Trajectory-Based 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 paper, 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

General Terms

Algorithm, Experimentation, Measurement

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 existing localization methods, radio-frequency (RF) based device-free passive (DfP) localization does not inconvenience people, is unobtrusive, and offers good privacy protection [7, 9, 4, 6]. Especially, PC-DfP [6] is proposed as a general framework for probabilistic classification based device-free passive localization technique by formulating the localization problem as a classification problem. To achieve high classification accuracies, PC-DfP takes extra care to mitigate the adverse impact of indoor multipath. The results show that in an indoor area that is partitioned into 32 cells, PC-DfP can classify the occupied cell by a 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 human mobility can actually introduce new opportunities for optimizing the localization accuracies in a real indoor environment. In a deployed indoor area, PC-DfP discretizes physical locations into cells, which simplifies the representation of the neighbor relationship among cells, given that the size of the cell is small enough to satisfy the required localization precision. We conduct our experiments using existing sensors/tags deployed in a 10 $\times$ 15 meter indoor lab office, which is shown in 1(a). We partition the deployed area into 32 cubicle-sized cells, as shown in 1(b). Throughout the experiments, we have two key observations. First, people usually move on continuous trajectories, and as a result their locations should exhibit continuity with time. In other words, a subject's next location should be bounded within a list of cells adjacent to his/her current cell. Second, various obstacles such as walls and pillars in an indoor environment also bound human movement, further reducing the number of possible cells that a subject can move to from a given cell. Both of these observations suggest that mobility may actually improve localization accuracies. Our experimental results confirm our hypotheses and show that we can improve our tracking performance from 93.7% to 94.6% in terms of cell estimation accuracy and 1.2 to 1.0 meter in terms of average localization error distance comparing a stationary and a moving subject.

2. TRACKING STRATEGIES

In this section, we first provide an overview of the working of PC-DfP, and then we introduce how we exploit human mobility information to assist PC-DfP in tracking mobile subjects.

2.1 Overview of PC-DfP

The key innovation of PC-DfP is the measures we devise to mitigate the errors caused by the multi-path effect correctly characterize a room. PC-DfP has the following steps. First, we slice a deployed region into cells, and seek to identify the occupied cell of the subject. Second, we collect received signal strength (RSS) values of each radio link, which compose our training data, by having the subject make random movements within each cell and treating

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RSS vectors from all the links as a class. Third, based on the training data, we build a proper classifier and use it to determine the cell with the maximum likelihood of containing the subject. Particularly, in [6], Linear Discriminant Analysis (LDA) [2] is proven as a satisfactory classification algorithm to solve the indoor localization problem. We assume the density of each class k is multivariate Gaussian with mean μ_k and a common covariance matrix Σ:

$$f_k(x) = \frac{1}{(2\pi)^{\frac{L}{2}} |\Sigma|^{\frac{1}{2}}} exp\left[-\frac{1}{2}(x-\mu_k)^T \Sigma^{-1}(x-\mu_k)\right].$$

Applying Bayes rule, we have the objective function

$$\hat{y} = argmax_k f_k(x)\pi_k.$$

In the log-scale, we can write the discriminant function as

$$\delta_k(x) = x^T\Sigma^{-1}\mu_k - \frac{1}{2}\mu_k{}^T\Sigma^{-1}\mu_k + \log \pi_k,$$

and we find the cell estimation model:

$$\hat{y} = argmax_k \delta_k(x).$$

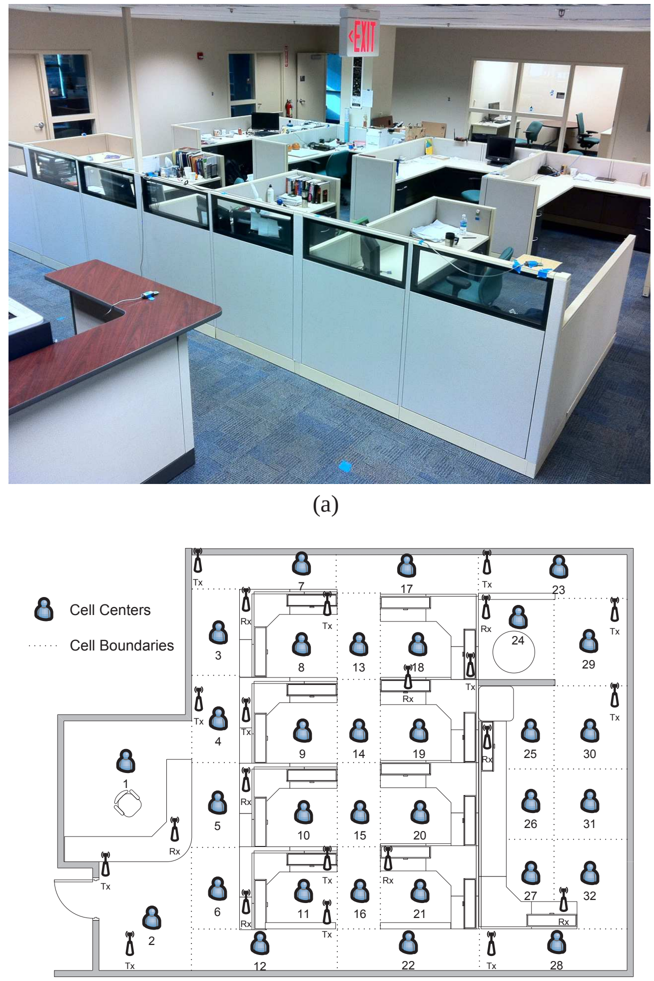
Thus, $\hat{y}$ is the estimated cell based on the observed RSS vector x. In our experiment, the number of samples n_k for each class is the same across the all the cells. Therefore the class prior probability $\pi_i = 1/K$ for all the classes, where K is the total number of class.

2.2 Exploiting Human Mobility Trajectory Under PC-DfP

PC-DfP 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 cell-based approach, we define neighbors and rings for each cell.

Cell neighbors is defined as a list of cells which are possibly reachable by a subject in next reasonable time interval with respect to the current cell. Here, we introduce the concept of the *order of neighbor*. For an arbitrary cell c, its 1-order neighbors are its immediate adjacent cells in physical space in terms of human trajectory, and its 2-order neighbors are all the immediate adjacent cells of its 1-order neighbors, etc. In particular, we define the 0-order neighbors as the case in which we do not consider any its neighbor information. For instance, in Figure 1(b), cell 15 is cell 10's 1-order neighbor, and cell 14 is cell 10's 2-order neighbor. We would like to point out that in a real indoor space, the geometric distance is not equivalent to the physical distance in terms of human trajectory. A good example is that cell 5 is a adjacent to cell 15 in geometry, but in most cases human subject cannot walk from cell 10 to cell 5 within a short time interval. Therefore, in our approach, 5 is excluded from the list of cell 10's 1-order neighbors.

Cell ring is defined as the area consisting of all the cell neighbors including the cell itself under the certain number of order. In other words, 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. For instance, in Figure 1(b), cell 10's 1-th ring consists of cells 10, 15, and its 2-th ring consists of cells 10, 14, 15, 16, 20. Particularly, 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



(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.

current interval. In [6], PC-DfP simply 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. In other words, when we say we adopt the r-order neighbor, each estimated cell comes from the cells inside the previous cell's rth ring. We now denote the state variable y_{t-1} and y_t to represent the cells at the previous time interval and the current moment respectively. The domain of this variable is the set of all the cells $\{c_1, c_2, ..., c_K\}$. Let $RING_r(c)$ be the cell c's rth ring and let $N_r(c)$ be the size of that set. Then our movement transition model ends up with:

$$P(y_t = k | y_{t-1} = j) = \mathbf{T}_{jk} = (1/N_r(j)\, if\ k \in RING_r(c)\, else\ 0).$$

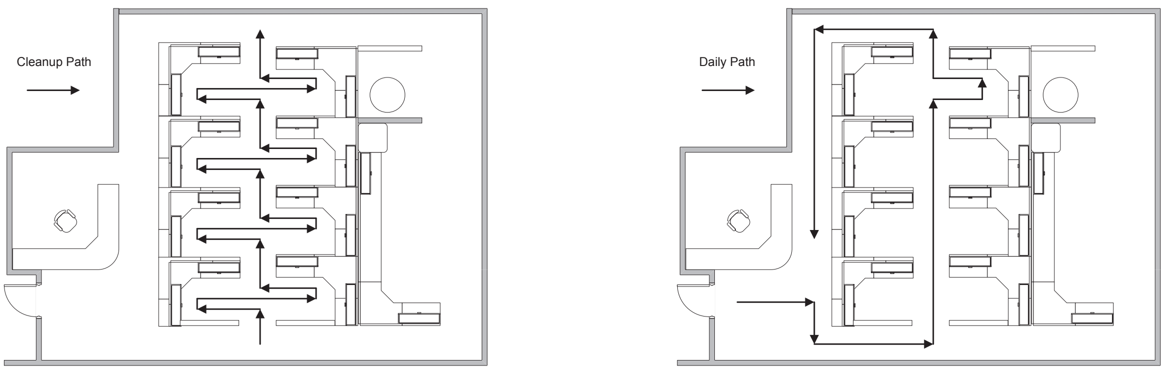
We derive our new cell estimation model as:

$$\hat{y_t} = argmax_k \delta_k(x_t)\mathbf{T}_{jk}, where\ \ j = \hat{y}_{t-1}$$

We believe the tracking performance can be improved by adding this additional constraint. The value r is an important parameter

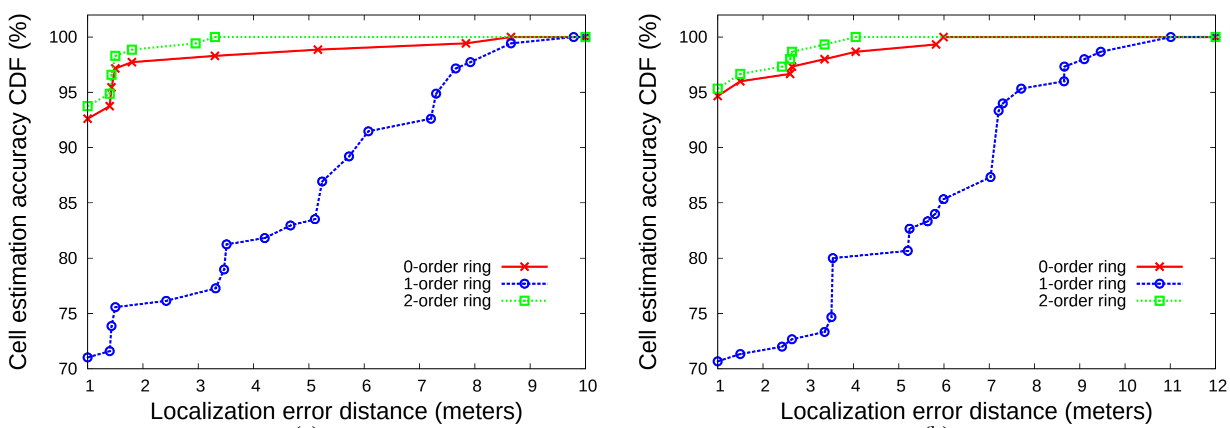
Table 1: Tracking performance when different order of rings are adopted.

Mobility Path	Cell Estimation Accuracy(%)			Average Error Distance(m)		
	0-order	1-order	2-order	0-order	1-order	2-order
Cleanup	92.6	71.0	93.8	1.1	2.2	1.0
Daily	94.7	70.7	95.3	1.2	2.5	1.0
Average	93.7	70.9	94.6	1.2	2.4	1.0



(a) (b)

Figure 2: Two mobility paths: (a) a cleanup path and (b) a daily path.



(a) (b)

Figure 3: Tracking performance: (a) a cleanup path, and (b) a daily path.

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-sized 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(a) and 2(b), the first author follows two mobility patterns: (1) *cleanup path*, in which the first author imitates the path when the cleanup person walks through all the cubicles to clean the trash bin everyday, and (2) *daily path*, in which the first author follows the most frequent mobility pattern in real-life: 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 and take the median value as our observation data. 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.

Table 1 summarizes the tracking performance of all the experimental results. We notice that both paths show the similar behavior. First, 1-order neighbor case is worse than 0-order neighbor. We check all the testing errors in 0-order cases and found that most of these mis-estimated cells are the 1-order neighbors of the actual cell. In the 1-order case, if the mis-estimated cell's 1-th ring does not cover the actual cell for the next interval, then this mistake in a single interval may cascade to subsequent intervals, which we call *dead loop error*. In other words, the solution space might converge into several cells adjacent to each other forever, while the subject is actually far away. This problem, however, can be solved by adopting 2-order neighbor because once such a dead loop error begins, there is a high probability that the actual cell (which is also with the maximum likelihood among all the cells) for the next time interval can still be captured within the 2-th ring of the mis-estimated cell at the current moment and consequently be correctly estimated. We believe adopting 2-order neighbor can reduce the errors in 1-order case based on two observations in the 0-order case. First, we did not have two errors in any consecutive time interval, which provides a basis to prevent the dead loop error from being continued if we choose an appropriate number of order. Second, as we mentioned before, most of the error cells are the 1-order neighbors of the actual cells, which potentially offer the chances that the system can stop dead loop error for the next time interval by increasing the solution space. However, we need to point out the case that if the error cell happens to be one of the 2-order neighbor of the actual cell, the dead loop error might happen in the 2-order neighbor case as well. We did not encounter this issue in our experiments, and will conduct more experiments to attach this potential challenge. Either adopting higher-order neighbor or randomly adopting the 0-order neighbor might help reduce the error in this situation. We will conduct a more solid study in our future work.

Our experimental results show that we achieve 94.6% 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, both Figure 2(a) and 2(b) show 2-order neighbor case has a shorter tail than 0-order and 1-order cases in both paths, which suggest 2-order neighbor performs the best in the worst case. This is because for every single test, 2-order neighbor bounds the localization error distance between two most far away cells. 1-order neighbor bounds more tight, but might suffer from the dead loop error. 0-order neighbor does not bound the error distance at all.

4. RELATED WORK

Several DfP approaches have been proposed in the literature. In this section, we discuss the related work in device-free passive tracking.

In [7, 3], DfP tracking is done through fingerprint matching. A passive radio map is constructed during the training phase by recording RSS measurements with a subject standing at pre-determined locations. During the testing phase, the subject appears in one of these locations, and the system can match the observed RSS readings to the RSS readings from one of the trained locations based upon minimum Euclidean distance. PC-DfP [6] shares the same philosophy with [7, 3] and takes special care in the training phase to minimize the RF signal variation within short distances to mitigate the error caused by the multipath effect.

Radio tomography imaging [4, 1] is a technique to reconstruct the tomographic image for tracking device-free subjects. Here, the authors assume that the relationship between a subject's location and the radio signal variation can be mathematically modeled. In [4, 1], based upon the shadowing effect, i.e. radio signal strength (RSS) is attenuated when the Line-of-Sight (LoS) is blocked caused by the subject. A linear attenuation model and a Sequential Monte Carlo model are proposed respectively. These techniques are unlikely to fare well in a cluttered indoor environment because the in [6] authors observed that a person blocking the LoS can only attenuate the RSS with a 50% probability.

In [9, 10], a grid sensor array is deployed on the ceiling for the tracking purpose. An "influential" link is one whose RSS change exceeds a preset threshold. The authors calculate a subject's location based upon the observation that these influential links tend to cluster around the subject. This work is extended in [8] with triangle sensor array deployment and training information. In VRTI [5], the authors leverage the RSS dynamics caused by the moving subject to generate a radio tomographic imaging for tracking.

Among all the existing works, we would like to point out not only fingerprint-based schemes (including ours) need a training phase, but other schemes such as radio tomography and grid sensor array also need a training phase to determine a suitable threshold value to detect if a subject is on the radio LoS.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we extend 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. Experimental results show that we achieve better localization accuracy by carefully tuning the system parameter – the neighbor order. More study will be conducted to further improve the tracking performance and to track multiple subjects.

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