LNAI 5271

Emilio Corchado
Ajith Abraham
Witold Pedrycz (Eds.)

Hybrid Artificial Intelligence Systems

Third International Workshop, HAIS 2008
Burgos, Spain, September 2008
Proceedings

Springer

Volume Editors

Emilio Corchado
Universidad de Burgos
Escuela Politécnica Superior
GICAP Research Group
E-mail: escorchado@ubu.es

Ajith Abraham
Norwegian University of Science and Technology
Center of Excellence for Quantifiable Quality of Service
7491 Trondheim, Norway
E-mail: ajith.abraham@ieee.org

Witold Pedrycz
University of Alberta
Department of Electrical and Computer Engineering
Edmonton, Alberta T6G 2V4, Canada
E-mail: pedrycz@ee.ualberta.ca

Library of Congress Control Number: 2008935394

CR Subject Classification (1998): I.2.6, I.2, H.3, H.4, H.2.8, F.2.2, I.4-6

LNCS Sublibrary: SL 7 – Artificial Intelligence

ISSN 0302-9743
ISBN-10 3-540-87655-3 Springer Berlin Heidelberg New York
ISBN-13 978-3-540-87655-7 Springer Berlin Heidelberg New York

Springer is a part of Springer Science+Business Media

springer.com

Printed in Germany

Typesetting: Camera-ready by author, data conversion by Scientific Publishing Services, Chennai, India
Printed on acid-free paper SPIN: 12522033 06/3180 5 4 3 2 1 0

Preface

The Third International Workshop on Hybrid Artificial Intelligence Systems (HAIS 2008) presented the most recent developments in the dynamically expanding realm of symbolic and sub-symbolic techniques aimed at the construction of highly robust and reliable problem-solving techniques. Hybrid intelligent systems have become increasingly popular given their capabilities to handle a broad spectrum of real-world complex problems which come with inherent imprecision, uncertainty and vagueness, high-dimensionality, and non stationarity. These systems provide us with the opportunity to exploit existing domain knowledge as well as raw data to come up with promising solutions in an effective manner. Being truly multidisciplinary, the series of HAIS workshops offers a unique research forum to present and discuss the latest theoretical advances and real-world applications in this exciting research field.

This volume of *Lecture Notes on Artificial Intelligence* (LNAI) includes accepted papers presented at HAIS 2008 held in University of Burgos, Burgos, Spain, September 2008

The global purpose of HAIS conferences has been to form a broad and interdisciplinary forum for hybrid artificial intelligence systems and associated learning paradigms, which are playing increasingly important roles in a large number of application areas.

Since its first edition in Brazil in 2006, HAIS has become an important forum for researchers working on fundamental and theoretical aspects of hybrid artificial intelligence systems based on the use of agents and multiagent systems, bioinformatics and bio-inspired models, fuzzy systems, artificial vision, artificial neural networks, optimization models and alike.

This conference featured a number of special sessions: Hybrid Systems Based on Negotiation and Social Network Modelling, Real-World Applications of HAIS Under Uncertainty, Hybrid Intelligent Systems for Multi-robot and Multi-agent Systems, Genetic Fuzzy Systems: Novel Approaches and Applications of Hybrid Artificial Intelligence in Bioinformatics.

HAIS 2008 received over 280 technical submissions. After a through peer-review process, the International Program Committee selected 93 papers which are published in this conference proceedings. The large number of submissions is certainly not only a testimony of the vitality and attractiveness of the field but an indicator of the interest in the HAIS conferences themselves.

As a follow-up of the conference, we anticipate further publication of selected papers in special issues scheduled for the journal of *Information Sciences*, Elsevier Sciences, The Netherlands and the *International Journal On Computational Intelligence Research* (IJCIR).We would like to express our thanks to the Program Committee whose members did an outstanding job under a very tight schedule. Our thanks go to the keynote speakers: Bogdan Gabrys from Bournemouth University (UK), Francisco Herrera from the University of Granada (Spain), Xindong Wu from the University of Vermont (USA), and Hujun Yin from the University of Manchester (UK).

Organizing Committee

Corchado, Emilio	University of Burgos (Chair)
Baruque, Bruno	University of Burgos (Co-chair)
Herrero, Álvaro	University of Burgos (Co-chair)
Arroyo, Angel	University of Burgos
Burgos, Pedro	University of Burgos
Bustillo, Andrés	University of Burgos
Canales, Jacinto	CPIICyL
Corchado, Juan Manuel	University of Salamanca
Curiel, Leticia	University of Burgos
Lara, Ana M	University of Burgos
López, Carlos	University of Burgos
Manzanedo, Miguel Ángel	University of Burgos
Marticorena, Raúl	University of Burgos
Martín, David	University of Burgos
Martín, Juan Vicente	University of Burgos
Pérez, Juan Carlos	University of Burgos
Sáiz, Jose Manuel	University of Burgos
Sáiz, Lourdes	University of Burgos
Sedano, Javier	University of Burgos
Vaquerizo, Belén	University of Burgos

Table of Contents

Invited Talks

Agents and Multi-agent Systems

Evolutionary Computation

Connectionist Models

Optimization Systems

Fuzzy Logic Systems

Classification and Classifiers

Cluster Analysis

Video and Image Analysis

Learning Systems, Algorithms and Applications

Hybrid Systems Based on Negotiation and Social Network Modelling

Real World Applications of HAIS Under Uncertainty

Hybrid Intelligent Systems for Multi-robot and Multi-agent Systems

Applications of Hybrid Artificial Intelligence in Bioinformatics

Genetic Fuzzy Systems: Novel Approaches

Multi-robot Route Following Using Omnidirectional Vision and Appearance-Based Representation of the Environment

Luis Payá, Oscar Reinoso, Arturo Gil, and Javier Sogorb

Departamento de Ingeniería de Sistemas Industriales,
Miguel Hernández University
Avda. de la Universidad, s/n.
03202 Elche (Alicante), Spain
{lpaya,o.reinoso}@umh.es

Abstract. In this work, a framework to carry out multi-robot route following is presented. With this approach, a team of mobile robots can follow a route that a leader robot has previously recorded or is recording at the moment. Each robot has a catadioptric system on it that provides omnidirectional images of the environment. To carry out the localization and control of each robot during route following, we have made use of an appearance-based philosophy in combination with compression techniques in the Fourier Domain and the Principal Components Analysis subspace. These techniques are especially interesting in the case of panoramic images due to their invariance to orientation and robustness to small changes in the environment. Several experiments with a team of mobile robots have been carried out to demonstrate the robustness of the approach in realistic office and laboratory environments.

Keywords: 1D Fourier Transform, Panoramic images, Principal Components Analysis, Probabilistic localization.

1 Introduction

Nowadays, the presence of robots in our houses and factories is continuously increasing. These robots have moved to such environments to fulfill our needs, usually, in repetitive or unpleasant tasks. However, it is desirable they show a higher degree of autonomy, fulfillment and robustness to expand its range of home applications. In order to achieve these aims, one of the most important skills a robot needs is the efficient environment representation and navigation, taking into account that in real working environments, the robot has to deal with some typical situations such as variation in illumination, occlusions and change in the position of some objects in the scene. The representation of the environment must cope with these features so that the robot is absolutely autonomous.

Previous research has shown how to face the problem of environment representation. In [1], a complete survey is presented with information about robot mapping and the different approaches that have been developed recently. Current works show how

E. Corchado, A. Abraham, and W. Pedrycz (Eds.): HAIS 2008, LNAI 5271, pp. 680–687, 2008.

a graph representation may be very efficient, such as [2], that constructs a weighted graph in which nodes are the images taken at certain positions and links denote similarity between images. SIFT features and the epipolar restriction are used to obtain a robust heading estimation between each pair of panoramic images. A similar approach is presented in [3], that is based on the use of hierarchical cognitive maps. The place cells represent the scenes through a PCA compression and the information provided by an electronic compass is used to compute the connectedness between nodes. A similar probabilistic representation is presented in [4]. Based on objects, they build a global topological representation of places with object graphs serving as local maps. The objects are recognized by means of the SIFT points extracted from the images captured by a stereo pair. Finally, the work in [5] presents a framework approach to robot mapping using omnidirectional vision and Fourier transformation that allows hierarchical localization with variable accuracy and self-organization of the visual memory of the environment.

In some applications, the use of a team of robots may help to make the achievement of the task faster and more reliable. In such situations, each robot works with incomplete and changing information that has, also, a high degree of uncertainty. This way, only a suitable choice of the representation and an effective communication between the members of the team can provide the robots with a complete knowledge of the environment where they move. As an example, [6] presents a probabilistic EKF algorithm where a team of robots builds a map online, while simultaneously they localize themselves. In [7], a map is build using visual appearance. From sequences of images, acquired by a team of robots, subsequences of visually similar images are detected and finally, the local maps are merged into a single map.

A typical problem in collaborative robotics implies following a path e.g., to perform a surveillance task in an office environment or an assembly or delivery task in an industrial environment. Also, the problem of formations, where a team of robots must navigate keeping a relative spatial distribution of the robot positions can be seen as a problem of path following, where one or several robots must follow the path the leader is recording with an offset either in space or in time. Some approaches suggest that this process can be achieved just comparing the general visual information of the scenes, without necessity of extracting any feature. These appearance-based approaches are especially useful for complicated scenes in unstructured environments where appropriate models for recognition are difficult to create. As an example, [8] addresses a method where several low-resolution images along the route to follow are stored. This approach is not able to cope with large and varying environments and is not robust. [9] uses PCA compression of the scenes in an incremental way, what allows multi-robot route following.

In this paper, we present an appearance-based method for multi-robot route following where 1D Fourier Transform on omnidirectional images is used to build the database, PCA compression is used to compute the control action of the robot and a probabilistic Markov process is implemented for robot localization. Section 2 presents the appearance-based process used to represent the environment and the previous work done in this field. Section 3 shows the implementation of the multi-robot route following application. Some experiments have been carried out with two mobile robots, whose results are exposed in section 4. To finish, the conclusions of the work are detailed.

2 Representation of the Environment

The main goal of the work is to create a framework to carry out multi-robot route following using just visual information and with an appearance-based approach. In this task, a leader robot goes through the desired route while a team of robots follows it. The first step to accomplish this task is the learning phase, where the leader robot stores some general visual information along the route to follow. In this step, it is important to define correctly the representation of the environment to allow that any robot can follow the route of the leader one with an offset either in space or/and in time in an efficient way. An appearance-based approach for robot navigation implies using the information of the whole images without extracting any kind of landmark. Previous works [10] have used PCA compression of the scenes captured with a forward looking camera to reduce the amount of memory needed and the computational cost during the navigation task. However, to allow multi-robot route following while the leader is still going through the route, an incremental model to build the database is needed. Previous works have made use of incremental PCA with this goal [9].

In the current work we use the information provided by a catadioptric system composed by a forward looking camera and a hyperbolic mirror. This system provides omnidirectional images of the environment that can easily be transformed into panoramic images as shown on fig. 1(a) and 1(b).

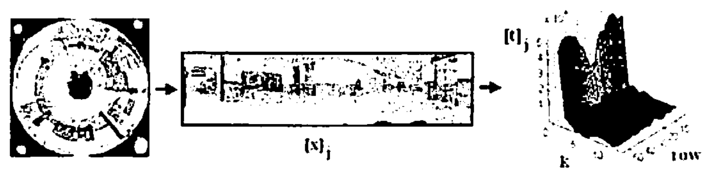

Fig. 1. (a) Original omni-directional image, (b) corresponding panoramic image and (c) power spectrum of the 1D Fourier Transform of the panoramic image computed row by row

This kind of images can be transformed to another compact representation into the Fourier domain [5]. The sequence of complex numbers $\{a_n\} = \{a_0, a_1, \ldots, a_{N-1}\}$ can be transformed into the sequence of complex numbers $\{A_n\} = \{A_0, A_1, \ldots, A_{N-1}\}$ using the Discrete Fourier Transform using the following expression:

$$A_k = \sum_{n=0}^{N-1} a_n \cdot e^{-j\frac{2\pi nk}{N}}; \qquad k = 0,\ldots,N-1. \tag{1}$$

Using this expression, each row of the panoramic image can be transformed into the Fourier Domain. This transformation presents two interesting properties for robot mapping and localization when omnidirectional images are used. First, the most relevant information in the Fourier domain concentrates in the low frequency components. Furthermore, removing high frequency information can lead to an improvement in localization because these components are more affected by noise. The second interesting property is the rotational invariance. If two images are acquired at the same point of the environment but having the robot different headings, then, the power spectrum of each row is the same in both cases. This is because these two rotated omnidirectional images lead to two panoramic images that are the same but shifted along the horizontal axis. If each row of the first image is represented with the sequence $\{a_n\}$ then and each row of the second image will be the sequence $\{a_{n-q}\}$, being q the amount of shift, that is proportional to the relative rotation between images. The rotational invariance can be deducted from the shift theorem, which can be expressed as:

$$\Im[\{a_{n-q}\}] = A_k \cdot e^{-j\frac{2\pi qk}{N}} \qquad k = 0,\ldots,N-1. \tag{2}$$

where $\Im[\{a_{n-q}\}]$ is the Fourier Transform of the shifted sequence and A_k are the components of the Fourier Transform of the non-shifted sequence. According to this expression, the Fourier Transform of a shifted sequence of numbers is equal to the Fourier Transform of the original signal multiplied by a complex number whose magnitude is the unit. This means that the amplitude of the Fourier Transform of the shifted image is the same as the original transform and there is only a phase change, proportional to the amount of shift q. This way, while the leader robot goes through the desired route, it captures N omnidirectional views, transforms them to the panoramic representation, resulting the images $[x]_j \in \Re^{RxC}$, $j = 1,\ldots,N$, and computes the 1D Fourier Transform row by row. After this process, the robot has created a database containing the Fourier matrixes $[t]_j \in \Re^{RxF}$, $j = 1,\ldots,N$, arranged by order of acquisition, being F the number of Fourier components retained.

3 Multi-robot Route Following

3.1 Localization of the Robot

Once the database is created or while it is being built, during the navigation phase, the second robot is situated on a point near the learned route. Then, it has to recognize which of the stored images is the nearest one to the image captured at the current position and drive to tend to the route, following it till the end. It must be carried out just comparing its current visual information with the information stored in the database. Two processes must run successively: auto-localization and control. During the auto-localization, the Fourier matrix of the current image is compared with the information in the database. Theoretically, the most similar point should correspond to the nearest position of the robot. However, in office environments which present a repetitive visual appearance, this simple localization method tends to fail often as a result of the aperture problem. This means that the visual information captured at two different locations that are far away can be very similar. To avoid these problems, a probabilistic approach based on a Markov process has been used. The current position of the robot can be estimated using the Bayes rule, using the next expression:

$$p(x_j \mid [t]_i;\theta)\,\alpha\, p([t]_i \mid x_j;\theta)\cdot p(x_j). \tag{3}$$

where $p(y_j)$ denotes the probability that the robot is on the position y_j before observing the Fourier matrix $[t]_i$. This value is estimated using the previous information and the motion model. $p([t]_i|y_j)$ is the probability of observing $[t]_i$ if the position of the robot is y_j. This way, a method to estimate the observation model must be deducted. In this work, the distribution $p([t]_i|y_j)$ is modeled through a sum of Gaussian kernels, centered on the n most similar points of the route:

$$p([t]_i | y_j;\theta) = \frac{1}{n}\cdot\sum_{i=1}^{n}\left(\gamma_{ij}\cdot e^{-\left(\frac{y_j - y_i}{\sigma}\right)^2}\right); \quad j = 1,\ldots,N. \tag{4}$$

Each kernel is weighted by the value of confidence γ_{ij}, that is the degree of similarity between the Fourier matrix of the currently captured image, $[t]_i$ and the j-th Fourier matrix of the database. Then, these kernels are convolved with a Gaussian function that models the motion of the robot, and that depends on the previous position and velocity of the robot. At last, the new position is considered at the point with highest contribution probability.

3.2 Control of the Robot

Once we have a new matching, in the control phase, the current visual information must be compared with the matched information of the database, and from this comparison, a control law must be deducted to lead the robot to the route. To do it, once the robot knows its position, it has to compute its orientation, comparing to the original heading that the first robot had when it captured the image at that position.

When working in the Fourier domain, eq. 2 allows computing the amount of shift q and so, the orientation of the robot. However, after some localization experiments, this expression has showed a very unstable behavior, and it has not been able to deal with small changes in illumination, noise and changes in the position of some objects in the environment. This way, an alternative procedure to retrieve the orientation has been developed, which is based on the use of sub-windows on the panoramic images. From each panoramic image stored in the database, $[x]_j$, a set of N' sub-windows is obtained from the whole image, where $\vec{w}_j^i \in \Re^{M \times 1}$ is each sub-window. These sub-windows are obtained scanning the original scene with a step in the horizontal axis (fig. 2). Carrying out a process of PCA compression, the PCA components $\vec{f}_j^i \in \Re^{K' \times 1}$ of each sub-window are calculated where $K' \leq N'$. Fig. 2 shows these projections as crosses in the case $K'=3$. On the other hand, during the autonomous navigation, another set of N' sub-windows is obtained form the current image, where $\vec{w}_N^i \in \Re^{M \times 1}$ is each sub-window. These windows are then projected onto the PCA subspace of the sub-images of the current image, giving as a result the dots on fig. 2. Then, the most similar projections to each one of them are extracted.

Arranging this information on a chart, we obtain the fig 3(a). To build this chart, the two most similar sub-images to each one are extracted. Extracting two sub-images instead of only one makes the method more robust to partial occlusions and small changes in the environment. The orientation of the robot is extracted from this chart using several least square fittings in an iterative process where data are shifted before

each new regression. After all the iterations, the best fitting results in a line whose ordinate in the origin is near to zero, whose slope is near to one and whose correlation coefficient is near to one. The orientation of the robot is proportional to the number of shifts until the best fitting is achieved. This method has demonstrated to be robust to recover the orientation of the robot.

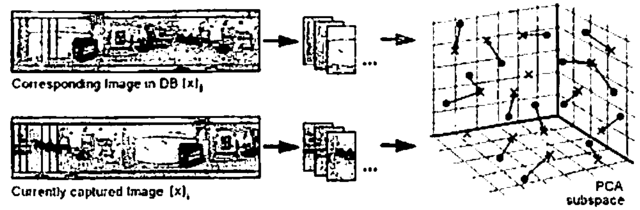

Fig. 2. From each image in the database, a set of sub-images is extracted and compressed using PCA methods. Then, a set of sub-images is extracted from the current images and projected on the same subspace. The most similar views to each of them are computed.

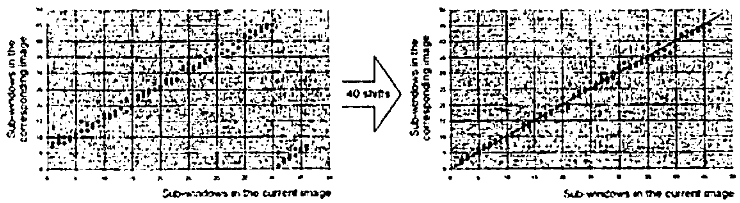

Fig. 3. (a) The sub-windows correspondences are arranged on a chart. The points of this chart are consecutively shifted until the best fitting is achieved (b). At each shift, all points are moved one position to the left and the first points are moved to the last position. The orientation of the robot is proportional to the number of shifts.

4 Results

Two Pioneer 3-AT robots with an omnidirectional vision system on each of them, and with processors P_A and P_B on-board, have been used to test the algorithms. R_A is the leader robot, which is recording the route and R_B is the follower one. Also, an independent processor P_C has been used. All the computers are connected in a CORBA-based architecture. To begin, the robot A is teleoperated through the desired route. After a while, R_B begins following this route. P_A is in charge of reading the new image, and storing it if is different enough to the previous ones. Then it computes the corresponding Fourier matrix and sends the panoramic image to P_C, which computes the PCA subspace of the sub-windows. When P_B captures a new image, it computes its Fourier matrix and calculates the nearest position of the database using the probabilistic approach. After this, P_C computes the control action to apply to R_B.

Several experiments have been carried out to validate the approach. Fig. 4 shows a typical route of around 50 meters, recorded in an office environment, and the route of the follower robot when it starts from two different points around it. Typically, the follower robot tends to the route and follows it, showing a great performance on the straight lines and a relatively bigger error in the turnings. However, with this approach, the robot is able to find the route and tend to it, showing a very stable behavior till the end. The control action implemented makes the robot move forward only if its orientation is close to the correct orientation. Otherwise, the robot will be applied only a steering velocity to correct the heading. In fact, in the second experiment, the robot is situated near to the route but with an orientation of about 180° with respect to the route. First, the robot turns until its orientation is correct and then it starts moving forward, with slight steering movements to correct its trajectory.

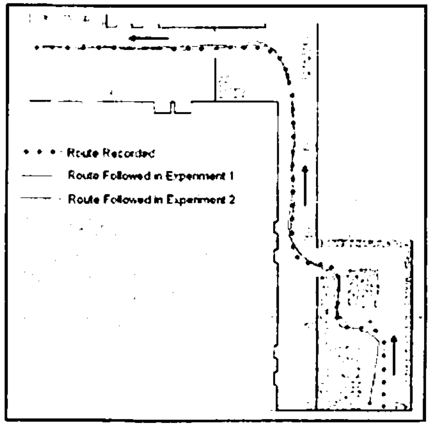

Fig. 4. Route recorded by the leader robot and routes followed by a follower robot in two experiments with different initial point

5 Conclusion

In this paper, an appearance-based multi-robot route-following scheme is presented. The proposed solution uses low resolution panoramic images and techniques for dimensionality reduction to extract the most relevant information along the environment. Thanks to its invariability to rotation, these techniques are especially interesting to be used in applications of map building and navigation. Also, an appearance-based method has been proposed to compute the orientation of the robot.

The final objective of the work is that other robots can follow a route from a distance (as in space or in time). To do it, a probabilistic algorithm has been implemented to calculate their current position among those that the leader has stored, and a controller has been implemented, also based on the appearance of the scenes, to calculate the linear and turning speeds of the robot.

Some experiments have been carried out with two Pioneer 3-AT robots using a CORBA-based architecture for communication. These experiments show how the process employed allows following a route in an accurate and robust way.

We are now working in other control methods to reduce the error during the navigation, studying the effects of illumination changes and scene changes more accurately. At last, more sophisticated ways of building a map are being evaluated so that the robot can find the route and follow it although its initial position is far from this route. These more complex maps should contain information of additional locations of the environment and they are expected to be useful in a number of applications in multi-robot navigation. Also, this application can be extended to a team of heterogeneous robots, equipped with different kinds of sensors. In this case, the hybrid systems approach would be useful to improve the performance of the task. Fuzzy logic and reinforced learning can be used both to build the database with information from several different sensors and to compare the information captured by the follower robot with the information in the database.

Acknowledgments. This work has been supported by MEC through the project DPI2007-61197: "Sistemas de percepción visual móvil y cooperativo como soporte para la realización de tareas con redes de robots".

References

1. Thrun, S.: Robot Mapping: A Survey. Technical report, Exploring Artificial Intelligence in the New Milenium, pp. 1–35. Morgan Kaufmann, San Francisco (2003)
2. Booij, O., Terwijn, B., Zivkovic, Z., Kröse, B.: Navigation using an Appearance Based Topological Map. In: IEEE International Conference on Robotics and Automation, pp. 3297–3932. IEEE Press, New York (2007)
3. Vasudevan, S., Gächter, S., Nguyen, V., Siegwart, R.: Cognitive Maps for Mobile Robots - An Object Based Approach. Robotics and Autonomous Systems 55, 35–371 (2007)
4. Stimec, A., Jogan, M., Leonardis, A.: A Hierarchy of Cognitive Maps from Panoramic Images. In: 10th Computer Vision Winter Workshop, Zell an der Pram, Austria (2005)
5. Menegatti, E., Maeda, T., Ishiguro, H.: Vimage-based Memory for Robot Navigation using Properties of Ominidirectional Images. Robotics and Autonomous Systems 47(4), 251–276 (2004)
6. Thrun, S.: A probabilistic online mapping algorithm for teams of mobile robots. International Journal of Robotics Research 20(5), 335–363 (2001)
7. Ho, K., Newman, P.: Multiple Map Intersection Detection using Visual Appearance. In: 3rd International Conference on Computational, Intelligence, Robotics and Autonomous Systems, Singapore (2005)
8. Matsumoto, Y., Ikeda, K., Inaba, M., Inoue, H.: Visual Navigation Using Omnidirectional View Sequence. In: IEEE International Conference on Intelligent Robots and Systems, pp. 317–322. IEEE Press, New York (1999)
9. Payá, L., Reinoso, O., Gil, A., Pedrero, J., Ballesta, M.: Appearance-Based Multi-Robot Following Routes Using Incremental PCA. In: Apolloni, B., Howlett, R.J., Jain, L. (eds.) KES 2007, Part III. LNCS (LNAI), vol. 4694, pp. 1170–1178. Springer, Heidelberg (2007)
10. Payá, L., Vicente, M.A., Navarro, L., Reinoso, O., Fernández, C.: Continuous Navigation of a Mobile Robot with an Appearance-Based Method. In: 2nd International Conference on Informatics in Control, Automation and Robotics, Barcelona, Spain, pp. 443–446 (2005)