Exploiting Human Mobility Trajectory Information In Indoor Device-Free Passive Tracking

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ABSTRACT

Device-free passive (DfP) localization is proposed to localize human subjects indoors by observing how the subject disturbs the pattern of the radio signals without having the subject wear a tag. In our previous work, we have proposed a probabilistic classification based DfP technique, which we call PC-DfP in short, and demonstrated that PC-DfP can classify which cell (32 cells in total) is occupied by the stationary subject with an accuracy as high as 97.2% in a one-bedroom apartment. In this poster, we focus on extending PC-DfP to track a mobile subject in indoor environments by taking into consideration that a human subject's locations should form a continuous trajectory. Through experiments in a 10 $\times$ 15 meters open plan office, we show that we can achieve better accuracies by exploiting the property of continuous mobility trajectories.

Categories and Subject Descriptors

C.3 [**Special-Purpose and Application-Based Systems**]: Real-time and embedded systems

Keywords

Device-free Passive Tracking, Linear Discriminant Analysis, Trajectory

1. INTRODUCTION

The ability to continuously track human subjects in indoor environments can enable a large array of important applications. Among the existing localization methods, radio-frequency (RF) based device-free passive (DfP) localization does not inconvenience people, is unobtrusive, and offers good privacy protection [3, 2]. In our previous work [2], we propose PC-DfP, a probabilistic classification based device-free passive localization technique by formulating the localization problem as a linear classification problem. To achieve high classification accuracies, we take extra care to mitigate the adverse impact of indoor multipath. Our results show that PC-DfP can classify which cell (32 cells in total) is occupied by the stationary subject with an accuracy as high as 97.2% in a one-bedroom apartment, and an accuracy of 93.8% in an open-plan office.

In this paper, we focus on tracking mobile subjects using PC-DfP. We argue that mobility can introduce new opportunities for optimizing the localization accuracies. First, people usually move on continuous trajectories, and as a result their locations should exhibit continuity with time. Second, various obstacles in an indoor environment also bound human movement, further reducing the problem space. With preliminary experimental results in a 10 $\times$ 15 meters office environment, we demonstrate that we can track a subject's movement with a cell estimation accuracy of 95.3%.

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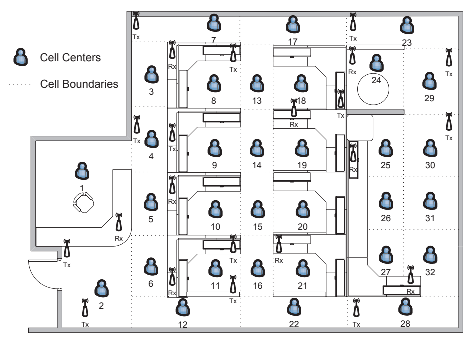
(a)



(b)

Figure 1: In (a), we show the first author's lab in which we deployed our system. In (b), we show the experimental topology. The office deployment region is partitioned into 32 cubicle-sized cells. Thirteen transmitters and nine receivers are deployed. We show the cell boundaries in this plot.

2. TRACKING STRATEGIES

To mitigate multi-path effect, we use training data to characterize the deployed room. In our approach [2], we first slice a deployed region into cells, and then we localize a subject to a cell. For this purpose, we obtain the training data by collecting the Received Signal Strength (RSS) of each radio link when the subject moves around within each of these cells. Based on this training information, we

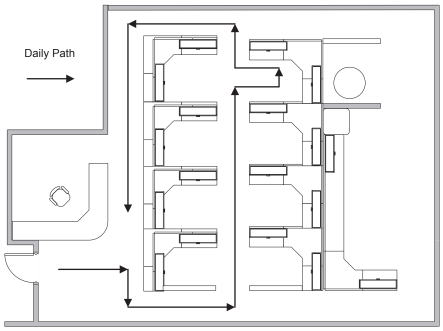


Figure 2: Experimental trajectory simulating a subject's daily path in a office's environment.

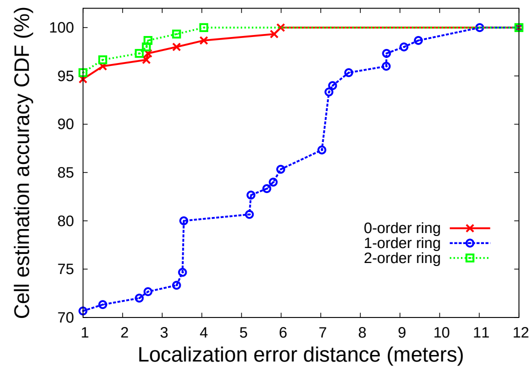


Figure 3: Tracking performance of a daily path when different number of order neighbor are adopted.

can determine the cell with the maximum likelihood of containing the subject. We treat all the possible RSS vectors from all the radio links when a subject is located in a cell as a class. We treat each class as a multi-variate Gaussian, construct a multi-class training dataset, and use Linear Discriminant Analysis (LDA) [1] as our classification algorithm to solve the indoor localization problem.

This approach can be used to not only localize a static subject's position, but also track his/her moving trajectory. Tracking a moving subject actually introduces new optimization opportunities - we can improve our localization results by considering the fact that human's locations from adjacent time intervals should form a continuous trajectory. In our cell-based approach, we define neighbors and rings for each cell. A cell's neighbors is defined as the cells which are possibly reachable by a subject in next reasonable time interval. For an arbitrary cell c, its 1-order neighbors are its immediate adjacent cells in physical space, and its 2-order neighbors are all the immediate adjacent cells of its 1-order neighbors, etc. Further, the i-th ring of cell c is the area consisting of the following cells: c itself, its 1-order neighbors, ..., up to its i-order neighbors. In particular, we define the 0-order neighbors as not considering its neighbors, and 0-th ring of cell is the cell itself. If the subject appears in a specific cell in an interval, then we assume the subject can only appear within this cell's rth ring in the next time interval. In more detail, suppose the subject is in cell c in the previous interval, and we are using PC-DfP to estimate in which cell the subject is in the current interval. In our previous work, PC-DfP only returns the cell with the highest likelihood. In this paper, we search for the cell with the highest likelihood from cell c's rth ring. We believe the tracking performance can be improved by adding this additional constraint. When we say we adopt the r-order neighbor, each estimated cell comes from the cells inside the previous cell's rth ring. The value r is an important parameter that we are going to study and evaluate through experiments in this paper.

3. EXPERIMENTAL RESULTS

Our experimental setup consists of a centralized PC serving as the system manager, thirteen wireless transmitters and nine wireless receivers. Each transmitter broadcasts a packet with its unique id every 0.25 second. The receivers receive the packets, extract the RSS values and forward them to the centralized PC for data collection and analysis.

The deployment takes place in a office room with the total area of 10×15 meters, which contains office furniture as shown in Figure 1(a). The room is spatially divided into 32 cubicle-size cells as shown in Figure 1(b). In the training phase, the first author moves around within each of these cells and makes 100 RSS measurements for all the links. Then, in the testing phase, as shown in Figure 2, the first author follows a daily path: enters the room, crosses an aisle, prints paper in his cubicle, and walks through another aisle to retrieve his paper. We consider a tracking interval successful if the estimated cell is the same as the occupied cell. We sample the RSS measurements every second. To evaluate our tracking performance, we define cell estimation accuracy as the success rate among all the tracking intervals, and localization error distance as the average distance between the actual location and the center of the estimated cell. We test our tracking performance when we adopt 0-order, 1-order, and 2-order neighbors respectively. For instance, in Figure 1(b), cell 28 is cell 22's 1-order neighbor, and cell 32 is cell 22's 2-order neighbor.

Table 1 shows that tracking performance of 1-order neighbor case is worse than 0-order neighbor. We found that most of the mis-estimated cells are the neighbors of the actual cell. In this way, if the mis-estimated cell's 1-th ring does not cover the actual cell for the next interval, then this single mistake in one interval may cascade to subsequent intervals. This problem, however, can be solved by adopting 2-order neighbor. Our experimental results show that we achieve 95.3% cell estimation accuracy and 1.0 m localization error distance in the 2-order neighbor case, which is the best among these three cases. In addition, Figure 3 shows 2-order neighbor case has a shorter tail than 0-order and 1-order cases, which suggest 2-order neighbor performs the best in the worst case.

Neighbor Order	Cell Estimation Accuracy (%)	Localization Error Distance (m)
0	94.7	1.2
1	70.7	2.5
2	95.3	1.0

Table 1: Comparison of tracking performance when different number of order neighbor are adopted.

4. REFERENCES

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