Indoor localization based on CSI in dynamic environments through domain adaptation

Liuyi Yang^1a), Tomio Kamada^1, and Chikara Ohta^2

^1 Graduate School of Engineering, Kobe University
1-1 Rokkodai-cho, Nada-ku, Kobe, Hyogo 657-8501, Japan

^2 Graduate School of Science, Technology and Innovation Graduate School of System Informatics, Kobe University
1-1 Rokkodai-cho, Nada-ku, Kobe, Hyogo 657-8501, Japan

a) yangliuyi1995@yahoo.co.jp

Abstract: As the demand for indoor localization applications continues to grow, device-free localization based on Wi-Fi Channel State Information (CSI) has become a popular research topic. Wi-Fi signals are, however, easily affected by environmental factors such as furniture changes. These factors disable the original localization system, and rebuilding it will cost a lot of time and workforce. This is a major challenge of device-free Wi-Fi localization. To address this issue, we use a transfer learning method, “Integration of Global and Local Metrics for Domain Adaptation (IGLDA),” and improve it, aiming to adapt the original localization model to the changing environment. Consequently, the localization accuracy is improved from 26.3 % to 82.2 % by only recollecting 37.5 % of data.

Keywords: device-free localization, channel state information, domain adaptation, transfer learning

Classification: Wireless Communication Technologies

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1 Introduction

In recent years, research on indoor localization has been progressing rapidly, involving technologies such as Wi-Fi, Bluetooth, and Radio Frequency Identification. Among them, WiFi-based indoor localization technology based on Channel State Information (CSI) is of great practical value because almost all shopping malls, office buildings, and even households have installed Wi-Fi access points (APs), achieving extensive area coverage of Wi-Fi signals and making the technology to be widely used. However, Wi-Fi received signals, i.e., CSIs, could change due to, e.g., moving furniture, which renders the trained localization system ineffective and requires a lot of time and effort to retrain the localization system.

To solve this problem, we adopt a method of domain adaptation. For example, suppose that furniture has moved so that the environment has changed. In this context, the original environment and the changed one are regarded as the source domain and the target domain, respectively. Domain adaptation works to minimize the difference in the distribution between these domains. As shown in Fig. 1, in the proposed solution, only part of the data is recollected and sent to domain adaptation with the data before the environment change. The new data after domain adaptation are utilized for training the localization model. In the localization phase, the collected data are mapped and fed into the localization model to get the result. The mapping matrix is generated by domain adaptation. Thanks to this process, as shown later, the accuracy of indoor localization in a dynamic environment increased from 26.3 % to 82.2 % by only recollecting 37.5 % of data.

The contribution of this paper is as follows. In CSI-based indoor localization, location labels are easy to obtain, while collecting CSI data at each location is time- and labor-intensive. Considering this feature, we improved IGLDA to utilize location labels, too. By recollecting location labels and CSI data for 37.5 % of the locations, an accuracy of 82.2 % was achieved.

![Flowchart of indoor localization in dynamic environments through domain adaptation.](image)

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2 Channel State Information

Wi-Fi signals are transmitted under standard protocols using Orthogonal Frequency Division Multiplexing (OFDM) modulation, which is a method of encoding data onto several different frequency carriers. CSI reflects the channel characteristics of the communication link between the transmitter and the receiver. It provides information on the transmission process and contains information such as signal scattering, fading (multipath fading or shadowing fading), and power decay of distance.

Each CSI depicts the amplitude and phase of a subcarrier [1]:

\[
H(f_k) = \|H(f_k)\| e^{j\angle H(f_k)},
\]

where \(H(f_k)\) is the CSI at the subcarrier with central frequency \(f_k\), and \(\angle H(f_k)\) denotes its phase. Since robustness of amplitude is better than phase [2], only amplitude is used in this study.

3 Domain Adaptation

All well-known machine learning algorithms, including supervised and semi-supervised learning, can only work well under one common assumption: the training data and the test data follow the same distribution. When the distribution changes, as the indoor environment changes, we have to recollect CSI data and location labels and rebuild the model. This problem has given rise to the development of transfer learning, which can take data from related domains and use it in similar domains. A domain is a group of data. This reduces the cost of obtaining new labeled samples and greatly improves the efficiency of machine learning. Domain adaptation is currently the most popular sub-topic.

Distribution adaptation is the most common type of domain adaptation method. The basic idea is that since the probability distributions of the source and target domains are different, the most straightforward way is to bring the different data distributions closer together using some transformations. In this study, the source domain is the group of CSI data before environment change, and the target domain is the group of CSI data after environment change.

3.1 IGLDA

IGLDA [3] assumes that there exists a mapping function. When source and target domains are mapped to a high-dimensional space by it, e.g., Hilbert space, mapped source and target domains are in the same marginal distribution. In measuring whether the source and target domain data are close in the high-dimensional space, it uses Maximum Mean Difference (MMD) [4] to evaluate the distance between the high-dimensional data. And it preserves the local geometric property described by the intra-class distance of those labeled data in the source domain. The mapping function should satisfy two conditions; one is that the value of MMD is as close as possible, and the other is that intra-class distance is as close as possible.
Let $D_s = \{(x^s_1, y^s_1), \ldots, (x^s_{n_s}, y^s_{n_s})\}$ and $D_t = \{(x^t_1), \ldots, (x^t_{n_t})\}$ be a source domain and a target domain, respectively, and $\kappa(x, y) = \langle \phi(x), \phi(y) \rangle$ be a kernel function, where $\phi(\cdot)$ is the feature mapping.

Let us consider another function $\varphi(\cdot) = \tilde{W}^T \phi(\cdot)$ and this function will project the data in the feature space into a $d$-dim Hilbert space, where $\tilde{W}^T$ is a $d \times (n_1 + m)$ matrix. We hope that in this $d$-dim space, the value of MMD will be as small as possible. The multi-objective problem is described by the following formula:

$$\arg\min_{\tilde{W}} \{ \mu \cdot \text{MMD}(\varphi(X_s), \varphi(X_t)) + \lambda \cdot \text{CD}(\varphi(X_s)) \},$$  \hspace{1cm} (2)

where $\text{MMD}(\cdot, \cdot)$ is an MMD value and $\text{CD}(\cdot)$ is the value of intra-class distance of a set of samples, $\mu$ and $\lambda$ are trade-off parameters.

Suppose the sample set in the source domain is $X_s = \{x^s_1, \ldots, x^s_{n_s}\}$ and that the sample set in the target domain is $X_t = \{x^t_1, \ldots, x^t_{n_t}\}$. Based on the definitions in the section above, we have

$$\text{MMD}(X_s, X_t) = \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} \varphi(x^s_i) - \frac{1}{n_t} \sum_{i=1}^{n_t} \varphi(x^t_i) \right\|^2_{\mathcal{H}},$$  \hspace{1cm} (3)

where $\mathcal{H}$ is the Hilbert space.

Let the data in the source domain be $X = \{x_1, \ldots, x_n\}$, let $c$ be the number of labels, and let $n_l$ be the number of the samples in the class $l$ ($1 \leq l \leq c$). We denote the source domain’s samples in the $l$-th class as $X_l^s = \{x^s_{l1}, \ldots, x^s_{ln_l}\}$.

In the Hilbert space, the intra-class distance of the samples in the $l$-th class can be represented by the following equation:

$$\text{CD}_l(X_l^s) = \frac{1}{n_l(n_l - 1)/2} \sum_{i=1}^{n_l} \sum_{j=i+1}^{n_l} \left\| \varphi(x^s_{li}) - \varphi(x^s_{lj}) \right\|^2.$$

So, the total intra-class distance of the source domain samples is

$$\text{CD}(X_s) = \frac{1}{c} \sum_{l=1}^{c} \frac{1}{n_l(n_l - 1)/2} \sum_{i=1}^{n_l} \sum_{j=i+1}^{n_l} \left\| \varphi(x^s_{li}) - \varphi(x^s_{lj}) \right\|^2.$$

### 3.2 Improvement to IGLDA

When calculating MMD distance, IGLDA’s approach calculates the distance between the mean of all source domain data and the mean of the target domain data. Our goal is to reconstruct the localization model with only a part of the data recollected so that the correct approach is to use the recollected location labels to make sure that when we calculate the MMD distance, data are under the same location labels. Because $n_t < n_s$, Eq. (3) should be modified to:

$$\text{MMD}(X_s, X_t) = \left\| \frac{1}{n_t} \sum_{i=1}^{n_t} \varphi(x^t_i) - \frac{1}{n_t} \sum_{i=1}^{n_t} \varphi(x^t_i) \right\|^2_{\mathcal{H}}.$$

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Based on the above, we use CSI amplitude with location labels before environment change and recollected CSI amplitude with location labels of a part of locations after environment change to calculate $\tilde{W}$ and further use the corresponding kernel function to get the mapping function $\varphi(\cdot)$. The localization model is trained by new data which the amplitude of the subcarrier before the environment change has been mapped by the mapping function $\varphi(\cdot)$. Then we use the kernel function corresponding to the amplitude after environment change and $\tilde{W}$ to calculate another mapping function $\varphi'(\cdot)$. Finally, we use this mapping function to map the data after the environment change and send them to the localization model to get the location.

4 Experiment

4.1 Experiment Setup

We conducted the experiments in a meeting room in the Rokkodai Campus of Kobe University, of which the layout is presented in Fig. 2 (a). There, we used a total of 40 locations in a grid fashion for evaluation. The distance between the two locations was 0.5 m. We put three desktops in the corner of our laboratory’s meeting room as receivers and connected them to a Wi-Fi AP as a transmitter set in another corner. The Wi-Fi AP was a TP-LINK with two antennas operating on the 2.4 GHz band with a bandwidth of 20 MHz. Every desktop was set with an Intel 5300 network interface controller with three antennas. CSI data can be collected for 30 sub-carriers between each antenna pair. Therefore, the collected CSI data was 540 dimensions as $2$ transmitting antennas $\times$ $3$ receiving antennas $\times$ $30$ CSI data between each antenna pair $\times$ $3$ receivers.

We collected the CSI data while a person was standing at each location, and stored these data with the location label.

4.2 Environment Change

As shown in Fig. 2 (b), we put a table in the room to change the environment.
Table I. Accuracy of IGLDA.

| Location labels | None  | 1–5   | 1–10  | 1–15  | 1–20  |
|-----------------|-------|-------|-------|-------|-------|
| Measurement ratio | 0.0 % | 12.5 % | 25.0 % | 37.5 % | 50.0 % |
| Accuracy        | 26.3 % | 54.7 % | 68.7 % | 75.4 % | 76.4 % |

| Location labels | 1–25 | 1–30  | 1–35  | 1–40  |
|-----------------|------|-------|-------|-------|
| Measurement ratio | 62.5 % | 75.0 % | 87.5 % | 100.0 % |
| Accuracy        | 78.2 % | 78.6 % | 85.1 % | 90.2 % |

4.3 Evaluation

In this paper, values of the parameters $d$, $\mu$, and $\lambda$ were 30, 10, and 0.1 respectively. We selected the Support Vector Machine (SVM) model as a machine learning model to classify the locations by their CSI data. When training the model, we used the classification learner tool in MATLAB 2016a. To reduce the cost of calculation, we used 200 training data and 200 test data per location. The accuracy was the number of correctly located 40 locations divided by the total amount of data collected. Since each location used 200 data, the amount of data collected was 8000.

If we did not change the environment, the accuracy of the localization model was 99.9 %. However, once we put a table in the room, the accuracy dropped to 26.3 % as shown in Table I.

Then we recollected only a part of data and location labels for domain adaptation. We gradually increased the amount of recollected data, using one more row of data at a time than before. The results are shown in Table I. When we used CSI data and location labels from location 1 to location 5 after the environment change, the accuracy was 54.7 %. When we used them from location 1 to location 10, the accuracy was 68.7 %. When we used them from location 1 to location 15, the accuracy was 75.4 %. But from then on, the gradual increase in the amount of data used shown no significant improvement in accuracy when the amount of data used was gradually increased. When we used them from location 1 to location 30, the accuracy was only 78.2 %, an improvement of only 2.8 %. Then, we continued to increase the amount of data, and when we used them from location 1 to location 35, the accuracy increased significantly to 85.1 %. When we used data from all locations, the accuracy reached 90.2 %.

We found that the location close to the antenna helped to improve accuracy. To recollect as little data as possible and to achieve a high accuracy rate, we made different attempts and finally found that the most efficient way to recollect data was to collect location 1–10 and 36–40. Accuracy rate of 82.2 % was achieved with 37.5 % data recollected rate.

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