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IMAGE-BASED VISUAL SERVOING FOR MANIPULATION *VIA* PREDICTIVE CONTROL – A SURVEY OF SOME RESULTS

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In this paper, a review of predictive control algorithms developed by the authors for visual servoing of robots in manipulation applications is presented. Using these algorithms, a control predictive framework was created for image-based visual servoing (IBVS) systems. Firstly, considering the point features, in the year 2008 we introduced an internal model predictor based on the interaction matrix. Secondly, distinctly from the set-point trajectory, we introduced in 2011 the reference trajectory using the concept from predictive control. Finally, minimizing a sum of squares of predicted errors, the optimal input trajectory was obtained. The new concept of predictive control for IBVS systems was employed to develop a cascade structure for motion control of robot arms. Simulation results obtained with a simulator for predictive IBVS systems are also presented.

Keywords: predictive control, image prediction, reference trajectory, internal model predictor.

1. INTRODUCTION

Grasping of an object by a vision-controlled robot is an important operation encountered in many manipulation tasks. These tasks require the robot to autonomously manipulate objects which can be placed in front of it at any orientation. Robot manipulators must have knowledge on the object geometry in order to plan their motion and to successfully complete grasping. The most conventional methods for robotic grasping assume the availability of a complete 3D model of the object to be grasped obtained from a stereo vision system or laser equipment. Recent researches in the field of robotic grasping are based on methods that do not require full 3D models of the objects. Most of these approaches consider the objects lying on a horizontal surface and described by geometric features computed from the individual point cluster corresponding to each object.

Image based visual servoing (IBVS) is an attractive strategy for the motion control of robot manipulators [6–8]. The desired grasping position of the robot is described by a reference image of the object and the corresponding visual features determined off line. Starting from an initial position, a sequence of images with the corresponding visual features is obtained during the motion to the desired grasping position. The robot motion is controlled by minimizing the error between the current features and the desired ones, considered as set-point. Combining the path-planning and the trajectory tracking, it is possible to deal with constraints handling [3, 14].

The predictive approach in image-based visual servoing has already been explored in many papers in literature. Thus, in [8], an ARIMAX multivariable model which permitted to implement a GPC controller for high speed visual servoing of a robot manipulator is presented. An IBVS scheme based on Nonlinear Model Predictive Control is presented in [15], considering the direct dynamic model of the robot, its joint and torque limits, the camera projection model and the visibility constraint. For image prediction, a nonlinear global model is used. A visual predictive control strategy based on a nonlinear global model combined with the IMC structure is developed in [1] for a robotic system subject to mechanical and visibility constraints. To overcome the complexity of the nonlinear global model used for image prediction, an internal model was proposed in [9] and [10] based on the relation between the camera velocity and the time variation of the visual features given by the interaction matrix. In [2], a nonlinear predictive control algorithm is presented for visual servoing, which uses a nonlinear global model or a local model based on the interaction matrix for image prediction similar to the internal model presented in [9] and [10].

In this paper, a review of predictive control algorithms developed by the authors for visual servoing of robot manipulators in grasping applications is presented. Firstly, considering point features, we introduced an internal model predictor based on the interaction matrix [9,10], different from those used in other image based predictive controllers, but perfectly suitable for image predictions. Two years later, the same model (called local model) is used for image prediction in [2]. Secondly, we introduced the reference trajectory concept from predictive control to image-based predictive controllers [11] and [4]. Finally, we proposed a control predictive framework for IBVS applications [11–13], as detailed in this paper.

2. CONVENTIONAL IBVS CONTROL

A very brief review of IBVS control is presented in this section. Visual servoing is a way to control the motion of a robot using the feedback obtained from computer vision. For IBVS, the control objective is directly expressed in the image feature parameter space. Image measurements are usually the pixel coordinates $[u_i \quad v_i]$ of the set of image points $\mathbf{f} = [\mathbf{f}_1 .. \mathbf{f}_i .. \mathbf{f}_m]$. The error signal is measured in the image plane, and mapped directly, through a control algorithm, to actuator commands.

Figure 1 presents a conventional IBVS cascade control structure with an eye-in-hand configuration. The velocity controller is designed as an inner loop system, to control camera velocity. Whereas the camera is attached to the robot end-effector, the image based visual servoing involves the estimation of the camera’s velocity screw $\mathbf{v}_c^*$ so as to move the image plane features $\mathbf{f}$ to a set of desired locations $\mathbf{f}^*$.

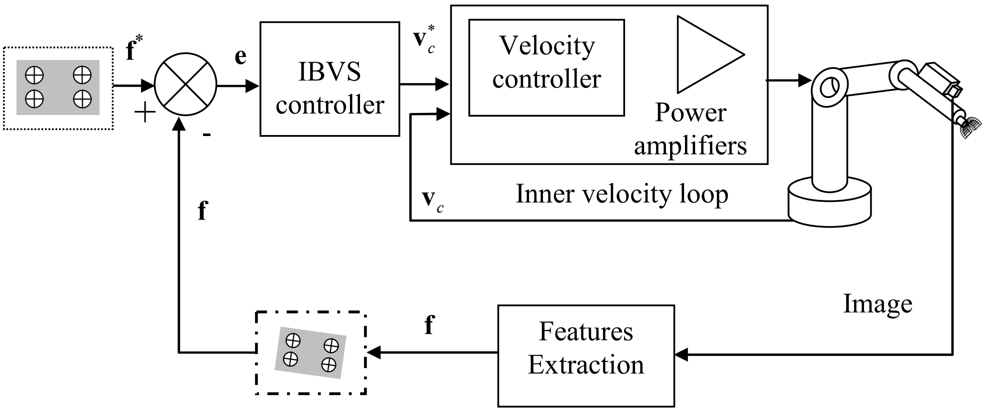


Fig. 1. IBVS control system.

An important role in designing the IBVS control algorithm is played by the interaction matrix **L**, which is a linear transformation that relates the end effector (camera) velocity in the task space to the image features rate of change in feature (image) space. The relationship between camera's velocity screw $\mathbf{v}_c = \begin{bmatrix} \mathbf{v}^T & \boldsymbol{\omega}^T \end{bmatrix}^T$ and its translational $\mathbf{v} = \begin{bmatrix} v_x & v_y & v_z \end{bmatrix}^T$ and rotational $\boldsymbol{\omega} = \begin{bmatrix} \omega_x & \omega_y & \omega_z \end{bmatrix}^T$ components and the image feature rates of change is given by [6]:

$$\dot{\mathbf{f}} = \mathbf{L}\mathbf{v}_c . \tag{1}$$

For a point feature $[u \quad v]$ in the image plane corresponding to a Cartesian point with coordinates $[x\ y\ z]$ in the camera frame, using a perspective projection model with the focal distance λ, equation (1) becomes [6]:

$$\begin{bmatrix} \dot{u} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} \dfrac{\lambda}{z} & 0 & \dfrac{u}{z} & \dfrac{uv}{z} & -\left(\lambda + \dfrac{u^2}{\lambda}\right) & v \\ 0 & -\dfrac{\lambda}{z} & \dfrac{v}{z} & \lambda + \dfrac{v^2}{\lambda} & -\dfrac{uv}{\lambda} & -u \end{bmatrix} \begin{bmatrix} \mathbf{v} \\ \boldsymbol{\omega} \end{bmatrix} \tag{2}$$

where z is the depth of the corresponding point in the camera frame.

Image-based visual servo systems express the control error function directly in 2D image space. If the image positions of point features are used as measurements, the error function is defined as the difference between the current and the desired feature positions:

$$\mathbf{e} = \mathbf{f}^* - \mathbf{f}\ . \tag{3}$$

Usually, the dynamics of the inner velocity loop is considered unitary ($\mathbf{v}_c^* = \mathbf{v}_c$) and, using (1) and (3), one obtains:

$$\mathbf{e} = -\mathbf{L}\mathbf{v}_c \tag{4}$$

and, considering an exponential decoupled decrease of the error (*i.e.* $\dot{\mathbf{e}} = -\gamma\mathbf{e}$), a simple proportional control results:

$$\mathbf{u} = \mathbf{v}_c = \gamma\mathbf{L}^+\mathbf{e} \tag{5}$$

where $\mathbf{L}^+ \in R^{6xm}$ is the Moore-Penrose pseudoinverse of **L**.

The vector of reference measurements $\mathbf{f}^*$ is usually generated using a so-called "teach by showing" approach, where the robot is first moved to a desired grasping position and the image coordinates of feature positions are recorded. After that, the robot is moved to some other initial position in a closed–loop manner, and the robot is controlled while moving to the desired or "taught" grasping position.

3. A PREDICTIVE CONTROL FRAMEWORK FOR IBVS SYSTEMS

The proposed predictive control framework for IBVS is based on the interaction matrix $\mathbf{L}\left(\mathbf{f}(k),\mathbf{z}(k)\right)$, where k is the current discrete-time and **z** is a vector with the depth of point features. In order to obtain the internal model for the plant of the visual servo loop, which has as input the camera velocity screw and point features as output, the m point features are considered. This internal model, introduced for the first time in [9], has been used to build predictors $\mathbf{f}(k+i\,|\,k),\ i=\overline{1,h_p}$ that calculate the future evolution of the plant output over the prediction horizon h_p.

According to the basic concept of predictive control, a reference trajectory over the prediction horizon is used to make a gradual transition from the current plant output to the desired set point. The future control sequence is obtained by minimizing the sum of squares of the deviations between the predicted future outputs and a specific reference trajectory. For the predictive control of IBVS systems, we introduced a reference trajectory $\mathbf{w}(k+i\,|\,k),\ i=\overline{1,h_p}$ in [11] and [4], along which the plant should go to the set point (desired features **f***), starting from the current features **f**(k), over the prediction horizon. Figure 2 illustrates the new concept of predictive control for IBVS introduced in [12–13]. Considering the dependence of the interaction matrix on depth, we put z as vertical axis. We assume a discrete-time setting and thus, the current time is k.

For the current discrete-time, plant output $\mathbf{f}(k)$ is measured by an image acquisition and processing system, on assuming that the previous history of the plant input/output trajectories is known. The set point trajectory $\mathbf{r}(k+i\,|\,k),\ i=\overline{1,h_p}$ over the prediction horizon is also known. We considered in Figure 2 a constant set point equal to the desired point features **f*** obtained for depth z^*. Distinctly from the set-point trajectory, we introduced the reference trajectory $\mathbf{w}(k+i\,|\,k)$, $i=\overline{1,h_p}$ which starts at the current output $\mathbf{f}(k)$ and ends at time $k+h_p$ with the desired point features **f*** ($\mathbf{w}(k+h_p\,|\,k)=\mathbf{f}^*$). In this way, the dynamic behavior of the closed loop is established through the reference trajectory, so that the plant output will reach the set point trajectory as fast as possible.

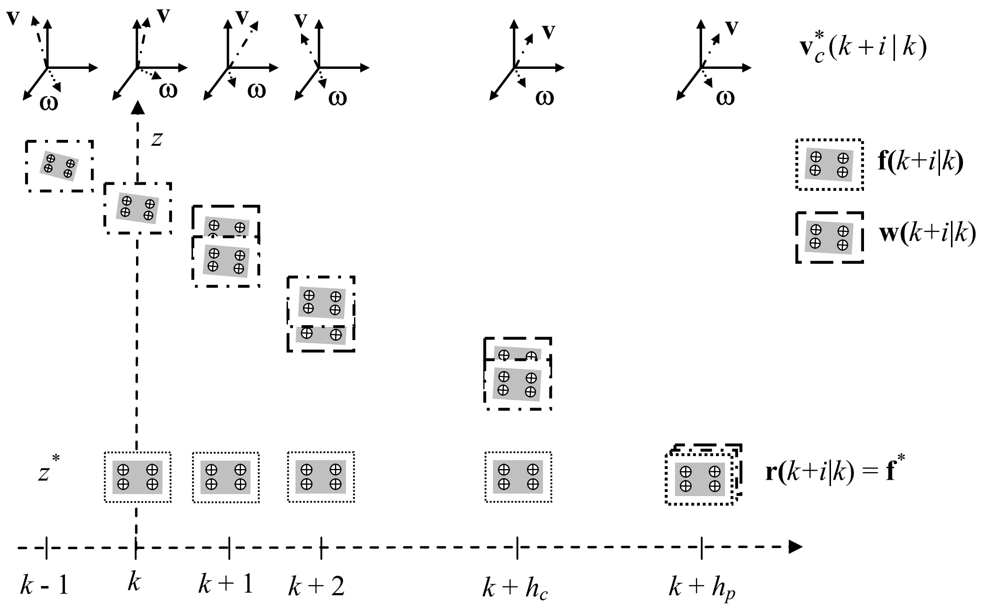


Fig. 2. Predictive control: the basic idea for IBVS applications.

Using an internal model, we can predict how the output of the plant will evolve over the prediction horizon ($\mathbf{f}(k+i\,|\,k),\ i=\overline{1,h_p}$). The predicted output depends on the input trajectory $\mathbf{v}_c^*(k+i\,|\,k),\ i=\overline{0,h_p-1}$ which is the future control sequence over the prediction horizon. The future control sequence is chosen in order to bring the visual loop plant output at the end of the prediction horizon and the desired point features, *i.e.* $\mathbf{f}(k+h_p \mid k)=\mathbf{f}^*$. After computing the optimal input trajectory by minimizing a sum of squares of errors, $\sum_{i=1,h_p}\left[\mathbf{f}(k+i \mid k)-\mathbf{w}(k+i \mid k)\right]^2$, only the first element $\mathbf{v}_c^*(k \mid k)$ is applied to the plant and, for the following sampling time, the whole cycle will be repeated once more, according to the receding horizon strategy.

Using the new concept of predictive control for the IBVS systems presented in Figure 2 and taking into account the structure of an IBVS control system illustrated in Figure 1, we developed the cascade structure presented in Figure 3 for the motion control of robot arms [11]. The inner loop regulates the camera velocity screw $\mathbf{v}_c$, while the outer one regulates the robot arm motion in order to obtain a desired grasping position described by $\mathbf{f}^*$.

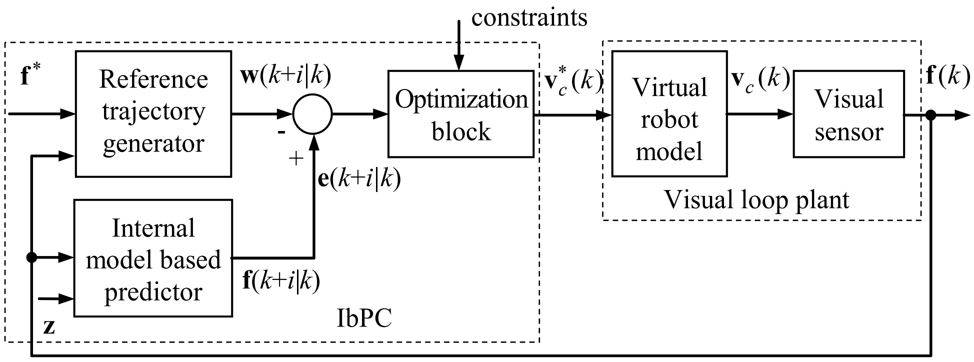


Fig. 3. Cascade structure for robot arm motion predictive control.

The inner velocity loop is considered a virtual robot model, described usually by a transfer matrix, with camera velocity set-point $\mathbf{v}_c^*(k)$ as input and camera velocity $\mathbf{v}_c(k)$ as output. This transfer matrix approximates the nonlinear robot dynamics using different approaches [7, 8] and, typically, has a diagonal form obtained with a suitable design of the multivariable inner velocity control loop.

The outer loop, having the image-based predictive controller (IbPC) for IBVS control, computes the control signal $\mathbf{v}_c^*(k)$, so that the current point features $\mathbf{f}(k)$ should reach the desired ones $\mathbf{f}^*$. IbPC consists of a reference trajectory generator, an internal model-based predictor and an optimization block.

The internal model for image prediction was developed starting from the model of the visual loop plant presented in [9] and [10]. Thus, the diagonal transfer matrix $\mathbf{G}$(s) from [7] was used as a virtual robot model, considering the inner velocity loop as an analogous system, because of its very short sampling period (usually 1 ms). For the visual sensor model, we used the relation between the camera and point features velocities given by (1). Applying Z transform to the virtual robot continuous model, the discrete transfer matrix is obtained:

$$\mathbf{G}(z) = \left(1 - z^{-1}\right) Z\left\{\mathbf{G}(s)/s\right\} \tag{6}$$

Then, discretizing (1) with Euler's method and the sampling period T_s, the one-step ahead prediction of the image point features evolution can now be calculated using the discrete model (6) of the virtual robot, resulting:

$$\mathbf{f}(k+1\,|\,k) = \mathbf{f}(k) + T_s \mathbf{L}_k \mathbf{G}(z) \mathbf{v}_c^*(k\,|\,k) \tag{7}$$

where notation $\mathbf{f}(k+1\,|\,k)$ indicates that the prediction is computed at the discrete time k. The interaction matrix $\mathbf{L}_k$ is computed with the point features $\left(u_i(k), v_i(k)\right)$ acquired for the current discrete time k. It is assumed that the depth $z_i(k)$ of the current point features may be computed for every sampling period with respect to the camera frame. By shifting of the one-step ahead prediction model (7) by recursion, the i-step ahead predictor $\mathbf{f}(k+i\,|\,k)$ is obtained:

$$\mathbf{f}(k+i\,|\,k) = \mathbf{f}(k+i-1\,|\,k) + T_s \mathbf{L}_{k+i-1} \mathbf{G}(z) \mathbf{v}_c^*(k+i-1\,|\,k) \tag{8}$$

used as the internal model based predictor.

For IBVS control systems, the set-point refers to the desired features $\mathbf{f}^*$ obtained from a reference image of the grasping position. This image describes what the camera should see when the end-effector is correctly positioned relatively to the target object. Starting from the current features $\mathbf{f}(k)$, a reference trajectory is necessary in the visual predictive control to define the way of reaching the desired features $\mathbf{f}^*$ over the prediction horizon. Beginning at the current discrete time k with the current image I_k and having the point features $\mathbf{f}(k)$, the reference trajectory was designed from the image sequences $\left\{I_{k+i},\ i = \overline{1, h_p}\right\}$ with point features $\mathbf{w}(k+i\,|\,k)$ in order to obtain $\mathbf{w}(k+h_p\,|\,k) = \mathbf{f}^*$, as presented in [11] and [4]. To generate the image plane trajectories for tracked points in an eye-in-hand system, we have chosen the 3D motion planning approach for the image-based visual servoing task from [3]. Consider that the initial image is I_k with point features $\mathbf{f}(k)$, the final one is I_{k+hp} with the point features $\mathbf{f}^*$, and the object is fixed, being described by four point features assumed to be coplanar but not collinear. The reference trajectory gradually varies from the current point features $\mathbf{f}(k)$ at time k

to the desired point features $\mathbf{f}^*$ at time $k+h_p$. Considering the collineation matrix **C**, representing the projective homography between the initial image I_k and the final image I_{k+hp}, the homogeneous coordinates of the four point features from the final image $\tilde{\mathbf{f}}_i^* = \left[u_i^*, v_i^*, 1\right]^T$ can be expressed with respect to the coordinates of points from the current image $\tilde{\mathbf{f}}_i(k) = \left[u_i(k), v_i(k), 1\right]^T$, resulting $\tilde{\mathbf{f}}_i^* = \mathbf{C}\tilde{\mathbf{f}}_i(k),\ i=\overline{1,4}$, and the reference trajectory $\left\{\mathbf{w}(k+i\,|\,k), i=\overline{1,h_p}\right\}$ can be possibly computed.

The optimization block is developed to make the future system outputs to converge to the reference trajectory. To this end, the objective function J is established, generally defined as a quadratic function of the predicted control error given by:

$$\mathbf{e}(k+i\,|\,k) = \mathbf{f}(k+i\,|\,k) - \mathbf{w}(k+i\,|\,k),\ i=\overline{1,hp} \tag{9}$$

and control. Thus, the objective function to be minimized is defined by:

$$J = \frac{1}{2}\sum_{i=1}^{h_p}\mathbf{e}^T(k+i\,|\,k)\mathbf{Q}\mathbf{e}(k+i\,|\,k) + \sum_{i=0}^{h_c-1}\mathbf{v}_c^{*T}(k+i\,|\,k)\mathbf{R}\mathbf{v}_c^*(k+i\,|\,k) \tag{10}$$

where **Q** and **R** are positively definite, symmetric weighing matrices and h_c is the control horizon in (10).

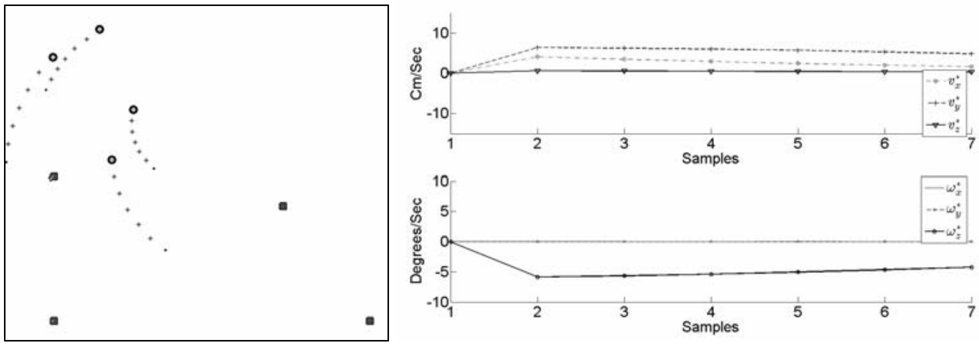
The main constraints are associated to the limits of the image called the visibility constraint, ensuring that all features are always visible:

$$\left(u_i(k), v_i(k)\right) \in \left[\left(u_{\min}, v_{\min}\right), \left(u_{\max}, v_{\max}\right)\right],\ i=\overline{1,m} \tag{11}$$

4. SIMULATION RESULTS

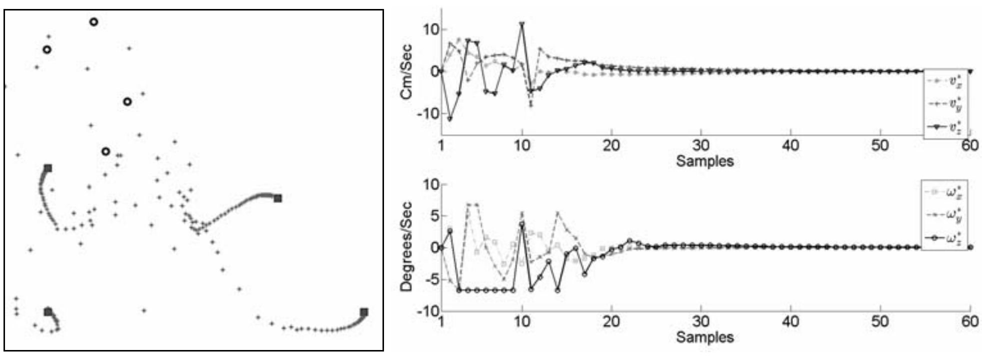
The developed predictive control framework for IBVS applications was implemented both in Matlab, resulting more simulators [4, 11] and in real-time applications [4, 5]. Using the simulator from [11] and considering, for the sake of simplicity, an object defined by four planar points in the Cartesian space, three controllers were tested: the proportional one described by (5) and two IbPSs, one without reference trajectory generator and the other one with generator. The predictive control architecture can be also used for more complicated object structures.

Applying the proportional control law (5), the best simulation results were obtained with $\gamma = 2.5$. The parameters of the predictive controller were tuned as follows: $h_p = 4$, $h_c = 1$, $\mathbf{Q} = e^{1-i}\mathbf{I}_8,\ i=\overline{1,4}$ and $\mathbf{R} = \mathbf{I}_6$.



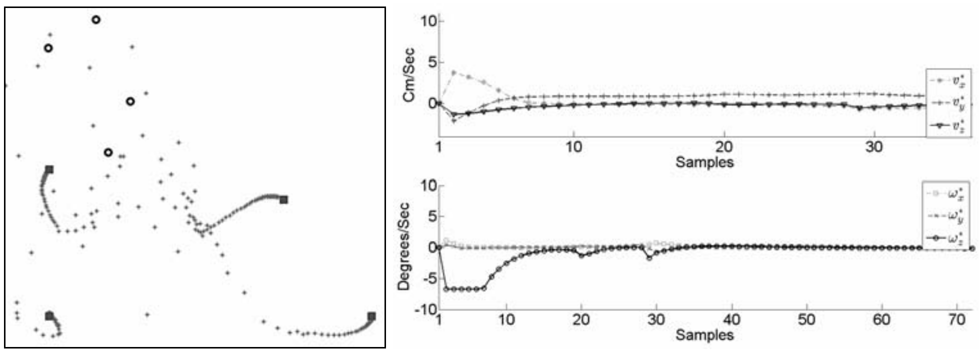
(a) (b)

Fig. 4. Proportional controller: a) point features trajectories; b) control effort.



a) b)

Fig. 5 a, b. IbPC without reference trajectory generator: (a) point features trajectories; (b) control effort.



a) b)

Fig. 6 a, b. IbPC with reference trajectory generator: a) point features trajectories; b) control effort.

In the simulation results presented in Figures 4–6 a, the initial configuration of the 4 object points in the image plane is represented by circles, and the desired configuration – by squares.

These simulations show clearly the superiority of the predictive controller over the proportional one. The predictive approach is viable where the proportional one fails, mainly in handling visibility constraints and in dealing with singularity configuration. As shown in Figure 4 a, the proportional controller fails to maintain the point features in the visibility area, thus generating the stop of the control algorithm. Meanwhile, both predictive techniques, with or without reference trajectory, manage to fulfill the servoing task (Figs. 5–6 a). It can also be observed in Figures 5–6 b, that the reference trajectory-based predictive approach has a smoother behavior than the direct one, thus, making it more suitable for a real-time implementation.

5. CONCLUSIONS

In this paper was presented a review of the predictive control framework for IBVS systems developed by the authors for visual servoing of robot manipulators. Considering the point features, we introduced an internal model predictor based on the interaction matrix, different from those used in other image based predictive controllers, but perfectly suitable for image predictions. Using for IbPCs a reference trajectory concept and an internal model based predictor, the convergence and stability of robot motion for manipulation have been obtained through nonlinear constraint optimization.

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