Fingerprinting Localization of RFID tags with Real-Time Performance-Assessment, using a Moving Robot

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***Abstract*—This work is focused on unmanned inventorying and localization, by deploying an RFID-equipped autonomous robot. The robot is able to perform Simultaneous Localization and Mapping (SLAM), thanks to its optical sensors. As the robot moves inside the target area, it continuously interrogates all RFID tags within range. Passive RFID tags, placed at known locations, are used for the estimation of the locations of the target tags, by properly manipulating the measured backscattered power. The proposed method does not depend on the location of the reader, but only on the locations of the reference tags. Hence, positioning-errors related to SLAM are not accumulated. Mobility of the robot ensures rich collection of measurements. We propose a method for dynamic, real-time configuration of the parameters of the fingerprinting algorithm and real-time evaluation of the localization error of the unknown tags. This is achieved by treating the reference tags as target tags. Thanks to this property, we further exploit mobility of the robot, repeating inventorying and localization in areas, where poor performance is initially recorded. Measurements indicate a mean error of 18cm, with standard deviation of 11cm, deploying a single antenna.**

***Index Terms*—RFID, Positioning, Fingerprinting, Robot.**

Fig. 1. RFID-equipped robot.

I. Introduction

In this paper we focus on inventorying and localization, exploiting Radio Frequency IDentification (RFID) technology. Inventorying is typically carried out by personnel, working overtime, usually once a month. In most cases, barcode technology is used, which demands optical reading of labels, one at a time. As a result, the process is slow and associated with errors, due to the repetitive actions that need to be taken by a human. Furthermore, the state of the stock is not continuously updated. In contrast, RFID technology, ensures much better read-rates (in the order of hundreds of tags per sec); still personnel must be involved. We propose the deployment of an RFID equipped robot, capable to autonomously move inside a previously unknown place, demonstrated in Fig. I.

In addition to simple inventorying, i.e. reporting the existence of a product somewhere in the search space, we deploy a localization algorithm, suitable for accurate and fast (real-time) pinpointing of all RFID-tagged objects (products) inside the search space. Key applications include, real-time inventorying in warehouses, large retail stores, libraries, etc.

An alternative approach to the problem would have been to deploy readers and antennas at fixed locations; thus covering the entire space. However, such a solution is very expensive, even for moderate-sized spaces, due to the small range of passive (battery-less) RFID systems; thus requiring a large number of equipment. In contrast, a *single* moving robot is capable to cover any environment at the expense of greater reading-time, depending on the size of the area and the speed of the robot. Furthermore, the moving robot has an additional advantage over any fixed solution: reduction of the errors of any localization algorithm, due to multipath [1]. Any fixed link inside a fixed geometry would always suffer from the same fading pattern (complex diversity techniques should be deployed) [2]. On the contrary a moving robot, presents a wealth of measurements for any RFID-tag, which can diminish fading effects, when manipulated properly.

State-of-the-art localization methods are based on measuring at the reader *i)* the backscattered power or, *ii)* the phase of the modulated backscattered signal from each tag. Depending on how this information is handled, we can discriminate:

- Methods based on Bayes Theorem and Conditional probability, exploiting the measured backscattered power [3]-[7],
- direction-finding methods, exploiting the phase of the backscattered field [8], [9],
- "holographic" methods, exploiting the phase of the backscattered field [10]- [12],
- distance-estimation method, "emulating" an UWB system [13],
- fingerprinting methods [14], [15].

All methods, except for fingerprinting, need to know the actual location of the robot [16] (actually of the antennas located on top of the robot). Very good accuracy is reported in [12] (less than 10cm error), where holographic method is used. However, the robot's trace is considered known. Actually, estimation of the robot's trace is a typical problem in robotic's prior-art by itself; depending on the environment and whether the robot needs to perform mapping as well (SLAM) [17], errors above 10cm are expected, even if expensive sensors are deployed (lidar, depth cameras, etc.) combined with state-of-the-art techniques. This error will be accumulated in the tag's estimation error, leading to an expected actual error in the order of 20cm.

Fingerprinting localization pinpoints the unknown tag's position that "best" matches a set of measurements collected from "reference" tags at known locations with the measurements collected for the specific tag. Therefore, the path of the reader is not needed. Only the locations of reference tags are necessary. The speed and the accuracy of the method depends on the number of reference tags, as well as the number of collected samples. The moving robot allows for any desired number of samples, by adjusting the speed of the robot. The small cost of each passive RFID tag (0.02$), allows for any density of installation of reference tags.

Among the most successful fingerprinting algorithms is "Landmark", initially deployed in [14]. However, its accuracy depends on "properly" setting a range of parameters, which in turn depend on the environment.

In this paper, we propose a method to exploit the reference tags, involved in fingerprinting localization, in order to:

- optimally set the parameters of the fingerprinting algorithm dynamically, such that the best estimation is derived for the specific environment,
- evaluate the performance of the localization method in real-time, thus allowing to repeat the method in specific areas, where poor performance is recorded.

II. Fingerprinting algorithm

Passive RFID tags are placed at known locations around the region, where the unknown tags are "tracked". These will be used as reference tags to evaluate the unknown locations of target-tags around them. The estimation is based on evaluating the similarity of measurements collected at an antenna grid between reference tags with each unknown tag. Let n reader antennas collecting measurements of m "reference" tags and u "tracked" tags. Let $\mathbf{X}^j = (X_1^j, X_2^j, , X_n^j)$ be the signal-strength measurements' vector of tracked tag j by the n reader antennas, where $j \in [1, u]$ and

$$X_i^j = \begin{cases} E_i^j & \text{if tag } j \text{ is identified by antenna } i \\ null & \text{else} \end{cases} \tag{1}$$

where E_i^j is the measured backscattered signal strength of tag j at antenna i. Similarly, let $R^l = (R_1^l, R_2^l, , R_n^l)$, be the corresponding collection of RSSI measurements of reference tag l, $l \in [1, m]$, from the same n antennas:

$$R_i^l = \begin{cases} E_i^l & \text{if tag } l \text{ is identified by antenna } i \\ null & \text{else} \end{cases} \tag{2}$$

For each pair of tracked tag j and reference tag l, we define the following indicator function:

$$I_i(j,l) = \begin{cases} 1 & \text{if } (X_i^j \neq null) \cap (R_i^l \neq null) \\ 0 & \text{else} \end{cases} \tag{3}$$

where i corresponds to the i^{th} antenna location. The function becomes 1 if from the specific antenna location i, both tags (j and l) have been identified. Therefore, the non-zero elements of the following vector $\mathbf{I}$ indicate the common measurements of the pair of tags (j,l) for all antenna locations:

$$\mathbf{I}(j,l) = [I_1(j,l), I_2(j,l), ..., I_n(j,l)] \tag{4}$$

and the number of common measurements is:

$$C_l^j = \sum_{i=1}^{n} I_i(j,l) \tag{5}$$

For each tracked tag j and each reference tag l, we define the following distance-"resemblance" metric:

$$D_l^j = \begin{cases} \sqrt{\sum_{i=1}^{n} (X_i^j - R_i^l)^2} & \text{if } I_i(j,l) = 1 \\ \infty & \text{else} \end{cases} \tag{6}$$

For each tracked tag, we create a distance-resemblance vector:

$$\mathbf{D}^j = (D_1^j, D_2^j, ..., D_m^j) \tag{7}$$

and the corresponding common measurements counter vector:

$$\mathbf{C}^j = (C_1^j, C_2^j, ..., C_m^j) \tag{8}$$

When a tracked tag j is physically close to a reference tag, it is expected to have many common measurements. The corresponding element in vector $\mathbf{C}$, defined in (8), will be large. On the contrary, distant tags will have small or zero values in (8). We define the mean of common measurements **for each** tracked tag:

$$C_{mean}^j = \frac{\sum_{l=1}^{m} C_l^j}{a}, \tag{9}$$

where a is the number of non-zero elements of $\mathbf{C}^j$. Then, in order to discard reference tags with few common measurements with the tracked tag, we define a threshold L^j

to be proportional to the above mean of each tag j by an optimization parameter g:

$$L^j = gC^j_{mean}, \tag{10}$$

Then, we modify (6), in order to discard reference tags with few common measurements with the specific tracked tag:

$$D'^j_l = \begin{cases} D^j_i & \text{if } C^j_i > L^j \\ \infty & \text{else} \end{cases} \tag{11}$$

Vector in (7) is updated accordingly:

$$\mathbf{D'}^j = (D'^j_1, D'^j_2, ..., D'^j_m) \tag{12}$$

The smallest element in (12) represents the reference tag, for which the measured power-values best fitted the corresponding measured values of the tracked tag, while enough common measurements are collected. Hence, we expect the actual location of the tracked tag to be "closer" to that reference tag. Furthermore, the "resemblance" vector can be used as a distance indicator from each reference tag, thus "weighting" the distance of the "target" tag from each reference tag. Since the smallest elements in (12) are more significant, the corresponding resemblance metric should be inverted. In fact, one can select the k^{th} smallest values in vector $\mathbf{D'}^j$, (quoted as k-nearest neighbors and abbreviated as "k-nn") and estimate the coordinates of target tag j by the following two equations:

$$(x^j, y^j) = \sum_{i=1}^{k} w_i(x^i, y^i) \tag{13}$$

where the weights are calculated as follows:

$$w_i = \frac{1/(D'^j_i)^v}{\sum_{i=1}^{k} 1/(D'^j_i)^v} \tag{14}$$

and v represents an optimization parameter.

Summarising, so far, with respect to prior art [14], we have introduced the common measurements counter vector in (8). Then, we defined a threshold to discard reference tags with few common measurements with the tracked tag in (10). This is essential for the proper application of the proposed algorithm, since it was found that there were elements which seemed to have great resemblance with the tracked tag, according to (6), but were actually far away from the tag, having only a few common measurements.

In the following sections, we focus on the three optimization parameters that came up from the mathematical analysis of the algorithm:

- the common measurements' threshold optimization parameter g in (10),
- the number of neighbors k in (13).
- the exponent v in (14).

III. Real-time performance assessment

Our experiments were contacted inside a corridor-type laboratory room in the Campus, as shown in Fig. 2. RFID tags are attached to a 10m-long millimetre-paper on top of a bench. The RFID-equipped robot moves autonomously next to the bench. Initially, the robot creates a map of the room using SLAM techniques. Then, it moves through the room collecting measurements from the tags while continuously updating its location on the map. The robot repeated this process several times, passing along different trajectories inside the corridor, as demonstrated in Fig. 3.

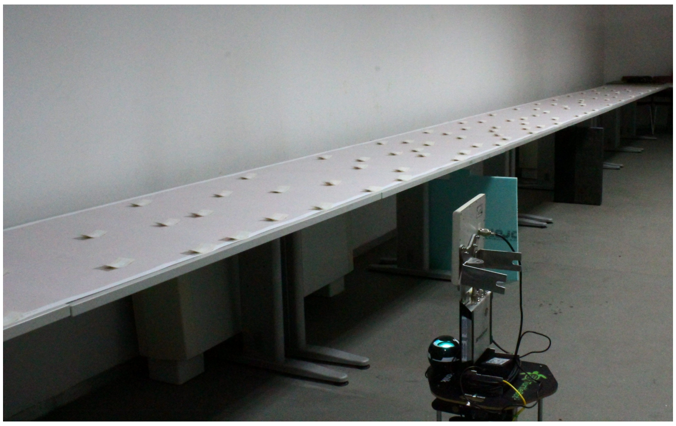

Fig. 2. The setup of the measurements

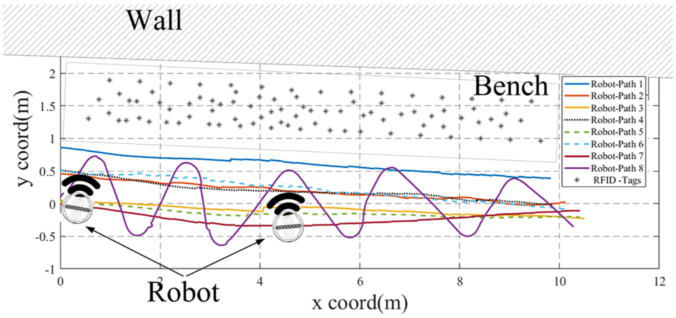

Fig. 3. Estimated trajectories of the robot for different experiments, based on SLAM.

Due to the continuous movement of the robot, only one tag is measured at a given location. In order to apply the fingerprinting localization algorithm, we group all measurements collected within 5cm robot-displacement; these are considered as measurements collected by the same antenna-location. During the different experiments, the robot moved with 5cm/s to 20cm/s, achieving a measured mean read-rate of 245 tags/s (the read-rate depends on the tags' population, since a slotted ALOHA protocol is deployed). Therefore, the mean number of measured tags per considered antenna location ranges from 61 to 245, depending on the robot's speed. As the number of tags within the read-range of the reader was much smaller, each tag was measured multiple times per antenna location. The mean of the measured back scattered power for each tag is calculated.

The fingerprinting algorithm was applied in each experiment, using a set of different values for each optimization parameter, in order to find those that achieve the best location-estimation of the tracked tags. It was found that for each different path or speed of the robot, a different selection of the three optimization parameters minimized the localization error. This property is illustrated Figs. 4-5, where x-axis represents the different experiments and y-axis the best value of one of the three optimization parameters for the corresponding experiment.

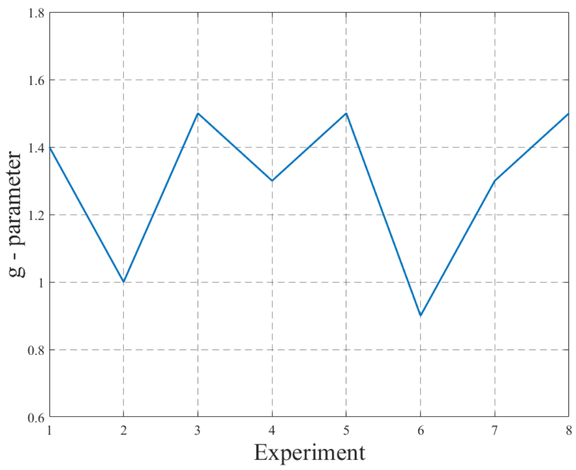

Fig. 4. g-parameter variation among different experiments

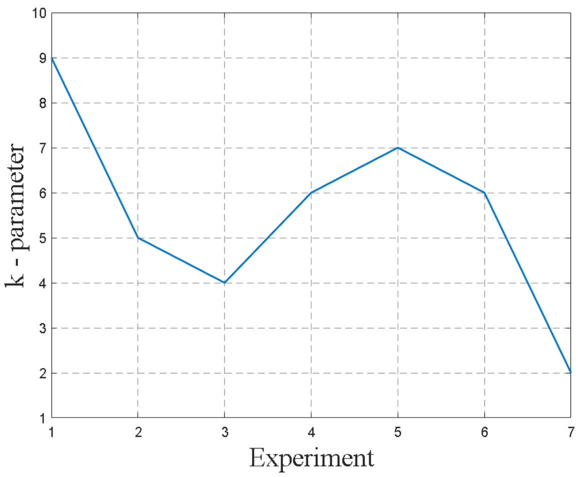

Fig. 5. k-parameter variation among different experiments

Considering the variability of the optimization parameters shown above, there is no optimal selection that is suitable for all cases. Depending on the propagation environment, different selection should be made. It is found that even a small deviation of a parameter from the best value, could lead to 5-10 cm increment of the mean error of the corresponding measurement. Therefore, a method to select the optimal parameters during the measurements is necessary.

We propose the exploitation of the reference tags for this purpose. Since the reference tags are placed on known positions, we propose to *i*) treat the reference tags as unknown tags, *ii*) evaluate their positions, by changing the 3 optimization parameters, *iii*) find the set of parameters that minimized the estimation error of the reference tags and *iv*) apply the same set of parameters (which is optimal for the reference tags) on the tracking algorithm for the unknown tags. Potential success of the method depends on the similarity of ”fading” that is expected to take place for the reference tags and the tracked tags. Carefully notice that when a reference tag is being tracked the population of the remaining reference tags that participate in the estimation is reduced only by one. Hence, for large density of reference tags and similar environment (which is true by definition, since the reference tags are placed in the vicinity of the tracked tags), good agreement of the optimal parameters is expected.

In Fig. 6, we compare the mean localization error of the reference tags vs. the tracked tags by increasing parameter g. Excellent agreement is recorded for $g \in (0.7, 1.4)$; i.e. a large region around the optimal, while the minimum error is recorded for the same value of g.

Another interesting property is revealed. The mean estimation error is similar for the reference and tracked tags. Therefore, by calculating the localization error of the reference tags, we have an excellent estimator of the achieved accuracy for the unknown tags. This idea is particularly important for all applications, since the robot can be instructed to re-scan an area, where poor localization-accuracy has been recorded. The importance of this property is summarized in Table I, where the accuracy of the fingerprinting method for the four experiments, demonstrated in Fig. 3 is given. Even though the robot followed each path with the same speed (5cm/s), a great deviation of the mean error is detected when the distance between the robot and the bench changes. Multipath has changed (systematically) along each route, due to the different geometrical relationship of the antenna of the robot with the wall opposite to the experiments. However, thanks to the proposed method, this deviation of the error is also recorded in the reference tags. Hence, the results of a specific path (”Path 2” in the example) are known to be the most accurate and the localization error is also well estimated. Hence the error is reduced to only 18.53cm with a small standard deviation of 11.17cm. Therefore, in this case, the reference tags are used as the means to select the best estimations among different measurements (as diversity-technique indicator).

IV. Conclusion

In this work, we have presented a fingerprinting localization method, based on comparing the measured backscattered power of target tags with that of reference tags at known locations. The key for the success of the method is

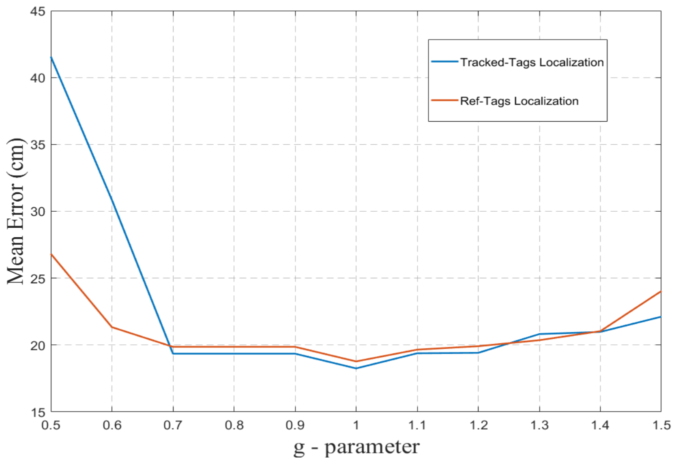

Fig. 6. Localization of Tracked and Reference Tags vs g-parameter

TABLE I
EXPERIMENTAL RESULTS

Robot's path	Robot's speed	Mean Error	Std
Path 1	5 cm/sec	69.89cm	163.55cm
Path 2	5 cm/sec	18.53cm	11.17cm
Path 3	5 cm/sec	24.03cm	18.57cm
Path 4	10 cm/sec	19.42cm	11.87cm
Path 5	10 cm/sec	29.21cm	20.40cm
Path 6	20 cm/sec	19.50cm	12.60cm
Path 7	20 cm/sec	30.32cm	17.42cm
Path 8	20 cm/sec	20.72cm	11.62cm

the proposed exploitation of the reference tags in order to optimally set the parameters of the fingerprinting method. Furthermore, by applying the method on the reference tags, we evaluate the localization accuracy achieved for the tracked tags. This allows for re-scanning areas where poor accuracy was originally recorded, ultimately achieving a mean error below 20cm. As the estimation-time is small, the proposed method can be applied in real-time unmanned inventorying. Further improvements are expected when multiple antennas and multiple frequencies are deployed on the robot, exploiting space and frequency diversity.

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REFERENCES

[1] T. Faseth, M. Winkler, H. Arthaber, and G. Magerl, "The Influence of Multipath Propagation on Phasebased Narrowband Positioning Principles in UHF RFID," *2011 IEEEAPS Topical Conference on Antennas and Propagation in Wireless Communications (APWC)*, Torino, Italy, 2011.

[2] A. G. Dimitriou, A. Bletsas, J. N. Sahalos, "Room Coverage Improvements of UHF RFID with Commodity Hardware,"*IEEE Antennas and Propagation Magazine*, vol. 53, no. 1, February 2011.

[3] S. Siachalou, A. Bletsas, J. N. Sahalos and A. G. Dimitriou, "RSSI-based Maximum Likelihood Localization of Passive RFID Tags Using a Mobile Cart," *IEEE Wireless Power Transfer Conference (WPTC)*, Aveiro, Portugal, 2016.

[4] S. Subedi, E. Pauls, and Y. D. Zhang, "Accurate Localization and Tracking of a Passive RFID Reader based on RSSI Measurements," *IEEE Journal of Radio Frequency Identification*, vol. 1, no. 2, pp. 14454, 2017.

[5] J. Zhang, Y. Lyu, J. Patton, S.C. G. Periaswamy, and T. Roppel, "BFVP: A Probabilistic UHF RFID Tag Localization Algorithm Using Bayesian Filter and a Variable Power RFID Model," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 10, pp. 8250-8259, 2018.

[6] F. Martinelli, "A Robot Localization System Combining RSSI and Phase Shift in UHFRFID Signals," *IEEE Transactions on Control Systems Technology*, vol. 23, no. 5, pp. 17821796, 2015.

[7] P. Yang, and W. Wu, "Efficient Particle Filter Localization Algorithm in Dense Passive RFID Tag Environment," *IEEE Transactions on Industrial Electronics*, vol. 61, no. 10, pp. 56415651, 2014.

[8] J. Zhou, H. Zhang, and L. Mo, "Twodimension Localization of Passive RFID Tags Using AOA Estimation," *2011 IEEE Instrumentation and Measurement Technology Conference (I2MTC)*, Binjiang, China, 2011.

[9] S. Azzouzi, M. Cremer, U. Dettmar, R. Kronberger, and T. Knie, "New Measurement Results for the Localization of UHF RFID Transponders Using an Angle of Arrival (AoA) Approach," *2011 IEEE International Conference on RFID*, Orlando (Fl), 2011.

[10] R. Miesen, F. Kirsch, and M. Vossiek, "Holographic Localization of Passive UHF RFID Transponders," *2011 IEEE International Conference on RFID*, Orlando, Florida, 2011.

[11] L. Yang, Y. Chen, X.Y. Li, C. Xiao, M. Li, and Y. Liu, "Tagoram: Realtime Tracking of Mobile Rfid Tags to High Precision Using Cots Devices," *In Proceedings of the 20th annual international conference on Mobile computing and networking*, pp. 237248, 2014.

[12] L. Shangguan, and K. Jamieson, "The Design and Implementation of a Mobile Rfid Tag Sorting Robot," *In Proceedings of the 14th Annual International Conference on Mobile Systems, Applications, and Services*, pp. 3142, 2016.

[13] Y. Ma, N. Selby, and F. Adib, "Minding the Billions: UltraWideband Localization for Deployed RFID Tags," *MobiCom 2017, 23rd Annual Conference on Mobile Computing and Networking*, Utah, USA, 2017.

[14] L. M. Ni, and Y. Liu, "LANDMARC: Indoor Location Sensing Using Active RFID," Wireless Networks, vol. 10, no. 6, pp. 701710, 2004.

[15] J. Wang, and D. Katabi, "Dude, Where's my Card?: RFID Positioning that Works with Multipath and Nonline of Sight," *Proceedings of the ACM SIGCOMM 2013 conference on SIGCOMM*, pp. 5162, Hong kong, China, 2013.

[16] P. V. Nikitin, R. Martinez, S. Ramamurthy, H. Leland, G. Spiess, and K. V. S. Rao, "Phase Based Spatial Identification of UHF RFID Tags," *2010 IEEE International Conference on RFID*, Orlando, Florida, 2010.

[17] C. Cadena, L. Carlone, H. Carillo, Y. Latif, D. Scaramuzza, J. Neira, I. Reid, and J. J. Leonard, "Past, Present, and Future of Simultaneous Localization and Mapping: Toward the Robust-Perception Age," *IEEE Transactions on Robotics*. vol. 32, no. 6, Dec. 2016.