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Occupancy Detection and People Counting Using WiFi Passive Radar

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***Abstract*—Occupancy detection and people counting technologies have important uses in many scenarios ranging from management of human resources, optimising energy use in intelligent buildings and improving public services in future smart cities. Wi-Fi based sensing approaches for these applications have attracted significant attention in recent years because of their ubiquitous nature, and ability to preserve the privacy of individuals being counted. In this paper, we present a Passive Wi-Fi Radar (PWR) technique for occupancy detection and people counting. Unlike systems which exploit the Wi-Fi Received Signal Strength (RSS) and Channel State Information (CSI), PWR systems can directly be applied in any environment covered by an existing WiFi local area network without special modifications to the Wi-Fi access point. Specifically, we apply Cross Ambiguity Function (CAF) processing to generate Range-Doppler maps, then we use Time-Frequency transforms to generate Doppler spectrograms, and finally employ a CLEAN algorithm to remove the direct signal interference. A Convolutional Neural Network (CNN) and sliding-window based feature selection scheme is then used for classification. Experimental results collected from a typical office environment are used to validate the proposed PWR system for accurately determining room occupancy, and correctly predict the number of people when using four test subjects in experimental measurements.**

***Index Terms*—WiFi Sensing, Occupancy Detection, Crowd Counting, Passive WiFi Radar, CNN**

I. Introduction

Low-cost, non-invasive technologies for occupancy detection and people counting could bring about new applications across a range of scenarios. For example, they could be used to optimise energy use in intelligent buildings by reducing unnecessary lighting and heating [1], or monitoring queues and seated people in shopping malls and restaurants to inform staff resourcing [2]. In public transportation, estimating the number of passengers on a train platform or bus stop could be used to adjust scheduling arrangements to minimise overcrowding while in security and law enforcement, occupancy detection can be employed to ensure no one has entered an area after it has been cleared by security services [3]. Infra-Red and camera-based systems have been employed in such applications, but are subject to detection errors owing to obstruction and contrast effects. Moreover they suffer from privacy issues which can limit public acceptance and subsequent uptake of the technology. On the contrary, WiFi based detection systems are able to overcome these limitations; by leveraging the ubiquitous nature of Wi-Fi transmissions and object/wall penetration characteristics of the signals, these systems offer the ability to monitor large areas whist being less limited by lighting conditions and field-of-view requirements, whilst also preserving privacy [4].

WiFi based sensing research has mainly focused on approaches based on Received Signal Strength (RSS) or Channel State Information (CSI) measurements. RSS provides an index measurement of relative RF energy which decreases as a function of distance from the WiFi AP. Using this feature, RSS-based systems can be used for localization [5] and gesture recognition [6][7]. For occupancy sensing many studies have been reported. For example, in [8], the authors estimate the number of passengers on a bus by deploying four WiFi sensors to collect RSS data from mobile devices that are carried by subjects. Furthermore, researchers in [9] propose a device-free RSS-based system which uses existing WiFi networks and applies classifiers to estimate the number of people. They report 98.20% accuracy for determining ”occupied” or ”non-occupied” state but this drops to 77.20% when attempting to count the exact number of people in a crowd. However, the presence of multiple reflection and scattering paths results in unpredictable fluctuations which leads to significant false positives. Moreover, RSS-based approaches often require intensive offline training and densely deployed WiFi communication links which reduces the simplicity and real-world practicality of such systems. On the other hand, CSI-based systems have become one of the most popular WiFi sensing techniques. The approach is to extract fine-grained information in the communication channel using multi-path propagation components. Orthogonal Frequency Division Multiplexing (OFDM)-based transmission schemes utilised in WiFi communications are encoded with a set of orthogonal sub-carriers with corresponding CSI values. The system can gather raw CSI values via a Network Interface card (NIC). For example, in [10], using a modified firmware of the IWL 5300 can collect CSI values for 30 OFDM subcarriers. Studies have shown its ability to detect bulk human motions such as walking and sitting [11], as well as slight movements such as breathing [12], heartbeats [13] and lip movements. [14][15][16][17] have proposed CSI-based device-free crowd counting systems. Nevertheless, most of CSI-based systems require a laptop or PC with a modified WiFi NIC to act as a receiver. Meanwhile, some CSI-based systems require manipulation of WiFi APs to transmit high data-rate signals in order to make use of it's full allowable bandwidth, which has real-world implications in terms of how it may affect the throughput for the users of the communication network. For implementing occupancy detection system in all kinds of scenarios and reducing system complexity, we need an effective strategy leveraging existing WiFi infrastructure without any additional modifications, as well as maintaining even improving detection accuracy.

In recent years there has been significant interest in PWR systems because of its low cost, ubiquitous nature and ability to covertly detect and track non-cooperative targets. Many applications of PWR have been reported in the literature, from through-the-wall sensing [4] and vehicle tracking [18], to gesture recognition [19] and localisation of UAV's [20]. In contrast to RSS and CSI-based systems, PWR systems extract target Doppler information through CAF processing. The Doppler spectrograms can present meaningful information related to target motions allowing detection of individuals in high-clutter indoor environments [21] and even the small perturbations of the chest-wall during breathing [22]. Additionally, PWR does not require any modifications to existing WiFi networks. To the best of our knowledge no work exists in the literature which examines the use of PWR system for occupancy detection and people counting. This paper presents our first attempt of applying PWR system in this area. Specifically, we used a CLEAN algorithm to suppress the unwanted direct signal interference (DSI) and enhance the detection performance. Convolutional Neural Networks (CNNs) are then employed to learn a general model from Doppler spectrograms. Rather than directly feeding CAFs into CNNs, we employed a sliding-window to select features from Doppler spectrogram which resulted in improved estimation accuracies. With these techniques we demonstrate the ability of the system to outperform the aforementioned systems for occupancy sensing and people counting.

In summary, the work presented in this study makes the following contributions:

- To the best of author's knowledge, we are the first to demonstrate the use of PWR for occupancy detection and people counting.
- We propose new feature selection scheme rather than directly training a single CAF to increase prediction accuracy.
- Experimental results have validated that the PWR system is able to achieve maximum 99.53% occupancy detection accuracy and 98.14% people counting accuracy(up to 4 people).

The rest of the paper is organized as follows: Section II describes the fundamental workings of PWR. Next, Section III explains the experimental work including equipment setup, experiment design and data collection. Section IV presents the experimental results and evaluates the performance of different CNN models. Finally, we conclude this paper and discuss possible future directions in Section V.

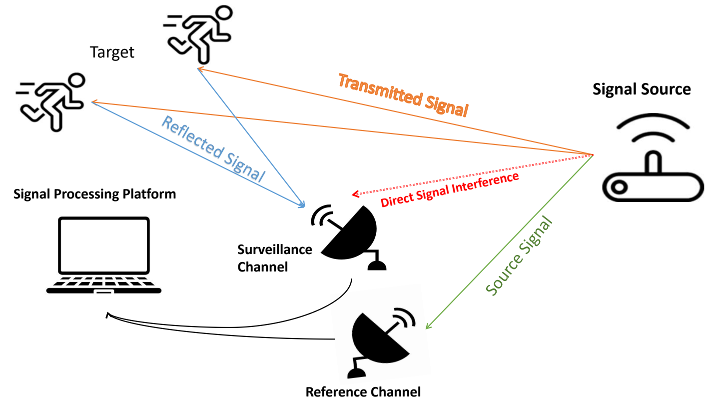


Fig. 1: Architecture of a WiFi based passive radar system

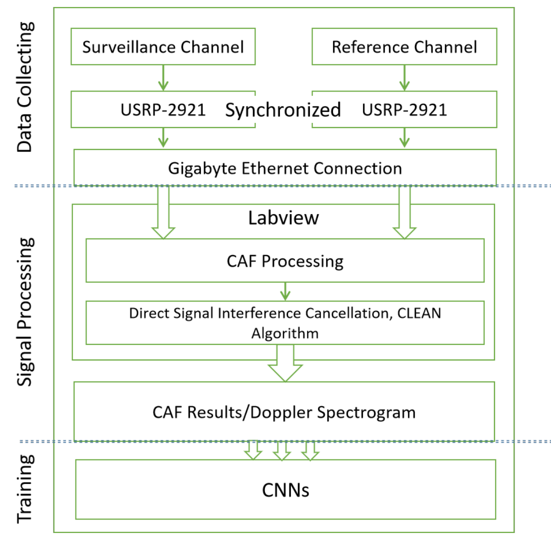


Fig. 2: Block Diagram of System

II. PASSIVE WIFI RADAR SYSTEM

A. System Architecture

Passive Radar is a form of bi-static radar system [23] which uses the RF signals emitted by existing signal sources such as TV, radio and satellite signals to achieve detection. Recent applications include tracking airborne targets [24], monitoring traffic [25] and sensing human activities [26]. Passive radar system uses separately located surveillance and reference antennas alongside cross-correlation signal processing to measure variations between reflected signals from the target and the direct signal from the illuminator of opportunity. It should be noted that two channels need to be synchronized. Thereby, the corresponding Doppler strength and range information from the RF source via the target to the surveillance antenna is determined. Fig. 1 illustrates the setup of a typical WiFi based passive radar system. Specially, PWR exploits transmitted WiFi communication signals. The bandwidth of commercial

WiFi signals are fixed at 20 to 40 MHz corresponding to 7.5 to 15 meters range resolution, which is too coarse for indoor monitoring applications. As a result, the radar focuses on measuring both bulk motions and smaller micro-movements using Doppler based processing. Fig. 2 shows the block diagram of proposed system.

B. Signal Processing for PWR System

In passive radar, signals from surveillance channel and time-delayed copies of the reference signals undergo CAF processing to extract range and Doppler information. A CAF mapping equation can be defined as equation (1):

$$CAF(\tau, f_d) = \int_0^T S_{sur}(t) S^*_{ref}(t-\tau) e^{j2\pi f_d t} dt \quad (1)$$

where $S_{sur}(t)$ represents received signal from surveillance channel, $S_{ref}(t-\tau)$ is replicas of time-delayed reference signals and τ is the delay, f_d is the Doppler shift and f_c represents the carrier frequency, the $[*]$ operator denotes the complex conjugate. Note that the integration time T relates to the duration of the recorded signal which is processed by (1) and determines the Doppler resolution of the system. In the IEEE 802.11 standard, WiFi signal propagation is modulated by OFDM scheme[27], so we can define pure reference signals (S_{ref}) as equation (2):

$$S_{ref}(t) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} a_n e^{j2\pi n t} \quad (2)$$

where N is the number of OFDM symbols for each carrier a_n, and n is the index of a symbol. On the other hand, WiFi signal propagation has multiple paths caused by reflections from stationary objects or moving people. Compared with their source signal, they might be attenuated, delayed or have phase shift. In this case, these signals i.e. S_{sur} can be received and described in the form of equation (3):

$$S_{sur}(t) = \sum_p A_p e^{j2\pi f_d f_c t} x(t-\tau) + n(t) \quad (3)$$

where p represents the number of transmission paths, A_p is the attenuation factor, and $n(t)$ represents the Additive White Gaussian Noise (AWGN). Substitute equation (2) and (3) into (1), CAF values involving range and Doppler information can be obtained. However, the system is impacted by the direct signal from the WiFi access point, known as the direct signal interference (DSI) which can mask the target signal and can cause unwanted peaks in the zero-Doppler range bin. The CLEAN algorithm can remove the DSI through self-cancellation described by equation (4):

$$CAF^{'}(\tau, f_d) = CAF(\tau, f_d) - \alpha CAF_{self}(\tau - T_k, f_d) \quad (4)$$

where $CAF_{self}(\tau, f_d)$ represents the CAF over the reference channel, α is the maximum absolute value of $CAF(\tau, f_d)$. Then, after employing CLEAN algorithm, the desired Doppler information is extracted.

C. Monitoring occupancy information with Doppler spectrogram

PWR systems have the ability to detect small movements such as breathing due to it is Doppler sensitivity. Unlike Infra-Red sensors, as long as there is one person in the monitoring area, the Doppler power will be non-zero. As a consequence it is straightforward to determine the occupancy state of a room via analyzing whether Doppler power is zero in the CAF output. However, tasks involving counting multiple people becomes more complicated. As mentioned previously, the 7.5 to 15 meter range resolution of PWR will not permit the locations of people in a typical 5x5m room to be determined, prohibiting any type of counting ability. To solve this problem, we make use of the fact that although locations of people are unknown, the Doppler power and density will vary with changes of the number of people. For example, one person cannot move in two directions at the same time, therefore, if the Doppler spectrogram shows a non-zero Doppler power in both directions, it means there are at least two people in the monitoring area. On the other hand, the strength of Doppler power for different activities for one person has a certain range, moreover, the range is normally quite limited because people do not frequently make sudden and rapid movements. As a result, if Doppler power of one bin exceeds maximum value of the range, one can infer that more than one person is present in the monitoring area. Meanwhile, human activities have temporal relations. For example, we can observe a clear sinusoidal waveform while one person is breathing. Hence, if such the waveform can be recognized, it will be an index for detection.

Based on one of these characteristics or combination of them, the PWR system can achieve both occupancy state detection and people counting. But due to random movements of people, patterns of Doppler spectrogram are still hard to extract by observing or specific mathematical model, we introduced CNN to automatically learn a general model from dataset.

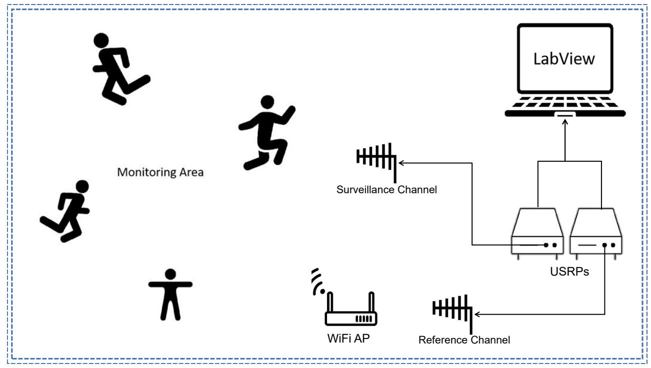


Fig. 3: An example layout in experimental environment

III. System Implementation

In this section, we describe the PWR experimental scenarios including details of the equipment and example layouts. We also provide further details on the experiments and dataset collected.

A. System Overview

Fig. 3 shows an example system layout in our experimental environment. A Yagi antenna is used for reference channel and another is used for the surveillance channel were employed to monitor region of interest. In addition, two NI USRP-2921 software defined radios for real-time signal acquisition are connected to a PC through a Gigabyte Ethernet for processing on LabVIEW software. Moreover, a camera system operated by Raspberry Pi and synchronised to the USRP radio through an NTP server is used to capture the ground truth data.

B. Experiments Design

We designed a 45 minute continuous recording experiment to verify the feasibility of PWR system for occupancy detection and people counting. The whole measurement involved four participants and includes nine sub-experiments (lasting five minutes each). Initially, the monitoring area was a non-occupied state i.e. no people were present. After the first five minutes, four participants successively entered into the monitoring area and walked around in a random fashion to simulate a scenario that mimicked people walking in a train station. Thereby, the occupancy state in the monitoring area varied from a non-occupied state to occupied state and the number of people increased from one person to the maximum four people. During the 45 minute recording the number of people in the monitoring area continually varied from 0,1,2,3,4,3,2,1 and 4.

C. Dataset Explanation and CNNs

The measuring rate of PWR system is 10 CAFs, referred to as 10 frames per second. The 45 minute data recording has around 27,000 frames, which are labelled according to recorded video from the camera system. There are two labelling schemes corresponding to different purposes. For occupancy state detection, we labelled 'non-occupied' and 'occupied' for zero people state and the rest of states respectively. For people counting, we labelled data according to the number of people such as 'one person', 'two people', etc. Meanwhile, the CAF strength is normalized within $[0, 1]$ at the beginning. This is not only for faster gradient descent in deep neural network, but also for reducing impact of varied WiFi signals and different monitoring areas.

As discussed in Section III.C, due to spatial-temporal relation of movements of multiple people, rather than learning from one single CAF, combining continuous frames as one feature, could highly improve estimation accuracy. To verify this guess, we used different sizes of sliding-window to extract features from different lengths of the sliding window. The width of the sliding-window was set to 5, 7 and 10 (i.e. around 0.5 seconds, 0.7 seconds and 1 second length spectrogram) for each training where we also trained single CAF data for comparison. With the increase of window size, more information is encompassed within the Doppler spectrogram. Moreover, the label of a feature is determined by labels of each frames in the window. For simplicity, we ensured that there is only one label type existing in the window. Features including mixed labels will be not fed into CNNs.

To implement the deep neural network, we selected CNNs techniques to train the dataset and leveraged 5-folds cross-

Parameters	Non-occupied	One person	Two people	Three people	Four people
Mean	0.002	0.005	0.011	0.013	0.014
Median	0.000	0.0017	0.002	0.003	0.004
std	0.005	0.018	0.028	0.029	0.032

TABLE I: Mean, Median and Standard deviation values for different occupancy states

validation methods to evaluate models. To determine which structures more fit to our case, we employed three popular architectures including LeNet [28], AlexNet [29] and ZFNet [30] and slightly modified them according to the demand. Specifically, we set learning rate and decay rate of the Stochastic Gradient Descent (SGD) optimizer to $1e3$ and $2e5$, respectively. The zero padding was applied on every convolutional layers and the batch size for training was set to 32. Apart from these aspects, the biggest modification is that we reduced the number of pooling layers. That is because each pixels on Doppler spectrogram involves strength and direction information, but pooling layers may degrade or eradicate important information, negatively affecting the predictive capability of the network.

IV. Experimental and Neural Network Results

Fig. 4 presents fragments of Doppler spectrogram for different occupancy states. Additionally, Fig. 5 presents examples of CAF plots for different states. Note that the Doppler spectrogram has 100 Doppler bins in one frame/column where bins above the middle line represent positive movement direction while bins below the middle line is negative direction. Here, positive and negative directions refer to moving towards and away surveillance antenna, respectively. Furthermore, the color bars indicate level of Doppler power. On the other hand, Table I shows parameters for different states. Finally, Table II presents the results output from the CNN's.

In Fig. 4, the spectrogram for an empty room (a) indicates that low-amplitude (< 0.01) noise exists but this will have minimal effect on results. For spectrograms of one person (b), we can clearly see a sinusoid-like wave which represents continuous forward and backward walking. But with the increase of the number of people (Fig. 4(c)(d)(e)), the strength and density of Doppler power increased resulting in the entire Doppler spectrogram becoming significantly more complex.

On the other hand, in Fig. 5, the CAF of an empty room exhibits low-levels of noise but with much less amplitude than other results of occupied states. Furthermore, different from CAFs in Fig. 5(c)(d)(e), the CAF of one person only has strength in one direction which is consistent with analysis in Section III.C.

TableI shows measures of central tendency and dispersion for different people states. As can be seen, differences between each corresponds to changes on Doppler spectrogram. The results of CNNs have been listed in TableII, whilst example confusion matrices of ZFNet results with different window sizes is shown in Fig. 6. TableII counts estimation accuracy of both occupancy state detection and people counting. We

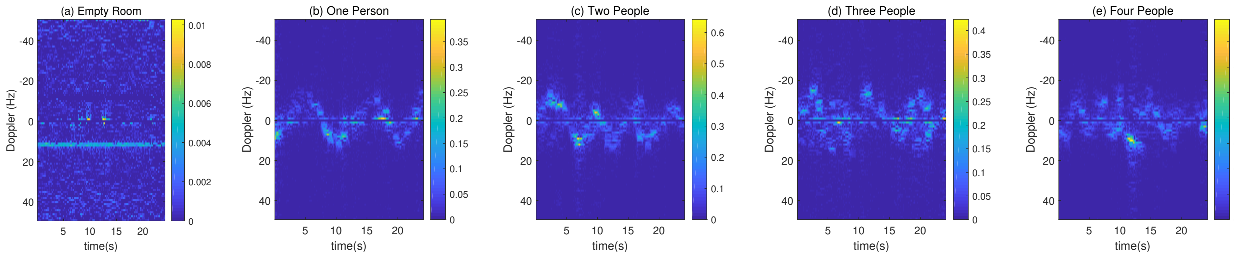


Fig. 4: Doppler spectrogram fragment of different occupancy states

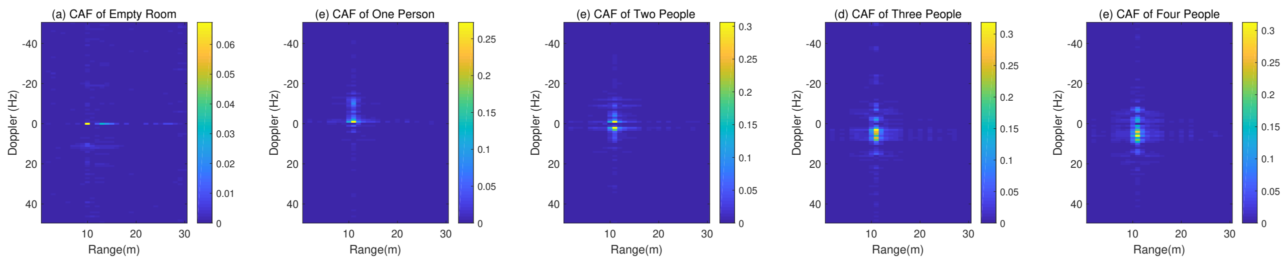
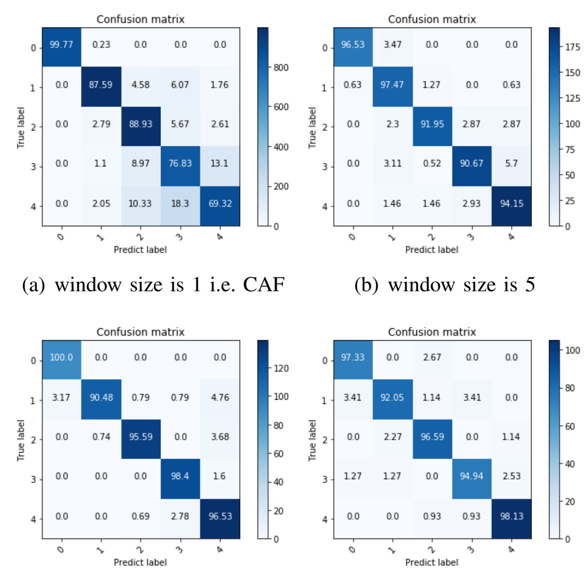


Fig. 5: CAF results of different occupancy states

Neural Network	Window Size	Classes	Accuracy(%)
LeNet	CAF	occupancy sensing	91.5
		people counting	83.4
	5	occupancy sensing	96.6
		people counting	95.6
	7	occupancy sensing	98.2
		people counting	96.9
	10	occupancy sensing	**99.5**
		people counting	**98.8**
AlexNet	CAF	occupancy sensing	91.2
		people counting	84.1
	5	occupancy sensing	96.9
		people counting	93.2
	7	occupancy sensing	97.2
		people counting	96.1
	10	occupancy sensing	98.6
		people counting	98.3
ZFNet	CAF	occupancy sensing	92.4
		people counting	85.2
	5	occupancy sensing	95.9
		people counting	94.3
	7	occupancy sensing	96.4
		people counting	95.3
	10	occupancy sensing	98.7
		people counting	97.3

TABLE II: Experimental Results



(a) window size is 1 i.e. CAF
(b) window size is 5
(c) window size is 7
(d) window size is 10

Fig. 6: Confusion matrix ZFNet with different window sizes, where labels represents the number of people

find that estimation accuracy imporves with increasing window size, especially when using a single CAF (i.e. window size = 1) to using a short period of Doppler spectrogram (i.e. window size is greater than 1). Overall, PWR occupancy sensing system can achieve our 99.54% accuracy for occupancy detection tasks (using the modified LeNet with window size equals 10) and maximum 98.80% accuracy for people counting (using the modified LeNet with window size equals 10).

V. Conclusion and Future Work

In this paper, we demonstrate that a PWR system is able to achieve both occupancy state detection and people counting of up to 4 people. In contrast to other WiFi sensing systems, the PWR system does not require any modifications to the WiFi access point or additional devices like NIC on WiFi networks and can directly leverage any commercial WiFi AP for detection. Moreover, instead of measuring RSS and CSI data, PWR exploits target reflections through cross-correlation based processing to determine range and Doppler information. After suppressing the problematic DSI componenet using a modified CLEAN algorithm, time-frequency processing is employed to generate Doppler spectrograms to highlight time varying target characteristics. Compared with RSS and CSI outputs, the Doppler spectrogram can be interpreted in a more meaningful way through observation of the temporal traces. Finally, by training with CNNs, we obtain general models for occupancy sensing which provides good estimation accuracy. Moreover, we have summarized some techniques for training with Doppler spectrogram data including applying sliding-window method, a more complex CNN and reducing pooling layers in the earlier layers. In longer-term, it is envisioned that a PWR occupancy sensing system can be extensively applied in many scenarios because of its low-cost, simplicity and high-sensitivity to motion. The work presented was mainly focused on exploring the feasibility of PWR for occupancy sensing and people counting and as such is limited by the small number of participants and the diversity of experimental scenarios. Future work will therefore focus on much larger crowds and experiments in more natural environment, less curated settings, for example a busy office environment where the subjects go about a normal day, and data is measured over this longer time-period.

ACKNOWLEDGMENTS

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