Exploring Tag-free RFID-based Passive Localization and Tracking via Learning-based Probabilistic Approaches

Lina Yao
The University of Adelaide
Adelaide, Australia
lina.yao@adelaide.edu.au

Wenjie Ruan
The University of Adelaide
Adelaide, Australia
wenjie.ruan@adelaide.edu.au

Quan Z. Sheng
The University of Adelaide
Adelaide, Australia
qsheng@cs.adelaide.edu.au

Xue Li
The University of Queensland
Brisbane, Australia
xueli@itee.uq.edu.au

Nicholas J.G. Falkner
The University of Adelaide
Adelaide, Australia
nickolas.falkner@adelaide.edu.au

ABSTRACT

RFID-based localization and tracking has some promising potentials. By combining localization with its identification capability, existing applications can be enhanced and new applications can be developed. In this paper, we investigate a tag-free indoor localizing and tracking problem (e.g., people tracking) without requiring subjects to carry any tags or devices in a pure passive environment. We formulate localization as a classification task. In particular, we model the received signal strength indicator (RSSI) of passive tags using multivariate Gaussian Mixture Model (GMM), and use the Expectation Maximization (EM) to learn the maximum likelihood estimates of the model parameters. Several other learning-based probabilistic approaches are also explored in the localization problem. To track a moving subject, we propose GMM based Hidden Markov Model (HMM) and k Nearest Neighbor (kNN) based HMM approaches. We conduct extensive experiments in a testbed formed by passive RFID tags, and the experimental results demonstrate the effectiveness and accuracy of our approach.

Categories and Subject Descriptors

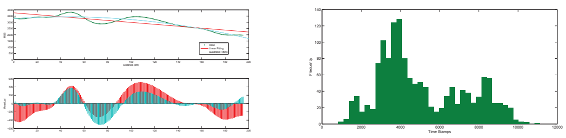
H.4.0 [**Information Systems Applications**]: General; H.2.8 [**Database Management**]: Database Applications

Keywords

Localization; RFID; Hidden Markov Model; Gaussian Mixture Model; Kernel-based; Nearest Neighbour

1. INTRODUCTION

Ambient intelligence has been drawing growing attention recently since it enables a smart environment which can respond to people's locations and behaviors using various wireless signal, sensors and Radio Frequency Identification (RFID) [7]. Under such smart environments, many promising applications can be realized such as aged care, surveillance, and indoor navigation [10]. A key prerequisite of enabling this intelligence is to localize and track people in the indoor environments.



(a) (b)

Figure 1: (a) RSSI variation along with distance (b) RSSI distribution when a person shows up at a certain location

RFID-based localization has gained much interest due to its low-cost and many RFID-based techniques for localization have been proposed [3, 4, 5, 8]. Most of these techniques, however, require the subjects to be attached with tags. This requirement has several inherent impractical issues (e.g., the tags may be lost or damaged by people accidentally or on purpose). As a result, a tag-free RFID-based localization applications is highly desirable.

It is well known that RSSI is quite complicated in real environments due to variability caused by multipath effects and ambient noise interference as well as physical antenna orientation, and fluctuations in the power source. The signal attenuates while increasing the distance. Figure 1(a) shows the relation of a certain tag' RSSI and its distance with antennas. Figure 1(b) shows the RSSI distribution at a particular location from a fixed access point. To sum up, RSSI is highly nonlinear and uncertain in a complex environment, which may be further corrupted when introducing people's presence or mobility. However, some underlying distinguishable patterns can be observed (e.g., how people disturb the pattern of received signal strength). In particular, two general intuitions are used in this paper. The first one is that when a subject appears in the testing area, the RSSI will change compared with a static environment. Secondly, when a subject appears at different locations, the RSSI of the same tag will embody various fluctuation patterns. Figure 2 shows the RSSI variations when people present in different locations. Based on these two intuitions, it is possible to develop an approach decoding the changes and learn people's locations.

Recently, some works have been proposed to target the tag-free RFID-based localization. For instance, Zhang et.al [11] and Liu et.al [1] propose to set up RFID tags (mix of passive and active tags) into an array, which captures the Received Signal Strength Indicator (RSSI) sequences for all tags. The trajectories information can then be recovered by exploring variation of RSSI series. Inspired by their work, we set up a *pure passive* tag arrays to make

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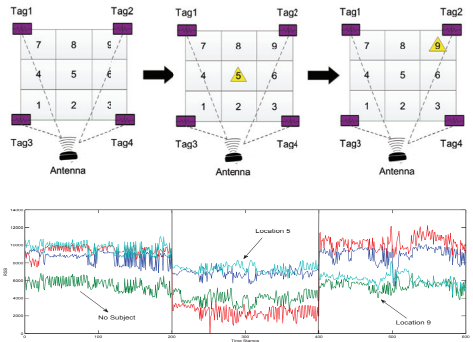


Figure 2: RSSI changes are different due to the presence of people in different locations

an economical sensing environment and treat the location estimation as a machine learning problem. In particular, a sequence of RSSI of anchoring tags are collected from various known locations along with corresponding correct location label are used to train a model, which is then used to estimate the subject's location given a new RSSI. Our main contributions are summarized as follows:

- We treat the localization as a multi-class classification problem by learning the RSSI changes. We explore a series of probabilistic approaches to study the feasibility of localization in a pure passive tag array. We propose a Gaussian Mixture Model based Hidden Markov Model to track a moving subject. To the best of our knowledge, our work is first few to conduct such research in a pure passive-tag environment.
- We set up a a testbed and conduct extensive experiments. The initial results demonstrate the feasibility of our approach. Good estimation accuracy is achieved when locating and tracking a moving subject.

The remainder of the paper is organized as follows. Section 2 presents the solutions to targeting problems of localization and tracking. The experimental results and analysis are reported in Section 3. Finally, Section 4 concludes our work.

2. PROPOSED SOLUTIONS

We describe our approaches for dealing with i) localization problem (i.e., given a sequence of RSSI values, localizing a stationary subject) and ii) tracking a moving subject (i.e., given a continuous sequence of RSSI values, tracking the subject's movement).

2.1 Localizing Stationary Subjects

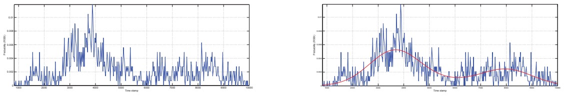
This problem can be formulated as to find the optimal posterior distribution $p(l_j|\mathbf{o}_i)$ given a new sequence of observed RSSI vectors:

$$j^* = \arg\max_j Pr(l_j|\mathbf{o}_i) \tag{1}$$

2.1.1 Gaussian Mixture Model

As stated in Equation 1, our goal is to maximize $Pr(l_j|\mathbf{o}_i)$. It is noted that we will drop the subscripts i and j for sake of simplicity and clarity in the following.

$$\begin{aligned} \arg\max_{l \in \mathbf{1}} Pr(l|\mathbf{o}) &= \arg\max_{l \in \mathbf{1}} \frac{Pr(\mathbf{o}|l)Pr(l)}{Pr(\mathbf{o})} \\ &\propto \arg\max_{l \in \mathbf{1}} Pr(\mathbf{o}|l) \cdot Pr(l) \end{aligned} \tag{2}$$



(a) (b)

Figure 3: (a) Distribution pattern of RSSI (b) Fitted GMM with learned two components

where $Pr(l)$ is the probability of finding the subject at location l, and it is set as a uniform distribution $Pr(l) \sim 1/J$. In this work, we assume that this distribution of RSSI values x at each grid l follows a multivariate Gaussian Mixture Model. Figure 3 (a) shows an example of GMM distribution of RSSI values in our dataset.

$$\begin{aligned} f_l(x) = Pr(x|l) &= \sum_{m=1}^{M} q_{l,m}\mathcal{N}(x|\mu_{l,m}, \mathbf{\Sigma}_{l,m}) \\ &= \sum_{m=1}^{M} \frac{q_{l,m}}{\sqrt{(2\pi)^{\mathcal{D}}|\mathbf{\Sigma}_{l,m}|}} \exp(-\frac{1}{2}(x-\mu_{l,m})^T \mathbf{\Sigma}_{l,m}^{-1}(x-\mu_{l,m})) \end{aligned} \tag{3}$$

Here $q_{l,m}$,$\mu_{l,m}$, and $\Sigma_{l,m}$ form the model parameter set $\mathbf{\Phi}_l$ at grid l. q_m is the mixture weighted factor that describes the prior probability of the m^{th} mixture component. $\mu_{l,m}$ and $\mathbf{\Sigma}_{l,m}$ are the mean and covariance of the m^{th} Gaussian distribution. For each grid, the maximum likelihood estimation $\hat{\mathbf{\Phi}}_l$ of $\mathbf{\Phi}_l$ is expressed as:

$$\hat{\mathbf{\Phi}}_l = \arg\max_{\mathbf{\Phi}_l} Pr(x|l, \mathbf{\Phi}_l) = \arg\max_{\mathbf{\Phi}_l} \prod_{i=1}^{N} Pr(\mathbf{s}_i|l, \mathbf{\Phi}_l) \tag{4}$$

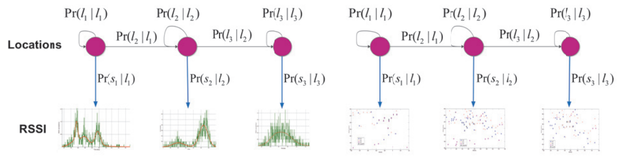
where $\mathbf{s} = \{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_N\}$ is the training set.

We use the Expectation Maximization (EM) to solve Equation 4. The EM algorithm is an iterative process consisting of two steps: the expectation step (E-step) and the maximization step (M-step). During the iterations, a sequence of model parameters $\mathbf{\Phi}_l^0, \mathbf{\Phi}_l^1 ..., \mathbf{\Phi}_l^*$, where $\mathbf{\Phi}_l^0$ is the initial parameter and $\mathbf{\Phi}^*$ is the converged parameter when algorithm converges and terminates with satisfying predefined conditions. The sequence of model parameters can guarantee monotonic improvement of the likelihood function and can converge to a local maximum-likelihood estimation. The E-step is to find the posterior probability $Pr(l|\mathbf{s})$ given training RSSI set $\mathbf{s}$. The M-step is to maximize the expected log-likelihood of the observed data. This leads us to re-estimating the parameters for the next iteration based on the posterior probabilities calculated.

After learning the model parameters with EM, given the new RSSI signals $\mathbf{o}$ collected from tag arrays, the probability that the subject may present at certain grids is calculated according to the GMM parameters $\mathbf{\Phi}_l$ on each grid, then taking the location with maximal probability as the predicted location in Equation 2. In our approach, we adopt the AIC as the model selection criterion to select the best number of components for each GMM [2]. Figure 3 (b) shows the fitted GMM of RSSI with two components.

2.2 Tracking Moving Subjects

We propose the multivariate Gaussian mixture models based Hidden Markov models (GMM+HMM) and k nearest neighbor based Hidden Markov Models (kNN+HMM) to improve the performance of our approach on tracking a moving subject based on *continuous* sequence of RSSI, as shown in Figure 4. HMM has shown tremendous success in spatio-temporal features recognition and it defines a distribution over a sequence of observable RSSI $O_{1:T}$ and corre-



(a) (b)

Figure 4: (a) GMM + HMM; (b)kNN + HMM

sponding locations $l_{1:T}$:

$$Pr(\mathbf{o}_{1:T}, l_{1:T}) = Pr(l_1)Pr(\mathbf{o}_1|l_1)\prod_{t=2}^{T}\underbrace{Pr(\mathbf{o}_t|l_t)}_{B}\underbrace{Pr(l_t|l_{t-1})}_{A} \tag{5}$$

Our HMM recognition approach is divided in three main steps, namely *emission matrix*, *state matrix*, and *viterbi searching*.

Emission Matrix. The emission matrix $B_{ij} = Pr(b_t = \mathbf{o}_i|b_t = l_j)$ in our case infers to the current state based on the observation RSSI vector $\mathbf{o}$ at each time stamp, which is generated by a grid map of corresponding $\mathbf{o}$. We aim at maximizing the likelihood $Pr(l_j|\mathbf{o}_i)$ when grid i is occupied. For GMM based HMM, its emission matrix can be obtained from Equation 3 in Section 2.1.1. For kNN+HMM, assuming for each observation $\mathbf{o}_j$, we find its k nearest neighbors from the training set $\mathbf{s}$, denoted as $N(\mathbf{o}_j)$, and $N^i(\mathbf{o}_j) = \{\mathbf{s}_k|\mathbf{s}_k \in \mathcal{N}(\mathbf{o}_j) \cap \mathbf{s}_k \in l_i\}$, $|N^i(\mathbf{o}_j)|$ denotes the total number of elements in $N^i(\mathbf{o}_j)$, the emission matrix is:

$$Pr(\mathbf{o}_j|l_i) = \frac{\sum_{\mathbf{s}_k \in \mathcal{N}^i(\mathbf{o}_j)}^{|\mathcal{N}^i(\mathbf{o}_j)|}\frac{1}{dis(\mathbf{o}_j, \mathbf{s}_k)}}{\sum_{\mathbf{s}_{k'} \in \mathcal{N}(\mathbf{o}_j)}^{|\mathcal{N}(\mathbf{o}_j)|}\frac{1}{dis(\mathbf{o}_j, \mathbf{s}_{k'})}} \tag{6}$$

State Matrix. For the state transition matrix, the subject can transit to next location at each time t. The transition is a Markov process where each state is conditionally independent of all other states given the previous state. The transition model can be defined as $A_{ij} = Pr(a_t = l_i|a_{t-1} = l_j)$. We adopt two strategies to calculate the next state for each given current state. The first one is 0 order, where we assume subject can move to any other locations in this testing area. The second strategy is 1-order move, where we consider subject only move to the locations which are immediate adjacent to his current location.

Viterbi Searching. The Viterbi algorithm defines $V_j(t)$, the highest probability of a single path of length t which accounts for the first t observations and ends in state l_j:

$$V_j(t) = \arg\max_{l_1, l_2, \ldots, l_{t-1}} Pr(l_1 l_2 \ldots l_t = j, \mathbf{o}_1\mathbf{o}_2\ldots, \mathbf{o}_t|A, B) \tag{7}$$

by induction

$$\begin{aligned} V_j(1) &= B_j(\mathbf{o}_1) \\ V_j(t+1) &= \arg\max_i V_i(t)A_{ij}B_i(\mathbf{o}_{t+1}) \end{aligned} \tag{8}$$

3. EXPERIMENTS

3.1 Data Collection and Metrics

We used one Alien ALR 9900 reader, two Circular Antennas and squiggle Higgs-4 passive tags in our experiments. We virtually divided the testing area into 9 grids, and each roughly $0.6m\times0.6m$ in size. The RFID reader monitored and collected RSSI measurement at sampling rate of 0.5s. We collected training RSSI measurement from tags for each grid based on two strategies [9]. In the first case, the subject stood at the center of each grid and spun around so that the resulting training data would focus on the gird center but involve different orientations. In the second case, the subject walked randomly within the cell. We mixed two RSSI collections together as the final training dataset.

We used two metrics, *accuracy* and *error distance*, to measure our proposed approaches in terms of localizing and tracking respectively. Accuracy is defined by:

$$Acc. = \frac{\sum_i^N \mathbb{I}(\hat{l}_i, l_i)}{N} \tag{9}$$

where $\mathbb{I}(a, b)$ is an indicator, 1 if a is equal to b, 0 otherwise. $\hat{l}_i$ is the predicted grid and l_i is the actual number of grids. N is the total number of observation RSSI vectors.

The error distance denotes the average accumulated deviation of error distance for each grid in each continuous trajectory:

$$Dis_{err.} = \frac{\sum_i^{|T|} dis(\hat{c}_i, c_i)}{|T|} \tag{10}$$

where c_i is the coordinates of the center of grid i, $dis(\hat{c}_i, c_i)$ is the distance between predicted grid and actual grid regarding their coordinates, $|T|$ is the total number of grids passed through by a subject in a trajectory, and t_i is the centroid distance between predicted grid and actual grid.

3.2 Results on Stationary Subject

As shown in Figure 1, RSSI collected from passive RFID tags is not free from noise, so we did some operations using sliding windows for better accuracy. We performed a moving average smoothing on the raw RSSI data, the sliding window size is set as 5.

When k is set as 2, kNN method gets the best performance in our case. The linear kernel is the best setting in SVM, and the number of weak classifiers is $1,000$ in boosting method. We adopted AIC for selecting the best number of components for each GMM. Table 1 shows the results of localizing a static subject with four different methods on varying training ratios (from 10% to 90%). Our proposed approach performs very well, and the accuracy can reach as high as 98.91%. The accuracy of all four methods are improved after preprocessing the raw data with smoothing, which reduces the effect of random fluctuations and improves the overall performance.

3.3 Results on Tracking Moving Subject

Before evaluating our approach in tracking a moving subject, two main issues closely related to dynamic tracking scenario need to be considered. One is experimental setting, e.g., what is the optimal grid size, and the other is how to deal with delay issue we found during the experiments.

Determining the Grid Size. In the experiment, we found that when the grid size is big ($0.9m \times 0.9m$), the 1-order strategy is better than the 0-order. When the grid size is small (e.g., $0.5m \times 0.5m$), the 0-order is better than the 1-order. The possible reason may lie in subject's step would become smaller under the smaller grid situations, in which the RSSI will not be distinguishable due to the increase of RSSI quick disturbance. We therefore determined each grid size as $0.6m$ based on our empirical study.

Coping with Impact of Latency. When we applied our proposed approach on tracking, we found that the latency of detecting a subject in the corresponding grid number is ≈ 1.5 seconds, which is mainly caused during the RSSI collection process. The RSSI collector is programmed with a timer to poll the RSSI with a predefined order of transmission, and needs to take around 1 second to

Table 1: Results Comparison on Localizing a Subject with Different Training Ratios

Train%	10		20		30		40		50		60		70		80		90	
	Raw	Smooth	Raw	Smooth	Raw	Smooth	Raw	Smooth	Raw	Smooth	Raw	Smooth	Raw	Smooth	Raw	Smooth	Raw	Smooth
kNN	0.863	**0.892**	0.916	**0.950**	0.943	**0.945**	0.963	**0.964**	0.962	**0.964**	0.963	**0.967**	0.970	**0.977**	0.976	**0.982**	0.987	**0.989**
SVM	0.851	**0.856**	0.888	**0.907**	0.893	**0.911**	0.908	**0.927**	0.930	**0.938**	0.933	**0.952**	0.933	**0.959**	0.878	**0.967**	0.953	**0.971**
GMM	0.752	**0.778**	0.855	**0.863**	0.909	**0.911**	0.930	**0.941**	0.936	**0.943**	0.946	**0.947**	0.967	**0.974**	0.974	**0.976**	0.979	**0.984**
AB	0.671	**0.735**	0.691	**0.779**	0.760	**0.799**	0.777	**0.810**	0.804	**0.862**	0.834	**0.881**	0.849	**0.910**	0.860	**0.927**	0.859	**0.966**

Table 2: Error Distance on Tracking Moving Subjects (m)

Methods	0-order	1-order
GMMHMM+Raw data	0.61	0.60
GMMHMM+Calibration	0.48	0.39
GMMHMM+Smooth	0.69	0.63
GMMHMM+Smooth+Calibration	0.60	0.50
kNNHMM+Raw data	0.63	0.53
kNNHMM+Calibration	0.42	0.35
kNNHMM+Smooth	0.59	0.53
kNNHMM+Smooth+Calibration	0.49	0.43

complete a new measurement with no workarounds. To cope with the impact of this latency, we adopted a forward calibration mechanism to calibrate the estimated location sequences [6]. We used a sliding time averaging window to smooth the location estimates. The technique obtains the location estimate by averaging the last few location estimates obtained by either the discrete space estimator or the spatial averaging estimator. The estimated location l_t at time t can be calculated as:

$$\hat{c}'_t = \frac{\sum_{i=t}^{t+|w|-1} \hat{c}_i}{|w|} \tag{11}$$

where $|w|$ is the window length, set as $|w| = 8$ based on our empirical study in this work. $\hat{c}_i$ is uncalibrated coordinates of the center of predicted grids at time t by Equation 7.

Table 2 shows the results on tracking a moving subject using GMM-based HMM and kNN-based HMM with the 0-order and 1-order strategies respectively. It is noted that the performance becomes worse compared with the one without smoothing the raw RSSI. This is different from the result of localizing a static subject. The possible reason may lie in that we still use the fixed length sliding window to smooth the raw RSSI in the dynamic tracking case. For example, an incorrect length may break the consistency of RSSI samples from one single grid, specially, when the window overlaps the end RSSI generated from one grid and the beginning of the next one. Or, the window length may be too short to provide the best information for the tracking process especially when the subject's walk velocity is not consistent. In our future work, we will explore a dynamic sliding window method to perform an adaptive varying length sliding window smoothing.

4. CONCLUSION

In this paper, we present the design, implementation, and evaluation of a tag-free RFID-based localization method based on probabilistic classification, in a pure passive RFID tag array. We propose to model RSSI distribution at each grid as a multivariate Gaussian Mixture Model, and Expectation Maximization (EM) is used to learn the maximum likelihood estimates of the model parameters. This approach enables us to localize a single subject based on the maximum a posteriori estimation. Furthermore, we present multivariate Gaussian mixture models (GMM) based HMM and k nearest neighbor (kNN) based HMM to track a moving subject based on continuous sequence of RSSI. We validate and evaluate our proposed approaches using a testbed consisting of pure passive RFID tags. The results demonstrate the feasibility and effectiveness of our proposed approaches.

The experimental results show that the performance of tracking a moving subject is relatively worse than localizing a stationary subject in our current work. We will investigate how to improve the accuracy in real-time tracking in terms of reducing RSSI noise to more informative and stable features. We will also explore how to enhance our approach to enable multi-subjects localization and tracking.

5. REFERENCES

[1] Y. Liu, L. Chen, J. Pei, Q. Chen, and Y. Zhao. Mining frequent trajectory patterns for activity monitoring using radio frequency tag arrays. In *Pervasive Computing and Communications, 2007. PerCom'07. Fifth Annual IEEE International Conference on*, pages 37–46. IEEE, 2007.

[2] G. McLachlan and D. Peel. *Finite mixture models*. John Wiley & Sons, 2004.

[3] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil. Landmarc: indoor location sensing using active rfid. *Wireless networks*, 10(6):701–710, 2004.

[4] L. M. Ni, D. Zhang, and M. R. Souryal. Rfid-based localization and tracking technologies. *Wireless Communications, IEEE*, 18(2):45–51, 2011.

[5] C. Qian, H. Ngan, Y. Liu, and L. M. Ni. Cardinality estimation for large-scale rfid systems. *Parallel and Distributed Systems, IEEE Transactions on*, 22(9):1441–1454, 2011.

[6] M. Seifeldin and M. Youssef. A deterministic large-scale device-free passive localization system for wireless environments. In *Proceedings of the 3rd International Conference on PErvasive Technologies Related to Assistive Environments*, page 51. ACM, 2010.

[7] Q. Z. Sheng, X. Li, and S. Zeadally. Enabling next-generation rfid applications: Solutions and challenges. *IEEE Computer*, 41(9):21–28, 2008.

[8] P. Wilson, D. Prashanth, and H. Aghajan. Utilizing rfid signaling scheme for localization of stationary objects and speed estimation of mobile objects. In *RFID, 2007. IEEE International Conference on*, pages 94–99. IEEE, 2007.

[9] C. Xu, B. Firner, Y. Zhang, R. Howard, J. Li, and X. Lin. Improving rf-based device-free passive localization in cluttered indoor environments through probabilistic classification methods. In *Proceedings of the 11th international conference on Information Processing in Sensor Networks*, pages 209–220. ACM, 2012.

[10] L. Yao, Q. Z. Sheng, A. H. H. Ngu, and B. Gao. Keeping you in the loop: Enabling web-based things management in the internet of things. In *Proceedings of the 23rd ACM International Conference on Information and Knowledge Management*. ACM, 2014.

[11] D. Zhang, J. Zhou, M. Guo, J. Cao, and T. Li. Tasa: Tag-free activity sensing using rfid tag arrays. *Parallel and Distributed Systems, IEEE Transactions on*, 22(4):558–570, 2011.