FALE: Fine-grained Device Free Localization that can Adaptively work in Different Areas with Little Effort

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ABSTRACT

Many emerging applications and the ubiquitous wireless signals have accelerated the development of Device Free localization (DFL) techniques, which can localize objects without the need to carry any wireless devices. Most traditional DFL methods have a main drawback that as the pre-obtained Received Signal Strength (RSS) measurements (i.e., fingerprint) in one area cannot be directly applied to the new area for localization, and the calibration process of each area will result in the human effort exhausting problem.

In this paper, we propose FALE, a fine-grained transferring DFL method that can adaptively work in different areas with little human effort and low energy consumption. FALE employs a rigorously designed transferring function to transfer the fingerprint into a projected space, and reuse it across different areas, thus greatly reduce the human effort. On the other hand, FALE can reduce the data volume and energy consumption by taking advantage of the compressive sensing (CS) theory. Extensive real-word experimental results also illustrate the effectiveness of FALE.

CCS Concepts

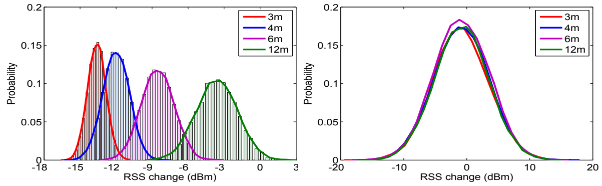
•Human-centered computing → Ubiquitous and mobile computing design and evaluation methods;

Keywords

Device Free Localization; Received Signal Strength; Area Diversity; Transferring

1. INTRODUCTION

Recent years have witnessed a surge in the DFL [3] approaches for plenty of emerging applications. The fingerprint based DFL, which provides a fine-grained localization accuracy by using the RSS measurement (change) distorted by the object as priori knowledge, have gone mainstream.



(a) before transferring (b) after transferring

Figure 1: Gaussian estimation of the RSS measurements across 4 diffeptient link lengths under the same location. (a) shows that the distributions of RSS measurements are significantly differ from each other, and after transferring by FALE, the distributions are made as close as possible in (b).

However, underlying current DFL approaches is a premise that the monitoring area is fixed, which, unfortunately, is unlikely in most practical settings. Actually, the pre-obtained fingerprint in one area is distinct from another area which has a different size. Therefore, it needs one to spend a lot of time to calibrate each location in all the areas, which is an human effort exhausting process.

To cope with this problem, this paper introduces FALE, an transferring DFL method that can adaptively works in different areas, with a fine-grained localization accuracy and without the process of exhausted retraining in each area, thus greatly reduce the human effort.

Specifically, different areas require to deploy different length of links [1], and the differences of RSS measurements are reflected in their distributions, as shown in Fig.1(a). Based on this, by utilizing the Fisher Linear Discriminant Analysis (FLDA) as subspace learning algorithm and the Bregman Divergence as a regularization term to measure the distribution distance, FALE projects the RSS measurements into a low-dimensional subspace where the distribution distance across diffrent link lengths are made as close as possible (Fig.1(b)), then the fingerprint of one area can be reused by different areas, thus greatly reduce the human effort. Moreover, we use the CS approach in [1] to perform localization accurately with a small number of RSS measurements.

2. TRANSFERRING SCHEME

In a high level, FALE goes through the following steps, and the detailed transferring is shown in Fig.2: **First**, we constructs the sensing matrix $\mathbf{x}^l$ of area $l \times a$, and collects a few of RSS measurements $\mathbf{x}^u$ for n randomly chosen locations in area $u \times b$. **Second**, based on $\mathbf{x}^l$ and $\mathbf{x}^u$, FALE solves the transferring matrix. **Third**, we transfer the sensing matrix of area $l \times a$ and the real-time RSS measurements

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[1] Length of a link is the distance between the transceivers.

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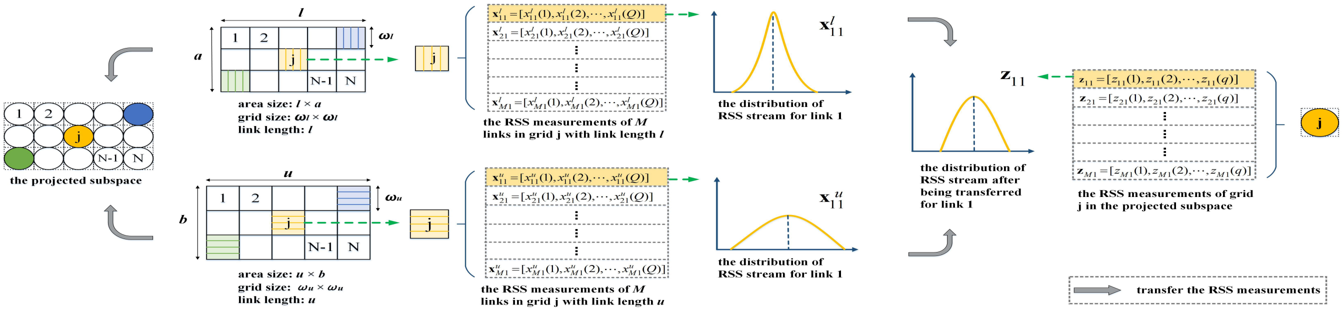

Figure 2: Transferring overview. By dividing the area into grids and deploy transceivers in the midpoint of the grid edge along two sides, the object locates in grid j will interfere some of M links, and for the same link 1, the distributions of Q continuous RSS measurements with link length l and u are distinct. By transferring the RSS streams $\mathbf{x}^l_{11}$ and $\mathbf{x}^u_{11}$ into a subspace $\mathbb{R}^q$ as $\mathbf{z}_{11}$, the distribution distance can be minimized.

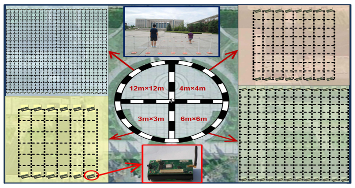

Figure 3: deployment view.

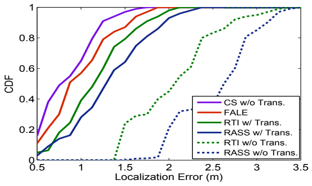

Figure 4: localization performance.

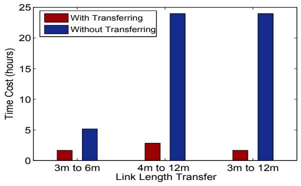

Figure 5: time cost.

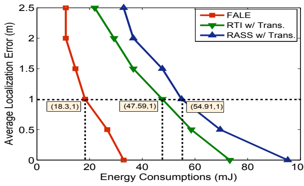

Figure 6: energy consumption.

of area $u \times b$, and estimate the locations based the CS theory.

The general framework can be presented as

$$\mathbf{z} = W^T \mathbf{x}, \tag{1}$$

$$W = \underset{W \in \mathbb{R}^{Q \times q}}{\arg} \min\{F(W) + \lambda D_W(p_l || p_u)\}, \tag{2}$$

with respect to $W^T W = I$. $F(W)$ is the FLDA which projects the RSS streams of $\mathbf{x}^l$ or $\mathbf{x}^u$ as $\mathbf{z}^l$ and $\mathbf{z}^u$. $D_W(p_l || p_u)$ is the Bregman Divergence that measures the distribution distance between $p_l(\mathbf{z})$ and $p_u(\mathbf{z})$. And the optimal W obtained by the Gradient Descent algorithm as

$$W_{k+1} = W_k - \eta(k)\Big(\frac{\partial F(W)}{\partial W} + \lambda \cdot \frac{\partial D_W(p_l || p_u)}{\partial W}\Big), \tag{3}$$

where $\eta_k = \eta_0 / k$ is the learning rate, and

$$\begin{aligned} \frac{\partial F(W)}{\partial W} &= 2tr(W^T S_B W)^{-1} tr(S_W W) \\ &- 2tr[(W^T S_B W)^{-1}]^2 tr(W^T S_W W) tr(S_B W), \end{aligned} \tag{4}$$

$$\frac{\partial D_W(p_l || p_u)}{\partial W} = \sum_{i=1}^{N} \frac{\partial D_W(p_l || p_u)}{\partial \mathbf{z}^l_i} \mathbf{x}^l_i + \sum_{i=1}^{n} \frac{\partial D_W(p_l || p_u)}{\partial \mathbf{z}^u_i} \mathbf{x}^u_i, \tag{5}$$

$$\begin{aligned} \frac{\partial D_W(p_l || p_u)}{\partial \mathbf{z}^l_i} &= \frac{(\sum_l)^{-1}}{N^2 \sigma_l^4} \sum_{i'=1}^{N} (\mathbf{z}^l_{i'} - \mathbf{z}^l_i) G_{2\sigma_l^2 \sum_l}(\mathbf{z}^l_i - \mathbf{z}^l_{i'}) \\ &- \frac{2(\sigma_l^2 \sum_l + \sigma_u^2 \sum_u)^{-1}}{N n \sigma_u \sigma_l} \sum_{i'=1}^{n} (\mathbf{z}^u_{i'} - \mathbf{z}^l_i) G_{\sigma_l^2 \sum_l + \sigma_u^2 \sum_u}(\mathbf{z}^l_i - \mathbf{z}^u_{i'}), \end{aligned}$$

$$\begin{aligned} \frac{\partial D_W(p_l || p_u)}{\partial \mathbf{z}^u_i} &= \frac{(\sum_u)^{-1}}{n^2 \sigma_u^4} \sum_{i'=1}^{n} (\mathbf{z}^u_{i'} - \mathbf{z}^u_i) G_{2\sigma_u^2 \sum_u}(\mathbf{z}^u_i - \mathbf{z}^u_{i'}) \\ &- \frac{2(\sigma_l^2 \sum_l + \sigma_u^2 \sum_u)^{-1}}{N n \sigma_u \sigma_l} \sum_{i'=1}^{N} (\mathbf{z}^u_i - \mathbf{z}^l_{i'}) G_{\sigma_l^2 \sum_l + \sigma_u^2 \sum_u}(\mathbf{z}^l_{i'} - \mathbf{z}^u_i). \end{aligned}$$

Then in order to improve the localization accuracy in area $u \times b$, by using the RSS measurements of neighbor locations, FALE generates RSS measurements for the locations which are not represented as grids. Finally, we prove that after transferring, the transferred sensing matrix satisfies the RIP.

3. DEPLOYMENT AND RESULTS

We perform extensive experiments in an open-space depicted in Fig. 3, and we set the grid edge length as $\omega = 0.5$m when the link length is $4m$. We add our transferring scheme into two state-of-the-art algorithms RASS [4] and RTI [2], refer as RASS w/ Trans. and RTI w/ Trans. for a fair comparison. And we also compare with the traditional CS based localization method as CS w/o Trans. And we demonstrate the effectiveness of FALE as follows.

Localization Performance. Fig. 4 illustrates the performance of FALE is approximate to the CS w/o Trans., and FALE performs best with 50% and 80% error of 0.87m and 1.23m, respectively. And the performance of RTI and RASS improve 58% and 66% for 80% error respectively. **Human Effort Cost.** We use the time-cost of the pre-deployment to examine the human effort, Fig. 5 shows that the human effort decreases are 41% under transferring from 3m to 6m, 88% from 4m to 12m, 93% from 3m to 12m. **Energy Consumption.** We compare the energy consumption by increasing the number of links to reach an given localization accuracy. Fig. 6 shows that the energy consumption for FALE, RTI w/ Trans. and RASS w/ Trans. are 18.3 mJ, 47.59 mJ, and 54.91 mJ, respectively.

4. ACKNOWLEDGMENTS

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