MOBILE ROBOT LOCALIZATION SCHEME BASED ON FUSION OF RFID AND VISUAL LANDMARKS

Younes Raoui[1,2,3], El Houssine Bouyakhf[1] and Michel Devy [2,3]
[1]*Faculty of Sciences, University Mohamed V at 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: A key function required on an autonomous mobile robot is the ability to localize itself accurately. This paper reports an RFID and vision-based localization scheme, which uses new rotation and scale invariant features as natural landmarks in static environments. The invariance of these features to image translation, scaling and rotation makes them suitable landmarks for mobile robot localization. Our RFID-based localization method presented in (Duarte et al., 2010) is made active minimizing the information entropy and improving the positioning accuracy. Then methods based on the detection of a priori learnt RFID tags and visual landmarks are combined in order to make more robust the method.

1 INTRODUCTION

Mobile navigation can be viewed as the art of correcting the unaccuracy of internal sensors by taking advantage of exteroceptive sensors like cameras, laser range finders... Many strategies have been proposed for robot localization based on interesting objects and landmarks. Simultaneous Localisation and Mapping attains a maturity in the last decade, so that environment models can be acquired before exploiting it only for robnt localization.

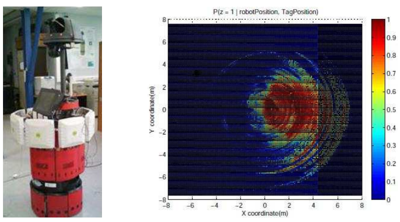

Figure 1: The RACKHAM demonstrator from LAAS(left), Cartesian Detection Model of every RFID antenna (right).

Sensors like RFID antennas, laser range finders and cameras have the ability to estimate the egomotion of the robot. These sensors may give complementary information and may also sometimes be redundant. There are many possible architectures to fuse sensory data. Mobile robots are generally endowed with dead reckoning sensors such as wheel encoders and inertial sensors. All these sensor measurements can be fused to estimate the robot position by using filtering methods like Kalman, Particle or Information filter.

This paper focuses on the self-localization function, required when the robot has to reach a given objective with a good accuracy, e.g. at maximum, 20cm. Two solutions are proposed: the first uses RFID sensor to estimate the robot position from the Monte-Carlo approach using RFID tags detected by antennas mounted on the robot. The second one fuses two types of sensors, RFID reader and an embedded camera. Thus, we propose a new method for image description that has been used as landmarks in a monoSLAM algorithm using the Davison approach (Davison and al, 2007).

In the first chapter we present a new image descriptor with an application to object recognition. In the second chapter we present a method for robot navigation with RFID technology. In the third section we present our method for navigation based on sensor fusion from RFID and vision.

2 RELATED WORKS

Several recent works in robotic localization are based either on vision or on RFID technology. An RFID

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based method close to ours is presented in (Hahnel and al, 2005); they also used a probabilistic sensor model for their RFID reader; they associate the probability of tag detection with the relative position of their tag. This model is used to map positions of passive RFID tags, considering the robot is located from a previously learnt map through laser based SLAM. Vorst and al (Vorst and Zell, 2010) have developped a method of localisation on which the estimation is based only on odometry and RFID measurements. The technique requires no prior observation model and makes no assumptions on the RFID setup. On the other hand, using vision based approach, Zhou and al (Zhou and al, 2007) proposed an indoor localization method with modified active RFID tags, equipped with LEDs which make the recognition much easier. In (Ziparo and al, 2007), RFID tags are detected to coordinate a team of robots for an exploration in unstructured areas. In (Raoui and al, 2009), two strategies are presented for metrical and topological navigation with tags merged on shelves and on the ground. Other researchers use vision based localization, but the work of (Davison and al, 2007) is considered as a turning point in the monoSLAM based navigation.

The fusion of many types of sensor data makes more accurate the robot position. In (Deyle and al, 2009), an RFID-enabled mobile manipulator can grasp an object to which a self-adhesive passive RFID tag has been fixed; this new mode of perception produces a map of the spatial distribution of received signal strength indication for each of the tagged objects in an environment.

3 GENERATING FEATURES

Our visual features (Raoui and al, 2009) are based on the Harris detector because of its suitability in computation time. We extend it to the colored images by using the Gaussian color model(Geusebroek and al, 2001). It is based on the second moment matrix also called the auto correlation matrix. The detector is made invariant to scale computing four characteristic scales aroud each feature point, by the use of the LoG operator (K.Mikolajzyk and C.Schmid, 2004).

The orientation for interest points is computed as in (Lowe, 2004). It has good performances comparing to other descriptors because it mixes localized information and the distribution of gradient related features. Thus, for each scale the image is processed to extract the orientation for the feature point and all points around it (4 points). We concatenate these orientations in the same descriptor. Then, we compute the descriptor around each feature point (figure 2) by

Algorithm 1

for i← Feature Point-2 to Feature Point+2 **do**
  box ← Create a box around a point i
  result ← box * Gaussians(scales)
  Compute norm(result)
  V ← 4 highest values
  Add V to the Feature Point
end for

using a set of 9 Gabor wavelets (Gabor, 1946). In order to evaluate our detector and descriptor, we use the repeatability score as suggested in (K.Mikolajzyk and C.Schmid, 2004); a comparison is shown on figure 3.

x y	σ	r	t
space	scale	orientation	texture

Figure 2: Structure of our descriptor, 2 bin for space, 21 for scale, 5 for orientation, 9 for texture.

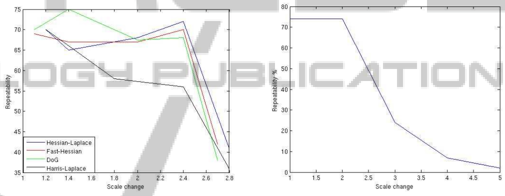

Figure 3: Repeatability of Fast Hessian, DoG, Harris-Laplace, Hessian-Laplace interest points detectors with respect to scale(left).Repeatabilty of our detector descriptor with respect to scale(right).

4 RFID-BASED ROBOT LOCALIZATION

Our method for stochastic localization from RFID Tags, is presented in (Duarte et al., 2010); it is based on a particle filter in order to estimate the robot pose from RFID observations. Such a filter represents the state at step k by a random vector x_k . Then a probability distribution over the position and orientation of the robot x_k , known as belief, $Bel(x_k)$ represents the uncertainty of the state. In the particle filter scheme, the belief function is represented by a set of n pairs $< x_i^k, w_i^k >$ defined by a position x and a weight w. This weight is a measure of how much its related position x represents the real robot position with respect to the environment model. A function $p(x_k|x_{k1})$, known as prediction function, and a correction function of w_k must be defined. $p(x_k|x_{k1})$ models the dynamic of the moving object, using here the odometry model. w_k is corrected depending on how much the actually sensed data fit the position x_k.

In order to maximize localization performances, we apply an active control strategy, coupling control actions into the estimation process. Then, an information theoretic control is used. In fact, information measures quantify the uncertainty in a probabilistically representation estimation and are used as cost functions for potential control actions. Thus, the information metric is defined as a function of probability distribution.

$$I[x] = f[p(x)]$$

where p(x) represents the estimates of the robot positions [x y], which is considered as a gaussian with a mean $hat(x)$ and a covariance P. The information metric is $h(x) = \frac{1}{2} log[(2\pi e)^n |P|]$. The information gain is defined as the difference in the information of our estimation before and after a particular action.

$$I[x,a] = h[p(x/a)] - h[p(x)]$$

While the vehicle moves it follows the following procedure: (1) choose a trajectory that maximizes I[x,a], (2) propose several trajectories and (3) estimate the observation based on the antenna reception field that will be made along each trajectory

Algorithm 2: Algorithm ActiveMCL(X_{t-1} , u_t , z_t , m).

1: $X_t \leftarrow 0$
2: **for** m $\leftarrow$ 1 to M **do**
3: **for** i $\leftarrow$ 1 to I **do**
4: $x^m_{t,i} \leftarrow$ sampleMotionMmodel($u_{t,i}, x^m_{t-1}$)
5: $w^m_{t,i} \leftarrow$ measurementModel(z_t, x^m_t,m)
6: $X_{t,i} \leftarrow X_{t,i} + < x^m_{t,i}, w^m_{t,i} >$
7: **end for**
8: **end for**
9: **for** i $\leftarrow$ 1 to I **do**
10: $x_{t,i} = mean(x^m_{t,i})$
11: $x_{t-1,i} = mean(x^m_{t-1,i})$
12: $L(i) \leftarrow$ entropy($x_{t,i}$)-entropy($x_{t-1,i}$)
13: **end for**
14: $i_{max} \leftarrow max(L)$
15: $xa_t \leftarrow x_{t,i_{max}}$
16: **for** m $\leftarrow$ 1 to M **do**
17: draw i with probability w^i_t
18: add xa^i_t to Xa_t
19: **end for**
20: return Xa_t

Line (4) in our algorithm create samples from present belief as starting point. The perception model of RFID antennas is then applied as indicated in line (5) to determine the importance weight of each particle. In line (3) we make an iteration over all possible actions from t to t+1. So we have possible posterior positions $x^m_{t,i}$ and weights $w^m_{t,i}$. The initial belief $bel(x_0)$ is obtained by randomly generating M such

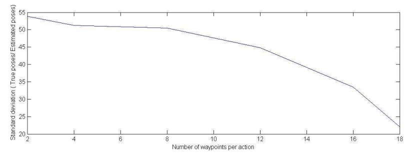

Figure 4: Robot localization at different positions with the computation of standard deviation for x, y, θ

particles from the prior distribution $p(x_0$, and assigning the uniform importance function $M^{-1}$to each particle. For each action i, we compute the difference in the entropy between the mean of the particles at time t and t+1. In line 12, we look for the index of the action that maximizes L(i).

5 FUSION OF RFID AND IMAGE DATA

An efficient method for localization fuses signal detection from RFID tags and for fine localization, it incorporates visual landmarks detection, using image descriptors presented in section 1. In order to compute the camera motion, we use an angular contraint, a linear velocity model and odometry model. The state vector is expressed with $x_v = \left(r^{WC} q^{WC} v^W W^w\right)$, where r^{WC} is the position of the camera optical center, q^{WC} is the quaternion that defines orientation, v^W and W^w are the linear and angular velocities.

At every step, we compute the next step by using the odometry model $P(x_t/x_{t-1}, u)$ and an angular acceleration zero mean Gaussian process a^W and α^w, which produces an impulse of linear and angular velocity. Thus,

$$n = \begin{pmatrix} V^W \\ \omega^W \end{pmatrix} = \begin{pmatrix} a^W \delta(t) \\ \alpha^W \delta(t) \end{pmatrix} + P(r^{WC}_t / r^{WC}_{t-1}, u) \quad (1)$$

Let us suppose that a set of euclidean points have been previously learnt by a bearing-only approach. We compute the predicted position of a point feature relative to the camera with estimates, x_v of camera position and y_i of feature position. the camera is expected to be: $h^R_L = R^{RW}(y^W_i - r^W)$

With a perspective camera, the position (u v) at which the feature would be expected to be found in the image is found using the standard pinhole model: $u = -fk_u \frac{h_x}{h_z} + u_0$; $v = -fk_v \frac{h_y}{h_z} + u_0$, where f_{ku} , f_{kv} , u_0 and v_0 are the standard camera calibration parameters. The state update produced is given with:

$$f_v = \begin{pmatrix} r^w_{new} \\ q^{WR}_{new} \\ v^W_{new} \\ \omega^W_{new} \end{pmatrix} = \begin{pmatrix} r^w + (v^w + V^w)\delta_t \\ q^{WR} * q((\omega^W + \Omega^W))\delta_t \\ v^W + V^W \\ \omega^W + \Omega^W \end{pmatrix}$$

EKF updates the robot state by fusing odometry and vision data. The estimate of the new state is $f_v(x_v, u)$ and the state uncertainty Q_v for the camera are estimated after each motion or observation. We would therefore like to improve the odometry estimate of the ego-motion by matching the extracted features between frames. Once the features are matched, we can then use the matches in a least-squares procedure to compute a more accurate camera ego-motion and hence better localization. A match between two descriptors is accepted only if distance is less than 5 times the distance to the second closest match.

We simulate an environment by taking a sequence of colored images from an office room where we have distributed RFID tags. In order to localize itself, the robot uses both these tags and captured images. If it succeeds in detecting tags, which obey to the sensor model described in the figure (1), it apply the method described in section 2. At the same time, it captures an image with its camera. If no tag is detected, it extracts our developped feature points and computes their descriptors. It will then match these image features with the memorized ones. The robot will use them to compute its current position. This strategy allows the robot to acquire data from the environment at each time. The algorithm 3 explains our method.

Algorithm 3

for i ← 1 to $NumberOfImages$ **do**
  CaptureImage()
  pos(i) ← addNewFeature(i)
  match (pos(i),pos(i-1))
  $[x_{i/i-1}, p_{i/i-1}]$=EKF Prediction(x_{i-1}, p_{i-1})
  add pos(i) to $x_{i/i-1}$ (The state vector)
  Get Odometry
  $[z_i]$=Get measurement
  H_i=dataAssociation($x_{i/i-1}$,z_i)
  $[x_i, p_i]$=EKF Update (x_i, p_i, z_i, H_i)
end for

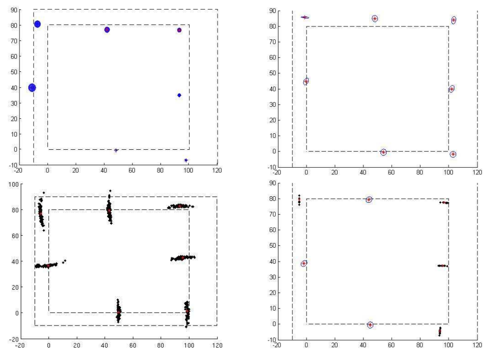

Figure 5: Predicted positions of the robot (top left), positions estimated from visual landmarks (top right), positions estimated friom RFID tags (bottom left), positions estimated from the fusion (bottom right).

6 CONCLUSIONS

This paper proposes first the computation of interest point descriptor for colored images which is invariant to scale and rotation. Then we have developped a localization method based RFID sensor readings. The integration of both measurements permits to localize a mobile robot with a bounded error estimation, and with a better robustness.

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