REAL-TIME INDOOR EVENT MONITORING USING CSI TIME SERIES

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ABSTRACT

Environmental information is recorded in the multipath propagation, and can be accessed in the form of channel state information (CSI) through commodity WiFi devices. A single CSI reading for event detection is adopted in most existing CSI based indoor monitoring system. However, due to the impact of noise, event inconsistency and environmental dynamics, this type of approaches is not very robust. In this work, we design efficient algorithms to fully exploit the information embedded in the CSI time series to combat interference introduced by CSI perturbations, and propose an indoor event monitoring system that achieves accurate real-time monitoring. The accuracy and robustness of the proposed system is evaluated through experiments, which illustrate its potential in future smart home applications.

***Index Terms*—** Smart radio; real-time monitoring; indoor event monitoring.

1. INTRODUCTION

During the wireless transmission, wireless signals propagate through a multipath channel such that the received signal consists of copies of the transmitted signal reflected and scattered by different objects in the environment. The multipath propagation enables wireless passive sensing, because each indoor environment can be interpreted with the help of the wireless channel state information (CSI) which records the environmental information.

Early approach for wireless passive sensing systems relies on detecting changes in the received signal strength (RSS) [1–5]. The major drawback for RSS-based systems is that the multipath brings in undesirable changes to the RSS and thus corrupts it. To address this problem, RSS-based sensing systems often require a line-of-sight (LOS) path between the target and transceivers, resulting in a limited accuracy and coverage in detection. Another category of wireless passive sensing uses the time-of-flight (ToF) information of radio signals to track moving objects [6–9]. Due to the fact that the spatial resolution of wireless sensing is inversely proportional to the sensing bandwidth, in order to extract the fine-grained ToF information, extremely large bandwidths or special designed frequency sweeping signals are required, both of which are infeasible in commodity WiFi devices. Recently, the CSI becomes available in commodity WiFi devices and can be extracted from the PHY layer. Since the CSI is a feature with a higher sensitivity to the change of wireless propagation, it has been utilized in fine-grained classification applications to detect human activities [10–17]. Due to the random phase distortion, only CSI amplitude was leveraged in most of existing works, in spite of how informative the CSI phase is. Although both the amplitude and phase information of the CSI was utilized in [11], it can only differentiate between the static and dynamic states in a LOS setting. In [16], Xu *et al.* proposed a time-reversal (TR) based indoor event detection system (TRIEDS) that utilizes TR technique to distinguish among different indoor events. However, as based on a single CSI reading, TRIEDS may not be robust due to the perturbations in EM propagation introduced by noise and environmental dynamics. To our knowledge, none of the previous works exploits both full CSI information and the temporal relationship in the CSI time series for indoor multi-event monitoring. Recently, Ohara *et al.* proposed to use a deep neural network (DNN) and hidden Markov model (HMM) for CSI based indoor event detection [18], which introduces significantly high complexity in training data collection and network learning.

On the contrary, in this paper, we propose an indoor monitoring system that monitors the occurrence of different indoor events in real time with commercial WiFi devices, by exploiting the temporal information embedded in the CSI time series. Since the occurrence of an indoor event lasts for a certain period and possesses a similar transition pattern among different realizations, information is embedded not only in each CSI sample but also in that of how CSI changes along time. Instead of treating each CSI as an independent feature, in this work, the time series of CSI samples captured continuously is used for identifying and classifying different indoor events. Feature extraction algorithms is designed to refine the most distinct and representative sequence of CSI from the entire time series, and to reduce the feature dimension by removing the correlation among different subcarriers. A modified classifier based on the k-nearest-neighbor (kNN) is proposed to overcome the perturbation and divergence in the real-time measured feature introduced by event inconsistency, and unknown start and end point of the occurrence. We use the door opening and close in smart home scenario as a representative set of events to study the CSI time series classification, and the technique can be generalized to other types of events.

The rest of the paper is organized as follows. We introduce the proposed feature extraction algorithms in Section 2. In Section 3, the classification methodology designed for the proposed system is discussed. The performance of the proposed system is studied and evaluated through experiments in Section 4. This work is concluded in Section 5.

2. FEATURE EXTRACTION

In this section, we present the proposed algorithm that refines the measured CSI time series and extracts distinct features for all indoor events of interest during the training phase.

2.1. Multi-Antenna Diversity

MIMO transmission provides a large number of degrees of freedom delivered through spatial diversity for RF sensing. Suppose there is a number of $|S|$ indoor events to be monitored and let $\mathbf{H}_i^{(m,n)}[l]$ denote the l^{th} complex-valued CSI vector, a.k.a., channel frequency response (CFR), measured on the link between the m^{th} transmitter (TX) antenna and the n^{th} receiver (RX) antenna during event $S_i \in S$. To fully utilize the spatial diversity, we concatenate CSI vectors from different links into a single column vector as the augmented CSI, i.e.,$\widetilde{\mathbf{H}}_i[l] = \left[\mathbf{H}_i^{(1,1)}[l]^{\mathrm{T}}, \cdots, \mathbf{H}_i^{(N_{TX}, N_{RX})}[l]^{\mathrm{T}}\right]^{\mathrm{T}}$. Here, $\widetilde{\mathbf{H}}_i[l]$ is a complex-valued column vector of length $N_{sub} \times N_{TX} \times N_{RX}$, N_{sub} denotes the number of accessible subcarriers, and N_{TX} and N_{RX} denote the number of TX and RX antennas respectively.

A real-valued waveform vector $\mathbf{G}_i[l]$ is generated by concatenating the real and imaginary part of the obtained augmented CSI. Even though information on all transmission links is included in $\mathbf{G}_i[l]$'s, the dimension of feature increases dramatically and makes the classification more difficult. In this work, we propose a feature extraction algorithm that performs refinement and dimension reduction on $\mathbf{G}_i[l]$'s.

2.2. Refinement of CSI Time Series

The essential part of the proposed algorithm is to extract the most representative segment in the CSI time series captured during the occurrence of each indoor event for building a good classifier later. In the training phase the CSI time series received at the RX may capture some indoor status similar to other indoor events at the beginning and the end part of the series. Resembling CSI sub-sequences, captured from different indoor events, introduce ambiguity into pattern matching and degrade the classification performance. To address that, a waveform extraction algorithm is proposed to track the change in waveform series and only keep a portion of waveform sequence that contains significant changes.

For example, during the training phase, a time series of $\mathbf{G}_i[l],\ l = 1, 2, \cdots, L$ is captured for event S_i. The proposed algorithm is to find the index $l_{s,i}$ and $l_{e,i}$ such that the subsequence of $\mathbf{G}_i[l],\ l_{s,i} \leq l \leq l_{e,i}$ contains significant variations introduced by event S_i. The algorithm is as follows.

1. The Euclidean distance $D_{s,i}[l] = \|\mathbf{G}_i[l] - \mathbf{G}_i[1]\|$ is obtained for all CFR samples.
2. Given the CSI sampling period T_s, a median filter with length $L_m = 1/2T_s$ is applied to the sequence of $D_{s,i}[l]$'s and outputs $\widehat{D_{s,i}}[l]$'s.
3. $l_{s,i}$ is determined by $l_{s,i} = \arg\min_{l} \{l | \widehat{D_{s,i}}[l] > \gamma_{s,i}\}$ with an empirical threshold $\gamma_{s,i}$.

The index $l_{e,i}$ can be determined similarly by tracking the changes from the end point $\mathbf{G}_i[L]$ with the help of threshold $\gamma_{e,i}$. The $\gamma_{s,i}$ and $\gamma_{e,i}$ are determined by both the overall dynamics in $\mathbf{G}_i[l]$'s and the environmental dynamics learnt from waveforms captured in the static environment.

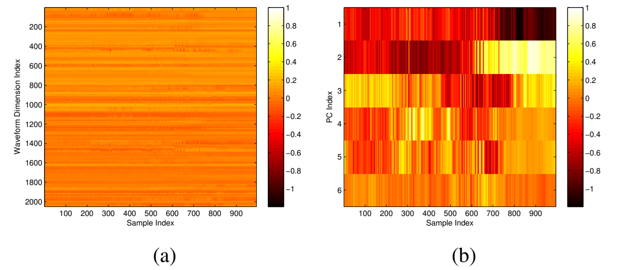


Fig. 1: Study on PCA denoising and dimension reduction. (a) Waveform series $\mathbf{G}_i[l]$'s before PCA. (b) Feature series $\mathbf{Z}_i[l]$'s after PCA.

2.3. PCA based Denoising & Compact Representation

In reality, the obtained CSI is inherently noisy due to thermal noise and imperfection on hardware, and the channel information on all subcarriers are correlated. Based on that, the proposed algorithm applies principal component analysis (PCA) to remove noise, de-correlate, and reduce dimensions for the CSI. Also, PCA is applied to waveform vectors of all indoor events for the purpose of seeking a good feature representation that amplifies the distinction among waveforms.

Let Ω_{all} denote the super waveform matrix generated as $\Omega_{all} = \left[\mathbf{G}_1[l_{s,1} : l_{e,1}], \cdots, \mathbf{G}_{|S|}[l_{s,|S|} : l_{e,|S|}]\right]$. By applying PCA on columns of matrix Ω_{all}, a projection matrix Φ of dimension $p_c \times P$ is obtained as the collection of eigenvector of the correlation matrix of Ω_{all}, and p_c represents the number of principle components (PCs) to be kept. Also, a waveform $\overline{\mathbf{G}}$ is generated as the mean of all columns in Ω_{all}, which can be viewed as the background information in the waveform vectors. Then, for each event S_i, the final feature vector $\mathbf{Z}_i[l]$ can be obtained by $\mathbf{Z}_i[l] = \Phi \times (\mathbf{G}_i[l] - \overline{\mathbf{G}})$, where the projected feature vector $\mathbf{Z}_i[l]$ is of length p_c. An example of comparison between $\mathbf{G}_i[l]$'s and $\mathbf{Z}_i[l]$'s is plotted in Fig.1, where the projected feature series $\mathbf{Z}_i[l]$'s exhibits a significant variations among all PC dimensions while changes in original waveform series $\mathbf{G}_i[l]$'s is too small and too diffuse to be observed.

In practice, the value of p_c is determined by picking the first several largest eigenvalues that cover 80% of the total

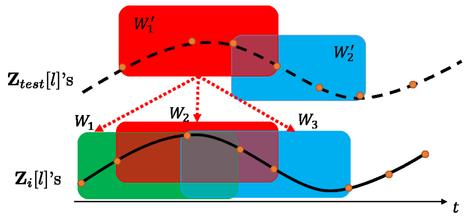


Fig. 2: Illustration of the proposed real-time monitoring algorithm using CSI time series.

energy of Ω_{all}. Since only the first few PCs are considered, the PCA can be computed efficiently through thin-SVD.

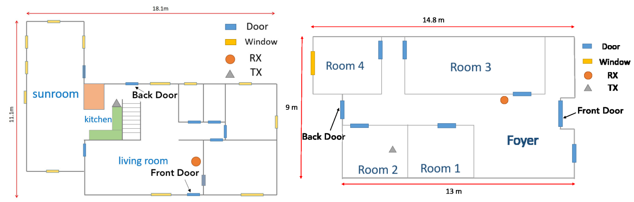
3. CLASSIFICATION

After obtaining the projected feature $\mathbf{Z}_i[l]$'s, the proposed system builds a classifier that can detect the occurrence of trained events in real time based on the distinct time series of feature vectors. The proposed classification algorithm adopts dynamic time warping (DTW) proposed in [19, 20] to quantitatively evaluate the similarity between the training series and the real-time measured testing series of $\mathbf{Z}_{test}[l]$'s. In addition, without a global view over $\mathbf{Z}_{test}[l]$'s, it is difficult to locate the start and end point of the occurrence of an event to extract the entire feature patten. The current series of $\mathbf{Z}_{test}[l]$'s may only contain partial information of the event occurrence. On the other hand, due to the event inconsistency, the event occurs during the testing phase may exhibit a perturbed feature pattern, e.g., happening with a different speed. In what follows, we propose a classification algorithm that addresses all the aforementioned difficulties.

3.1. Dynamic Time Warping

In the proposed algorithm, given two sequences of feature series $\mathbf{Z}_1[l]$'s and $\mathbf{Z}_2[l]$'s with equal length L, the DTW optimal cost c is defined as the distance of a warping path, i.e., $c(\mathbf{Z}_1, \mathbf{Z}_2) = \sum_{w=1}^{|P^*|} \left\|\mathbf{Z}_1[l_{1,w}^*] - \mathbf{Z}_2[l_{2,w}^*]\right\|^2$, where P^* denotes the optimal warping path with length $|P^*|$, and $l_{1,w}^*$ and $l_{2,w}^*$ are the indexes of $\mathbf{Z}_1[l]$'s and $\mathbf{Z}_2[l]$'s at the w^{th} point on P^*. For all possible warping paths $(P,\ l_{1,w},\ l_{2,w})$, P^* is the optimal in that $\sum_{w=1}^{|P^*|} \left\|\mathbf{Z}_1[l_{1,w}^*] - \mathbf{Z}_2[l_{2,w}^*]\right\|^2 \leq \sum_{w=1}^{|P|} \left\|\mathbf{Z}_1[l_{1,w}] - \mathbf{Z}_2[l_{2,w}]\right\|^2, \ \forall P$.

With a warping step-size larger than 1, the DTW algorithm is able to overcome issues of missing feature samples introduced by event inconsistency and WiFi traffic collision. In addition, in the proposed algorithm, the Sakoe-Chiba Band introduced in [21] is adopted which reduces the number of searchable indexes and thus the proposed algorithm benefits from a quick and low-complexity computation of DTW. Consequently, a simple kNN classifier is sufficient to classify testing features, provided that both testing and training sequences contain the same information.



(a) (b)

Fig. 3: Experiment setting: floorplan. (a) Facility 1: single family house. (b) Facility 2: offices.

3.2. Real-Time Monitoring

However, due to the event inconsistency and unknown start and end point of event occurrence, the current testing series often contains only partial event information or a perturbed pattern of the training series. Also, real-time monitoring is sensitive to latency. In this part, a sliding window based classifier is proposed and an example is shown in Fig.2 to demonstrate the concept. As shown in Fig.2, $\mathbf{Z}_{test}[l]$'s is the incoming testing series with an infinite length denoted by the orange dot on the dashed curve, and $\mathbf{Z}_i[l]$'s is the training series with a finite length marked by the orange dot on the solid curve. Although the two curves share the similar shape, collections of sampled points (orange dots) are different.

To promptly and accurately detect the indoor states, the current testing feature vector $\mathbf{Z}_{test}[l]$ along with its antecedent feature samples form a temporary testing series of finite length denoted by $\mathbf{W}_l'$. Meanwhile, the training series $\mathbf{Z}_i[l]$'s is also divided into several segments of adjacent feature vectors with the same length of $\mathbf{W}_l'$ and a certain overlap, denoted by $\mathbf{W}_j,\ \forall j$. Then the similarity between $\mathbf{W}_l'$ and event S_i is evaluated by the normalized distance $\hat{c}(\mathbf{W}_l', \mathbf{Z}_i)$ as $\hat{c}(\mathbf{W}_l', \mathbf{Z}_i) = \min_j \frac{1}{|P_{warp,j}|} c(\mathbf{W}_l', \mathbf{W}_j)$, where $\mathbf{W}_j$ is in $\mathbf{Z}_i[l]$'s and $|P_{warp,j}|$ is the length of the optimal warping path between testing $\mathbf{W}_l'$ and training $\mathbf{W}_j$.

Based on the obtained similarity scores, the decision output for current testing series $\mathbf{W}_l'$ is determined by

$$D_{test}(\mathbf{W}_l') = \begin{cases} \arg\min\limits_{S_i \in S} \hat{c}(\mathbf{W}_l', \mathbf{Z}_i), \text{ if } \min\limits_{S_i \in S} \hat{c}(\mathbf{W}_l', \mathbf{Z}_i) \leq \beta \\ \text{Unknown, otherwise} \end{cases} \tag{1}$$

where β is an empirical threshold on the similarity score.

In reality, the length of the temporary testing series and training segments is $2/T_s$ based on the intuition that indoor events often lasts for several seconds and features within a couple of seconds should be distinct enough for classification. The length of the stride, i.e., the number of antecedent feature samples to be included in the temporary testing series is set to be $1/T_s$ and the overlap in generating training segments is often set to be $1/2T_s$ to avoid misdetection and unnecessary calculation complexity.

4. PERFORMANCE EVALUATION

To evaluate the performance of the proposed algorithms, extensive experiments have been conducted to protect a single

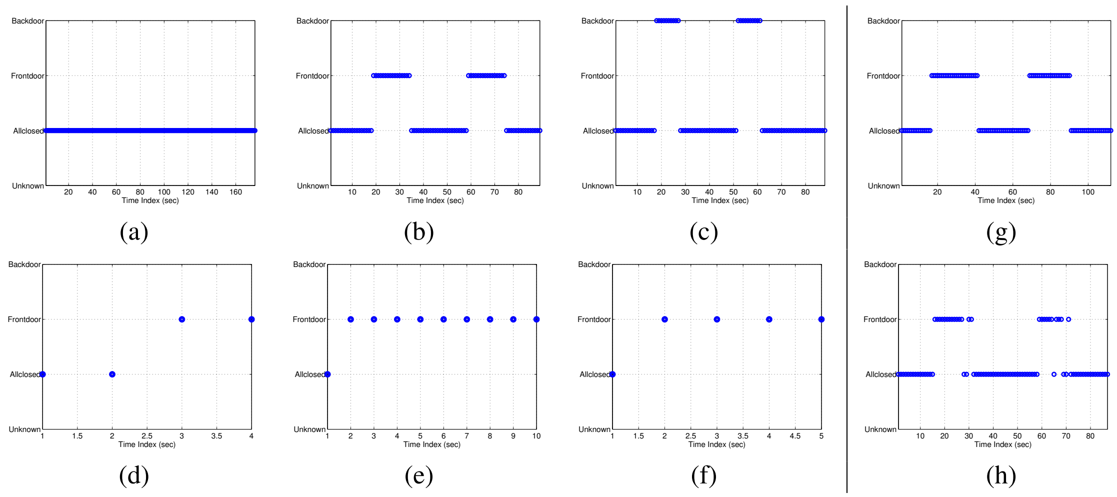


Fig. 4: Experimental results. (a)Accuracy test: 3 minutes under "all-doors-closed" with someone walking outside and close to front and back door. (b) Accuracy test: front door is opened and closed twice from outside. (c)Accuracy test: back door is opened twice from outside. (d) Robustness test: front door is opened under a fast speed. (e) Robustness test: front door is opened under a slow speed. (f) Robustness test: front door is opened to half-open. (g) Front door opened at Day 2. (b) Front door opened at Day 9.

family house and a multi-room office from intrusion whose floorplans are shown in Fig.3. A prototype of the proposed indoor monitoring system is implemented using a pair of commercial WiFi devices, which performs 3×3 MIMO transmission with the carrier frequency being 5.845GHz and under a 40MHz bandwidth. Both of the TX and the RX are placed in the protected area under a NLOS setting to monitor the status of the front door and the back door.

In the training phase, one tester, as the intruder, intentionally opens the front door and the back door from outside once, and one CSI time series is collected during the occurrence of each event. In addition, an "all doors closed" event is defined as the state that both the front door and the back door are closed and no one is moving inside the facility. The channel sampling rate is 30 Hz. For the search range of the DTW algorithm, the width of the Sakoe-Chiba Band is set to be $0.03 \times 2/Ts$ and the step-size is 2.

I. Accuracy of Event Detections: Experiments are conducted in Facility 1 to validate the feasibility and accuracy of the proposed system. Results are shown in Fig.4a-4c where the x-axis is the time index and y-axis is the output of the proposed system. Validated by experiments, the proposed system can detect the occurrence of all trained events accurately and it is robust to outside activities.

II. Robustness to Event Inconsistency: Further experiments are conducted in Facility 2 to investigate the impact of event inconsistency on the real-time monitoring. In the testing phase, a second tester opens the same door at different speeds and also performs a half-open test where the door is only opened to approximately 45 degree. As shown in Fig.4d-4f, it is verified that the proposed system is robust to individual diversity and event inconsistency, and detects the occurrence accurately even when only partial trained information is captured by the testing series.

III. Long-Term Monitoring: To study the long-term behavior of the proposed system, the prototype is deployed in Facility 1 for 9 days with everyday resident activities and a commercial home security system is installed to provide ground truth. The resident activities may jeopardize the proposed system by changing the indoor environment, given the training conducted at Day 1. Examples are shown in Fig.4g, 4h. Because each door opening and closing event takes several seconds to complete, several decisions will be output continuously during the occurrence as the proposed system updates every second. As long as one decision matches the real event, we consider it as detected. Hence, the overall detection rate for each single event is 100%, even if occasional misdetections happen since propagation environment changes over time. Without significant environment changes, the proposed system successfully detects the occurrence of all 30 intrusions performed by testers during 9 days.

5. CONCLUSIONS

We propose a real-time indoor event monitoring system that utilizes CSI time series to differentiate between indoor states. A feature extraction algorithm is proposed to refine and extract features and the proposed classifier is capable of overcoming CSI perturbations, event inconsistency, and unknown start and end point of event occurrence. Experimental results illustrate the potential of the proposed system in future real-time indoor monitoring applications.

6. REFERENCES

[1] Dian Zhang, Jian Ma, Quanbin Chen, and Lionel M. Ni, "An rf-based system for tracking transceiver-free ob-

jects," in *Fifth Annual IEEE International Conference on Pervasive Computing and Communications*, March 2007, pp. 135–144.

[2] Stephan Sigg, Shuyu Shi, Felix Buesching, Yusheng Ji, and Lars Wolf, "Leveraging RF-channel fluctuation for activity recognition: Active and passive systems, continuous and RSSI-based signal features," in *Proceedings of International Conference on Advances in Mobile Computing & Multimedia*. 2013, pp. 43–52, ACM.

[3] Chunmei Han, Kaishun Wu, Yuxi Wang, and L.M. Ni, "Wifall: Device-free fall detection by wireless networks," in *Proceedings of the International Conference on Computer Communications*, April 2014, pp. 271–279.

[4] Yu Gu, Fuji Ren, and Jie Li, "Paws: Passive human activity recognition based on wifi ambient signals," *IEEE Internet of Things Journal*, vol. 3, no. 5, pp. 796–805, Oct 2016.

[5] Heba Abdelnasser, Moustafa Youssef, and Khaled A. Harras, "WiGest: A ubiquitous wifi-based gesture recognition system," in *2015 IEEE Conference on Computer Communications*, April 2015, pp. 1472–1480.

[6] Ram M Narayanan, "Through-wall radar imaging using UWB noise waveforms," *Journal of the Franklin Institute*, vol. 345, no. 6, pp. 659–678, 2008.

[7] Debora Pastina, Fabiola Colone, Tatiana Martelli, and Paolo Falcone, "Parasitic exploitation of WiFi signals for indoor radar surveillance," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 4, pp. 1401–1415, April 2015.

[8] Fadel Adib, Zach Kabelac, Dina Katabi, and Robert C. Miller, "3D tracking via body radio reflections," in *Proceedings of the 11th USENIX Symposium on Networked Systems Design and Implementation*. Apr. 2014, pp. 317–329, USENIX Association.

[9] Fadel Adib, Zachary Kabelac, and Dina Katabi, "Multi-person localization via RF body reflections," in *Proceedings of the 12th USENIX Symposium on Networked Systems Design and Implementation*. May 2015, pp. 279–292, USENIX Association.

[10] Fadel Adib and Dina Katabi, "See through walls with WiFi!," in *Proceedings of the ACM SIGCOMM 2013 Conference*. 2013, pp. 75–86, ACM.

[11] Kun Qian, Chenshu Wu, Zheng Yang, Yunhao Liu, and Zimu Zhou, "Pads: Passive detection of moving targets with dynamic speed using phy layer information," in *Proceedings of the 20th IEEE International Conference on Parallel and Distributed Systems*, Dec 2014, pp. 1–8.

[12] Arijit Banerjee, Dustin Maas, Maurizio Bocca, Neal Patwari, and Sneha Kasera, "Violating privacy through walls by passive monitoring of radio windows," in *Proceedings of the ACM Conference on Security and Privacy in Wireless & Mobile Networks*. 2014, pp. 69–80, ACM.

[13] Wei Wang, Alex X Liu, Muhammad Shahzad, Kang Ling, and Sanglu Lu, "Understanding and modeling of WiFi signal based human activity recognition," in *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking*. ACM, 2015, pp. 65–76.

[14] Mohammed Abdulaziz Aide Al-qaness, Fangmin Li, Xiaolin Ma, and Guo Liu, "Device-free home intruder detection and alarm system using wi-fi channel state information," *International Journal of Future Computer and Communication*, vol. 5, no. 4, pp. 180, 2016.

[15] Hao Wang, Daqing Zhang, Yasha Wang, Junyi Ma, Yuxiang Wang, and Shengjie Li, "Rt-fall: A real-time and contactless fall detection system with commodity wifi devices," *IEEE Transactions on Mobile Computing*, vol. 16, no. 2, pp. 511–526, Feb 2017.

[16] Qinyi Xu, Yan Chen, Beibei Wang, and K. J. Ray Liu, "TRIEDS: Wireless events detection through the wall," *IEEE Internet of Things Journal*, vol. 4, no. 3, pp. 723–735, June 2017.

[17] Qinyi Xu, Zoltan Safar, Yi Han, Beibei Wang, and K. J. Ray Liu, "Statistical learning over time-reversal space for indoor monitoring system," *IEEE Internet of Things Journal*, vol. PP, no. 99, pp. 1–1, 2018.

[18] Kazuya Ohara, Takuya Maekawa, and Yasuyuki Matsushita, *Detecting State Changes of Indoor Everyday Objects Using Wi-Fi Channel State Information*, vol. 1, ACM, Sept. 2017.

[19] Meinard Müller, *Information retrieval for music and motion*, pp. 69–84, Springer Berlin Heidelberg, 2007.

[20] Hiroaki Sakoe and Seibi Chiba, "Dynamic programming algorithm optimization for spoken word recognition," *IEEE transactions on acoustics, speech, and signal processing*, vol. 26, no. 1, pp. 43–49, 1978.

[21] Eamonn Keogh and Chotirat Ann Ratanamahatana, "Exact indexing of dynamic time warping," *Knowledge and information systems*, vol. 7, no. 3, pp. 358–386, 2005.