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Nearest Neighbor Localization Finder using RFID Hidden Markov Gaussian Mixture using Kernel based

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Abstract

Device-free passive localization aims to localize or track targets without requiring them to carry any devices or to be actively involved with the localization process. This technique has received much attention recently in a wide range of applications including elderly people surveillance, intruder detection, and indoor navigation. In this paper, we propose a novel localization and tracking system based on the Received Signal Strength field formed by a set of cost-efficient passive RFID tags. We firstly formulate localization as a classification task, where we compare several state-of-theart learning-based classification methods including k Nearest Neighbor (kNN), Multivariate Gaussian Mixture Model (GMM) and Support Vector Machine (SVM). To track a moving subject, we propose two Hidden Markov Model (HMM)-based methods, namely GMM-based HMM and kNNbased HMM. kNN-based HMM extends kNN into a probabilistic style to approximate the Emission Probability Matrix in HMM. The proposed methods can be easily applied into other fingerprint-based tracking systems regardless of their hardware platforms. We conduct extensive experiments and the results demonstrate the effectiveness and accuracy of our approaches with up to 98% localization accuracy and an average of 0.7m tracking error.

Keyword: Localization; RFID; Hidden Markov Model; Gaussian Mixture Model; Kernel-based; Nearest Neighbor.

1. Introduction

Ambient intelligence has been drawing growing attention recently since it enables a smart environment which canrespond to people's locations and behaviors using various wireless signals, sensors, and radio frequency identification (RFID). Under such smart environments, many attractive applications can be realized, which will have huge impact to our daily lives, such as aged care, surveillance, and indoor navigation [17]. A key prerequisite of enabling this intelligence is to localize and track people in the indoor environments. Over the past decade, localization and tracking has been an active research area with several proposed solutions such as LANDMARC [5], WILL [14], and Nuzzer [11]. RFID-based localization has gained much interest due to its low-cost, easy deployment and scalability. Recently, many RFID-based techniques for localization have been proposed [5, 6, 8, 13]. Most of these techniques, however, require the target subject to either carry a tag/reader or be actively involved with the localizing process, which might not be practical. For instance, the attached tag/reader may be lost or damaged, or elderly people with dementia may forget to carry the device. As a result, a device-free RFID-based passive localization solution is highly desirable. Localizing and tracking subjects using such a solution does not require subjects to carry any devices (e.g., wearable sensors or tags).

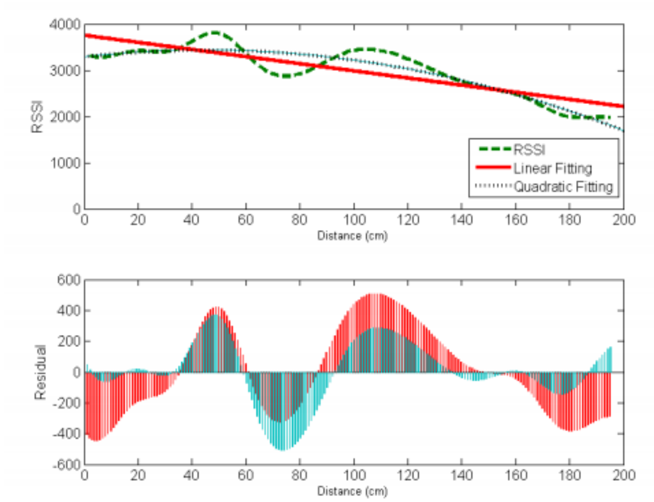

Fig 1: RSSI variation with distance

It is well known that Received Signal Strength (RSS) is quite complicated in real environments due to variability caused by multipath effects and ambient noise interference, physical antenna orientation, and fluctuations in the power source. The signal attenuates while increasing the distance. Figure 1 shows the relationship between Received Signal Strength Indicator (RSSI) of a passive RFID tag and itsdistance to an antenna. The RSSI does not strictly decrease with the increase of distance, which cannot be expressed by a linear or even a quadratic model. Thus, RSSI is highly nonlinear and uncertain in a complex environment, which may be further corrupted when introducing people's presence or mobility. However, on the other hand, some underlying distinguishable patterns can be observed like how people disturb the pattern of RSS through certain learningbased probabilistic methods. In this work, we deploy passive RFID tags in the corners of the monitored area (see Figure 2) which can form an RSS field (quantified by a 4-dimensional RSSI vector). When a subject appears in different locations inside the monitored area, the RSSI vector will present different patterns. According to aforementioned observations, our proposed approach works on the following two intuitions:

- When a subject presents in an RSS field, the RSSI vector in this field will change compared with the static environment (no subject in this area).
- When a subject appears in different locations in an RSS field, the RSSI vector of this field will embody different fluctuation patterns.

Device-free RFID-based passive localization in general works as follows. The RSSI vectors are first collected when people present in various predefined locations, and then a given testing location is mapped to one of these trained locations based on the observed RSSI vector. Two existing research efforts on RFID-based device-free localization [4, 20] are based on the first intuition, which explore people's location based on an array of densely-deployed active tags [4] or an array of mixed passive and active tags [20]. In this paper, we propose a new approach by considering both intuitions. Our approach not only captures the binary information of RSSI, but also quantifies the variation information to decode a more accurate location. We verify our approach by setting up a testbed. In particular, we deploy passive RFID tags and an RFID antenna as a single RSS field (as showed in Figure 2). A sequence of RSSI vectors collected from various known locations along with corresponding correct location labels are used to train a model, which is then used to estimate the subject's location for a given new RSS vector. Our main contributions are summarized as follows:

2. Related Work

Localization has been an active research area over the decades. In this section, we first review some state-of-the-art localization systems, and then focus on RFID-based devicefree passive localization which is more related to our work. Criket [7] adopts an ultrasonic Time-Of-Flight (TOF)- based method to locate target subjects which carries a Bat (transmitter) periodically emitting a short pulse of ultrasound. In [5], Ni et al. design a system to localize the target object carrying an active RFID tag. It employs densely deployed RFID tags to alleviate the fluctuation feature in RSSI and then estimates target location by matching the measurements with the stored fingerprints. With the popularity of smart phones, FTrack [18] proposes to use the accelerometer in mobile phones to capture user encounters and trails for locating the number of floor levels where people present. WILL [14] presents a wireless indoor localization approach to locate people's positions, requiring no prior knowledge of access point locations. All these systems require a tracked entity to carry a device (e.g., RFID reader/tags or mobile phones), which might be impractical for some applications.

Device-free localization recently has become an active research area since Youssef et al. first identify the challenges of device-free passive localization in [19]. Most recent stateof-the-art localization and tracking systems are based on wireless sensor networks. Patwari et al. [21] propose a kernel distance-based RTI (radio tomographic imaging) by using a kernel distance of histograms to locate a moving or stationary person based on wireless TelosB nodes. Nuzzer [11] estimates the location of entities by monitoring the RSS at certain monitoring points using wireless networks, which first constructs a passive radio map in an offline style, and then uses a Bayesian-typed inference algorithm to optimize a location with the largest probability. Xu et al. [16] develop a fingerprinting-based device-free passive localization system, in which several discriminant analysis approaches are explored. In [15], the authors further extend the system to count and localize multiple subjects based on the same hardware platform, in which they first iteratively estimate the number of subjects by a successive cancellation algorithm and then a conditional random field (CRF) is used to localize multiple subjects simultaneously. Ichnaea introduced by [9] realizes the device-free passive motion tracking by exploring several statistical anomaly detection methods, an anomaly scores-based particle filter model, and a human motion model.

WSNs-based localization systems require maintenance (e.g., replacing batteries). In contrast, passive RFID-based localization systems are cost-efficient (cheap passive tags), easy to deploy, and maintenance-free. Recently, some research efforts have been proposed to deal with the device-free passive localization based on RFID technology. For instance, based on densely-deployed passive tags, [12] utilizes RTI for device-free indoor localization. Twins [3] is another very re-cent system, which leverages observations caused by interference among passive tags to detect a single moving subject. Liu et al. [4] propose to deploy active tags into an array, which captures localization information when the RSSIs of tags (known position) variate beyond a threshold, and frequent trajectory patterns can be mined based on estimated localization sequences. Zhang et al. [20] develop another tag array-based localization scheme using both active and passive tags, which is more cost-efficient and much effective on RSSIs noise reduction. However, those two schemes focus more on mining frequent trajectory patterns and only model the mapping from the binary information of tags (RSSIs changed bigger than a threshold or not) to locations rather than quantifying variation of RSSIs to locations. By comparison, our approach explores the relations between variation of RSSIs and locations, and only based on "pure"passive RFID tags, which are more cost-efficient and practical (e.g., no maintenance needs).

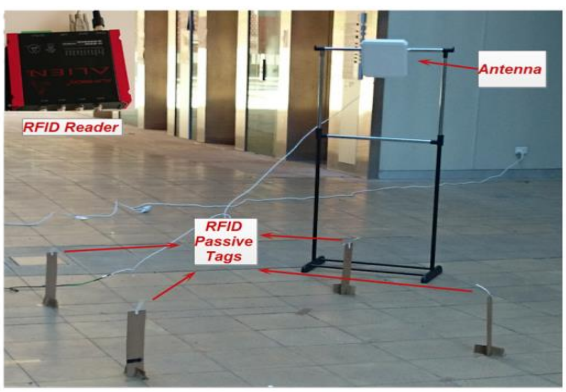

Figure 2: Hardware Setup

3. Implementation

3.1 Hardware Deployment:

Figure 2 shows hardware, including an Alien ALR-9900+ Enterprise RFID Reader (20.3cm × 17.8cm × 4.1cm), twocircular antennas (20cm×20cm×3cm), and squiggle Higgs-4 passive tags (1cm × 10cm). The reader operates at 840- 960MHz and supports UHF RFID standards such as ETSI EN 302 208-1. We set the sample rate as 0.5s and each tag reading contains a timestamp, a tag ID and an RSSI value, which are processed by a computer with an I7-3537U 2.5GHz processor and 8G RAM, running in WINDOWS 7. We describe our antenna and tag placement strategies show an RSS field formed by passive tags (see Figure 2), which can be easily extended into a larger area by combining multiple RSS fields

Antenna Placement: Ideally, all tag readings should be captured by the antenna. Based on our preliminary experiments, we place the antenna in 1.5m above the ground, facing tags with approximately 45◦. However, during the localization and tracking, an antenna can not guarantee to readall tags, particularly for passive tags. We solve the problem based on a fingerprint framework and develop a strategy to deal with missing readings.

Tags Placement: Tags can be deployed in any geometric shape since our proposed approach targets to learn a model mapping different RSS distribution patterns to its corresponding locations. For the simplicity, we place tags as a square-shaped array.

Reading RFID tags: To be consistent and easy to feed into algorithms, we send an RSSI request to all tags within a sampling time. If we cannot receive RSSI readings of a certain tag, the RSSI value is set to 0. Thus, mathematically, for all the time stamps, we have the RSSI vectors with the same dimensions. In our settings, the tag detection range can be up to 6 meters.

3.2. Intuitions Verification

In this section, we verify the two intuitions discussed in Section 1. First, we design a simple

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testbed (see Figure 2) which is a standard single RSS field formed by 4 passive tags (in 4 corners) and an antenna. Then, we manually divide the field into 9 virtual grids, which represent 9 different locations l1, l2, ..., l9. To verify the intuitions, we compare the patterns of RSSI vector when a subject is located in different locations.

4. Experimental Result

Single RSS Field Experiment:

Before evaluating our approach in localization and tracking, we need to take care of two main issues: one is about experimental setting, e.g., what is the optimal grid size, and the other is about how to deal with delay issue we found during the experiments. Based on our empirical study during this work, the smaller the grid size, the worse localization accuracy will be due to more indistinguishable disturbance, and more profiling data are needed as well. In our work, high resolution for locations is not our main concern. For instance, in an elderly people assistant system, caregivers are generally interested to know which sub-area or room the elderly is other than a very fine-grained location point. Therefore, in our experiment, we divided one single RSS field into 9 virtual grids, which can locate people in a 0.6m×0.6m resolution. For the latency, we adopted the forward calibration algorithm to recalculate the coordinates for tracking.

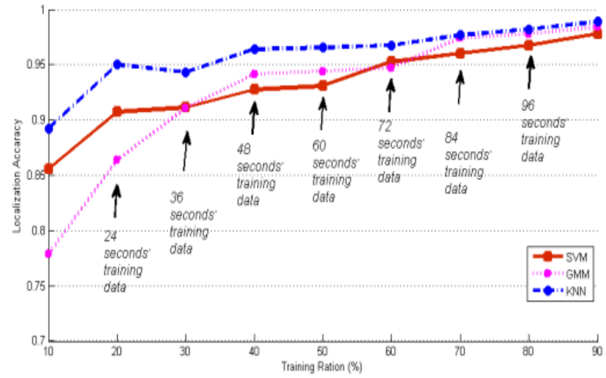

Fig 3: Results Comparison on Localizing a Subject with Different Training Ratio

5. Conclusion

In this paper, we propose a novel device-free object tracking scheme, Twins. We contribute to both the theory and practice of a new observed phenomenon, i.e., critical state on two adjacent tags. We also design a practical tracking method using passive tags. The extensive real experiments demonstrate the effectiveness of our method. Our future work includes studying critical state on a single tag, utilizing Twins to track multiple objects, and extending the detection region by refining the tracking algorithms.

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