Self Localization of an Autonomous Robot: Using an EKF to merge Odometry and Vision based Landmarks

Armando Jorge Sousa
FEUP – ISR
R. Dr Roberto Frias, s/n
4200-465 Porto, Portugal
asousa@fe.up.pt

Paulo José Costa
FEUP – ISR
R. Dr Roberto Frias, s/n
4200-465 Porto, Portugal
paco@fe.up.pt

António Paulo Moreira
FEUP – ISR
R. Dr Roberto Frias, s/n
4200-465 Porto, Portugal
amoreira@fe.up.pt

Adriano Silva Carvalho
FEUP – ISR
R. Dr Roberto Frias, s/n
4200-465 Porto, Portugal
asc@fe.up.pt

Abstract

Localization is essential to modern autonomous robots in order to enable effective completion of complex tasks over possibly large distances in low structured environments.

In this paper, a Extended Kalman Filter is used in order to implement self-localization. This is done by merging odometry and localization information, when available. The used landmarks are colored poles that can be recognized while the robot moves around performing normal tasks.

This paper models measurements with very different characteristics in distance and angle to markers and shows results of the self-localization method.

Results of simulations and real robot tests are shown.

1.Introduction

A robot with a high degree of autonomy needs self-localization to fulfill its goals. These autonomous robots generally move on a low structure environment. Usually the robot must find out where it is, using measurements made by on-board sensors and using known features of the environment that surround the robot.

Some technological approaches are frequently used:

- Laser measurements – expensive but accurate, sometimes may be unsafe and crude[1], [2], [3], [4]
- Ultrasonic sonar – limited range, low frequency, quality of measurements dependent of target type and angle [5], [6], [7], [8], [9], [10] e [11]
- Infrared – limited range, quality of measurements dependent of target angle and reflectivity
- RF techniques – may be expensive, frequently require active structure on the environment [12], [13], [14]
- Vision – Least intrusive. High amount of data allowing recognition of different types of landmarks, hard to guarantee the reliability

Robot localization using vision to find ceiling lamps is an example of using interesting characteristics of the real scene where the robot will be deployed [15], [16]. Some authors [17] study several interesting features that could be used for robotic localization. By finding the contour of the closed corridor where the robot moves, [18] it is able to calculate orientation of the moving robot. Other authors [19] use a Kalman Filter variant to keep track of visual landmarks over an outdoor environment for a moving robot. In [20] it is proposed a strategy where both local and global localization is made by use of the lines of the field where the robot moves (the global method is used when the local method, a match between expected and actual measurements is not achieved).

The present work aims at achieving self-localization by only using vision and odometry. The motivation of such work is the robotic soccer competition, namely the F2000 league of the RoboCup Federation. This league uses poles as artificial colored landmarks usable for localization. In the actual setup of the localization system, a pole measurement is a distance and a direction. Distance information is of poor quality but direction is of high accuracy. Using only the distance and angle to a single pole does not fully determine the (x, y, θ) values for the robot. Such measure allows however to improve a previous estimate. By using measures from several different landmarks, the amount of independent information will generate a high quality estimate of the localization of the robot. In order to generate this estimate, a Kalman Filter is used (KF). This tool allows data fusion from localization landmarks and odometry to converge the estimate of the robot's state to the real state of the robot (its localization). The described work uses the setup described in [21], [22] and [23].

The organization of this paper is as follows: firstly, the presentations of formal parameters of the robot and of the Kalman Filter. After that, some simulations are shown in order to ascertain the validity of the method and showing how interesting the method is. Real robot testing is also shown before the presentation of the conclusions of this paper.

0-7803-9402-X/05/$20.00 © 2005 IEEE

2.Model of the robot

Let us assume a robot with differential locomotion without slip [22] [23]such as in figure 1.

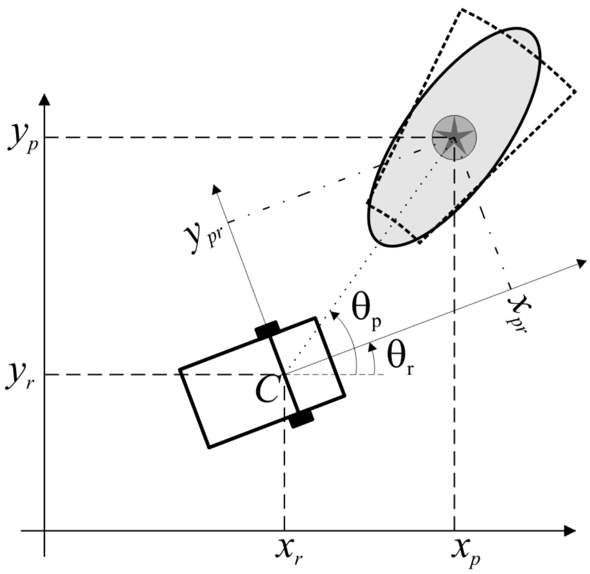

Figure 1. Model of the robot and its axis

The complete state of the real robot is X'(t) and given by (Figure 1):

$$X'(t) = [x(t) \quad y(t) \quad \theta(t) \quad v(t) \quad \omega(t)]^T \quad (1)$$

Where $x(t)$ and $y(t)$ are the position of the center point C of the robot on the xy plane, $\theta(t)$ is the orientation, $v(t)$ the tangential speed of the C point and $\omega(t)$ is the corresponding angular velocity. Using odometry to measure speed of each wheel, v1(t) and v2(t), the following apply:

$$v(t) = \frac{v_1(t) + v_2(t)}{2} \quad (2)$$

$$\omega(t) = \frac{v_1(t) - v_2(t)}{b} \quad (3)$$

where b is the distance between the two traction points, usually approximated by wheel distance.

The kinematics of the robot are given by:

$$\frac{d}{dt}\begin{bmatrix} x(t) \\ y(t) \\ \theta(t) \end{bmatrix} = \begin{bmatrix} v(t)\cos(\theta(t)) \\ v(t)\sin(\theta(t)) \\ \omega(t) \end{bmatrix} \quad (4)$$

All numeric values used in the paper are taken from the values found for the robots of the “5dpo 2000” team.

3.Extended Kalman Filter

With the dynamic model given by (4) and considering control signals changing only at sampling instants, the state equation is [24]:

$$\frac{dX(t)}{dt} = f\left(X(t), u(t_k), t\right), \quad t \in]t_k, t_k+1] \quad (5)$$

where $u(t) = [v(t) \;\; \omega(t)]^T$, that is, odometry measurements are used in the kinematic model as inputs.

This state should be linearised over $t=t_k$, $X(t)=X(t_k)$ and $u(t)=u(t_k)$:

$$A^*(k) = \begin{bmatrix} 0 & 0 & -v(t_k).\sin(\theta(t_k)) \\ 0 & 0 & v(t_k).\cos(\theta(t_k)) \\ 0 & 0 & 0 \end{bmatrix} \quad (6)$$

With state transition matrix:

$$\Phi^*(k) = exp(A^*(k)(t_k - t_{k-1})) \quad (7)$$

When a robot sees a marker at global coordinates (x_p, y_p) the relative measure taken is (x_{pr}, y_{pr}) on a referential local to the robot at (x,y,θ).

Thus the measures are:

$$z(t) = h(X(t)) = \begin{bmatrix} x_{pr} \\ y_{pr} \end{bmatrix} = \begin{bmatrix} (x_p-x)\cos(\theta) + (y_p - y)\sin(\theta) \\ -(x_p-x)\sin(\theta) + (y_p - y)\cos(\theta) \end{bmatrix} \quad (8)$$

and by differentiating the observations matrix:

$$H^*(k) = \begin{bmatrix} -\cos(\theta(t_k)) & -\sin(\theta(t_k)) & y_{pr}(t_k) \\ \sin(\theta(t_k)) & -\cos(\theta(t_k)) & -x_{pr}(t_k) \end{bmatrix} \quad (9)$$

The Extended Kalman Filter (EKF) equations are as follows [24]:

i) state estimate at time $t=t_k$, $X(k^-)$, knowing previous estimate $t=t_{k-1}$, $X(k-1)$ and control $u(t_k)$ that can be calculated by numerical integration of equation (5).

ii) Propagation of the covariance of the state

$$P(k^-) = \Phi^*(k)P(k-1)\Phi^*(k)^T + Q(k) \quad (10)$$

where Q(k) is the covariance of the noise in (5) and also relates to the accuracy of the model used.

If there is a measurement, the following also apply:

iii) Kalman Gain calculation:

$$K^{temp} = \left(H^*(k)P(k^-)H^*(k)^T + R(k)\right)^{-1}$$
$$K(k) = P(k^-)H^*(k)^T K^{temp} \qquad (11)$$

iv) State covariance update.

$$P(k) = \left(I - K(k)H^*(k)\right)P(k^-) \qquad (12)$$

v) State update.

$$X(k) = X(k^-) + K(k)\left(z(k) - h\left(X(k^-, t_k)\right)\right) \qquad (13)$$

4.Simulation

As mentioned before, all data is taken from real robots and field experience [21], [23]. In this environment, the robots move in a field of more than 5 over 10 meters and localize themselves by the coloured poles at the corners.

Using the axis system that connects robot and pole, the estimate of the standard error for the distance measurement to the pole is (*sdv_dist_m*distp*). This means that distance error is proportional to actual distance. For the angle measure, a given constant *sdv_ang* exists wich makes y_{pr} = *sdv_ang*distp* (see figure 1).

$$R' = \begin{bmatrix} (sdv\_dist\_m * distp)^2 & 0 \\ 0 & (sdv\_ang * distp)^2 \end{bmatrix} \qquad (13)$$

In order to have the measurements in an absolute referential, a rotation is necessary:

$$\theta_p = tg^{-1}\left(\frac{y_p - y}{x_p - x}\right) - \theta \qquad (14)$$

where (x_p, y_p) are the known landmark coordinates in the (absolute) world and (x, y, θ) is the state of the robot. The state rotation matrix is then:

$$Rot = \begin{bmatrix} \cos(\theta_p) & \sin(\theta_p) \\ -\sin(\theta_p) & \cos(\theta_p) \end{bmatrix} \qquad (15)$$

This rotation affects covariance according to [24], [25]:

$$R(k) = Rot * R' * Rot^T \qquad (16)$$

The simulation presented uses *sdv_dist_m = 0,1 m/m* and *sdv_ang = 0,06rad*. These values are calculated experimentally in 1000 measurements made with a static robot in 10 different positions – currently one measurement is possible every 40 ms. P(k) and Q(k) are initialised as identity matrices multiplied by the scalars respectively 10^{-3} and $2*10^{-5}$.

The simulated measurements are given by equation (8) and adding noise according to the model of the measurement mentioned previously.

4.1.Convergence test – stopped robot

For an initial test, let us test the convergence of the EKF in a very simple situation.

In the following simulations, the robot's position and estimated localization are calculated and shown every 40 ms (that is also the control cycle period of the real system). In order to supply a good amount of localization information, the simulated robot always changes the seen landmark every 2 seconds. The real position of the robot is represented by a square and estimates are circles. The first landmark is a 5 points star and the second is a 6 points star.

Observing figure 2 where the robot stands still in state (x,y,θ)=(4 m, 0 m, 0 rad) and the estimate starts from (0,0,0) it is possible to see the estimate converging to real robot position over time. The change in the "seen" marker may be identified by the resulting change in the direction of convergence for the estimate. One can observe that a single marker does not produce a good estimate but the frequent change in markers viewable by the robot at very different angles produces an interesting localization information leading to a low covariance estimate with a high degree of confidence.

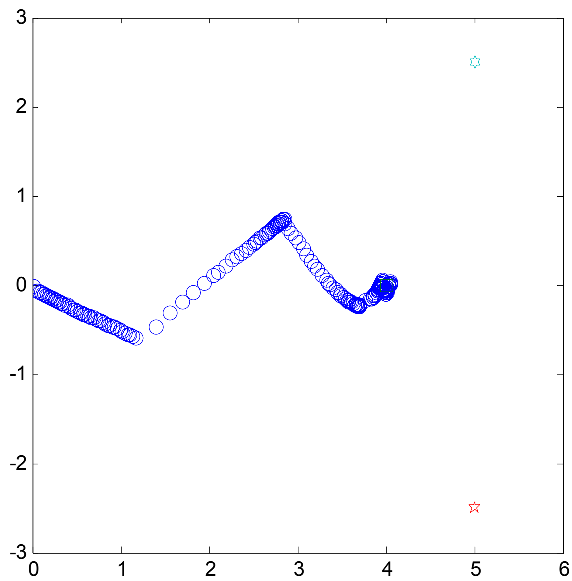

Figure 2. Convergence of the estimate with the robot standing still (estimate is circle, real robot is square and markers are stars)

4.2.Moving robot

Let us now consider figure 3. The estimate starts from (0,0,0) and the real robot from (0,-2,0). The speeds of the moving robot follows a Gaussian distribution N(average, standard deviation) with the following numerical values:

$v = N(1, 1)$ [m/s]

$\omega = N(0.5, 0.5)$ [rad/s]

The simulation in figure 3 shows even more that only the change in seen markers provides good localization information. As time goes on, angle to marker 1 is smaller and thus a small error in localization is noticeable.

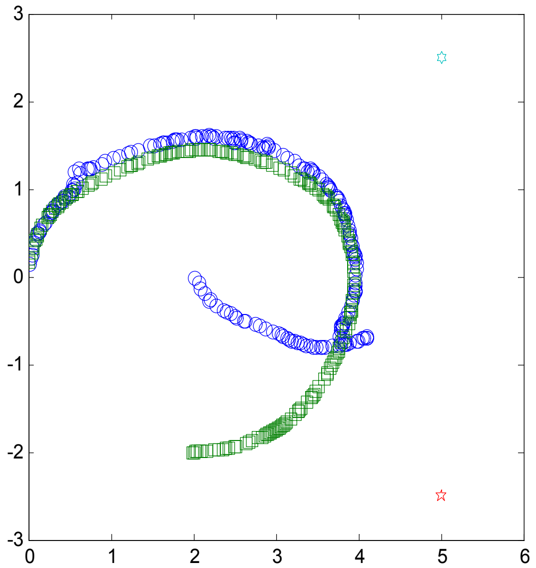

Figure 3. Convergence of the estimate with a moving robot

4.3.Bump simulation

Localization is critical when odometry fails to provide accurate information and this happens when robots travels through irregular ground, touches things or slides in the ground. In any of these cases, the robot unpredictably changes its localization. Simulation of such events is shown in figure 5. When robot is near position (3,1), its position and attitude are changed instantaneously. As measurements from the two markers are received by the robot, its localization estimate is corrected approaching the real robot state. The quality of the information gathered by the system is better when the angle to both markers is large – in that situation, convergence is faster because the measurements ellipses have less overlapping (see figure 4).

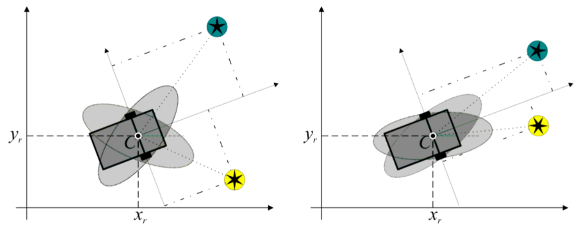

Figure 4. Left: Small overlap of covariance matrices hint high confidence localization; Right: Small angle between markers result in large overlap of covariance thus hinting low quality in localization

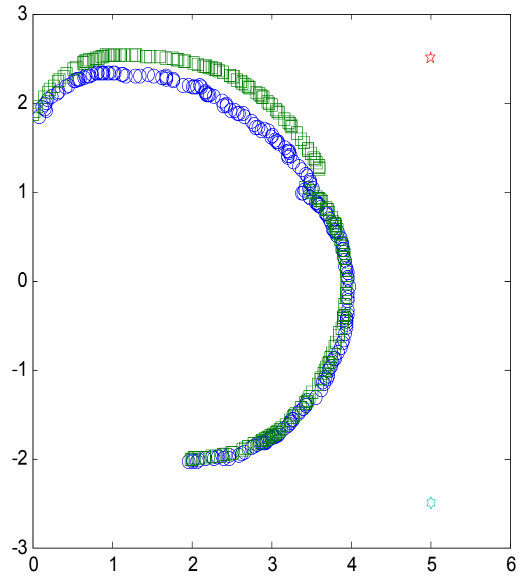

Figure 5. Localization when the robot crosses a bump

5.Real robot experiences

An experimental setup was built that allows for automatic localization over two methods: an external localization method (figure 6) that is assumed with low errors and the self localization method based on the EKF that runs inside the robot.

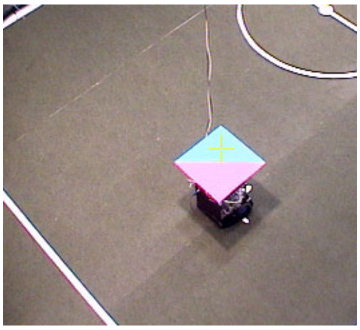

Figure 6. Robot seen from above; this type of image is used for external localization

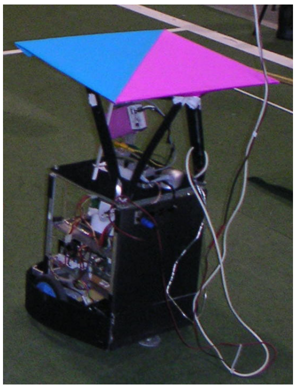

Figure 7. Close up of the robot, without covers and showing wirings

Figure 8 presents the diagram for representing robot position for the real robot and its estimate (to be used in figure 9). Additional information presented in figure 9 is the covariance of the estimate.

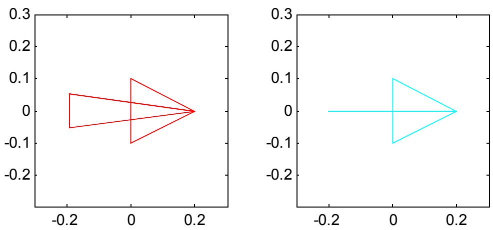

Figure 8. Left: Real robot; Right: Estimated robot; both at $(x=0, y=0, \theta=0)$

The real experimental setup has four markers placed on each corner of the field presented in figure 9. The situation depicted is a turning robot following a circle that sees poles in sequence. As the robot sees different markers, the state estimate inside the robot convergences over its real position. All data is taken at intervals of 40 ms; times in figure 9 are given in seconds.

The robot uses an on-board PAL camera and real time vision processing in the on-board PC in order to determine colours and provide pole localizations for poles of 3 colours, 1 meter high, 20 cm diameter. This calculation is made every 40 ms. A photo of the actual robot can be seen in figure 7.

The actual dynamic test of the robot describing circles is presented in figure 9. As time passes, the estimate converges to the real robot state. It can also be seen the covariance changing over time as several different poles are measured and global the covariance changed according to model mentioned earlier in the EKF rules.

6.Conclusions

The presented localization problem for the state of this robot needs an EKF. For this tool, no theoretical proof of convergence is possible. Additionally, there is no proof that this filter is optimal.

Simulated and real tests indicate however that practical convergence exists and that indeed the method is usable and interesting.

The presented model is taken from the experimental data gathered. The measurements taken are to robocup coloured poles with 5dpo-2000 hardware based on PAL cameras. This set-up provides measurements of direction and distance with very different errors.

The presented model of the measurements is adaptable to self-localization problems using any kind of markers where direction and distance to marker have different errors such as the experimental setup features.

Localization information from one pole alone is poor and the availability of several measurements from different markers is essential for a localization with a low covariance and a high degree of confidence.

In the real setup it is not possible to view simultaneously two poles (the viewing angle of the camera does not allow that). The theoretical approach given does allow for that and that would be interesting in order to reduce covariance of the localization estimate.

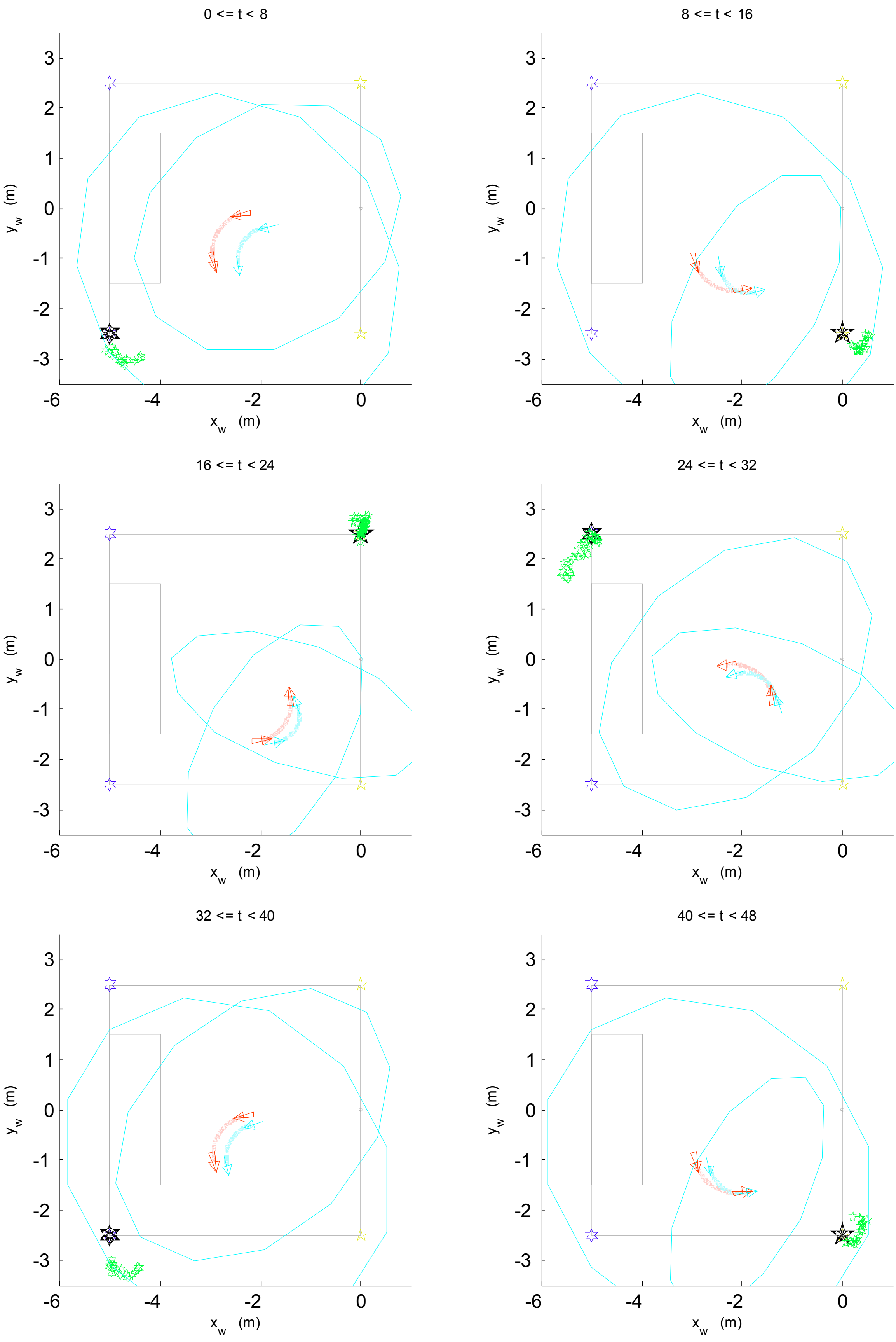

Figure 9. Real robot run; four poles; times in seconds

Bibliography

1 Patric Jensfelt, "Approaches to Robot Localization in Indoor Environments",Royal Institute of Technology, Estocolmo, Suécia , 2001

2 Mª Isabel Ribeiro, João G. M. Gonçalves, "Natural Landmark based Localization of Mobile Robots Using Laser Range Data",Proceedings EUROBOT 1996 ,

3 Artur Arsénio and M. Isabel Ribeiro, "Absolute Localization of Mobile Robots using Natural Landmarks",5th IEEE International Conference on Electronics, Circuits and Systems (ICECS'98), Lisbon, September 7-10, 1998 , 1998

4 João Gomes-Mota, Maria Isabel Ribeiro, "Mobile robot localization on reconstructed 3D models",Journal of Robotics and Autonomous Systems 31 (1-2) pp. 17-30, Elsevier Science, Abril 2000 , 2000

5 M. Drumheller, "Mobile Robot Localization Using Sonar",IEEE Transaction on Pattern Analisys and Machine Intelligence, vol 9, n.2 pp 352-332 , 1987

6 O. Vijk, P. Jensfelt and H. Chistensen, "Triangulation based Fusion of Ultrasonic Sensor Data",Proceedings of the IEEE International Conference on Robotics and Automation (ICRA-98), Leuven, Belgium, May 16-20, 1998. IEEE Computer Society, 1998, ISBN 0-7803-4301-8, Volume 4 3419-3424 , 1998

7 R.N. Aguilar, G.C.M. Meijer , "Low-Cost Ultrasonic Fusion Sensor for Angular Position",Proceedings of SeSens 2002, November 29, 2002 - Veldhoven, the Netherlands , 2002

8 L. Girod, D. Estrin, "Robust Range Estimation Using Acoustic and Multimodal Sensing",International Conference on Intelligent Robots and Systems (IROS 2001) , 2001

9 Ching-Chih Tsai, "A localization System of a Mobile Robot by Fusing Dead-Reckoning and Ultrasonic Measurements",IEEE Instrumentation and Measurment Technology Conference, Minnesota, USA, 1998 , 1998

10 O. Wijk; H.I. Christensen, "Localization and navigation of a mobile robot using natural point landmarks extracted from sonar data",Robotics and Autonomous Systems 31 (2000) pp. 31–42 , 2000

11 Figueroa, F., Mahajan, A, "A Robust Navigation System for Autonomous Vehicles using Ultrasonics", Control Engineering Practice, Vol. 2, No. 1, 1994. pp. 49–59 , 1994

12 R. Want, A. Hopper, V. Falcao, J. Gibbons, "The active badge location system",ACM Transactions on Information Systems - vol. 10, no. 1, Jan. 1992 91-102 , 1992

13 Jeffrey Hightower, Gaetano Borriello and Roy Want, "SpotON: An Indoor 3D Location Sensing Technology Based on RF Signal Strength",University of Washington CSE Technical Report 2000-02-02 , 2000

14 Kai-Wei Chiang, Aboelmagd Noureldinn Naser El-Sheimy, "Multisensor integration usingneuron computing for land-vehicle navigation",Springer-Verlag 2003 , 2002

15 Fabien Launay, Akihisa Ohya and Shin'ichi Yuta, " Vision-Based Navigation of Mobile Robot using Fluorescent Tubes",The 10th International Conference on Advanced Robotics (Aug. 2001) , 2001

16 Fabien Launay, Akihisa Ohya and Shin'ichi Yuta, "A Corridors Lights based Navigation System including Path Definition using a Topologically Corrected Map for Indoor Mobile Robots",Proceedings 2002 IEEE International Conference on Robotics and Automation, pp.3918-3923 (May 2002) , 2002

17 Toyama, K., & Hager, G. D., "Tracker fusion for robustness in visualfeature tracking",SPIE Photonics East, Philadelphia, PA, 2589 pp. 38-49 , 1995

18 Sinisa Segvic e Slobodan Ribaric, "Determining the Absolute Orientation in a Corridor Using Projective Geometry and Active Vision",IEEE Transactions on Industrial Electronics, vol. 48, no. 3, june 2001 , 2001

19 Evgeni Kiriy, Martin Buehler, "Three-state Extended Kalman Filter for Mobile Robot Localization",Tech. Report Centre for Intelligent Machines (CIM), McGill University, April 12, 2002 , 2002

20 Robert Bartelds, "Real Time Vision Based Self-Localization",Technical University of Delft, 4-4-2002 , 2002

21 Paulo Costa, António Moreira, Armando Sousa, Paulo Marques, Pedro Costa, Aníbal Matos, "5dpo Team Description",Robocup 1999 – Robot World Cup Soccer Games and Conference, Stockolm, Sweeden, pp 85-89, 1999 , 1999

22 Paulo José Costa, "Localização em Tempo Real de Múltiplos Robots num Ambiente Dinâmico",Tese Doutoramento, Faculdade de Engª Univ. Porto , 1999

23 Armando Jorge Sousa, "Arquit. de Sist. Robóticos e Localização em Tempo Real através de Visão",PhD in Electrical Engineering and Computers at Fac. of Engineering of the Univ. Porto, Portugal , 2004

24 A. Gelb, J. Kasper, Raymond Nash, Charles Price, Arthur Sutherland, "Applied Optimal Estimation",The M. I. T. Press , 1974

25 Greg Welch e Gary Bishop, "An Introduction to the Kalman Filter",Technical Report 95-041 - Department of Computer Science University of North Carolina at Chapel Hill, EUA , 2002