Modeling and Analysis of Queuing Effect of Two-Level Approach to Network Localization

Byungsung Park, Jaeyeong Yoo, and Hagbae Kim

In this letter, a novel method for localizing a user in a smart home environment is presented. We propose a two-level structure, in which the first level determines an occupant's location in the block level using RSSI in a ZigBee network, while the second level accurately estimates the occupant's location using a particle filter to handle the variations in the signal strength measurement. We devise an experimental setup with people performing significant tasks in the smart home. The results obtained from the testbed indicate that the proposed model leads to an improvement in the mean distance error.

Keywords: Location estimation, two-level structure, ZigBee network, RSSI, particle filter.

I. Introduction

The recent growth of interest in ubiquitous computing and location-aware services has motivated the development of techniques for the dependency of an occupant's communication, resource, and information needs at their physical location. This dependency has led to the materialization of ubiquitous computing environments that cater to changing occupant contexts by delivering location-based services in a wide range of personal and commercial applications [1], [2]. To enable and support the operation of such environments, the use of positioning methods such as RF, wireless local area networks, Bluetooth, and ZigBee are needed. Among these techniques, ZigBee positioning is considered a promising open standard that is used with low data rates and low power in cost-effective wireless network products [3], [4]. In particular, many location estimation approaches that are based on received signal strength indication (RSSI) are used in indoor environments. Since RSSI readings are provided by network interface cards available on most mobile devices, no additional hardware or installation costs are incurred. However, the mean distance error (MDE) of RSSI-based location estimation is larger than that of other methods because of an irregular model caused by interference and obstacles.

To overcome these problems, we introduce a novel algorithm with a two-level structure. Beginning with the RSSI data collected at the ZigBee nodes, which are spatially distributed in the observation area (where the occupant is moving), the aim of the proposed approach is to define the rough location of the occupant.

We then propose an adaptive particle filter that increases the accuracy because of the location estimation obtained from the first level. This filter effectively tracks motion in situations in which the Kalman filter and its variants are inapplicable, while maintaining a computational complexity comparable to that of the Kalman filter [4]. Particle filters have demonstrated promising performance. Our adaptive particle filter has come at a high computational cost for real-time location tracking, but it can be applied to real-time because of the information based on the first level [5], [6].

II. Location Estimation Using Two-Level Structure

Figure 1 shows the configuration of the ZigBee sensors for the proposed two-level structure in the simulation environment where the estimation range is established according to the rough estimation of the occupant's location based on the RSSI signal generated when joining a ZigBee end device (ZED) and all ZigBee routers (ZRs). Hence, we can treat the function of the first level as a preprocessing function for the conventional

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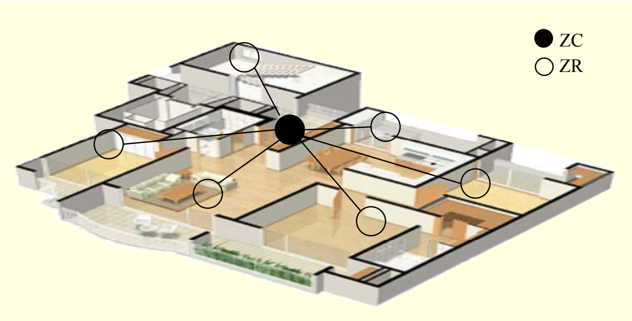

Fig. 1. Constructed ZigBee network in testbed environment.

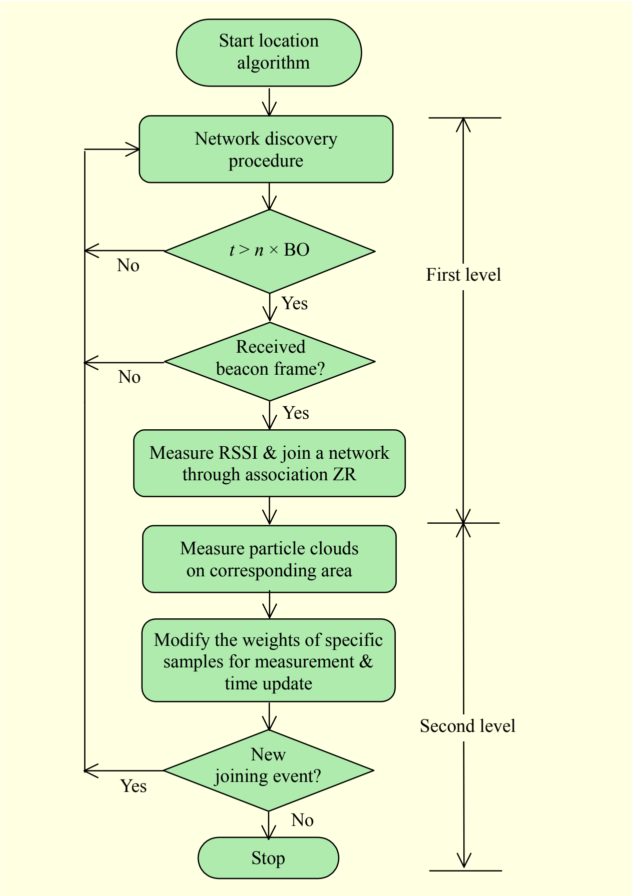

Fig. 2. Flow chart of proposed algorithm.

particle filter given in the second level. The preprocessing function provides more reliable evidence for the occupant's location, which in turn improves the tracking performance of the conventional particle filter. Figure 2 shows a schematic flowchart of the proposed two-level location estimation algorithm consisting of six rules: 1) initiate the network discovery procedure in the period of $n \times$ beacon order (BO), 2) check whether or not the beacon frames were received, 3) measure RSSI and then join a network associated with the ZR with the largest value, 4) measure particle clouds in the corresponding area, 5) modify the weights of all the samples for a measurement and time update, and 6) check whether or not a joining event has occurred.

1. First Stage: RSSI-Based Location Estimation in ZigBee

The role of the first level is to provide a reliable estimate of the occupant's rough location. We first focus on the location estimation algorithm using pair-wise RSSI measurements in the star topology. Consider the ZigBee network shown in Fig. 1, which includes a ZigBee coordinator (ZC) and ZRs, and a mobile ZED whose location is estimated. Based on the statistical model and maximum-likelihood estimation [2], our occupant's location is obtained from the following equation:

$$User\text{'s } location = MAX(RSSI_{\theta=1}, \cdots, RSSI_{\theta=n}), \quad (1)$$

where $RSSI_{\theta=n}$ is the RSSI obtained by attempting to join the mobile ZED and room number n. In this situation, the RSSI is such that the larger the signal strength to a receiving ZR, the shorter the distance to that receiving ZR. Since a room number is included in each ZR, the occupant's rough location can be identified.

2. Second Stage: Particle Filter for Location Tracking

The role of the second level is to provide an accurate assessment of an occupant's location based on the estimation of the occupant's location obtained from the first level. The algorithm based on particle filters estimates the location with the aid of a set of ZR positions and n particles. At first, a particle filter scatters these particles randomly, but uniformly, in the available space. An equal weight is assigned to each particle ($1/n$ for the sake of normalization) obtained from the first level results. This model of particles, $Bel(x_0)$, is uniform. When an event occurs (at t=1), $Bel(x_0)$ is computed according to

$$Bel(X_t) = \alpha P(R_t \mid X_t, Y_t) \int P(X_t \mid X_{t-1}) Bel(X_{t-1}) dX_{t-1}. \quad (2)$$

This operation changes the weights of the sample. The obtained distribution is then used to draw a new sample with equal weights. From this point on, the new sample is more focused on the latest event position. This operation is repeated every time a new event is observed. At any time, an estimate of the occupant's position is obtained by simply adding the weights of all the particles confined in that location. Consequently, we can observe in practice a cloud of particles following the occupant. Before using this technique for location estimation in our testbed environment, we must use all the ZigBee sensors in the first level and then attribute probability density functions to them. We also need to model the occupant's motion.

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Initialization: σ=0, sample S_0(s) from P(X_0)
if t>0 then
  for s∈samples do
    sample S_t(s) from P(X_t|X_{t−1})|_{X_{t−1}=S_{t−1}(s)}
    weight W(s)=P(R_t|X_t, P_t)
    σ=σ+W(s) {update normalization factor}
  end for
end if
for s∈samples do
  W(s)=W(s)/σ {normalize weights}
end for
resample S_t(s) according to W(s) with replacement
return S_t
```

Fig. 3. Particle filtering algorithm.

To implement the derived particle filter in localization, here, we design the localization algorithm and propose a practical message-passing mechanism to incorporate RSSI evidences into the tracking service. The particle-filtering algorithm starts from the results of the first level (RSSI readings), predicts the next state by the transition model, weights these particles according to the sensitivity model, and resamples them by observing the posterior probability.

$$\textit{Transition model}: \; P(X_t \mid X_{t-1}), \tag{3}$$

$$\textit{Weighting model}: \; P(R_t \mid X_t, Y_t), \tag{4}$$

$$P(R_t \mid X_t, Y_t) = \prod_{j \in B} P(r_{ij} \mid d'_{ij}, p_{ij})_t \; . \tag{5}$$

To illustrate the whole idea of particle filtering for location tracking, the pseudocodes of the main function, the weighting function, and the resampling function are listed in Fig. 3.

III. Experiment and Simulation Results

Location tracking experiments are performed in a real home environment, which has two bedrooms, a study, a kitchen, a living room, and a bathroom in a 10 m × 9 m space. Also included in the house are indoor walls, various appliances, and furnishings. We implement a ZigBee module, TI's single-chip 2.4 GHz IEEE 802.15.4 compliant RF transceiver CC2420, and Microchip's *Enhanced* FLASH. In location estimation applications, the ZigBee modules are usually fixed to the ceiling. To obtain an even covering in the estimation area, we use a 2.4 GHz 50 Ω inverted-F antenna that receives a 1.1 dB gain and an omnidirectional radiation pattern in the PCB plane [7]. In the testbed, one ZC, six ZRs, and one mobile ZED are deployed using the star topology. To validate the effective performance of our algorithm, we conducted tests based on various scenarios. The simulation results, based on a run of 100 changing locations and 100 iterations, are presented in Table 1. Figure 4 illustrates the test scenario example. In Fig. 4(a), if the occupant moves toward the kitchen and living room, two ZRs contend to join with the ZED.

Table 1. MDE of algorithms for location estimation.

Algorithm of location estimation	RSSI	Particle filter	Two-level
Average of MDE	1.26 m	1.16 m	0.72 m

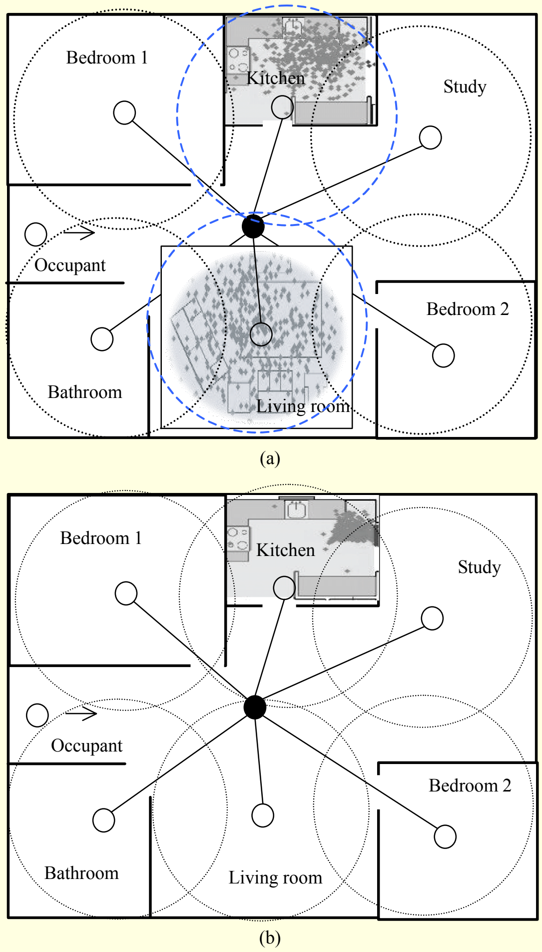

Fig. 4. Localization system based on scenario.

After the joining event, the system computes that the occupant is near the ZR connected to the ZED with a probability of 91%; this is the estimate of the occupant's location made in the first level. The points show the particle cloud, while the shaded areas indicate where the occupant is likely to be present. In Fig. 4(b), the system concludes that the occupant is in the kitchen and opens the refrigerator door. In addition, a door contact event is received because the particle cloud is quickly focused on the corresponding area.

Table 1 shows the MDEs of the existing methods and the proposed algorithm. The MDE measurements show that the proposed two-level algorithm's ability to accurately estimate an occupant's location is far greater than that of existing algorithms [2], [5]. Although the result is affected by the network structure (our network structure is a star topology) and obstacles such as walls and open doors, the MDE in the estimated locations for each scenario averages 0.7 m to 0.8 m. Therefore, our algorithm using the two-level estimation method proves to be highly accurate.

IV. Conclusion

In this letter, a location estimation algorithm using RSSI and a particle filter to track the location of an occupant in an indoor ZigBee network was proposed. In traditional location-tracking approaches, significant RSSI variability (even at the same location) can cause a high number of errors when determining whether the occupant is moving or still. To address this issue, our proposed method consists of a two-level structure in which the first layer performs a rough estimation of the location using the RSSI technique while the second layer performs an accurate estimation of the location using a particle filter whose last location cues come from the first layer's rough estimation. Experiments conducted in a real home environment confirmed the superiority of our method, which shows a clear improvement over existing tracking methods in accurately identifying positions. We implemented our algorithm and evaluated it with commercially available ZigBee hardware and a protocol stack. The proposed location-tracking algorithm is so general that it can be applied to any type of location-tracking module.

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