Gesture Recognition using Wireless Signal

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Abstract—This paper presents WiSee, a novel gesture recognition system that leverages wireless signals (e.g., Wi-Fi) to enable whole-home sensing and recognition of human gestures. Since wireless signals do not require line-of-sight and can traverse through walls, WiSee can enable whole-home gesture recognition using few wireless sources. Further, it achieves this goal without requiring instrumentation of the human body with sensing devices.

Key words: Gesture Recognition, Wireless Sensing, MIMO, PMDs, HMMs, and DTW etc.

I. INTRODUCTION

A. History of Information Hiding

As computing moves increasingly away from the desktop, there is a growing need for new ways to interact with computer interfaces. Gestures enable a whole new set of interaction techniques for always-available computing embedded in the environment. For example, using a swipe hand motion in-air, a user could control the music volume while showering, or change the song playing on a music system installed in the living room while cooking, or turn up the thermostat while in bed. Such a capability can enable applications in diverse domains including home-automation, elderly health care, and gaming. However, the burden of installation and cost make most vision-based sensing devices hard to deploy at scale, for example, throughout an entire home or building. Given these limitations, researchers have explored ways to move some of the sensing onto the body and reduce the need for environmental sensors

This paper presents WiSee, the first whole-home gesture Recognition system that requires neither user instrumentation nor an infrastructure of cameras. WiSee achieves this by leveraging wireless signals (e.g. Wi-Fi) in an environment. Since these signals do not require line-of-sight and can traverse through walls, very few signal sources need to be present in the space (e.g., a Wi-Fi AP and a few mobile devices in the living room). WiSee works by looking at the minute Doppler shifts and multi-path distortions that occur with these wireless signals from human motion in the environment.

We address the following two challenges:

1) How do we capture information about gestures from Wireless signals?

WiSee leverages the property of Doppler shift which is the frequency change of a wave as its source moves relative to the observer.

In the context of wireless signals, if we consider the multi-path reflections from the human body as waves from a source, then a human performing a gesture, results in a pattern of Doppler shifts at the wireless receiver. Thus, a user moving her hand away from the receiver results in a negative Doppler shift, while moving the hand towards the receiver results in a positive Doppler shift.

The challenge, however, is that human hand gestures result in very small Doppler shifts that can be hard to detect from typical wireless transmissions (e.g. Wi-Fi). Specifically, since wireless signals are electromagnetic waves that propagate at the speed of light (c m/sec), a human moving at a speed of v m/sec, results in a maximum Doppler shift of 2fc v, where f is the frequency of the wireless transmission.

Thus, a 0.5 m/sec gesture results in a 17 Hz Doppler shift on a 5 GHz Wi-Fi transmission. Typical wireless transmissions have orders of magnitude higher bandwidth (20 MHz for Wi-Fi). Thus, for gesture recognition, we need to detect Doppler shifts of a few Hertz from the 20 MHz Wi-Fi signal.

At a high level, WiSee addresses this problem by trans-forming the received signal into a narrowband pulse with a bandwidth of a few Hertz. The WiSee receiver (which can be implemented on a Wi-Fi AP) then tracks the frequency of this narrowband pulse to detect the small Doppler shifts resulting from human gestures.

2) How can we deal with other humans in the environment?

A typical home may have multiple people who can affect the wireless signals at the same time. WiSee uses the MIMO capability that is inherent to 802.11n, to focus on gestures from a particular user. MIMO provides throughput gains by enabling multiple transmitters to concurrently send packets to a MIMO receiver. If we consider the wireless reflections from each human as signals from a wireless transmitter, then they can be separated using a MIMO receiver.

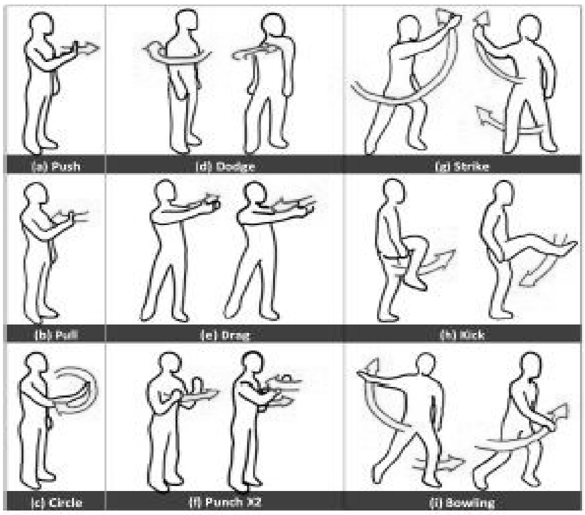

Fig. 1: Gesture sketches: WiSee can detect and classify these nine gestures in line-of-sight, non-line-of-sight, and through-the-wall scenarios

Traditional MIMO decoding, however, relies on estimating the channel between the transmitter and receiver antennas. These channels are typically estimated by sending a distinct Known preamble from each transmitter. Such a known signal structure is not available in our system since the human body reflects the same 802.11 transmitter's signals.

In WiSee the target human performs a repetitive gesture, which we use as that person's preamble. A WiSee receiver leverages this preamble to estimate the MIMO channel that maximizes the energy of the reflections from the user. Once the receiver locks on to this channel, the user performs normal (non-repetitive) Gestures that the receiver classifies using the Doppler shifts. WiSee can classify the nine whole-body gestures shown in Fig. 1.

II. RELATED WORK

Our work is related to prior art in both wireless systems and in air gesture recognition systems.

1) *Wireless Systems:*

One can classify the related work in this domain into three main categories: wireless localization, wireless tomography, and through-the-wall radar systems.

WiSee is also related to work on wireless tomography that aims to localize humans by deploying a network of sensors throughout the environment these systems typically use the RSSI value observed at each sensor to localize humans. WiSee builds on this work but significantly differs from it in that it extracts Doppler shifts from wireless signals to perform human gesture recognition. Further, we demonstrate that one can perform whole-home gesture recognition without requiring wireless devices in every room.

Finally, WiSee is related to work on through the wall radar systems that can identify objects such as metal pins behind a wall. These systems use expensive ultra wide band transceivers that use bandwidths on the order of 1 GHz. In contrast, WiSee focuses on gesture recognition and shows how to extract gesture information from wireless transmissions. The closest to our work in this domain is recent work that demonstrates the feasibility of using Wi-Fi signals to detect running in through-the-wall scenarios.

2) *In-Air Gesture Recognition Systems:*

In-air gesture recognition is being incorporated into consumer electronics and mobile devices, including laptops, smart phones, and GPS devices. The related work in this domain use four main techniques: computer vision, ultra-sonic, electric field, and inertial sensing.

Vision-based systems extract gesture information using Advances in the hybrid camera technology like pixel mixed devices (PMDs). Likewise, ultra-sonic systems leverage Doppler shifts on sound waves to perform gesture recognition. Both these systems, however, require a line of sight channel between the sensing device and the human. In contrast, WiSee leverages wireless signals that can operate in non-line of sight scenarios and can go through wooden walls and obstacles like curtains and furniture.

Electric Field sensing systems like Magic Carpet instrument the floor with multiple sensors to perform human localization and gesture recognition. However, this imposes heavy instrumentation of the environment and is not practical. Inertial sensing and other on-body sensing methods on the other hand, require the users to wear multiple sensors or carry a device such as a wristband. While attractive, in many instances, such an approach can be inconvenient (for instance, while showering). In contrast, WiSee enables whole-home gesture recognition without the need to instrument the human body.

III. WISEE

WiSee is a wireless system that enables whole-home gesture recognition. Since wireless signals can typically propagate through walls, and do not require a line of sight channel, WiSee can enable gesture recognition independent of the user's location. To achieve this, we need to answer three main questions: First, how does WiSee extract Doppler shifts from conventional wireless signals like Wi-Fi? Second, how does it map the Doppler shifts to the gestures performed by the user? Third, how does it enable gesture recognition in the presence of other humans in the environment? In the rest of this section, we address each of these questions.

A. *Extracting Doppler shifts from Wireless Signals*

Doppler shift is the change in the observed frequency as the transmitter and the receiver move relative to each other. In our context, an object reflecting the signals from the transmitter can be thought of as a virtual transmitter that generates the reflected signals. Now, as the object (virtual transmitter) moves towards the receiver, the crests and troughs of the reflected signals arrive at the receiver at a faster rate. Similarly, as an object moves away from the receiver, the crests and troughs arrive at a slower rate.

The observed Doppler shift depends on the direction of motion with respect to the receiver. For instance, a point object moving orthogonal to the direction of the receiver results in no Doppler shift, while a point object moving towards the receiver maximizes the Doppler shift. Since human gestures typically involve multiple point objects moving along different directions, the set of Doppler shifts seen by a receiver can, in principle, be used to classify different gestures.

Higher transmission frequencies result in a higher Doppler shift for the same motion. Thus, a Wi-Fi transmission at 5 GHz results in twice the Doppler shift as a Wi-Fi transmission at 2.5 GHz. We note, however, that much higher frequencies (e.g., at 60 GHz) may not be suitable for whole-home gesture recognition Faster speeds result in larger Doppler shifts, while slower speeds result in smaller Doppler shifts. Thus, it is easier to detect a human running towards the receiver than to detect a human walking slowly. Further, gestures involving full-body motion (e.g. walking towards or away from the receiver) are easier to capture than gestures involving only parts of the body (e.g., hand motion towards or away from the receiver). This is because a full-body motion involves many more point object moving at the same time. Thus, it creates Doppler signals with much larger energy than when the human uses only parts of her body.

1) *Practical Issues*

We answer the following questions:

a) How does WiSee deal with frequency offsets?

A frequency offset between the transmitter and the receiver creates a shift in the center frequency, which can be confused for a Doppler shift. To address this issue, a WiSee receiver takes a two-pronged approach. First, it leverages prior work to get a coarse estimate of the frequency offset using the preamble at the beginning of the transmission; it compensates the estimated frequency offset in the rest of the transmission. Second, to account for any residual frequency offset, WiSee leverages the fact that in the absence of residual offsets, the energy in the DC frequency (center frequency of each OFDM sub-channel) corresponds to the paths from the transmitter to the receiver that do not involve the human. However, with residual offsets, both the DC and the Doppler frequencies are shifted by the same amount (the solid line in the figure). Since the DC energy (i.e., the energy from the transmitter to the receiver minus the human reflections) is typically much higher than the Doppler energy (reflections from the human), the WiSee receiver tracks the frequency corresponding to the maximum energy and corrects for the residual frequency offset.

b) Does the transmitter have to continuously transmit on the wireless medium?

So far, we assume that the transmitter transmits continuously and the receiver uses the signal to compute the Doppler shifts. This is, however, not feasible since 802.11 packets are typically less than a few milliseconds. Further, while transmitting continuously might be feasible in an un-utilized network, it can significantly affect the throughput of other devices in a busy network. WiSee instead performs the following procedure: it linearly interpolates the received OFDM symbols to fill the time slots where no transmission happens. The interpolation is done per sub-channel after the OFDM symbols are transformed into the frequency domain. After interpolation, the receiver transforms all OFDM symbols, both original and interpolated, back to the time domain and forms a synthesized time-continuous trace. The underlying assumption here is that during the short time-period between two transmissions, the user's motion does not dis-continuously change the wireless channel. To see the effects of this interpolation, we perform an experiment where the user performs two simple gestures—either moves her arm towards the receiver or away from the receiver. The user is ten feet away from the receiver. We apply our gesture classification algorithm, which we describe in the next section. The plot shows that the classification accuracy is high even when the transmission occupancy is as low as 3%.

c) What about the cyclic prefix?

The above discussion assumes that the transmitter sends the OFDM symbols back-to-back. However, an 802.11 transmitter sends a cyclic prefix (CP) between every two OFDM symbols to prevent inter symbol interference. The CP is created by taking the last k samples from each OFDM symbol. We consider the CP to be a specific kind of discontinuity between the OFDM symbols. Thus, we can perform interpolation between the OFDM symbols as described earlier. We note, however, that since all the CPs has a fixed length, such an interpolation is equivalent to re-sampling the OFDM symbols at a constant rate given by Symbol length + CP length/ Symbol length where Symbol length and CP length denote the length of the OFDM symbol and CP respectively. Since such re-sampling of the symbols does not change the Doppler pattern, in practice we simply skip the CPs to reduce the computation.

B. Mapping Doppler Shifts to Gestures

So far we described how to transform the wideband 802.11 transmissions into a narrowband signal at the receiver. In this section, we show how to extract the Doppler information and map it to the gestures. Specifically, we describe the following three steps:

Step. 1 : Doppler extraction which computes the Doppler shifts from the narrowband signals

Step. 2 : Segmentation which identifies a set of segments that correspond to a gesture

Step. 3 : Classification which determines the most likely gesture amongst a set of gestures. We describe how WiSee performs each of these steps. We focus on the single user case

1) Doppler Extraction:

WiSee extracts the Doppler information by computing the frequency-time Doppler profile of the narrowband signal. To do this, the receiver computes a sequence of FFTs taken over time. Specifically, it computes an FFT over samples in the first half-a-second interval. Such an FFT give a Doppler resolution of 2 Hertz. The receiver then moves forward by a 5 ms interval and computes another FFT over the next overlapping half-a-second interval. It repeats this process to get a frequency-time profile.

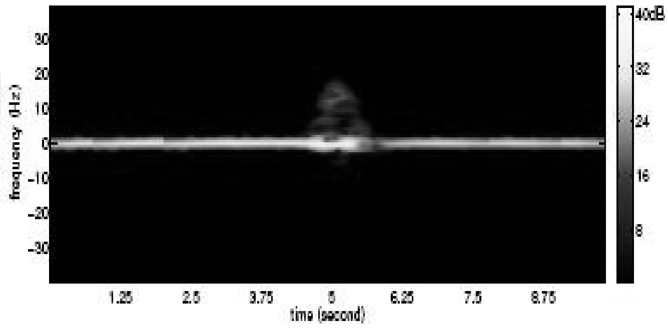

Fig. 2: Frequency-time Doppler profile of an example gesture. The user moves her hand towards the receiver.

Above Fig. 2 plots the frequency-time Doppler profile (in dB) of a user moving her hand towards the receiver. The plot shows that, at the beginning of the gesture most of the energy is concentrated in the DC (zero) frequency. This corresponds to the signal energy between the transmitter and the receiver, on paths that do not include the human. However, as the user starts moving her hand towards the receiver, we first see increasing positive Doppler frequencies (corresponding to hand acceleration) and then decreasing positive Doppler frequencies (corresponding to hand deceleration).

We note that the WiSee receiver is only interested in the Doppler shifts produced by human gestures. Since the speeds at which a human can typically perform gestures are between 0.25 m/sec and 4 m/sec, the Doppler shift of interest at 5 GHz is between 8 Hz and 134 Hz. Thus, the WiSee receiver reduces its computational complexity by analyzing the FFT output corresponding to only these frequencies. Segmentation: To do this, WiSee leverages the structure of the Doppler profiles, Below Fig. These correspond to the gestures in Fig 1. The plots show that the profiles are a combination of positive and negative Doppler shifts. Further, each gesture comprises of a set of segments that have positive and negative Doppler shifts. Further, within each segment, the Doppler energy first increases and then decreases (which correspond to acceleration and deceleration of human body parts).

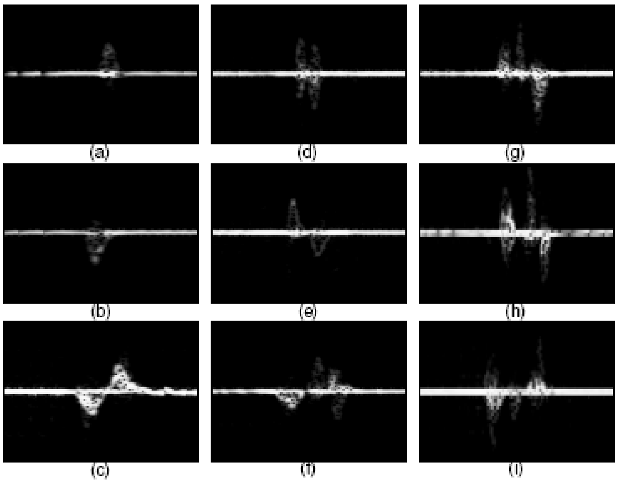

Fig. 3: Frequency-time Doppler profiles of the gestures in Fig. 1. WiSee segments the profiles into sequences of positive and negative Doppler shifts, which uniquely identify each gesture.

A WiSee receiver leverages these properties to first find segments and then cluster segments into a gesture. Our process of finding segments is intuitively similar to packet detection in wireless communication systems. In communication, to detect the beginning of a packet, the receiver computes the average received energy over a small duration. If the ratio between this energy and noise level is greater than a threshold, then the receiver detects the beginning of a packet. Similarly, if this ratio falls below a threshold, the receiver detects the end of the packet. Likewise, in our system, the energy in each segment first increases and then decreases. So the WiSee receiver computes the average energy in the positive and negative Doppler frequencies (other than the DC and the four frequency bins around it). If the ratio between this average energy and the noise level is greater than 3 dB, the receiver detects the beginning of a segment. When this ratio falls below 3 dB, the receiver detects the end of the segment. To cluster segments into a single gesture, WiSee's receiver uses a simple algorithm: if two segments are separated by less than one second, we cluster them into a single gesture.

Gestures Classification: As described earlier, the Doppler profiles in Fig 3. can be considered as a sequence of positive and negative Doppler shifts. Further, from the plots, we see that the patterns are unique and different across the nine gestures. Thus, the receiver can classify gestures by matching the pattern of positive and negative Doppler shifts. Specifically, there are three types of segments: segments with only positive Doppler shifts, segments with only negative Doppler shifts, and segments with both positive and negative Doppler shifts. These can be represented as three numbers, '1', '-1', and '2'. Each gesture in Fig. 3 can now be written as a unique sequence of these three numbers. Now, gesture classification can be performed by comparing and matching the received number sequence with the set of pre-determined sequences. We note that our classification algorithm works with different users performing gestures at different speeds. This is because, different speeds only change the duration of each segment and the specific Doppler frequencies that have energy, but do not change the pattern of positive and negative shifts. Thus, the gestures performed at different speeds result in the same pattern of numbers and hence can be classified.

We briefly comment on the selection of the gestures in Fig.1. In this paper, we picked gestures that can be encoded by a sequence of positive and negative Doppler shifts. As shown in Fig. 1, this covers a variety of interesting gesture patterns. In principle, one can imagine extending WiSee to more general gesture patterns by modeling the human body motion and leveraging additional features from the signal; this, however, is not in the scope of this paper.

We note that it is unlikely that random gestures such as eating, stretching, etc. would be confused with the specific gestures used to control devices. This is because, as we describe in the next section, a user gains control of the system by performing a special, hard-to-confuse gesture sequence that acts as a preamble. We also note that one can leverage techniques like Hidden Markov Models (HMMs) and Dynamic Time Warping (DTW) to increase the gesture space.

C. Multiple Humans

WiSee leverages MIMO to improve the accuracy and robustness of the system, and to enable it to work in the presence of multiple humans. MIMO decoding requires a known preamble to compute the MIMO channel of the target user. WiSee uses a repetitive gesture as a preamble. Specifically, the user pushes her hand towards and away from the receiver, and repeats this gesture to form the preamble. This creates a sequence of alternating positive (+1) and negative (-1) Doppler shifts, i.e., an alternating sequence of +1 and -1 symbols. The WiSee receiver uses this sequence to correlate and detect the presence of a target human. Note that, similar to communication system, this correlation works even in the presence of interfering users, since their motion is uncorrelated with the preamble's alternating sequence of positive and negative Doppler shifts. Next, WiSee finds the MIMO channel that maximizes the Doppler energy from the target user. At a high level, it runs an iterative algorithm (similar to [10]) on each segment of the preamble gesture to find the MIMO direction that maximizes the Doppler energy. It then averages the MIMO direction across segments to improve the estimation accuracy.

Using this estimated MIMO direction, a WiSee receiver mitigates interference from other users and locks onto the target user by projecting the received signal on the desired direction.

We note the following: Firstly, the iterative algorithm occasionally gets stuck in local minima where the Doppler energy does not considerably increase with iterations. To mitigate this problem, we select multiple initial points that are evenly spaced and repeat the algorithm starting from these points. Secondly, since WiSee's receiver uses up to five antennas, the search space significantly increases with the number of receive antennas. To minimize complexity, we run the iterative algorithm pair-wise on each antenna with respect to the first antenna. Specifically, we run the iteration algorithm to find the weights on the N-1 antennas independently where the weights are computed with respect to the first antenna.

Finally, using the repetitive gesture in the preamble, the receiver can improve the estimation accuracy by averaging across gestures. WiSee further improves this accuracy by tracking this channel as the user performs gestures. Specifically, the WiSee receiver applies the iterative algorithm on every gesture performed by the target user. This allows it to adapt the MIMO direction as different users interfere with the target user. Our results in show that, in the presence of three other interfering users, WiSee can classify the first two gestures in Fig. 1 with an average accuracy of 90% using a 5-antenna receiver.

We note that WiSee not only enables a user to perform gestures in presence of other humans, but also enables multiple users to concurrently interact with the system. Specifically, the WiSee receiver can track the MIMO direction of each user to classify the gestures from multiple users.

1) *Further Discussion*

We discuss how one may augment WiSee's current design to make it more robust and secure.

a) Tracking a mobile target user:

Our description and evaluation assume that the target user performs gestures from a fixed location and that she performs the repetitive motion (preamble) when she moves to a new location. However, in principle, one can reduce the need for repeating the pattern by tracking the user as she moves in the environment. Specifically, human motion (e.g., walking and running) creates significant Doppler shifts, which as explained in have a higher energy than human gestures. Thus, the receiver can, in principle, track the MIMO channel as the target user moves, reducing the need to perform the repetitive gesture again.

b) Providing security:

One of the risks of using a whole home gesture recognition system is enabling an unauthorized user outside the home to control the devices within. To address this problem, one may use a secret pattern of gestures as a secret key to get access to the system. Once the access is granted, the receiver can track the authorized user and perform the required gestures.

D. Addressing Multi-path Effects

So far we assumed that the reflected signals from the human body arrive at the wireless receiver along a single direction. In practice, however, the reflections, like typical wireless signals, arrive at the receiver along multiple paths.

Extracting general Doppler profiles in the presence of multi path is challenging. However, the use of only the positive and negative Doppler shifts for gesture classification simplifies our problems. Specifically, we have to address two main problems: First, due to multi-path, a user performing a gesture in the direction of the receiver from an adjacent room can create both positive and negative Doppler shifts at the receiver. Second, strong reflectors like metallic surfaces can flip the positive and negative Doppler shifts. For example, the receiver can observe stronger negative Doppler shifts from a user moving her hand towards the receiver, if the user is standing close to a metallic surface behind her.

The iterative algorithm used by WiSee intrinsically addresses the first problem. Specifically, as shown in recent work on Angle-of-Arrival (AoA) systems, multiple antennas can be used to separate multi-paths by adjusting the phase on each antenna. Since WiSee's iteration algorithm can adapt both the amplitude and the phase to maximize either the positive or the negative Doppler energy, it automatically finds a MIMO direction that can focus on multi paths that result in similar Doppler shifts. We note however that unlike AoA systems, computing Doppler shifts does not require distinguishing between the multi paths in the system. Instead WiSee only needs to distinguish between sets of paths that all create either a positive or a negative Doppler shift. Thus, one can perform gesture recognition using a lower number of antennas than is required in AoA systems.

To address the flipping problem between positive and negative Doppler shifts, WiSee leverages the preamble. Specifically, since the repetitive gesture in the preamble always starts with the user moving her hand towards the receiver, the receiver can calibrate the sign of the subsequent Doppler shifts. Specifically, if it sees a negative Doppler shift when it expects a positive shift, the receiver flips the sign of the Doppler shift. This allows WiSee to perform gesture recognition independent of the user location.

IV. EVALUATION

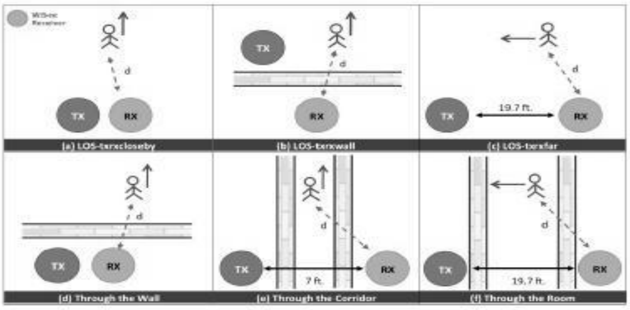

Fig. 4: Different Scenarios for Evaluation

1) Evaluate it in the six different scenarios
2) LOS-txrxcloseby: Here a receiver and a transmitter are placed next to each other in a room. The user performs gestures in line-of-sight to the receiver.
3) LOS-txrxwall: Here a receiver and a transmitter are placed in adjacent rooms separated by a wall. The user performs the gestures in the room with the transmitter.
4) LOS-txrxfar: Here a receiver and a transmitter are placed 19.7 feet away from each other. The user performs gestures in line-of-sight to the receiver.
5) Through the Wall: Here a receiver and a transmitter are placed next to each other close to a wall. The user performs gestures in the room adjacent to the wall.
6) Through the Corridor: Here a receiver and a transmitter are placed in different rooms separated by a corridor. The user performs the gestures in the corridor.

7) Through the Room: Here a receiver and a transmitter are placed in different rooms separated by a room. The user performs the gestures in the middle room.

V. CONCLUSION

In this paper, we take the first step towards transforming Wi-Fi into a gesture-recognition sensor. We present WiSee, a novel gesture recognition system that leverages wireless signals to enable whole-home sensing and recognition of human gestures. Since wireless signals do not require line-of-sight and can traverse through walls, WiSee can enable whole- home gesture recognition using few signal sources.

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