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# Application of motion-based visual servoing to target tracking

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## Abstract

*In this paper, the classical task of mobile target tracking using a pan and tilt camera is considered. We use recent results in motion-based visual servoing to deal with complex targets whose shape and texture are unknown. The first method we present consists in designing a control law directly from the estimated image motion. This leads to compute the pan and tilt acceleration necessary to reduce the tracking error. A second method, more efficient for target tracking, consists in retrieving the target position in the image from its estimated motion. This leads to classical image-based visual servoing. For both methods, experimental results obtained at video rate are presented and discussed.*

## 1 Introduction

Target tracking using a pan and tilt camera is one of the oldest task that has been studied in the robotics and vision communities. The main applications were in the military domain [17, 15] or in the design of active stereoscopic heads [2, 9]. Research dealing with the robotics aspect was generally not interested in vision issues, but in control strategy. As a consequence, there was often a strong a priori knowledge on the observed object to validate the control law. Most of these works [4, 10, 18, 26] use a quasi-binary image to easily separate the target from the background. In [27], a corner detection algorithm yields the position of a particular point of the target. However, this method is not robust with respect to occlusions. A solution to avoid these problems is to measure the motion in the image. Indeed, such a 2D motion is independent of the scene content, and targets with complex shape and texture can thus be considered. Now, several algorithms, such as the one presented in [25], are able to perform the estimation of a model of motion in real time, meaning fast enough to be implemented in a robotic loop. This idea has been used for example

in [29] for person tracking. The task can in fact be reduced to the detection of the mobile target in front of the background, and to the computation of the pan and tilt motion to maintain the target in the image center. For the target detection, methods presented in [3, 24] allow to track a small object, or at the best an object which covers a much smaller part of the image than the background. A 2D affine motion model is computed between two successive images, and the second image is compensated with the opposite motion. Thresholding the difference between the reconstructed image and the original one gives the position of the target. The method proposed in [22, 23] is similar, even if compensation is based on the measured motion of the camera, obtained using the odometry of the pan tilt head. Larger objects can be tracked but this method is sensitive to the calibration of the system, to make the link between the 3D motion of the camera and the 2D projected motion. Finally, in [1, 7, 21, 23], a stereo-vision system is used to build a 3D model of the target motion. However, this approach implies once again to have a good calibration of the system.

In this paper, we apply to target tracking the two approaches presented in [14], which both use an estimation of the target motion in the image. The first approach consists in designing a control law such that the measured motion field reaches a desired one. In that case, tracking a moving target is equivalent to cancel its apparent speed in the image. We will see that this method requires the design of an acceleration-based control law. Furthermore, we will see that it is not able to completely remove the tracking error. The second approach consists in recovering the target position in the image by integrating successively its estimated speed. In that case, classical image-based visual servoing can be used, and the target tracking task can be translated as observing the coordinates of the target center of gravity at the image center. Thanks to the motion estimation algorithm we used, we will see that this method is particularly efficient. It is also robust with respect to calibration errors.

In Section 2, we briefly describe the simplified model of image motion we used. It is adequate for the considered task, and allows one to obtain results at video rate. We also describe how the initial target position is simply obtained. The two approaches mentioned above are then presented and discussed in Section 3 and 4 respectively. Experimental results obtained on the pan tilt camera depicted on Figure 1 are included in these sections.



Figure 1: Experimental cell

## 2 Image processing for target tracking

### 2.1 Image motion model

The most classical image motion model used in computer vision has a particular quadratic form with respect to the  $x$  and  $y$  coordinates of a pixel (see [28, 14]):

$$\begin{cases} \dot{x} &= c_1 + a_1x + a_2y + q_1x^2 + q_2xy \\ \dot{y} &= c_2 + a_3x + a_4y + q_1xy + q_2y^2 \end{cases} \quad (1)$$

Indeed, this model perfectly represents the image motion field when the camera observes a planar object subject to rigid 3D motions. More precisely, we have:

$$\begin{cases} c_1 = -\frac{T_x}{Z_p} - \Omega_y & c_2 = -\frac{T_y}{Z_p} + \Omega_x \\ a_1 = \gamma_1 \frac{T_x}{Z_p} + \frac{T_z}{Z_p} & a_2 = \gamma_2 \frac{T_x}{Z_p} + \Omega_z \\ a_3 = \gamma_1 \frac{T_y}{Z_p} - \Omega_z & a_4 = \gamma_2 \frac{T_y}{Z_p} + \frac{T_z}{Z_p} \\ q_1 = -\gamma_1 \frac{T_z}{Z_p} - \Omega_y & q_2 = -\gamma_2 \frac{T_z}{Z_p} + \Omega_x \end{cases} \quad (2)$$

where  $T_x, T_y, T_z, \Omega_x, \Omega_y$  and  $\Omega_z$  respectively represent the three translational and the three rotational components of the kinematic screw between the camera frame and the object frame,  $Z = Z_p + \gamma_1 X + \gamma_2 Y$  being the equation of the object plane expressed in the camera frame. Of course, other motion models may be used. The most usual ones are the constant model (the restriction of the presented one to terms  $c_i$ ), and the affine one (the restriction to terms  $c_i$  and  $a_i$ ).

Whatever the chosen model may be, its parameters are computed using the robust multi-resolution method presented in [25], and briefly described in [14]. We just note that it is robust with respect to

outliers. Furthermore, it is possible to restrict the estimation on a particular part of the image. In our case, as explained below, we will only consider the projection of the target in the image.

In fact, there is a necessary compromise to find between the accuracy provided by a model and the computation load, such that the control rate is the closest possible to the video rate. Indeed, the real motion in the image is generally complex, and only an approximation can be obtained using a polynomial model. Currently, only the parameters of the constant model can be estimated at video rate without any dedicated image processing board. Since the stability of a target tracking task is directly related to the control rate, we chose to consider only this model.

From the form of  $c_1$  and  $c_2$  given in (2), we can note that these parameters contain all the information needed for the tracking task: translational motion  $T_z$  along the optical axis and rotational motion  $\Omega_z$  around the optical axis do not have any influence on  $c_1$  and  $c_2$ , but these motions can not be compensated by a pan and tilt camera. All other target motions ( $T_x, T_y, \Omega_x$  and  $\Omega_y$ ) will make change the value of  $c_1$  or  $c_2$ . The control law will thus be able to react to these motions.

Moreover, since we are able to estimate the position of the target in the image (see below), the speed of its center of gravity is given by the approximation at the 0-th order of the image motion, *i.e.* ( $c_1, c_2$ ). Whatever the polynomial model of motion may be considered, the parameters necessary to realize the tracking are thus only  $c_1$  and  $c_2$ .

## 2.2 Initial detection of the target

The detection of the target has first to be performed to initialize the tracking. Since we do not exploit any a priori information on the target, this detection step is achieved using the only property that the target undergoes motion. The camera remaining static until a mobile object is detected, the object location is simply determined by intensity difference between two successive images. In practice, because of noise in the images, we use a local spatial average of image intensities. Then, by considering a threshold difference between two successive averaged images, we get a binary image separating moving zones from static ones (see Figure 2). The coordinates  $(x_0, y_0)$  of the center of gravity of the detected mask are then easily computed from the binary image.

At the first iteration of the tracking, the estimation of motion parameters  $c_1$  and  $c_2$  is performed in a rectangular window including the mask, and centered at  $(x_0, y_0)$ . In this window, points outside the detected mask are considered as outliers. Then, at each iteration, the mask and the including window are translated with estimated values  $c_1$  and  $c_2$ , so that they correspond to the current position of the target.

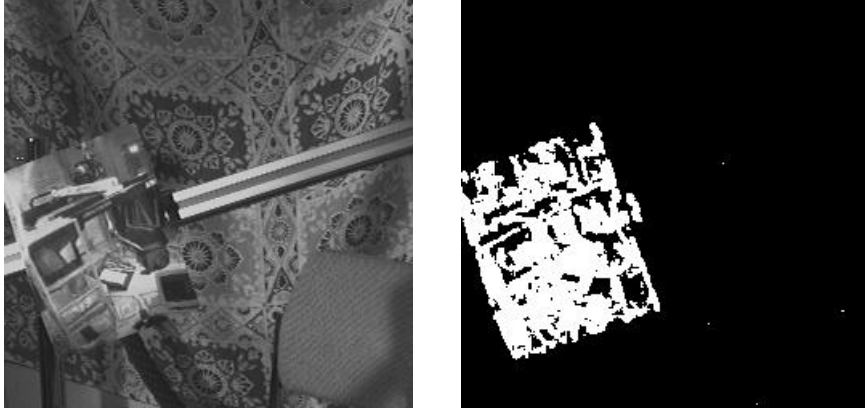


Figure 2: Detection of the initial target position

### 3 Target tracking using 2D motion visual servoing

We first only consider the estimated terms  $c_1$  and  $c_2$  in the control law. The set of visual features is thus  $s = (c_1, c_2)^T$ , with desired value  $s^* = (0, 0)^T$  so that the target remains static in the image.

#### 3.1 Control law

From the interaction relation between image motion parameters and camera 3D motions presented in [14], we obtain:

$$\dot{s} = \begin{pmatrix} \dot{c}_1 \\ \dot{c}_2 \end{pmatrix} = L \begin{pmatrix} \dot{\Omega}_{c,x} \\ \dot{\Omega}_{c,y} \end{pmatrix} + \frac{\partial s}{\partial t} = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} \dot{\Omega}_{c,x} \\ \dot{\Omega}_{c,y} \end{pmatrix} + \frac{\partial s}{\partial t} \quad (3)$$

where  $\dot{\Omega}_{c,x}$  and  $\dot{\Omega}_{c,y}$  are the camera pan and tilt acceleration,  $L$  is the interaction matrix related to  $s$ , and  $\frac{\partial s}{\partial t}$  represents the variations of  $s$  due to the target own motion. This equation can be easily obtain from (2).

We are thus in the case where the visual features are linked to the controlled camera degrees of freedom through a full rank invertible matrix. We thus obtain as control law, so that  $s$  exponentially decreases with gain  $\lambda$  ( $\dot{s} = -\lambda s$ ):

$$\begin{pmatrix} \dot{\Omega}_{c,x} \\ \dot{\Omega}_{c,y} \end{pmatrix} = -L^{-1} \left( \lambda s + \frac{\widehat{\partial s}}{\partial t} \right) = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix} \left( \lambda s + \frac{\widehat{\partial s}}{\partial t} \right) \quad (4)$$

where  $\frac{\widehat{\partial s}}{\partial t}$  can be obtained from two successive values of  $s$  and a measure of the camera pan and tilt

acceleration (see [14] for more details):

$$\widehat{\frac{\partial s}{\partial t}}(t) = \frac{s(t) - s(t - \delta t)}{\delta t} + L \begin{pmatrix} \widehat{\Omega}_{c,x}(t) \\ \widehat{\Omega}_{c,y}(t) \end{pmatrix} \quad (5)$$

Furthermore, a classical Kalman filter is used to smooth this estimation.

For the reader interested in the link between the general case presented in [14] and the particular case of target tracking described in this paper, we can note that the error vector  $e$  is here equal to  $s$ , meaning combination matrix  $C$  (such that  $e = C (s - s^*)$ ) is equal to  $\mathbb{I}_2$ . Furthermore, the interaction matrix  $L$  is constant and does not depend of unknown parameters ( $\widehat{L} = L$ ). Finally, from the stability condition exhibited in [14] ( $K = (CL)(C\widehat{L})^{-1} > 0$ ), the exponential decrease of  $\|s\|$  is ensured at each iteration of the control law, since  $K$  is nothing but  $\mathbb{I}_2$ .

### 3.2 Results

Images of size  $256 \times 256$ , acquired by a SunVideo board, are processed on an UltraSparc station with a 250 MHz clock. The complete processing rate is about 50 ms per iteration (meaning 20 Hz). For the camera we used for the experiments, a standard calibration procedure provided the coordinates of the principal point (132, 130.5), and the size of a pixel ( $19.8 \times 20.6 \mu\text{m}$ ).

The experiment has been carried out with a textured object from which no geometric features can be easily computed (see Figure 2). The camera was about 1 m away from the object, which appears near the image center before it starts moving. The object is translating along a rail alternatively to the right and to the left at constant speed (25 cm/s), with a 4 seconds pause between the two motion phases. Accelerations and decelerations were performed with an absolute value of  $40 \text{ cm/s}^2$ , meaning the constant level speed is reached in 15 iterations. In order to separate the object from the background, a motion detection step is first performed, as described in Section 2.2.

Two curves related to this experiment are presented in Figure 3. First, the two visual features  $c_1$  and  $c_2$  are given on Figure 3.a. Then, the computed control law  $\dot{\Omega}_{c,x}$  and  $\dot{\Omega}_{c,y}$  sent to the low level pan tilt controller is given on Figure 3.b. Despite some oscillations, the system brings the error to zero after each abrupt change in the object motion. The oscillations are not induced by noisy measurements of the visual features, but because of a noisy estimation of the object own motion  $\widehat{\frac{\partial s}{\partial t}}$ . Indeed, they appear mainly during the acceleration steps, which are very short. Since the noise variance on the state model of the Kalman filter has not to be too low to allow the system to react, it is difficult to obtain more accurate estimations during the abrupt changes of target motions.

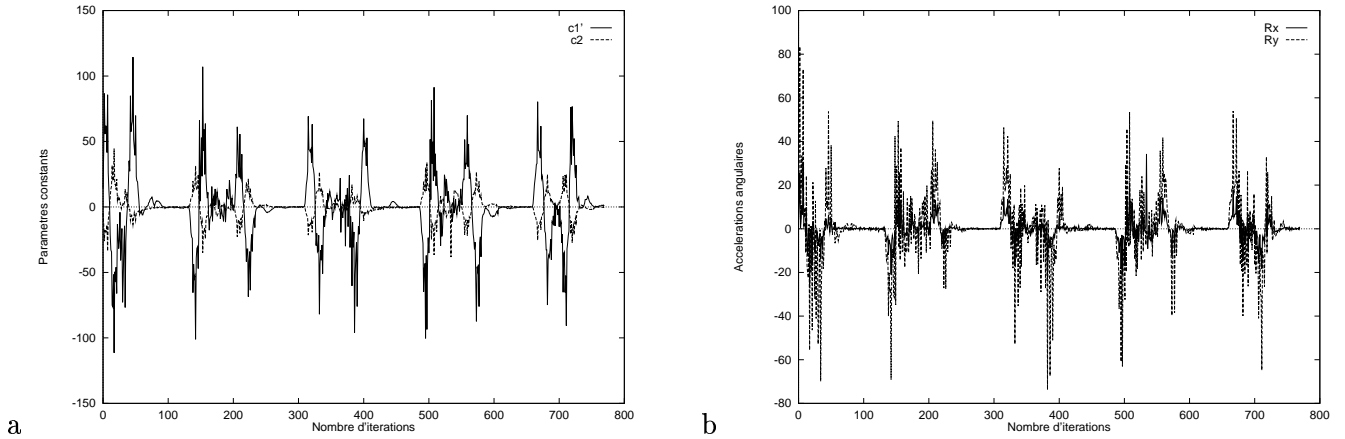


Figure 3: Target tracking using directly the motion parameters: (a) constant parameters  $c_1$  and  $c_2$ , (b) angular acceleration (in  $\text{deg/s}^2$ ).

Nevertheless, to show the accuracy of the method, we present on Figure 4 the two coordinates of the center of gravity of the target in the image. These values are computed by a simple integration of the speed, using as initialization the center of gravity of the detection mask. They are obviously unused in the presented control scheme.

We can note that a small deviation appears in the object position (approximately 10 pixels after 800 iterations). This deviation is due to the time needed, even if it is short, to bring the constant parameters to zero. Using a control law directly based on motion parameters, it is of course impossible to completely remove this lag. Furthermore, it is also impossible to reach a desired position of the target in the image. That is why we propose in the next section to use a control law based on the estimated position of the target in the image.

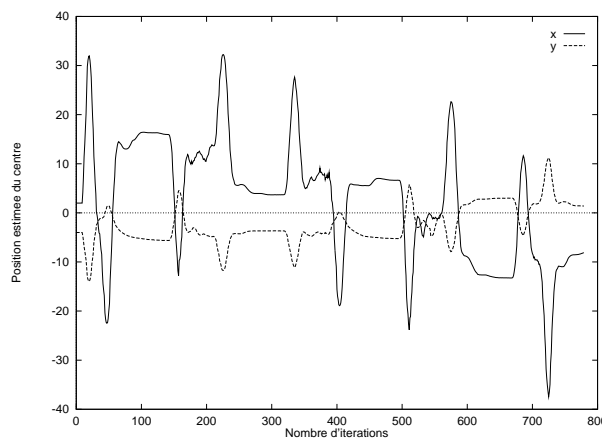


Figure 4: Object center position



To conclude this part, let us emphasize that, even if using motion parameters directly in the control loop does not seem to be the most efficient method for target tracking, this approach is sometimes the only one possible for more complex robotics tasks, as demonstrated in [14].

## 4 Target tracking by integration of 2D motion

We now consider as input of the control law the estimated position of the target position in the image. The visual features are thus  $s = (x, y)^T$ . They are simply obtained by successive summations of the estimated velocities  $c_1$  and  $c_2$ :

$$s_i(k) = s_i(0) + \sum_{i=1}^k c_i \delta t \quad (6)$$

where  $s_i(0) = (x_0, y_0)^T$  is the initial position of the target computed during the detection step (see Section 2.2), and  $\delta t$  is the period of the control loop.

The aim of the tracking task is to control the camera pan and tilt such that the image of the mobile target is, first, brought at the image center ( $s^* = (0, 0)^T$ ), and then remains at this position whatever the target motions are. This task is quite simple from the control point of view. Our contribution is more concerned with the complexity of the considered targets.

### 4.1 Control law

To design the control law, we use the relation between the temporal variation of  $s$  and the controlled camera motion, that is  $\Omega_{c,x}$  and  $\Omega_{c,y}$  around the  $x$  and  $y$  axes. We get from the classical equation between image point velocity and 3D kinematic screw [16, 20, 14]:

$$\dot{s} = L \begin{pmatrix} \Omega_{c,x} \\ \Omega_{c,y} \end{pmatrix} + \frac{\partial s}{\partial t} \quad \text{with } L = \begin{bmatrix} xy & -(1+x^2) \\ (1+y^2) & -xy \end{bmatrix} \quad (7)$$

We can see that the interaction matrix  $L$  only depends on the estimated position of the target in the image. Assuming this estimation accurate allows one to set  $\widehat{L} = L$ . Therefore, specifying as in the previous case an exponential decrease of  $s$  leads to [14]:

$$\begin{pmatrix} \Omega_{c,x} \\ \Omega_{c,y} \end{pmatrix} = -\lambda L^{-1} s - L^{-1} \frac{\partial s}{\partial t} = -\frac{\lambda}{1+x^2+y^2} \begin{pmatrix} y \\ -x \end{pmatrix} - L^{-1} \frac{\partial s}{\partial t} \quad (8)$$

In practice, the chosen gain  $\lambda$  is not constant but adaptive. More precisely, this gain is set to a low value when the error is great, in order to preserve the stability of the system. On the contrary, it is increased to a high value when the error is weak, to optimize the time to convergence.

Furthermore, as explained in [8], the estimation  $\widehat{\frac{\partial s}{\partial t}}$  of  $\frac{\partial s}{\partial t}$  can be obtained from (7):

$$\widehat{\frac{\partial s}{\partial t}} = \widehat{\dot{s}} - L \widehat{\Omega}_c \quad (9)$$

In our case, the measure  $\widehat{\dot{s}}$  of  $\dot{s}$  is directly supplied by the image motion estimation algorithm ( $\widehat{\dot{s}} = (c_1 \ c_2)^T$ ), while  $\widehat{\Omega}_c$  is the measured camera rotational velocity.

We can note that, if the target was motionless, a first order approximation gives:

$$s_{(k)/(k-1)} = s_{k-1} + \dot{s} \delta t_k = s_{k-1} + L \widehat{\Omega}_c \delta t \quad (10)$$

Thus, the estimation of the target own motion in the image at iteration  $k$  can be written:

$$\left( \widehat{\frac{\partial s}{\partial t}} \right)_{(k)} = \frac{s_{(k)} - s_{(k)/(k-1)}}{\delta t} \quad (11)$$

This value represents the discrepancy between the actual measure of the visual feature and the predicted one. It is null if the target is motionless, and constant if the target velocity is also constant. This means that the target motion and the discrepancy have the same model.

Let us now come back to the control point of view and let us consider robustness issues. Two different sources for noise are possible in our estimation scheme: it can be either introduced through the extraction of the visual data or due to camera velocity measurement errors.

According to several works investigating the field of filtering for target tracking [5, 19, 10, 1], two common approaches are employed: the first consists in using fixed tracking coefficients ( $\alpha - \beta$ ,  $\alpha - \beta - \gamma$  trackers), and the second, Kalman filtering, generating time-variable tracking coefficients that are determined by *a priori* models of target dynamics. While the first approach has computational advantages, the second one seems much more appealing, thanks to the adaptability of its coefficients for tracking highly maneuvering targets. However, implementing a Kalman filter requires first to define, or estimate, the state model evolution of the parameters, the simplest cases for motion parameters being the constant speed and constant acceleration models.

When a target maneuvers (for example when abrupt changes in its acceleration occur), a tracking filter should respond. Such maneuvering may be detected by a rapid increase in the normalized discrepancy. The recommended methods for dealing with those situations are numerous [4, 6] and we have chosen, for

robustness issues, to consider model maneuvers as “colored noise”. That is why we have chosen a constant acceleration state model with colored noise, the equations of which are given by:

$$\begin{cases} \left( \frac{\partial s}{\partial t} \right)_{(k+1)} &= \left( \frac{\partial s}{\partial t} \right)_{(k)} + \Delta t \left( \frac{\dot{\partial s}}{\partial t} \right)_{(k)} + \nu_{(k)} \\ \nu_{(k+1)} &= \rho \nu_{(k)} + v_{1(k)} \\ \left( \frac{\dot{\partial s}}{\partial t} \right)_{(k+1)} &= \left( \frac{\dot{\partial s}}{\partial t} \right)_{(k)} + v_{2(k)} \end{cases} \quad (12)$$

where  $\rho$  is the degree of correlation between successive accelerations and can range from 0 to 1 (0.3 in the experiments described below),  $v_1$  and  $v_2$  are the zero-mean Gaussian white noises on the chosen model. Furthermore, the relation involved in the Kalman filter relating the observed data to the chosen model is given by:

$$\left( \widehat{\frac{\partial s}{\partial t}} \right)_{(k)} = \left( \frac{\partial s}{\partial t} \right)_{(k)} + \omega_{(k)} \quad (13)$$

where  $\widehat{\frac{\partial s}{\partial t}}$  is the estimated value given by (9), and  $\omega$  is a zero-mean Gaussian white noise on the observations.

Finally, let us note that the control law given by (8) is insufficient to compensate for possible tracking errors due to non-zero target accelerations. To overcome this problem, the prediction of the target motion, provided by the Kalman filter, is used; this leads to the following adaptive predictive control law:

$$\begin{pmatrix} \Omega_{c,x} \\ \Omega_{c,y} \end{pmatrix} = -\frac{\lambda}{1+x^2+y^2} \begin{pmatrix} y \\ -x \end{pmatrix} - L^{-1} \left( \widehat{\frac{\partial s}{\partial t}} \right)_{(k+1)/(k)} \quad (14)$$

## 4.2 Sensitivity to calibration errors

In several articles [22, 23], the detection of the object of interest in a tracking scheme is based on the known motion of the camera. Indeed, it is well known that if a rotating camera is observing a fixed scene, the apparent motion field in the image is closed to a constant one. More precisely, the four affine parameters  $a_i$  that appear in (1) are equal to zero. Moreover, in such a case, there is no influence of the target depth on its apparent motion. It is thus possible to compensate the camera motion in the image from the measure of the camera rotation. Therefore, under the hypothesis that only one object is moving in the scene, a simple difference between the compensated image and the one acquired at current iteration gives the position of the object.

However, this approach necessitates a good calibration of the system. First, the center of rotation must be the optical center of the camera. If it is not the case, camera translational motions are also performed, and the depth of each point of the scene appears in the 2D motion equations. In the best case where the induced translation is known, these depths remain unknown. Therefore, some perturbations occurs in the compensation, especially if there are some great depth changes in the observed scene. Another point is that the computation of the 2D motion in the image from 3D motion necessitates a precise knowledge of the intrinsic parameters of the camera (size of pixel, position of the principal point, and radial distorsion). Using inaccurate intrinsic parameters, the image compensation can not be performed correctly, and it thus becomes impossible to separate the object of interest from the background.

In our approach, the measured camera velocity is only used in the control scheme to reduce the tracking errors (see (9)). If a wrong estimation of the camera velocity occurs due to a coarse camera calibration, it will have an effect on the response of the controller, but nothing more, since the measured camera velocity is not used at all to determine the target position in the image.

Furthermore, the motion parameters  $c_1$  and  $c_2$  used in the control law to estimate the target position are metric, meaning expressed in m/s and rad/s. However, the image motion estimation algorithm we use to compute these parameters provides results expressed in pixels/s. Therefore, it is necessary to express the former from the latter. The intrinsic parameters of the camera, or at least a coarse estimation of these parameters, should then be used. Nevertheless, we show now that our control scheme is not sensitive to calibration errors.

Indeed, if we denote with a  $p$  index the parameters of the motion model expressed in pixel, we have the corresponding relation with the metric ones [11]:

$$\begin{pmatrix} c_1 \\ c_2 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ q_1 \\ q_2 \end{pmatrix} = \begin{bmatrix} l_x & 0 & l_x d_x & l_x d_y & 0 & 0 & l_x d_x^2 & l_x d_x d_y \\ 0 & l_y & 0 & 0 & l_y d_x & l_y d_y & l_y d_x d_y & l_y d_y^2 \\ 0 & 0 & 1 & 0 & 0 & 0 & 2d_x & d_y \\ 0 & 0 & 0 & l_x/l_y & 0 & 0 & 0 & d_x l_x/l_y \\ 0 & 0 & 0 & 0 & l_y/l_x & 0 & d_y l_y/l_x & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & d_x & 2d_y \\ 0 & 0 & 0 & 0 & 0 & 0 & 1/l_x & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1/l_y \end{bmatrix} \begin{pmatrix} c_{1,p} \\ c_{2,p} \\ a_{1,p} \\ a_{2,p} \\ a_{3,p} \\ a_{4,p} \\ q_{1,p} \\ q_{2,p} \end{pmatrix}$$

where  $(l_x, l_y)$  is the ratio between the camera focal length and the size of a pixel, and  $(d_x, d_y)$  is the distance between the principal point and the center of the estimation window. Since the principal point is generally

close to the image center, we have in the neighborhood of convergence,  $(x, y) \approx (0, 0)$ , and  $(d_x, d_y) \approx (0, 0)$ .

We thus obtain:

$$\begin{pmatrix} \dot{x} \\ \dot{y} \end{pmatrix} \approx \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} \approx \begin{pmatrix} l_x c_{1,p} \\ l_y c_{2,p} \end{pmatrix}$$

We can see that an error on the position of the principal point has no effect. Furthermore, a wrong estimation of  $(l_x, l_y)$  only provides a scale factor error. Since the control law has a closed loop structure, this does not perturb the convergence. In the worst case, the convergence is simply obtained more slowly. It can even be obtained more quickly, since the influence of such an error is more or less like having a scale factor upon the decreasing gain  $\lambda$ . We will demonstrate the effective robustness of our method with respect to calibration errors in the next section.

## 4.3 Results

### 4.3.1 Tracking a rigid object

The same object as in Section 3.2 has first been considered. It again translates at constant speed along a rail alternatively to the right and to the left, with a 4 seconds pause between the two motion phases. First (till iteration 800), the object speed was 8 cm/s and then, it was 30 cm/s. Once again, the camera is about 1 m away from the object, but it does not appear near the center of the image before it starts translating.

The measured position of the target in the image ( $s = (x \ y)^T$ ) is plotted on Figure 5. This experiment shows that convergence is correctly obtained for an initial gap of about 40 pixels (the error is brought to zero in less than 40 iterations even if the object motion is initially on the opposite direction of the image center). At each abrupt change in the target motion (stop or start), there is an overrun due to the Kalman filter reacting time (approximately 30 pixels for a 30 cm/s speed of the object), but convergence is still obtained and tracking errors are suppressed in few iterations.

Upon Figure (6) are displayed some images acquired during this experiment (one image upon ten). Estimated target position is designed by a cross (+) and the image center by a diamond ( $\diamond$ ). We can notice that, as soon as the object is brought to the image center (which is already done on image 2), it remains there even if the object stops and restarts. Therefore, on the qualitative point of view, we can conclude that the motion estimation is accurate.

Other experiments, described in [11] and using a simpler object from which it was easy to extract the true position, have shown that the difference between the real and the estimated positions was always less than half of a pixel. In those experiments, the object had four markers. The 2D motion was computed from

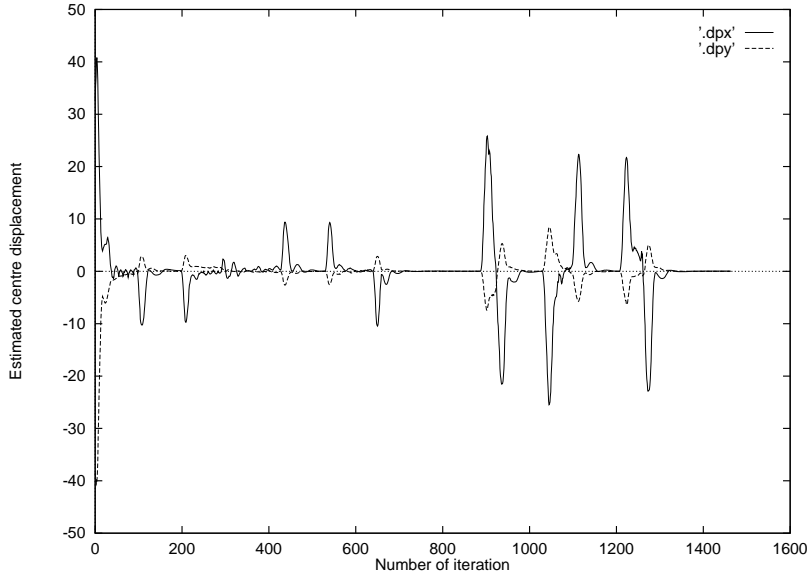


Figure 5: Estimated target position (in pixel) versus iteration number

the displacement of these markers. Of course, the measured 2D position of the markers were not used in the control loop, but were only used to estimate the object center as the center of gravity of the four markers. Moreover, it was also shown on known object motion at a given distance from the camera that the image motion estimation algorithm gives equivalent results than the estimation provided by the computation of the four markers. It was even better for slow motions. We can thus conclude that the motion estimation algorithm is unbiased since no drift appears, even after a large number of iterations of the control law.

Another thing important to underline is the poor illumination quality (the object is very dark when it is on the right part of the rail) and also the varying of this illumination. This independence to illumination conditions is due to the robustness of the image motion estimator. We can also notice that it seems to be very difficult to extract the object from the background using only geometric image processing. Finally, even if other objects are moving behind the target from image 8 to 14 and 17 to 25, the tracking system remains stable. This can be explained by the fact that the motion computation relies on the initial mask, and then the estimation is only performed on pixels belonging to the mask. Moreover, the estimation algorithm is robust with respect to potential outliers.

### 4.3.2 Sensitivity

Several experiments have been done to prove the reliability of our approach in case of weak calibration of the system. The camera has been displaced of approximately 5 cm in two different directions with respect

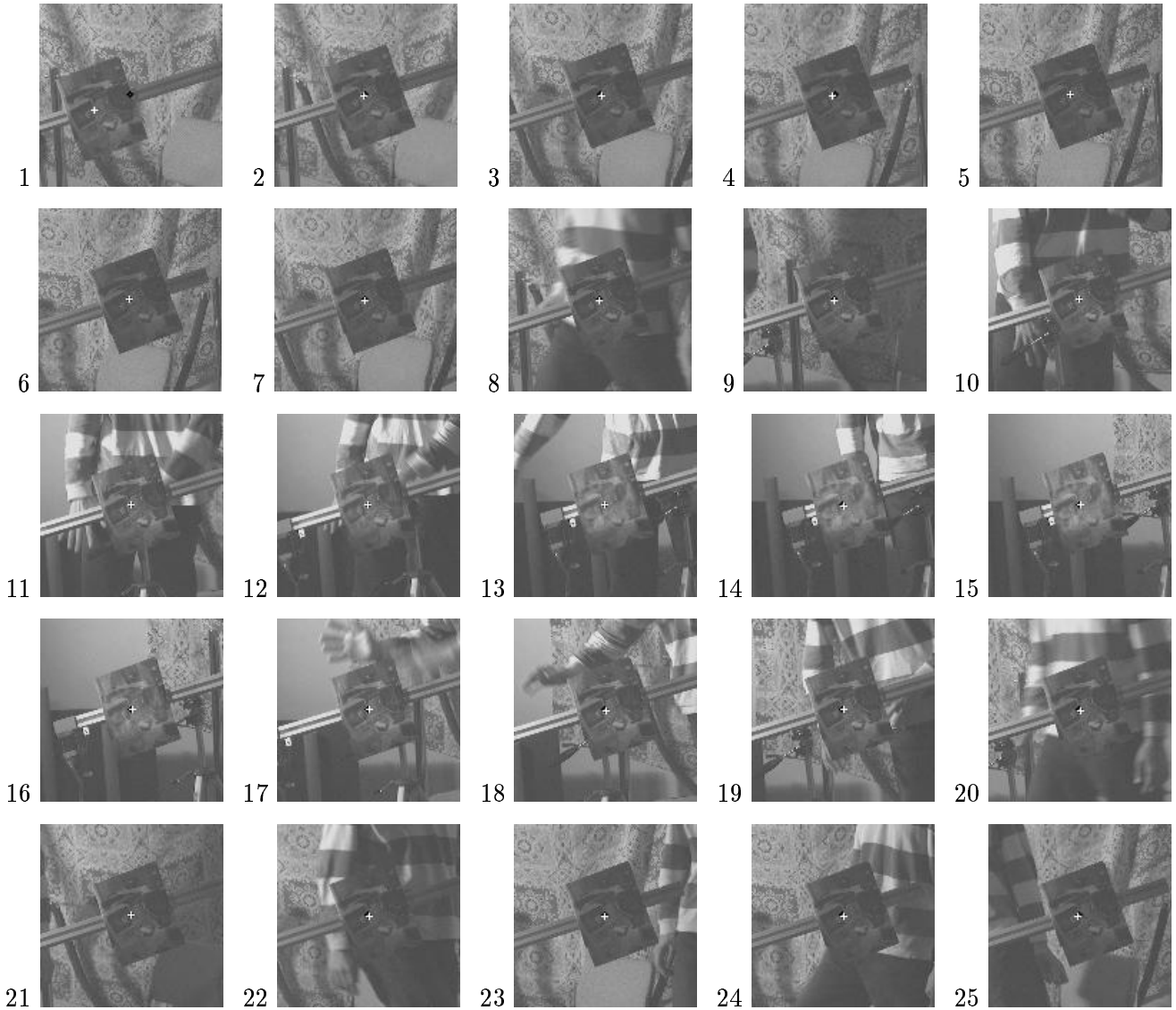


Figure 6: Tracking a textured object. An image upon ten of the acquired sequence (approximately 2 frames per second). Cross (+) stands for the estimated c.o.g. and black diamond (◊) for the image center

to the pan-tilt cell (along the  $y$  axis of the image plane and along the optical axis). This means that pan and tilt rotations are not performed around the optical center. This implies translational motions of the camera (nearly 10% of the distance between the camera and the target). Moreover, errors have been introduced in the intrinsic parameters of the camera. The principal point has been considered to be the image center (128, 128), and a 10% error has been added on the size of each pixel, going up to  $21.8 \times 22.7 \mu\text{m}$ . All other conditions were the same as for the previous experiment. On Figure (7) is displayed the estimated target position versus iteration number. We can notice that the behaviour is very close to the one observed in the previous experiment, with a better calibrated system. The initial error is quickly brought to zero, and the overrun after each change of the object motion is rapidly compensated. These overruns are not higher in this case than previously. The only difference is that small oscillations appears (always less than 2 pixels), but they do not generate any divergence. They are even decreasing in permanent step.

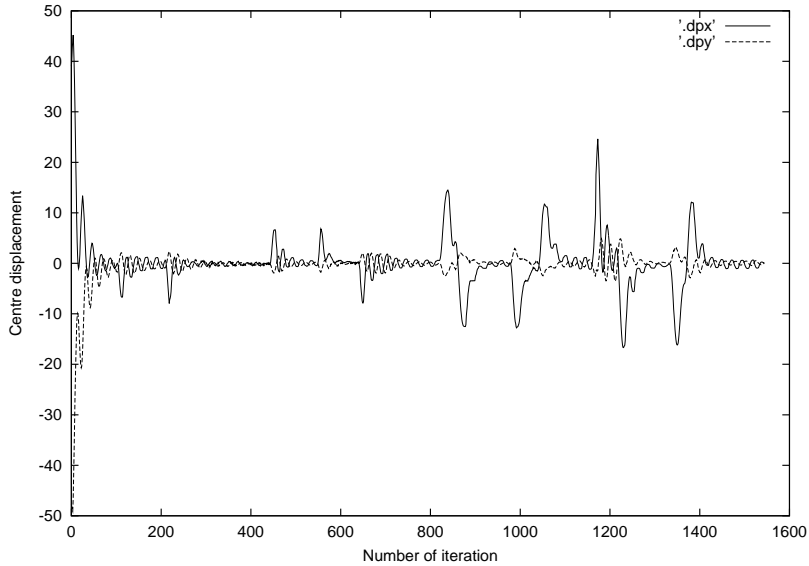


Figure 7: Estimated target position with a weakly calibrated system

#### 4.4 Other applications

The method presented above can be used in other applications. Two of them have been developed with exactly the same control law.

A pedestrian tracking task is presented in [12]. The aim is the same as the application presented above, even if a pedestrian is not a planar rigid object. Let us point out that the estimation of 2D motion parameters with the algorithm we used involves the discarding of non-coherent local motions considered as outliers. Therefore, motions related to deformations of non-rigid objects (such as a human being) do not



affect greatly the estimation of the dominant motion.

Figure 8.a displays the mask obtained from the detection step, where moving zones appear in white. Figure 8.b presents an image acquired during the tracking. The white rectangle represents the including rectangle of the detected mask on which the estimation is performed.

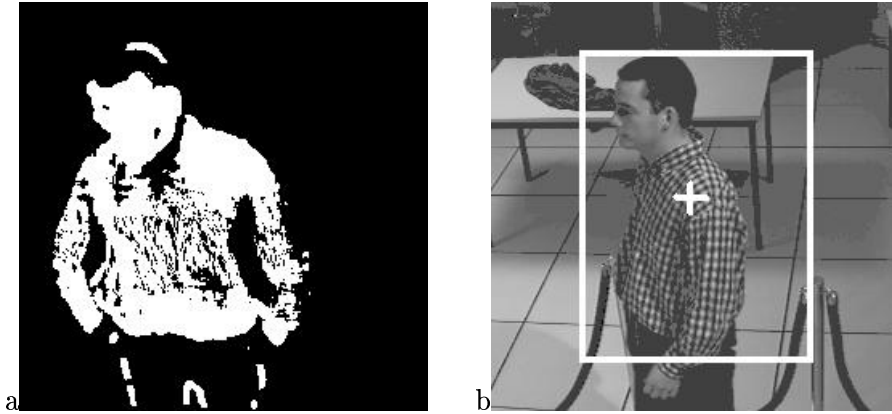


Figure 8: a) Detected mask. b) Estimation window and estimated position of the pedestrian

Figure 9 contains one image over 10 of the sequence acquired during the tracking. Motion of the person is first sideways, and not always facing the camera. Then, the pedestrian comes back to the camera. On each image, the estimated position is represented by a black cross (+) and the image center by a black square ( $\diamond$ ). Despite the complexity of motion, the pedestrian always appears at the image center. This demonstrates the robustness of the motion estimation algorithm and of the control scheme. Small tracking errors appear, due to reacting time of the Kalman filter, but they are always less than 8 pixels. Finally, from image 10 to 13, another person crosses the tracked one. In spite of this perturbing supplementary motion, the camera is still fixating at the selected person.

Finally, in [13], we have used the same algorithm for image stabilization of a camera mounted on an underwater engine. In that case, the motion in the image is, in part, due to the observed scene own motion and overall, to the undesirable motion of the engine, because of underwater currents. Once again, even if the quality of the images used is poor (they had low spatio-temporal gradients), the results presented in [13] show that the drift in the image remains very weak (less than half a pixel after 250 iterations). A typical image sequence acquired during the stabilization is given in Figure 10 where the considered scene is a rock from which smoke and gas escape.

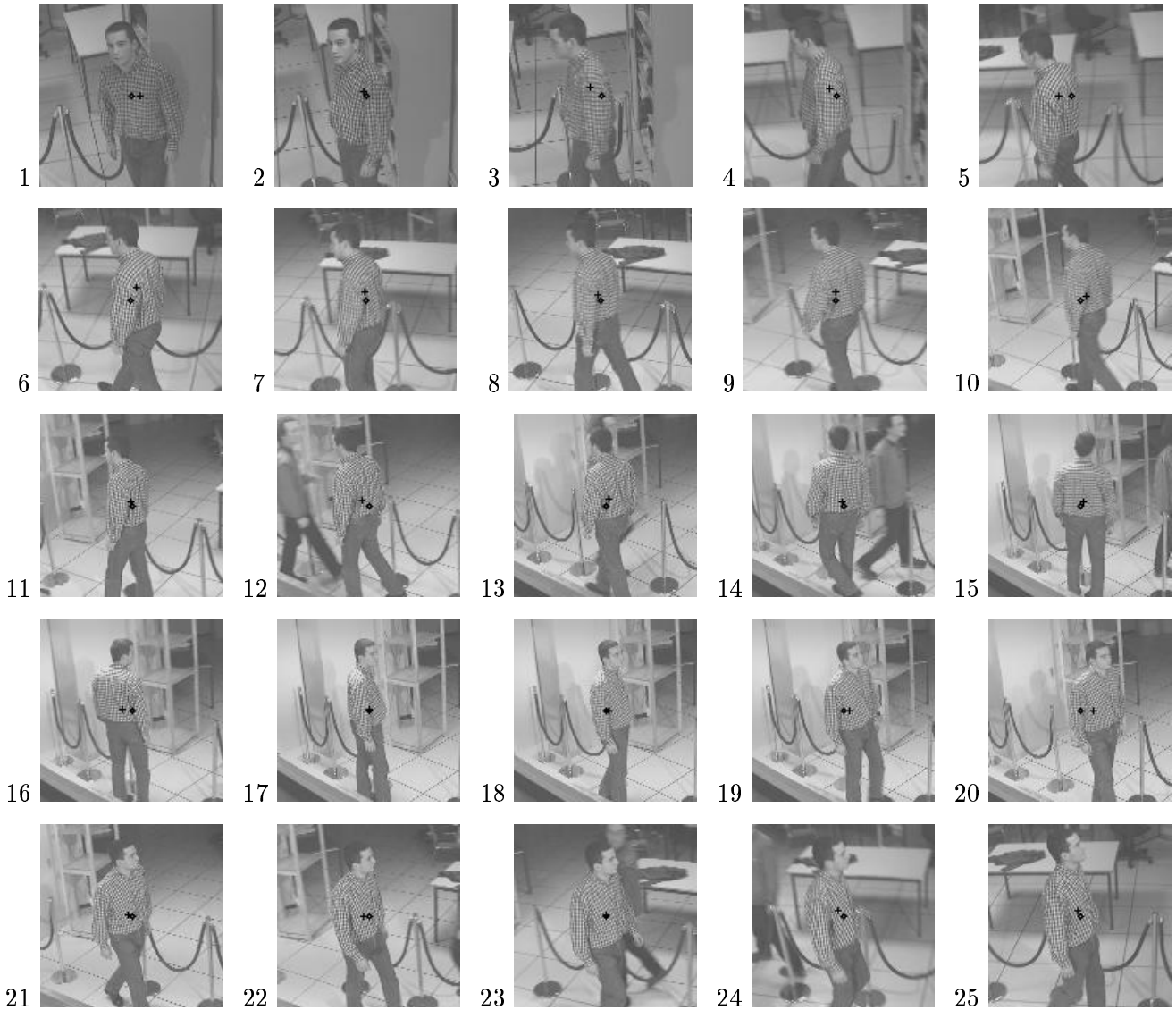


Figure 9: Tracking of a pedestrian. An image upon ten of the acquired sequence (approximately 2 frames per second). Cross (+) stands for the estimated c.o.g. and diamond ( $\diamond$ ) for the image center

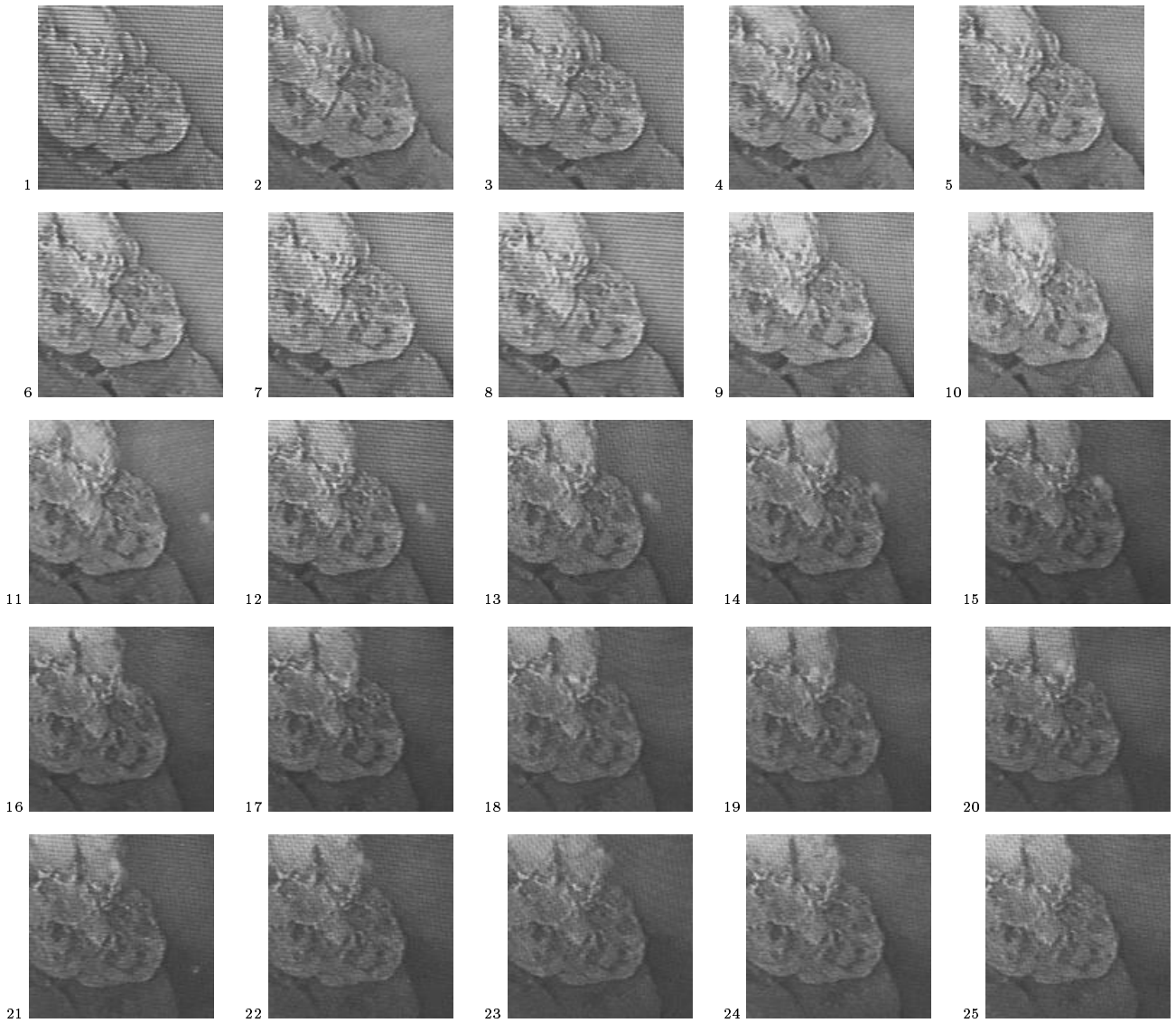


Figure 10: One image over 10 of a sequence acquired during submarine images stabilization

## 5 Conclusion

In this paper, we have presented an application of the two methods presented in [14] to perform visual tracking without any a priori knowledge on the object appearance. Both are based on the use of image motion. The principle of the first method is to control the camera motions in order that the current image motion reaches a desired value. In the second method, the position of the target is retrieved by successive summation, and classical image based visual servoing is then used.

These methods were applied to the tracking of real objects, meaning not designed to simplify any visual processing algorithm. In both cases, satisfying results were obtained, even if the direct use of motion parameters as input of the control law is less powerful. It thus seems that, for visual tasks where both approaches are applicable, it is more interesting to adopt the second one (integration of motion). Indeed, the control loop of the second approach can be seen as the combination of the control loop given by the first approach and an integrator. It thus allows to avoid tracking errors. We can also emphasize that the image motion estimation algorithm we used seems to be unbiased since no drift appears in the experiments.

Improvements could be done on the practical level. In particular, the goal of the tracking experiments presented here was just to validate the two control strategies. It explains why the initialization step was based on the strong hypothesis of a single moving target. An image processing algorithm dedicated to the automatic selection of a target in case of multiple detections should be developed for real survey applications.

## References

- [1] P.K. Allen, A. Timcenko, B. Yoshimi, and P. Michelman. Automated tracking and grasping of a moving object with a robotic hand-eye system. *IEEE Trans. on Robotics and Automation*, 9(2):152–165, Apr. 1993.
- [2] R. Bajcsy. Active Perception. *Research Report MS-CIS-88-24*, University of Pennsylvania, Philadelphia, March 1988.
- [3] M.G.P. Bartholomeus, B.J.A. Kröse, and A.J. Noest. A robust multi-resolution vision system for target tracking with a moving camera. In H. Wijshof, editor, *Computer Science in the Netherlands*, pages 52–63. CWI, Amsterdam, Nov. 1993.

- [4] F. Bensalah and F. Chaumette. Compensation of abrupt motion changes in target tracking by visual servoing. In *IEEE Int. Conf. on Intelligent Robots and Systems*, volume 1, pages 181–187, Pittsburgh, Aug. 1995.
- [5] S. Blackman. *Multiple Target Tracking with Radar Application*. Artech House Inc., 1986.
- [6] C. Brown, H. Durrant-Whyte, Leonard. J., and B. Rao. Centralized and decentralized kalman filter techniques for tracking, navigation, and control. In *Image Understanding Workshop*, pages 651–675, San Mateo, May 1989.
- [7] C. Brown. Gaze control cooperating through prediction. *Image and Vision Computing*, 8(1):10–17, Feb. 1990.
- [8] F. Chaumette and A. Santos. Tracking a moving object by visual servoing. In *12<sup>th</sup> World Congress IFAC*, volume 9, pages 409–414, Sydney, Australia, July 1993.
- [9] J. J. Clark, N. J. Ferrier. Control of Visual Attention in Mobile Robots. *IEEE Int. Conf. on Robotics and Automation*, pp. 826-831, Scottsdale, Arizona, May 1989.
- [10] P.I. Corke and M.C. Good. Controller design for high performance visual servoing. In *12th World congress IFAC*, volume 9, pages 395–398, Sydney, Australia, July 1993.
- [11] A. Crétual. *Asservissement visuel à partir d'informations de mouvement dans l'image*. PhD thesis, Rennes 1 University, Nov. 1998.
- [12] A. Crétual, F. Chaumette, and P. Bouthemy. Complex object tracking by visual servoing on 2D image motion. In *IAPR Int. Conf. on Pattern Recognition*, volume 2, pages 1251–1254, Brisbane, Australie, Aug. 1998.
- [13] A. Crétual and F. Chaumette. Dynamic stabilization of a pan and tilt camera for sub-marine image visualization. *Computer Vision and Image Understanding*, 79(1):47–65, July 2000.
- [14] A. Crétual and F. Chaumette. Visual servoing based on image motion. submitted to *International Journal of Robotics Research*, 2001.
- [15] K. A. Dzialo, R. J. Schalkoff. Control Implications in Tracking Moving Objects Using Time-Varying Perspective-Projective Imagery. *IEEE Trans. on Industrial Electronics*, 33(3):247–253, Aug. 1986.

- [16] B. Espiau, F. Chaumette, and P. Rives. A new approach to visual servoing in robotics. *IEEE Trans. on Robotics and Automation*, 8(3):313–326, June 1992.
- [17] A. L. Gilbert, K.G. Giles, G. M. Flachs, R. B. Rogers, Y. H. U . A Real-Time Video Tracking System. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 2(1):47–56, Jan. 1980.
- [18] K. Hashimoto, T. Ebine, K. Sakamoto, and H. Kimura. Full 3D visual tracking with nonlinear model-based control. In *American Control Conference*, pages 3180–3185, San Francisco, California, June 1993.
- [19] A.H. Hunt and A.C. Sanderson. Vision-based predictive robotic tracking of a moving target. Technical Report CMU-RI-TR-82-15, Department of Electrical Engineering & The Robotics Institute, CMU, Pittsburgh, 1982, Robotics Institute-CMU, 1982.
- [20] S. Hutchinson, G. Hager, and P.I. Corke. A tutorial on visual servo control. *IEEE Trans. on Robotics and Automation*, 12(5):651–670, Oct. 1996.
- [21] E. Milios, M. Jenkin, and J. Tsotsos. Design and performance of TRISH, a binocular robot head with torsional eye movements. *International Journal of Pattern Recognition and Artificial Intelligence*, 7(1):51–68, Feb. 1993.
- [22] D. Murray and A. Basu. Motion tracking with an active camera. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 16(5):449–459, May 1994.
- [23] D.W. Murray, K.J. Bradshaw, P.F. Mc Lauchlan, I.D. Reid, and P.M. Sharkey. Driving saccade to pursuit using image motion. *International Journal of Computer Vision*, 16(3):205–228, Mar. 1995.
- [24] P. Nordlund and T. Uhlin. Closing the loop: detection and pursuit of a moving object by a moving observer. *Image and Vision Computing*, 14(4):265–275, May 1996.
- [25] J.M. Odobez and P. Bouthemy. Robust multiresolution estimation of parametric motion models. *Journal of Visual Communication and Image Representation*, 6(4):348–365, Dec. 1995.
- [26] N.P. Papanikolopoulos, B. Nelson, and P.K. Khosla. Six degree-of-freedom hand/eye visual tracking with uncertain parameters. *IEEE Trans. on Robotics and Automation*, 11(5):725–732, Oct. 1995.
- [27] I.D. Reid and D.W. Murray. Active tracking of foveated feature clusters using affine structure. *International Journal of Computer Vision*, 18(1):41–60, Apr. 1996.

- [28] M. Subbarao and A. Waxman. Closed-form solutions to image equations for planar surface in motion. *Computer Vision, Graphics, and Image Processings*, 36(2):208–228, Nov. 1986.
- [29] T. Yamane, Y. Shirai, and J. Miura. Person tracking by integrating optical flow and uniform brightness regions. In *IEEE Int. Conf. on Robotics and Automation*, pages 3267–3272, Leuven, Belgium, May 1998.