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Human-Robot Collision Avoidance with RFID Sensors Using Fuzzy Logic and Extended Kalman Filter

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Abstract

At the down of the new millennium, robotic has tendency to contribute to a major transformation in scope and dimension. From a largely dominant industrial focus, robotics is expending into challenge of dynamic unstructured environment.
The emerging robots will increasingly touch people and their lives by interacting with, assisting, serving and exploring with them. In this paper, we propose a new strategy for human robot collision avoidance with position estimation. We have used RFID sensors for environment perception since they are frugal. We have used the fuzzy logic algorithm which we adapted to RFID sensor model in order to avoid collision with humans and we corrected the robot position with the well known Extended Kalman Filter. Finally we present some experiments which we have done with our experimental robot AX11.

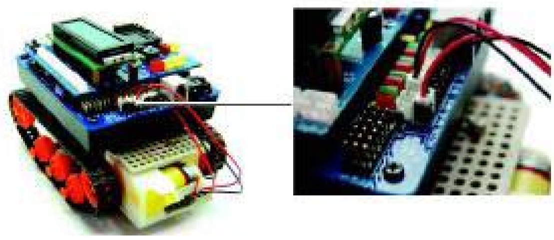

Figure 1: AX11 robot equipped with sonar sensors

Keywords: robotic, collision, the fuzzy logic algorithm and sensor model.

1 Introduction

Safety is the primary issue on interest when humans and robots share the same work space. It is not negligible also to prevent robot damages due to collisions with unforeseen obstacles. Manipulators and collision reaction strategies can prevent from unexpected human-robot impacts. However, in a dynamic and largely unpredictable environment, the use of exteroceptive sensors is necessary. Because of their close relationship navigation and obstacle avoidance should be integrated in the same strategy. Mobile navigation can be viewed as the art of correcting the inaccuracy of prediction based on proprioceptive sensors by taking advantage of exteroceptive sensors like cameras [1], laser range finders, RFID (Radio Frequency Identifiers) or antennas. Many strategies have been developed allowing the navigation of a robot based either, on explicit localization of the robot; or on interesting objects and landmarks. One of the most popular strategies is the well known Simultaneous

Localization and Mapping (SLAM) developed in the last decade [2, 3], in particular EKF-SLAM since it uses non linear models. With the development of sensor technologies which construct a representation of the environment, SLAM has become well established in the robotic community. This is because it is based on the probabilistic approach which requires the perception of the environment before any actions [4].

Figure 2: Passive RFID tags used in the simulations

Sensors including RFID antennas, laser range finders and cameras have the ability to estimate the ego motion of the robot by providing observations that can be exploited by statistical methods. Moreover, RFID are actually among the most popular sensors in robotics [5]. Approximate physical models of range finders are used as perception models. These sensors are associated with some small objects called tags distributed within the environment.

In order to integrate the robot in a social environment, it should correct its behavior depending on the structure of its surrounding. Also it should avoid humans, in particular in public areas like supermarkets, airports or museums. We propose in this paper a new method for Human-robot collision avoidance based on RFID technology since it reaches actually a maturity.

Thus, the scenario which we will consider is the following: When the human enters in a public area, we give it an RFID tag that he puts on his clothes. Therefore, robots while moving, they will avoid human by detecting these tags through their RFID antennas.

The behavior generation algorithm which we use in this paper is fuzzy logic having as inputs the distance and direction from the robot to the RFID transponder.

Meanwhile, we will filter the robot positions using the Extended Kalman Filter based on RFID sensors. This paper will be organized as following: In the first section, we present the related works to position estimation with Hidden Markov Models and to obstacle avoidance and behavior generation. In the second section, we present our method for Extended a Klman Filtering with RFIDs using a range and bearing model. In the third section, we propose a method which allows the robot to do self localization and obstacle avoidance based on fuzzy logic and EKF filtering. In the fifth section, we present our experiments performed in our Lab with the AX11robot.

2 Related works

In [6] presented recently sensor-based collision avoidance in motion control system using depth data. This method consists to project depth data into a robot oriented space, reassemble representations of obstacles in this space and finally compute the information needed for collision avoidance. At the same time, they suggested to compute the information needed for the collision avoidance directly in depth space. In [7], a real-time vision-based obstacle detection and avoidance method in an indoor environment is proposed. An algorithm based on 3D data acquired with laser scanners and active stereo camera system more recently, [8] designs and validates a new tentacle-based approach, for avoiding obstacles during appearance-based navigation with a wheeled mobile robot. In this method, they improve older techniques for obstacle avoidance using potential vector fields. This more sophisticated and efficient method, which exploit robot kinematic model and predicts collision at look-ahead distances. Besides, we find also important to cite some seminal obstacle avoidance techniques although the actual methods are all almost real time. [9] Developed 3 methods for obstacle avoidance, edge-detection extracts the obstacles vertical edges and pushes the robot to drive around one of these edges. Nevertheless, this method shows some drawbacks because of uncertainties in the sensors measurements: poor directionality, frequent misreading and specular reflexions. [10] Pioneered the concept of grid cells. Such a probabilistic method allows fusing data from different sensors. The environment is decomposed on several cells where each of them is represented with a probability relied to the existence of an obstacle. Consequently, the robot will use this occupancy grid to navigate safely on its path. Meanwhile, another method called Steer Angle Field Approaches based on the admissible robot velocities was proposed. In 1997, Fox, Burgard and Thrun developed the Dynamic Window Approach (DWA).

This method uses the robot kinematics constraints in order to calculate all possible sets of velocity vectors (v, w) in the velocity space. Where v and w are the robot translational and rotational velocities, respectively. In these approaches all the velocities of the velocity space are reduced to the dynamic window, which contains only the velocities that can be reached within the next time interval. The dynamic window is simply a rectangle centered on the robot. It presents velocity and its vertex positions depend on the accelerations which can be applied. All velocity vectors outside the dynamic window are excluded and thus should not be considered for the obstacle avoidance. The motion direction is chosen based on an objective function to all admissible velocity vectors in the dynamic window which depends on the robot velocity, the distance between the robot and the closest obstacle. In [9], Broke et al improved significantly the dynamic window approach. Their new method was called Global Dynamic Window Approach (GDWA). They added a global thinking to the DWA by using the grassfire technique for finding routes in the certainly grid cells. Each cell is labeled with distance to the robot's goal position, where the robot is considered like a wave which is moving to the target. The desired trajectory is obtained by linking adjacent cells that are closer to the robots goal position. This procedure improves the performance of the robot by using some advantages of global path planning without complete a priori knowledge.

Figure 3: A mobile robot equipped with RFID antennas

3 Localization with EKF using RFID

In this section, we are interested to robot localization in a structured environment using the probabilistic approach. This approach has induced a revolution in robotics since Thrum introduced it in 95. Indeed, it takes into account the uncertainty in the movement of the robot. This uncertainty is caused with many factors like"slippage, bumping". Through the fusion of sensor and motion model, the robot can correct its positions. In the figure"ground", we show the positions where the robot should be. These states are of crucial importance because all the steps of filtering are depending on it. The robot has to compare its noisy position with the ground truth.

3.1 RFID Sensors

Radio-frequency identification (RFID) is new technology which allows for the contactless
identification of objects which can be fixed like shelves in a supermarket or mobile like humans. Its growing use in economy makes it attractive also for robotic domain in particular of service. Whenever a mobile robot is already equipped with an on-board RFID reader, it can cost-efficiently exploit remote RFID transponders (also called tags) as uniquely identifiable landmarks for navigation. The drawback of long-range passive RFID (860-915), which model detects tags positioned up to 10m suffers from frequent non detections in read range. Moreover, we note that passive RFID almost entirely lacks distance and bearing information between RFID reader (robot) and transponders, and often measurements are influenced by materials such as glasses or water. Consequently, we use in this work an active RFID
model which main property is that both antennas and tags are emitting energy.

3.1.1 RFID Sensor model

We use the RFID sensor model presented in [11]. Because we use the EKF algorithm we need distance and direction information's which explains the choice of this model. The distance between a detected RFID and the antenna is estimated from the power of the signal received with the robot sensor.

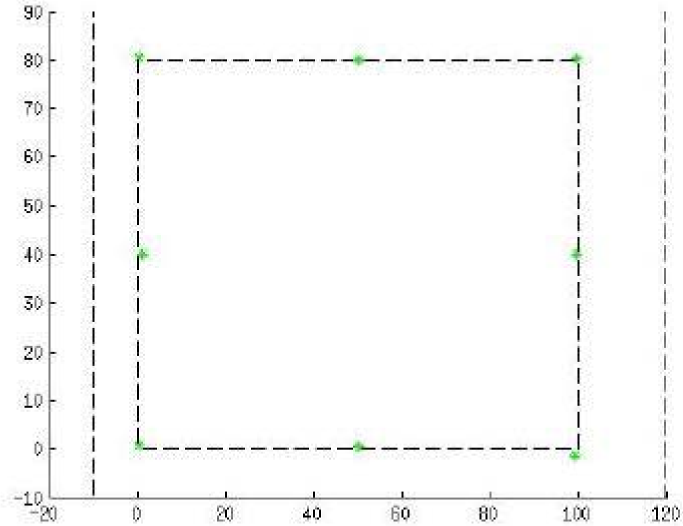

Figure 4: The ground truth of our simulation

However factors of noise such as damping and reflections of radio waves perturb the signal propagation in the indoor environment. This perturbation depends on the layout of the building, the intrinsic properties of the material used and the kind and number of objects in the building. Seidel and Rapport introduced a model for path attenuation prediction which takes into account different aspects of the building like number of floors between transceiver and receiver. We use as in [11] a simpler version of the model from [12] using the assumption that RFID detections are not possible through walls.
This model relates the power of the signal P to the distance:

$$P(d)[dB] = p(d_0)[dB] - 10n\log^{d}_{d0} + X_{\sigma}[dB], \qquad (1)$$

Where s is the standard deviation of the signal. P (d_0) is the signal's power at reference
distance d0 and is an intrinsic parameter of the environment expressing the mean path loss exponent. Seidel and Rapport fixed for transmissions at 914MHz a path loss of 31.7dB at reference distance of 1m. We present in the following the steps of the EKF which are prediction and update using the"Sensing and Action "paradigm:

3.2 Prediction of the position

The most important thing to consider in the prediction phase is the motion model or the model of displacement of the robot. It should be in fact determined with a probabilistic way, in order to move the mobile robot. Let’s have the following probability with rely the robot position from x_t tox_{t+1} with an action u.

$$p\ (x_{t+1}/x_t,\ u)$$

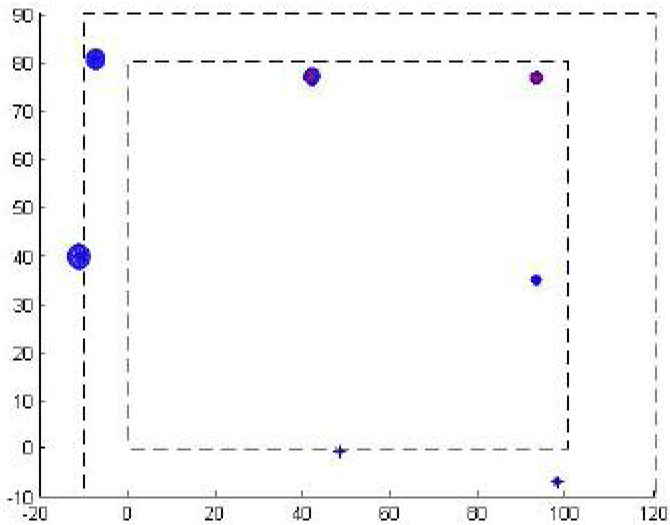

Figure 5: The predicted positions

In order to implement this equation, we use the prediction step of the Kalman filter:

$$X_{t+1} = A.\ X_t + B*u$$

In this implementation, we consider the robot state as a couple of the robot means position and the covariance. This distribution wills evolutes until the robot ends its path. The figure1 shows the movement of the robot in a structured environment. We consider the state of the robot represented with (, ,q) which simplifies its estimation. For more complete formulation, we should integer Euler angles. As shown in the figure, the robot positions are affected with error which disables the robot to close the loop. This ability is important for both indoor and outdoor environments. At the same time, the ellipse of uncertainty grows also because the predicted covariance is growing. Thus, a step of correction must be included so as we can reduce this ellipse of uncertainty, in other words decrease the values of the diagonal of the covariance matrix.

3.3 Correction of the position

To update the state of the robot, we use the measures obtained with the sensors. So as the sensor is precise as it gives a good correction of the position. The advantage of the so called RFID sensors is that they can either be used with range and bearing or it

can even give weight values for particle filters We give in the following the model for RFID sensors: The update step is done using the Bayesian filter as following:
To implement this model, we use the following equations:

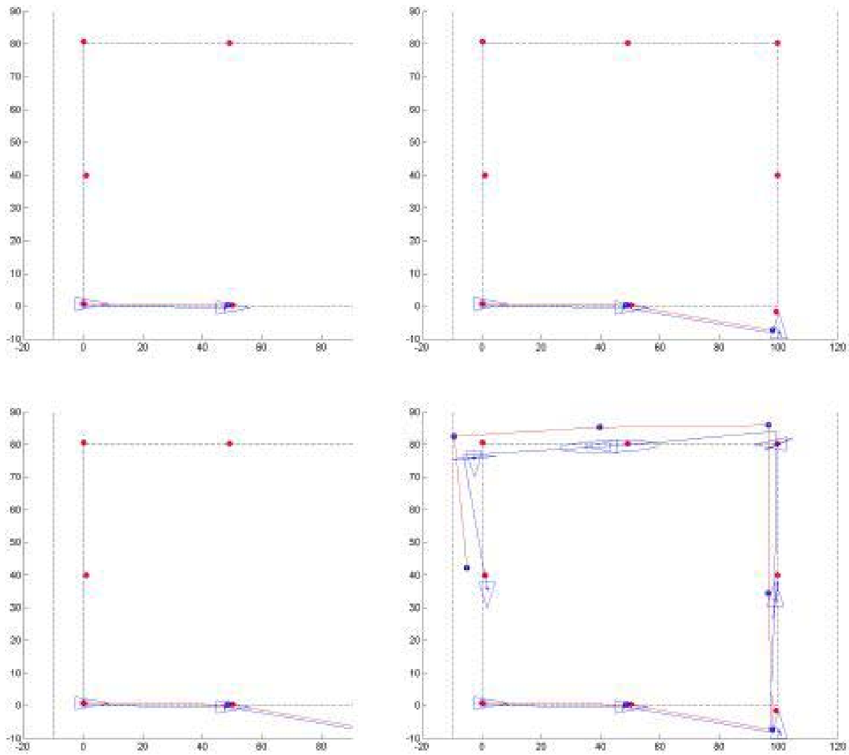

Figure 6: The predicted positions

4 Obstacle avoidance

4.1 Fuzzy logic

In the sixtieth, Lotfi Zadeh developed the soft computing techniques. Nowadays, they gain an increasingly importance. The Fuzzy logic belongs to this class of methods. It is based on the concepts of points and transitions between these points. Indeed, the fuzzy systems are based on the concept of fuzzy sets. Each element of this set is weighted with a particular function defining the degree of relationship between the element and its corresponding set. This function is based on the selection of a certain number of variables and the choice of its form.

Theorem: *The robustness of the fuzzy system is always higher than the one which is produced with a binary partition. Besides, the robustness is maximal if the rules of the fuzzy partitions are respected.*

4.1.1 Fuzzy rules

The fuzzy systems use the inference rules in order to model the input/output of the process which we want to give a degree of autonomy. In our case, it concerns the connexion between sensor data and the behavior of the robot. These rules are expressed as following: if (antecedents) then (consequences) where consequences can be relied with and, antecedents can be relied with and, or, not. Moreover, we mentioned that the sentences are of linguistic type (i.e. linguistic variables and fuzzy set labels).

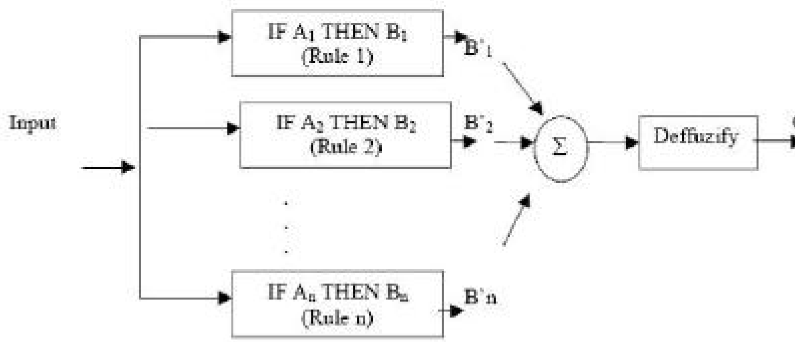

Figure 7: Fuzzy controller used in our method for robot collision avoidance

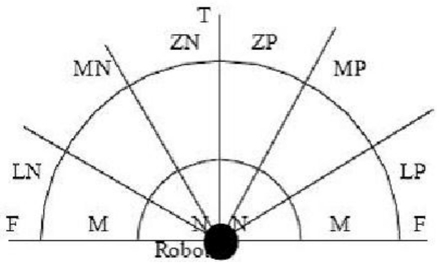

Figure 8: Fuzzy logic schème

4.1.2 Fuzzy controller

These rules are used through these steps (fig 4.1.2):

1. Fuzzy faction of the inputs;
2. Combination of the degree of belonging;
3. Combination of the weights of the rules;
4. Aggregation of the outputs of the rules;
5. Defuzzy faction of the computed output.

4.2 Navigation with obstacle avoidance (Combining EKF and Fuzzy logic)

The algorithm which we propose consists to avoid obstacles which may appear in the path of the robot using laser range finders. We combine this behavior with the position correction using EKF algorithm. Thus, the robot will move using the motion model until it receives an obstacle. Then it changes its direction using the algorithm of Fuzzy logic 8. This combination allows it to insure a strategy of exploration combining of computing and probabilistic navigation 1.

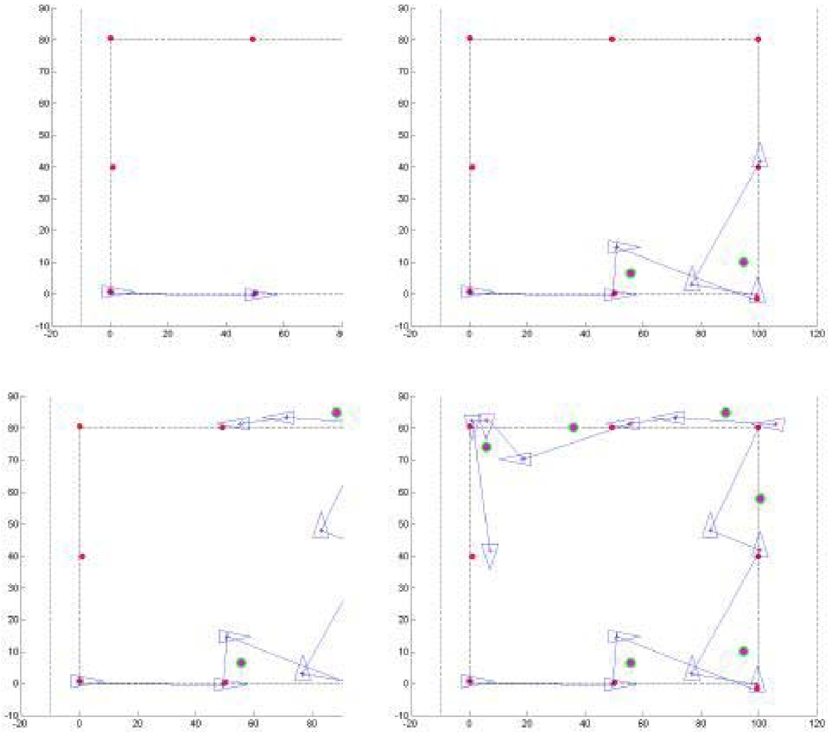

Figure 9: *Robot navigation with avoidance of dynamical obstacles (humans) represented with bold discs surrounded with a green circle*

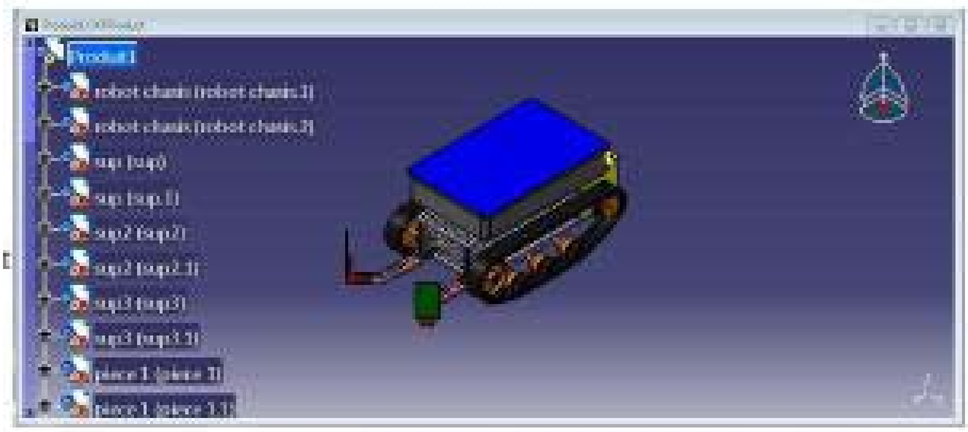

Figure 10: Conception of AX11 with the software CATIA

5 Experiments

The AX11 (fig. 10) is a mobile robot platform developed in the MIT laboratories to insure courses for mobile robotic. The AX11 is based on the 68HC11microcontroller. It has 32KB non volatile RAM, 9 digital inputs, 21 analog inputs, 4 DC motor drivers and 6 servo-motors. Moreover, the AX11 robot can be programmed with Windows or Linux operating systems if we install the suitable driver for RS232 serial cable. It uses a soft version on C language called Interactive C which is the main compiler for many Motorola 681 based robots and embedded systems. In order to test the Fuzzy Logic algorithm for collision avoidance, we use ultrasonic sensors instead of RFID. That is because Interactive C is delivered with a dedicated function called that returns a signal which is associated to the distance (from estimated position of the robot the human). The ultra-sonic sensors which we use send sonar signal to the surrounding of the robot, the time it takes to reflect back. We note that one of the advantages of these sensors is that they deliver a signal with a low frequency. Consequently, it can be detected and measured easily with the sonar antenna.

Figure 11: Photos from the video sequence in our Lab of the closely spaced obstacles experiment. Repulsive forces obliged the robot to turn away when it in front of our colleague

6 Conclusions

We present in this paper a method for behavior generation for dynamical obstacle avoidance tasks in a structured environment. We integrate this algorithm in an EKF framework based on RFID sensors to insure accurate localization. We have shown that fuzzy logic is efficient in changing the robot direction while correcting its relative position. We aim after this work to implement it on a wheeled robot and then to generalize the navigation to Simultaneous Localization and Mapping with RFID transponders and tags.

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