COMPARING DETERMINIST AND PROBABILISTIC METHODS FOR RFID-BASED SELF-LOCALIZATION AND MAPPING

Younes Raoui[1,2,3], Michel Devy[2,3], El Houssine Bouyakhf[1] and Fakhita Regragui[1]

[1]*Faculty of Sciences, University Mohamed, V-Agdal Rabat, Morocco*

[2]*CNRS, LAAS, 7 avenue du colonel Roche, F-31077 Toulouse Cedex 4, France*

[3]*Université de Toulouse, UPS, INSA, INP, ISAE, UT1, UTM, LAAS, F-31077 Toulouse Cedex 4, France*

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Abstract: This article deals with Simultaneous Localization and Mapping for an indoor robot equipped with a camera and RFID antennas. RFID tags are sparsely disseminated in the environment. First RFID-based self-localization is considered; the robot position is predicted from odometry; it is corrected first by a sequential Monte-Carlo localization based on a particle filter. An active strategy built on the theoretical basis of information entropy is applied in order to improve the position accuracy. Then two methods for RFID-based mapping are described, considering the robot pose is given from natural visual landmarks learnt by a classical visual SLAM function.

1 INTRODUCTION

Roboticists must make more efficient and safe the navigation of a robot in complex and dynamic environment like shopping centers or airports. This work concerns the design, implementation and evaluation of a trolley robot that must learn advanced behaviors so as to assist a user when doing shopping in a commercial center. Missions are defined in terms of trajectories that the robot will execute using robust control behaviours. Trajectories and robot positions are expressed with respect to metrical representations of the store. At each time instant, the robot requires to know its position $(XY\theta)$ coordinates so that it can reach its objective with a high accuracy. In (Raoui et al., 2009), two RFID-based methods are compared to deal with a two-steps localization strategy, considering either tags merged on the ground (RFID barriers) or disseminated on shelves.

This paper focuses first on the self-localization from a known RFID map, and then on the construction of this map. Self-localization is first based on RFID tags considered as landmarks. So we equip our robot with RFID antennas and at the same time we place RFID tags in the environment. Two approaches are compared, either deterministic based on Kalman filtering, or stochastic based on the Particle filtering. The latter one is more realistic because it takes better into account uncertainties. Then, we propose a technique to enhance the location information with data of antennas which don't have observations Secondly, we use visual landmarks for localization. Besides, in each part, we show the results of robot navigation on a predefined map.

Then mapping is considered only for RFID tags; it is assumed that vision-based SLAM is executed using classical methods in order to learn visual landmarks (Davison et al., 2007). By applying the model perception of the RFID antennas, we estimate the position of tags assuming that the robot is located from visual SLAM. We propose two algorithms, deterministic and probabilistic, which construct a map with RFID tags.

This paper is organized as follows. After discussing related works, we will present the metrical method for self localization in section 3. Then we describe stochastic localization with par- ticle filter. In section 5, we describe how we can localize our robot with visual landmarks using the Pinhol camera model. Finally, we present a deterministic and bayesian methods for mapping with RFID tags.

2 RELATED WORKS

Trajectory can be estimated by using low cost passive RFID tags and odometry in unknown environment. This is a prerequisite for mapping RFID with

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particle filters approach without any other positionning systems. This method avoids the noisy nature of RFID measurements and the absence of distance and bearing information as it is based on a non-parametric model for spatial relationships between RFID measurements. One of the first surveys of localizing a mobile robot via RFID was developed by Hanel et al. (Hahnel et al., 2005). They used a probabilistic sensor model for their RFID reader, in order to express the probability of tag detection from the relative position between the tag and the antenna. This model is exploited to map the positions of passive RFID tags, considering that the robot has already learnt an environment model from a laser based FastSLAM function (Montemerlo et al., 2002). Finally, given the RFID-based map, the robot was finally able to localize itself with only RFID and odometry; tags positions are represented by a number of particles, and weights are updated at each detection of the tag. Another set of particles is used to represent the robot pose according to the MonteCarlo localization.

Kleiner et al (Kleiner et al., 2007) have performed trajectory correction and GraphSLAM with sparsely spread passive transponders. Other works have exploited active RFID tags. For example, Kantor et al (Kantor et al., 2003) used EKF for localization, mapping and SLAM. They exploit measured signal strength received from transponders in order to measure the robot-tag distance, but such a measurement is not available for passive RFID systems. Yamano et al (Yamano et al., 2004) examinate how Support Machine Vector could learn robot localizations. This is applied by generating feature vectors from the signal strength information acquired with active RFID tags. Ziparo et al (Ziparo et al., 2007) used RFIDs to coordinate a team of robots for an exploration in unstructured areas.

Several authors combine vision and RFID based sensing. Chae et al (Chae and Han., 2005) computed a weighted sum of the currently detected tags positions; then the robot was localized at a finer scale by monocular vision involving SIFT features. Tsukiyama et al (Tsukiyama., 2003) developped a simple navigation mechanism on the basis of vision for free space detection. RFID tags were considered as labels for the topological robot localization. Recently Zhou et al ((Zhou et al., 2007)) proposed a vision based indoor localization method based on modified active RFID tags; tags were equipped with LEDs which make the recognition much easier.

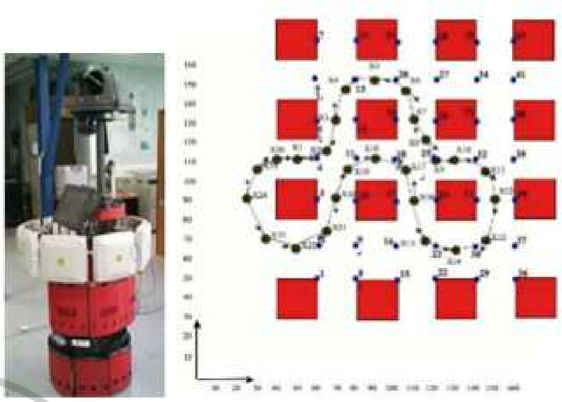

Figure 1: The RACKHAM demonstrator (left); a simulated trajectory (right).

3 METRICAL AND DETERMINISTIC METHOD FOR SELF-LOCALIZATION

We propose an approach for topological navigation based on sparsely distributed RFID tags. The operator sets RFID tags (with known labels) in dedicated places so that when the robot receives the signal from one tag, it knows that this tag is in the reception field of the antenna. The Rackham demonstrator (figure 1(left)) is equipped with 8 directional antennas. Figure 1(right) presents a simulated environment, with a simulated trajectory the robot has to execute: the blue dots numbered from 1 to 42 are RFID tags the positions of which are assumed to be known at this step. The robot starts from the position X_1; its position after a motion between two successive positions X_i and X_{i+1} is predicted from odometry.

The robot model is known so that the odometer delivers motion measurements (u;Q) In the current robot reference frame , with $u = (dx; dy; d\theta)$ and Q the covariance matrix on u. Figure 2 shows the predicted robot position X_i for the simulated trajectory, executed without observation. The odometry errors are cumulative, so that at the end, the robot position prediction has a high uncertainty. This uncertainty can be maintained constant when observing RFID tags, using a stochastic framework that allows to fuse measurements acquired by odometry (in order to predict the robot position from the estimated motions) with other information coming from RFID observations.

Taking into Account Only Observations. Figure 3 describes the different steps of our deterministic method. We analyze these steps between the

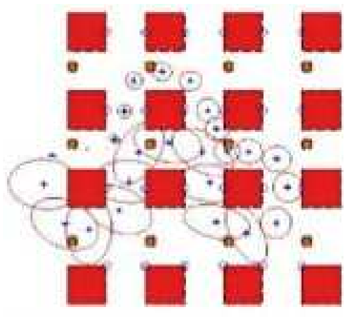

Figure 2: Predicted positions from the robot model (odometry, EKF update of the last estimated position).

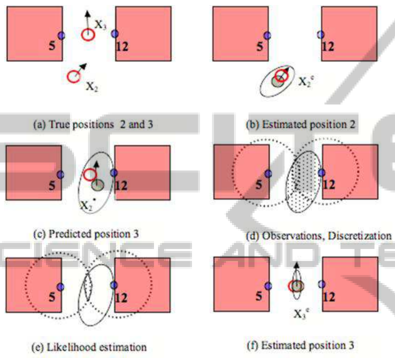

Figure 3: Mixed approach: EKF used to fuse odometry measurements, MLE used to evaluate consistent hypothesis with the RFID observations.

two positions 2 and 3: the true positions are presented in (a). Two tags labelled 5 and 12 will be detected when arriving at position 3. In (b) the estimated X_2^e position is presented with the elliptic uncertainty area in which the true robot position must be with a probability 0.95: this ellipse is computed from the covariance matrix P_2^e on the position vector $(X;Y;\theta)$. In (c), the robot moved from X_2 to X_3, and predicts its new position from the odometry measurements u, thanks to a function F: $X_3^* = F(X_2^e, u)$ The error P_3^* on X_3^* is computed using a linearization of F: $P_3^* = \frac{dF}{dX} P_2^e \frac{dF^t}{dX} + \frac{dF}{du} Q \frac{dF^t}{du}$

In (d) the robot receives RFID signals. If the robot is only equipped with one omnidirectional antenna, when it receives the signal from an RFID located in a position $(X_t;Y_t)$, we can apply a constraint on its position $(X_r;Y_r)$:

$(X_t + X_r)^2 + (Y_t + Y_r)^2 < R^2$

where R is the maximal distance between the tag and the antenna. So without considering the orientation, when the robot receives in X_3, the RFID signals from tags 5 and 12, it means that its true position is located inside the two discs drawn in (d). Using the classical EKF-based framework for robot localization, it is not possible to express such a constraint.

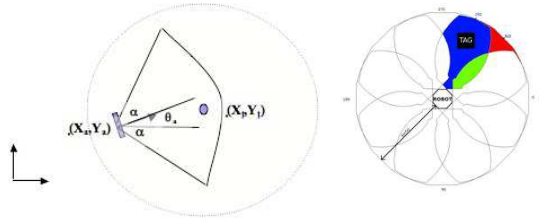

Figure 4: Reception field of one antenna (left). Reception field of eight antennas mounted on a circular robot (right).

Hypothesis on the robot position are randomly sampled from the gaussian distribution (X_3^*, P_3^*) : then the likelihood of each particle is estimated with respect to the observation constraints. In (e) only the particles in the two discs intersection are kept, and finally in (f), the estimated position X_3^e is computed using the barycenter of the acceptable particles, and the uncertainty P_3^e is evaluated from the eigen vectors and eigen values of the cloud of the acceptable particles.

Using only an omnidirectional antenna, it is not possible to update the robot orientation. But if the robot is equipped with several directional antennas, other constraints can be applied on the robot position and orientation from the observation of one RFID tag from one known antenna. Figure 4 presents the calibrated reception fields: antennas receive signals emitted in a 120 deg cone, from less than 4,5 meters. A tag can be received from one, two or three antennas, depending on its position with respect to the robot in the red, blue and green regions. When a tag located in $(X_t;Y_t)$ is received by an antenna located in $(X_a;Y_a)$ with an orientation θ_a with respect to the world frame (see figure 4(right)), it gives two new constraints : the tag must be in the reception field, i.e. in the disk, but also between two straight lines.

Similar constraints can be applied also if a tag is not received. So these constraints are applied in order to estimate the likelihood of a robot position estimate from observations of tags with our RFID reader connected to eight antennas. Figure 5 shows the estimated robot positions and orientations X_i^e with the simulated environment and trajectory.

Filtering Non-observations. The method presented in the previous section, doesn't use the information about antennas of the robot which does not have observations. These information can be integrated to have more precision in the localization. In order to increase such accuracy, we apply the following algorithm on each step of the robot path:

- Computing the robot observation in the current step based on the model of the antennas.
- Finding the particles around each predicted posi-

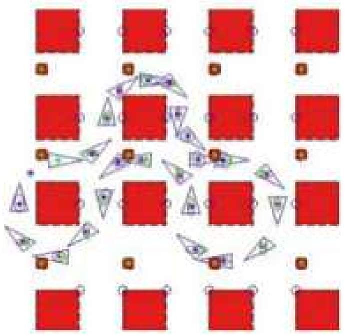

Figure 5: Robot localization at different positions with the computation of standard deviation for x, y, θ.

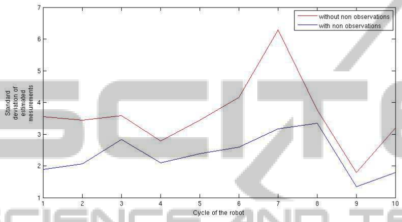

Figure 6: True error on ¡X coordinate for 10 robot cycles, considering non observations.

tion with a covariance of P_y computed in the Kalman update step, that receive the same RFID tags as the observation.

• Considering only the particles that receive the same tags as observation.

• Rejecting particles that receive other tags.

We do statistical measures in order to show how the performances of localization are improved with the non observation operation. For that, we move the robot with different error noises. At each cycle, we compute the standard deviation of measurements (xEst-xTrue) for the case of using non observations or not using non observations. The results are presented in figure 6: errors are decreased when taking into account non observations. Figure 7 shows the distribution of particles on the robot poses.

4 STOCHASTIC LOCALIZATION USING PARTICLE FILTER

The method is based on the particle filter and includes some modifications that improve the localization performance. We consider then the approach based on the modeling of physical properties of the sensor and the observation process. We explain the principal steps of the algorithm and the improvement that we

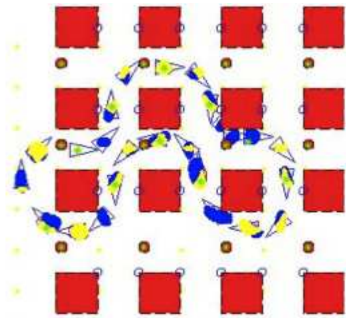

Figure 7: Evolution of the distribution of particles (by consideration of non observations, we keep only yellow particles).

do. First, we initialize the algorithm with a uniform distribution of the positions of our environment if we don't know the first position of the robot; or with a distribution centred on the first position if we know it. Then at each iteration, we apply the following steps((Vorst et al., 2008)) :

- Prediction of the movement :in this step we use the displacement estimated by the odometer and the displacement model for taking the next position in the probability distribution of the next positions. We modify this behavior by taking N_t positions instead of 1 position. We obtain the set M_k and we associate for each particle Mk[i] the probability of $\frac{F_{k-1}[i]}{N_t}$. We obtain then $N_t.N_{sample}$ particles.
- Insertion of random particles : We insert N_{aux} particles uniformly distributed in the environment with an association of a low probability p_{aux}. This step allows a quicker correction if the robot is lost which influences all the generated particles
- Integration of the observations: We change the probabilities of $N_t.N_{sample} + N_{aux}$ points with the measure of the correspondences with observations.
- The resampling step This step takes in entry the precedent points with their new probabilities and generates the final set with taking uniformly N sample particles among them. The probabilities associated to these new particles will be equal each other and equal to $\frac{1}{N_{sample}}$.

We present below the results of the simulation in which 300 samples are used, with the probability distribution of the odometer set to be 3, the number of injected particles set to be 30. Figure 8, presents the aggregation of the first 20 displacements.

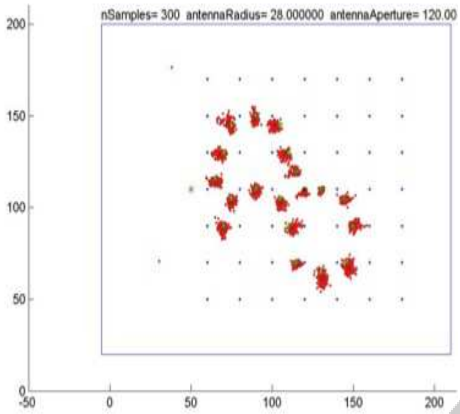

Figure 8: Stochastic simulation, the particles are illustrated with red points.

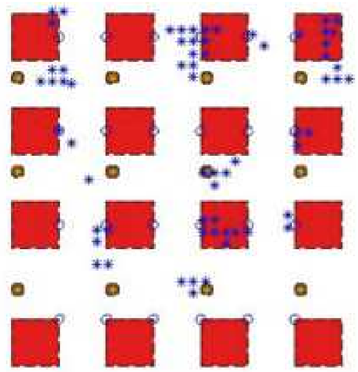

Figure 9: Estimated positions of the tags with blue stars (First algorithm).

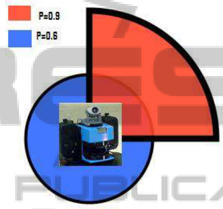

Figure 10: Simplified sensor model for one robot antenna.

5 MAPPING WITH RFID TAGS

RFID-based mapping is processed separately from localization, which means that we perform first localization, obtain the positions of our demonstrator, then we do mapping. Because the RFID-based map is initially unknown, another localization method must be integrated in the robot; it is the reason why a visual SLAM function is integrated on the robot. Considering the robot pose is known, two methods are proposed in order to build the RFID map.

5.1 Deterministic Method

The robot circulates in the environment. At each time it detects a new tag, it reduces its areas of mapping. Supposing it is firstly in the area A, it draws a zone of existence that corresponds to the model of perception of the antennas; after advancing, the new zone is the intersection of the two zones, and so on. We follow these steps until we don't receive any more tag. The algorithm 1 describes this method.

Algorithm 1

for tag $\leftarrow$ 1 to N **do**
  for robot-position $\leftarrow$ 1 to P **do**
    detected-tags = scan(environment)
    if detected-tags $\neq \emptyset$ **then**
      memorize this zone $z_{robot-position}$
      intersect with the precedent $z_{robot-position-1}$
    end if
  end for
end for

5.2 Probabilistic Method

While the robot moves, it verifies whether it receives some tags. If not, it continues until it receives a tag. It discretizes the zone according to the perception model and then, for each particle it verifies if it is received from the past zones. If not, it is discarded. We need to know the posterior $p(x|z_{1:t})$) for each particle. x is the predicted pose of the tag and z1:t represents the data gathered in the time step 1:t. We use the Bayes rule which considers the assumption of independence of consecutive given measurements. We obtain the following recursive update rule : $p(x|z_{1:t}) = \alpha.p(z_t|x)p(x|z_{1:t-1})$, where $p(z_t|x)$ specifies the likelihood of the observation z_t given the pose x of the tag relative to the robot pose. Algorithm 2 describes the different steps of the method.

For this mapping process, a simplified antenna model is made of 2 components. Figure 10 shows the detection range for each antenna. It consists of an arc with an opening angle of 95 degrees in the direction of the antenna. Besides, RFID tags which are close are always detected. This is modeled by a circle around the center of the receiver. The corresponding likelihood is depicted for two detection ranges.

We apply this method by considering the posterior positions which do not receive any tag that allows to filter more particles. We evaluate our method by computing both for x and y coordinates of the tag, the

Algorithm 2

for tag ← 1 to N **do**
  for robot-position ← 1 to P **do**
    repeat
      R=Memorize the robot position
    until received-tags $\neq \emptyset$
    P ← ellipse(robot-position)
    for $x_i \leftarrow 1$ to size(P) **do**
      $p(x_i|z_{1:t}) = \alpha . p(z_t|x_i) p(x_i|z_{1:t-1})$
      if R_i receives p_i **then**
        reject p_i
      end if
    end for
  end for
end for

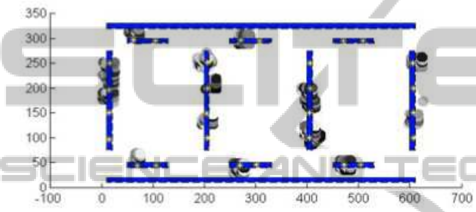

Figure 11: Estimated positions of the RFID tags. The color of the circles represent the posterior probability of the corresponding positions.

difference between the average of the predicted positions, and its true position. We show in figure 12 the error on x coordinate (blue), and on y coordinate (green). The accuracy is found to be about 0.2 m on x axis, and 0.4 m on y axis.

6 CONCLUSIONS

This paper is focused on two approaches for RFID-based self localization and mapping, using deterministic and probabilistic methods. These methods use

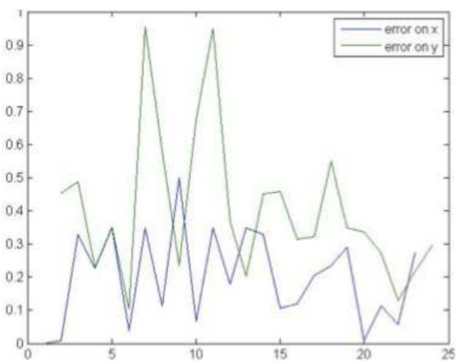

Figure 12: Error positionning of the tags.

respectively Kalman and Particle filters. First the Monte Carlo localization has been implemented for self localization. To improve the performances, we have discarded the predicted positions that receive tags not belonging to the observation. Secondly, for the mapping, our sensor model allows us to compute the likelihood of tag detection given the robot pose, computed by a visual SLAM approach.

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