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Visual Servoing Approach Based on Global Descriptor Using Robust Control

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Abstract—**This paper presents robust visual servoing approach based on global descriptor. Our work aims to improve real-time performance of the visual servoing scheme. Indeed, the use of our new descriptor reduces the computation time of the visual servoing task. The error-dynamics considered in all visual servoing schemes were, usually, a first-order dynamics. In this paper, in order to ameliorate the mobile robot robustness regarding to kinematic modeling errors, we propose new way to achieve visual servoing tasks based on a second-order error-dynamics. Experimental results are presented to validate our approaches and to demonstrate its efficiency.**

Keywords—***visual servoing, global descriptor, mobile robot, robust control law.***

I. Introduction

Computer vision is progressively playing more important role in service robotic applications. In fact, the movement of a robot equipped with a camera can be controlled from its visual perception using visual servoing technique. The aim of the visual servoing is to control a robotic system using visual features acquired by a visual sensor [1]. Indeed, the control law is designed to move a robot so that the current visual features s, acquired from the current pose r, will reach the desired features s^* acquired from the desired pose r^*, leading to a correct realization of the task.

The control principle is thus to minimize the error $e = s - s^*$ where s is a vector containing the current values of the chosen visual information, and s^* its desired values. The basic step in image-based visual servoing is to determine the adequate set of visual features to be extracted from the image and used in the control scheme in order to obtain an optimal behavior of the robot.

In the literature several works were concerned with simple objects and the features used as input of the control scheme were generally geometric: coordinates of points, edges or straight lines [2, 3].

These geometric features have always to be tracked and matched over frames. This process has proved to be a difficult step in any visual servoing scheme. Therefore, in the last decade, the researchers are focused on the use of global visual features. In fact, in [4] the visual features considered are the luminance of all image pixels and the control law is based on the minimization of the error which is the difference between the current and the desired image.

Others works are interested in the application of image moments in visual servoing, like in [5] where the authors propose a new visual servoing scheme based on a set of moment invariants. The use of these moments ensures an exponential decoupled decrease for the visual features and for the components of the camera velocity. However this approach is restricted to binary images. It gives good results except when the object is contrasted with respect to its environment.

In [6], the authors present a new criterion for visual servoing: the mutual information between the current and the desired image. The idea consists in maximizing the information shared by the two images. This approach has proved to be robust to occlusions and to very important light variations. Nevertheless, the computation time of this method is relatively high.

The work of [7] proposes the image gradient as visual feature for visual servoing tasks. This approach suffers from a small cone of convergence. Indeed, using this visual feature, the robotic system diverges in the case of large initial displacement. Another visual seroving approach which removes the necessity of features tracking and matching step has been proposed in [8]. This method models the image features as a mixture of Gaussian in the current and in the desired image. But, using this approach, an image processing step is always required to extract the visual features.

Numerous research studies focused on the control of mobile robots [14, 15, 16, 18]. Thus, highly nonlinear control techniques were developed since these systems are associated with nonholonomy constraints [20]. In the literature, several effective control strategies are used for nonholonomic platforms [13, 19, 17]. The control techniques are designed mainly for unicycle-type and car-like mobile robots.

In this work, the control of a unicycle mobile platform using a single camera attached to the robot (eye-in-hand) is addressed. The error-dynamics considered in all visual servoing schemes were, usually, a first-order dynamics. In this paper, in order to ameliorate the mobile robot robustness regarding to kinematic modeling errors, we propose new way to achieve visual servoing tasks based on a second-order error-dynamics.

The main contribution of this paper consists in the application of our robust control law on the new global visual features: random distribution of limited set of pixels luminance.

Our features improve the computation time of visual servoing scheme and avoid matching and tracking step. We illustrate in this work an experimental analysis of the robotic system behavior in the case of visual servoing task based on our new approaches.

This paper is organized as follows: section 2 illustrates our new visual features and the corresponding interaction matrix. Section 3 presents our robust control law based on the second-order error-dynamics. Finally, experimental results are presented in section 4.

II. Random Distrubition of Limited Set of Pixels Luminance as Visual Features

The use of the whole image luminance as global visual features for visual servoing tasks, as in [9], requires too high computation time. Indeed, the big size of the interaction matrix related to the luminance of all image pixels leads to a very slow convergence of the robotic system.

Therefore, we propose in this paper a new visual feature which is more efficient in terms of computation time and doesn't require any matching nor tracking step.

In fact, instead of using the luminance of all image points, we work just with the luminance of a random distribution of a limited set of image points (n pixels) [21]. Thus, the visual features, at a position r of the robot, are:

$$s_i(r) = E_I^i(r) \tag{1}$$

with $E_I^i(r)$ is the luminance of random set of image pixels taken at frame i.

$$E_I^i(r) = (I_1^i, I_2^i, I_3^i, \dots, I_n^i) \tag{2}$$

where I_k^i is the luminance of the pixel k taken randomly at the frame i.

For each new frame, we get a new random set of image pixels. Thus, the desired and the current visual features will continuously change along the visual servoing scheme. In that case, the error e will be:

$$e_i = E_I^i(r) - E_{I^*}^i(r^*) \tag{3}$$

where $E_I^i(r)$ represent the current visual features and $E_{I^*}^i(r^*)$ the desired ones at the frame i.

Consequently, in our method, the error used in the building of the control law is variable, it changes at each frame.

The choice of n is based on the image histogram. We take n equal to the maximum value of the current image histogram. We can then avoid the fact that the n pixels randomly chosen will have the same luminance. Hence, we guarantee the good luminance representation of the image.

Since the number n depends on the histogram of the current image, it slightly changes during the visual servoing scheme. Let us point that n is always very small compared to the total number of image pixels (in our case 320×240). We note that the more the image is textured, the smaller n is.

The visual servoing is based on the relationship between the robot motion and the consequent change on the visual features. This relationship is expressed by the well known equation [10]:

$$\dot{s} = L_s v \tag{4}$$

where L_s is the interaction matrix that links the time variation of s to the robot instantaneous velocity v [1].

After identification of the visual features, the control law requires the determination of this matrix which is at the center of the development of any visual servoing scheme. In our case, we look for the interaction matrix related to the luminance of a pixel x in the image.

This interaction matrix that relates the temporal variation of the luminosity $I(x)$ to the control law v_c is:

$$L_{I(x)} = -\nabla I^T \, L_x \tag{5}$$

In this case, we can write the interaction matrix $L_{I(x)}$ in terms of the interaction matrices L_x and L_y related to the coordinates of $x = (x, y)$ and we obtain:

$$L_{I(x)} = -(\nabla I_x \, L_x + \nabla I_y \, L_y) \tag{6}$$

with ∇I_x et ∇I_y are the components along x and y of $\nabla I(x)$ and we have:

$$L_x = \begin{pmatrix} -\frac{1}{z} & \frac{x}{z} & -(1 + x^2) \end{pmatrix} \tag{7}$$

$$L_y = \begin{pmatrix} 0 & \frac{y}{z} & -xy \end{pmatrix} \tag{8}$$

We get the interaction matrix related to our new features ($L_{E_I^i}$) by combining the interaction matrices related to the n pixels randomly chosen.

Thus, the size of the interaction matrix related to our visual features ($L_{E_I^i}$) is very small compared to the size of the interaction matrix related to the whole image luminance.

III. Control Law Based on Second-Order Error-Dynamics

In our work we use global photometric visual features. In this case most of classical control laws fail. Therefore, we have interest in turning the visual servoing scheme into an optimization problem to get the convergence of the mobile robot to its desired pose [11, 12]. In fact, the aim of the control law will be the minimization of a cost function which is the following:

$$C(r) = \left(s(r) - s(r^*)\right)^T \left(s(r) - s(r^*)\right) \quad (9)$$

where $s(r)$ are the current visual features ($E_I^i(r)$) and $s(r^*)$ are the desired ones ($E_{I^*}^i(r^*)$).

The cost function minimization is, essentially, based on the following step:

$$r_{i+1} = r_i \oplus d(r_i) \quad (10)$$

where "$\oplus$" denotes the operator that combines two consecutive frame transformations, r_i is the current pose of the mobile robot (at frame i), r_{i+1} is the next pose of the mobile robot and $d(r_i)$ is the direction of descent.

This direction of descent must ensure that $d(r_i)\, \nabla C(r_i) < 0$. In this way, the movement of the robot leads to the decrease of the cost function.

Optimization methods depend on the direction of descent used in the building of the control law. The control law usually used in visual servoing context is given by:

$$v = -\lambda\, {L_s}^+ \left(s(r) - s(r^*)\right) \quad (11)$$

where λ is a positive scalar and ${L_s}^+$ is the pseudo inverse of the interaction matrix.

This classical control law gives good results in the case of visual servoing task based on geometric visual features [10]. Since we work with photometric visual features this classical control law fails and doesn't ensure the convergence of the robot [4]. Thus, the solution consists in the use of a control law based on the Levenberg-Marquardt approach.

This approach is based on the error usually used in visual servoing applications which has an exponential decrease defined by:

$$\dot{e} + \lambda e = 0 \quad (12)$$

This error-dynamics leads to the following control law:

$$v_c^i = -\lambda \left(H_{E_I^i} + \mu\, \mathrm{diag}\left(H_{E_I^i}\right)\right)^{-1} {L_{E_I^i}}^T e_i \quad (13)$$

In this work, we move from the first-order error-dynamics to the second-order error-dynamics defined by the following equation:

$$\ddot{e} + k_1 \dot{e} + k_2 e = 0 \quad (14)$$

Thus,

$$\dot{e} = -\frac{1}{k_1}\ddot{e} - \frac{k_2}{k_1} e \quad (15)$$

The new control law, used in the visual servoing scheme, has then the following form:

$$V = -L_s^+ \left(\frac{1}{k_1}\ddot{e} + \frac{k_2}{k_1} e \right) \quad (16)$$

where the second derivative of the error is defined by:

$$\ddot{e} = \frac{e_k - 2e_{k-1} + e_{k-2}}{T^2} \quad (17)$$

with $e_i = s_i - s_i^*$

The control law generated to the robot, using our new features, is then given by:

$$v_c^i = -\left(H_{E_I^i} + \mu\, \mathrm{diag}\left(H_{E_I^i}\right)\right)^{-1} {L_{E_I^i}}^T [A] \quad (18)$$

with $A = \frac{1}{T^2 k_1}\left(e_{i-2} - 2e_{i-1} \right) + \left(\frac{1}{T^2 k_1} + \frac{k_2}{k_1}\right) e_i$

where e_i is the error corresponding to these new features:

$$e_i = E_I^i(r) - E_{I^*}^i(r^*) \quad (19)$$

and with

$$H_{E_I^i} = {L_{E_I^i}}^T L_{E_I^i} \quad (20)$$

This approach ensures more robustness regarding to mobile robot modeling errors during visual servoing task. We choose the coefficients k_1 et k_2 in such a way that the roots of the characteristic polynomial of (14) have negatives real parts.

The following equations present the kinematic model of the mobile robot with error (ρ):

$$\begin{aligned} \dot{x} &= v_R \cos\theta + \rho \\ \dot{y} &= v_R \sin\theta \\ \dot{\theta} &= \omega_R \end{aligned} \quad (21)$$

The kinematic modeling errors induce mobile robot singularities. Thus, during a positioning task, the robot diverges and doesn't reach its desired pose. In fact, in the presence of modeling error, the movement performed by the mobile robot doesn't correspond to the velocities generated by the control law.

Using this new error–dynamics the robot converges to its desired pose even in the presence of modeling errors. However, this convergence was not guaranteed in visual servoing scheme based on an exponential decrease of the error.

IV. Experimental Results

We present the results of a set of experiments conducted with our visual features. All the experiments reported here have been obtained using a camera mounted on a mobile robot. In each case, the mobile robot is first moved to its desired pose r^* and the corresponding image I^* is acquired. From this desired image, we extract the desired visual features s^*. The robot is then moved to a random pose r and the initial visual features s are extracted. The velocities (v, ω) computed, at each frame, using the control law, are sent to the robot until its convergence. The interaction matrix is calculated at each frame of the visual servoing scheme. We involve here our new method based on the second-order error-dynamics and we compare it to the classic visual servoing approach based on a first-order error-dynamics. We conduct our experiments on a virtual platform of VRML, therefore we can recuperate, at each frame, the pose of the mobile robot in terms of position along two translational axes and around one rotational axe.

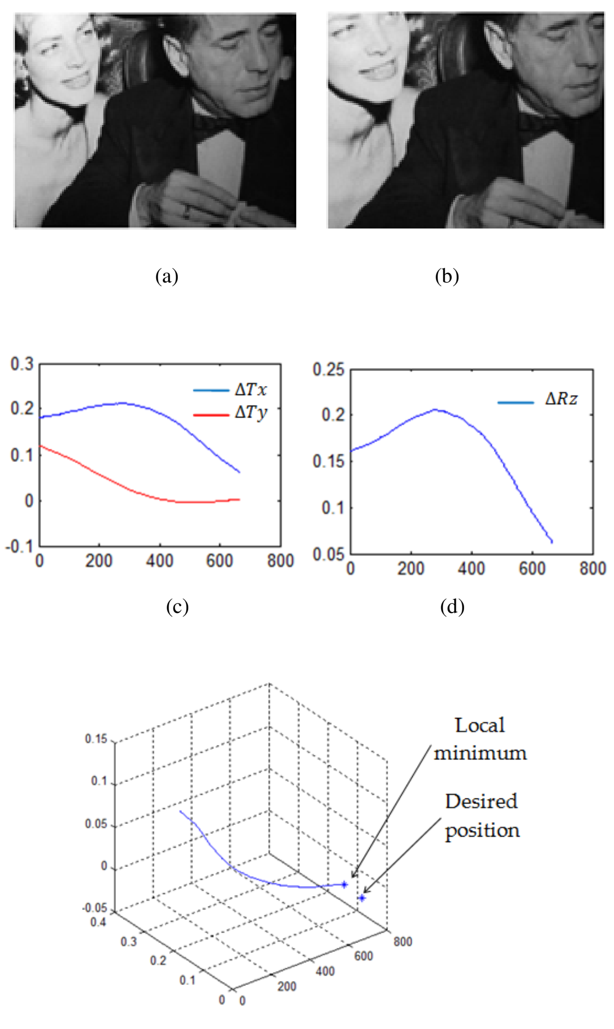

Fig. 1. Visual servoing task (x axis in frame number) : (a) Initial image, (b) Final image, (c) Translational positioning errors: ΔTx and ΔTy in meter (m) , (d) Rotational positioning error: ΔRz in radian (rad), (e) Mobile robot path.

During the experiments conducted on the VRML environment we take as initial positioning error: $\Delta r_{int} = (18\,cm, 12cm, 9°)$.

In a first experiment, we suppose the existence of error in the kinematic model of the wheeled mobile robot: $\rho = 0.5$. In the presence of such a modeling error, the classic Levenberg-Marquardt approach based on the exponential decrease of the error doesn't ensure the convergence of the robot to its desired pose.

In fact, the mobile robot gets at a local minimum (Fig. 1e). It is clear from Fig. 1e that the system has been attracted to a local minimum far away from the desired configuration. Figure 1a shows the scene corresponding to the initial pose of the robot. Figure 1b illustrates the scene corresponding to the desired pose which is not reached by the robot in this case. The translational and the rotational positioning errors during the positioning task (Fig. 1c and Fig. 1d) don't converge to zero due to the local minimum. We present on Fig. 1e the mobile robot path during the visual servoing task.

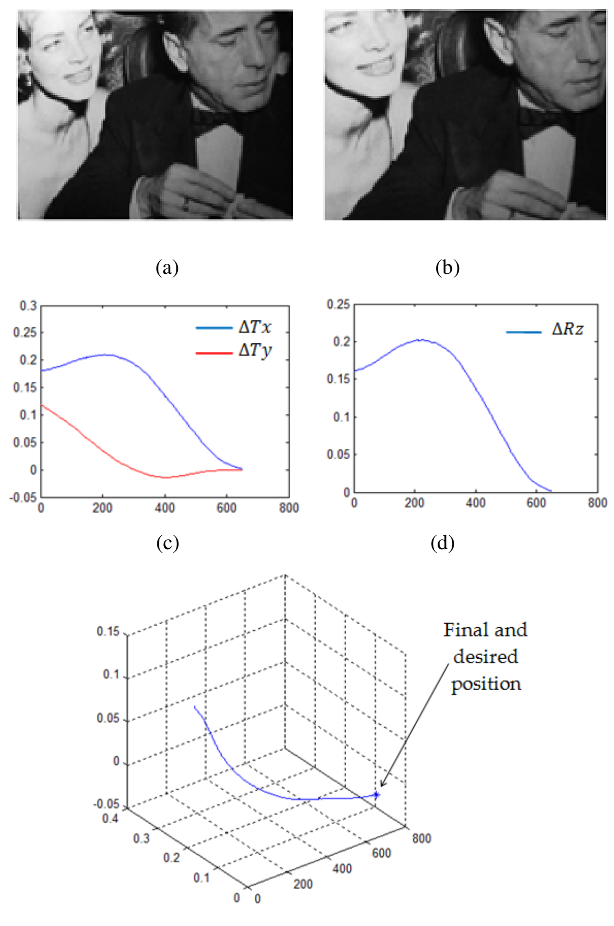

Fig. 2. Visual servoing task (x axis in frame number) : (a) Initial image, (b) Final image, (c) Translational positioning errors: ΔTx and ΔTy in meter (m) , (d) Rotational positioning error: ΔRz in radian (rad), (e) Mobile robot path.

In a second experiment, we keep the same error ρ in the kinematic model of the mobile robot. Nevertheless, the visual servoing task is, now, performed using the new error-dynamics with k_1=8 and k_2=39. We remark that the mobile robot converges to its desired pose without singularities.

Figure 2a illustrates the initial scene while the desired one is shown on Fig. 2b. The translational positioning errors $(\Delta Tx, \Delta Ty)$ between the current and the desired pose during the positioning task are shown on Fig. 2c. The rotational positioning error (ΔRz) is illustrated on Fig. 2d. We present on Fig. 5e the mobile robot path during the visual servoing task.

V. CONCLUSION

In this paper we combine two approaches leading to robust visual seroing using new global feature. Generally, when the used global feature is the whole image luminance the mobile robot takes so much time to reach its desired pose; therefore we propose a new approach to achieve fast and real-time visual servoing tasks. This approach is based on new global feature which is the luminance of a random distribution of image points.

In the literature, the error used in the building of the control law, was usually characterized by an exponential decrease. In order to achieve robust control law, we propose, in this work, new way of error decrease that guaranties robust visual servoing. In fact, we replace the first-order error-dynamics by the second-order error-dynamics. In such a way, the mobile robot reaches its desired pose even in the case of kinematic modeling errors.

Future works can be intended to verify the robustness of our approach with respect to partial occlusions and large illumination changes.

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