Device-free Indoor Localization and Tracking through Human-Object Interactions

Wenjie Ruan†, Quan Z. Sheng†, Lina Yao†, Tao Gu§, Michele Ruta*, and Longfei Shangguan‡
†School of Computer Science, The University of Adelaide, Australia; Email: {wenjie, qsheng, lina}@cs.adelaide.edu.au
§School of Computer Science and IT, RMIT University, Australia; Email: tao.gu@rmit.edu.au
*Politecnico di Bari, via E. Orabona 4, I-70125, Bari, Italy; Email: michele.ruta@poliba.it
‡Department of Computer Science, Princeton University, USA; Email: longfeis@cs.princeton.edu

***Abstract*—Device-free indoor localization aims to localize people without requiring them to carry any devices or being actively involved in the localizing process. It underpins a wide range of applications including older people surveillance, intruder detection and indoor navigation. However, in a cluttered environment such as a residential home, the Received Signal Strength Indicator (RSSI) is heavily obstructed by furniture or metallic appliances, thus reducing the localization accuracy. This environment is important to observe as human-object interaction (HOI) events, detected by pervasive sensors, can potentially reveal people's interleaved locations during daily living activities, such as watching TV, opening the fridge door. This paper aims to enhance the performance of commercial off-the-shelf (COTS) RFID-based localization system by leveraging HOI contexts in a furnished home. Specifically, we propose a general Bayesian probabilistic framework to integrate both RSSI signals and HOI events to infer the most likely location and trajectory. Experiments conducted in a residential house demonstrate the effectiveness of our proposed method, in which we can localize a resident with average 95% accuracy and track a moving subject with 0.58*m* mean error distance.**

I. Introduction

Ambient intelligence has been drawing a growing attention 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). 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 all these applications is to accurately localize and track people in a cluttered living environment [1], [2], [3]. To tackle this challenge, many state-of-the-art indoor localization systems have been developed over last decades such as LANDMARC [4], WILL [5], Tagoram [6]. Most of these techniques, however, require the target to either carry sensors/smartphones/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, *device-free* (or *unobstructive*) indoor localization has gained significant momentum recently and several approaches have been proposed [7], [8]. One popular device-free technique category is based on computer vision, such as using RGB camera [9], depth camera [10], however they are usually regarded as being privacy-invasive and causes uncomfortable feeling to the residents. Another technique category is

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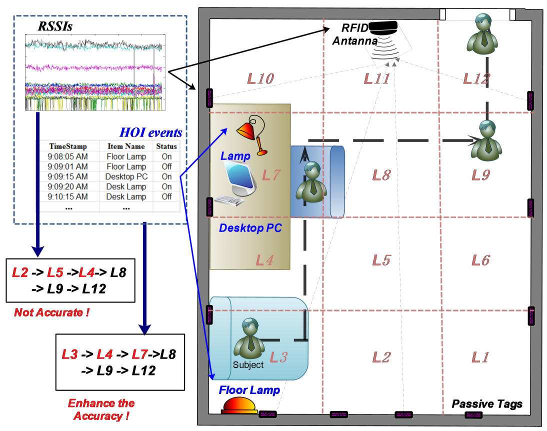

Fig. 1: Intuition of *HOI-Loc*

based on RF (radio frequency) signals, *e.g.,* detecting human locations by measuring RSS (received signal strength) or CSI (channel state information) in WLANs (wireless local area networks) [7], [11], [12], or tracking a target through a wall based on the RF signal reflected from human body [13]. However, most of such systems often require regular maintenance (*e.g.,* replacing the batteries regularly), or need specialized WIFI signals, *e.g.,* Frequency-Modulated Continuous-Wave (FMCW), or special-purpose devices, hindering their wide application and deployment in reality [14], [15], [8].

Thus, passive RFID based localization has emerged recently due to its low-cost (5∼10 cents each, still dropping quickly) and maintenance-free nature (e.g., no need batteries) [14]. However, existing RFID-based device-free techniques usually work in clear or semi-clear spaces (*i.e.,* empty spaces or spaces with very few objects), and none of them are actually tested in clustered residential environments, especially in a multiple-room scenario. 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). Besides, many state-of-the-art RFID-based systems (*e.g.,* [14], [8], [6]) heavily rely on ideal propagation models of RF phase or RSSI, which may not be feasible in a full-furnitured residential room where rich multi-path reflections and frequent electromagnet interference exist (*e.g.,* turning on/off electronic appliances in a kitchen) [16], [17]. To tackle these challenges, in this paper, we design *HOI-Loc*, an RFID-based device-free localization and

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tracking system to achieve *high accuracy* in *clustered* living environments using *Human-Object Interactions*.

With the booming of IoT (Internet of Things), human-object interaction has been advocated as an essential component of Cyber Physical System [18] (*e.g.,* smart homes, intelligent space, and home automation). In each week, there are more than 1.9 billion devices launched into the market that can connect to the residential home [19]. With such tremendous smart devices, we can easily access, retrieve and monitor HOI events in our daily lives [20]. For instance, a smart home equipped with various sensors (see Fig. 1) is capable of reporting the operating conditions of the floor lamp, desktop computer and desk light [21]. Moreover, we observe that the locations causing severe signal decay are usually full of furniture or electrical appliances, and such locations are exactly where HOI frequently occurs. Whereas, from another perspective, we can substantially improve the localization accuracy by utilizing such interaction events [22]. 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 a *microwave oven*. Inspired by this intuition, we propose to incorporate HOI into existing RSSI based methods to improve localization accuracy in clustered indoor spaces.

Transforming the use of HOI into a practical system, however, requires addressing a number of challenges. First, localization from weak RSSI signals of passive RFID tags in a clustered environment is difficult. Unlike active RFID tags or wireless sensors that have their own power supplies, passive tags can only obtain energy from the interrogating field, which can easily be obstructed by furniture and metal appliances (*e.g.,* RSSI reading loss, RSSI jumps due to on-and-off of electronic appliances). In particular, this task is typically accomplished using COTS RFID readers, which currently do not support any low-level signal access or modification. In addition, HOI contexts are discrete events which occur from time to time, but RSSI readings are continuous signal (can be sampled as high as 10 times per second). How to feasibly incorporate the discrete HOI events with continuous RSSI signal under rigid mathematical reasoning is a challenging task. Moreover, the inherent signal diversity of passive tags caused by human mobility would introduce many unknown effects on the RSSI attenuation and reading disturbance, leading to unpredictable tracking errors.

To address these issues, in *HOI-Loc* system, we first set up several RSS fields formed by passive RFID tags attached on the bedroom's walls[1] to continuously generate RSSI signals, and then deploy various kinds of sensors (*e.g.,* infrared sensor, touch sensor and light sensor etc.) to detect the resident's interaction events with electrical appliances. We introduce three main techniques to tackle the aforementioned challenges. First, we propose a Probabilistic Polyhedron Isolation (PPI) method to model the likelihood of the target's locations by measuring the Euclidean distance of testing RSSI readings with each isolated high-dimension *polyhedron*, which is robust to the signal attenuation and jumping (see §IV). Second, we develop a rigid Bayesian probabilistic framework to fuse the discrete HOI events (*i.e.,* indicating where and when people interact with objects) with continuous RSSI signals. In particular, we first estimate the *RSSI probability*, then update the likelihood by computing the *HOI probability*, and finally optimize a location with largest confidence (see §IV). To track a moving subject, we introduce a Hidden Markov Model (HMM) to quantify the continuous location transition process to eliminate the negative impact caused by human mobility. In particular, we first approximate the *Emission Matrix* by a probabilistic scheme that considers both evidence of the RSSI sequence and HOI event stream based on *Bayesian Inference*, then propose a practical but efficient strategy to estimate the *Transition Matrix*, finally use the *Viterbi Search* to recover the target's trajectory (see §V). In a nutshell, our main contributions are summarized as follows.

- We introduce an approach that utilizes HOI events to facilitate device-free localization based on passive RFID tags. Our experiments demonstrate the feasibility and accuracy of *HOI-Loc* in a furnished, clustered living environment. To the best of our knowledge, the proposed system is a very first effort to do so.
- We propose a general Bayesian-based probabilistic framework that provides a way to feasibly fuse HOI events with RSSI signals to enhance the tracking performance. Specifically, for a multiple-room scenario (including two bedrooms and a kitchen), *HOI-Loc* can achieve average 95% localization accuracy and $58cm$ tracking error, offering about 1.3×, 1.86× and 2.86× improvement compared with Twins [14], TagTrack [15] and SCPL [23].
- *HOI-Loc* can accurately track up to three residents with average $85cm$ error distance in a non-concurrent case, and it is capable of decoding four basic living postures with overall 94.7% accuracy.

II. Preliminary

A. Received Signal Strength Indicator (RSSI)

Passive RFID system communicates based on the backscatter radio link since the passive tags (no batteries powered) can purely harvest energy from the antenna's signal. As Fig. 2 shown, the *Path Loss* is the difference of the power that delivered to the transmitting antenna and obtained from the receiving antenna. We derive the *Friis Equation* for the power received from a transmitting antenna TX by a receiving antenna RX, modeling the backscatter signal prorogation as [24]:

$$\begin{aligned} P_{RX,reader} &= P_{TX,tag} G_{tag} G_{reader} (\lambda/4\pi r)^2 \\ &= P_{TX,reader} T_b G_{tag}^2 G_{reader}^2 (\lambda/4\pi r)^4 \end{aligned} \quad (1)$$

where G_{tag} is the tag antenna gain and T_b is the backscatter transmission loss. As we can see, the above equation theoretically proves that the power received by reader and backscattered from tag goes as the inverse fourth power of the distance. However, the RSSI signal depicts highly nonlinear and uncertain relations with the distance in a residential room. Thus how to model the relation of RSSI signals with locations

[1]Unlike other device-free RFID systems (*e.g.,* LANDMARC [4], TagArray [2], TASA [17] and Tadar [8]), we do not need to know the locations of passive tags, meaning tags can be attached on the wall in an arbitrary shape

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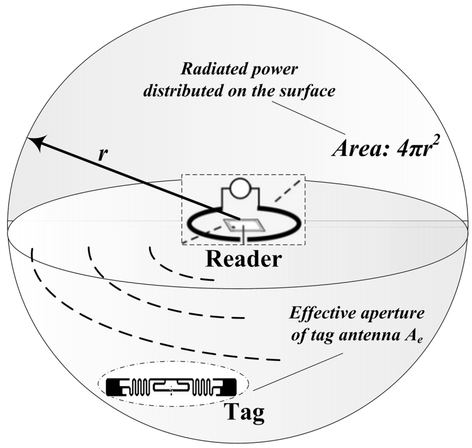

Fig. 2: Path loss illustration

in our case is quite challenging. Rather than building complicated signal propagation models[2], we seek the solution from statistical machine learning - accurately mining the relation between subject's potential locations and the human inference to signal. We will elaborate it in §IV.

B. Human-Object Interactions (HOI)

Human-Object Interactions study the interactions between human and the surrounding smart objects. In our daily lives, we observe that a resident's interactions with surrounding devices can be very helpful to reveal her locations in a home environment. Considering the following scenarios, when the door of a *microwave oven* is opened, it is very likely the person is near the oven; if the *desk lamp* is from on to off, or from off to on, we can almost be certain that the subject currently is in her home office. Thus, inspired by the observation, some HOI contexts can be valuable to infer the target's possible locations.

III. Problem Formulation

In this paper, we focus on device-free localization based on passive UHF tags. The COTS RFID readers have an operating range of around $10m$, which is enough for a residential room. We also focus on locating and tracking residents that are not moving at a high speed ($< 1m/s$) since moving in a high speed in a residential room is unlikely.

We consider the target resident moving within a surveillance house. For each monitored house with D passive tags deployed, we divide it into J zones, denoted by $\mathcal{L} = \{L_1, L_2, ..., L_J\}$. When a subject appears in zone L_i, we collect N sample data $\mathbf{S}_i = \{\mathbf{s}_{i1}, \mathbf{s}_{i2}, ..., \mathbf{s}_{iN}\}$, where $\mathbf{s}_{ij} \in \mathbb{R}^D$ means data collected in jth sampling period. As a result, when going through all the zones, we can obtain a dataset $\mathcal{S} = \{\mathbf{S}_0, \mathbf{S}_1, ..., \mathbf{S}_J\}$, quantifying how a subject affects RSSIs from each zone. Here the environmental RSSIs without a subject is represented by $\mathbf{S}_0$. Similarly, for modeling HOI events, we assume that we overall have M different objects $C = \{I_1, I_2, ..., I_M\}$ available (e.g., electrical kettle, fridge, microwave oven etc.). Then we represent the interaction events 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 (interacted with by a resident), otherwise $I_1 = 0$. Formally, given both signal available, this paper targets the following two problems.

Problem 1 (Localization): Given an RSSI vector and interaction events, we need to correctly estimate the subject's location.

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

Localization: Mathematically, *Problem 1* can be formulated as modeling the posterior distribution $Pr(l|\mathbf{o}, C)$ for each possible location. Specifically, given observed RSSI signals $\mathbf{o}$ and corresponding interaction events $C = \{I_1, I_2, ..., I_M\}$, we find the most likely location by using

$$l^* = \arg\max_{l \in \mathcal{L}} Pr(l|\mathbf{o}, C) \tag{2}$$

which is essentially a classification task. We need to model how RSSIs are distributed in different geographical areas based on a sample of measurements collected at several known locations and how to feasibly update the posterior probability of the classifier based on the contexts of HOI. We present our method in §IV.

Tracking: When a resident walks in random zones, we can collect T continuous RSSI vectors $\mathcal{O} = \{\mathbf{o}_1, \mathbf{o}_2, ..., \mathbf{o}_T\}$. Then, mathematically, *Problem 2* can be formulated as modeling the posterior distribution:

$$Pr(l_{1:T}|\mathcal{O}, \mathcal{C}) = Pr(l_{1:T}|\mathbf{o}_{1:T}, C_{1:T}), l_{1:T} \in \mathcal{L} \tag{3}$$

Then, given observed continuous RSSI vector sequence $\mathbf{o}_{1:T}$ and interaction event stream $C_{1:T}$, we need to find the location sequence with largest likelihood.

$$l^*_{1:T} = \arg\max_{l_{1:T} \in \mathcal{L}} Pr(l_{1:T}|\mathbf{o}_{1:T}, C_{1:T}) \tag{4}$$

The tracking problem can be regarded as given a continuous RSSI stream and a HOI event sequence, how we can recover the underlying location sequence which is as accurate as possible to the true location trajectory. We elaborate our solution in §V.

IV. Localization

As aforementioned in Eqn.2, for localizing a static resident, we need to model the posterior distribution $Pr(l|\mathbf{o}, C)$ given RSSI signal and HOI events. First, we revisit the Eqn. 2. Based on the *Bayesian Inference Theorem*, we can decode the equation as

$$\begin{aligned} Pr(l|\mathbf{o}, C) &= \frac{Pr(l)Pr(\mathbf{o}, C|l)}{Pr(\mathbf{o}, C)} = \frac{Pr(l)Pr(\mathbf{o}|l)Pr(C|l, \mathbf{o})}{Pr(\mathbf{o}, C)} \\ &\propto Pr(l)Pr(\mathbf{o}|l)Pr(C|l, \mathbf{o}) \end{aligned} \tag{5}$$

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

$$Pr(l|\mathbf{o}, C) \propto Pr(l)Pr(\mathbf{o}|l)Pr(C|l) \tag{6}$$

[2]This relation also depends on the room layout and furniture settings, consequently it is difficult to develop an accurate universal propagation model.

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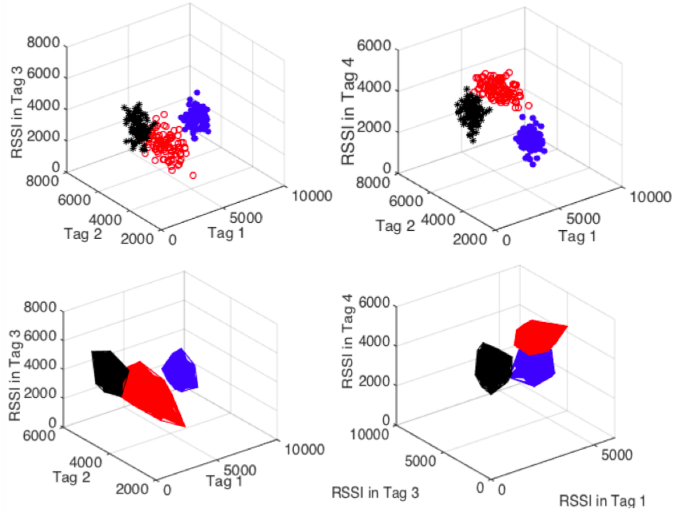

Fig. 3: RSSIs from different locations are bounded by isolated HD polyhedrons

where $Pr(l)$ is the prior probability distribution, which is set as $Pr(l) \sim 1/J$ without losing generality (means the target can be possible in any locations beforehand). So far, we successful find a way to model the posterior distribution $Pr(l|\mathbf{o}, C)$. We give the following two definitions.

Definition 1 (RSSI Probability): Given the resident appearing a certain location, RSSI Probability measures the probabilistic distribution $Pr(\mathbf{o}|l)$ of RSSI signals.

Definition 2 (HOI Probability): Given the resident interacting with objects in a certain location, HOI Probability measures the probabilistic distribution $Pr(C|l)$ of HOI events.

In the next, we need to deal with how to accurately measure $Pr(\mathbf{o}|l)$ and $Pr(C|l)$.

RSSI Probability: As elaborated in §II, mapping the RSSI signal to locations is very challenging under a clustered environment due to rich multi-path effect. Seeking solutions from backscatter propagation analysis is impractical in our case, laying in the facts: most backscatter communication models depend on the assumption that the position of reference tag is accurately measured beforehand [8], which is not applicable in *HOI-Loc* (we relax the assumption, no need to know tag's coordinates). From Fig. 3, we can observe that the RSSI readings always cluster in a relatively same HD (high-dimension) space (treating one tag's signal as one dimension) when the resident appearing in a same location. Thus, based on this intuition, we propose a Probabilistic Polyhedron Isolation (PPI) method to efficiently locate the high-dimension space. The PPI method works as follows. Assuming for each observation $\mathbf{o}$, we search its k nearest neighbors from the training set $\mathcal{S}$ in the high-dimension space, 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 $N(\mathbf{o})$ is represented as $N^i(\mathbf{o}) = \{\mathbf{s}_k^i|\mathbf{s}_k^i \in N(\mathbf{o}) \cap \mathbf{s}_k^i \in \mathbf{S}_i\}$. In fact, $N^i(\mathbf{o})$ represents each isolated *HD-polyhedron*. Geometrically, the ith HD polyhedron (mapping to location L_i) is formed by several high-dimension points (*e.g.,* RSSIs from all tags within a sampling time) in $N^i(\mathbf{o})$, illustrated as Fig. 3. Then, we can estimate *RSSI Probability* by measuring the Euclidean distance of testing RSSI readings with each isolated HD Polyhedron.

$$Pr(\mathbf{o}|l_i) = \begin{cases} \dfrac{\sum_{\mathbf{s}_k^i \in N(\mathbf{o})} \dfrac{1}{dis(\mathbf{o}, \mathbf{s}_k^i)}}{\sum_{\mathbf{s}_k \in N(\mathbf{o})} \dfrac{1}{dis(\mathbf{o}, \mathbf{s}_k)} + \sum \alpha}, & \text{if } |N^i(\mathbf{o})| \geq 1 \\ \\ \dfrac{\alpha}{\sum_{\mathbf{s}_k \in N(\mathbf{o})} \dfrac{1}{dis(\mathbf{o}, \mathbf{s}_k)} + \sum \alpha}, & \text{if } |N^i(\mathbf{o})| = 0 \end{cases} \tag{7}$$

where l_i indicates the target appears in location L_i, $(i = 1, .., J)$; $|N^i(\mathbf{o})|$ means the number of elements contained in $|N^i(\mathbf{o})|$, so does $|N(\mathbf{o})|$; α is a parameter with a very small value to avoid 0 probability for some locations where no training sample included in $|N(\mathbf{o})|$. In our case, it is chosen by

$$\alpha = 0.001 \max_{\mathbf{s}_k \in N(\mathbf{o})} \frac{1}{dis(\mathbf{o}, \mathbf{s}_k)} \tag{8}$$

Eqn.7 gives the posterior distribution by finding its HD polyhedron and measuring its distance with the test sample. However, merely based on RSSI Probability, we still cannot achieve satisfied localization accuracy in a clustered environment. We run a pilot experiment in a residential master-room (see Fig. 6, Area: $3.6m \times 4.8m$). As Fig. 4 (a) shows, the average accuracy is around 80%, and it mis-classifies the adjacent locations such as *L2* and *L3*, *L4* and *L5*. Thus the unsatisfied localization performance motivates us to exploit the HOI events.

HOI Probability: HOI contexts basically reflects the interacting status of the resident with her environment at a particular point of time, which can be utilized to facilitate the localization. Based on the problem definition in §III, for N continuous time slots, we can retrieve an interaction events data set $\mathcal{C} = \{C_1, C_2, ..., C_N\}$, where $C_i = \{I_1^i, I_2^i, ..., I_M^i\}$ represents statuses of M interacting events at ith time. We assume that, for each HOI event happening, there exists at least one candidate location, which is the criterion we choose HOI events. Thus, for each object I_i , its possible locations can be denoted as $L_{I_i} = [L_1^{I_i}, L_2^{I_i}, ..., L_J^{I_i}]^T$, where $L_j^{I_i} = 1$ means L_j is the possible location of the subject regarding interaction event I_i; $L_j^{I_i} = 0$ means L_j is not the possible location. 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 events with all objects $C = \{I_1, I_2, ..., I_M\}$, we can infer all the possible locations based on *HOI Matrix*, defined as:

Definition 3 (HOI Matrix): HOI Matrix indicates all the possible locations for HOI events happen at a certain time, calculated by $M_{HOI} = [I_1 L_{I_1}^T, I_2 L_{I_2}^T, ..., I_M L_{I_M}^T]^T$.

To avoid the cases that no available interaction events can be utilized to infer some certain candidate locations, we smooth the zero probability with adding a small value parameter β. Based on our numerical experiences, β does not affect the final estimation as long as it is small enough since it produces much smaller probability comparing to other cases. In this paper, we choose $\beta = 0.001$. Then, we can estimate $Pr(C|l)$ for each possible locations based on *Algorithm 1*. Specifically, for each timestamp, we receive a M_{HOI} to

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	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10
L1	178	0	1	0	0	0	0	0	0	1
L2	7	145	19	2	1	0	2	0	1	3
L3	2	17	153	5	2	0	0	0	0	1
L4	3	2	7	139	26	1	0	1	0	1
L5	2	0	4	17	148	7	1	0	0	1
L6	0	0	0	0	6	170	3	1	0	0
L7	0	0	0	0	0	5	171	4	0	0
L8	0	0	0	0	0	0	0	176	2	2
L9	0	0	0	0	0	0	1	1	176	2
L10	0	0	0	0	0	0	0	2	1	177

Ground Truth

(a)

	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10
L1	180	0	0	0	0	0	0	0	0	0
L2	0	179	1	0	0	0	0	0	0	0
L3	0	2	176	2	0	0	0	0	0	0
L4	0	0	2	175	3	0	0	0	0	0
L5	0	0	0	1	176	3	0	0	0	0
L6	1	0	0	0	3	172	2	0	0	2
L7	0	0	0	0	0	3	174	2	0	1
L8	0	0	0	0	0	0	1	176	3	0
L9	0	0	0	0	0	0	0	2	177	1
L10	0	0	0	0	0	0	0	0	1	179

(b)

Fig. 4: (a) Localization result based on RSSI signal (k=2); (b)Localization result of fusing HOI events with RSSI signal (k=2)

indicate current HOI status, then we feed it into *Algorithm 1* to get the *HOI Probability*.

Algorithm 1: HOI Probability $Pr(C|l)$ Estimation

Input: HOI Matrix $M_{HOI} \in \mathbb{R}^{M \times J}$, β
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**
    $Pr(C|l_j) = \frac{\textit{PossibleLocaSumj}}{\textit{PossibleLocaSum}};$
  end
  else
    $Pr(C|l_j) = \frac{\beta}{\textit{PossibleLocaSum}};$
  end
end

In summary, based on Algorithm 1 and Eqn.7 and Eqn.6, we can conveniently integrate HOI events with RSSI signals under a *Bayesian Inference* probabilistic framework to estimate a subject's location with maximum likelihood. Through fusing these two signals, *HOI-Loc* greatly increases the localization accuracy, illustrated by Fig. 4 (b). With fusing HOI events, our method achieves overall more than 96% accuracy.

V. TRACKING

We introduce a Hidden Markov Model to model the tracking process. We need to deal with how to feasibly integrate both RSSI signal sequence and HOI event stream into a HMM framework. First, we revisit the definition of *Tracking Problem* in §III. Actually, we can decode Eqn. 3 based on *Bayesian Inference* in the same way. Similarly, since RSSI signal and HOI events are from independent sensor sources, and current state only conditionally depends on previous one, we can model the tracking process as:

$$
\begin{aligned}
&Pr(l_{1:T}, \mathbf{o}_{1:T}, C_{1:T}) \\
&= Pr(l_1)Pr(\mathbf{o}_1|l_1)Pr(C_1|l_1)\prod_{t=2}^{T}\underbrace{Pr(\mathbf{o}_t, C_t|l_t)}_{A}\underbrace{Pr(l_t|l_{t-1})}_{B} \\
&= Pr(l_1)Pr(\mathbf{o}_1|l_1)Pr(C_1|l_1)\prod_{t=2}^{T}\underbrace{Pr(\mathbf{o}_t|l_t)}_{A_1}\underbrace{Pr(C_t|l_t)}_{A_2}\underbrace{Pr(l_t|l_{t-1})}_{B}
\end{aligned}
\tag{9}
$$

So far, we decompose our tracking problem into estimating two *Emission Matrix* A_1 and A_2, and *Transition Matrix* B. We observe that A_1 and A_2 are exactly the same forms (except the times-tamps) as the *RSSI Probability* and *HOI Probability*. As a result, for tracking problem, we can also apply Eqn. 7 and Algorithm 1 to estimate the two emission matrices A_1 and A_2 respectively.

Transition Strategy: Transition matrix measures the probability of a subject moving to next location at each time t, which is defined as $A_{ij} = Pr(a_t = l_j | a_{t-1} = l_i)$. However, based on the common-sense, a subject can only move a step within a sampling time ($0.5s$ in our case). Therefore, we adopt an *Adjacent Transition* strategy to calculate the probabilities of next candidate locations given current location.

Definition 4 (Adjacent Transition): The subject can only move to a feasible location that is adjacent (including current location which means still) to current location with equal probabilities, and the probabilities of moving to other locations are very small.

Based on the proposed strategy, we assume that location l_i denotes the appearance of the subject in zone L_i. Given current location l_i, all the possible locations that the subject can move to belong to the set $\mathbf{\Psi}_i$, and the number of locations contained in the set is $|\mathbf{\Psi}_i|$. Thus, the transition probability matrix can be expressed as

$$
A_{ij} = Pr(l_j|l_i) = \begin{cases} \dfrac{1}{|\mathbf{\Psi}_i|} & \text{if } l_j \in \mathbf{\Psi}_i \\ 0 & \text{if } l_j \notin \mathbf{\Psi}_i \end{cases} \tag{10}
$$

where $\mathbf{\Psi}_i$ is defined according to the proposed strategy.

Viterbi Searching: Having *Emission Matrix* and *Transition Matrix*, we can search the most likely sequence of state transitions in a continuous time stream via the *Viterbi* algorithm defined by $V_j(t)$, the highest probability of a single path of length t which accounts for the first t observations and ends in location L_j:

$$
V_j(t) = \arg \max_{l_1, l_2, \ldots, l_t} Pr(l_{1:t-1}, l_t = L_j; \mathbf{o}_{1:t}; C_{1:T}|A, B) \tag{11}
$$

where A and B can be found in Eqn.9. Further, by induction:

$$
\begin{aligned}
V_j(1) &= A_{1j} = (A_1)_{1j}(A_1)_{1j} \\
V_j(t+1) &= \arg \max_i V_i(t)B_{ij}(A_1)_{t+1,j}(A_2)_{t+1,j}
\end{aligned}
\tag{12}
$$

where $(B_1)_{1j} = Pr(\mathbf{o}_1|l_j)$ and $(B_2)_{1j} = Pr(C_1|l_j)$. Finally, we can recovery an optimal path with the maximum likelihood.

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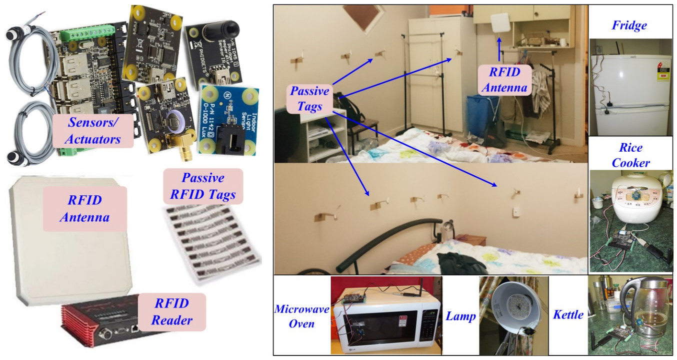

Fig. 5: Sensors and RFID hardare deployment

In the next, we need to deal with the latency issue in tracking system.

Forward Calibration: We find some latency in detecting the subject, which is mainly caused during the RSSI collection process and by the delay of signals sent by passive tags [24]. To cope with the issue, we adopt a forward calibration mechanism that uses a moving time averaging window to recalculate the coordinates of location sequence obtained by *Viterbi Searching*. Specifically, the estimated coordinates $\hat{c}_i : (\hat{x}_i, \hat{y}_i)$ location l_t at time t can be calculated as:

$$\hat{c}_t = \frac{\sum_{i=t}^{t+|w|-1} \tilde{c}_i}{|w|} \tag{13}$$

where $|w|$ is the window length. $\tilde{c}_i$ is uncalibrated coordinate of predicted grids centroid at time t. In our experiments, we find that *HOI-Loc* achieves the best performance at $|w| = 7$.

VI. Implementation and Evaluation

We setup COTS RFID hardware in a residential house with two bedrooms and a kitchen (see Fig. 6), including an Alien ALR-9900+ Enterprise RFID Reader, 4 two-circular antennas, and multiple squiggle Higgs-4 passive tags. The reader operates at 840-960MHz and supports UHF RFID standards such as ETSI EN 302 208-1. We set the sampling rate as $2Hz$ and each tag reading contains time stamp, tag ID, antenna ID and the RSSI value, which are then processed by a computer with an i7-3537U 2.5G processor and 8G RAM, running WINDOWS 7.

We place the antenna about $1.7m$ above the ground and facing tags with approximately 45° in order to catch all readings of reference tags in a non-subject environment. We attach passive RFID tags to the wall with an approximate $0.6m$ interval (shown as Fig. 5). During the localization and tracking, we send an RSSI request to all tags within a sampling period. If we cannot receive RSSI readings of a certain tag, its RSSI value will be set to 0. Thus, for all timestamps, we have the RSSI vectors with the same dimension. We defined our virtual zones as shown in Figure 6. For HOI events, the priority is given to the objects that the resident frequently interacted or used, and their operation status can be easily monitored based on COTS sensors. We treat the zones that is adjacent to the object as the possible candidate locations when interacting events happen.

Evaluation Metrics: We adopt standard localization accuracy and error distance to measure our proposed approaches in terms of localization and tracking respectively [2]. The *localization accuracy* is defined as

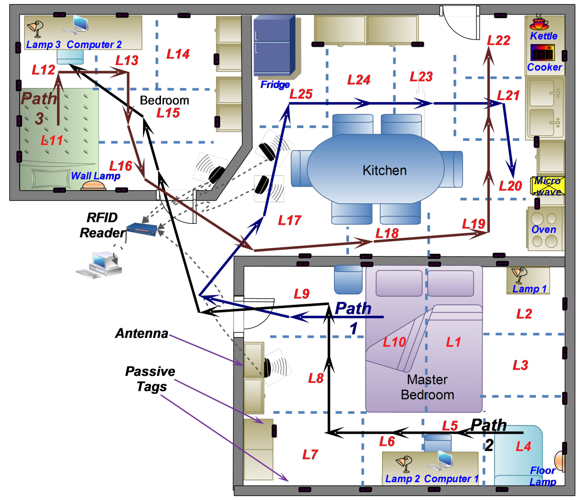

Fig. 6: Experiment settings and paths. *Testing Area: master bedroom:* $3.6m \times 4.8m$, *bedroom:* $3m \times 3.2m$, *kitchen:* $3.6m \times 4.6m$

$$Accu. = \frac{\sum_i^N \mathbb{I}(\hat{l}_i, l_i)}{N} \tag{14}$$

where $\mathbb{I}(\hat{l}_i, l_i)$ is an indicator, which equals to 1 if estimated zone $\hat{l}_i$ is as same as the ground truth zone l_i, otherwise equals to 0; N is the total number of the testing RSSI measurements.

The error distance denotes the averaging accumulated error distance of the testing samples in each continuous trajectory, and it is calculated using

$$Dis_{err.} = \frac{\sum_i^{|T|} dis(\hat{c}_i, c_i)}{|T|} \tag{15}$$

where c_i is the coordinates of the actual location of the subject at time i, and $dis(\hat{c}_i, c_i)$ is the Euclidean distance between predicted coordinates and actual coordinates, $|T|$ is the total number of testing samples generated by a trajectory.

Localization: Shown as Fig. 6, we test the performance in a residential home that is divided into 25 virtual grids. To be more practical, we define the following three scenarios to mimic daily-living activities in our experiments.

- *Scenario 1 (Stationary)*: Assuming a subject is standing/sitting in an unknown place in the monitored area still, such as watching TV or waiting for someone.

- *Scenario 2 (Dynamic)*: Assuming a subject keeps moving around or with some activities in a small unknown area, such as cooking in the kitchen.

- *Scenario 3 (Mixed)*: Assuming a subject presents in an unknown place and performs a combination of Scenario 1 and Scenario 2, such as doing some exercises for a while and then watching TV.

Based on the predefined three scenarios, we collect three types of data to test our method: *i)* a subject is standing in each grid for 120 seconds, *ii)* a subject keeps moving around within each grid for 120 seconds, and *iii)* combining both activities

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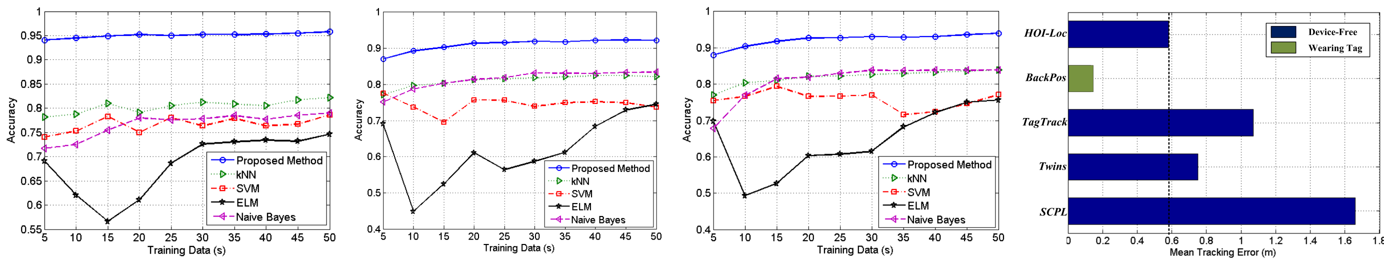
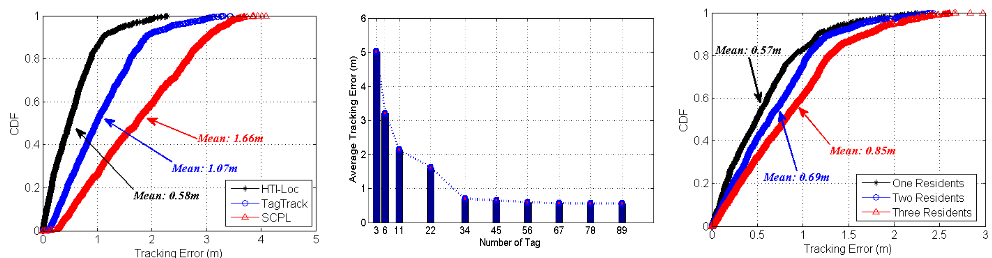


(a) (b) (c) (d)

Fig. 7: (a) Localization result for Stationay Scenario; (b) Localization result for Dynamic Scenario;(c) Localization result for Mixed Scenario; (d) Compare tracking accuracy of *HOI-Loc* with other state-of-the-art systems. Parameters used for Figure (a)∼(c): k=2; SVM (linear kernel, terminate criterion=0.01, C=1, others as default); ELM (*hardlim* activation function, *NumberofHiddenNeurons*=600, others as default, average result of running 20 times); NaiveBayes (normal distribution, uniform prior probabilities, others as default)



(a) (b) (c)

		Sitting	Standing	Lying	Walking	Recall
Ground Truth	Sitting	880	0	4	20	0.973
	Standing	4	708	56	14	0.905
	Lying	0	8	1160	18	0.978
	Walking	8	16	36	560	0.903
	Precision	0.987	0.967	0.924	0.915	0.947

(d)

Fig. 8: (a) Trackng error CDF (cumulative distribution function) for different device-free methods; (b) Mean tracking errors using different tag numbers; (c) Tracking errors for mutiple residents; (d) Confusion matrix of detecting four basic postures. Parameters used: TagTrack and HOI-Loc ($k = 2$); GMM-CRF in SCPL (GMM component number=4)

for 120 seconds in each grid. Three participants with different genders, heights and weights join our experiments. Then we randomly divide it as training data (*i.e.,* 5 seconds∼50 seconds data per grid) and testing data (*i.e.,* 115 seconds ∼70 seconds data per grid). In each case, we do experiments 20 times to get the mean accuracy. The testing result is shown as Fig. 7 (a)∼(c). For Scenario 1, all classification methods achieve more than 75% localization accuracy with 50 seconds' training data. In particular, the proposed method is able to achieve 95.6% accuracy with only 5 seconds' training data, which exhibits great advantage than other fingerprint-based schemes. In previous work, the shortest time needed for collecting training data to get same localization accuracy is about 60 seconds [25]. Our system only needs to collect 5 seconds training data to reach a better localization accuracy, improving 12 times. For Scenario 2, the best localization accuracy is 93.7%, achieved by our method. It is worth to mention that, performance in this case is more sensitive to the size of training data. It may lie in fact that more training data can better interpret more informative RSSI patterns for the *dynamic* scenario compared to the *stationary* scenario. For Scenario 3, the accuracy can reach 95.2%. To conclude, *HOI-Loc* achieves a better localization performance, and also be more robust to the RSSI uncertainties in case of limited training data.

Tracking: We evaluate tracking performance on three paths (see Fig. 6), which respectively simulate three real-life scenarios: i) 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; ii) the subject stands up from sofa in the master bedroom and goes to *work on the desk* in the study room, and iii) the subject gets up from the bed in the small bedroom and walks through the kitchen and *boils water* using the *electric kettle*. Three subjects with different heights and weights join the tracking experiments, and each participant walks the three paths 20 times. We also review and compare *HOI-Loc* with the state-of-the-art RFID-based systems, shown as Fig. 7 (d) and Fig. 8 (a).

- *TagArray:* TagArray [2] is the very first attempt that utilizes RFID tags to achieve device-free localization. It deploys active tags as an array to localize a subject when RSSI of some anchoring tags variate beyond a threshold. It requires high tag density, relatively expensive and needs pre-calibrate the tags' locations.

- *TASA:* TASA [17] is another tag array-based localization scheme using both active and passive tags. Its tracking error is heavily correlated with the tag density, and need to calibrate all tags' coordinates.

- *SCPL:* SCPL proposes a GMM (gaussian mixer model) based CRF (conditional random field) to track a moving subject using wireless sensor nodes [23]. It reports average 1.3m tracking error. We apply its GMM-CRF in our testbed, achieving average 1.66m error.

- *Twins:* Twins [14] is a very recent device-free localization work based on pure passive tag. It reports an average 0.75m tracking error in a relatively spacial warehouse. It requires to know the reference tags' locations in advance.

- *BackPros:* BackPros [26] is the latest RFID-based positioning system that can achieve decimeter-level accuracy (*i.e.,*

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report $13cm$ mean tracking error). It also requires the target to be attached with a tag.

• *TagTrack:* TagTrack [15] is a similar attempt using RFID signals to passively localize the objects. It deploys the passive tags as an array and uses the RSSI changes as the tracking indicator. However, it is only workable in a spacial, clear area. We also utilize its method to our test environment, achieving $1.07m$ mean error.

Unlike above methods, *HOI-Loc* does not require the location contexts of reference tags, achieving $0.58m$ mean error distance in the testbed. As Fig. 7 (d) shows, it offers about $1.3\times$, $1.86\times$ and $2.86\times$ improvement compared with Twins [14], TagTrack [15] and SCPL [23] in a residential house[3]. We also explores the relation of tag density with tacking error (see Fig. 8 (b)). We can see that the tracking performance will greatly degenerate when using less tags, e.g., in the case of 6 tags (2 tags per room), the error is more than $3m$. However, adding more tags (e.g., more than 34 tags) cannot enhance the performance significantly since a large number of tags are difficult to be interrogated by an antenna within a sampling time, causing more lost readings. As a result, the overall performance decays in this circumstance. To summarize, *HOI-Loc* can achieve high tracking accuracy using 34 passive tags, which relaxes the requirement of high-density tags deployment in TagArray and TASA

Beyond the Limits: To push the limits of *HOI-Loc*, we also conduct experiments in a multi-residents scenario. Two residents walked randomly among different rooms and interacted with the environment (where the instrumented objects are available), and then for three residents[4]. As shown in Fig. 8 (c), our method can track two residents with 0.69*m* average error and track three residents with 0.85*m* mean error. We also attempt to detect different postures of the resident, such standing, sitting, lying down and walking using our system. We observe that, similar to localization, the RSSI signals embody different patterns when a resident performs different postures, which means the RSSI signal also can be exploited as a human-activity indicator. Thus, we collect RSSI readings to feed into our Probabilistic Polyhedron Isolation method when the resident performing different postures in the bedroom. As Fig. 8 (d) shows, we can successful detect resident's postures with 94.7% accuracy. The results suggest that *HOI-Loc* provides an enabling primitive to recognize postures, besides tracking a moving resident. We can use this capability to better understand a resident's daily-living habits.

VII. Related Work

Localization has been an active research area over the decades. Criket localization system [27] adopts an ultrasonic Time-Of-Flight method to locate target objects. Ni *et al.* [4] design the LANDMARC to localize a target object carrying an active RFID tag, which estimates target's location by matching the measurements with the stored fingerprints. Recently, Tagoram [6] exploits the tags mobility to build a virtual antenna array that can real-time pinpoint the tag position to an extremely high accuracy with a few centimeters. However, all these systems require the tracked subject to carry a device, either RFID antenna/tag or smartphone, which may not practical for some applications. Thus device-free localization recently has received much attention [1].

WLANs-based Device-free Localization: Patwari *et al.* [28] propose a kernel distance-based Radio Tomographic Imaging (RTI) by using a kernel distance of histograms to locate a moving or stationary person based on wireless TelosB nodes. Xu *et al.* [25] develop a fingerprint-based device-free localization system, in which several discriminant analysis approaches are explored. In SCPL [23], the authors further extend the system to count and localize multiple subjects. Ichnaea [29] realizes the device-free passive motion tracking by exploring several the already installed wireless networks, in which it first uses statistical anomaly detection methods to achieve its detection capability and then employs an anomaly scores-based particle filter model and a human motion model to track a single entity in the monitored area. More recently, Adib *et al.* [13] designs WiTrack that is capable to infer subject's movement from the RF signal (*i.e.,* specialized FMCW signal) reflected off the body, even the person is occluded from the device or in different rooms.

RFID-based Device-free Localization: Although WSN/active RFID tags-based localization systems have some advantages (e.g., medium cost, tiny size), they require the maintenance (e.g., replacing batteries). In contrast, RFID-based device-free localization systems have more attractive characteristics including cost-efficient, easy to deploy, and maintenance-free (cheap passive tags). As a result, a few pioneer research efforts have been proposed recently based on RFID technology. For instance, Wagner *et al.* [30] enhance traditional RTI method to track the subject in a small, clear surveillant area using densely-deployed passive tags. Twins [14] leverages observations caused by interference among passive tags to detect a single moving subject, achieving an average error $0.75m$. Liu *et al.* [2] 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 location sequences. Zhang *et al.* [17] 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. More lately, Yang *et al.* [8] design a device-free, see-through-wall tracking system with high accuracy, in which they attached a group of passive RFID tags on the outer wall to track a moving subject by analyzing the reflected signals from the environment and human body. However, most existing localization systems based passive RFID tags are deployed and tested in an controlled/semi-controlled or cleared space (*i.e.,* a room or office equipped only with a few objects, lack of metal electronic appliances). In contrast, *HOI-Loc*, a device-free localization system based on pure COTS RFID tags, can beyond the limits of current similar systems and achieve high-accuracy localization in a real-world living environment.

VIII. Discussion & Conclusion

Hardware Deployment: In our system, we attach passive RFID tags on the walls to capture RSSIs, and install sensors on the electronic appliances, which is considered not being very

[3] In a residential home testbed, we do not compare *HOI-Loc* with TagArray and TASA since these two works need to put the tags in an array which is impractical especially in a full-furnitured house.

[4] Make sure there is only one resident in each room at a certain time, overall we collected 10,800 measurements.

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practical. However, we can mount readers and antennas on the ceiling, and embed passive tags into wall decorations. Also, with the development of IoT, it will be a standard configuration for smart-homes to monitor domestic appliances. *HOI-Loc* will be more practical and enable valuable applications with the prevalence of smart-homes in the near future.

Learning based Methods: One of limitations is that we need to learn the RSSI patterns based on subject's locations, although for a $20m^2$ room, according to our experiments, it only needs $50s$ training data to achieve more than 90% accuracy. In the future, we will investigate the prorogation mechanism of backscatter signal to facilitate our method, thereby further eliminating the learning burden.

Number of Users: In a living room, our approach only tracks a single resident, aiming to support elderly people who lives alone. When there are multiple residents in the same room, the RSSI patterns will be overlapped and need to be learned multiple times (learning time increases exponentially with the resident number). In the future, we will attempt to retrieve other signals from RFID tags (*e.g.,* RF Phase, Reading Rate, Doppler Frequency etc.), which provide more fine-grained location indicators to decrease the pattern overlapping caused by multiple residents.

To summarize, this paper has shown how human object interaction events can be used to facilitate the COTS RFID-based device-free localization under a rigid probabilistic framework. The real-world experiments demonstrate the feasibility and effectiveness of our system, which marks an important step toward enabling accurate device-free indoor localization in a residential house.

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