Machine Learning empowered Occupancy Sensing for Smart Buildings

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Abstract

Over half of the global electricity consumption is attributed to buildings, which are often operated poorly from an energy perspective. Significant improvements in energy efficiency can be achieved via intelligent building control techniques. To realize such advanced control schemes, accurate and robust occupancy information is highly valuable. In this work, we present a cutting-edge WiFi sensing platform and state-of-the-art machine learning methods to address longstanding occupancy sensing challenges in smart buildings. Our systematic solution provides comprehensive fine-grained occupancy information in a non-intrusive and privacy-preserving manner, which facilitates eco-friendly and sustainable buildings.

1. Introduction

Energy consumption of buildings, both residential and commercial, account for more than 50% of global electricity and 40% CO_2 emissions worldwide (Allouhi et al., 2015). In efforts to improve energy efficiency in buildings, researchers and industry leaders have attempted to implement various control and automation approaches alongside techniques like incentive design and price adjustment to more effectively regulate the energy usage. Lighting, heating, ventilation and air-conditioning (L-HVAC) systems are the most energy consuming components in a building, which contribute over 70% of the total building energy consumption (Klein et al., 2012). Prior studies have shown that huge amounts of energy is wasted from L-HVAC systems in unoccupied spaces since most of Building Management Systems (BMSs) operate based on static schedules (Yang et al., 2016; Pan et al., 2015). Occupancy based control algorithms for L-HVAC have proven effective in saving considerable amount of energy (Jia et al., 2018). Thus, accurate and robust occupancy and occupant activity sensing in buildings serves as the precursor for intelligent control and energy efficiency.

With the pervasive availability of WiFi infrastructure in both residential and commercial buildings, and nearly every mobile device (MD) is embedded with a WiFi module, WiFi has been acknowledged as the most promising modality for indoor context-aware services and location-based services (Lymberopoulos et al., 2015). In this work, we introduce WiFi enabled occupancy sensing platform, and propose Machine Learning (ML) algorithms, including adversarial learning, deep learning and transfer learning, to address longstanding challenging problems in occupancy sensing, such as extensive human intervention, environmental and temporal dynamics.

2. WiFi-based Occupant Positioning System

WiFi-based Occupant Positioning System (OPSs) usually adopt fingerprinting method as the localization engine as it can capture signal variations in complex indoor environments (Yang et al., 2012). It comprises of 2 steps: *1) Offline site survey phase:* Received Signal Strength (RSS) measurements from multiple WiF access points (APs) at predefined calibration points (CPs) and their physical coordinates are collected and formed a fingerprint database (a.k.a radio map); *2) Online testing phase:* the location of a MD is estimated by comparing the real-time RSS readings to the fingerprints stored in the database. Two major bottlenecks hinder WiFi-based OPS for pervasive implementation: 1) the offline site survey process is extremely labor-intensive and time-consuming; 2) the manual calibrated radio map is vulnerable to temporal and spatial dynamics. Thus, an automatic scheme capable of constructing and updating the radio map for adaptive and robust localization is desired.

2.1. Adversarial Learning for Radio Map Adaptation

To overcome these bottlenecks, we propose WiGAN, an automatic fine-grained radio map construction and adaptation scheme that is empowered by Gaussian Process Regression (GPR) and Generative Adversarial Network (GAN) (Goodfellow et al., 2014). Indoor space can be classified into 2 categories based on the accessibility: 1) free space (e.g. corridors, open space) where occupants can move freely; 2) constrained space where areas are blocked by furniture (e.g. table in cubicles and conference rooms) or personal office that requires special authentication. In free space, we develop a mobile robotic platform to construct and update the spatial map (via LiDAR SLAM) and radio map simultaneously and automatically.

In constrained space, we propose WiGAN to synthesize realistic RSS via GPR conditioned GAN. The overview of

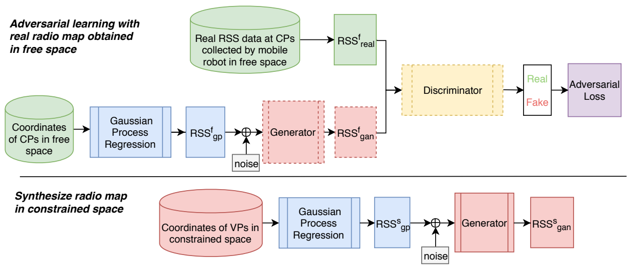
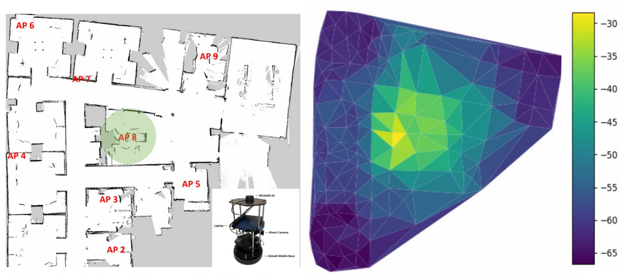


Figure 1. An overview of WiGAN.



(a) Constructed spatial map with AP locations (b) WiGAN generated radio map of AP8

Figure 2. (a) Constructed spatial map via LiDAR SLAM with AP locations; (b) WiGAN generated radio map of AP8 .

WiGAN is presented in Fig. 1. Its functioning includes 4 steps: **Step 1:** a GPR model $\mathcal{GP}$ is constructed using the real RSS values collected by the robot in the free space, as well as their 2D coordinates $(\boldsymbol{S}^f, \boldsymbol{l}^f)$ to capture the RSS variations on a rough level; **Step 2:** coarse RSS estimations $\hat{\boldsymbol{S}}^f_{\mathcal{GP}}$ from $\mathcal{GP}$ are adopted as inpurt for the generator $\mathcal{G}$ of GAN instead of random noise. As a result, the probability space on the generator gets further refined, to better describe the real RSS distribution in the latent feature space. The input for the discriminator $\mathcal{D}$ are randomly sampled batch of real RSS data $S^f \sim P_r(\boldsymbol{S}^f)$ and synthesized RSS data $\hat{S}^f_{\mathcal{GP}} \sim P_n(\hat{\boldsymbol{S}}^f_{\mathcal{GP}})$ in the free space. Similar to GAN, the parameters of $\mathcal{G}$ and $\mathcal{D}$ are optimized in min-max fashion as $\min_{\mathcal{G}} \max_{\mathcal{D}} \mathbb{E}_{S^f \sim P_r(\boldsymbol{S}^f)}[\log \mathcal{D}(\boldsymbol{S}^f)] + \mathbb{E}_{\hat{S}^f_{\mathcal{GP}} \sim P_n(\hat{\boldsymbol{S}}^f_{\mathcal{GP}})}[\log(1 - \mathcal{D}(\mathcal{G}(\hat{\boldsymbol{S}}^f_{\mathcal{GP}})))]$. Following steps detail the procedure to generate RSS values in constrained space. **Step 3:** we leverage the GPR model to generate coarse estimations at some virtual points (VPs) $\hat{\boldsymbol{S}}^f_{\mathcal{GP}}$; **Step 4:** $\hat{\boldsymbol{S}}^f_{\mathcal{GP}}$ are used as input for the generator. The fine-grained RSS estimations at VPs in the constrained space are calculated via the generator $\mathcal{G}$ trained in Step 2 as: $\hat{\boldsymbol{S}}^s = \mathcal{G}(\hat{\boldsymbol{S}}^f_{\mathcal{GP}})$. In this manner, a fine-grained radio map that covers both free and constrained space is automatically generated and continuously updated, substantially facilitating the large-scale implementation of WiFi OPS.

The experimental results are presented in Fig. 2. WiGAN captures the irregular RSS distributions in complex indoor spaces and outperforms pure GPR by 44.9%. By leveraging the radio map synthesized via WiGAN, 1.96 m localization accuracy is achieved while tremendously reducing the overhead of time and labor for manual site survey process. By leveraging the occupancy location information provided by our WiFi OPS, our occupancy-driven lighting control achieves 93% energy savings compared to conventional lighting control scheme. Moreover, WiGAN can be extended for other RF signal's radio map construction and adaptation, e.g. GPS and LTE. This substantially broadens the application of GAN framework to an entirely new domain of Internet of Things (IoT).

3. Device-free Human Activity Recognition

With the booming development of IoT, billions of WiFi enabled IoT devices, such as thermostats, smart speaker, switch and TV, are en-route to being widely deployed in indoor environments. The WiFi connection among them provides a rich web of reflected rays that spread every corner. Although these WiFi signals are designed for communication and data transmission, they have great potential to provide a unique opportunity to sense nearby human activities, requiring no privacy intrusive cameras or inconvenient wearables. We explore Channel State Information (CSI) from WiFi physical layer, which reveals detailed information about how human movement interferes the WiFi signal propagation from one node (transmitter) to another node (receiver). We develop an OpenWrt firmware that can run on commercial WiFi routers for CSI data acquisition, creating potential for large-scale real-life applications.

3.1. Deep Learning for Human Activity Recognition

Conventional feature extraction algorithms require extensive human intervention and expert knowledge. To address this issue, we treat CSI time-series data from multiple subcarriers as the source of 'video monitoring 'for occupancy sensing. As shown in Fig. 4, different human activities generate distinct perturbations on CSI readings. We divide these CSI time-series data into small chunks and the data in each window forms a CSI frame. These CSI frames are served as the input dataset for our deep learning engine.

Fig. 4 illustrates the network architecture of our proposed deep learning method. We first sanitize the inherent noise in each CSI frame and learn a sparse representation of it using an autoencoder (AE) module. After that, we use a convolutional neural network (CNN) module to extract the most discriminative local features from the output of AE. Since the sequence of CSI frames can be viewed as consecutive video, the temporal dependencies among them are vital properties for accurate human activity recognition. Therefore, we use long short-term memory (LSTM) to capture them. Since all the parameters in the DNN are automatically fine-tuned in an end-to-end fashion, excessive expert knowl-

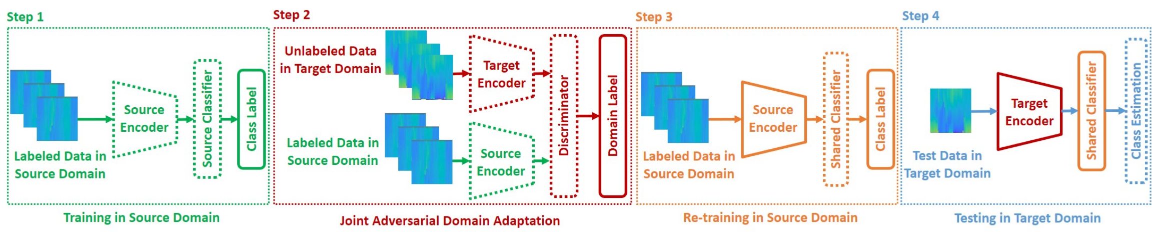


Figure 3. Proposed Adversarial Domain Adaptation.

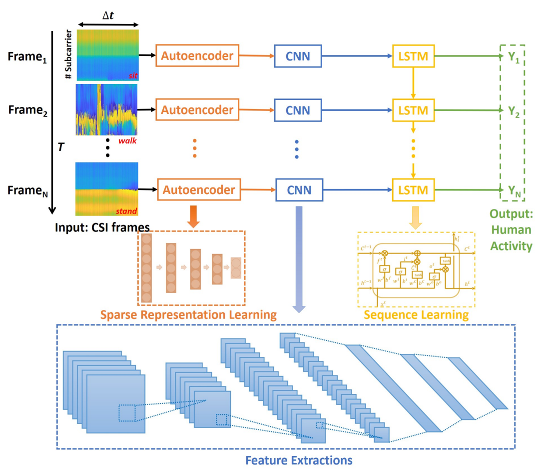


Figure 4. WiFi CSI frames depicting different activities and the DNN architecture for device-free human activity recognition.

edge is not needed for feature engineering, making it much more efficient and extendable. Real-world experiments were conducted which demonstrate that the proposed method can identify a number of human activities (e.g. sit, stand, walk, run) with 97.6% recognition accuracy by leveraging only two commodity WiFi routers.

3.2. Domain Adaptation for Robust Sensing

Another challenging task is to improve the adaptability of the sensing system (i.e. to make it operate in an entirely new environment with minimal re-configuration and re-calibration). To address this, we propose a novel adversarial domain adaptation (ADA) scheme. Fig. 3 illustrates its training procedure, which consists of 4 steps. **Step 1:** Train a source encoder M_s and a source classifier C_s by optimizing the loss ($\mathcal{L}_{C_s}$) to construct a good baseline of the feature space and the classifier. **Step 2:** Train a target encoder M_t while giving freedom to the source encoder M_s to fine-tune via adversarial learning by optimizing the discriminator loss ($\mathcal{L}_D$), the source encoder loss ($\mathcal{L}_{M_s}$) and the target encoder loss ($\mathcal{L}_{M_t}$). In this manner, both unlabeled target data and labeled source data are embedded to a domain-invariant feature space defined by both domains, in a way that a domain discriminator cannot distinguish the domain labels of them. **Step 3:** A shared classifier C_{sh} is constructed with the labeled source domain data by optimizing loss ($\mathcal{L}_{C_{sh}}$).

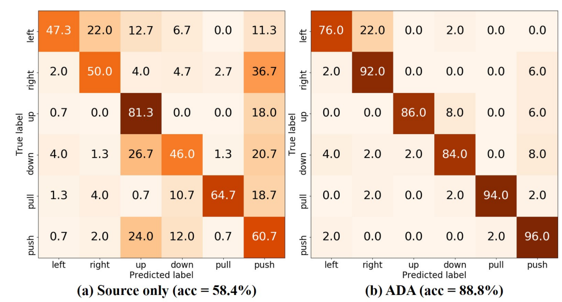


Figure 5. Confusion matrices for gesture recognition via (a) Source only network (b) Proposed ADA method (large conference room as source domain, small conference room as target domain).

Step 4: Employ the trained target encoder M_t to map test samples from the target domain into the domain-invariant feature space and use the shared classifier C_{sh} to identify the category of each testing sample in the target domain. The training of the proposed ADA scheme is thusly equivalent to solving $\min_{C_{sh}} \min_{M_t, M_s} \max_D \min_{M_s, C_s} \mathcal{L}_{C_s} + \mathcal{L}_D + \mathcal{L}_{M_s} + \mathcal{L}_{M_t} + \mathcal{L}_{C_{sh}}$. Experiments were conducted in 2 conference rooms with different sizes to validate the propose method for spatial adaptation of WiFi enabled device-free gesture recognition. Volunteers performed 6 common gestures, moving a hand right and left, up and down, push and pull between the two IoT devices. Fig. 5 compares the confusion matrices of the gesture classification accuracies with source only network and with our proposed ADA method. Our method enhances the accuracy by 21% and the recognition accuracy of each gesture is improved. Resilient WiFi-enabled device-free gesture recognition is achieved against spatial variations without time-consuming and labor-intensive data collection and labeling process in a new environment.

4. Conclusion

In this work, we introduced our WiFi sensing platform and our proposed ML algorithms to address longstanding occupancy sensing challenges in smart building. Our systematic solution performs occupancy sensing and behavior inference in a non-intrusive and privacy-preserving manner. This in turn enables occupancy adaptive L-HVAC building control achieving energy efficiency and reduce CO_2 emissions while maintaining the occupant comfort and productivity.

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