# RFID-based topological and metrical self-localization in a structured environment

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***Abstract*— This paper describes several methods proposed for RFID-based self-localization for a Trolley Robot executing motions and interacting with a User in a store: such a robot must know precisely its position so that it can guide the User until shelves where Products are put on display. The robot position is expressed as a vector $(area, x, y, \theta)$, so that the localization is both topological (to determine when the robot goes from one area to another one) and metrical (to know where is the robot with respect to an area reference frame). It is proposed two different strategies based on RFID tags for the topological and metrical localization, either with tags merged in the ground or with tags set on the shelves. Experiments or simulations are presented, and a final discussion stresses the pros and cons of every solution.**

***Index Terms*— self-localization, topological map, RFID tags, landmarks**

## I. INTRODUCTION

New challenges for roboticists and new markets for robot makers, come from advanced services proposed by robots to humans in public areas. Many on-going projects study Guide Robots for museum, Person Movers in pedestrian streets, Assistant Robots for elder and disabled people at home or in hospitals... [12], [10] This work aims at developping Advanced Behaviours for a Trolley robot that must assist a User, when doing shopping in a commercial center: our current demonstrator is presented on figure 1 on the left, while a guide robot developped at LAAS is shown on the right.

The Trolley is endowed with several sensors in order to detect, track and identify its User (vision, Radio Frequency Identification i.e. RFID, audio), to interact with him (haptic, stereo, audio), to navigate safely in the store detecting and avoiding obstacles (Laser Range Finder, belt of micro-cameras) and finally, to locate itself (RFID, vision). Several User-Trolley interaction modes have been defined in [7]:

- In the Steering and Following Modes, the User knows the store and does not need to be guided: in the Steering mode, the Trolley could be used as a manual one, but with an active control by the User thanks to an haptic handle; in the Following Mode, the User asks the Trolley to follow him, using visual servoing to control robot motions without contact.
- On the contrary, in the Guiding and Autonomous Modes, the Trolley has to plan and execute trajectories in the store. In the Guiding mode, the User enters a list of Products to be purchased; the Trolley guides the User along an optimal trajectory in the store, managing the distance with the User. In the Autonomous Mode, the User can order the Trolley to go autonomously until a meeting point.

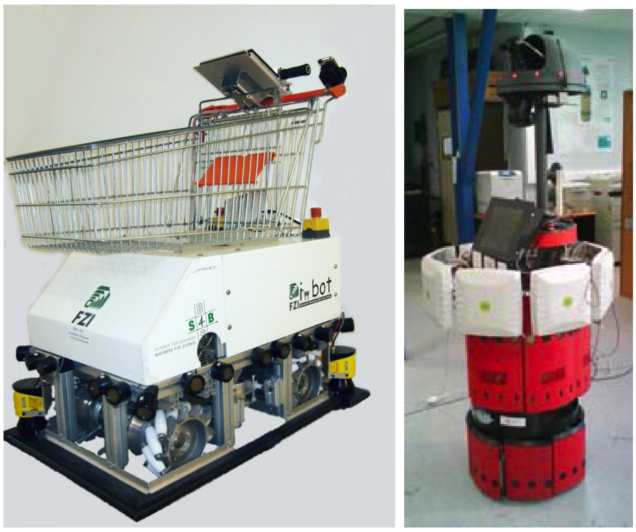

Fig. 1. The Shopping Trolley demonstrator from FZI (left); the RACKHAM demonstrator from LAAS (right).

This paper focuses only on the self-localization function, required mainly in the Guiding or Autonomous modes when the robot navigates towards a given objective (in fact the exact robot position will be tracked all the time even when the user is pushing the trolley, because the mode can suddenly be changed). The Trolley must know precisely its position and orientation, so that it can reach the objective with a good accuracy, i.e. at maximum, 25cm. from the goal, typically the shelf where the next product to be purchased is

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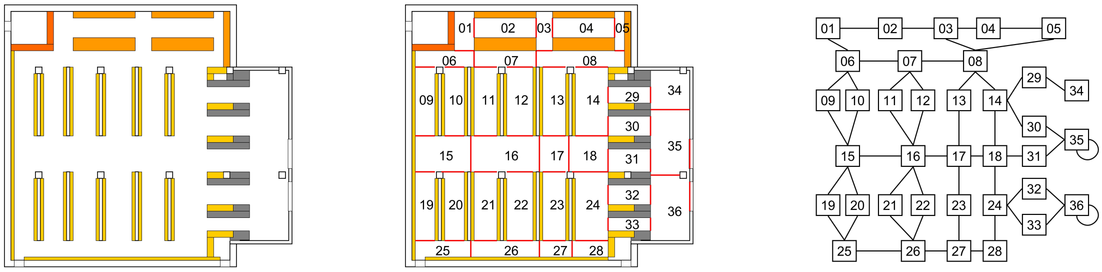


Fig. 2. The environment representations: (left) the map, (middle) the place structuration, (right) the topological map.

put on display. The robot position is expressed as a vector $(area, x, y, \theta)$, so that the localization is both topological (to determine when the robot goes from one area to another one) and metrical (to know where is the robot with respect to an area reference frame). Two RFID-based solutions are developped, with RFID tags either merged in the ground or set in the environment, e.g. on panels associated to every corridor between shelves, or on price labels. It is supposed here that the position of every RFID tag has been learnt off line.

So at first, in the section II, an overview of the navigation strategy is presented, as well as some works on RFID-based localization. Then the section III describes how the topological localization is determined from the detection of RFID barriers merged in the ground, while the section IV presents how RFID tags are used to cope both with topological and metrical localization. A discussion on the pros and cons of these two approaches is proposed in the section V before concluding and describing some future works in the section VI.

## II. The Navigation Strategy

The shopping application has been studied in some projects [1] [9]: let us stress on the ShopBot project [4], very similar to our work, but where classical probabilistic methods are proposed to cope with self-localization using mainly vision. Our Trolley will use several modalities in order to locate itself both in a topological map of the environment (*In which area am I moving?*) and in the metrical map of this area (*Where am I with respect to Products put on display in this area?*).

### A. Environment representations

The strategy selected for the navigation of the Trolley in the store, leads us to select a specific world representation with two main layers:

- The Topological world model describes the organization of the store in areas (alleys, corridors), and their connections.
- The Semantical world model (here the Product map) allows to transform a task (e.g. *Go to Apples*) in a trajectory.

Figure 2 presents the topological map extracted from a store structuration in areas. It was supposed that these Topological and Product maps are provided by the store manager. The robot localization is expressed first in the Topological map, by an area $K$ e.g. the robot is in the corridor $K$. Then, the metrical robot position $(X, Y, \theta)$ is relative to this area. Finally, this global position $(K, X, Y, \theta)$ corresponds to a Product family (Apples).

The topological position is obtained from RFID tags: two approaches are proposed. LAAS is evaluating an approach based on sparsely distributed RFID tags, while FZI has implemented a more practical and robust (but more invasive) strategy based on RFID-Barriers with tags merged in the ground. The metrical position in the area is computed either from odometry (FZI) or from the recognition and the localization of visual landmarks added on purpose on the shelves (LAAS). Basically the robot knows it is located in front of a Product, thanks to this localization.

### B. Related works

RFID technology is very attractive when tackling robotics problems: object recognition, topological localization, person tracking ... many problems can be made simpler assuming that RFID transponders are integrated on objects or in the environment. So many researchers tried to take advantage of this technology in robotics using either active RFID tags (long range detection) or passive ones (short range).

RFID-lines have been proposed as optical lines or electric wires integrated in the ground [2] the robot could easily follow; it has been generalized with RFID-carpets on which the robot is always located. Several authors have studied how to use the classical probabilitic framework for self-localization [11]; EKF-based, Markovian or Monte-Carlo methods have been proposed to update the robot position from observations of RFID tags disseminated in the environment [16] [5] [14] [15] [8]. It is widely assumed that RFID-based self-localization is too unaccurate, but it has been shown with new methods based on particle filtering [13] that an accuracy of less than 0.3m. is possible using only RFID-tags.

In the first approach based on passive RFID tags merged in the ground, boundaries between topological areas are marked by RFID-barriers, so that the robot detects when moving from one area to another one. In the second approach based on passive RFID tags set on shelves, RFID observations will be fused with visual ones using the same EKF-based

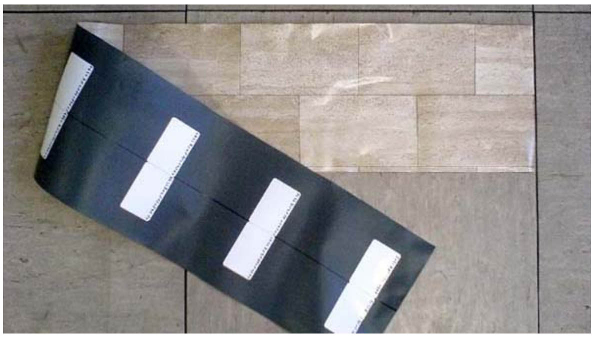

Fig. 3. The RFID barrier.

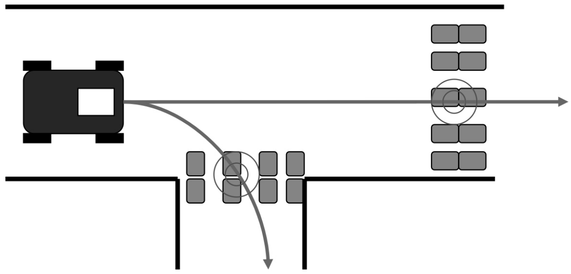

Fig. 4. Environment structuration from RFID barriers.

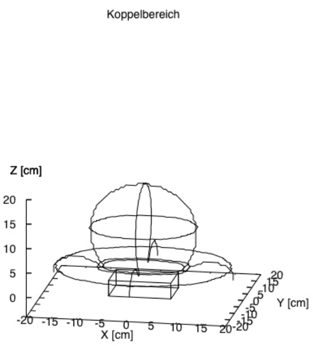


Fig. 5. The Coupling area in 3D view.

framework.

## III. RFID-BARRIERS FOR THE TOPOLOGICAL LOCALIZATION.

At first, it has been proposed in [3], to use ground-mounted RFID barriers as artificial landmarks: figure 3 shows a barrier made of several RFID transponders (small white rectangles) that are glued beneath a piece of PVC flooring. These special RFID barriers are placed on the place boundaries, in order to divide the environment into several areas, e.g. across corridors like on figure 4. A RFID reader is placed inside the robot (white box), so the robot is able to detect a barrier by moving over it.

The robot knows all IDs of the tags contained in a barrier. By driving over a barrier the robot recognizes that it just entered a new area. By doubling the tags, as depicted in figures 3 and 4, it even knows in which direction it has driven past the barrier. To identify a proper height for assembling the RFID reader on the robot, the readers coupling area was measured with the transponder parallel to the reader; figure 5 shows the balloon like shape of the main area and the circular shape of the side area. The distance with the largest diameter is 2cm where both of the areas meet. Here the coupling area, consisting of a combination of the main and a side area, has approx. 35cm in diameter.

The larger the coupling area in diameter the faster the robot can move past the barrier without missing it. Additionally using two tags in the barrier, the reading operation is made more robust; figure 6 shows the reading performance of a double RFID tag depending on the velocity of the reader. Up to a velocity of 2m/s at least one of the two tags of a double tag could be detected in all tests; the reading performance with a single tag is significantly inferior.

Figure 7(left) presents the sketch of the RFID-barrier detection: the topological position $area$ is changed on a deterministic way by now, as soon as the robot goes across a barrier. Figure 7(right) shows a mesh of relative positions of product locations inside a topological area. The relative positions are stored in the Product Map, with respect to a virtual origin of the area.

Finally this method has been validated by a number of experiments. Figure 8 presents the trajectory of a robot executing a planned loop trajectory in an environment structured in 4 areas. The robot starts from the X position in the bottom left area: it must return on this place, after reaching the two X positions in the top right and bottom right places. The executed trajectory is the red curve; the robot detects successively the four traversed RFID-barriers.

## IV. RFID-BASED AND VISUAL-BASED METRICAL LOCALIZATION

LAAS proposed another approach on topological localization, 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,

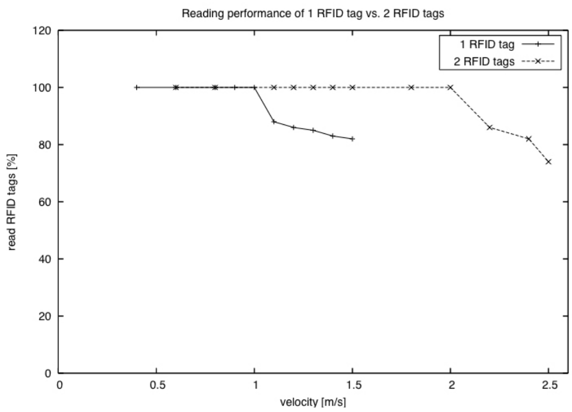


Fig. 6. Reading performance with one or two tags.

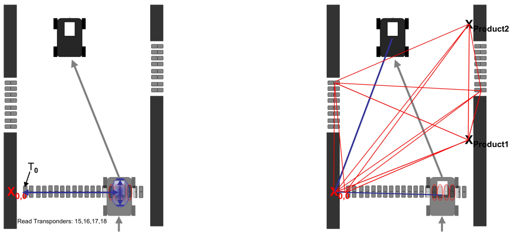


Fig. 7. RFID-barrier detection and relative positions of Products with respect to a local corridor frame.

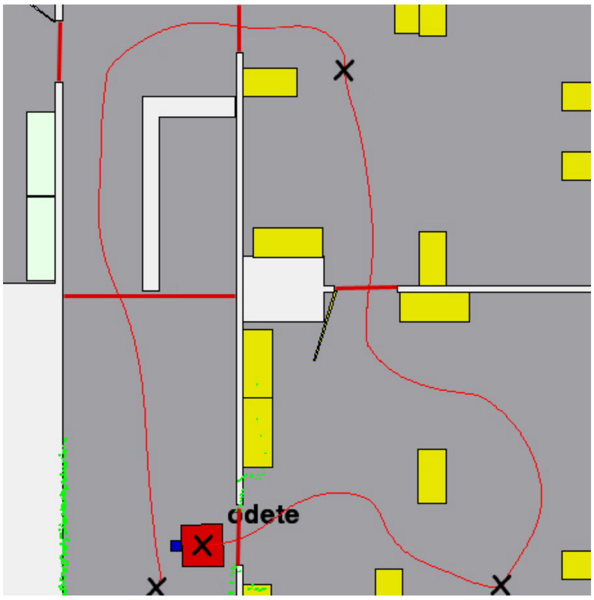


Fig. 8. A trajectory between 4 topological areas.

it knows that this tag is in the reception field of the antenna. Figure 9 represents 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 $u$.

LAAS has evaluated how a virtual robot could cope with self-localization when executing this trajectory, 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 the reception of a RFID signal or from the detection of a visual landmark. By now, only metrical localization is evaluated, without taking into account the world structuration in different areas.

Figure 10 describes the different steps required to cope with robot localization from the observation of RFID tags. We analyze these steps between the 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, using jacobians of $F$ with respect to $X$ and $u$:

$$P_3{}^* = \frac{\delta F}{\delta X} P_2{}^e \frac{\delta F}{\delta X}^t + \frac{\delta F}{\delta u} Q \frac{\delta F}{\delta u}^t$$

Figure 11 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 huge uncertainty.

This uncertainty can be maintained constant when observing RFID tags. 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 figure (d). Using the classical EKF-based framework for robot localization, it is not possible to express such a constraint: so we apply here a particle filtering approach. Hypothesis on the robot position are randomly selected from the gaussian distribution $({X_3}^*, {P_3}^*)$ : then the likelihood of each particle is estimated with respect to the observation constraints. In figure (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. Figure 12 shows the estimated robot positions ${X_i}^e$ when executing all the trajectory taking into account RFID observations.

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. The Rackham demonstrator (figure 1(right)) is equipped with 8 directional antennas. Figure 14(left)) presents the calibrated reception fields: antennas receives signals emitted in a $120\,\mathrm{deg}$ 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 $\theta_a$ with respect to

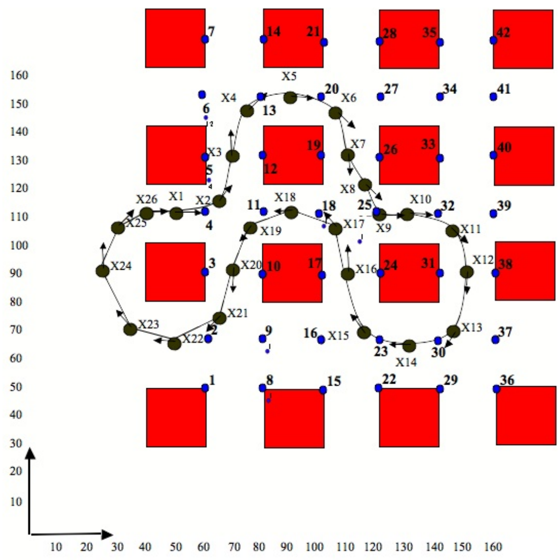

Fig. 9. A simulated environment with tags (blue dots) and a robot trajectory (Xi positions).

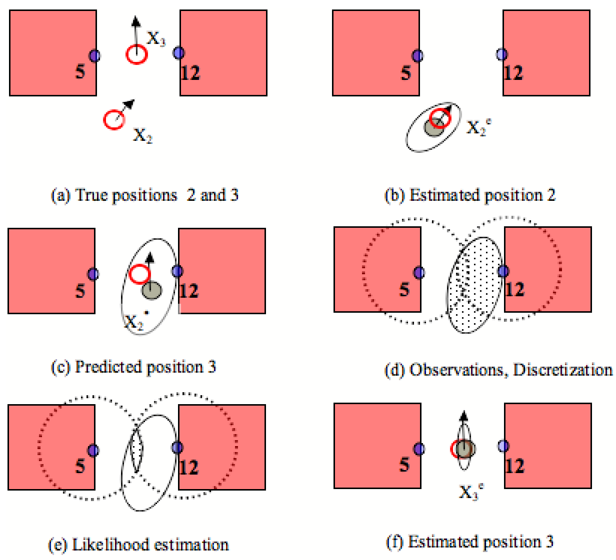


Fig. 10. Prediction, Observation, Estimation.

the world frame (see figure 14(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 :

$$Y_t - [tg(\theta_a - \alpha)(X_t - X_a) + Y_a] < 0;$$

$$Y_t - [tg(\theta_a + \alpha)(X_t - X_a) + Y_a] > 0$$

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 13 shows the estimated robot positions and orientations $X_i{}^e$ with the simulated environment and trajectory (figure 9).

## V. Discussions

Two approaches for RFID-based localization have been proposed. Even if implementation and validation are on the way, some drawbacks and advantages can be stressed.

At first, the installation of RFID-barriers is more invasive even if simpler than a dense RFID carpet. These barriers make use of very short range passive RFID devices, involving no potential inconveniences for humans; ground-based RFID tags cannot be occluded and as far as our own evaluation has shown, they are always detected.

On the contrary, (wall, shelf or ceiling)-mounted long-range RFID-based systems can be occluded as well as other landmark-based systems proposed for localization; it is an important disadvantage compared to a short-range RFID system. The potential inconvenience for humans is more important: so only a sparse RFID distribution could be tolerated. Nevertheless, for existing environments, the RFID installation could be very fast, above all if a SLAM-like procedure is provided in order to learn the tags positions,

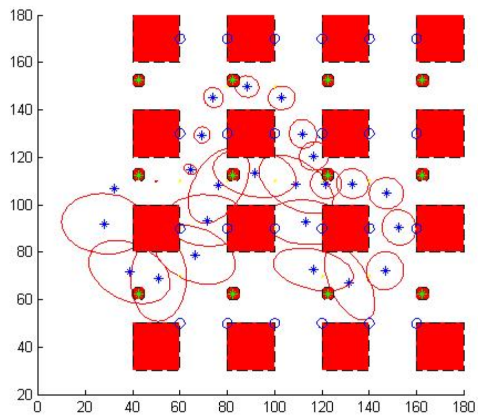

Fig. 11. The predicted positions (without any observation).

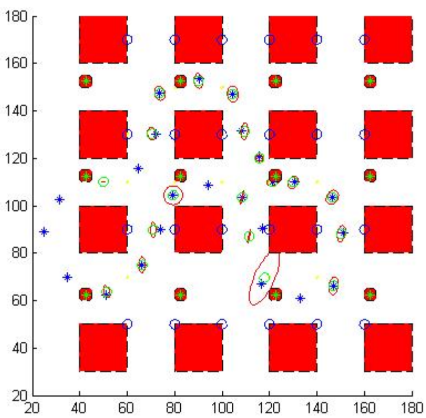

Fig. 12. The estimated positions from RFID observations.

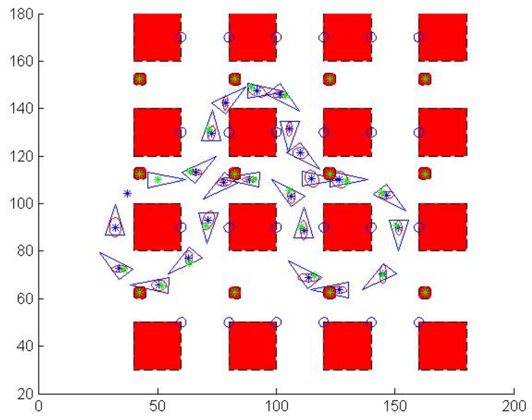


Fig. 13. The estimated positions and orientations from RFID observations.

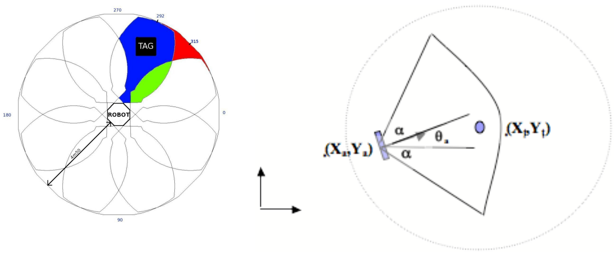


Fig. 14. Directionnal antennas on the robot.

or to update these positions on line. First experiments with the Shopping Trolley demonstrator with a metallic basket (figure 1(left)), equipped by our directional antennas, are on the way: we are designing more compact antennas in order to make simpler their integration on such a trolley.

So the first approach could be more suitable for new stores, while the second one could be easily carried out in existing stores. They could be fused in the same system, with RFID-barriers used only for topological localization wheras shelf-mounted tags could be used with other modalities (vision) for metrical localization in an area. Several methods have been developped by LAAS for visual-based robot localization from planar landmarks [6].

Moreover, for our shopping application, the possibility to detect tags on the shelf, could be used also to detect products, assuming that RFID tags could be added in the price labels on the shelves, not on products in order to limit the tags density.

## VI. Conclusions and futures works

This paper has presented two different, but finally complementary methods in order to take advantage of RFID tags for the self-localization of a mobile robot in a commercial center. By now topological localization has been integrated on the Trolley demonstrator using RFID-barriers and a very short range RFID reader mounted under the robot. Topological and metrical localization from both RFID tags and visual landmarks set on shelves, is studied using an RFID reader and directionnal antennas mounted all around the robot. This sensor will also allow to detect and identify the User, who will take an RFID key when taking the Trolley at the session initialization.

In the next period, the two approaches will be integrated and fused on the Trolley; the topological and semantical maps will be learnt or updated from a priori maps, using cooperative behaviours amongst several robots.

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