Poster Abstract: Towards Robust Device-Free Passive Localization Through Automatic Camera-Assisted Recalibration

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Abstract

Device-free passive (DfP) localization techniques can localize human subjects without wearing a radio tag. Being convenient and private, DfP can find many applications in ubiquitous/pervasive computing. Unfortunately, DfP techniques need frequent manual recalibration of the radio signal values, which can be cumbersome and costly. We present SenCam, a sensor-camera collaboration solution that conducts automatic recalibration by leveraging existing surveillance camera(s). When the camera detects a subject, it can periodically trigger recalibration and update the radio signal data accordingly. This technique requires camera access occasionally each month, minimizing computational costs and reducing privacy concerns when compared to localization techniques solely based on cameras. Through experiments in an open indoor space, we show that this scheme can retain good localization results while avoiding manual recalibration.

Categories and Subject Descriptors

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

Keywords

Device-free Passive Localization, Linear Discriminant Analysis, Automatic Recalibration, RSS fingerprint, Computer Vision

1 Introduction

In the vision of pervasive computing, future smart environments will contain hybrid sensors to enhance life; examples include elder care, security at commercial places, etc. The key to these ubiquitous applications is the ability to localize various subjects and objects in the environment. Device-free passive (DfP) localization [3] has been proposed as a way of detecting and tracking subjects without the inconvenience and loss of privacy associated with carrying tags or devices.

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Several RF-based DfP localization techniques have been proposed in [3, 2, 1]. These approaches observe how people disturb the pattern of radio waves in an indoor space and derive their positions accordingly. They either calibrate the system by fingerprinting [3, 2], or use attenuation models based on the position of the subject relative to a line-of-sight radio link [1].

Limitation In State-of-Art Work Because of changes in radio attenuation as objects or people move in the environment, the received signal strength (RSS) changes enough to require frequent recalibration to maintain localization accuracy. As shown in [2], the localization accuracy can drop from 97% to 20% without any recalibration after only one month. Frequent recalibration entails high overheads in time and effort, especially in a large space.

Camera-Assisted Automatic Recalibration We design SenCam, an automatically calibrated DfP system that leverages cameras that already exist in many indoor environments, such as supermarkets, grocery stores and offices that have been equipped with surveillance cameras for security reasons. Many data collected by these cameras can be processed to provide recalibration data for a DfP system without the interference associated with RF-based approaches. SenCam works as follows: first, when we collect radio fingerprinting data from multiple radio links in the region and image data from one or more cameras. From time to time, when camera is on, it detects the subject location, records the time and radio data, and updates the radio training data accordingly. Thus, we can retain good localization results while avoiding manual recalibration over time.

2 Camera-Assisted DfP Localization

The goal is to localize a subject without requiring that they carry any device. We slice a deployed region into cells, and seek to identify the occupied cell of the subject. To characterize the environment, we take fingerprints in both radio RSS values and camera images while having the subject make random movements within each cell. Then, we treat each cell's fingerprints as a class, and adopt proper classification algorithms to build RSS and image classifiers respectively. After the initial training phase, the camera will

Figure 1. 10 wireless transmitters and 6 receivers are deployed in this 20 × 20 m open space.

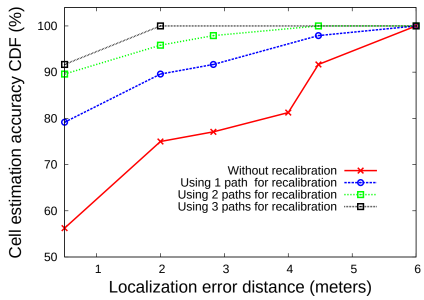

Figure 2. Comparing the CDF of localization error distances with different recalibration effort.

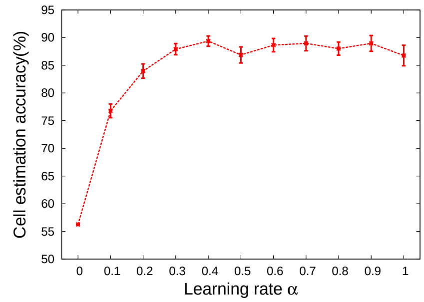

Figure 3. Cell estimation accuracy with 95% confidence interval error bar versus the learning rate.

occasionally capture images and identify the occupied cell through computer vision techniques. Meanwhile, it can trigger the sensors to take new RSS values and refresh and recalibrate the radio fingerprints.

Radio Frequency Approach Our radio fingerprints for each cell consist of RSS values of each radio link when the subject appears in that cell. Using these RSS values, Linear Discriminant Analysis (LDA) is used to solve the RF-based DfP indoor localization problem [2]. Essentially, the RSS vectors will be collected and fitted into a multivariate Gaussian when a subject is in different cells for training and testing.

Computer Vision Approach Starting with camera images, pixel-wise absolute differences between each incoming image $I(k)$ and the known background image B are computed. The pixels are assumed to contain the subject if the absolute difference exceeds a predefined threshold level. After getting the foreground image, we detect the boundary of the foreground subject. The bottom position of the subject boundary indicates the subject location. Features extracted using this method are ready for training and testing. We use Support Vector Machine (SVM) to identify the subject location in the incoming images.

Sensor-Camera Collaboration While image fingerprints remain stable over time, radio RSS fingerprints may quickly age and become invalid because radio signals are easily affected by changes in the environment. For instance, battery drain can reduce output power, which can directly change how much a subject can disturb ambient radio signals. As another example, movement of the other objects in the environment can change the multipaths of the links, leading to an unpredictable impact on the radio RSS values. Through background subtraction, image training data is rather stable over time. We make use of this property to recalibrate the radio RSS fingerprints automatically. Specifically, we turn on the camera from time to time to capture images. Once the subject is identified in one of the cells, the system collects the RSS data on all the radio links, and refreshes the radio RSS fingerprints for this specific cell with the latest RSS readings. In this way, we have implemented a DfP scheme that is robust against environmental changes.

3 Experimental Evaluation

SenCam setup consists of a centralized PC serving as the system manager, 10 wireless transmitters and 6 receivers. Each transmitter broadcasts 10 beacons every second. After receiving these beacons, the receivers extract the RSS values in dBm and forward them to the centralized PC for data collection and analysis. We also set up a webcam by placing it at 2.5 m above the floor, taking images (each frame including 320 × 240 pixels) every second. SenCam system is deployed in a 20 × 20 m room whose picture is shown in Figure 1. We choose a 8 × 8 m area, which is further partitioned into 16 cells, each of 2 × 2 m in size.

We use cell estimation accuracy as our performance metric, which is defined as the ratio of successful cell estimations with respect to the total number of estimations. We randomly choose a path consisting of 7 cells to test the tracking performance one month after initial profiling. Figure 2 shows the cell estimation accuracies for four different cases. In the first case, there is no recalibration, and we just use initial RSS fingerprints in the testing phase. In the second case, we conduct one recalibration, during which the subject walks along the path, and we refresh the RSS fingerprints with the help of camera. We conduct two rounds of recalibration in the third case, and three rounds in the fourth case. Using initial fingerprints without any recalibration, DfP is not robust against environmental changes and leads to poor localization results, i.e. only 56% cell estimation accuracy. The more recalibration we conduct, the better the localization performance. For instance, when we have three rounds of recalibration, we can retain a 91% cell estimation accuracies in spite of large environmental changes, which is shown in "no calibration" case.

In each recalibration round, we can choose to update only a subset of RSS fingerprints. We then define a parameter called *learning rate* α, the proportion of the RSS fingerprints we update in each recalibration round. We vary the value of α and show our experimental results in Figure 3. We observe that by updating less than half of the RSS training data, we can achieve better localization accuracies.

4 References

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