Efficient RFID-Based Mobile Object Localization

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***Abstract*—Location-awareness of mobile objects is the key to numerous emerging ubiquitous computing applications. We show that RFID technology can be leveraged to achieve mobile object localization in an inexpensive, power efficient, scalable, widely applicable, flexible, and user-friendly manner. We outline the challenges that can adversely affect RFID-based localization techniques, and propose solutions to mitigate them. We present several algorithms for RFID-based mobile object localization that compare favorably or exceed previous methods in terms of accuracy, speed, reliability, scalability, and cost.**

Keywords - RFID, Object localization, RFID-based positioning

I. INTRODUCTION

The confluence of radio frequency identification (RFID) and other wireless technologies lies at the heart of many emerging applications, such as remote medicine, robotic teams, wireless sensing, early warning systems (e.g., for tsunamis, earthquakes, and chemical spills), locating points of interests (e.g., ATMs, banks, and hospitals), and automated inventory management [1, 2, 9, 10, 13, 15, 16, 17, 24]. Such applications require capabilities that include object identification, real-time object tracking, and position localization.

While typical RFID technology is sufficient for object tracking and identification, it does not normally provide object localization capabilities. Several RFID-based localization techniques for mobile objects have been proposed [5, 8, 11, 12]. However, these localization techniques tend to compromise key requirements such as accuracy, speed, power, cost, scalability, and reliability, which severely degrade the utility of these methods. Moreover, some previous localization methods also require cumbersome non-RFID technologies such as ultrasonic sensors, vision sensors, cameras, etc.

We propose to address these limitations by developing a scalable and reliable RFID-based localization approach that accurately and quickly determines the positions of mobile objects. Our approach consists of two separate techniques to localize target tags, as well as localize readers attached to mobile objects. To localize mobile target tags, we vary the reader power levels over a set of calibrated reference tags having known sensitivities. Separately, we determine the positions of target mobile readers by measuring their proximity to reference tags. Moreover, these two approaches can be combined to yield even higher accuracy and efficiency.

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We have implemented, tested, and evaluated the proposed approach to confirm its general applicability, scalability, and reliability. Our approach suits a wide-range of requirements and tradeoffs including accuracy, speed, cost, and power. We have also identified several key challenges (e.g., environmental interferences, tag sensitivity, spatial arrangements of tags etc.) that adversely affect the performance of RFID-based object localization, and we propose mitigating techniques.

This paper is organized as follows. In section II, we describe related research efforts to localize mobile objects based on RFID technology. Several localization challenges and mitigating techniques are presented in section III. We present our localization approach in section IV, discuss implementation details and results in section V, and conclude in section VI with future research directions.

II. RELATED WORK

RFID-based localization for mobile objects can be broadly classified into tag and reader-based localization techniques, wherein position estimates of tags and readers attached to such objects are determined. In this paper, we focus on the localization of mobile objects by utilizing the far-field radio-wave interaction between the RFID tags and readers (i.e., other RF-based localization approaches utilizing near-field, surface acoustic waves, microwaves, GPS, etc. are outside the scope of this work). Related research work includes the following.

Chae and Han [5] describe a two-step approach to localize mobile robots in an indoor environment. In their first step, an onboard RFID reader is coarsely localized with respect to neighborhood active reference tags. In the second step, a vision sensor combined with a feature detection algorithm identifies key environmental features to minimize the localization error to an average of 0.23 meters. Their approach is less applicable in different scenarios as the onboard vision sensor requires a sufficiently illuminated environment and objects must be within line-of-sight (a fundamental drawback that RFID was intended to eliminate in the first place).

Choi and Lee [8] propose to localize mobile robots in an indoor environment by utilizing ultrasonic sensors in combination with an onboard reader. In the first stage, the global position of the mobile robot is estimated through onboard reader localization with respect to the neighborhood passive reference tags. The second stage uses ultrasonic sensors for local position estimates. While their approach can yield higher accuracy, it is inherently not a pure RFID-based method, but rather a sound-based approach and is thus highly limited by issues such as environmental noise, line-of-sight, etc.

Hähnel et al [11] propose using a laser range scanner combined with an RFID reader onboard a mobile robot. The laser range scanner is used to learn a map comprised of reference tags, which in turn is used to estimate the position and orientation of mobile robots. However, this approach imposes line-of-sight constraints, and moreover tag orientation issues degrade the detection probability of the reference tags, resulting in high localization errors in the 1 to 10 meters range.

Han et al [12] propose mobile object localization by using reference tags and onboard mobile readers. Localization error is minimized using a triangular tag arrangement scheme, yielding average localization error of 0.09 meter in a small test region of one meter square. Koch et al [14] propose mobile object localization technique based on passive and active reference tags and onboard readers. Position estimates of the mobile objects can be determined within 0.1 meter accuracy on average.

Milella et al [18] utilize an onboard monocular camera, a reader and a tag bearing estimation technique based on "fuzzy inference system" to localize mobile robots. The average localization error is 0.64 meter. Senta et al [20] present a mobile robot localization technique based on reference tags, onboard readers, and a support vector machine (SVM)-based machine learning approach. This method yields localization errors of over 0.2 meters, and is limited by the spatial tag arrangement, measurement noise, and tag-reader proximity.

Seo and Lee [21] describe a mobile object localization system that transmits an RFID signal from an onboard reader to the neighborhood beacon, which in turn responds with an ultrasonic signal. The estimated distance is computed based on the time difference between transmitted and received signals, with an average localization error in the range of 0.2 to 1.6 meters. Vorst et al [23] present a mobile object localization approach using reference tags, onboard readers, and a particle filter-based technique. They compare prior-obtained training data with real-time RFID measurements to yield an average localization error in the range of 0.2 to 0.6 meters.

The effectiveness of the previous approaches is hindered by reliance on line-of-sight techniques, combining multiple non-RFID (e.g., ultrasonic sensors, cameras, lasers etc.) and RFID components in an ad-hoc manner, large numbers of onboard components, high localization delays, and heavy power requirements [5, 8, 11, 18]. Moreover, some of the above methods are too expensive or unwieldy due to the cost, size, and weight of the required infrastructure. Finally, the above approaches ignore the key issue that the RFID equipment itself can introduce significant amount of experimental errors. For example, previous works ignore the fact that identical tags can have widely varying detection sensitivities, which can greatly affect the experimental outcomes, as shown by Chawla, Robins, and Zhang [6]. Thus, instead of addressing and mitigating these basic principles (as we do in this paper), previous research efforts resort to Herculean efforts to reduce errors on other fronts, often resulting in a hodgepodge of ad-hoc and ineffectual techniques.

III. Localization Challenges

All RFID-based localization techniques have inherent position estimate errors due to various external (e.g., environmental) and internal (e.g., RFID tags and reader related) factors. This section describes key issues that induce localization errors and propose techniques to mitigate them.

A. *Interferrence and RF Occlusion*

Environmental factors such as radio noise and occlusions by liquids or metals can cause radio-wave scattering and attenuation, which can in turn result in localization errors. Mitigating techniques such as electrostatic shielding, full faraday cycle analysis, and path-loss contour mapping can help reduce the impact of such factors on localization accuracy [22]. Deploying more tags and readers in the experimental region can also reduce adverse interference and occlusion effects.

B. *Tag Sensitivity*

Tag detection sensitivity is characterized by the minimum power needed to read the tag at a particular distance. It is a function of chip threshold power sensitivity, tag antenna gain, and the chip's high impedance state [19]. Moreover, tag manufacturing variability can dramatically affect the detection sensitivities of tags. Thus, tags with low sensitivities become invisible at shorter distances than their higher-sensitivity counterparts, leading to position estimation errors. To address this issue, we propose a pre-processing step of sorting (i.e., "binning") the tags based on their detection sensitivities, and classify them as "highly sensitive", "average sensitive" and "low sensitive" using read measurements over different power and distance combinations [6]. This enables only uniformly-sensitive tags to be deployed in the same experiment, resulting in more meaningful and consistent experimental results. Curiously, previous works all seem to ignore this critical issue.

C. *Tag Spatiality*

RFID-based mobile localization techniques typically utilize reference tags placed in known locations. The positions of these reference tags can significantly affect the localization accuracy, and regular placements of reference tags tend to yield lower positioning errors, as opposed to random arrangements.

D. *Tag Orientation*

Tag and reader interaction is significantly affected by the tag orientation. For example, Bolotnyy and Robins analyzed how tag orientation impacts the tag detection probability [3, 4]. In particular, they discovered that when multiple tags are placed on same object, orthogonal orientations yield much higher detection probabilities than parallel orientations.

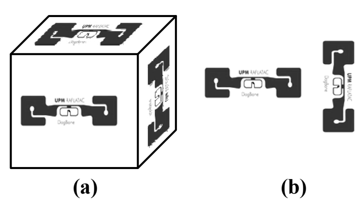

Figure 1. Tag orientations: (a) 3D orthogonal, (b) Planar orthogonal

Figure 1(a), shows a 3D object with multiple orthogonally oriented tags, and Figure 1(b) shows an orthogonal planar (i.e., horizontal and vertical) orientations of two tags. In section IV, our experiments indicate that horizontal planar orientation increases tag sensitivity. Thus, utilizing multiple tags in orthogonal spatial and horizontal planar orientation improves localization accuracy.

E. Reader Locality

Theoretically, the RFID power-distance relationship is characterized based on the Friis transmission equation given as follows [7]:

$$\frac{P_R}{P_T} = G_R G_T \left(\frac{\lambda}{4\pi D} \right)^2 \qquad (1)$$

Here, P_R is the power transmitted by the reader, P_T is the power received at the tag, G_R and G_T are the antenna gain of the reader and the tag, λ is the radio-wave wavelength, and D is the distance between the tag and reader. For a typical RFID system, the variables λ, G_R, and G_T are the design parameters. Thus, by knowing the reader and tag power levels, the distance between them can be estimated. Alternatively, if the distance between the readers and tags are known, then the received power at the tags can be determined. Thus, the reader location impacts the localization accuracy. We propose that more tags should be placed in the region near the trajectory of mobile objects in order to improve the overall localization accuracy.

Our main principle behind above mitigating techniques is "to identify and minimize possible errors at the sources where they arise". This leads to efficient localization techniques, fewer onboard components, lower power requirements, and higher localization accuracy. In the following section, we use this principle to develop techniques for minimizing the mobile localization errors.

IV. MOBILE OBJECT LOCALIZATION USING RFID

The proposed localization approach utilizes two different techniques. In the first technique, an onboard reader and reference tags embedded in the environment are used to coarsely localize the mobile object. The second technique varies the power levels of environment-embedded readers to localize the onboard tag via the empirical power-distance relationship (calibrated using reference tags at known positions). To ensure uniform behavior from the tags, we test, sort, and select them on their (similar) detection sensitivity. Also, by employing multi-tags [3, 4], we reduce the uncertainties when inferring the position of onboard tags. Finally, we combine these localization techniques and propose several heuristics for significantly improving the localization accuracy.

While tags are sorted, placed, and calibrated as part of offline pre-processing phase, the actual localization and error-minimization heuristics are performed in real-time. By dividing the task of localization into separate phases, we reduce the time required to estimate positions of mobile objects. We describe key aspects of the proposed localization approach below.

A. Calibrated Tags

The accuracy of our localization approach relies on the tags having uniform detection sensitivities. Also, this property can help localization speed improve with higher tag sensitivities. Thus, as an offline pre-processing quality-control check, the sensitivities of all the tags are tested and characterized, to ensure that only tags with uniform (and high) sensitivities are used in our subsequent localization experiments. We have also developed a four-way multi-tag platform that provides higher operational reliability, as illustrated in Figure 2.

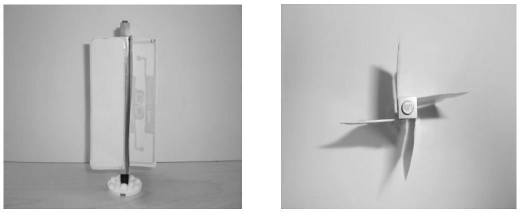

Figure 2. A four-way multi-tag platform

Figure 2 shows the design of our four-way multi-tag platform consisting of four "Impinj Dogbone Monza 3" UHF passive tags mounted on a vertical stand made of Lego bricks (our choice of Lego components is based on the versatility of Lego bricks as well as the transparency of their plastic material to radio-waves). We have built 33 such platforms, and each tag on the platform was calibrated separately using the techniques described by Chawla, Robins, and Zhang [6]. We have performed two types of platform calibration experiments to ensure uniform detection sensitivity across variables such as tag rotation and proximity, described as follows.

1) Proximity Sensitivity Calibration: In this experiment, we ensured that the four-way multi-tag platforms consisting of four proximate equally sensitive tags (Figure 2) all have similar sensitivities. This was achieved by determining the average read count of constituent tags having matching orientations with respect to the reader's antennas. Thus, tags at position one, two, three, and four were oriented towards antenna one, two, three, and four, respectively. We kept the reader power level constant at 31.6 dBm and varied the distance between the reader and the multi-tags within the range of 1.27 to 3.81 meters.

We also varied the reader power level within the range of 25.6 to 31.6 dBm, keeping the distance between them constant at 2.54 meters. We repeated the calibration experiment three times and computed the average. While the combination of power level and distance range was comparatively small, variations in the tag sensitivities are evident at this scale. Figures 3(a), 3(b), and 3(c) illustrate the results of this experiment by varying the distance and keeping the reader power constant. For example, at a distance of 2.54 meters away from the reader, position four yields the highest average read counts. This is due to antenna four being nearer to the tag at position four than antenna one. Also, at 2.54 meters tag position three yields the lowest average read count, due to the shape of the RF signal lobe emitted by the antenna. Similar conclusions can be drawn from Figures 3(d), 3(e), and 3(f).

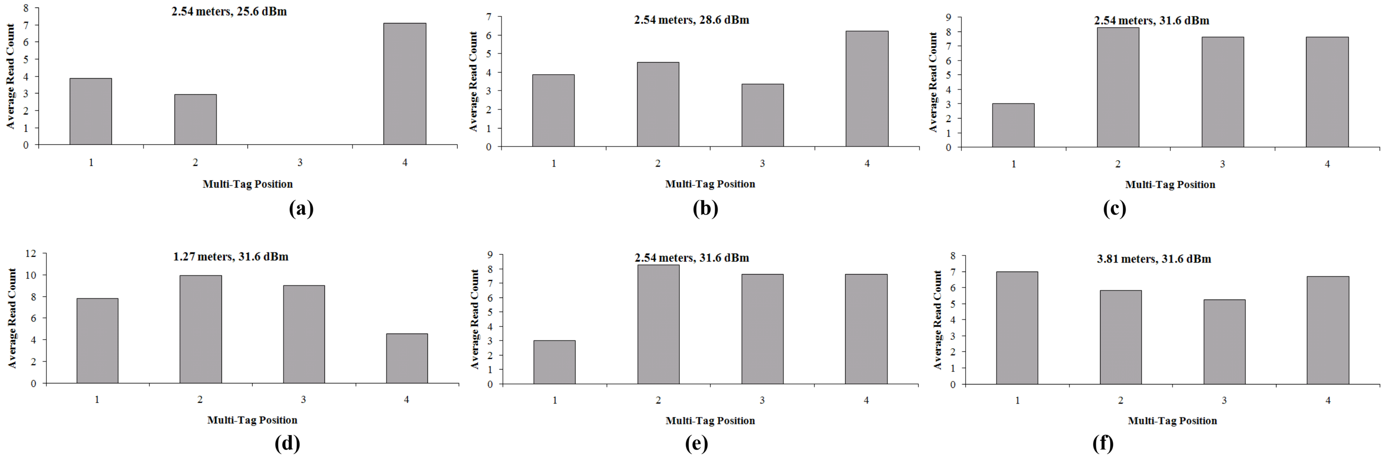

Figure 3. Multi-tag sensitivity measurements under proximity metric using constant-distance/variable-power and variable-distance/constant-power configurations.

2) Rotation Sensitivity Calibration: In this experiment, we determined the impact on tag sensitivity of rotating the multi-tag platforms. We varied the reader power level between 25.6 and 31.6 dBm and kept the distance between the reader and the four-way multi-tag platform constant at 2.54 meters. Separately, we varied the distance between the reader and the four-way multi-tag platform within the range of 1.27 to 3.81 meters and kept the reader power level constant at 31.6 dBm. We then rotated each multi-tag platform counter-clockwise, repeating each calibration three more times and computed their average.

Figures 4(a)-4(l) and 5(a)-5(l) illustrate the impact of rotation on the average read-counts. In particular, each row of graphs depicts the average read count of four tags facing four antennas. When the platform is rotated counter-clockwise, these values are interchanged (e.g., tag at position one faces antenna one, and after a rotation, tag two takes that position and retains the read-count within permissible error range).

By combining the calibration results from the proximity and rotation experiments, it is evident that the 33 four-way multi-tags consisting of individually equally-sensitive tags are sensitivity invariant. This provides confidence that using these uniformly-sensitive multi-tags in subsequent localization experiments will help to minimize uncertainties due to tag variations, measurement noise, spatial orientations, etc.

B. *Localization Approach*

We now describe the proposed mobile object localization approach that consists of two different techniques based on the four localization algorithms. In the first technique, we localize readers onboard the mobile objects with respect to an environment instrumented with stationary reference four-way multi-tags. We measure the encountered unique tag IDs as the object moves around the environment. We associate a timestamp with each such measurement, resulting in a list of tuples of the type ⟨Tag ID, Timestamp⟩. Thus, we determine the path of the mobile objects by knowing the location of reference tags and the measurement time. We call this algorithm "Measure and Report".

Mobile objects can be localized more accurately by using a regular arrangement of stationary reference tags. However, the limited read-range of the onboard reader, as well as the uncertainties in the actual locations of the reference tags, can introduce errors into the resulting position estimates. To minimize such errors, in our second technique we vary the power levels of the readers embedded in the environment in order to localize the target multi-tags onboard mobile objects using empirical power-distance relationships calibrated against reference tags. We provide three algorithms that control the reader power level in different ways, yielding tradeoffs between localization accuracy and overall speed.

In the first algorithm, we linearly increment the reader power level from lowest to highest in order to determine the minimum power level required to detect reference and onboard multi-tags. While this approach finds the minimum tag detection power levels, it may take more time to converge. Alternatively, we can instead vary the power level from highest to lowest in order to detect tags, since tags are typically not located near readers. Thus, stepping down the power level (i.e., from highest to lowest) will minimize the average number of iterations required to determine the minimum tag detection power level. We call this algorithm "Linear Search".

In the second algorithm, we start at a mid-value power level, and then either step-up or step-down based on the reader's ability to find the tags. Thus, we can converge faster on the minimum power level required for tag detection. We call this algorithm "Binary Search". Note that these two algorithms search for only one tag per execution cycle. Our third algorithm addresses this limitation by determining the minimum power levels of large groups of tags in parallel. Thus, it is equivalent to running a Linear Search algorithm in parallel for all the tags. This algorithm is called "Parallel Search". Since Parallel Search can determine the minimum power-levels of onboard tags in parallel, it enables the simultaneous localization of multiple mobile objects.

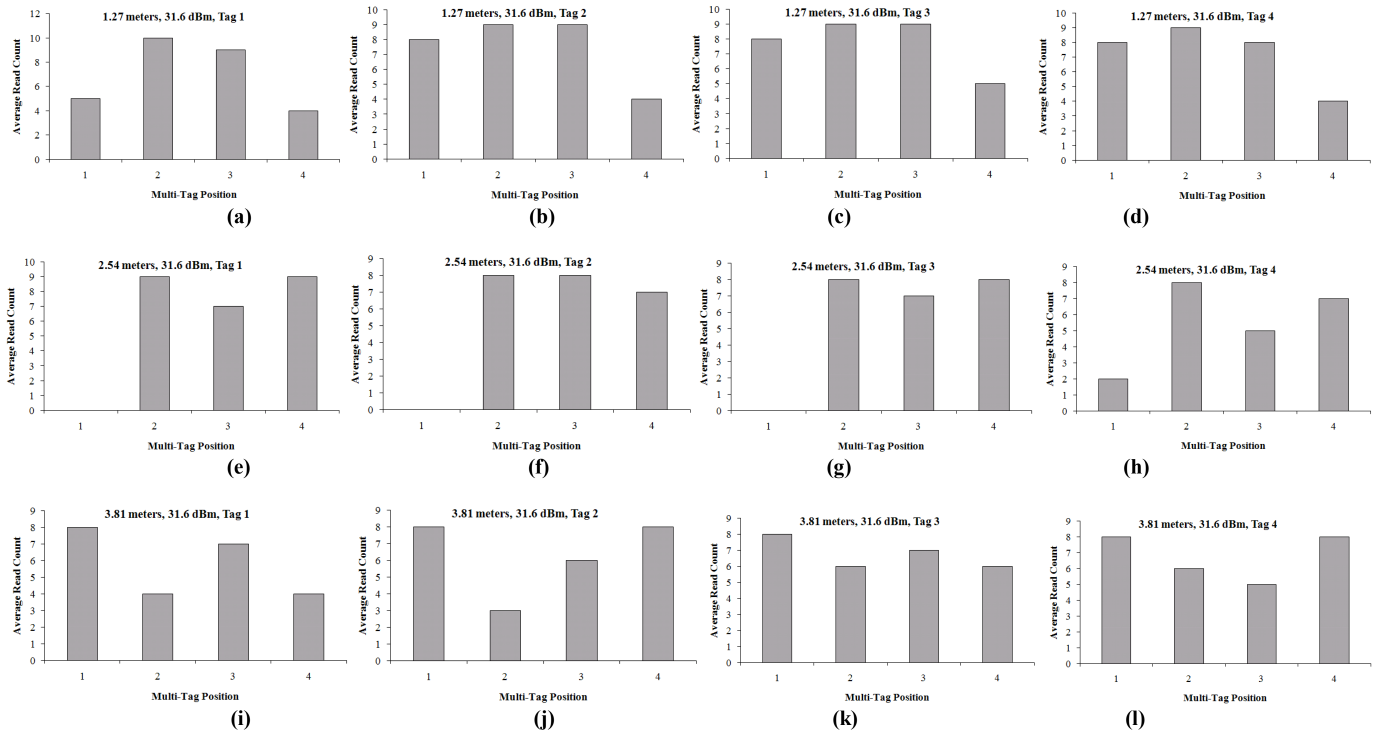

Figure 4. Multi-tag sensitivity measurements under rotation metric using variable-distance/constant-power configuration

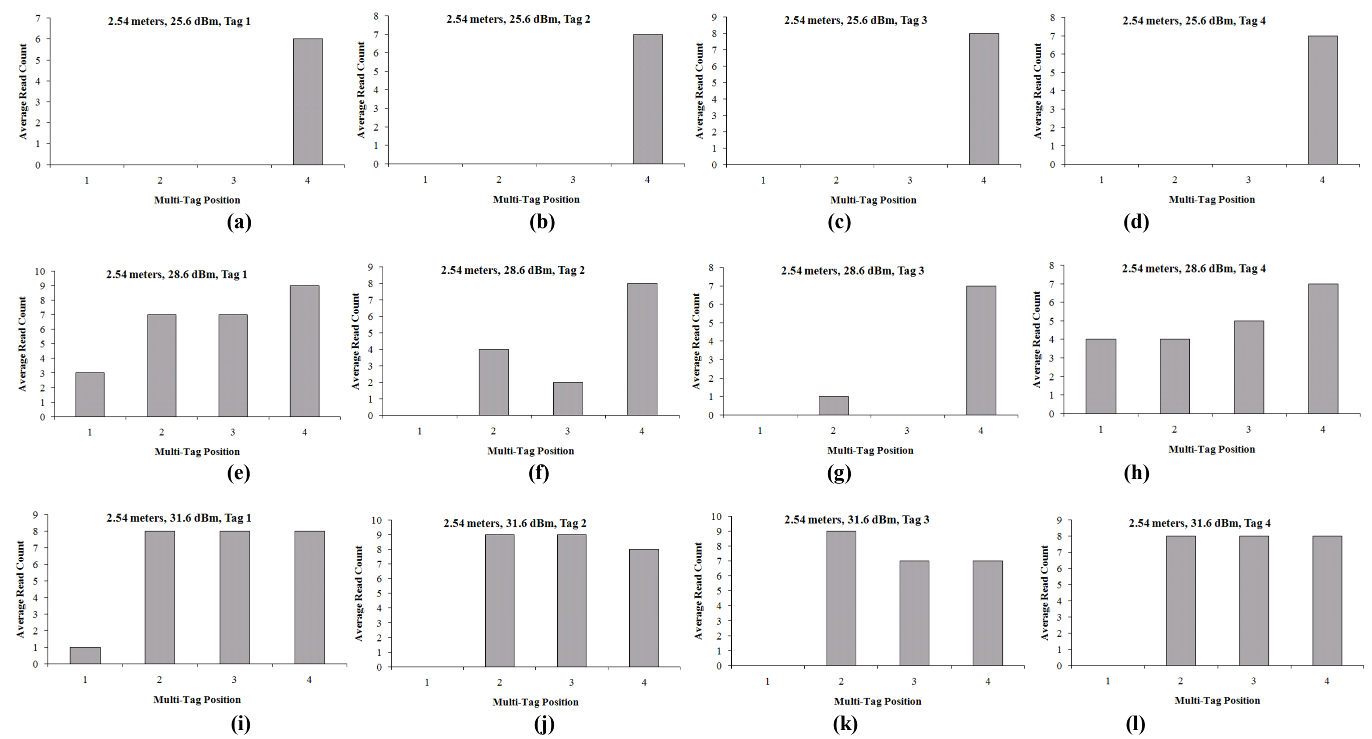

Figure 5. Multi-tag sensitivity measurements under rotation metric using constant-distance/variable-power configuration.

Table I gives the time complexity of each algorithm. While the Measure-and-Report algorithm is the fastest algorithm, both the Linear Search and Binary Search algorithms take considerably more time due to their operating in a serial manner. Since, the Parallel Search algorithm is independent of the number of tags and only dependent on the number of power

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