HOI-Loc: Towards Unobstructive Human Localization with Probabilistic Multi-Sensor Fusion

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***Abstract*—Unobtrusive indoor localization aims to localize people without requiring them to carry any devices or being actively involved with the localizing process. It underpins a wide range of applications including older people surveillance, intruder detection and indoor navigation. However, in a residential home, the Received Signal Strength Indicator (RSSI) is heavily obstructed by furniture or domestic appliances, reducing the localization accuracy. This environment is important to observe as human-object interaction (HOI) events, detected by pervasive sensors, can reveal people's interleaved locations during daily living activities. Thus, this paper aims to enhance the performance of the RFID-based localization system by fusing human-object interactions. Specifically, we propose a general Bayesian probabilistic multi-sensor fusion framework to integrate both RSSI signals and human-object interaction events to infer the most likely location and trajectory. Unlike other RFID-based unobtrusive localization systems, which are limited to deployment and testing in cleared spacial areas, our system can work in a furnished environment. The extensive experiments with this system have a localization accuracy up to 96.7%, and average 0.58*m* tracking error.**

I. Introduction

Ambient intelligence has been drawing a growing attention recently as it enables a smart environment that can respond to people's locations and behaviors using various wireless signals, sensors, or Radio-Frequency Identification (RFID) [1]. Many attractive applications can be realized in these smart environments that will have huge impact on our daily lives, such as aged care, surveillance and indoor navigation. A crucial prerequisite of these applications is to accurately localize and track people in a cluttered living environment [2], [3], [4]. Most of indoor localization techniques, however, require the target to either carry sensors/smart phones/tags or be actively involved in the localizing process, which has several limitations in practice. The attached sensor/smart phone/tag may be lost or damaged or elderly people with dementia may forget to carry the device. As a result, *unobstructive* (or *device-free*) indoor localization has gained significant momentum recently [5], [6], [4]. In particular, passive RFID-based localization has attracted much attention due to its low-cost (5∼10 cents each) and maintenance-free (no battery needed) nature [7], [8]. However, existing unobstructive techniques based on RFID usually work in clear or semi-clear spaces (*i.e.,* empty spaces or spaces with very few furnitures). None of them work in clustered residential environments, especially multiple-room scenarios. In addition, most RFID-based localization techniques are based on the assumption that knowing the tags' coordinates in advance, which is impractical in real-world applications (accurately locating the tag's position is a time-consuming and challenging task itself).

In this paper, we design *HOI-Loc*, an RFID-based device-free localization system to achieve *high accuracy* in *clustered* living environments using Human-Object Interaction events. With the rapid expansion of smart devices, we can easily access, retrieve and monitor the HOI events in our daily lives [9], [10], [11]. We also observe that such HOI can be served as a coarse-grained location indicator. For example, localizing a person in the kitchen (equipped with rich electrical appliances) purely based on RSSI is difficult since the signals are severely interfered by electrical devices made of metals (i.e., microwave oven, fridge or cooker). However, we can offset such signal disturbance and improve accuracy by using HOI, such as opening a fridge, turning on a kettle or microwave oven.

As a result, in this paper, we first set up RSS fields formed by passive RFID tags in living environments to contentiously generate RSSI signals since RSSI can be treat as a continuous location indicator [12]. Then, to facilitate localization, we deploy various kinds of sensors (e.g., infrared sensor, touch sensor and light sensor) to monitor the working conditions of domestic electrical appliances, through which we can detect the resident's interaction events. Given both RSSIs and interaction events, we develop a general Bayesian probabilistic framework to fuse these two signal sources. We first adopt a probabilistic k Nearest Neighbors (kNN) to model the likelihood of locations based on observed RSSIs, then we update the likelihood by retrieving corresponding interaction information, and we finally optimize the solution by selecting the location with the largest likelihood. To track a moving subject, we introduce a Hidden Markov Model (HMM) to quantify the continuous location transition process. The main contributions in this paper are:

- We introduce an approach that utilizes HOI events to facilitate unobtrusive localization based on maintenance-free passive RFID tags. Our experiments demonstrate its feasibility and accuracy in a fully furnished environment. To the best of our knowledge, the proposed system is a very first effort to do so.
- We propose a probabilistic multi-sensor fusion framework

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that provides a way to feasibly fuse HOI events with RSSI signals to enhance localization performance, which can generally serve other fingerprint-based localization systems that have multiple location indicators available.

II. Proposed Solutions

For each monitored area with D passive tags deployed, we divide it into J zones, denoted by $\mathcal{L} = \{L_1, L_2, ..., L_J\}$. We collect N training data $\mathbf{S}_i = [\mathbf{s}_{i1}^T, \mathbf{s}_{i2}^T, ..., \mathbf{s}_{iN}^T]^T$, where $\mathbf{s}_{ij} \in \mathbb{R}^D$ means data collected in jth time when a subject appears in zone L_i . Then, we have dataset $\mathcal{S} = \{\mathbf{S}_0, \mathbf{S}_1, ..., \mathbf{S}_J\}$, quantifying how a subject affects the RSSIs from each zone, where $\mathbf{S}_0$ represents the environmental RSSI without a subject. For modeling HOI events, assuming that we have overall M different objects $C = \{I_1, I_2, ..., I_M\}$, then interaction events can be represented in a binary way, i.e., $I_i = 1$ means an interacting event happens. For example, if I_1 represents *fridge door*, then $I_1 = 1$ means the *fridge door* has opened from closed, or closed from opened (be interacted), otherwise $I_1 = 0$. Thus, for N continuous time, we have an interaction events dataset $\mathcal{C} = \{C_1, C_2, ..., C_N\}$, where $C_i = \{I_1^i, I_2^i, ..., I_M^i\}$ represents all interacting events at ith time. Formally, this paper targets:

Problem 1 (Localization): Given a set of RSSI vectors and interaction events, we need to correctly estimate the subject's location.

Problem 2 (Tracking): Given a continuous RSSI sequence and the interaction event stream, we need to accurately estimate the subject's trajectory.

A. Localization

Mathematically, we can model *Problem 1* as finding the most likely location given the observed RSSIs $\mathbf{o}$ and interaction events C, formulated as

$$l^* = \arg\max_{l \in \mathcal{L}} Pr(l|\mathbf{o}, C) \tag{1}$$

Based on *Bayesian Inference*, we can infer

$$\begin{aligned} Pr(l|\mathbf{o}, C) &= \frac{Pr(l)Pr(\mathbf{o}|l)Pr(C|l, \mathbf{o})}{Pr(\mathbf{o}, C)} \\ &\propto Pr(l)Pr(\mathbf{o}|l)Pr(C|l, \mathbf{o}) \end{aligned} \tag{2}$$

Since RSSI signal and HOI events are from independent sensor sources, we have $Pr(C|l, \mathbf{o}) = Pr(C|l)$. Thus, based on Eqn. 2, we model the posterior probabilities of candidate locations as

$$Pr(l|\mathbf{o}, C) \propto Pr(l)Pr(\mathbf{o}|l)Pr(C|l) \tag{3}$$

where $Pr(l)$ is the prior probability distribution, set as $Pr(l) \sim 1/J$. We will next introduce how to estimate $Pr(C|l)$ and $Pr(\mathbf{o}|l)$, called *Human-Object Interaction (HOI) Probability* and *RSSI Probability* respectively, given a certain location.

HOI Probability. For each object I_i , its possible locations can be denoted as $L_{I_i} = [L_1^{I_i}, L_2^{I_i}, ..., L_J^{I_i}]^T$, $L_j^{I_i} = 1$ means L_j is a possible location of the subject when an interacting event happens, otherwise $L_j^{I_i} = 0$. For overall M objects, we have $L_I = [L_{I_1}^T, L_{I_2}^T, ..., L_{I_M}^T]^T$. Thus, given the interaction contexts with all objects $C = \{I_1, I_2, ..., I_M\}$, we can infer all the possible locations, denoted by $M_{HOI} = [I_1 L_{I_1}^T, I_2 L_{I_2}^T, ..., I_M L_{I_M}^T]^T$, called ***HOI Matrix***. Finally, we can estimate $Pr(C|l)$ based on Algorithm 1.

Algorithm 1: $Pr(C|l)$ estimation

Input: Human-Object Interaction Matrix $M_{HOI} \in \mathbb{R}^{M \times J}$
Output: $Pr(C|l_j), l_j \in \mathcal{L}$

$PossibleLocaSum = 0$;
for $i = 1 : M$ **do**
  for $j = 1 : J$ **do**
    if $M_{HOI}(i, j) == 1$ **then**
      PossibleLocaSum=PossibleLocaSum+1;
    end
  end
end
for $j = 1 : J$ **do**
  PossibleLocaSumj=0;
  for $i = 1 : M$ **do**
    if $M_{HOI}(i, j) == 1$ **then**
      PossibleLocaSumj=PossibleLocaSumj+1;
    end
  end
  if $PossibleLocaSumj \neq 0$ **then**
    $Pr(C|l_j) =$ *PossibleLocaSumj*/*PossibleLocaSum*;
  end
  else
    $Pr(C|l_j) = 0.0001$;
      %To avoid zero probability under such cases
  end
end

RSSI Probability. For the localization system based on passive RFID tags, kNN achieves better accuracy and with less computation compared to other methods [12]. Therefore, to feasibly fuse passive RFID tag detection with the likelihood generated by interaction events, we propose a probabilistic kNN to model $Pr(\mathbf{o}|l)$. Specifically, given a set of training RSSI dataset and a testing RSSI vector, the location is estimated by a majority vote and assigned to the most common zone among its k nearest neighbors from the training samples. Assuming for each $\mathbf{o}$, we search its k nearest neighbors from training dataset $\mathcal{S}$, denoted as $N(\mathbf{o}) = \{\mathbf{s}_k | \mathbf{s}_k \in k\text{NN}(\mathbf{o})\}$. The training samples collected in location L_i among its k nearest neighbors is represented as $N^i(\mathbf{o}) = \{\mathbf{s}_k^i | \mathbf{s}_k^i \in N(\mathbf{o}) \cap \mathbf{s}_k^i \in \mathbf{S}_i\}$. Then, it can be modeled as:

$$Pr(\mathbf{o}|l_i) = \frac{\sum_{\mathbf{s}_k^i \in N(\mathbf{o})} \frac{1}{dis(\mathbf{o}, \mathbf{s}_k^i)}}{\sum_{\mathbf{s}_k \in N(\mathbf{o})} \frac{1}{dis(\mathbf{o}, \mathbf{s}_k)} + \sum \alpha}, \text{ if } |N^i(\mathbf{o})| \geq 1 \tag{4}$$

where l_i indicates the subject is in location L_i, $(i = 1, .., J)$; $|N^i(\mathbf{o})|$ means the element number in $|N^i(\mathbf{o})|$; if $|N^i(\mathbf{o})| = 0$,

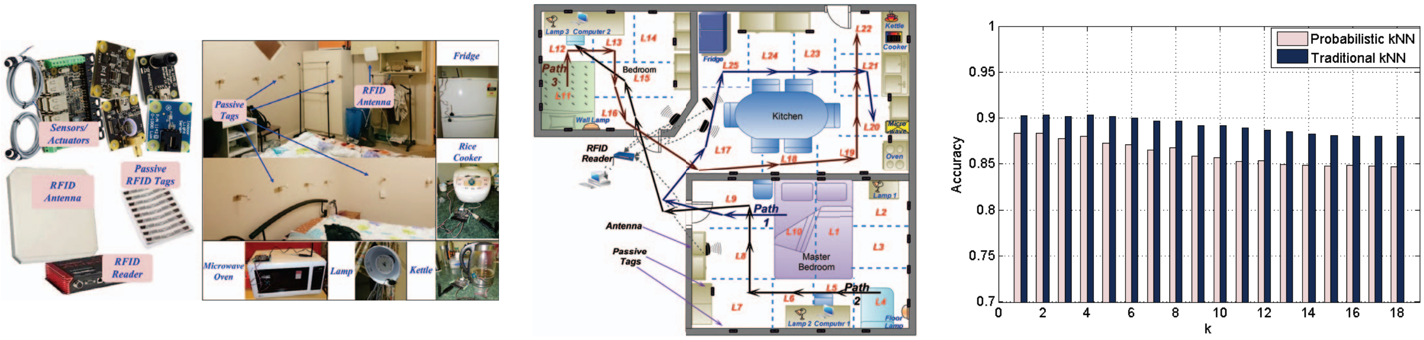

Fig. 1: From left to right: (a) Hardware deployment; (b) Experiment layout (master bedroom $3.6m \times 4.8m$, bedroom $3m \times 3.2m$, kitchen $3.6m \times 4.6m$); (c) Localization accuracy with k values;

we choose $Pr(\mathbf{o}|l_i) = 0.0001$ to avoid zero probability. Eqn. 4 gives the posterior distribution by finding its k nearest neighbors and measuring their distances with the testing sample. We compare our method with the localization classifiers that are frequently adopted by other systems [13], including SVM[1], Extreme Learning Machine[2] (ELM) and Naive Bayes[3].

B. Tracking

Problem 2 can be mathematically modeled as finding a location sequence with the largest likelihood given observed continuous RSSI vector sequence $\mathbf{o}_{1:T}$ and interaction event stream $C_{1:T}$.

$$l^*_{1:T} = \arg \max_{l_{1:T} \in \mathcal{L}} Pr(l_{1:T}|\mathbf{o}_{1:T}, C_{1:T}) \tag{5}$$

Assuming that the current location is only conditionally depend on previous one, then we can introduce a HMM-based method to decode the sequential RSSI observations and interaction events into continuous subject's trajectories, which is formed by *Emission Matrix* and *Transition Matrix*. According to Eqn. 3, we can do inference as follows:

$$\begin{aligned} &Pr(l_{1:T}|\mathbf{o}_{1:T}, C_{1:T}) \propto Pr(l_{1:T}, \mathbf{o}_{1:T}, C_{1:T}) \\ &= Pr(l_1)Pr(\mathbf{o}_1|l_1)Pr(C_1|l_1) \prod_{t=2}^{T} \underbrace{Pr(\mathbf{o}_t|l_t)}_{A_1} \underbrace{Pr(C_t|l_t)}_{A_2} \underbrace{Pr(l_t|l_{t-1})}_{B} \end{aligned} \tag{6}$$

Thus, to solve the problem, we first estimate *Emission Matrix* A and *Transition Matrix* B, then utilize the *Viterbi Search* to find the most likely location sequence.

Emission Matrix A. To fuse RSSI signal and HOI events into the HMM model, we divide *Emission Matrix* $A_{ij} = Pr(\mathbf{o}_i, C_i|l_j)$ into two sub-matrices: $(A_1)_{ij} = Pr(\mathbf{o}_i|l_j)$ and $(A_2)_{ij} = Pr(C_i|l_j)$, governing the probability distributions of observed RSSI and interaction events respectively at a particular time conditionally on locations. We then apply Eqn. 4 and Algorithm 1 to estimate these two sub-matrices correspondingly, which together will give emission probabilities at each time stamp.

Transition Matrix B. Taking a common-sense approach, it is highly unlikely for a subject to move from a lower-left corner to a upper-right corner in a bedroom within a sampling time ($0.5s$ in our case) or walk through a bed, so we assume that the subject can only move to a feasible zone that is adjacent to the subject's current location with equal probability. Given a current location l_i, all possible zones that the subject can move to belong to a set $\mathbf{\Psi}_i$, the element number in the set is $|\mathbf{\Psi}_i|$. Then, the transition probability matrix can be expressed as $A_{ij} = Pr(l_j|l_i) = 1/|\mathbf{\Psi}_i|$.

Viterbi Search. Having *Emission Matrix* and *Transition Matrix*, we search the most likely location sequence that accounts for the first t observations and ends at L_j in a continuous time stream via *Viterbi Search* [12].

[1] www.csie.ntu.edu.tw/~cjlin/libsvm/
[2] www.ntu.edu.sg/home/egbhuang/elm_codes.html
[3] mathworks.com/help/stats/fitnaivebayes.html

III. Experimental Evaluation

To monitor the interaction events, we use Phidgets sensors including light sensor, touch sensor and WiFi module. We deploy the RFID hardware in the house, e.g., Alien ALR-9900+ Readers, two-circular antennas and Squiggle Higgs-4 passive tags (see Fig. 1(a)).

Experimental Setting. We place RFID antennas $1.7m$ above the ground, facing tags with around $60°$, and attach RFID tags to the wall with an approximate $0.6m$ interval. We adopt standard accuracy and error distance to evaluate our method [5].

$$Accuracy = \frac{\sum_i^N \mathbb{I}(\hat{l}_i, l_i)}{N}; \quad Dis_{error} = \frac{\sum_i^{|T|} dis(\hat{c}_i, c_i)}{|T|} \tag{7}$$

where $\mathbb{I}(\hat{l}_i, l_i)$ is an indicator that equals to 1 if estimated zone $\hat{l}_i$ is equal to ground truth l_i, otherwise is 0; N is the total number of test samples, $dis(\hat{c}_i, c_i)$ is the *Euclidean Distance* between predicted coordinates (center of zone $\hat{c}_i$) and actual coordinates, $|T|$ is the total number of testing samples generated by a trajectory.

Localization Results. We first explore the relations of k values with localization accuracy (half of the collected data for training, and rest for testing). As Fig. 1(b) shows, our proposed probabilistic kNN outperforms traditional kNN in most k values, verifying its feasibility. To be more practical, we then define three realistic scenarios to test our system: i) *Scenario 1 (Stationary)*: a subject is standing still in an unknown place in the monitored area, such as watching TV or waiting for someone; ii) *Scenario 2 (Dynamic)*: a subject keeps moving around or with some activities in a small unknown area, such as cooking in the kitchen. Overall three participants join the experiments to collect these two types of

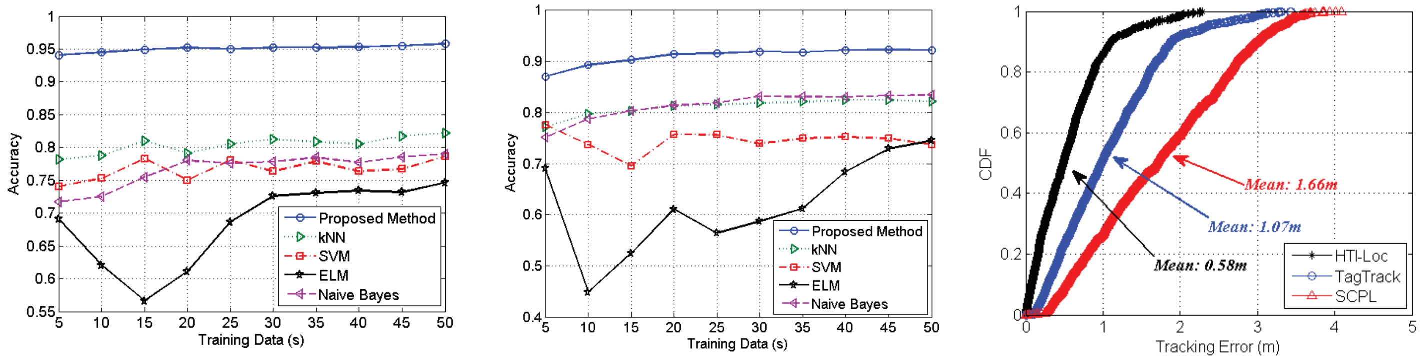

Fig. 2: From left to right: (a) Localization accuracy for Scenario 1; (b) Localization accuracy for Scenario 2. Parameters: kNN (k=2); SVM (linear kernel, terminate criterion=0.01, C=1, others as default); ELM (*hardlim* activation function, *NumberofHiddenNeurons*=600, others as default, running 20 times); NaiveBayes (normal distribution, uniform prior probabilities, others as default); (c) Tracking error for different methods. Parameters: GMM-HMM in SCPL (GMM component = 4); TagTrack and HOI-Loc choose $k = 4$

data correspondingly: i) the subject is standing in each zone for 120 seconds; ii) the subject keeps moving around within each zone for 120 seconds. For Scenario 1 (see Fig. 2(a)), all localization methods achieve good accuracy when using 50 seconds training data (the rest 70 seconds data for testing). More importantly, our method achieves 94.7% accuracy with only 5 seconds of training data, which greatly simplify the pre-calibration process. For Scenario 2 (see Fig. 2(b)), the best localization accuracy is 92.4%, and the performance is more sensitive to the size of training data. For such challenging dynamic scenario, more training data can interpret more informative RSSI patterns to achieve a better accuracy. During the experiments, we find that, for other methods, most errors happen in identifying the adjacent locations (e.g., L5 and L6). The *HOI-Loc* can explore the interacting events (e.g., Lamp 2) to distinguish such locations that cannot be accurately classified by RSSIs alone.

Tracking. We compare our method with other two recent device-free tracking methods [5], [12] on three paths that simulate three real-life scenarios (see Fig. 1(b)). *Path 1:* the subject gets up from the bed in the master bedroom and opens the fridge, takes out some food to do cooking in the kitchen; *Path 2:* the subject stands up from sofa in the master bedroom and goes to work on the desk in the small bedroom; and *Path 3:* the subject gets up from bed in the small bedroom and walks through the kitchen, boils water using the kettle. Fig. 1(c) shows the tracking performance in three paths. *HOI-Loc* achieves a better result, the average tracking error is $0.58m$. It offers about $1.84\times$, $2.86\times$ improvement compared with TagTrack [6] and SCPL [5] using the same number of tags.

IV. Related work and Conclusion

Recently, several unobtrusive localization solutions based on RFID tags have emerged. Liu et al. [4] propose to deploy active tags as an array, which localizes the subject when RSSIs of some tags (known positions) variate beyond a threshold. Zhang et al. [6] develop a tag array-based localization scheme using both active and passive tags. In TagTrack [12], a device-free localization system based on pure passive tags is proposed, which maps the variation of RSSIs to locations under an HMM-based framework. Twins [7] leverages an observation caused by interference among passive tags to detect a single moving object. However, most of the works are deployed and tested in an open and clear area rather than in a residential environment. In summary, this paper has shown how human-object interaction events can be used to facilitate the RFID-based localization system under a rigid probabilistic framework, which marks an important step toward enabling accurate device-free indoor localization in a residential environment.

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