because it is not as crowded as 2.4GHz band. When the area behind the wall is illuminated with wireless signals, most of the incident energy gets reflected from smooth wall acting as good reflector. If receiver is placed on the same side of wall, there is high probability that it's analogue-to-digital converter(ADC) would get saturated from strong wall reflections, a phenomenon known as flash effect [4]. Due to saturation of receiver, weak reflections from human body moving behind the wall will hardly be registered at receiver. To overcome this problem, we use standard pyramidal horn antenna to direct most of the energy towards area behind the wall and place it adjacent to the wall for maximum penetration of wireless signal. The idea is to protect receiver from direct wall reflection and to minimize illumination of area where transmitter and receiver are placed. During the one-way traversal through 13-inch thick wall, RF waves will get attenuated by approximately 13dB and roundtrip loss will be 26dB[3]. Therefore, use of high gain directional antenna becomes necessary for reliable detection of moving human target.

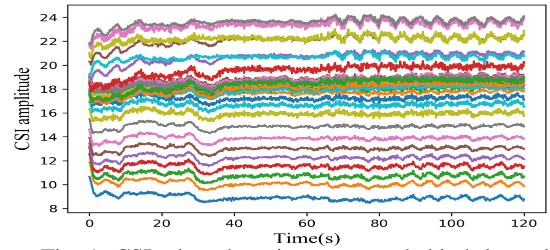

Fig. 1: CSI when there is no person behind the wall

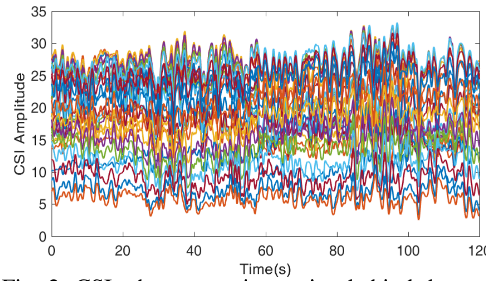

Fig. 2: CSI when target is moving behind the wall

V. Effects of Through-wall Movement on CSI

Human body has complex shape and can be considered as polyhedron structure. When RF signal strikes human body, it undergoes reflection, scattering and absorption. Movement of human body in the presence of wireless signals creates multipath rich environment. CSI corresponding to i-th subcarrier, denoted as $\mathbf{H}_i$, can be written as

$$\mathbf{H}_i = \sum_{k=1}^{K} r_k e^{-j2\pi F_i \tau_k} = |\mathbf{H}_i| e^{j\theta_i} \tag{2}$$

where K represents total number of multipath components, r_k is the attenuation and τ_k is the propagation delay of k-th path, $|\mathbf{H}_i|$ and θ_i correspond to magnitude and phase of $\mathbf{H}_i$ respectively. As the number of moving persons in target area increases, the number of multipaths (K) also increases. Movement also causes these multipaths to vary dynamically. Dynamically varying multipaths result in constructive and destructive interference at receiver. In this way, variation in received signal can be considered as a function of number of moving persons/objects. We leverage this fact later to predict the number of persons moving behind the wall by applying machine learning algorithms on processed CSI data. All these factors are accumulatively exhibited in CSI. CSI maintains a relatively stable profile when there is no movement in the room as shown in Fig. 1. As soon as movement occurs, all subcarriers undergo fluctuations as dictated by targets movement. This observation is depicted in Fig. 2.

According to discussion provided in §VI, dimension of CSI data on all three received antennas for 5-second though-wall target/s movement is 15000×30. We apply principal component analysis(PCA) for dimensionality reduction. PCA outputs 30×30 matrix in which columns represent principal components sorted in ascending order. We vectorize PCA output of 5-second CSI data into one row (1×900) to form one observation as a training/testing example for machine learning algorithms. This CSI to PCA output conversion process is shown in Fig. 3.

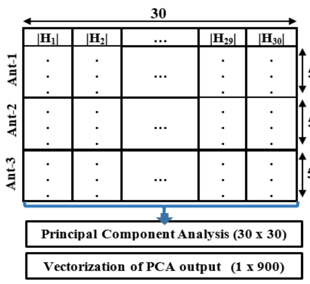

Fig. 3: Conversion of CSI of three antennas to vectorized form after PCA

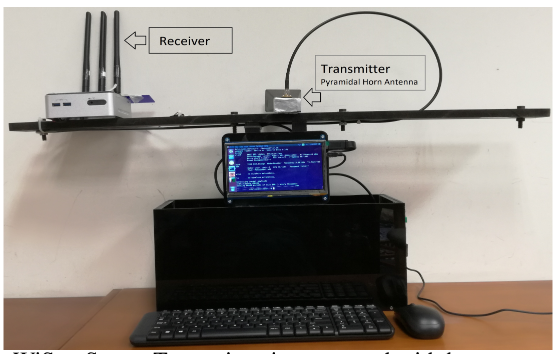

Fig. 4: WiSpy Setup: Transmitter is connected with horn antenna and receiver is connected with three omni-directional antennas.

VI. Implementation and Experimental Setup

We prototype WiSpy system using commodity off-the-shelf devices. Two Intel NUC boards(D54250WKH) were used, one acting as transmitter and other as receiver. Both boards are equipped with Intel 5300 WiFi radios. Transmitting node is connected with ~9dBi standard pyramidal horn antenna and receiving node is connected with three omnidirectional WiFi antennas. We use 20MHz wide wireless channel(CH36) having center frequency 5.18GHz. When 802.11n compliant WiFi packets are sent from transmitter, receiver estimates channel conditions for these packets that are later processed to figure out possible number of moving targets behind the wall. Experimental setup for WiSpy is shown in Fig. 4. Three volunteers having different heights and weights participated in behind-the-wall movement experiments . Specifically, we performed four types of through-wall sensing experiments. In first type, there was no person behind the wall and environment was static. In 2nd, 3rd and 4th type, the number of persons moving behind the wall was one, two and three respectively. In these experiments, movement of targets was continuous and random during CSI data acquisition. Transmitter is configured to transmit 802.11n compliant WiFi packets in high throughput mode with 1ms delay between adjacent packets. Each experiment lasts for 60 seconds and $60,000$ CSI recordings are collected. For each category, we conducted 10 repetitions. In total, we collected data for 40 experiments that amount to $60,000 \times 40 = 2400,000$ CSI recordings. To remove initial and final transients in CSI data of each experiment, we drop first and last 5,000 CSI recordings. We later divide data in 5-second window, perform PCA and give PCA output to machine learning algorithms for classification. Conclusive results obtained from different machine learning algorithms are discussed in following section.

VII. Results

Different machine learning algorithms have been applied to PCA output of processed CSI data.These algorithms include k-nearest neighbor(KNN),stochastic gradient descent(SGD), support vector machine(SVM), Naive Bayes(NB) and decision tree(DT). Our empirical results show that decision tree algorithm surpasses all other algorithms in accuracy (96.97%) as shown in Fig.5. Confusion matrix obtained from decision tree algorithm is given in Fig. 6.

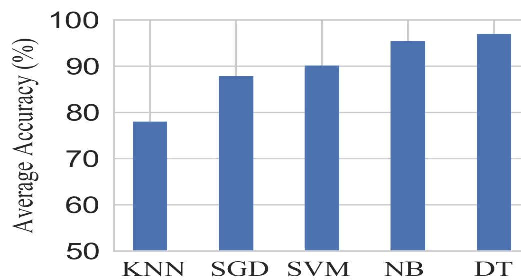

Fig. 5: Comparison of ML algorithms on PCA output

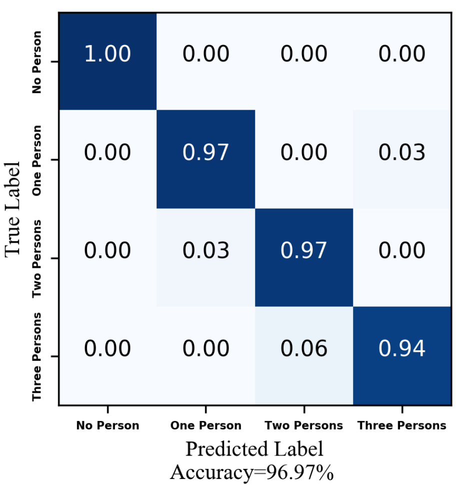

Fig. 6: Confusion matrix shows output of decision tree algorithm

VIII. Conclusion

We present WiSpy, a system that uses commercial off-the-shelf(COTS) hardware and commdity WiFi signals to sense and predict number of moving targets behind the wall. To the best of our knowledge, it is the first system that uses CSI from COTS devices to reliaze through-wall sensing and counting of moving persons.

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