Device-Free People Counting and Localization

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UbiComp'13 Adjunct, September 8–12, 2013, Zurich, Switzerland.

ACM 978-1-4503-2215-7/13/09.

Abstract
Device-free passive (DfP) localization has been proposed as an emerging technique for localizing people, without requiring them to carry any devices. Potential applications include elder-care, security enforcement, building occupancy statistics, etc.

We first present PC-DfP, an accurate and efficient RF-based device-free localization solution. PC-DfP adopts a stochastic fingerprinting approach to mitigate the error caused by the multipath and meanwhile minimize the system calibration overhead. Second, we present SCPL, a RF-based device-free people counting and localization technique. SCPL takes the calibration data collected with one person and the map information to accurately count people sequentially and localize them in parallel. Finally we present Crowd++, an unsupervised speaker counting technique through audio inference with smartphones to estimate the number of people in social hotspot places.

Author Keywords
Counting, Localization, Device-Free

ACM Classification Keywords
C.3 [Special-Purpose and Application-Based Systems]: Miscellaneous

Introduction

Ambient Intelligence (AmI) envisions that future smart environments will be sensitive and responsive to the presence of people, thereby enhancing everyday life. Potential applications include elder-care, rescue operations, security enforcement, building occupancy statistics, etc. The key to enable these ubiquitous applications is the ability to localize various subjects and objects in the environment of interest. Device-free passive (DfP) localization has been proposed as a way of detecting and tracking people without the need to carry any tags or devices. It has the additional advantage of being unobtrusive while offering good privacy protection. Over the past decades, researchers have studied ways of tracking device-free people using different techniques such as camera [4], capacitance [9], pressure [5], infrared [1] and ultrasonic [2]. However, they all suffer from serious limitations such as occlusion [4, 1], high deployment cost [5, 9] or short range [2].

Radio frequency (RF)-based techniques have the advantages of long-range, low-cost, and the ability to work through non-conducting walls and obstacles. In 2007, Youssef et al. [17] first proposed the idea of RF-based device-free passive localization through fingerprinting approach - first collect a radio map with the subject present in a few predetermined locations, and then map the test location to one of these trained locations based upon observed radio signals. Another branch of geometric based methods, such as RF tomography [6], try to capture the statistical relationship between the received signal strength (RSS) of a radio link and whether the subject is on the Line-of-Sight (LoS) of the radio link, and consequently determine the subject's location. However, all the methods mentioned above might lose their localization accuracy in cluttered indoor environments because the rich multipath will cause deep fading [7] and further make it a challenging problem to compute people's relative location to the radio link based on the link's RSS measurements.

In this paper, we take on the challenge and strive to improve the performance of DfP localization. First, we present PC-DfP [14], a lightweight and accurate RF-based device-free localization technique for one person. Second, we present SCPL [12], an efficient 2-step algorithm to accurately count and localize multiple people. Last, we present Crowd++ [16], an accurate and energy efficient speaker counting system to estimate the number of people in social public space. In short, we made the following contributions:

- We proposed certain optimization techniques to mitigate the error caused by the multipath and improve the localization accuracy in RF-based device-free passive localization problem.
- We designed and implemented SCPL, an efficient and accurate RF-based device-free people counting and localization technique by only collecting the calibration data with one person and the map information.
- For the first time we demonstrate that it is possible to efficiently and accurately estimate the number of speakers in an unsupervised manner using smartphone.

Related Work

During the past years, several RF-based DfP approaches have been proposed in the literature, which can be categorized into two groups as follows.

Location-based schemes: This approach is also known as "fingerprinting", a popular approach for RF-based localization. It was first studied in [17] in the context of passive localization. The authors first collect a radio map with the subject present in a few predetermined locations, and then map the test location to one of these trained locations based upon observed radio signals. This method explicitly measures the multipath effect on RSS in each different position, and thus avoids modeling errors. In addition, it does not require a node deployment as dense as in link-based schemes because when the subject is in the position has no intersection with any radio LoS links, the RSS ground truth still can provide a distinguishable record from other positions. This work is extended to a much larger deployment in Nuzzer [8]. The downside of fingerprinting is also evident: the calibration procedure is relatively tedious.

Link-based schemes: These techniques look for those radio links close to the target subjects and further determine the locations of the targets based on the RSS dynamics. Zhang et al. [18] set up a sensor grid array on the ceiling to track subjects on the ground. An "influential" link is one whose RSS variance exceeds a empirical threshold. The authors determine a subject's location based upon the observation that these influential links tend to cluster around the subject. This technique forms a consistent link-based model to relate the subject's location relative to the radio link locations. Another sets of work following Link-based DfP is radio tomographic imaging (RTI). Wilson et al. [10] use tomographic reconstruction to estimate an image of human presence in the deployment area of the network. RSS attenuation is used as data primitive in [10], which effectively works in outdoor or uncluttered indoor space without rich multipath. Recognizing the nature of multipath fading, Wilson et al. defined the concept of fade-level [11], which captures the ambient RSS characteristics of each link and categorize the links into deep fade (the RSS will increase on average when the LoS is blocked) and anti-fade (the RSS decreases when the LoS is obstructed) through fitting the calibration data to a skewed Laplace distribution. The authors demonstrate this technique's effectiveness through testing in same setting over time and a totally different setting without the effort of re-estimating the model parameters. Kaltiokallio et al. [3] further exploit channel diversities to enhance the tracking accuracy. Zhao et al. [19] proposed to use kernel distance to quantify the distance between two histograms of signal strength measurements. In general, link-based schemes have two advantages: (i) the algorithms are robust to the environmental change because the subject's location is directly estimated based on its relative distance to each individual radio link LoS; (ii) it requires less calibration effort - only sensor locations and ambient RSS for each link is needed. However, it requires a dense nodes deployment to provide enough radio LoS links to cover all the physical space.

Methodologies and Results

The overall goal is to provide efficient device-free people counting and localization strategies in most indoor environments. In this section, we present PC-DfP, SCPL and Crowd++ with preliminary results.

PC-DfP

Considering the complexity of multipath, we choose to adopt the fingerprinting approach, and try to achieve good results while keep the calibration overhead low. We first partition the deployed area into a number of cells based context information, such as cubicle, aisle, sofa, etc., and we aim to find which cell the person is located in. We believe this cell-based localization is more practical than traditional spot-based localization because this context-based localization precision is good enough for most applications, and it can reduce the calibration overhead as well. In the profiling phase, the experimenter performed random walk rather than stood still in the center of the cell to collect the data so that the multipath effect can be smoothed out and the data quality can be improved. We then formulate this localization problem into a probabilistic classification problem by using linear discriminant analysis classification algorithm to localize a subject by finding the cell/class ID with the maximum likelihood. In our experiments, we first deploy our sensor nodes in a 40 m^2 home apartment and slide the room into 32 cells. The wireless receivers forward the received packets to a standalone host PC for data collection and analysis. We validated the proof-of-concept of this cell-based fingerprinting method and achieve 97% cell estimation accuracy with 0.36 m localization error distance [13] for one person. In [14], we performed a thorough study on the impact of the different radio frequency, number of calibration sample, number of devices and show that we can achieve promising results with lower radio frequency, fewer data samples and fewer receivers. We also demonstrated that our framework can be used to localize multiple subjects no matter static or mobile without extra calibration effort. To verify that our approach is scalable, we deployed our system in a larger office area with 150 m^2, and the system reported 1 m localization error distance.

SCPL

Recognizing that merely tracking an individual might not be sufficient for typical indoor scenarios, we then propose SCPL [12], an efficient algorithm that uses the profiling data collected with only one subject present, to count and localize multiple subjects in the same environment with no extra hardware or data collection. SCPL works in two phases: it first counts how many people by finding each location and subtracting his/her impact on the radio links. After the counting phase, SCPL begins to keep tracking all the detected people's location. In addition, we showed that though a complex environment like the office cubicles is expected to have worse radio propagation, SCPL can leverage the increased mobility constraints that go with a complex environment to maintain or even improve accuracy in these situations. Through extensive experimental results, we showed that SCPL works well in two different typical indoor environments of 150 m^2 (office cubicles) and 400 m^2 (open floor plan) deployed using an infrastructure of only 20 to 22 devices. In both spaces, we can achieve about an 86% average counting percentage and 1.3 m average localization error distance for up to 4 subjects.

Crowd++

Lastly, we note that RF-based device-free counting and localization techniques rely on a relatively dense array of radio sensors. These techniques might be suitable for home applications, but not very practical in many social public spaces, such as restaurants, malls, bars, or conference rooms. To overcome this limitation, we generally assume that people usually engage in conversations in these social public spaces, and therefore take number of speakers as the proxy of number of people. We designed and implemented

Crowd++ [16], an unsupervised speaker counting mobile application on Android systems. Crowd++ estimates the number of active speakers in a group of people. It consists of three steps: (1) *speech detection*, (2) *feature extraction*, and (3) *counting*. In the speech detection phase, we extract the speech segments from the audio data by filtering out silence periods and background noise. In the feature extraction phase, we compute the feature vectors such as MFCC and pitch from the active speech data. In the counting phase, we first select cosine similarity distance as the energy-efficient distance function that is used to maximize the dissimilarity between different speakers' voice, and then apply an unsupervised learning technique that, operating on the feature vectors with the support of the distance function, determines the speaker count. Our experiments involve 120 participants in 10 very different environments and report an average error distance of 1.5 speakers. In spite of Crowd++ not being perfect and potentially affected by limitations the count is based on active speakers and noise can possibly impact the count accuracy we still believe that ours is a competitive approach in many different application scenarios. In the social realm for example: people are often interested in finding "social hotspots," where occupants engage in different social behaviors: examples are restaurants, bars, malls, and meeting rooms. It can also be applied in many other research fields, including social sensing and personal wellbeing assessment.

Ongoing Work

A practical system should demonstrate good temporal and spatial scalability. We identified the two main limitations of our current approach for ongoing work.

Tracking Accuracy Improvement

The current version of SCPL and Crowd++ are still far from perfect. SCPL had success with tracking the count and location for up to 4 subjects, but were not very accurate with more subjects. This is mainly because multiple people will cause nonlinear fading effect to the radio links they mutually affect. Therefore, a more deep study needs to be performed to tackle this problem. Crowd++ cannot work very well in very noisy places, which urge us to design adaptive noise cancellation techniques to further improve the counting accuracy.

Temporal Robustness

In a long-run test, any RF-based localization schemes suffer not only from temporal fading, but also from environmental changes. A small piece of metal can change the tuning of the antenna shift the radiation pattern or even the radio frequency of the nearby transmitter or receiver. Either or both of these effects can change the underlying propagation pattern and, hence, the RSS values on the links. To avoid frequent manual recalibration, we presented SenCam [15], a camera-assisted automatic recalibration scheme to maintain the localization accuracy over a long-term test – when the camera occasionally turns on, it localizes the subject and recalibrates the RF data automatically. We are investigating a more sophisticated sensor fusion approach to improve the localization accuracy.

Acknowledgements

The author would like to acknowledge his Ph.D. advisors Prof. Dr. Yanyong Zhang and Dr. Richard Howard for their guidance to shape the framework of this thesis. The author would also like to thank his collaborators Prof. Dr. Xiaodong Lin, Dr. Jun Li, Prof.

Dr. Wade Trappe and Prof. Dr. Richard Martin from Rutgers University. Finally, the author would like to thank the researchers Dr. Yih-Farn Chen and Dr. Emiliano Miluzzo from AT&T Research Labs.

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Biography

Chenren Xu received his B.E. (Hons.) degree in 2008 from Department of Automation, Shanghai University, Shanghai, China and M.S. degree in 2011 from Wireless Information Network Laboratory - WINLAB in Department of Electrical and Computing Engineering, Rutgers University, NJ, USA. Since 2011, he has been a Ph.D. candidate advised by Prof. Dr. Yanyong Zhang and Dr. Richard Howard at WINLAB. His research interests focus on indoor human location and count tracking, context sensing, energy efficient computing, and sensor fusion. He expects to finish his Ph.D. dissertation in 2014.