CSI Sampling for Room-by-Room Device Grouping in Practical Environments

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***Abstract*—To reduce the cost of Internet of Things (IoT) system deployment, we are focusing on the cost reduction of device location information setup and developing a room-by-room device grouping system. In our previous work, we presented a room-by-room IoT device grouping based on wireless LAN (WLAN) channel state information (CSI) using unsupervised learning. The performance in a practical environment, however, is significantly degraded due to the nonuniform time distributions of where people stay in each room. In this paper, we present CSI sampling, namely, a CSI data selection method, relying on independent component analysis (ICA) to improve the device grouping performance in a practical environment. An experimental evaluation conducted in a practical environment reveals that our CSI sampling greatly improved device grouping performance with an adjusted Rand index (ARI) of up to 44.9%.**

***Index Terms*—IoT device location information setup, unsupervised learning, independent component analysis (ICA).**

I. Introduction

Internet of Things (IoT) systems are becoming prevalent due to advances in computing and networking technologies. IoT systems have been deployed in the industry for telemetry and factory automation and are now extended to be used in smart house scenarios.

With a large number of IoT devices, the cost of setup became a big burden in the IoT system deployment. IoT systems capable of automatic configuration that mainly focus on automatic network configuration, known as zero configuration (zeroconf), self-configuration, and automatic provisioning, have been proposed to reduce the cost of IoT system deployment [1]–[3]. Semi-automatic network configuration methods have also been proposed or have already been used [4]–[8]. There are mixed reality (MR) based device coordinators and automatic device association methods to realize IoT applications and services [9]–[12].

However, we still need to set up device location information, resulting in a high cost when there are a large number of devices. Although the number of IoT devices is limited in a smart house scenario, a non-expert needs to complete the device location information setup. Localization techniques reduce the cost of the device location setup, though, which requires prerequisites such as a site survey and reference node installation in an indoor scenario.

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To reduce the cost of the device location information setup, we are developing a room-by-room device grouping system, which maps devices to groups based on the room where the device is installed [13]. The device grouping system groups devices based on the changes in wireless LAN (WLAN) channel state information (CSI) caused by human movement using an unsupervised machine learning algorithm. We then ask a user for the actual location information of each group to complete the location information setup. Combined with existing relative localization methods, we can complete the device location setup for all the devices. For non-experts, i.e., in a smart house scenario, we can ask a user for the location information such as the name of the room where the device is installed when the device in a group is used. Note that our focus is on the location information setup for stationary installed IoT devices. We assume that the location of mobile IoT devices are estimated by existing localization methods after we obtain the location of stationary IoT devices.

However, our device grouping system presented in [13] shows poor performance in a practical environment because of the nonuniform time distributions of where people stay in each room. The device grouping system randomly samples CSI data from a huge amount of data to create a feature vector for grouping. To accurately group IoT devices, we need to extract the separate influences on CSI from people in different locations. In a practical environment, we may spend a long time in a living room, while we may spend a short time in a bathroom. Random CSI-data sampling tends to extract CSI changes in the common situation of people's location distribution.

In this paper, we extend our previous work to group IoT devices in a practical environment. To efficiently extract the influences on CSI from people in different locations, we sample CSI data in many situations in terms of people's distribution, i.e., how people stay in rooms. The influence of different people on CSI can be considered to be independent. We apply independent component analysis (ICA) to feature vectors extracted from CSI to separate the CSI changes caused by different people. We then perform clustering on the ICA components to group the feature vectors based on the people's distribution. Finally, feature vectors are randomly sampled from each cluster to group IoT devices.

By conducting experiments in a one-bedroom actual house

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where four people are living, we show the improvement in grouping performance by our proposed CSI sampling method. Our main contributions are threefold:

- We experimentally show the poor performance of the room-by-room IoT device grouping presented in our previous work [13] in a practical environment.
- We present the design of a CSI-data sampling method for the IoT device grouping in a practical environment. Our design is based on an observation that CSI changes caused by different people are independent. We apply ICA to separate CSI changes caused by different people.
- We conducted experiments to evaluate our CSI-data sampling method in a real environment. The experimental evaluations show that our CSI-data sampling improved the IoT device grouping performance with an adjusted Rand Index (ARI) by up to 44.9%.

The remainder of this paper is organized as follows. Section II summarizes related work. Section III briefly shows the room-by-room IoT device grouping system presented in [13], followed by the design of CSI-data sampling method proposed in this paper in Sect. IV. In Sect. V, we evaluate the device grouping performance. Finally, Sect. VI concludes the paper.

II. Related Work

This study relates to IoT system configuration, including network configuration, device coordination, and device localization. We perform room-by-room device grouping, which relates to proximity-based device grouping. Note that device-free human sensing is out of scope in this paper as our focus is on device grouping.

IoT systems capable of automatic or semi-automatic configuration have been proposed as zeroconf, self-configuration, and automatic provisioning [1]–[3]. These studies focus on networking and device configuration for sensing, where location information setup is out of scope.

Automatic network configuration is a well-studied field and is widely used. In our daily lives, we are using bootstrap and dynamic host configuration protocols (BOOTP, DHCP). IEEE 802.11 provides a secure network configuration named WiFi protected setup (WPS). In the field of IoT, automatic peer-to-peer and ad-hoc network configuration using WiFi Direct has been presented [4]–[8]. We can use these methods to semi-automatically configure a network for an IoT system.

For IoT device coordination, mixed reality (MR) based device coordination systems have been presented [9], [10]. In [11], the authors proposed the device coordination method based on device usage and user context information. An event-based device coordination approach has also been proposed [12]. These approaches can be used to realize a PnP IoT system.

To complete the device location information setup, indoor localization methods are useful. Fingerprinting is popularly studied in the field of indoor localization [14]. Especially, recent papers have focused on WLAN CSI-based fingerprinting due to its high performance [15]–[18], after the pioneering work PinLoc [19]. Model-based localization methods such as FUSIC [20] and SpotFi [21], which use CSI, have also been

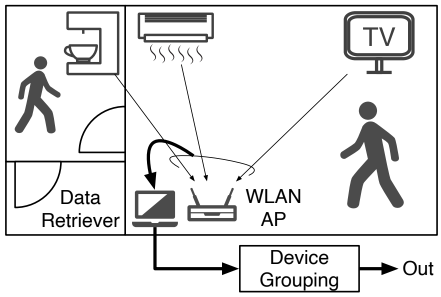

Fig. 1. Overview of CSI-based room-by-room IoT device grouping

reported to improve localization accuracy and robustness to environment changes. We can estimate the location of IoT devices using these methods. However, we can obtain no device-context information such as the room and its name where a device is installed in addition to the actual location of the device. Device grouping presented in this paper can be combined with the room-context estimator [22], resulting in an automatic IoT device location information setup.

Proximity-based device grouping and paring is another related topic mainly studied in the field of network security. These studies include device grouping relying on ambient sound [23]–[26], magnetism [27], controlled lighting [28], and multi-sensor readings [29], [30]. These approaches require a special infrastructure or IoT devices with specific sensors.

Radio-based device grouping methods can be applied for IoT device grouping because IoT devices are equipped with a wireless communication module. Amigo [31] is a proximity-based authentication method based on the received signal strength of WLAN. PSP [32] is a secure device-paring method based on WLAN CSI. Although devices in a range of several tens of millimeters can be grouped in the same group with these methods, the grouping distance is too short for device grouping in the IoT system setup. When two devices are installed at a distance more than the radio wavelength, wireless channels between a WLAN access point (AP) and the two devices are different, which makes it difficult to estimate proximity using these methods in our scenario.

III. CSI-based Room-by-Room IoT Device Grouping

Figure 1 shows an overview of the CSI-based room-by-room IoT device grouping system. The device grouping system consists of a data retriever and device grouping block.

The data retriever collects CSI data sent from IoT devices when the devices communicate with a WLAN AP. We use the CSI collector presented in [33] to collect IEEE 802.11ac compressed CSI data from multiple devices. The compressed CSI data is described as two CSI angles $\phi_{ij}(0 \leq \phi_{ij} < 2\pi)$ and $\psi_{lj}(0 \leq \psi_{lj} < \pi/2)$, which correspond to phase and amplitude difference between antennas, respectively. The range of index numbers i, j, l is defined by the number of antennas on the transmitter and receiver. We use ψ_{lj} in this paper based on the results in [13].

The device grouping block extracts features from the CSI angle ψ_{lj} and groups IoT devices by the room where the

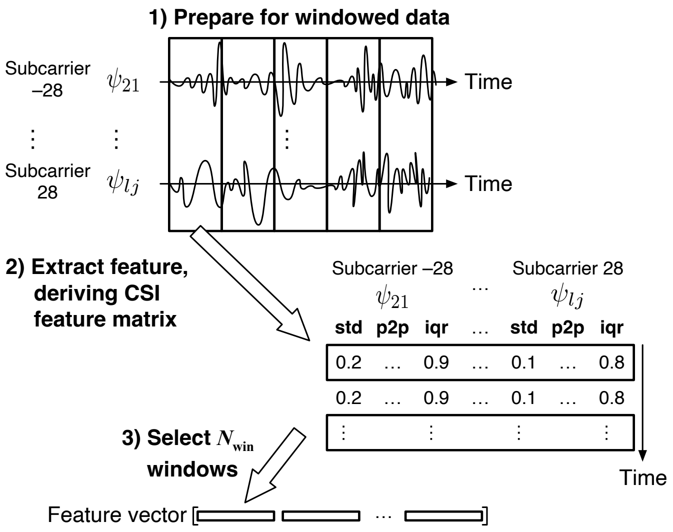

Fig. 2. Feature extraction procedure

devices are installed using a clustering algorithm. Figure 2 shows a feature extraction procedure for a single IoT device. 1) The time series data of the CSI angle for each subcarrier is first divided into fixed-length windows. 2) The device grouping block then calculates features for each window, deriving a CSI feature matrix. The rows and columns of a CSI feature matrix correspond to the windows and features, respectively. We use standard deviation (std), peak-to-peak (p2p), and interquartile range (iqr) features based on the results in [13]. 3) Finally, we pick N_{win} windows from the CSI feature matrix and align each row in a 1-dimensional vector to derive a feature vector. IoT devices are grouped by a clustering algorithm with the feature vector calculated for each IoT device.

In [13], we presented that the selection of N_{win} windows had a big impact on the grouping performance. We confirmed that the grouping performance was highly degraded when we used the CSI data collected when people stayed in a specific room. In a practical environment, people spend uneven time in each room, which leads to low grouping performance. To achieve a high grouping performance, CSI sampling, i.e., the selection of the rows of a CSI feature matrix, is important.

After the device grouping, the location information is collected to complete the device location setup. We assume that we collect the location information from users. For example, we can ask a user for the name of the room when one of the device in a group is used. We may also rely on existing relative localization methods to modify incorrect device grouping. Based on the relative location, we can find incorrect device grouping to modify device groups, which is out of scope in this paper and is our future work.

IV. CSI Sampling for Practical Environments

A. Key Idea

The key idea of CSI sampling for grouping IoT devices in practical environments is to select rows of the CSI feature matrix such that feature vectors include the CSI changes collected in various situations. The CSI features can be associated with CSI changes caused by physical changes such as human movements. Assuming that people in different locations have separate influences on CSI, we observe the mixed CSI changes caused by the people in different locations. We perform the independent component analysis (ICA) to separate the CSI changes caused by the people in different locations.

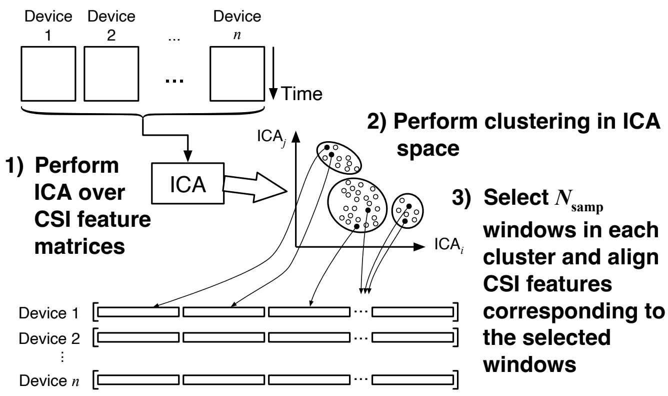

Fig. 3. Overview of CSI sampling using ICA

TABLE I
NOTATIONS

Notation	Description
ϕ_{ij}, ψ_{lj}	CSI angle in compressed CSI
N_{win}	Number of windows used in IoT device grouping
N_{ica}	Number of ICA components in ICA clustering
N_{clus}	Number of ICA clusters
N_{samp}	Number of windows selected in each ICA cluster

B. Overview

Figure 3 shows an overview of CSI sampling using ICA. The proposed CSI sampling consists of 1) ICA, 2) ICA clustering, and 3) feature vector extraction steps. In step 1), we perform ICA on the CSI feature matrix, followed by clustering on the independent components in step 2) to obtain clusters of windows with similar independent components. In step 3), windows of a fixed number N_{samp} from each cluster are selected. The rows of the CSI feature matrix corresponding to the selected windows are randomly sampled to derive a feature vector. We perform the device grouping as presented in Sect. III using the feature vector.

The following subsections describe each step in detail. Notations in this paper are summarized in Table I for reference.

C. ICA Step

The ICA step performs ICA on CSI feature matrices to obtain time-series data of independent components. The row of a CSI feature matrix corresponds to a window of CSI data, i.e., CSI data at a specific time. We derive time-series CSI features of all IoT devices by joining the CSI feature matrices of all the IoT devices, as shown in Fig. 3.

In general, the dimension of the CSI features, i.e., the number of columns of a CSI feature matrix, exceeds 150. As described in Sect. III, we calculate three CSI features of standard deviation (std), peak-to-peak (p2p), and interquartile range (iqr), for each CSI angle ψ_{lj} for each subcarrier. There are at lease one CSI angle ψ_{lj} for more than 52 subcarriers. The dimension of the CSI features is more than $3 \times 52 \times |\psi_{lj}| = 156|\psi_{lj}|$, where $|\psi_{lj}|$ is the number of CSI angles ψ_{lj} for each subcarrier.

To reduce computation for ICA on the large dimensional data, we perform principal component analysis (PCA) before ICA. CSI feature matrices of all IoT devices are joined horizontally. We perform PCA on the joined CSI feature matrix, extracting principal components. Then ICA is performed on the extracted principal components.

The number N_{ica} of independent components is set to the same as the number of extracted principal components, which is a general approach of ICA on high dimensional data. In this paper, we assume that the CSI change caused by each human appears as an independent component. Independent components might also include the CSI changes caused by the changes in wireless equipment, environment, and IoT devices. We determine the number N_{ica} of independent components so that the sum of the contribution ratios of the principal components exceeds a specific value such as 0.8.

D. ICA Clustering Step

The ICA clustering step applies a clustering algorithm to the independent components obtained in the ICA step to group the rows of the CSI feature matrix, which corresponds to windows in Fig. 2. We assume that independent components can be associated with the CSI changes caused by individual humans. Windows with similar independent components can be considered to be obtained in a similar distribution of people's location.

We don't limit a clustering algorithm in this paper. Clustering algorithms that require no number of clusters or estimate the number of clusters is desirable because the number of the similar situations is unknown.

E. Feature Vector Extraction Step

The feature vector extraction step selects rows of joined CSI matrix based on the ICA clusters and makes a feature vector for each IoT device. For each ICA cluster, we randomly select N_{samp} samples. We then extract the rows of the joined CSI feature matrix corresponding to the selected ICA samples, obtaining a joined independent CSI feature matrix. We split the joined independent CSI feature matrix for each IoT device and construct a feature vector for each IoT device by aligning the rows of the independent CSI feature matrix.

The selection of rows in this step corresponds to the window selection of N_{win} windows in Fig. 2. The number N_{win} of selected windows can be calculated as $N_{\text{win}} = N_{\text{clus}} N_{\text{samp}}$, where N_{clus} is the number of clusters in the ICA clustering step.

V. Evaluation

To verify the effectiveness of the CSI sampling method described in Sect. IV, we conducted an initial evaluation using CSI data collected in an actual one-bedroom condominium.

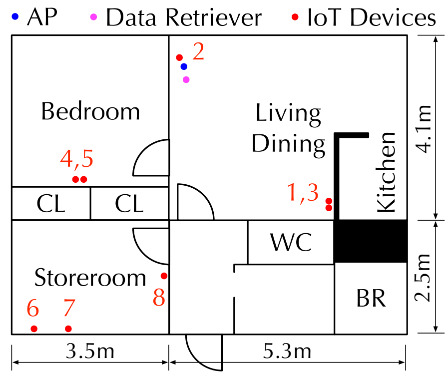

Fig. 4. Experiment setup

TABLE II
NUMBER OF COLLECTED CSI DATA PACKETS

Device ID	(a) # of packets	(b) # of valid windows
1	290663	2358
2	2968	0
3	198929	2357
4	268754	2880
5	308506	2880
6	347484	2880
7	369627	2880
8	247124	2880

A. Experiment Setup

Figure 4 shows the experiment setup for CSI data collection. We installed a WLAN AP, an Intel Compute Stick computer as a CSI data collector, and eight Raspberry Pi 3A+ as IoT devices in the experiment environment. These devices were installed on a floor or on a shelf with a height of approximately 2 meters. The experiment environment was located on the first floor of a lightweight steel-frame condominium building. The interior walls in the environment were mainly made of wood. There were rooms occupied by other residents in the left and right directions in Fig. 4, which are not shown in Fig. 4.

Raspberry Pies run a shellscript to continuously communicate with a Web server via the WLAN AP so that compressed CSI data would be periodically sent from the AP. We installed OpenWRT, which is a lightweight OS for access point, on the Compute Stick computer and collected the compressed CSI data using a tcpdump command. Note that no modification was made on Raspberry Pi or Compute Stick hardware, the Raspberry Pi OS, or OpenWRT. This CSI collection system was made of softwares running on off-the-shelf devices.

We collected CSI data for 24 hours in such an environment where a family of four, i.e., one in his 40s, one in her 30s, and two under 10 years old, were living. No instruction or restriction were given to the family members because the purpose of this experiment is to collect CSI data in an actual environment.

The CSI data was sent from IoT device, i.e., Raspberry Pi, at a non-uniform rate. Due to packet reception errors on the CSI collector, we observed uneven amount of CSI data for each IoT device. Table II(a) shows the number of CSI data packets collected for each IoT device. The device IDs correspond to the numbers of the IoT devices in Fig. 4.

The window size used in step 1) in Fig. 2 was set to 60 seconds. This value was determined based on the difference of CSI data collection rate between this experiment and the experiment in [13]. In [13], we show that the device grouping accuracy almost saturated with the window size greater than 1 second. The CSI data collection rate was 10 Hz in [13], while in this experiment the average collection rate was 1 to 2 Hz as calculated from Table II. We calculated the packet loss rate for each window and for each IoT device. Windows with a packet loss rate exceeding 20% were discarded.

Table II(b) shows the number of valid windows for each IoT device, which equals to the number of rows in the CSI feature matrix. Our proposed CSI sampling method requires CSI features of all the IoT devices. We excluded device 2 that had no valid window and grouped the remaining seven devices to calculate the grouping accuracy.

To demonstrate the effectiveness of the proposed CSI sampling, we compared the performance of the following three CSI sampling methods.

1) ICA sampling (proposed method)
   The ICA sampling is the proposed method described in Sect. IV. Windows are selected based on the results of ICA.
2) PCA sampling
   The PCA sampling selects windows based on the results of PCA instead of ICA. A clustering algorithm and the number N_{clus} of clusters are set to the same values as the ICA sampling method.
3) Random sampling
   The random sampling, which is a baseline method, randomly selects N_{win} of windows. For fairness, N_{win} is calculated in each trial from the number N_{clus} of clusters and the number N_{samp} of samples extracted from each cluster used in the ICA sampling.

The device grouping performance is evaluated using an adjusted Rand index (ARI), which is widely used in the evaluation of clustering. The ARI takes the value in the range between -1 and 1. The higher value indicates the higher clustering accuracy. The purpose of this study is to group IoT devices without room labels and not to classify IoT devices into each room. We cannot obtain a confusion matrix that is popularly used in a classification performance evaluation.

B. The number N_{ica} of independent components

The number N_{ica} of independent components was first determined as the number of components such that the sum of the contributions of principal components exceeds 0.8 in PCA, as described in Sect. IV-C. Figure 5 shows the cumulative contributions of principal components as a function of the number of principal components. We can confirm that the cumulative contributions exceeds 0.8 when the number of principal components is greater than 12. In this paper, we set $N_{\mathrm{ica}} = 12$ in the following evaluations.

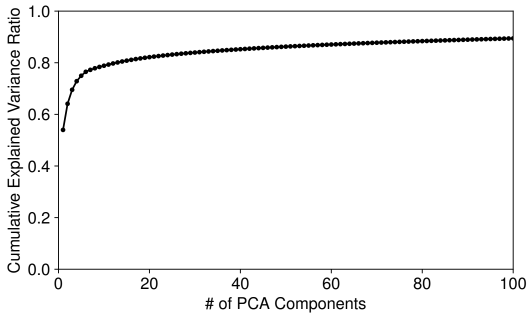

Fig. 5. Cumulative contributions of principal components

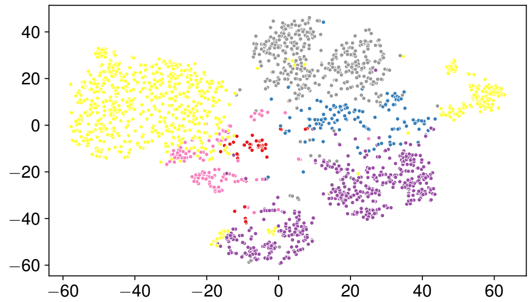

Fig. 6. Clustering result in ICA space

C. ICA Clustering

Figure 6 shows the result of clustering in ICA space. To visualize the clustering result, we reduced the dimensions: 12-dimensional ICA space was reduced into two-dimensional space using t-SNE. We used the k-means algorithm for clustering in this paper, although we don't limit the clustering algorithm. The number N_{clus} of clusters was set to 6.

D. Device Grouping Performance

The performance of the proposed CSI sampling method was evaluated using the mean ARI of the IoT device grouping results. We calculated feature vectors as described in Sect. IV-E and grouped IoT devices using the calculated feature vectors. We repeated the grouping 500 times to calculate the mean ARI.

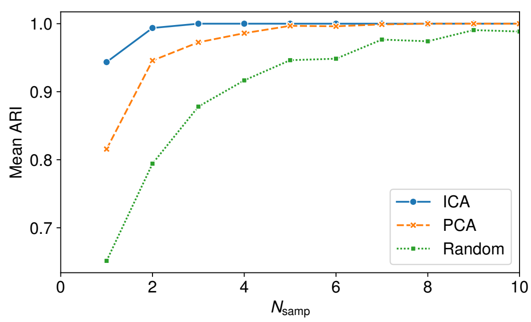

Fig. 7. Mean ARI as a function of the number N_{samp} of selected windows

Figure 7 shows the mean ARI as a function of the number N_{samp} of selected ICA samples. Figure 7 indicates the following:

1) The proposed ICA sampling showed the highest mean ARI. We can confirm that the ICA sampling was effective in improving the grouping performance in a practical environment. The mean ARI was 0.9435 and 0.6513 at $N_{\mathrm{samp}} = 1$ for the ICA and random sampling, respectively. The mean ARI was improved by $0.9435/0.6513 - 1.0000 = 0.4486$, i.e., 44.9%.
2) Compared to random sampling, both the ICA and PCA sampling significantly increased the mean ARI. Clustering in independent- and principal-component spaces allows us to group windows with similar CSI changes. We could efficiently extract CSI changes in different distributions of people's location by selecting windows in each group, resulting in the high IoT device grouping performance.
3) As N_{samp} increased, the improvement by ICA and PCA sampling became smaller. The ICA and PCA sampling were effective when the amount of CSI data used in the device grouping was limited.

The above results confirm that the proposed ICA sampling significantly improved IoT device grouping performance in a practical environment.

VI. Conclusion

In this paper, we presented a CSI sampling method for room-by-room IoT device grouping proposed in our previous paper to improve the grouping performance in a practical environment. To address the performance degradation caused by the nonuniform time distributions of where people stay in each room, we perform ICA on CSI features to efficiently extract influences on CSI features caused by different distributions of people. The experimental evaluation revealed that the proposed ICA sampling successfully improved IoT device grouping performance with an ARI of up to 44.9%.

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