Preliminary Localization Results With An RFID Based Indoor Guiding System

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Abstract **– This paper reports preliminary work with an RFID based local positioning system (LPS) designed for location and guidance of people and autonomous vehicles in indoor environments. The system consists of an RF reader carried by the mobile user, and a number of active RFID tags, disseminated at known positions in the displacement region, which regularly emit RF signals with an identification code. Upon reception of a signal, the range of the user to the corresponding tag is estimated indirectly from the received signal strength (RSSI), using a previously obtained statistical model. A computationally efficient Bayesian localization method (particle filter) is used to process the measurements and produce an estimation of the user's position. The RFID-LPS is tested empirically in a displacement region comprised of three adjacent rooms, with a total area of 250 m^2, in which there are placed 21 tags. Our first results show a typical mean positioning error of 3.25 m, which compares favorably with other systems reported in the literature.**

Keywords **– Local positioning systems, RFID localization, particle filters**

I. Introduction

Knowledge of the position of people or mobile objects inside of buildings is fundamental in a variety of applications, which include assistance to people with disabilities, navigation of autonomous vehicles and robots and location-aware systems. One example is a localization system which can track and guide a person (possibly with a displacement disabilities or a difficulty for spatial orientation) in an unknown environment, like a hospital, a transport station, etc.

As it's well known, the GPS system was designed for outdoor localization, and will not usually work indoors. However, a much varied set of alternative Local Positioning Systems (or LPS) have been developed over the years, based in technologies like artificial vision, ultrasonic or sonic signals, infrared, and, with a growing importance, Radio Frequency (RF) signals [1], [2]. Belonging to this last category, many different possibilities have been explored: WiFi, Bluetooth, Ultra-WideBand (UWB), Radio Frequency Identification (RFID), etc. It should be noted that all these technologies (with the obvious exception of GPS and UWB, which permit direct measurement of the signal propagation times) were designed for digital communication rather than for localization purposes.

RFID systems, which provide easy, multiple reading of the tag's identification codes and an indirect estimation of their range to the receiver through the perceived signal strength (RSSI) are becoming very popular for many applications. Its advantages include not requiring wiring or line-of-sight to the reader, a relatively long read range (with active tags), an easy deployment of tags, with minimum infrastructure modification, a capability to remain operative in harsh environments, and an overall low cost. Besides, RFID has quickly become a mature technology, with a high degree of penetration in the market.

A. Introduction to RFID technology

Radio-frequency identification (RFID) is an identification method, based on storing data on an electronic data-carrying device (called a tag), and remotely retrieving it by wireless interrogation [3].

An RFID system consists of two components: readers and tags. Readers retrieve information from the tags with radio signals, and, depending on the technology, may also write information to them. The tags are a set of small devices attached to or incorporated into a product, animal, or person whose identification is desired. Tags might be passive, requiring no internal power source and transmitting an RF signal only when interrogated by the reader, or active, operating from its own power source and transmitting their identification signals at a fixed rate. The detectable range of passive tags is of a couple meters, while active tags might reach up to a hundred meters.

RFID (also called transponder) systems appeared around the Second World War, and were designed for military purposes. Nowadays, RFID technology is used for a multitude of applications: embedded in identification documents like passports, for transport toll controls, car keys, for animal identification, and in general for any application requiring automatic tracking and localization.

B. Objectives

This paper reports preliminary results with a long-range active RFID-based localization system. We want to determine the influence on localization accuracy of parameters like the tag distribution, statistical models of range-signal strength, and the attainable precision of Bayesian localization methods.

This paper is organized in the following way. Section II contains a review of the state of the art of systems similar to the one presented in this work. A basic framework of the Bayesian localization method is offered in section III, along with a particle filter implementation. In section IV we deal with the experimental setup and the calibration measurements carried out in order to find a statistical model for position estimation. Realization and analysis of experiments are discussed in section V. Closing the article, we present some conclusions about RSSI based RFID location, as well as future work lines and improvements.

II. State of the art of RSSI-Based localization

Many works related to RF localization based on measurement of the received signal strength are reported in the literature. Most of them utilize existing radio platforms (usually employed for wireless networking) with capacity of measuring RSSI, although recently RFID technology is becoming popular due to its low cost and ubiquity.

In the Radar system, developed at Microsoft Corp. [4], the mobile user emits RF signals (using a WaveLAN wireless link), which are received at three stations placed at known locations. The mobile position is determined by comparison of the received RSSIs with a set of previously stored calibration data (a fingerprint map of the floor at 70 different points). Two approaches for position estimation are offered: using an empirical database, or a model of RF propagation in the floor inferred from it. The median errors are, respectively, 2.9 and 4.3 m, in a floor area of 980 m^2, consisting of 50 rooms.

The VOR system [5] shares a similar design with RADAR, but estimates angles instead of ranges to the base stations, and does not require a previous signal map of the displacement region. The floor has an area of 1400 m^2, and a median error of 2.1 m is achieved with only 5 base stations. One serious shortcoming of the VOR design, for practical applications, is that the antenna of the mobile emitter must be constantly turning (much like a radar system), in order to achieve angular exploration.

Instead of IEEE 802.11 (WiFi) technology, the Landmarc system described in [6] uses RFID reference tags distributed rather densely in the environment (16 tags in a 40 m^2 area), and 4 readers. The position of the moving user, which carries a tag himself, is found by comparing the Euclidean distance between the set of RSSI measurements (obtained at all receivers) with those coming from the reference tags, and use of a weighted mean. The median positioning error is reported as 1 m, although the displacement area is much smaller than the above mentioned systems, and consists of a single room.

A simultaneous localization and mapping (SLAM) system for robot navigation based on RFID tags is presented by Haehnel *et al* [7]. The mobile robot carries a pair of patch (directive) antennas with which it can determine the range and angular position of detected tags relative to its current pose. The range-angular dependence of the RSSI is modeled statistically, and then a Bayesian filter is used for position estimation. The system is tested in a 780 m^2 environment with 100 low range, passive reference tags at known locations. The robot's location is estimated with a typical error of less than 2 m, by combining the range measurements with data obtained with odometry.

The approach followed in this paper combines elements from these previous works, including RSSI-based estimation of range, Bayesian localization and use of multiple tags in the environment, to explore the accuracy limits of long-range active RFID technology operating at 433 MHz (with relatively low fading and high penetration capability) for indoor localization.

III. Bayesian localization method

The propagation of RF signals in indoor environments is difficult to model exactly, due to multiple reflections, existence of obstacles, propagation through walls, etc. In consequence, the relationship of signal strength (RSSI) with range is not deterministic, but subject to much variation. Probabilistic (Bayesian) localization methods naturally take into account this variability and, in principle, permit accurate estimation of location from a set of numerous, but inaccurate, measurements [8].

In Bayesian localization schemes, the estimation of the current location of the user at time t, x_t, is represented by a probability distribution $Bel(x_t)$, called the *Belief*, which is based in the set of all past sensor measurements $z_1, z_2, \ldots, z_t$ obtained up till time t. The belief corresponds then to the conditional probability:

$$Bel(x_t) = p(x_t|z_1, z_2, \ldots, z_t). \tag{1}$$

Bayes localization estimates the mobile object location in two stages, called respectively the prediction and the correction steps. In the prediction step the estimated position is extrapolated from previous data, without actually taking a measurement. Bayesian localization schemes often use the Markov assumption, according to which the current location x_t is completely determined by the previous location x_{t-1}, and disregard all past position estimated. So, the belief at time t, $Bel(x_t)$ is calculated as:

$$Bel^{-}(x_t) = \int p(x_t|x_{t-1})Bel(x_{t-1})\,dx, \tag{2}$$

where the minus sign stands for the *a priori* probability (meaning that is computed before taking into account the sensor measurement), and $p(x_t|x_{t-1})$ is a motion model which represents our estimation of where the user might be at the next time interval. For example, if we know that the maximum displacement velocity of the user is v, the motion model might be the region contained within a circle of radius $v \cdot \Delta t$ around the current position, assuming that Δt is the interval between consecutive measurements.

Following the prediction stage, the correction step matches the computed estimation of position with the newly received sensor measurement, z_t. By the Bayes rule, the posterior probability is found by multiplying the prior probability $Bel^{-}(x_{t-1})$, with the observation model $p(z_t|x_{t-1})$:

$$Bel(x_t) = a_t p(z_t|x_{t-1})Bel^{-}(x_{t-1}). \tag{3}$$

The observation model $p(z|x)$ describes the probability of receiving measurement z when the user is standing at position x. This model is generated empirically from a large set of empirical measurements obtained at different locations in the workspace. In equation 3, a_t is a normalization constant such that the integral of the probability distribution over all possible positions is unity.

Equations 2 and 3 are applied consecutively each time a new measurement is available to refine the current estimation of the user's position.

Within the generic frame of Bayesian methods, many different practical implementations exist (Kalman filters, multiypothesis tracking, the grid-based approach, the topological approach, the Monte Carlo filter, particle filter, etc) [8]. In this work we have decided to use a particle filter technique, whose details are discussed in the next section.

A. Particle Filter

A Particle Filter method was applied for position estimation, since it is an efficient technique which reduces computation requirements by focusing in the area with higher position probability [9]. Particle filters approximate the belief by a discrete set of N points (called particles):

$$Bel(x_t) \approx \{(x_t^i, w_t^i)\}, \quad i = 1, \dots, N, \tag{4}$$

where x_t^i is the location of the *i*-th particle at time t, and w_t^i is a nonnegative weight called the *importance factor* of the *i*-th particle, that approximates the distribution probability at position x: $w_t^i \simeq P(x_t^i)$. As before, normalization ensures that the sum of weights for all particles is unity ($\sum_i w_t^i = 1$).

In this project, the measurements z consist in the RSSI values of the radio signals received by a reader, carried by the user, and coming from nearby RFID tags. The observation model $P(\text{RSSI}|r)$ links this RSSI value with the range r to the tag from which the signal originated. From this, the weight factors are assigned to particles as a function of their relative range to the detected tag:

$$r^{ij} = \|x^i - y^j\|, \tag{5}$$

where x^i is the position of the *i*-th particle, and y^j is the position of the *j*-th tag.

Initially, it is assumed that the particles are distributed randomly and uniformly all over the environment and all weights are equal to $1/N$, since the prior location probability $P(x^i)$ is unknown.

Following the steps of the Bayes filter, the posterior probability, or weight, of all particles is updated whenever a new measurement of the RSSI is received, using the prior probability (i.e., the previous weight) and the observation model:

$$P(x_t^i|\text{RSSI}_t^{1:m}) = a_t \prod_{j=1}^{m} (P(\text{RSSI}_t^j|r_t^{ij}))P(x^i), \tag{6}$$

where $P(x_t^i|\text{RSSI}_t^{1:j})$ is the probability of the being situated at the position x^i when we receive the measurements $\text{RSSI}^{1:m}$, m is the number of measurements received, and $P(\text{RSSI}_t^j|r_t^{ij})$ is the probability of receiving the value RSSI from the *j*-th tag which, at this particular time is situated at distance r^{ij} from the particle. A normal probability distribution is assumed for the signal strength RSSI at a given range, as we will see in the next section.

After the weights of the particles are updated with the Bayes equation, a new estimation of the person's location can be calculated by the weighted mean:

$$\widehat{x}_t = \sum_{i=1}^{N} w_t^i x_t^i. \tag{7}$$

This simple estimation can be modified to contemplate the possibility of multiple hypotheses of the position estimation.

In the interval between receiving a new set of RSSI measurements, the prior position probability is updated with the prediction step, which incorporates the available information on the motion of the user. In this work we have used a simplistic motion model which assumes that at time t, the person might be at any point within a circle of radius 2 m from the previous position (time $t-1$). The prediction step is achieved by resampling the set of particles which represent the previous belief, generating a new distribution $\{(x^i, 1/N)\}$, again with equal weights but nonuniform spatial density.

Resampling is done as follows. A fraction $0.1N$ of the new particles are placed randomly within a circle of 2 m around the current best estimation of the person's position (as given by equation 7). The biggest fraction of the particles, $0.8N$, are placed in circles of radius 2 m around the highest weight particles of the last estimation, in a number proportional to their previous weight $N_i \simeq 0.8Nw^i$. Finally, and as a precaution for the possibility of failure of the estimation, the remaining $0.1N$ particles are dispersed randomly and uniformly in the work area. The resampling of the particles is done in a physically sensible way; for example, a point which is within the 2 m radius from the original particle but separated from it by a wall is not eligible as a resampled particle position.

In our tests we have found that resampling every $m = 6$ measurements of RSSI, with a sample set of $N = 1000$ particles, offers a good compromise between precision and computation time. It should be noted that this particular resampling procedure is one of many existing alternatives for the implementation of the prediction step. The resampling process is recognized as one of the critical parts of particle filters, and is usually fine tuned depending on the the characteristics of the sensor model and the environment [10].

IV. System Setup and Generation of the Observation Model

A. RFID equipment's characteristics

The localization and guiding system is built around a commercial RFID equipment acquired from Wavetrend, with the following features: operating frequency of 433 MHz, high read range (up to 140 m), measurement of RSSI, ability to read multiple tags (up to 243 tags per second), serial port connection and low level programming capability. The received RSSI given by the reader varies between 60 and 135, in arbitrary units. The system operates with active tags, which transmit their ID code at intervals of 1.5 s (set in factory); they have a mean life of 5 years, and are relatively small ($85 \times 70 \times 9$ mm and a weight 25 g). These tags are easily attached to walls and furniture in the environment, as shown in figure 1. The reader incorporates an omnidirectional (stub) antenna, seen in figure 2.

B. Placement of the RFID equipment in the environment

Before the localization tests, we thought that it was necessary to investigate the optimal placement of the tags in the area and how it influences the received signal strength. For this reason we performed tests about:

- The placement of the RFID tags in the environment.
- The placement of the RFID reader on the human body.

Executing the first of the above tests, we tried three different positions: in the wall at a height of 2 m, in the angle between the ceiling and the wall, and finally in the ceiling. We received stronger signals in the position of 2 m on the wall. Testing the position of the reader on the human body, we also tried the three following positions: in the chest, in the back, and at a side of the body at the level of the hip. We studied the variation of signal RSSI standing at a fixed point and turning around 360 degrees. Our data shows that the relative body position has less influence over signal strength when the reader is placed at a side, as shown in figure 2. This is the configuration chosen for the remaining experiments.

Fig. 1. Placement of the RFID tags on the walls at a height of 2 m.

Fig. 2. Placement of the reader at the side of the human body at the hip level.

C. Generation of the Observation Model

The observation model quantifies the likelihood of receiving a given RSSI value while standing at a given range r from a tag. It is generated experimentally from a large set of experimental measurements obtained at different points in the displacement region. In this work, we stood at 101 different random points within the work area shown in figure 3, and at each of them we collected 200 different readings, obtaining a good sampling of all tags within reach. Based in these 20200 measurements we calculated the observation model, a part of which is shown as histograms of figure 4. The range r between receiver and tag was divided in discrete steps of 2 m spanning a distance from 0 to 32 m.

In each room, we were able to receive RF signals from tags placed nearby in adjoining rooms (this non requirement of direct line-of-sight between emitter and receiver is one of the advantages of RF-based localization systems). Actually, we observed that one third of the receptions came from tags in a different room, with usually lower amplitudes (a drop of 20 RSSI units was typical). For this fact, we thought that creating a different observation model for RSSI measurements

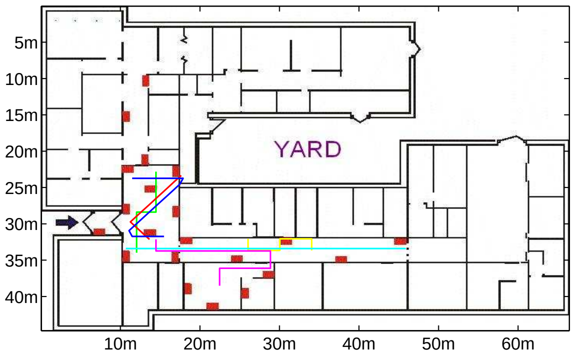

Fig. 3. Floor plan of the main building of the Institute of Industrial Automation used for the experimental tests. The red points represent the tag positions. We show the six routes used for experimental tests (route 1: green, route 2: blue, route 3: red, route 4: cyan, route 5: yellow, route 6: magenta)

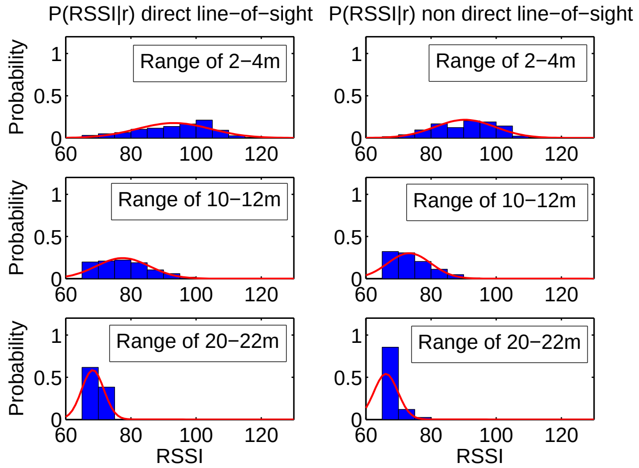

Fig. 4. Observation models $P(\text{RSSI}|r)$ for tags with LOS to the reader (left column) and with NLOS (right column). The raw data is shown as histograms, and the fitted normal distributions as red lines. The complete models consist of 16 different ranges of 2 m, of which three samples ($r = 2-4$, $10-12$ and $20-22$ m) are shown.

coming from tags in the same, or a different room could improve the position estimation. For a given range between reader and tag, a normal distribution was fitted to received RSSI values (red curves in fig. 4). The purpose of this is using smoothed out values for the probabilities, and also, a computational simplification of the observation model. In the tests in the next section, we will compare these different versions of the observation model.

V. Localization Experiments and Results

A. RFID-LPS deployment

The experiments were executed in the main building of the Institute of Industrial Automation (CSIC) (figure 3). In the experiments reported in this paper, the displacement of the user took place in the reception hall of the building (dimensions 12.4 m × 7.8 m), a long corridor (28.7 m × 2.55 m) and one of our labs (11.5 m × 6.8 m). A total of 21 tags (shown as red marks), were deployed in the work area: 1 tag in the entrance, 11 tags in the hall (3 of them in a short corridor to one side), 5 tags in the long corridor and 4 tags in the lab. Most of the tags were placed on the wall at a height of 2 m, although a few were on the ceiling at a higher height. In all experiments the user displacement took place in areas covered by tags. In the experiments data collection was done with a PC laptop, connected to the RFID reader through the serial port.

B. Paths in the building

In order to test our localization system, we executed 6 common routes in our building (see figure 3), all of them in both directions. Three of them were contained in the reception hall; another two in the long corridor, and finally, a sixth route began at the hall, crossed over to the corridor and finished at our lab.

In the tests, the computer recorded the received tag ID, the measured RSSI, the coordinates of the measuring point (we found the regular floor tiling useful for that purpose), and a time reference from the internal clock. Offline, after collection of all these measurements was completed, we applied the particle filter algorithm described in section III. Tests were done in real conditions, with people walking in the room and even approaching the user.

Some samples of the comparison between the real and estimated paths are shown in figures 5 to 7, for three of the six routes, while numerical results for all of them are offered in table I. The table shows data of estimations the two-part model (which distinguishes between LOS and NLOS), and using a normal probability density for RSSI or directly the probabilities from the collected histograms.

C. Localization results and discussion

The best results were obtained with the routes entirely contained in the hall (routes 1 to 3), although measurements from tags in the other rooms are considered nonetheless. The mean positioning error oscillates between 2.3 m and 3.1 m. For example, the estimation of the route 1, in both directions, is shown in (figure 5). We must state that the Bayesian filter has no a priori knowledge of the initial position of the person. From these results, it is seen that the route of a person can be tracked reasonably for navegation purposes.

When the route goes through several rooms, the positioning errors often increase, as shown with route 4 in figure 6 and route 6 in figure 7. The measured mean errors are 3.9 m and 3.8 m respectively. This is caused by the change between rooms and also by a relatively lower tag density in the corridor. We didn't artificially constrain the displacement area with our previous knowledge of the route, so any room of the work area was possible for the localization algorithm. Although with lower precision, the system is able to trace the trajectory of the user between rooms without problems.

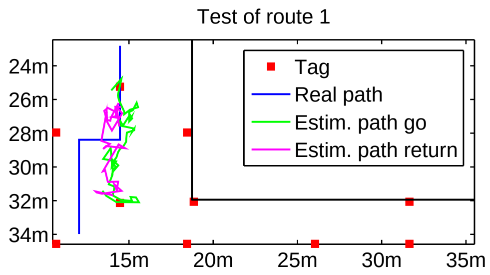

Fig. 5. ESTIMATION OF THE TRUE PATH OF ROUTE 1 (MEAN ERROR 2.3 M).

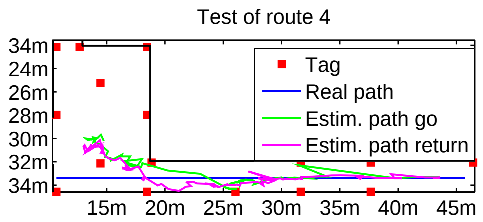

Fig. 6. ESTIMATION OF THE TRUE PATH OF ROUTE 4 (MEAN ERROR 3.9 M).

The results of this section are summarized as a mean estimation error of 3.25 m in an area of 250 m^2, using a total number of 21 tags. The position estimation accuracy is increased when normal distributions are fitted to the raw data (histograms) of the observation model, and also if different models are employed for tags with and without LOS to the reader. However, more refinement in this area is needed.

VI. CONCLUSIONS & FUTURE WORK

This paper has presented preliminary results with a long-range active RFID-based local positioning system (LPS) designed for the guidance of people or autonomous vehicles like wheelchairs in the interior of buildings. The first results with the system show a position estimation accuracy of 3.25 m (mean error) in an area of 250 m^2. Although precision deteriorates at some points, the algorithm is able to follow the real route of an user though different rooms, permitting the development of a guiding system in the future.

The density of tags at critical areas needs to be studied with

TABLE I.

POSITION ESTIMATION ERRORS FOR ALL ROUTES, WITH THE SINGLE PART MODEL, THE MODEL THAT COMBINES LOS AND NLOS, AND THE SAME MODEL USING NORMAL DISTRIBUTION FUNCTIONS.

Route	Mean error (m)		
	Single	LOS and NLOS	Norm. distrib.
1	1.5 m	1.4 m	2.3 m
2	6.7 m	6 m	3.1 m
3	7.91 m	5.9 m	2.6 m
4	5.1 m	4 m	3.9 m
5	7.2 m	6.65 m	3.8 m
6	3.3 m	2.5 m	3.8 m
All	5.3 m	4.4 m	3.25 m

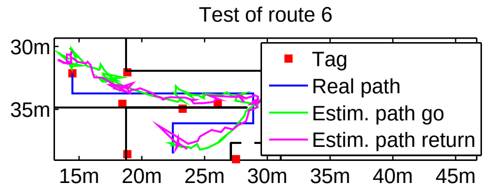

Fig. 7. ESTIMATION OF THE TRUE PATH OF ROUTE 6 (MEAN ERROR 3.8 M).

more detail. Also, better implementations of the particle filter (with respect to computation time and use of resources) have to be implemented in order to achieve real time guidance with a modest processing device (like a PDA).

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