Distance Estimation versus Fingerprinting Methods for Indoor Localization

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***Abstract*—Different approaches based on various wireless technologies have been proposed so far for indoor localization. Radio frequency Identification (RFID) indoor localization seems to be a promising way of research. The identification capability of this technology combined to localization methods improves the results obtained by other wireless technologies such as Wifi, GPS, Zigbee... This paper details some localization techniques used for RFID Tags localization in Indoor environment. In particular, Fingerprinting methods are compared to Distance estimation methods. We will show through several simulation experiments, using NS2 and Matlab software, that fingerprinting techniques outperform Distance estimation techniques for localization and tracking tasks.**

***Keywords*—RFID technology; Localization; Indoor environment; Fingerprinting.**

I. Introduction

Nowadays, we need to localize and identify objects and things in a precise way and within a short time. Localization difficulties appear when we have to locate an object in indoor environment (inside buildings). This is due to radio propagation channel in indoor environment which is subject to numerous problems such as absorption, diffraction or reflection [1]. Localization and identification in such environments (ie a non-GPS environment) is based on WSNs (wireless sensors networks) technologies such as WLAN, ZigBee, Bluetooth, RFID and more recently UWB [2], [3]. RFID is developed in accordance with a variety of standards by the International Organization for Standardization (ISO) [4]. Its advantage for WSNs is that it offers cheap low power passive antennas that could be considered for operation in smart home environments [5].

Object localization principle for most applications returns to find the position of RFID tags that has been stuck to them in the covered area by RFID readers. Localization techniques use the Received Radio Signal's metrics based on angle of arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA) measurements or received signal strength (RSS) measurements from several Reference Points [6], [2]. The reported signal metrics are then processed by the positioning algorithm for estimating the unknown location.

We can identify three major families of localization techniques Depending on how the signal metrics are used by the positioning algorithm: Distance Estimation, Fingerprinting (ie Scene Analysis) and Proximity [7], [8].

In distance estimation approach the target's location algorithms are based on triangles properties. among these techniques we can mention the well known SpotOn [9]. Fingerprinting methods require an off line phase for learning the RSS behavior within the specific area under study. This signal information is then stored in a database called Radio Map. During the real-time localization phase, the targets unknown location is inferred based on the similarity between the Radio Map entries and the real-time RSS measurements [10], [11]. The main purpose of this paper is to compare between two indoor localization approaches: Fingerprinting and Distance estimation. Different algorithms belonging to each approach have been detailed and implemented: Trilateration, Multilateration and Multidimensional scaling (MDS) for distance estimation while K-nearest neighbours (KNN) and Artificial Neural Network (ANN) were chosen for fingerprinting. Several simulation experiment were achieved, using NS2 and Matlab software, leading to interesting results for localization and even tracking tasks.

The remainder of this paper is organized as follows: we will briefly explain the indoor radio propagation model in section II. Section III describes the principle of the localization techniques considered in this papaer. Then section IV presents and comments the simulation results obtained for the differents methods. At last, conclusion is presented in section V.

II. Indoor Radio Propagation Models

The combined effects of reflection, diffraction, and scattering cause multi-path witch results when the transmitted signal arrives at the receiver by more than one path. So the biggest challenge is how to mathematically model the path loss which represents the variation of the RF signals level in dB between the transmitted and the received power [12]. In this paper we consider the log-normal Shadowing Path Loss model.

A. Log-normal Shadowing Path Loss

The log-distance path loss model assumes that path loss varies exponentially with distance. The log-normal shadowing model attempts to compensate for this, it predicts path loss as given in (1) taking into acount the Shadowing effects that can be caused by varying degrees of clutter between the transmitter and receiver.

$$PL(d) = PL(d_0) + 10nlog(\frac{d}{d_0}) + X_\sigma \quad (1)$$

where n is the path loss exponent which varies depending upon the environment, d is the distance between transmitter and receiver in meters, and d_0 is the close-in reference distance in meters. $PL(d_0)$ is computed using the free space path loss given in (2).

$$PL(d_0) = -10 \log \frac{G_t G_r \lambda^2}{(4\pi)^2 d_0^2} \tag{2}$$

X_σ is a zero-mean Gaussian random variable with standard deviation σ. X_σ attempts to compensate for random shadowing effects. Given the transmission power P_t, the transmitter antenna gain G_t, and the receiver antenna gain G_r, the RSS at distance d, $P(d)$(in dB) can be obtained as

$$P(d) = P_t + G_r + G_t - PL(d) \tag{3}$$

Then from (3) we can estimate the distance d in meters (m) from the measured RSS (P) in (dB) (4).

$$d = 10\frac{c - P}{10n} \tag{4}$$

$$c = P_t + G_r + G_t - PL(d_0) + 10nlog(d_0) \tag{5}$$

III. Localization techniques

A. Multilateration based localization

Multilateration estimates the coordinates of the target node from the distances between the target node and n reference nodes with known coordinates. If the number n is set to 3, we talk about the trilateration based positioning. We denote the reference nodes as $\{R_k; k = 1, 2, ..., n\}$ with known coordinates (x_k, y_k); and the distances between the target node T with unknown coordinates (x, y) and reference nodes as d_k $(k = 1, 2, ..., n)$ [13]. In this work we consider the RFID tag as a target node, and the RFID readers as references ones.

The coordinates of the target tag can be calculated as follow:

$$\begin{pmatrix} x \\ y \end{pmatrix} = (A^T A)^{-1} A^T B \tag{6}$$

where *A* and *B* are calculated using the two equations given in (7) and (8), respectively.

$$\mathbf{A} = \begin{bmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) \\ \vdots & \vdots \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - y_n) \end{bmatrix} \tag{7}$$

$$\mathbf{B} = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_n^2 - d_1^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_n^2 - d_{n-1}^2 \end{bmatrix} \tag{8}$$

B. MDS based localization

In the context of localization the raw data entering into an MDS analysis are the inter-tags euclidean distances and the outcome are the estimated RFID tags positions. Note that the inter-tags distances are obtained from the tag to reader distances using a triangular method [14]. The classical MDS algorithm steps are summaried in the following steps:

- Set up the matrix of squared proximities $P^{(2)} = \left[P^2\right]$
- Apply the double centering: $B = \frac{-1}{2} J P^{(2)} J$ using the matrix $J = In^{-1}11'$, where n is the number of objects.
- Extract the m largest positive eigenvalues $\lambda_1 ... \lambda_m$ of B and the corresponding m eigenvectors $e_1 ... e_m$.
- A m dimensional spatial configuration of the n objects is derived from the coordinate matrix $X = E_m \Lambda_m^{1/2}$, where E_m is the matrix of m eigenvectors and Λ_m is the diagonal matrix of m eigenvalues of B, respectively.

P is a distance matrix, and m is fixed to 2 to get a two dimensional position. Finally the readers are used as anchors to calculate the absolute coordinates based on linear transformations and rotations.

C. KNN based localization

Landmarc system [10] suppose n RF readers with m tags as reference tags and u target tags. The unknown target tags coordinates (x, y) are obtained as the sum of the weighted coordinates (x_i, y_i) of th k nearest reference tags as shown in (9):

$$(x, y) = \sum_{i=1}^{k} w_i.(x_i, y_i) \tag{9}$$

The weighting factor w_i is defined by (10), where E_i refers to the Euclidian distance between the received signal strength of the reference tags and the target tags:

$$w_i = \frac{\frac{1}{E_i^2}}{\sum_{j=1}^{k} \frac{1}{E_j^2}} \tag{10}$$

D. ANN based localization

Lieckfeldt et al. [15] propose a three layered neural network as part of a system process design as shown in Fig. 1. 69 passive transponders are placed on the ground of a 5x 8 m room, and 4 RFID reader antennas. The sensor data is regarded as the input of the perceptron. and the output layer should provide a two-dimensional user position. The neurons of the second and third layer are calculating their output due to:

$$Output = transf(Wxinput + B) \tag{11}$$

W is the vector of weightings and B is the vector of bias values.

The optimal weights's values used to estimate the unknown tag location in the real-time (test) phase are fixed from the off line (learning) one, such that the estimated reference accuracy is maximal.

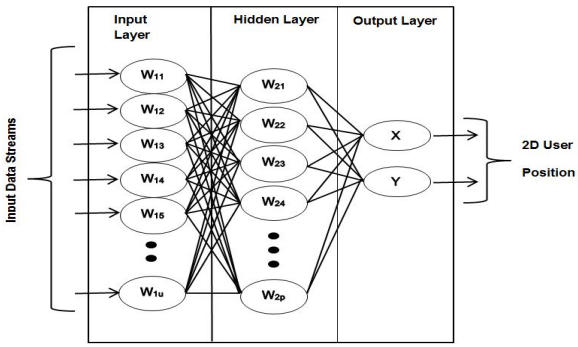

Fig. 1: Perceptron structure

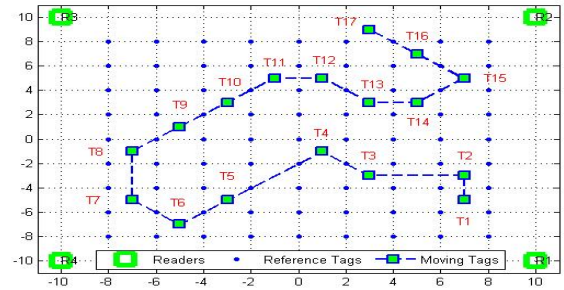

Fig. 2: System Configuration

IV. SIMULATION RESULTS

A. System setup

In order to evaluate the localization accuracy, we have implemented 5 algorithms: three belonging to Distance estimation approach (Trilateration, Multilateration, MultiDimensional Scaling) and two belonging to Fingerprinting approach (K-Nearest Neighbours, Artificial Neural Network).

Inputs for the different algorithms are RSS, that we generated with NS2 software, using shadowing propagation model pointed up in (3). The model parameters are the following: Power transmission $Pt = 2$Watts, frequency used $f = 900$Mhz, reference distance $d_0 = 1m$ and Gaussian standard deviation σ=2.5. Then, we have constructed a simulation environment constituted of a 20mx20m squared area. Four readers are placed at the corners and 81 reference tags are distributed in a uniform way over the area spaced by an inter reference tag distance of $2m$. We have also generated 17 targets to be localized with known coordinates as shown in Fig. 2. The targets are positioned along a winding opened trajectory.

For ANN, a MultiLayer Perceptron (MLP), with an input layer, one hidden layer with 5 neurons and an output layer of two neurons representing the 2D position of the tags was trained. For the learning phase, a matrix of reference tags RSS, noted $\{Ri; i = 1, 2, .l\}$, constitutes the entry of the input layer. The dimension of Ri is related to the number of readers. We have generated 5 RSS vectors Ri for each reference tag; So the dimension of the matrix l is equal to 5* number of tags. Last, 8 neighbours are fixed for KNN algorithm.

Evaluation criteria used in this work are localization error rate (ER) and global localization error rate (GER) given respectively by (12) and (13):

$$ER(m) = \sqrt{(x - \hat{x})^2 + (y - \hat{y})^2} \tag{12}$$

$$GER(m) = \frac{1}{n} \sum_{i=1}^{n} ER(i) \tag{13}$$

Where (x, y) are real positions and $(\hat{x}, \hat{y})$ estimated positions over N simulations with N=100. Both ER and GER decrease when accuracy is improved.

B. Performances evaluation

1) Evolution of ER and GER: From Table I, the biggest value of ER is obtained for Trilateration (Tag 15) and the lowest one for ANN (Tag 6).Table I gives also the GER (which is the mean of ER) and the standard deviation of ER for each method; We can note that GER (mean of ER) is decreasing from Distance Estimation methods to Fingerprinting methods which means that ANN and KNN accuracy values are more homogenous. This is confirmed by the values of standard deviation of ER (Std ER): ANN and KNN standard deviation are lower; Thus, ER for these methods is less scattered, leading to the conclusion that accuracy is then independent from specific tags positions.

TABLE I: ER and GER Evolution

	Distance Estimation Techniques			Fingerprinting Techniques	
	Trilat (m)	Multilat (m)	MDS(m)	KNN(m)	ANN(m)
Min ER	2.90	1.34	0.90	0.97	0.88
Max ER	12.38	5.16	4.12	2.43	1.57
GER (m)	**5.27**	**2.56**	**2.50**	**1.20**	**1.06**
Std ER	**2.46**	**1.07**	**0.73**	**0.31**	**0.15**

TABLE II: GER standard deviation through the 100 simulations

Trilateration	Multilateration	MDS	KNN	ANN
0.16	0.28	0.14	0.14	0.12

2) GER variations for different localizations techniques: We have computed GER for 100 simulations. We plotted on Fig. 3. the evolution of GER versus the number of simulations in order to visualize how many these localization techniques are robust against random changes of the received signal power in an indoor environment. The Fig. 3. shows that Trilateration's GER values are higher than those of Mulilateration and MDS's GER but ANN and KNN's GER outcome the others proofing the superiority of fingerprinting. We computed the standard deviation of GER according to each technique, see Table II. The largest standard deviation is found in the case of Trilateration and Multilateration with respectively 0.36 and 0.28. MDS standard deviation is reduced compared with that obtained for Multilateration although both techniques have the same average values of GER through the 100 simulations, which means that among Distance Estimation techniques, MDS is the most robust to environment changes. ANN and KNN with standard deviation of 0.14 and 0.12 show once again their superiority.

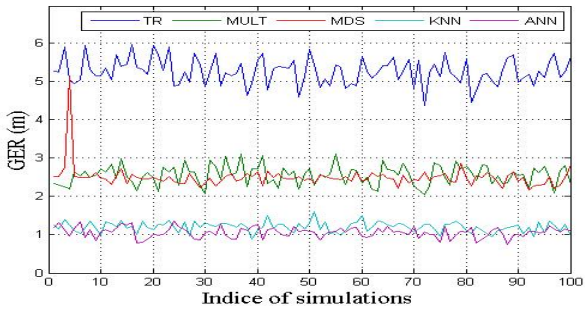

Fig. 3: GER distributions through the 100 simulations

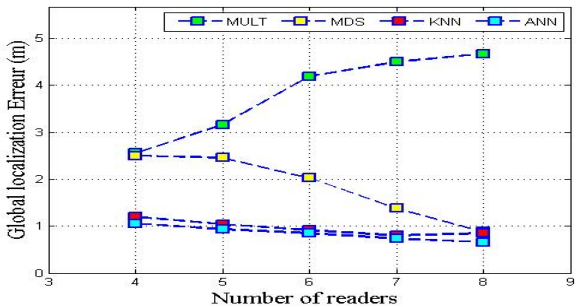

Fig. 4: GER distribution for different numbers of readers

3) GER for different numbers of readers: The simulation results for different numbers of readers are provided in Fig. 4. It can be noted that for all the techniques, the GER improves significantly as the number of readers increases except for Multilateration. When the number of readers is equal to 8, MDS converges approximately to the GER reached by KNN and ANN which is equal to 0.66m, whereas when the number of readers is equal to 4, MDS's GER is equal to 2.5. ANN and KNN's GER allow better results with a reduced number of RFID readers.

4) ANN for trajectory tracking: We simulated on Fig. 5. trajectory tracking by estimating the tag's positions thanks to ANN technique. We plotted on the same figure real positions and estimated ones. We notice that the two paths are approximately superimposed except for the last tag where ER=1.57. The same thing was observed in the case of KNN where ER=2.43; This is due to the reduced number of reference tags deployed around this position as shown in Fig. 2.

V. Conclusion

In this paper we made a comparison study between Trilateration, Multilateration, MDS, KNN, and ANN techniques for RFID Indoor localization problem. These techniques were classified according to their approaches: Distance estimation and Fingerprinting. In the data pre-processing step we used the log normal shadowing path loss model to generate the tag to reader distance and the RSS information. Simulation results shows that: ANN algorithm outperforms the other techniques for localization and tracking although it needs a large deployment of RFID reference tags in the work area. Futur works includes applying Fingerprinting techniques for

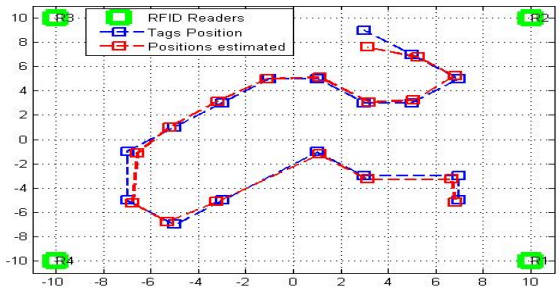

Fig. 5: Comparison between reel and estimated Tag-position using ANN based localization

RFID localization to a large scale system using data collected from a real indoor environment.

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