Indoor Positioning System for Beacon Tag Tracking

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***Abstract*—This paper presents an Indoor Positioning System (IPS) that can localize and track tags that broadcast beacon messages. The proposed IPS uses a Kalman filter to preprocess collected RSSI information and a particle filter to approximate locations of tags.**

***Index Terms*—Indoor Positioning, Localization, Beacon, Particle Filter, Kalman Filter.**

I. Introduction

Indoor positioning is the fundamental technology for location based services (LBS), which may include maps and navigation, tracking, information providing, and other derived applications [1]. An Indoor Positioning System (IPS) using wireless communications can employ a variety of information to localize a target, such as Received Signal Strength Indicator (RSSI), inertial information, channel state information, angle of arrival, time of flight, and phase of arrival. Positioning using RSSI information can be an easy but sometimes volatile way due to influences of signal multipath effects, noise and interference, and other factors. To improve accuracy and robustness of RSSI-based positioning systems, various approaches were proposed. For example, a dead reckoning approach [1] may combine RSSI and inertial information to localize and track a target.

This paper presents an IPS for tracking tags that broadcasts beacons. The proposed IPS uses a Kalman filter to preprocess RSSI information and a particle filter algorithm to approximate locations of a tag in a room. A tag periodically broadcasts beacon messages that include its ID, MAC address, RSSI information. Access Points (APs) deployed at corners and boundary areas of a room receive the beacons and forward the information inside the beacons along with APs' IDs and location information to a server. The server estimates the location of the target in the room by collecting all information from the APs. Note that the main idea for the proposed IPS in this paper is described in our previous work [2].

The rest of this paper is organized as follows. Section II summarizes the related work. Section III describes the design. Section IV shows the simulation. Section V demonstrates the experiment. Finally, in Section VI, we conclude this paper along with future work.

II. Related Work

Researchers have explored a variety of approaches to position targets at an indoor environment. SALA [3] was proposed to localize Internet-of-Things (IoT) devices by a smartphone. It uses inertial sensors of a smartphone and beacon messages from IoT devices to localize both the smartphone itself and the IoT devices. AP-Sequence [4] is a fingerprint-based indoor localization system that requires low-overhead of fingerprint data building and maintenance.

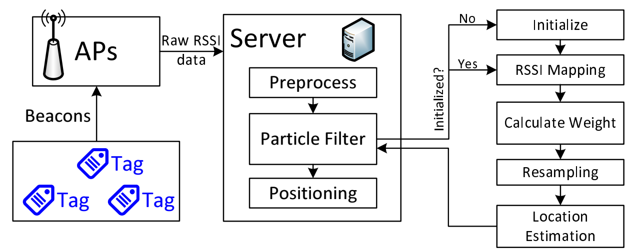

Fig. 1. The system framework of the proposed IPS.

III. Design

The proposed IPS uses a Kalman filter to preprocess the received RSSI data, and then inputs the preprocessed data into a particle filter. Fig. 1 shows the system framework of the proposed IPS. Assume that we have K tags to localize and J APs to collect RSSI data, and the location of each AP $j \in \{1..J\}$ is known as P_j. Initially, N particles are generated and distributed in a room uniformly.

At time t, based on a practical RSSI mapping function, an estimated distance, $\hat{d}^t_{k,j}$, between a tag $k \in \{1..K\}$ and an AP $j \in \{1..J\}$ can be obtained by the preprocessed RSSI data. It is assumed that the exact location P^t_i of a particle $i \in \{1..N\}$ is known, so we can accurately calculate the distance between the particle i and an AP j as $d(P^t_i, P_j)$. To better represent the distance differences, we can normalize the estimated distances $\hat{d}^t_{k,j}$ of the tag k and the exact distances of particles $d(P^t_i, P_k)$ as:

$$\hat{z}^t_{k,j} = \hat{d}^t_{k,j} / \hat{d}_{max}, \tag{1}$$

$$z^t_{i,j} = d(P^t_i, P_j) / d_{max}, \tag{2}$$

where $\hat{d}_{max}$ is the longest distance between a tag and an AP, and d_{max} is the longest distance of all particles to one of the APs. If a tag can be anywhere in a room, $\hat{d}_{max}$ equals the diagonal distance of the room.

By the two normalized distances, we can calculate a weight of a particle i as:

$$w^t_i = \frac{1}{J}\left(1 - \sum_{j=1}^{J}(|z^t_{i,j} - \hat{z}^t_{k,j}|)\right). \tag{3}$$

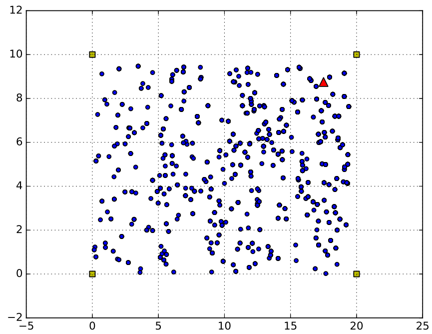

Fig. 2. Simulation with particles showing.

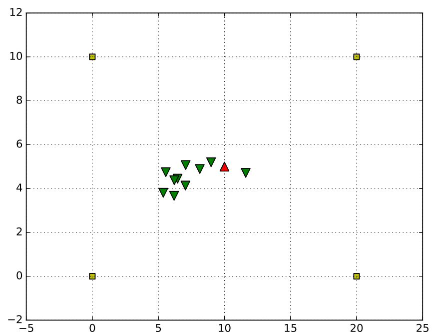

Fig. 3. Simulation to localize a target.

With weight w_i^t of each particle i at time t, we can resample all particles to reproduce a set of particles in which the particles with a high weight have a higher chance to be reproduced. For doing so, we use the Stochastic Universal Sampling (SUS) approach [5] to resample particles. The approximated location of a tag k at time t is the center of all the resampled particles, which can be expressed as:

$$\hat{P}_k^t = \frac{1}{N}\sum_{i=1}^{N} P_i^t. \tag{4}$$

IV. Simulation

To verify the proposed IPS, we setup a simulation environment with an area $20m \times 10m$ by Python. In this simulation, we place four APs at four corners of a room and one tag to be localized. For the measurement error of RSSI data, we added a random variable following Gaussian distribution ($N(0,1)$) to simulate the affects of noises. Fig. 2 and 3 show the simulation results. The yellow rectangles are APs. The red triangle is the actual location of a tag, the green triangle is the approximated location of the tag by the proposed IPS. Fig. 2 also shows the uniformly distributed particles at the beginning of the simulations by blue circles. The simulations showed the accuracy of the proposed IPS is about 5m.

V. Experiment

To evaluate performance of the proposed IPS in the real world, we also setup an experiment which is similar to the simulation settings. Fig. 4 shows the experiment configurations for the proposed IPS. In this experiment, we use several Raspberry Pi4B boards as basic devices. The server is configured to have a WiFi router function, so the four APs are associated with the server WiFi for collecting beacon messages sent from tags. Meanwhile, the tags in this experiment send Bluetooth beacons to the surrounding APs. By the proposed IPS, locations of the tags in this experiment can be shown in the server side.

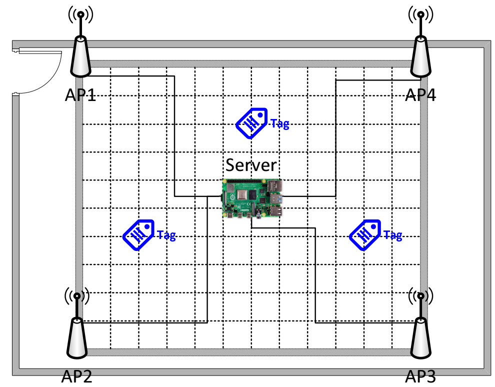

Fig. 4. Experiment setup of the proposed IPS.

TABLE I
Experiment Configuration

Name	Content
RSSI source	Bluetooth beacons
Server	Raspberry Pi4B
APs	Raspberry Pi4B
Tags	Raspberry Pi4B
Localization area	$6.0m \times 7.2m$

VI. Conclusion

This paper proposed an indoor positioning system to localize tags that can broadcast beacon messages. Through the simulations, we found that the localization accuracy of the proposed approach cannot reach sub-meter level, which is a different result from our primary work [2]. As future work, we will find the problem and improve the current approach.

VII. Acknowledgment

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