PERFORMANCE ANALYSIS OF A CONTINUOUS VISION-BASED CONTROL SYSTEM FOR THE NAVIGATION OF A MOBILE ROBOT

Rafael Aracil *, **N. García** **, **C. Pérez** **,
J.M. Sabater **, **J.M. Azorín** **, **O. Reinoso** **, **R. Saltarén** *

* *Dpto. de Automática, Ingeniería Electrónica e Informática Industrial, Universidad Politécnica de Madrid*
** *Dpto. Ingeniería de Sistemas Industriales*
Universidad Miguel Hernández
Avd. Universidad s/n Edif. Torreblanca, 03202
Elche(Alicante), Spain
nicolas.garcia@umh.es

Abstract: In the last year, we have proposed a new continuous visual navigation approach defining the navigation as a global visual control task. It implies continuity problems produced by the visibility changes of the image features during the navigation. To avoid the discontinuities in the control law, a smooth task function based on weighted features was proposed and a continuous control law was obtained and tested. In this paper, a performance analysis of this visual navigation approach is presented. First of all, the influence of the parameters selection in the weight functions is analyzed. The visual navigation approach presented in this paper is used to control the robot to repeat the walk learned before. The departure position of the robot must be near the initial position memorized before. The word *near* is in some way quantified in this paper. An exhaustive number of experiments using virtual reality worlds to simulate a typical indoor environment have been carried out to justify the affirmations made.

Keywords: Computer vision, control, robotics, continuous path control

1. INTRODUCTION

There are some references about using pre-recorded images to control the navigation of a mobile robot. For instance, in (Matsumoto *et al.*, 1996) the control system proposed for the navigation of a mobile robot is based on a visual representation of the route called *"View-Sequenced Route Representation (VSRR)"*. After the *VSRR* was acquired, the robot repeats the walk using an appearance-based method to control it by comparing the current view with the pre-recorded one (*VSRR*). In (Andersen *et al.*, 1997) a system which uses the concept of *VSRR* is presented. In short, sequence of images and associated actions (motion commands)is given to the robot. Using zero-energy normalized cross-correlation, the robot retrieves the image from the database that best matches the view image. If the match is above a certain threshold, the robot performs the commands associated with that image, otherwise it halts. Finally, another interesting work, which uses pre-recorded images and an appearance-based method for navigation, is presented in (Ohno *et al.*, 1996). The system proposed is similar to the other ones, but faster since it uses only vertical hallway lines. For this reason, the method proposed consumes less memory and allows computing control actions faster than previous ones.

There are some applications using visual servoing techniques for navigation or positioning of a mobile robot (Pissard-Gibollet and Rives, 1995). There are some works presented during the last years that studies the problem of the visibility changes of the image features during the navigation of a robot, but none treats it from the point of view shown in this paper . In (Swain-Oropeza and Devy, 1997), the application of a visual servoing approach to a mobile robot which must execute coordinate motions in a known indoor environment is presented. The main contribution of this paper was the execution of a path expressed as a sequence of several basic motions (like Go to an object, Follow a wall, Turn around a corner,...), where each one is a visually-guide movement. This is a solution for the problem of navigation using visual servoing techniques applying the concept of *divide and win.* In this case, the author uses also a smooth transition between the different basic motions that define the path.

We proposed a framework for robot navigation based on pre-recorded image features obtained during a training walk. In this framework, the mobile robot is controlled to repeat the same memorized walk by means of image-based (Hutchinson *et al.*, 1996) and intrinsic-free (Malis and Cipolla, 2000; Malis, 2002*c*) visual servoing techniques. The main contribution of our method is the definition of the visual navigation as a global visual control task. It implies continuity problems produced by the visibility changes of the image features during the navigation and the computing of a continuous control law associated (García *et al.*, 2004).

2. THEORETICAL BACKGROUND

In this section, the theoretical fundamentals of the autonomous visual navigation system used in this paper to control a mobile robot are presented. A more extensively description can be found in (García *et al.*, 2004).

The strategy of the navigation method is to divide the autonomous navigation in two stages: the first one is the *training step* and the second one is the *autonomous navigation step.* During the *training step*, the robot is human commanded via radio link or whatever interface and every sample time the robot acquires an image, computes the features and stores them in memory. Then, from near its initial position, the robot repeats the same memorized walk using the reference features acquired during the *training step* and controlled by the image-based or intrinsic-free visual servoing approach. Both approaches are based on the selection of a set $\mathbf{s}$ of visual features or a set $\mathbf{q}$ of invariant features that has to reach a desired value $\mathbf{s}^*$ or $\mathbf{q}^*$. Usually, $\mathbf{s}$ is composed by the image coordinates of several points belonging to the considered target and $\mathbf{q}$ is computed as the projection of $\mathbf{s}$ in the invariant space calculated previously. In the case of our navigation method, $\mathbf{s}^*$ or $\mathbf{q}^*$ is time variable since in each sample time the reference features are updated with the desired trajectory of $\mathbf{s}$ or $\mathbf{q}$ stored in the robot memory in order to indicate the path to be followed by the robot. Finally using the task function framework, we obtain the expression of the control law:

$$\mathbf{v} = -\lambda \; \mathbf{L}^+ \; (\mathbf{s} - \mathbf{s}^*(t)) + \mathbf{L}^+ \; \dot{\mathbf{s}}^* \tag{1}$$

where λ is a positive scalar factor which tunes the speed of convergence. Remember that the whole formulation is directly applicable to the invariant visual servoing approach changing $\mathbf{s}$ by $\mathbf{q}$.

The definition of the visual navigation as a global visual control task implies continuity problems in the control law (1) produced by the visibility changes of the image features during the navigation (García and Malis, 2004). To achieve a continuos control law, a weight is associated to every image feature and each feature is called as *weighted feature.*

To compute the weights, three possible situations must be taking into account:

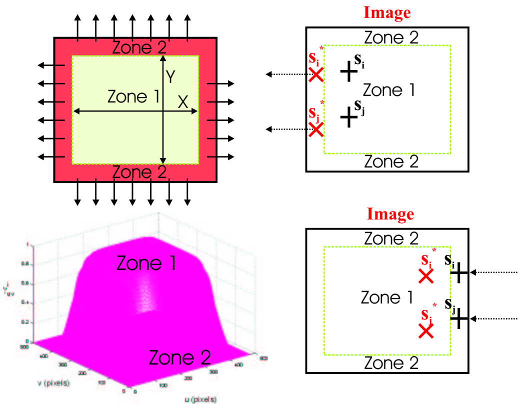
Situation 1: Changes of visibility through the border of the image (Zone 2 in Figure 1 (a))

To anticipate the visibility changes of the features through the border, a total weight Φ_{uv} is computed as the product of the weights of the current and reference features which are function of their position in the image (γ^i_{uv}, ${\gamma^i_{uv}}^*$). The weight $\gamma^i_{uv} = \gamma^i_u \cdot \gamma^i_v$ is computed using the definition of the function $\gamma_y(x)$ ($\gamma^i_u = \gamma_y(u_i)$ and $\gamma^i_v = \gamma_y(v_i)$ respectively):

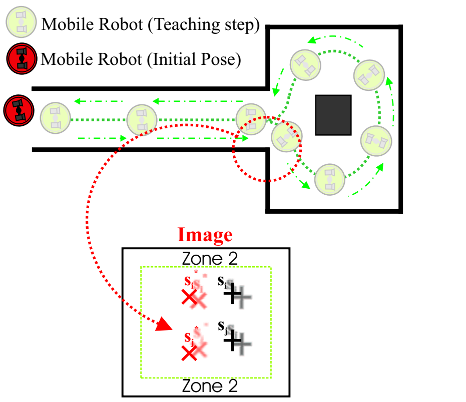
$$\gamma_y(x) = \begin{cases} e^{-\frac{(x-x_{med})^{2n}}{(x-x_{min})^m (x_{max}-x)^m}} & x_{min} < x < x_{max} \\ 0 & x = \{x_{min}, x_{max}\} \end{cases} \tag{2}$$

Situation 2: The sudden appearance of features on the image center (Zone 1 in Figure 1 (b))

To take into account this possible situation, every new features (current and reference) must be checked previously to known if they are in Zone 2 or Zone 1. If the new features are in Zone 2, the appearance of the features are considered in Situation 1. If they are in Zone 1, a new weight function must be defined to add these new features in a continuos way.



(a) Border of the image



(b) Center of the image

Fig. 1. Appearance/Disappearance of image features through the border and the center of the image during the navigation of the mobile robot.

The weight function proposed Φ_a^i is a exponential function that goes to 1, reaching its maximum value after a certain number of steps which can be modified with the α and β parameters:

$$\Phi_a^i(t) = 1 - e^{-\alpha \cdot t^{\beta}} \quad \alpha,\ \beta\ > 0 \qquad (3)$$

Situation 3: The sudden disappearance of features on the image center because of a temporal or definitive occlusion (Zone 1 in Figure 1 b)

In this situation, the occlusions produced in the teaching step on the Zone 1 are only considered since they can be easily anticipated by the observation of reference features vector prerecorded previously.

To take into account this possible situation, a new weight function must be defined to remove these features from the current and reference vector in a continuos way. The weight function proposed Φ_o^i is a exponential function that goes to 0, reaching its minimum value after a certain number of steps which can be modified with the ν and σ parameters:

$$\Phi_o^i(t) = e^{-\nu \cdot t^{\sigma}} \quad \nu,\ \sigma\ > 0 \qquad (4)$$

Finally, a global weight function Φ^i which includes the three possible situations commented before is computed. This function is defined as the product of the three weight functions (Φ_{uv}^i, Φ_a^i y Φ_o^i) which takes into account the three possible situations:

$$\Phi^i = \Phi_{uv}^i \cdot \Phi_a^i \cdot \Phi_o^i \ \text{ donde } \ \Phi^i \in [0, 1] \qquad (5)$$

2.1 *Continuous Control Law*

Suppose that n matched points are available in the current image and in the reference features stored. Everyone of these points (current and reference) will have a weight Φ^i which can be computed as it has been shown before. With them and their weights, a smooth task function can be built (Samson *et al.*, 1991):

$$\mathbf{e} = \mathbf{CW}\ (\mathbf{s} - \mathbf{s}^*(t)) \qquad (6)$$

where $\mathbf{W}$ is a $(2n \times 2n)$ diagonal matrix where its elements are the weights Φ^i of the current and reference features multiplied by the weights of the reference features. The derivate of the task function will be:

$$\dot{\mathbf{e}} = \mathbf{CW}\ (\dot{\mathbf{s}} - \dot{\mathbf{s}}^*) + (\mathbf{C}\dot{\mathbf{W}} + \dot{\mathbf{C}}\mathbf{W})(\mathbf{s} - \mathbf{s}^*(t)) \quad (7)$$

A simple control law can be obtained by imposing the exponential convergence of the task function to zero ($\dot{\mathbf{e}} = -\lambda\mathbf{e}$), where λ is a positive scalar factor which tunes the speed of convergence:

$$\mathbf{v} = -(\mathbf{W}^*\mathbf{L}^*)^+\ (\lambda\ \mathbf{W} + \dot{\mathbf{W}})\ (\mathbf{s} - \mathbf{s}^*(t)) + \\ + (\mathbf{W}^*\mathbf{L}^*)^+\mathbf{W}\dot{\mathbf{s}}^* \qquad (8)$$

A block diagram of the controller proposed is shown in Figure 2.

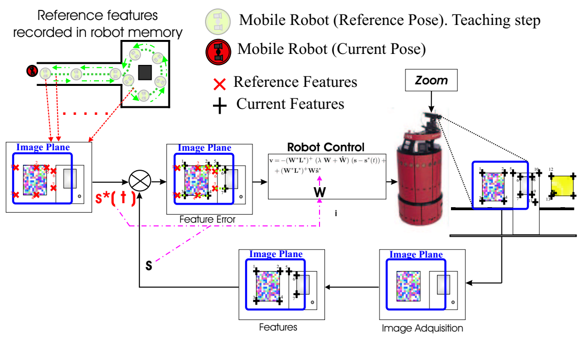


Fig. 2. Block diagram of the controller proposed

2.2 *Visual servoing techniques*

The visual servoing techniques used to carry out the navigation are the image-based and the intrinsic-free approaches. In the case of image-based visual servoing approach, the control law (8) is directly applicable to assure a continuous navigation of a mobile robot. On the other hand, when the intrinsic-free approach is used, this technique must be reformulated to take into account the weighted features.

2.2.1. Intrinsic-free approach The theoretical background about invariant visual servoing can be extensively found in (Malis, 2002*b*; Malis, 2002*c*). In this section, we modify the approach in order to take into account weighted features (García *et al.*, 2004).

Basically, the weights Φ^i defined in the previous subsection must be *redistributed*(γ_i) in order to be able to build the invariant projective space $\mathcal{Q}^{\gamma_i}$ where the control will be defined.

Similarly to the standard intrinsic-free visual servoing, the control of the camera is achieved by stacking all the reference points of the space $\mathcal{Q}^{\gamma_i}$ in a $(3n{\times}1)$ vector $\mathbf{s}^*(\boldsymbol{\xi}^*) = (\mathbf{q}_1^*(t), \mathbf{q}_2^*(t), \cdots, \mathbf{q}_n^*(t))$. In the same way, the points measured in the current camera frame are stacked in the $(3n{\times}1)$ vector $\boldsymbol{s}(\boldsymbol{\xi}) = (\boldsymbol{q}_1(t), \boldsymbol{q}_2(t), \cdots, \boldsymbol{q}_n(t))$. If $\boldsymbol{s}(\boldsymbol{\xi}) = \boldsymbol{s}^*(\boldsymbol{\xi}^*)$ then $\boldsymbol{\xi} = \boldsymbol{\xi}^*$ and the camera is back to the reference position whatever the camera intrinsic parameters.

In order to control the movement of the camera, we use the control law (8) where $\mathbf{W}$ depends on the weights previously defined and $\mathbf{L}$ is the interaction matrix. The interaction matrix depends on the current normalized points $\boldsymbol{m}_i(\boldsymbol{\xi}) \in \mathcal{M}$ ($\boldsymbol{m}_i$ can be computed from image points $\boldsymbol{m}_i = \boldsymbol{K}^{-1}\ \boldsymbol{p}_i$), on the invariant points $\boldsymbol{q}_i(\boldsymbol{\xi}) \in \mathcal{Q}^{\gamma}$, on the current depth distribution $\boldsymbol{z}(\boldsymbol{\xi}) = (Z_1, Z_2, ..., Z_n)$ and on the current redistributed weights γ_i. The interaction matrix in the weighted invariant space ($\boldsymbol{L}_{qi}^{\gamma_i} = \boldsymbol{T}_{mi}^{\gamma_i}\,(\boldsymbol{L}_{mi} - \boldsymbol{C}_i^{\gamma_i})$) is obtained like in (Malis, 2002*a*) but the term $\boldsymbol{C}_{\boldsymbol{i}}^{\boldsymbol{\gamma_i}}$ must be recomputed in order to take into account the *redistributed weights* γ_i.

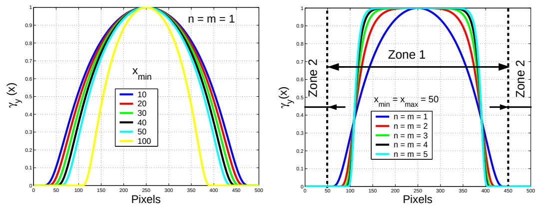
3. EXPERIMENTS IN A VIRTUAL INDOOR ENVIRONMENT

Many experiments have been carried out using a virtual reality tool for modeling an indoor environment. To make more realistic simulation, errors in intrinsic and extrinsic parameters of the camera mounted in the robot have been considered. An estimation $\widehat{\mathbf{K}}$ of the real matrix $\mathbf{K}$ has been used with an error of 25% in the focal length and a deviation of 50 pixels in the position of the optical center. Also an estimation $\widehat{\mathbf{T}}_{RC}$ of the camera pose respect to the robot frame has been computed with a rotation error of $u\theta = [3.75\ 3.75\ 3.75]^T$ *degrees* and a translation error of $t = [2\ 2\ 0]^T$ *cm* (Figure 4 (d)).

3.1 Parameters Analysis

The analysis of the weight function parameters has been only studied for the weight function used in the Situation 1 (Section 2). The results obtained in this section can be directly extended to the other two situations.

The weight function (2) has four parameters (x_{min}, x_{max}, n and m) which affect the performance of the continuous visual navigation system proposed in this paper. With them, the image plane can be divided virtually in two zones (Zone 1 and Zone 2, Figure 1) and the shape of $\gamma_y(x)$ can be controlled (Figure 3). The Zone 1 is the part of the image where the weights Φ_{uv}^i are equal to zero due to the definition of $\gamma_y(x)$. The width of the Zone 1 can be controlled by the parameters x_{min} and x_{max}. In Figure 3 (a), the representation of $\gamma_y(x)$ for different values of x_{min} and x_{max} with n and m constant is shown.

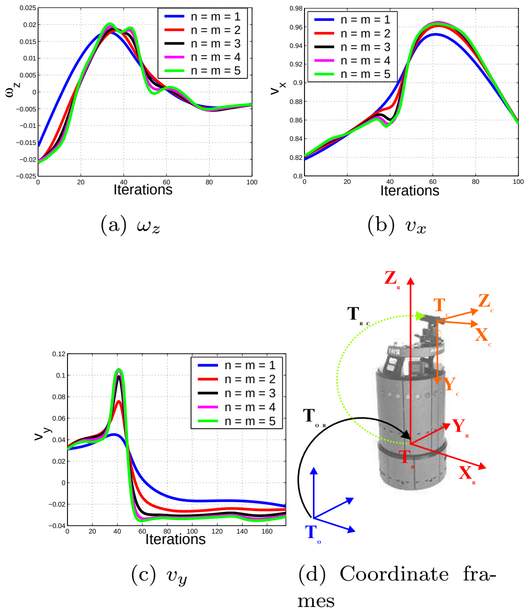


(a) $\gamma_y(x_{min}, x_{max})$ (b) $\gamma_y(n, m)$

Fig. 3. $\gamma_y(x)$ in function of x_{min}, x_{max}, n and m parameters

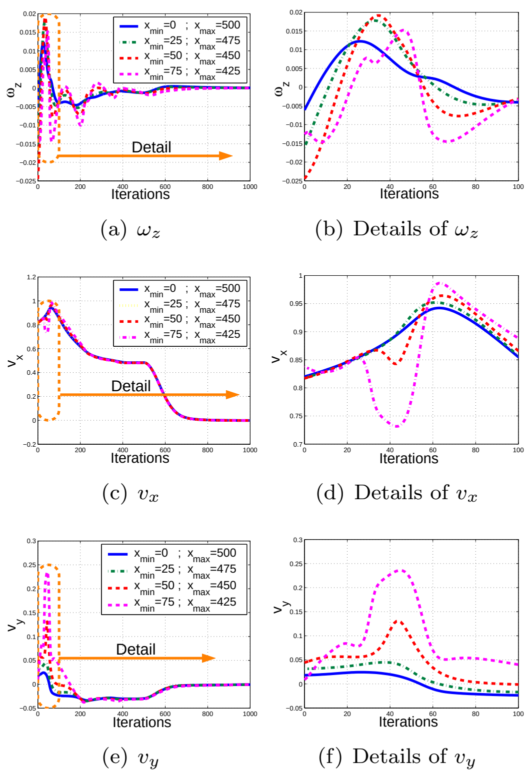
To show the effects produced by the values of n and m parameters of the weight function $\gamma_y(x)$ in the performance of the continuous visual navigation system proposed, a experiment in a virtual world have been carried out. The experiment has been repeat for different values of n and m (i.e. $n = m = i$ where $i = \{1,\ 2,\ 3,\ 4,\ 5\}$). When n and m are increased, the shape of the function $\gamma_y(x)$ is more abrupt as it can be seen in Figure 3 (b). To show the performance of the system with the changes in the n and m parameters, the control law is shown in Figure 4. In this figure, the oscillations in the control law produced by the increment in n and m parameters can be seen. We want the control law to be as smooth as possible, so the more suitable values for these parameters are 1.

In the same way, the effects produced by the values of the x_{min} and x_{max} parameters in the performance of the continuous visual navigation system used in this paper can be seen in Figure 5. The control law is shown in this figure and we can appreciate in it the increment in the number and magnitud of oscillations when the width of the Zone 2 is enlarged. In our control scheme, we are searching for a smooth control law , so the width of the Zone 2 must be as small as possible.



(a) ω_z (b) v_x (c) v_y (d) Coordinate frames

Fig. 4. Effects in the control law with n y m parameters .



(a) ω_z (b) Details of ω_z (c) v_x (d) Details of v_x (e) v_y (f) Details of v_y

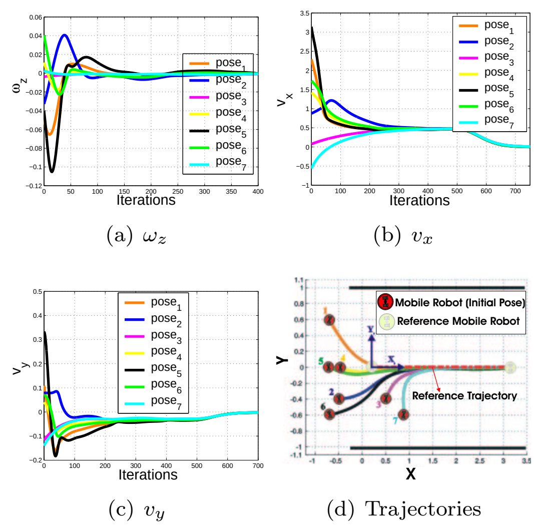
Fig. 5. Effects in the control law with x_{min} y x_{max} parameters.

3.2 Results from different initial positions

In this section, the performance of this navigation system from the departure position point of view has been analyzed. To do this, different experiments from different initial positions (Figure 6 d) have been carried out:

- Experiment 1: Initial position is $t_R(t_0) = [-0.9\ 0.6\ 0]$ *meters* and its orientation is $u\theta_R(t_0) = [0\ 0\ -15]$ *degrees*.
- Experiment 2: Initial Position is $t_R(t_0) = [-0.7\ -0.4\ 0]$ *meters* and its orientation is $u\theta_R(t_0) = [0\ 0\ 7.5]$ *degrees*.
- Experiment 3: Initial Position is $t_R(t_0) = [0.3\ -0.4\ 0]$ *meters* and its orientation is $u\theta_R(t_0) = [0\ 0\ -7.5]$ *degrees*.
- Experiment 4: Initial Position is $t_R(t_0) = [-0.7\ 0\ 0]$ *meters* and its orientation is $u\theta_R(t_0) = [0\ 0\ 0]$ *degrees*.
- Experiment 5: Initial Position is $t_R(t_0) = [-0.9\ 0\ 0]$ *meters* and its orientation is $u\theta_R(t_0) = [0\ 0\ 0]$ *degrees*.
- Experiment 6: Initial Position is $t_R(t_0) = [-0.9\ -0.6\ 0]$ *meters* and its orientation is $u\theta_R(t_0) = [0\ 0\ 15]$ *degrees*.
- Experiment 7: Initial Position is $t_R(t_0) = [0.5\ -0.6\ 0]$ *meters* and its orientation is $u\theta_R(t_0) = [0\ 0\ -7.5]$ *degrees*.

The control law and the trajectory of the mobile robot for all the experiments is shown in Figure 6. The control law is stable and the settling time is practically the same for all the experiments. In this figure, we can appreciate the increment in the number and magnitud of oscillations when the initial position is far from the memorized one (experiments 1, 2, 6) because of the magnitud of the initial image error and because also the number of features which changes their visibility when the magnitude of the image error is quite large. Taking into account these results, we can affirm that the system works well when 3 or more features memorized previously are visible from the departure position.



(a) ω_z (b) v_x (c) v_y (d) Trajectories

Fig. 6. Trajectories and Control Law from different initial positions.

4. CONCLUSIONS

In this paper, the influence of the weight function parameters on the performance of a recent visual navigation system has been analyzed and a possible selection of the parameters values has been proposed and tested in a virtual world. Also, different experiments from different initial positions have been carried out and the results obtained show that the system is stable and its performance seems quite good for every departure position of the mobile robot. The validation of this results with a real robot is on the way using a B21r mobile robot from iRobot company.

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