Recent results in visual servoing for robotics applications

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Abstract

This paper presents new advances in the eld of visual servoing for robot positioning tasks with respect to complex objects. A pose estimation and tracking algorithm is described to deal with real objects whose 3D model is known. Experimental results using image motion estimation are also presented.

1 Introduction

Visual servoing techniques consist in using the data provided by one or several cameras in order to control the motions of a robotic system [7, 8]. A large variety of positionning tasks, or mobile target tracking, can be implemented by controling from one to all the n degrees of freedom of the system. Whatever the sensor con guration, which can vary from one on-board camera on the robot end-efector to several free-standing cameras, a set of k measurements has to be selected at best, allowing to control the m degrees of freedom desired. A control law has also to be designed so that these mesurements $s(t)$ reach a desired value s^*, de ning a correct realization of the task. A desired trajectory $s^*(t)$ can also be tracked. The control principle is thus to regulate to zero the error vector $s(t) - s^*(t)$. With a vision sensor providing 2D measurements, potential visual features are numerous, since as well 2D data such as coordinates of feature points in the image can be considered, as 3D data provided by a localization algorithm exploiting the extracted 2D features (see Figure 1). It is also possible to combine 2D and 3D visual features to take the advantages of each approach while avoiding their respectives drawbacks [11]

In this paper, we present recent results in visual servoing for positioning tasks with respect to complex objects. In the next section, we recall some modeling aspects. In Section 3, a pose estimation and tracking algorithm is described to deal with real objects whose 3D model is known. In that case, any visual servoing scheme can be used: image-based (2D), position-based (3D), or hybrid scheme (2 1/2D). Finally, experimental results using image motion estimation are presented in Section 4.

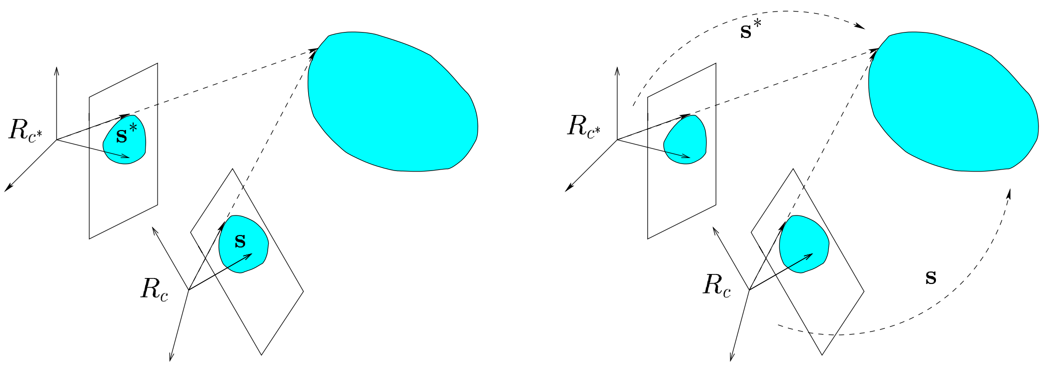
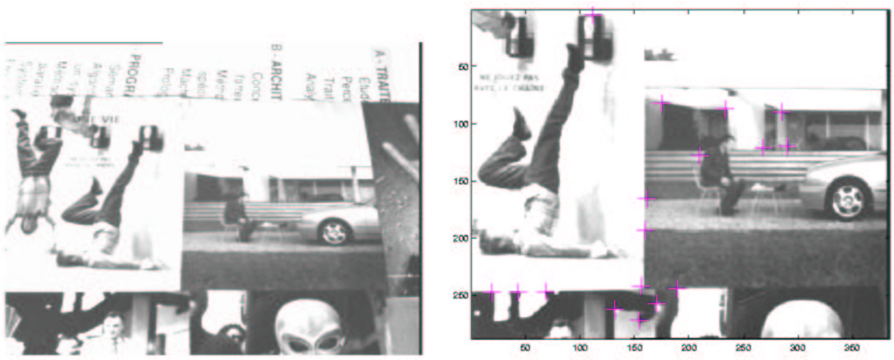


Figure 1: 2D or 3D visual servoing: to bring the camera frame from R_c to R_c , visual features directly extracted from the image are used in 2D visual servoing (left), while in 3D visual servoing, features estimated through a pose estimation or a 3D reconstruction are considered (right).

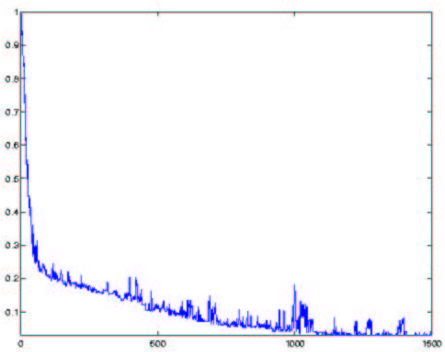
where is a proportional gain that has to be tuned to minimize the time-to-convergence, $\widehat{L_s}^+$ is the pseudo-inverse of a model or an approximation of the interaction matrix, and $\widehat{\frac{\partial e}{\partial t}}$ an estimation of the target velocity. The analytical form of the interaction matrix has been determined for many possible visual features, such as image point coordinates, 2D straight lines, 2D ellipses, image moments, 3D coordinates of points, etc. From the selected visual features, the behavior of the system will have particular properties as for stability, robustness with respect to noise or to calibration errors, robot 3D trajectory, etc. It is thus extremely important to choose adequate visual features for each robot task or application. Promising results have been obtained recently using image moments [13]. The first interest of using image moments is that they provide a generic and geometrically intuitive representation of any object, with simple or complex shapes that can be segmented in an image. They can also be extracted from a set of image points tracked along an image sequence by simple summation of polynomials that depend on the points position.

Furthermore, as already noticed, an important aspect is to determine the visual features to use in the control scheme in order to obtain an optimal behavior of the system. A good objective is to design a decoupled control scheme, i.e. to try to associate each robot degree of freedom with only one visual feature through a linear relation. A such totally decoupled and linear control would be ideal. Currently, it is possible to decouple the translational motions from the rotational ones. This decoupled control can be obtained using moment invariants as fully described in [13]. In few words, a set of adequate combination of moments has been selected so that the related interaction matrix L_s is as near as possible of a triangular constant matrix.

Experimental results are reported on Figure 3. They have beeen obtained with a six degrees of freedom eye-in-hand robot. The goal was to position the camera so that the corresponding image is the same as one image acquired during an off line learning step. Several points of interest have been extracted using the Harris detector and tracked using a SSD algorithm [14]. Image moments have then be computed from the coordinates of these points. The plots depicted on Figure 3 show that the system converges with an exponential decrease.



(a) (b)



(c) (d)

Figure 3: Results for complex images: (a) initial image, (b) desired image, (c) robot velocities versus time, (d) visual features errors mean versus time

Figure 6: 2D 1/2 visual servoing experiments: on these snapshots the tracked object appears in green and its desired position in the image in blue. The six first images have been acquired during an initial visual servoing step where the object is motionless. In the reminder images, object is moving along with the robot.

4 Image motion in visual servoing

To end this paper, we present some experimental results obtained on complex environments using an image motion estimation between two successive images. The task that corresponds to the images of Figure 7 consists in controlling the pan and tilt of a camera so that a moving pedestrian always remains in the camera field of view whatever his motion. We can note the robustness of the image processing and of the control law with respect to non rigid motion. More details are given in [3], as well as other experiments obtained for submarine robotics applications.

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Figure 7: Camera pan/tilt control for a tracking task.