A Robust Design for Image-based Visual Servoing

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Abstract: In this paper we introduce a new robust visual scheme intended to 2D visual servoing robotic tasks. The main object is to direct the robot to its desired position. To be able to carry out such a task robustly the tough and major step is primarily the image processing procedure. We should find good selections of visual data in order to be correctly matched and interpreted by the visual control law regardless of the different sorts of errors. The new proposed design combines the speed up robust features (SURF) algorithm and progressive sample consensus (PROSAC) algorithm to accomplish a good feature extraction and to rapidly resist the environment constraints while removing the erroneous matches.

1 INTRODUCTION

Vision-based robotic tasks termed visual servoing by (Hutchinson et al., 1996) has known a prominent advancement and has been employed in many fields: from military and medical applications to automotive areas. The idea of using visual data as an entry promotes the autonomy of the system. However many accuracy problems may occur because of camera calibration errors and environment uncertainties.

In order to build a stable and a robust control law, the visual feedback should be the result of a robust, efficient and real time data processing. Thus, robust techniques have to be utilized in order to determine the system references.

Related works in this field have shown the presence of two sorts of vision description in visual servoing: global and local description (Abidi et al., 2012). The global descriptors principle is to consider the entire image as input for the system. Global features could be for example the image luminance (Collewet et al., 2010) or the selection of random pixel luminance sets (Hammouda et al., 2012) also the mutual information between a current and a desired image (Viola and Wells, 1997). Despite their advantage of discarding the tracking and matching steps they still suffer from a high computation time and a definite divergence when considering large initial displacements. In the other hand local descriptors came to deal with global techniques issues.

Lowe, 2004, developed a scale and rotation invariant algorithm (SIFT) which targets the characterization of the image interest points by gathering both a detector and a descriptor. This algorithm has proved highly-efficient and outperforming the current state of art in visual control schemes. The (SIFT) moments (Nierobisch et al., 2007) have also been used and tested on a 6 DOF KATANA manipulator with an eye-in-hand camera. The visual servoing scheme relies on robustly-matched geometric moments which could resist occlusions and view point changes. Another derivative of (SIFT) called (PCA-SIFT) (Ke and Sukthankar, 2004) which seems to be faster than its predecessor but more sensitive to registration problems.

The complexity of these techniques has entailed a high computational time and therefore they seem to be very slow. SURF algorithm developed by Bay, 2006, came to fill this gap with a greatly- reduced computing time. This algorithm contains basically a detector to extract interest points and a descriptor of 64 dimensions to depict each single point. It is also invariant to image scale and rotation transformations and deal with many sorts of environment changes.

Melting speed and robustness, (SURF) could lead to a successful recognition task nevertheless when talking about robotic tasks with real life issues like blur, high illumination changes, and occlusions the mismatching probability increases which may generate the failure of the visual servoing task. Therefore, we need a method that guarantees a stable

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and correct matching that can be ensured with PROSAC (Chum and Matas, 2005). This technique allows the extraction of good correspondences by ordering the matched points according to a similarity function and not randomly in order to show up features from progressively larger sets. This method is not so far from the random sample consensus RANSAC algorithm (Fischler and Bolles, 1981) considered as a robust matching technique; the only difference is that RANSAC handles the samples uniformly and randomly. The progressive behavior beginning with high ranked matches makes PROSAC more efficient and a hundred times as fast as RANSAC.

The contribution of this paper consists on a robust design to avoid the system failure which is originally due to the closed loop injected outliers. Therefore, in this paper we will stress the utility of SURF in the extraction stage and PROSAC to cope with the infiltrated matching errors nay in presence of complex environment constraints. The design experimented and implemented on a mobile robot model can provide robust entries to the visual servoing system and lead to joining successfully and accurately the desired position.

This paper is organized as follows: section II provides an explanation of the major constraints opposing the 2D visual servoing robotic tasks. Due to the limitation of existing feature extraction techniques, a robust visual servoing design is proposed in section III based on a combination of an efficient image processing and statistics techniques. As to section IV, it demonstrates the simulation experiments applied on a 3 DOF eye-in-hand mobile robot model.

2 THE SYSTEM CONSTRAINTS

A visual servoing task is based at first on a recognition system to provide useful data for the control law such as points, lines or more complex structures. Figure 2 shows the basic steps of recognition. After being matched, features considered as inliers are going to be used as input for the visual servoing system. The control law aims to reduce a minimization criterion:

$$e(t) = f(p, r(t)) - f^* \tag{1}$$

Where e is the error between a set of visual features f(r) captured at each camera pose 'r' and their desired position f*. p presents the system parameters like the intrinsic camera or the object model parameters. Since f depends on the time variation we can write:

$$\frac{\partial f}{\partial t} = \frac{\partial f}{\partial x}\frac{\partial x}{\partial t} \tag{2}$$

$$\dot{f} = L_f V \tag{3}$$

V=(v,w) is the camera velocity (v is the linear velocity and w is the angular velocity). L_f is the interaction matrix attached to f that links the time variation of a set of current features to the camera motion.

If we consider that the desired position is fixed, we obtain:

$$\dot{e} = L_e V \tag{4}$$

For an exponential decoupling decrease of the error (Comport, 2006):

$$\dot{e} = -\lambda e \tag{5}$$

Using (4) and (5), we deduce that the control law can be defined as follows:

$$V = -\lambda \widehat{L_e^+} e \tag{6}$$

$\widehat{L_e^+}$ is the estimation of the pseudo-inverse of the interaction matrix.

$$Le = \begin{bmatrix} -\frac{1}{Z} & 0 & \frac{x}{Z} & xy & -(1+x^2) & y \\ 0 & \frac{-1}{Z} & \frac{y}{Z} & (1+y^2) & -xy & -x \end{bmatrix} \tag{7}$$

Z is an estimation of the depth relative to the camera frame and V is the robot controller entry.

$$\begin{cases} x = \frac{X}{Z} = \left(\frac{u-pu}{\gamma F}\right) \\ y = \frac{Y}{Z} = \left(\frac{v-pv}{\gamma F}\right) \end{cases} \tag{8}$$

Where (X, Y, Z) are the world coordinates of a point expressed in the camera frame and (x,y) are the projected image plan coordinates. (u,v) are the point coordinates expressed in pixel, (pu,pv) are the coordinates of the perspective image plan central point, F is the focal length and γ is the ratio of a pixel size.

We can see the important number of parameters that should be estimated at each camera pose. Besides, we note the projection in the image plane yielding a significant loss of accuracy. Furthermore, we should mention the presence of noise, occlusion (static and dynamic), and natural phenomena such as shadows, reflections, darkness and illumination changes.

According to the control law expression, we can see that the error value could be easily influenced by

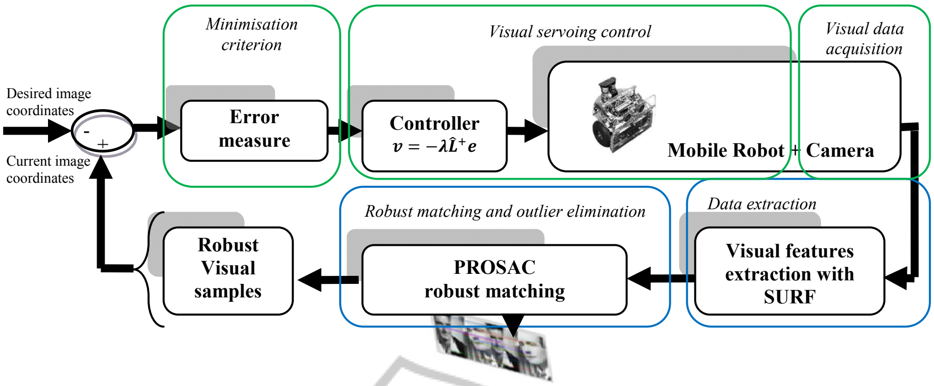


Figure 1: A flowchart of a robust visual design for visual servoing robotic tasks.

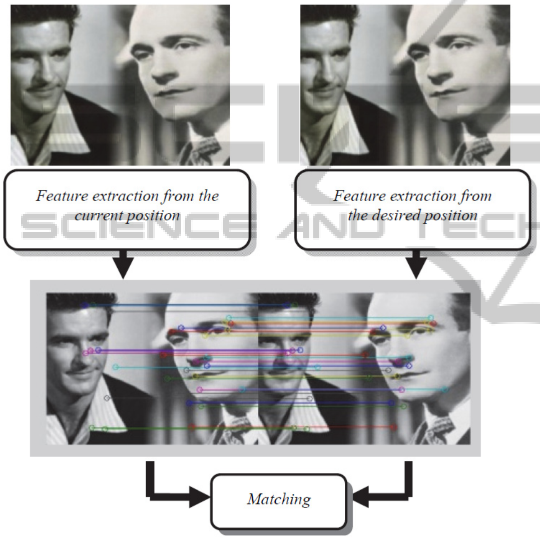


Figure 2: Description of the principle stages related to a recognition process.

these anomalies, that's why we are trying in this paper to show how to cope with these problems and robustly extract our system entries.

3 ROBUST FEATURE PROCESSING

The proposed architecture is based firstly on fast and efficient interest cues detection by using SURF detectors and descriptors. Secondly, a robust matching verification and outlier elimination is established through the PROSAC algorithm. A homography matrix is estimated so that good matches could be selected in every camera motion. Afterwards, an interaction matrix called image Jacobian, is built to create the robot control translational and angular velocities (Figure 1 illustrates the different steps of the proposed design).

3.1 Feature Extraction with SURF

A study done by (Juan and Gwun, 2009) has proved the efficiency of the SURF algorithm compared with other robust algorithms like SIFT and PCA-SIFT. This algorithm is mainly known for its calculation speed and its robustness to illumination changes. SURF has two main steps; the first one is to detect the image interest points and the second one is to describe these points. To save time, the captured image is transformed into an integral image (Viola and Jones, 2001) because of its fastness to deal with convolution computations. Next, we seek for the areas that have high pixel intensity changes. Interest points are, therefore, located where we find a maximal Hessian matrix determinant. Since the Hessian matrix is based on second order partial derivatives which are going to be computed by a convolution with Gaussians, an approximation with a function called the "box filter" seems useful to guarantee more rapidity for the system.

The Hessian matrix is calculated as follows:

$$H(x,\sigma)=\begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{yx}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \quad (9)$$

Where $L_{xx}(x,\sigma)$, $L_{yy}(x,\sigma)$ and $L_{xy}(x,\sigma)$ are a convolution of the Laplacian of Gaussian with the integral image in x.

A representation to a lower scale levels is obtained by raising the size of the Gaussian filters. Eventually, the points with a positive Hessian matrix determinant, and which are local maxima in a neighborhood 3 x 3 x 3 (representing x, y and scale) are kept. Once the interest points are extracted, descriptors should be assigned.

The SURF descriptor describes the intensity of pixels in a neighborhood around each point. The response for x and y Haar wavelets (dx and dy) is calculated in a neighborhood of 6 scales at which an interest point was found. From these values, the dominant orientation of each interest point is calculated by sliding an orientation window. A descriptor is obtained by extracting a square of size 20 scales directed along the dominant orientation. This area is also divided into 4x4 squares. For each of these sub-areas, the Haar wavelets are computed for 5x5 points.

Finally four values are calculated for each sub-region ($\sum dx$, $\sum dy$, $\sum|dy|$, $\sum|dy|$) and each extracted point is described by a 4x4x4 vector (length 64). In Figure 4, we found an example of feature extraction using SURF.

3.2 Matching with PROSAC

In practice, the erroneous matching induces the divergence of the controlled system. Thus, we can't rely only on good descriptors. A powerful outlier elimination method is necessary so that we can succeed in moving the robot to its desired position. In the proposed design (Figure 1) we are looking for more accuracy by applying a derivative of RANSAC called PROSAC which is a much more efficient and rapid. The fact that all matches are not necessarily equaled, PROSAC gradually progresses toward a uniform sampling. A thresholding of a similarity function allows to pick out the ordered samples. The PROSAC technique is based on progressively larger subsets of top-ranked correspondences leading to computational savings (Chum and Matas, 2005).

To outline, PROSAC assesses samples to follow a quality decreasing order. The lowest quality sets are treated in a second place. The algorithm can be summarized in the following steps:

step1/ In order to estimate a geometric model, PROSAC does not select randomly a set of samples but an order of magnitude is rather considered.

step2/ It searches for elements called inliers that may validate the model.

step3/ If there is not enough inliers, the algorithm returns to 1/, else the model is validated.

step4/ After a fixed number of testing, the algorithm stops.

According to the proposed design, PROSAC would estimate the homography matrix using robust matches in every captured image.

$$H=\begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \tag{10}$$

We suppose:

$$\begin{Bmatrix} p_c=\begin{bmatrix} x_c \\ y_c \\ 1 \end{bmatrix} \\ p_d=\begin{bmatrix} x_d \\ y_d \\ 1 \end{bmatrix} \end{Bmatrix} \tag{11}$$

p_d is the coordinate of an interest point in the desired position and p_c depicts the current position coordinates:

$$p'=\begin{bmatrix} \gamma x_c \\ \gamma y_c \\ \gamma \end{bmatrix}=H\, p_d \tag{12}$$

A good model estimation could guarantee an efficient matching for the entered samples. In Figure 3, we found a more detailed representation of the new matching system.

3.3 Comparison to other Robust Techniques

It is obvious that researches dealing with visual servoing robustness problems head predominately the powerful algorithms in vision, control and planning fields. As we are focusing to solve visual issues, we found in (Marquez-Neila et al, 2008) a method to locate planar landmarks involving RANSAC to eliminate outliers.

This technique targets mobile robots navigation. Also in (Song et al., 2010) RANSAC was

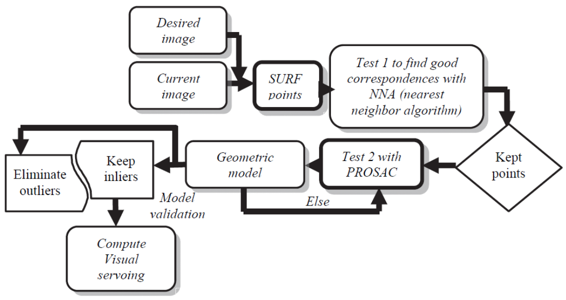


Figure 3: Robust outliers remove technique.

Figure 4: Example of feature extraction using SURF.

(a)Affine transformation

(b)Scale changes

(c)Illumination changes

(d)Rotation changes

Figure 5: Evaluation images taken from INRIA database (Juan, 2009): the first sample (a) presents the affine transformation of the image, the second one (b) indicates the scale changes, the third sample (c) is about illumination changes and the final one (d) points out the rotation changes.

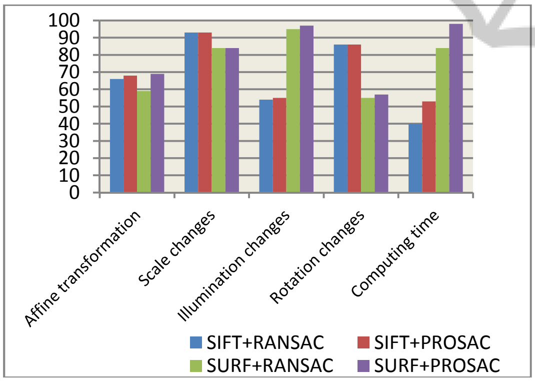


Figure 6: Matching efficiency percentage of some robust feature detection techniques.

used to upgrade SIFT visual cues for grasping tasks. Furthermore, SIFT features mixed with geometric 3D lines were used in (Lee, Kim and Park, 2006) to enhance certainty in 3D recognition.

After being established, SURF came to defeat these techniques notably when talking about the huge computational cost and high illumination changes. We have used different images sweeping different environment phenomena (Figure 5). As seen in Figure 6, we can't make conclusions about the entire efficiency of one technique but we can infer that SURF+PROSAC show a stable behavior by making a balance between the most visual constraints with 84% of matching efficiency in presence of scale changes, 97% when having changes in illumination and a fast processing speed with an efficiency percentage of 98%. We notice that computational time has been improved in all the cases due to PROSAC. SIFT+RANSAC or SIFT+PROSAC show also a good performance especially for rotation changes with 86% and scale changes with 93% but they still suffer from a very low computational time ranging between 40 and 53%.

4 EXPERIMENTS AND RESULTS

In this section experiments were applied on a two wheel eye-in-hand "Koala" mobile robot model with a CCD camera. In each test case the robot has as entry a desired pose defined as follows:

$$\begin{bmatrix} x^* \\ z^* \\ \theta_y{}^* \end{bmatrix} \tag{13}$$

According to this position desired visual cues are extracted using our visual design from the corresponding captured image I*. When a displacement is applied the robot is conducted to a random position and respectively the new current features must be defined. Primarily we begin with a robust identification and description using SURF algorithm. Second we try to compute similitude between desired and current references using Euclidian distance. When correspondences are found PROSAC establishes a descending matching order starting with sets of most confident cues. The considered order yields to a fast successful matching. To control the robot motion velocities should be calculated using the control law described previously in (6). In this case the computed interaction matrix for each interest point is:

$$\text{Le}=\begin{bmatrix} L_x \\ L_y \end{bmatrix} \tag{14}$$

$$L_x=\begin{bmatrix} -\frac{1}{Z} & \frac{x}{Z} & -(1+x^2) \end{bmatrix} \tag{15}$$

$$L_y=\begin{bmatrix} 0 & \frac{y}{Z} & -xy \end{bmatrix} \tag{16}$$

The elements of L_x and L_y correspond to the translation along x and z axis and the rotation according to y axis.

Simulations have been tested with virtual reality modeling language (VRML). For the first experiment we took as initial positioning error: Δ_r=(11 cm, 13 cm, 0.12 rad) in presence of 40% of illumination changes.

Figure 7(a) and Figure 7(b) show the current and desired positions captured by the camera. Figure 7(c) presents the initial difference between the two images. Curves in Figure 7(d) and 7(e) depict a smooth decreasing to zero of Δ_{Tx} , Δ_{Tz} and $\Delta_{\Theta y}$ even when illumination conditions were changed. Figures 7(f), 7(g) and 7(h) show that the translational robot velocities V_x and V_z and the rotational velocity Θ_y applied to the robot reach zero within only 70 iterations.

The same experiment was remade using RANSAC instead of PROSAC. Simulation results in Figure 8(a) and Figure 8(b) show that the positioning error reached zero in a much longer time.

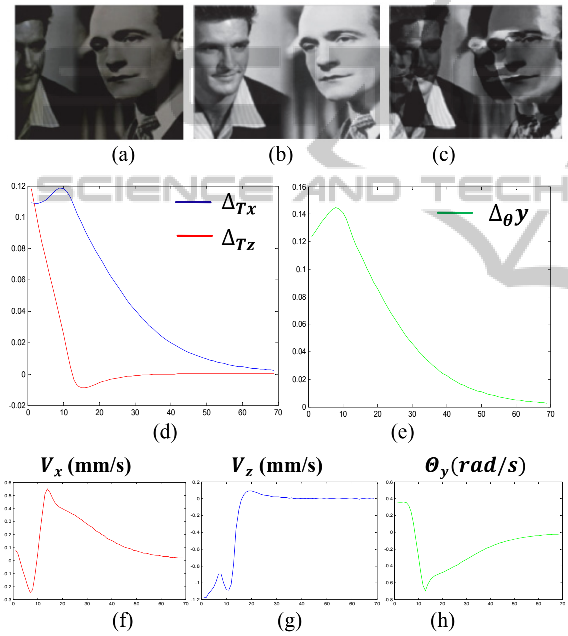


Figure 7: The positioning error variation using our robust visual servoing design (the abscissa axis indicates the iteration number): (a) the current camera pose and (b) the desired camera pose. (d) The translational error (Δ_{Tx} and Δ_{Tz}) expressed in meter (m). (e) The rotational error $\Delta_{\Theta y}$ expressed in radian (rad). (f, g and h) The robot velocities.

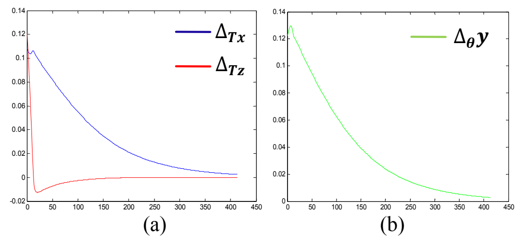


Figure 8: The positioning error variation using SURF+RANSAC during the same experimental conditions. (a) The translational error Δ_{Tx} and Δ_{Tz} in meter (m). (b) The rotational error $\Delta_{\Theta y}$ in radian (rad).

The system takes 400 iterations to converge toward its desired position. Figure 9 emphasizes the presence of two mismatches during the visual servoing task when RANSAC has been applied hereas in this case PROSAC proved a correct match for the same camera displacements.

In the second experiment we have tested scenes with different textures and in presence of illumination, rotation and scale changes. Table 1 presents the variation of the positioning errors relative to the frame number. We can see that the translational and rotational errors tend to zero for all the cases which means that the system converges robustly to its desired position.

The curve (2.c) of the second case when a rotation change has been applied shows that the system takes 700 frames to attain a global error norm equal to zero. In case of scale variation with a depth error of 50 cm, 350 frames were needed to reach the desired position however in the first case only 80 frames have been captured before convergence. Thus we notice the efficiency of the proposed system against many significant changes in scale, rotation and especially illumination.

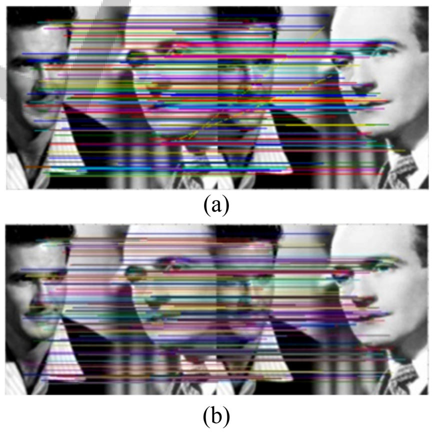
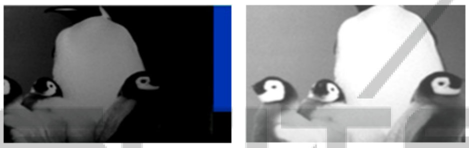
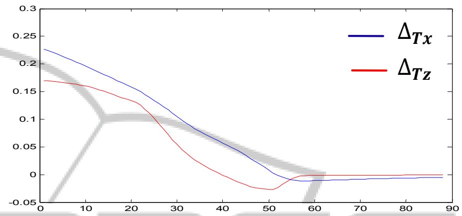
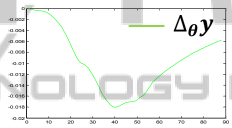
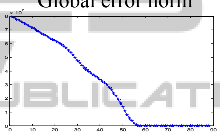
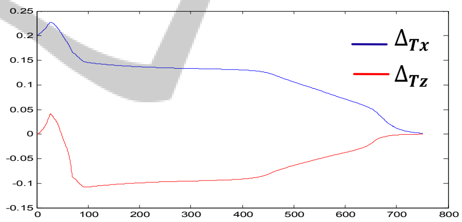
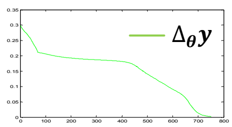
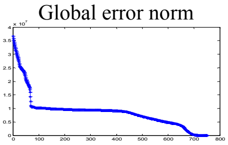
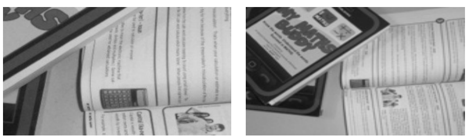
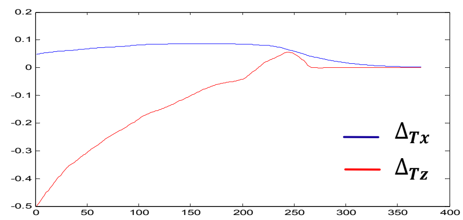
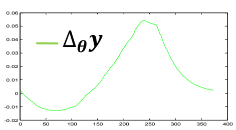
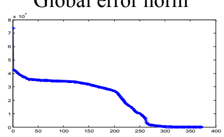


Figure 9: Example of matching between a current and desired pose. (a) Matching using RANSAC (presence of two mismatches in yellow lines). (b) Matching using PROSAC for the same camera pose.

5 CONCLUSIONS

The melting of the Speed up robust features and progressive sample consensus algorithms in a visual servoing design reflected a satisfying behavior. A notably improvement of the system performance was obvious with a smooth decreasing of positioning errors in presence of constraints like illumination, rotation and scale changes. Experiments with virtual reality modeling environment confirm the convergence of the control law in many cases and with diverse image textures. The new proposed design is able to guide the robot successfully and robustly to its desired position and ensure an important time saving. A future work aims to enhance the existing system in order to defeat all the external environment constraints and strengthen the robotic task convergence.

Table 1: Experimental results with different image textures: ((1.a) and (1.b)) translational (cm) and rotational (rad) positioning errors corresponding to brightness changes. ((2.a) and (2.b)) Translational (cm) and rotational (rad) positioning errors corresponding to rotation changes. ((3.a) and (3.b)) Translational (cm) and rotational (rad) positioning errors corresponding to scale changes. ((1, 2 and 3.c) The global error norm.

 Case 1: Brightness change (Positioning error : Δ_{Tx}=23 cm, Δ_{Tz}=17 cm)	 (1.a) Global error norm   (1.b) (1.c)
 Case 2: Rotaion change (Positioning error : Δ_{Tx}=20 cm, $\Delta_{\Theta y}$=0.3 rad)	 (2.a) Global error norm   (2.b) (2.c)
 Case 3: Scale change (Positioning error : Δ_{Tx}=5 cm, Δ_{Tz}= -50 cm)	 (3.a) Global error norm   (3.b) (3.c)

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