

# CONTINUOUS NAVIGATION OF A MOBILE ROBOT WITH AN APPEARANCE-BASED APPROACH

Luis Payá, M. Asunción Vicente, Laura Navarro, Oscar Reinoso, César Fernández, Arturo Gil  
*Departamento de Ingeniería de Sistemas Industriales, Miguel Hernández University, Av. de la Universidad s/n,  
Ed. Torreblanca, 03202, Elche (Alicante), Spain*

**Keywords:** Automated learning, Continuous navigation, Appearance-based method, View-sequence route-representation.

**Abstract:** Appearance-based approaches have become a feasible technique applied to robot navigation. They are based on the direct comparison of images without any feature extraction. This approach presents several advantages comparing to model-based methods, such as their application to non-structured environments and the relative simplicity of the control they offer. This work presents the continuous navigation of a mobile robot, using an appearance-based method. The objective is the following of pre-recorded routes, using just visual information acquired with a couple of parallel cameras. In this approach, low-resolution frontal images along the route to follow are stored. This is done in an automated way, what allows optimizing the database size. Several control schemas have been tested to improve the accuracy in the navigation, such as P, PD and PD with variable parameters, whose experimental results are presented.

## 1 INTRODUCTION

Conventional research on mobile robots has focused on approaches that use geometric models to outperform auto-location and navigation (Lebeque, 1993), (Swain 1999). These techniques make use of landmarks from the scene as references to guide the robot through the desired route. The recognition of patterns is achieved comparing features of the input image with previously stored features. It supposes high complexity due to the difficulty in features extraction and comparison of patterns in realistic and changing environments.

In appearance-based approaches, images are memorized without any feature extraction, and recognition is achieved based on the matching of the images. It is expected to be useful for complicated scenes in the real world in which appropriate models for recognition are hard to create. This approach consists on two phases; in the learning one, the robot stores general visual information from several points of view in the environment, and in the autonomous navigation, a control action is calculated comparing the current visual information with the stored one.

These techniques require huge amounts of memory and high computational cost to store the necessary information of the environment and make the comparisons, so researchers have proposed

several methods to outperform auto-location and navigation trying to minimize the database and the computing time. Matsumoto et al. addressed the VSRR (View Sequence Route Representation) method (Matsumoto, 1996), consisting on the direct comparison of low-resolution images. Jones et al. proposed a method using a couple of cameras and odometer information to carry out navigation (Jones, 1997). The computing time can be reduced working with the colour histogram instead of the entire image (Zhou, 2003). Also the complexity of the problem can be reduced working in the PCA subspace (Maeda, 1997).

The method proposed is based on the VSRR model with a couple of cameras, in which the size of the images to store is reduced by taking a low resolution, and the size of the database is optimized using an automated learning phase.

## 2 CONTINUOUS NAVIGATION USING LOW-RESOLUTION IMAGES

The application has been tested over the B21r mobile robot, which has 4-wheel drive with synchronous drive kinematics. The driving and the

steering systems can be controlled independently. The images are acquired using a couple of Sony XC999 cameras with their optical axis aligned. The simultaneous use of two cameras will make our method more robust.

Previous experiments with 32x32, 64x64 and 128x128 resolutions showed that 32x32 is a good value due to the low computational cost it supposes, although it slightly increases the error in the following (Payá, 2005).

The purpose of the work is to follow pre-recorded continuous routes. To achieve this, two phases need to be implemented: a learning stage, in which some visual information along the route is stored, and an autonomous navigation phase, in which the robot estimates its current position and drives to tend to the learned route.

### 2.1 Learning phase

In our previous work (Payá, 2005), the route was decomposed in straight segments before carrying out the learning phase. Then, the robot was manually guided through the route to learn, taking images along the decomposed route in the points the operator decided. This fact made necessary to store, apart from the images, the qualitative control action (left or right) that the robot should execute in the intersection of two adjacent segments. This way, in the navigation phase, when the robot arrived to one of these intersections, it had to stop and begin a pure turning movement. As well, the separation between two samples (and so, the size of the database) was decided by the operator.

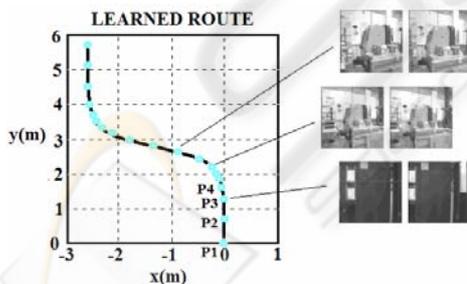


Figure 1: Database created during learning stage

The model presented proposes a new learning method that makes possible continuous navigation, with no need of storing additional information apart from the images along the route. Besides, to optimize the size of the database, the learning phase has been automated. This means the robot takes images simultaneously with both cameras at the first point of the route, and compares continuously the current views with those previously stored. The

criterion used is the zero-mean cross-correlation. When the correlation of the current images respect to the previous stored goes down a threshold, a new pair of images are acquired and stored in the database. Fig. 1 shows a possible route with the points where images have been taken. In the straight zones, the views change slowly, so new images are stored with less frequency. When the robot is turning, the information changes quicker, so the images are stored more frequently.

### 2.2 Autonomous navigation

During the autonomous navigation, the robot is located in a point near the learned route. Then, it has to recognize which of the stored positions is the nearest to the current one and drive to tend to the route, following it till the end. Two processes that are executed successively have been implemented: auto-location and autonomous navigation.

**Auto-Location:** To carry out auto-location, the current entire images are compared using the zero-mean cross-correlation with all those previously stored in the database (Payá, 2005).

During the navigation, the current image must be compared only with the previously matched and the following one, because navigation is continuous. This implies that, once the robot has started navigation, the time of processing is independent of the database size, and so, of the length of the route to be followed.

**Control:** The robot steering has to be corrected to make it tend to the route and follow it to the end. It is achieved through the tracking of two sub-windows taken on the matched images over the current images, as shown on fig. 2. The offsets  $x_l$  and  $x_r$  allow calculating the necessary steering velocity.

The linear velocity will be proportional to the average correlation, what means that when the robot is far from the route, the linear velocity is low to allow correcting the trajectory, but when the route is being followed quite well, the robot goes quicker. This equals to a proportional controller (eq. 1).

$$\begin{aligned} \omega^i &= k_l \cdot x_l^i + k_r \cdot x_r^i \\ v^i &= k_2 \cdot \gamma_{av}^i \end{aligned} \tag{1}$$

Being  $k_l$ ,  $k_r$  and  $k_2$  three constants. Taking into account the results experimentally obtained in our previous works (Payá, 2005), the given value to the constants is:  $k_l = k_r = 0.04$  and  $k_2 = 0.6$ .  $\gamma_{av}$  is the arithmetic average of the correlations of the left and right images. Fig. 3 shows the typical evolution of the correlation during autonomous navigation.

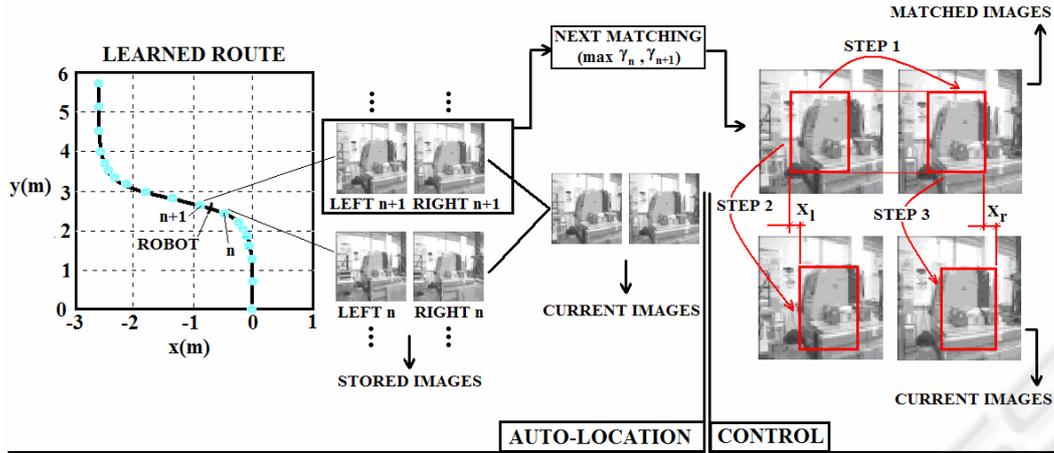


Figure 2: Tasks performed during autonomous navigation. First one, the robot makes auto-location, comparing current images with the previously matched, and the next ones. Once we have a match, we calculate, the linear and steering speeds based o the global correlation and the horizontal displacement of a template

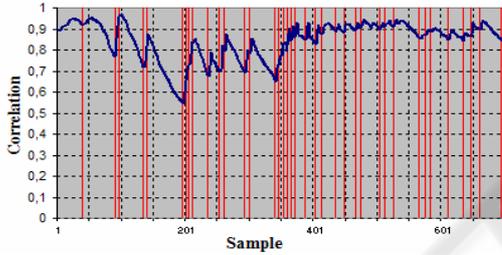


Figure 3: Evolution of correlation during navigation

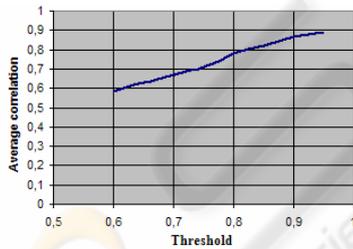


Figure 4: Average correlation during navigation for different learning thresholds

The vertical lines indicate the points where the matching images change. When this occurs, correlation begins increasing, reaches a maximum when he passes through the point where images were stored and begins decreasing until the next images are matched. Then, this behaviour is repeated. The average value of this correlation along the navigation can be used as a measure of the accuracy in the route following respect the pre-recorded one. After several experiments with different values for the learning threshold, the results obtained are shown on fig. 4.

To improve the behaviour during navigation, trying to perform it with a better degree of correlation, several control schemas have been tested. The second control schema includes differential effects in the control of linear and angular speeds.

$$\begin{aligned} \omega^i &= k_1 \cdot [x_l^i + x_r^i] + k_{1D} \cdot [(x_l^i - x_l^{i-1}) + (x_r^i - x_r^{i-1})], \\ v^i &= k_2 \cdot \gamma_{av}^i + k_{2D} \cdot (\gamma_{av}^i - \gamma_{av}^{i-1}). \end{aligned} \quad (2)$$

The effect this controller has in the navigation is a foresight of what is going to happen. In the case of the linear velocity, when the correlation is increasing, the robot is approaching to the route correctly. In this case, the derivative factor is positive, what means that the robot goes quicker because it is tending to the route correctly. When correlation decreases, the derivative factor is negative, so the robot reduces its velocity because it is moving away the route. This foresight effect can be applied to the turning speed too. This means that the differential effect may improve the overall speed during the navigation and the overall error in the following of the learned route. This second effect can be appreciated on fig. 5.

The last control schema tested is based in the differential one, but making the parameters variable.

$$\begin{aligned} \omega^i &= k_1 \cdot [\gamma_l^i \cdot x_l^i + \gamma_r^i \cdot x_r^i] + \\ &+ k_{1D} \cdot [\gamma_l^i \cdot (x_l^i - x_l^{i-1}) + \gamma_r^i \cdot (x_r^i - x_r^{i-1})], \\ v^i &= k_2 \cdot \gamma_{av}^i + k_{2D} \cdot (\gamma_{av}^i - \gamma_{av}^{i-1}). \end{aligned} \quad (3)$$

In this control schema, the effect of the horizontal offset of the left sub-windows is

multiplied by the correlation of the current left image with the matched left one, and the same with the right offset. This schema can be useful when the images of each camera are quite different or when there is an obstacle or occlusion that affects just to one of the cameras. In these cases, the control action of the camera that has the problem will be multiplied by a very low quantity, so it will have a poor effect on the robot navigation. As well, the experiments that have been carried out show how this control schema improves slightly the results that offers the differential one. These results are shown in fig. 5.

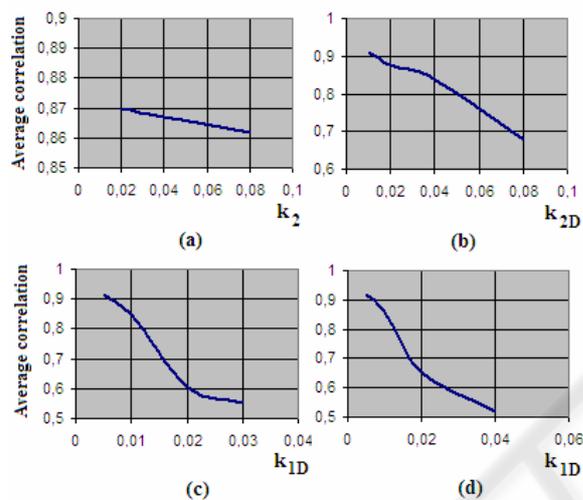


Figure 5: Average correlation during navigation for different control schemes. (a) P controller with  $K_1 = K_r = 0.04$ . (b) P controller with derivative effect in advance speed.  $K_2 = 0.04$ . (c) PD controller with  $K_2 = 0.04$  and  $K_{2D} = 0.04$ . (d) PD controller with variable parameters,  $K_2 = 0.04$  and  $K_{2D} = 0.04$

### 3 CONCLUSIONS AND FUTURE WORK

A solution to the problem of the continuous navigation using an appearance-based approach has been proposed. Several control schemas have been tested, including P, PD and PD with variable parameters controllers. With these laws, the robot is able to find itself and follow the route in a band of about two meters around the pre-recorded route. It can be done although the scene suffers small changes (illumination, position of some objects, partial occlusions in one of the cameras). We are now working in other control methods, such fuzzy logic.

The main drawback of this navigation method arises when the scenes are highly unstructured and

varying. In this case, it is necessary to increase resolution to get an acceptable accuracy in navigation. The solution proposed is based in the reduction of the information to store using PCA subspaces. This method shows two big advantages: the size of the vectors to compare is much smaller and we can calculate the majority of the information off-line so we have it available during navigation. Besides, the size of the vectors is independent of the resolution of the images so, it is expected to work well in very unstructured environments.

### ACKNOWLEDGEMENTS

This work has been supported by Ministerio de Educación y Ciencia through project DPI2004-07433-C02-01. 'Herramientas de teleoperación Colaborativa. Aplicación al Control cooperativo de Robots'.

### REFERENCES

- Jones, S.D., Andersen, C., Crowley, J.L., 1997. Appearance based processes for visual navigation. In *Proceedings of the IEEE International Conference on Intelligent Robots and Systems*. 551-557.
- Lebegue, X., Aggarwal, J.K., 1993. Significant line segments for an indoor mobile robot. In *IEEE Transactions on Robotics and Automation*. Vol. 9, nº 6, 801-815.
- Maeda, S., Kuno, Y., Shirai, Y., 1997. Active navigation vision based on eigenspace analysis. In *Proceedings IEEE International Conference on Intelligent Robots and Systems*. Vol 2, 1018-1023.
- Matsumoto, Y., Inaba, M., Inoue, H., 1996. Visual navigation using view-sequenced route representation. In *Proceedings of IEEE International conference on Robotics and Automation*. Vol 1, 83-88.
- Ohno, T., Ohya, A., Yuta, S., 1996. Autonomous navigation for mobile robots referring pre-recorded image sequence. In *Proceedings IEEE International Conference on Intelligent Robots and Systems*. Vol 2, 672-679.
- Paya, L., Reinoso, O., Gil, A., Garcia, N., Vicente, M.A., 2005. Accepted for *13<sup>th</sup> International Conference on Image Analysis and Processing*.
- Swain-Oropeza, R., Devy, M., Cadenat, V., 1999. Controlling the execution of a visual servoing task. In *Journal of Intelligent and Robotic Systems*. Vol 25, No 4, 357-369.
- Zhou, C., Wei, T., Tan, T., 2003. Mobile robot self-localization based on global visual appearance features. In *Proceedings of the 2003 IEEE International Conference on Robotics & Automation*. 1271-1276.