Author Responses to Review Comments

We are grateful to the the reviewer for the insightful and invaluable comments. Based on the comments, we have prepared a much better manuscript. The changes made in the revised manuscript according to the comments of the reviewer are highlighted in red. Below, we response in detail to the comments of the reviewer (each comment is shown in *italics*).

Reviewer Comment 1: *The paper describes interesting approach for indoor location tracking. But many features are not described in enough details. For example, how they repeat 100 times the test, and what was the test protocal. What device was used as the mobile terminal, a computer? Is it applicable to small mobile terminal? What was the trajectory tested? Was the results compared to some other RFID indoor localization solutions? What was the computational costs and how it could work on small terminal? As the terminal has 10m range it will have higher power consumption, was it measured? There was no problem with interference between different tags in range? How this is solved in this solution? How you physically distributed RFID tags? So you had physical position of each RFID tag and all of them are static?*

Response: We appreciate these valuable comments.

Due to the shortage of RFID devices and the limitation of the testing area, we evaluate the performance of the proposed approach using the simulated testbed built on TinyOS 2.1. TinyOS is an embedded, component-based operating system, which is especially useful for microcontroller-based devices that have sensors and/or networking capabilities. It provides interfaces and components for common abstractions such as packet communication, routing, sensing, actuation and storage. Moreover, Tossim is used in the simulation which replaces the components in TinyOS with simulation implementations. Thus we need not configure the test protocal especially.

In our F-RFID model, the RFID readers are considered as the mobile terminal and RFID tags are fixed deployed in the monitoring area. In addition, with the development of hardware, the portable and small RFID reader has been widely used in many real applications. Moreover, by using TinyOS platform, the estimation (computation) of locations of moving readers can be implemented easily. On the other hand, Since the LJYZN-107 RFID reader with 915MHz and $10m$ radio range is widely adopted in the moving objects tracking application, we adopt the RFID reader with type LJYZN-107 in our experiments.

Additionally, we simulate an application of indoor exhibition where the size of the visiting area is a $150m \times 150m$ rectangular region. The visitors (equipped with RFID readers) can move in the visiting area arbitrarily, and the RFID tags are deployed on the floor of the visiting area randomly and intensively (liking the deployment shown in Figure 1 introduced in Example 1 in the manuscript). Since the RFID tags are fixed deployed in the monitoring area, the location of each

tag is known and written in its own memory, and thereby the RFID tags are static in this paper. With static RFID tags, we can estimate the locations of moving readers (visitors) effectively and without extra tag location queries (as introduced in the Introduction in the manuscript).

Finally, to obtain reliable experimental results, we repeat each test 100 times and the average results are reported. In each test, we plan a trajectory for each moving object (RFID reader) randomly and estimate the locations of the moving object corresponding to the points in the trajectory. Moreover, we adopt the average Euclidean distance between the real locations and estimated locations to measure the accuracy of the location tracking approach.

In the revised manuscript, we have rewritten the subsection of Experimental Settings to make it clear as follows:

5.1 Experimental Settings

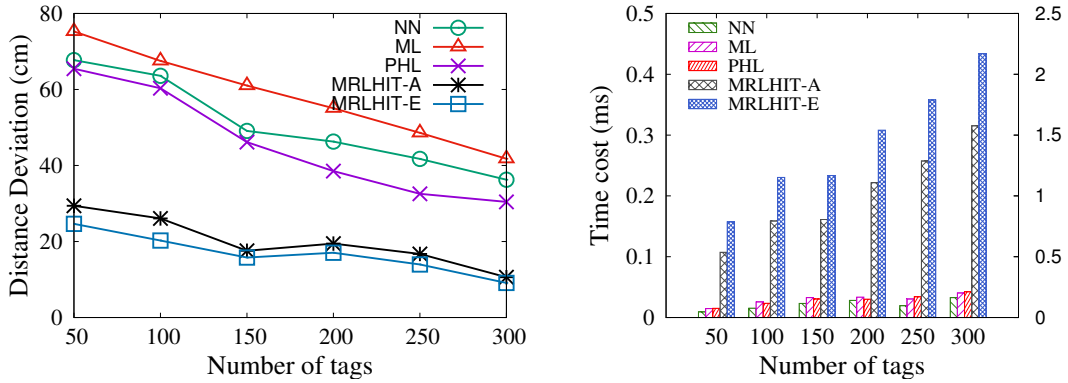
To evaluate the performance of the proposed MRLIHT, our experiments are deployed on the TinyOS 2.1. TinyOS [29] is an embedded, component-based operating system, which is especially useful for microcontroller-based devices that have sensors and/or networking capabilities. It provides interfaces and components for common abstractions such as packet communication, routing, sensing, actuation and storage. On the other hand, due to the limitations of RFID devices and testing area in practice, we adopt the Tossim as the simulated testbed and build it on TinyOS 2.1. We simulate an application of indoor exhibition where the size of the visiting area is a $150m \times 150m$ rectangular region with grid. The Visitors (equipped with RFID readers) can move in the visiting area arbitrarily. The RFID tags are deployed on the floor of the visiting area randomly and intensively (liking the deployment shown in Figure 1 introduced in Example 1). Since in our M-RFID model, the RFID tags are fixed deployed in the visiting area, the location of each tag is known and written in its own memory. In the testbed, the type of RFID reader is LJYZN-107 with power 915MHz and radio range is about $10m$, while the RFID tags are the labels conforming to the standard of EPC CLASSI G2. The reading rate of tags by readers are generated based on the reader detection model where the parameters are $a_i = 3.6423$ and $b_i = -7.5897$. In addition, we add a random term in range of $[0, 0.1]$ on the reading rate to simulate the noise in real application environment.

We adopt the average Euclidean distance between the real locations and estimated locations of RFID readers to measure the accuracy of various location tracking methods. Moreover, we implement two existing RSS-based indoor location tracking methods, i.e., nearest-neighbor (NN) [24, 25] and multilateration (ML) [26] and a newest phase-based mobile reader localization (shorted by PHL) method proposed in [23]. It is notable that in [23], the proposed localization algorithm focuses on determining the location of a mobile RFID reader at a certain axis (e.g., x-axis) while

assuming that the position on the other axis (e.g., y-axis) is known and the mobile reader moves along the certain axis. We suppose the assumption limits its application. Thus, in the experiments, we use the phase differences of the tags detected by the mobile reader to replace the RSS, and employ the multilateration to determine the final location of the moving individuals (readers). Finally, we repeat each test 100 times where in each test we randomly plan a trajectory for each visitor, and the average results are reported to obtain reliable experimental results.

Reviewer Comment 2: *Please add comparison with other indoor location tracking solutions.*

Response. Thanks for this comment. We have added a newest phase-based location tracking method (denoted by 'PHL') to compare with our proposed approaches. In the revised manuscript, we replotted Figure 8 and Figure 9. Moreover, we added more discussions about the experimental results. The revision is shown below.



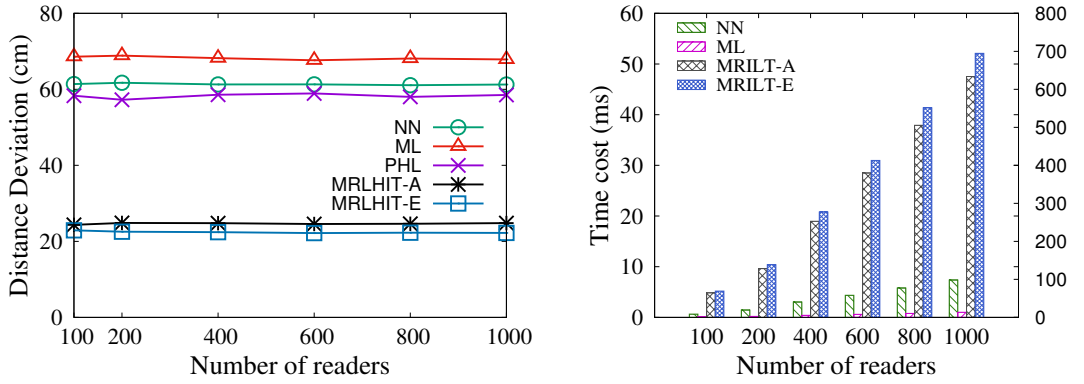
(a) Distance deviation (b) Time cost

Fig. 1. Varying the number of tags detected simultaneously with $\delta_d = 20cm$, $\delta_s = 3$, $grid_size = 60cm$

Fig. 1 shows the performance of various methods by varying the the number of tags detected by a reader simultaneously. It can be observed from Fig. 1(a) that the lowest distance deviation is achieved by the proposed MRLIHT. The reason is that we consider the uncertainty of the reading rate of a tag by a reader and first extend the candidate locations of a reader into a PLR rather than some certain points. On the other hand, by refining each grid, the positioning accuracy is further improved. Moreover, in NN and ML, the distance between an RFID reader and tags it detected are computed based on the reading rate model whose parameters are learned based on the historical data. During the parameter learning, it inevitably derives some deviations (due to the uncertainty of the reading rate). As a result, the localization algorithms (i.e., NN and ML) without considering this uncertainty derive a large localization deviation. By comparison, in PHL, since the phases are directly collected from reference tags, the distances (between an RFID reader and tags it detected)

estimated based on those phases contain relatively small deviations. Therefore, the localization accuracy of PHL is higher than those of NN and ML, but it is lower than our proposed approaches obviously.

As shown in Fig. 1(b), with the increase of the number of tags, it is not surprising that the time cost rises. The time costs of NN, ML and PHL are lower than those of MRLIHT-A and MRLIHT-E, but their localization accuracies are also lower. We can observe that the time costs of ML and PHL are close to each other, because both of them estimate the locations of indoor humans based on the multilateration. The main difference between ML and PHL is that the distance between an individual (reader) and a tag is computed based on the RSS and phase difference, respectively.



(a) Distance deviation (b) Time cost

Fig. 2. Varying the number of readers with $\delta_d = 20cm$, $\delta_s = 3$, $grid_size = 60cm$

Fig. 2 reports the evaluation of the scalability in terms of accuracy and efficiency by varying the number of readers. As shown in Fig. 2(a), the accuracy remains stable with the increase of the count of readers. However, the accuracy of the proposed MRLIHT is higher than existing methods obviously. For the time costs, as shown in Fig. 2(b), all methods increase linearly with the increase of the number of readers. The time costs of MRLIHT-A and MRLIHT-E are $47.5284ms$ and $694.6388ms$ with 1000 readers, respectively. In other words, we can estimate the locations of 20,000 and 1500 readers in one second based on MRLIHT-A and MRLIHT-E, respectively. Therefore, MRLIHT-A is more suitable for the large-scale monitoring applications without much accuracy sacrifice.

Reviewer Comment 3: *Please extend the conclusion and explain how your solution contribute to state of art solutions.*

Response: Thanks for this valuable suggestion. We have rewritten the conclusion and added more illustration to explain our contributions as follows.

In this paper, we have studied the indoor human tracking problem. Accordingly, we propose a novel M-RFID based localization approach for indoor human tracking, named MRLIHT. In MRLIHT, RFID tags are fixed deployed in the monitoring area intensively, and RFID readers are equipped on the moving objects (i.e., individuals) we targeting to locate. To improve the localization accuracy, we add a random disturbance term which reflects the uncertainty of the readings by an RFID reader on the reading rate. As a result, the response region of an RFID tag to the reader is extended from a circle to a circular, which enriches the candidate positions of the reader. Moreover, in MRLIHT, the indivduals can move in the monitoring area arbitrarily without pre-defined motion model, which are more applicable in real world. In time cost, since the locations of RFID tags are fixed and can be written in their own memories, the location information of RFID tags (which are used for location tracking) can be obtained by RFID readers directly. Therefore, the extra queries for tag locations are saved, and thereby the location estimation efficiency is improved. Finally, the extensive experimental results show that the proposed MRLIHT has higher location estimation accuracy than the state-of-the-art methods. Moreover, it is able to accommodate large-scale monitoring applications with good scalability.

Reviewer Comment 4: *Please check references and add more details of references (pages, Venue for conference papers, etc.), check capitalization (wiley & sons, rfid tags)*

Response: Thank you for pointing this out. We have examined the references carefully and fixed them.