Path-Planning for Visual Servoing: A Review and Issues

Chapter *in* Lecture Notes in Control and Information Sciences · March 2010

DOI: 10.1007/978-1-84996-089-2_11

3 authors:

Moslem Kazemi
Brain Corporation

Kamal Gupta
Simon Fraser University

M. Mehrandezh
University of Regina

Path Planning for Visual Servoing: A Review and Issues

Moslem Kazemi, Kamal Gupta, and Mehran Mehrandezh

Abstract In this survey we provide a comprehensive technical review of existing major approaches to path planning for visual servoing. Visual servoing has been introduced as a promising approach for sensor-based robotic tasks. The basic visual servoing task is to guide the motion of a robot with respect to a target object based on the feedback obtained through a vision system. Amalgamation of path planning techniques with reactive visual servoing strategies can robustify existing image-based tracking systems in robotics applications where a high disparity between the initial and desired views of a target is inevitable (e.g., target interception, space docking, reaching and grasping, etc.). The planning stage does so by accounting for critical constraints and uncertainties in the system resulting in a more robust visual servoing process. We discuss different planning approaches, explain the associated set of constraints and assumptions, and discuss the underlying path planning techniques along with the issues regarding their integration with reactive visual servo controllers.

1 Introduction

The role of vision as a sensor for autonomous machines to interact with complex, unknown, and dynamic environments is paramount. Visual servoing has been introduced as a promising approach for sensor-based robotic tasks such as positioning a robot with respect to a target and tracking a moving target via estimating its 3D motion, i.e. egomotion analysis using vision. The basic visual servoing task is to

Moslem Kazemi
Simon Fraser University, Burnaby, BC., V5A1S6, Canada, e-mail: moslemk@cs.sfu.ca

Kamal Gupta
Simon Fraser University, Burnaby, BC, V5A1S6, Canada, e-mail: kamal@cs.sfu.ca

Mehran Mehrandezh
University of Regina, Regina, Sask., S4S0A2, Canada, e-mail: mehran.mehrandezh@uregina.ca

guide the motion of a robot with respect to a target object based on the feedback obtained through a vision system [31]. Usually an error function **e** (also called *task function* [21]) is defined as

$$\mathbf{e}(t) = \mathbf{s}(t) - \mathbf{s_d} \tag{1}$$

where **s** and $\mathbf{s_d}$ denote the vectors of current and desired features, respectively. The visual servoing objective is set to regulate this error to zero.

The existing visual servoing techniques are classified into different categories based on the definition of error function, the underlying control architecture, and the robot-camera configuration (i.e., eye-in-hand vs. eye-to-hand configuration[1]). For a detailed review on existing techniques and their classification see [7], [8], and [31]. In summary, the existing approaches can be classified into two main categories: (1) Position-Based Visual Servoing (PBVS) where the feedback is defined in terms of the 3D Cartesian information derived from the image(s), and (2) Image-Based Visual Servoing (IBVS) where the feedback is defined directly in the image in terms of image features.

IBVS techniques have better local stability and convergence in presence of camera calibration and modeling errors. However, they suffer from global convergence problems, and, hence, will break down, in particular when the initial and desired camera poses are distant [6]. For example some of the image features might leave the camera's field of view and consequently result in failure of the servoing task. Moreover, there is no direct control on the robot/camera motion induced by the image-based control law. This might result in infeasible maneuvers due to the robot's joint limits and/or collision with workspace obstacles.

Amalgamation of path planning techniques with reactive image-based visual servoing strategies can robustify existing image based tracking systems by accounting for critical *constraints* and *uncertainties* in robotics applications where a high disparity between the initial and desired views of a target is inevitable (e.g., target interception, space docking, reaching and grasping, etc.). The main idea of path planning for visual servoing is to plan and generate *feasible* image trajectories while accounting for certain constraints, and then to servo the robot along the planned trajectories.

In this survey we provide a comprehensive technical review on existing and recent approaches to path planning for visual servoing. For each approach the set of constraints and the assumptions are explained and the underlying path planning technique is discussed along with the issues regarding its integration with the reactive image-based controllers.

In Section 2 we study the two sets of critical constraints in visual servoing context: (1) image/camera, and (2) robot/physical constraints. The existence of such constraints motivates the need for path planning techniques aimed at making the servoing process more robust especially in complex visual servoing scenarios. In Section 3 a comprehensive overview of the these approaches and their categorization based on the underlying path planning techniques are provided. In Section 4

[1] In an eye-in-hand configuration the camera is mounted on the end-effector of the robot and robot's motion results in camera's motion while in an eye-to-hand configuration, the camera is stationary and looks at the end-effector of the robot and robot's motion does not affect the camera pose [31].

we discuss the effect of uncertainties on visual servoing and report on some recent works aimed at path planning under uncertainty for visual servoing. Finally, we conclude the survey in Section 5.

2 Constraints in Visual Servoing

In [6], through simple, yet, effective examples, Chaumette outlined the potential problems of stability and convergence in both IBVS and PBVS techniques imposed by a number of constraints. Overall one can divide these constraints into two main categories: (1) Image/Camera, and (2) Robot/Physical constraints. These two categories are detailed as follows.

2.1 Image/Camera Constraints

The image/camera constraints are mainly due to the sensing limits of the vision system or the inter-relationship between the optical flow (i.e., rate of change) of the features $\dot{\mathbf{s}} \in \mathbb{R}^k$ in the image space and the camera's Cartesian velocity $\dot{\mathbf{x}} \in \mathbb{R}^n$ defined through the *image Jacobian* (also called *interaction* matrix) ${}^{\mathbf{s}}\mathbf{L}_{\mathbf{x}} \in \mathbb{R}^{k\times n}$ related to image features [31]:

$$\dot{\mathbf{s}} = {}^{\mathbf{s}}\mathbf{L}_{\mathbf{x}}\dot{\mathbf{x}} \tag{2}$$

These constraints are: (1) *field of view limits*, (2) *image local minima*, and (3) *singularities in image Jacobian*.

Field of View Limits The camera as a sensing system have certain limitations. For example the 3D target features projected into the image plane of the camera are visible if their projections fall inside the boundary of the image. The limits of the image are usually represented by a rectangular region which determines the visible region of the image plane. Although in IBVS context the control is directly defined in the image, there is still the possibility that the features leave the camera's field of view, in particular when the initial and desired poses of the camera are distant [6].

Image Local Minima As shown in [6], in IBVS context, image local minima might occur due to the existence of unrealizable image motions which do not belong to the range space of image Jacobian ${}^{\mathbf{s}}\mathbf{L}_{\mathbf{x}}$. Hence, there does not exist any camera motion able to produce such unrealizable motions in the image. In general, determining the image local minima is difficult without considering the specific target location and the initial and desired relative camera-target locations, which in turn, leads to an exhaustive search for local minima in the image for each instance of a visual servoing task. As demonstrated in [6], using a nominal value of image Jacobian estimated at the desired location might be of help to avoid local minima in visual servoing tasks. But this may lead to peculiar trajectories of features in the image, which in turn, might violate field of view limits. One should note that the PBVS techniques are known to be free of image local minima since the task function is defined in the Cartesian space.

Singularities in Image Jacobian At these singularities, certain camera motions cannot be achieved by the motion of image features in the image space. Several cases of image singularities have been considered in [6]: the image Jacobian ${}^{\mathbf{s}}\mathbf{L}_{\mathbf{x}}$ is known to be singular if the vector of image features $\mathbf{s}$ consists of the image of (1) three collinear points, or (2) three points belonging to a cylinder containing the camera optical center. Although using more than three non-coplanar points will avoid such singularities, the image Jacobian may still become singular no matter how many feature points (irrespective of their arrangements) are used to define the task function. For example, a visual servoing task involving a 180 degrees rotation around the optical axis results in a singular image Jacobian. As shown in [6] using line features instead of points helps to avoid such singularities, however, it does not completely eliminate the singularities in the image space. *Motion Perceptibility* [59] has been proposed as a measure of closeness to image singularities.

2.2 Robot/Physical Constraints

Motion of the robot/camera system induced by the visual servo control loop, especially in IBVS, may also violate certain constraints imposed by the robot and/or physical obstacles in the workspace. These are: (1) *robot kinematics* such as joint limits and singularities in robot Jacobian, (2) *robot dynamics*, (3) *collision* with obstacles or self-collision, and (4) *occlusion* due to obstacles, robot body, or self-occlusion by the target.

Over the past three decades a great deal of research in robotics community has been devoted to planning feasible paths avoiding robot kinematics and/or dynamics constraints and collision with physical obstacles or self-collision in various environments (see e.g. [39] and [40]). Path planning approaches have also considered occlusion constraints in applications that require target visibility, e.g. [41] and [51].

Since Chaumette's article [6] on the convergence and stability problems of classical visual servoing techniques, most of the efforts in visual servoing community have been devoted to taking the above image/camera and/or robot/physical constraints into account and incorporating them into the reactive visual servoing control loop.

First a number of researchers proposed *partitioned* (or decoupled) control schemes in which certain degrees of freedom are controlled in the manner of IBVS while others are controlled in the manner of PBVS, thereby taking advantage of each individual technique's benefit in avoiding some of the above constraints (see e.g. [16], [18], [44], [47], [52]). Each of these partitioned approaches has its own benefits and drawbacks in accounting for the aforementioned constraints. A performance test has been presented in [25] comparing the efficiency of some of the above partitioned strategies with IBVS technique.

Later on, inspired by the theory of hybrid systems, a number of researchers proposed *hybrid* (or switched) strategies consisting a set of visual servo controllers along with a switching rule to switch between them if required (see e.g., [13], [19], [24], [27]). Using switched strategies it might be possible to enlarge the stability region of classical visual servoing techniques and to switch between a set of unstable controllers to make the overall system stable.

Each of the above partitioned or hybrid strategies deals with only a subset of the above mentioned constraints. Incorporating all the image/camera and robot/physical constraints into the visual servo control loop is, if at all practical, quite challenging. Clearly some sort of path planning on top of the visual servo control loop is needed for incorporating all the aforementioned constraints, especially in complex visual servoing scenarios.

3 Path Planning for Visual Servoing

The main idea of path planning for visual servoing [49] is to plan and generate *feasible* image trajectories while accounting for the constraints mentioned in the previous section, and then to servo the robot along the planned trajectories. So, the initial large error is discretized and the error to regulate at each cycle of the servoing loop remains small. Overall, this results in a more robust servoing process with respect to the aforementioned image/camera and robot/physical constraints.

Over the past decade research has been devoted to incorporate aspects of path planning in visual servoing. Although there is no formal classification of the existing path planning techniques for visual servoing, considering the underlying path planning approach and the assumptions made in each technique, we divide them into four groups: (1) Image space path planning, (2) Optimization-based path planning, (3) Potential Field-based path planning, and (4) Global path planning. In this survey we discuss the major works done in each group to describe the main idea and the underlying problems.

3.1 Image Space Path Planning

Image space path planning techniques aim at interpolating a path in the image space between the initial and desired images without using any knowledge of camera calibration or target model. One of the difficulty of such approaches is that the planned image space path may not correspond to any single path for the camera. So, efforts have been devoted to planning image paths which correspond to feasible (yet unknown) camera paths in an uncalibrated domain. Various results from projective geometry have been applied in this context including: epipolar geometry, projective homography, and projective invariance.

Epipolar Geometry Given multiple views of the same scene, epipolar geometry [26] has been employed by a number of researchers for calibration-free visual servoing. In an early work [29], a trajectory generator for visual servoing was proposed directly in the image space based on epipolar constraints defined between the images obtained from a stereo camera mounted on a robotic arm (eye-to-hand configuration). The task was to accomplish obstacle avoidance (only for robot's end-effector) in an unknown environment. An uncalibrated visual servo controller based on a Jacobian estimator was used to track the planned image trajectories without using any knowledge of the system or camera calibration.

Park and Chung proposed an image space path planning approach for an eye-to-hand system using uncalibrated stereo cameras in a vision-based grasping scenario [54]. They generate a number of intermediate views of the robot's gripper along a straight line between the initial image and the final desired image in the projective space with the help of epipolar geometry and without using any 3D information regarding either the gripper or the target object. These intermediate views constitute the desired image trajectories. The robot is then controlled along the image trajectories using the IBVS technique presented in [22]. When followed by the robot, the planned trajectories allow the robot's gripper to track a straight line in the 3D workspace and through out its motion a selected set of features on the gripper are kept in the camera's field of view.

Projective Homography To avoid explicit computation of feasible camera paths which relies on the knowledge of the camera calibration and target model, a number of approaches have been developed using the projective geometry [23] relationship established between the initial and desired images. Working in projective space allows one to partially parameterize the Euclidean displacement of the camera without explicit reconstruction of the Euclidean components.

Projective homography matrix has been employed in the context of path planning for visual servoing. Projective homography captures the relationship between the images taken from different views of the same scene. Given the projective homogeneous coordinates $\mathbf{p} = (u, v, 1)^T$ and $\mathbf{p}^* = (u^*, v^*, 1)^T$ of a 3D point $\mathbf{P}$ in the current and desired images, respectively, the projective homography matrix $\mathbf{G}$, also called *collineation* matrix, is defined (up to an scale α_g) as

$$\alpha_g \mathbf{p} = \mathbf{G}\mathbf{p}^* \tag{3}$$

The projective homography matrix can be estimated form the knowledge of several features such as points, lines, and contours matched between two images [12], [26], and [46].

In [50] a calibration-free path planning approach is proposed which consists of interpolating for the *collineation* matrix $\mathbf{G}$ between the initial and desired images to obtain closed-form analytical collineation paths. The image feature trajectories are then derived and followed using an IBVS technique. The proposed approach guarantees convergence to the desired location, however, the convergence does not hold in presence of visibility constraints such as field of view limits. This approach has been extended in [58] to take visibility constraints into account by guiding the image of an arbitrary selected reference point on the target along a straight line in the image which guarantees that the reference point remains in the camera's field of view. However, the camera will not follow a straight line anymore and the other features may still leave camera's field of view. A depth modulation approach has been proposed to keep the visibility of other features by controlling the camera backwards along an optical ray whenever a feature reaches the borders of camera's field of view.

If the camera calibration is known, one could derive further information regarding the camera transformation. In particular, one can compute the Euclidean homography matrix $\mathbf{H}$ (up to a scale α_h) as

$$\alpha_h \mathbf{H} = \mathbf{K}^{-1}\mathbf{G}\mathbf{K} \tag{4}$$

where $\mathbf{K}$ is a non-singular matrix and contains the camera intrinsic parameters. The Euclidean homography (from a set of planar features) can be decomposed to obtain the corresponding (Euclidean) camera transformation parameters as

$$\mathbf{H} \Rightarrow \left\{\mathbf{R}, \frac{\mathbf{t}}{d^*}, \mathbf{n}^*\right\} \tag{5}$$

where $\mathbf{R}$ and $\mathbf{t}$ denote the translation and rotation from the desired to the current camera frame, and d^* is the distance of the plane containing the features from the desired camera frame and $\mathbf{n}^*$ is the normal to the plane expressed with respect to the desired frame.

Decomposition of Euclidean homography has been employed by some researchers to plan for image paths corresponding to feasible (yet unknown) camera paths without explicit reconstruction of the camera paths in the Cartesian space.

A shortest path approach has been proposed in [36] which avoids the use of 3D reconstruction by using homography-based partial pose estimation. The proposed approach moves the in-hand camera directly along the direction (obtained through the homography decomposition) towards the desired pose in the 3D workspace while maintaining the visibility of (only) a virtual point located at the origin of the target object. The virtual point is used to control two degrees of rotation of the camera (around $x-$ and $y-$axes) and the third rotation axis (around camera optical axis) is controlled using the rotation matrix retrieved from homography. This technique yields a straight line trajectory for the virtual point and, hence, keeps the virtual point always in the camera's field of view. However, the camera can get too close to the target so that some features may get lost. Switching between visual servoing strategies or using repulsive potentials can be employed to avoid such situations, however, without ensuring straight line trajectories.

In [1] a similar approach has been proposed based on homography decomposition in which helicoidal shape paths (instead of straight path) are chosen as the reference path to represent camera translation from the initial position to the desired position.

One should note that since the homography is known only up to an *unknown* scale, the actual camera path is not completely known and one can only determine its shape. However, regardless of the value of unknown scale factor, the entire image path will remain the same and since the control is defined directly in the image, the positioning task can be successfully accomplished given a feasible image path. In [4] a particular decomposition of homography is used to interpolate a path for a planar object with known model from the initial image to the desired final image. Given the known object model, the interpolated desired path is then transformed to a camera path by using 3D reconstruction. The camera path can then be checked for workspace boundary singularities.

Projective Invariance Malis [45] proposed an image-based path planning approach in an invariant space defined through a projective transformation. The basic idea of using projective invariance is to create a task function which is invariant to camera intrinsic parameters and only depends on the position of the camera with respect to the observed object and on its 3D structure. This allows one to generate a path for a feature vector in the invariant space (independent of camera's intrinsic parameters) which, when followed, results in a straight line path for the camera in the workspace. The visibility of the features is (partially) achieved using a motorized zooming mechanism available on the vision system.

The main advantage of direct path planning in image space is the independence of such approaches from camera calibration and/or object model. On the other hand, since the planning is done directly in the image space, robot/physical constraints cannot be handled through such approaches and these techniques are shown to be ineffective in complex visual servoing scenarios.

3.2 Optimization-based Path Planning

Planning optimal paths has absorbed a great amount of interest in robotics community. In a visual servoing task, there might be many different paths, which when followed, will result in successful accomplishment of the same task. This motivates optimization techniques aimed at finding the optimal path with respect to various costs such as distance from the image boundary, length of the path traversed by the robot, energy expenditure, etc.

In an early work [60], a path planning framework is proposed based on the concept of Perceptual Control Manifold (PCM) defined on the product of the robot's joint space and the space of all image features related to a target object. PCM can be considered as a mapping which relates a robot configuration to the vector of image features visible at that configuration. Given the model of the camera, the object, and the robot kinematic model, the PCM needs to be computed only once (in an eye-to-hand configuration) and is then applicable to any manipulation task. Constraints such as the camera's field of view and the robot joint limits and/or physical obstacles are mapped into the PCM to yield a subset of PCM as the feasible solution space. This mapping could be quite time consuming considering the number of constraints and the robot's degrees of freedom. Various optimization criteria such as minimum velocity, minimum interception time, and minimum robot movement have been considered to plan optimal paths in the feasible subset of the PCM. The proposed approach has been considered for the task of intercepting a moving target (with a known trajectory) using the visual feedbacks obtained from a fixed camera which simultaneously views both the robot's end-effector and the moving target.

In [50] closed-form collineation paths corresponding to minimum energy and minimum acceleration camera paths are planned in the image space. The proposed strategy is then generalized to the case where a number of relay (intermediate) images are available in addition of the initial and desired images. The proposed approach guarantees convergence, however, it does not take visibility constraints into account and image features might leave the camera's field of view.

In [63] a motion generation approach called visual motion planning has been proposed to plan optimal image paths for mobile robots under motion and visibility constraints. The constraints on the motion of the robot along with the field of view limits are described in form of a number of equalities and inequalities. An optimization problem is then solved numerically using Lagrange Multipliers to obtain optimal image paths minimizing a given weighted sum cost function (here kinetic energy). The proposed approach has been applied only to mobile robots moving in 2D and 3D environments.

To pose the problem of path planning for visual servoing as an optimization problem some researchers have introduced various parameterizations of camera trajectories. A polynomial parametrization of the scaled camera paths has been proposed in [14] where the translational path is linearly interpolated and Cayley's rotation representation is employed to rationally parameterize the rotation paths. This allows the distance of the image trajectories from the boundary of image for a single path to be easily calculated as the root of some polynomials. Hence, an optimization problem is then formulated to maximize the distance to the boundary of the image with respect to all parameterized paths. By following the planned image path, the camera follows a straight line in the workspace in the absence of calibration errors. In presence of calibration errors, the camera does not follow a straight line but moves along a different curve whose distance from the planned line grows as the calibration errors increase.

In [11] an optimal path planning approach is proposed which allows one to consider constraints on the camera's field of view, workspace and joint limits, in the form of inequalities, together with the objective of minimizing trajectory costs including spanned image area, trajectory length, and curvature. A polynomial parametrization is devised to represent all the camera paths connecting the initial and desired locations (up to a scale factor) through an object reconstruction from image measurements and, if available, the target model. Occlusion constraints and collision avoidance for the whole robot's body cannot be represented (in the form of inequality constraints) in their formulation. Moreover, the devised optimization is nonconvex which may lead to multiple feasible regions and multiple locally optimal solutions within each region and, hence, it makes it very difficult to find the global optimal solution across all feasible regions.

In a similar work [10], a general parameterizations of trajectories from the initial to the desired location is proposed via homogeneous forms and a parameter-dependent version of the Rodrigues formula. The constraints are modeled using positivity conditions on suitable homogeneous forms. The solution trajectory is obtained by solving a Linear Matrix Inequality (LMI) test which is a convex optimization. The proposed approach allows one to maximize some desired performances such as distance of features from the boundary of the image, camera's distance from obstacles, and similarity between the planned trajectory and a straight line.

Ideas from optimal control theory have been employed to devise image trajectories for visual servoing under visibility constraints. Planning shortest path for a Differential Drive Robot (DDR) maintaining the visibility of a landmark using a camera with limited field of view has been considered in [3]. It is shown that the set of shortest (optimal) paths for this system consist of curve segments that are either straight-line segments or that saturate the camera's field of view. The latter correspond to exponential spirals known as T-curves. In [42] these shortest paths are followed using a switched homography-based visual servo controller. The controls that move the robot along these paths are devised based on the convergence of the elements of the homography matrix relating the current image to the final desired image. In a recent work [28], a complete motion planner for a DDR is proposed in which optimal curve segments obtained in [3] are used as motion primitives to devise locally optimal paths in an environment cluttered with obstacles. The necessary and sufficient conditions for the feasibility of a path for the DDR in the presence of obstacles and with visibility constraints (i.e., sensing range and field of view limits) are also provided. In their proposed planner, occlusions due to workspace obstacles are not considered and the obstacles are assumed to be transparent.

In [56] the set of optimal curves obtained in [3] are extended and also described in the image space, so as to enable their execution using an IBVS controller directly in the image space. Feedback control along these optimal paths in the image is achieved through a set of Lyapunov controllers, each of which is in charge of a specific kind of maneuver. Nonetheless, the complete characterization of all the shortest paths and their analytic descriptions remain unsolved for a DDR.

Although the above optimization-based path planning techniques provide a better insight into the complexity of the problem and feasible optimal paths, they are more or less limited to simple scenarios and systems. Introducing general robot/physical constraints greatly adds to the complexity of the optimization problem and, hence, accounting for such constraints in the above frameworks would greatly increase the time complexity of such techniques.

3.3 Potential Field-based Path Planning

In the field of robot path planning, Potential Field method has been proposed as a promising local and fast obstacle avoidance strategy to plan safe and real-time motions for a robot in a constrained environment [33]. The main idea is to construct an artificial potential field defined as the sum of attractive potentials, pulling the robot towards the desired location, and repulsive potentials, pushing the robot away from various constraints such as the obstacles or robot's joint limits. A driving force computed along the negated gradient of the potential field moves the robot towards the goal location.

Mezouar and Chaumette [49] introduced robust image-based control based on the Potential Field method for a robotic arm with eye-in-hand configuration. In their proposed approach, two types of constraints are considered: field of view and robot's joint limits. To obtain valid robot trajectories, the motion of the robot is first planned in the workspace and then projected into the image space. The attractive potentials are defined in the workspace to pull the robot towards the final desired configuration. To account for field of view limits, repulsive potentials are defined in the image space pushing the image trajectories away from the image boundary. Joint limits are avoided by imposing repulsive potentials in the joint space of the robot. So, the total force applied to the robot is a weighted sum of the individual forces computed as the negated gradient of the above potentials. The image trajectories are obtained in an iterative scheme by moving along the direction of the total force applied to the robot. The discrete image trajectories are then time scaled and tracked using an IBVS technique. The above strategy has been applied to targets with known as well as unknown models. In the latter case, a scaled Euclidean reconstruction is employed to obtain scaled camera paths in the workspace. Image local minima are automatically avoided by updating the image Jacobian using the values of the current desired image features along the time scaled feature trajectories.

As an inherent deficiency of Potential Field-based path planning method, the above strategy might lead to local minima and the robot gets stuck. Although the authors reported no encounter of such local minima in their experiments, imposing physical constraints such as collisions with obstacles and occlusions highly increase the chance of having local minima in the overall potential field.

In [19] a potential field-based strategy is employed to account for workspace obstacles, field of view limits, and robot's joint limits in a global planning framework. To escape local minima generated by addition of the attractive and repulsive forces, *Simulated Annealing* [34] is employed in which proper tuning of the initial temperature and the cooling rates are required to probabilistically ensure the method to escape from local minima and converge to the global minimum. In the proposed planning framework two different trajectory generation strategies are employed: method A, in which a trajectory for the end-effector is planned with respect to the stationary target frame, and method B, in which a trajectory for the target is planned with respect to the current end-effector frame. The former results in a camera path close to a straight line in the workspace, while in the latter the image trajectory of the target's origin is constrained to move as close as possible to a straight line in the image which lessens the chance of image features leaving the camera's field of view. A local switching strategy is devised to switch from image-based control to position-based control when closeness to image local minima and image singularities are detected along the planned trajectories. This is done only once to avoid instability caused due to repetitive switching, however there is no complete guarantee that the field of view and joint limits are always ensured after the system is switched to position-based control.

One of the main advantage of Potential Field-based approaches is the fast computation of driving force which makes these approaches suitable for real-time applications such as visual servoing. For example, the above strategy can be employed when tracking image trajectories to account for possible deviations from the planned trajectory due to uncertainties in modeling and/or calibration (e.g. [11]).

3.4 Global Path Planning

The convergence problems and deficiencies of the above path planning techniques in accounting for all the constraints in visual servoing tasks motivates the need for general and global path planning approaches. A great deal of research has been carried out on global path planning for various robotic systems within the path planning community, see e.g. [39] and [40]. Here we report on some of these techniques which have been successfully incorporated into the visual servoing framework.

A global stabilizing strategy using navigation functions is presented in [17] which guarantees convergence to a visible goal from almost every initial visible configuration while maintaining viability of all features along the way without following a predefined reference image trajectory. One should note that constructing such navigation functions is limited to very simple scenarios only.

In [2] a probabilistic roadmap approach has been utilized to plan minimal-occlusion paths for an in-hand camera with respect to a target object. They employ the technique proposed in [61] to compute the boundary separating the visible regions (from where the target is visible) from the occluded regions (from where the target is not visible due to occlusion by workspace obstacles). Their proposed algorithm then assigns penalties to camera's trajectories within a given probabilistic roadmap (for camera translation) proportional to the distance the camera travels while outside the visible region. One should note that camera's orientation or field of view limits are not taken into account in their proposed approach.

Inspired by the work in [62] on global path planning with general end-effector constraints, we incorporated sampling-based global path planning with visual servoing for a robotic arm equipped with an in-hand camera and proposed a planner [32] which explores the camera space for camera paths satisfying field of view limits and occlusion constraints, and utilizes a local planner to track these paths in the robot's joint space to ensure feasible motions of the robot while accounting for robot's joint limits and collision with obstacles. The result is a search tree as in [35] which alternatively explores the camera and joint spaces (see Fig.1). The camera

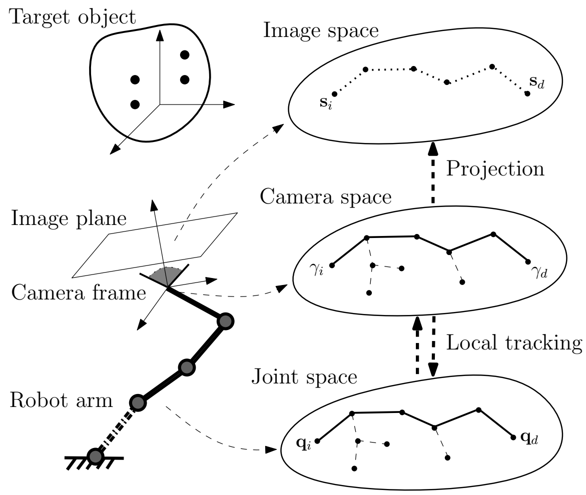

Fig. 1 Our proposed planner [32] alternatively explores the camera space and joint space for feasible robot/camera paths to obtain feasible feature trajectories in image space.

path connecting the initial and desired camera poses is then extracted from the tree and is projected into the image space to obtain sampling-based feature trajectories as a sequence of image waypoints. The image space waypoints are then time parameterized and scaled using *cubic splines*. The splined feature trajectories are tracked using an IBVS technique (as in [49]) at the execution stage.

We demonstrated via simulations and real experiments [32] that the robot is able to visual servo to a desired configuration while avoiding occlusions of target, keeping the target within the camera's field of view, and avoiding collision with obstacles. Such capabilities enhances the applicability of visual servoing to significantly more complex environments/tasks. In the proposed approach, we assumed that the 3D model of the target object and the camera's intrinsic parameters are known *a priori*. The 3D model of the object is required to estimate the corresponding camera poses at the initial and desired views. Furthermore, these parameters are required to transform camera paths to waypoints on the image feature trajectories. We also assume that obstacles in the workspace are known *a priori*.

To be successful, global path planning approaches require a complete and (relatively) precise knowledge of the environment, camera calibration, and object model. These requirements can be limiting in many visual servoing scenarios. The need for such exact knowledge can be relaxed by accounting for modeling and calibration uncertainties at planning stage. In the following section we discuss the effects of uncertainties in visual servoing, especially in tracking planned trajectories at the execution time, and report on a few recent works on path planning under uncertainties for visual servoing.

4 Path Planning under Uncertainty for Visual Servoing

Planned paths need to be executed and the robot may not exactly follow the planned path due to the uncertainties and in fact, in some cases, the followed paths in the workspace and in the image space can be quite different from the planned ones thereby resulting in violation of some of the constraints even if they have been fulfilled at the planning stage. The influence of errors in intrinsic and extrinsic camera parameters on the performance of visual servoing scheme has been examined in [20]. In [37] the propagation of image error through pose estimation and visual servoing control law has been analyzed.

A number of researchers have proposed local and real-time techniques to account for likely deviations from the planned path at the execution (tracking) stage. For example, these could be locally taken care of using Potential Field type techniques, however as mentioned before, such techniques are prone to failure due to local minima [49]. An alternative framework to deal with unmodelled uncertainties is to retreat the robot/camera and/or re-plan quickly when encountering violation in a constraint. A variable zooming technique was suggested by [38] to bring the target back within the visibility range if occluded by an obstacle. This zooming effect can also drastically improve the performance of the underlying image-based visual servoing technique by reducing the measurement noise in fixed-size objects viewed by a camera from distance.

Comport et al. [15] proposed an augmented reality approach for visual servoing. Although their approach mainly focuses on camera pose estimation by means of a virtual visual servoing method, but this can be extended to scenarios in which some feature points on the target may go out of sight temporarily, e.g. due to unmodelled uncertainties. An augmented reality approach can then be utilized to virtually position the missing feature points in the image based on rudimentary information obtained from other objects in a scene cluttered with known features, i.e. straight edges, etc. In this case, the target is used as the primary object for visual servoing while other image features can contribute to the pose estimation, and eventually to the servoing task, when a finite number of feature points fall off the cameras field of view.

Non-linear model predictive control strategies have been proposed to account for uncertainties in planned trajectories in visual servo control loop as well, e.g. [57]. Systems' parameters would be corrected beyond a temporal receding horizon (i.e., the time span during which the optimal control action is computed and executed) after each iteration. The discrepancy between the predicted system's behavior based on the computed control action and that in real implementation is then used to further correct the estimates of the system's parameters. The time required to estimate these parameters via a non-linear optimization technique must be way shorter than the receding horizon in which this optimization is carried out. Otherwise, the applicability of this technique for real-time scenarios would be questionable. Developing a guideline for selecting the optimal size for the receding horizon for robust visual servoing in real time remains an open research area.

Robustness with respect to calibration errors in terms of the tracking error boundness along the planned trajectories has been considered in [53]. Given a user defined bound on the tracking error, they propose a control strategy to modulate control gains and/or the desired tracking velocity to guarantee error boundness. Through the proposed velocity modulation technique, one could use low control gains while keeping the tracking error bounded. While this technique and those mentioned above, to some extent, are expected to take care of the deviations from the planned trajectories in the image space, the deviations from the physical space trajectories can cause robot/physical constraints violations. The above mentioned local strategies for accounting deviations from planned path are either prone to local minima or not general enough to account for all types of constraints (and the related uncertainties), in particular robot/physical constraints. Hence, there is need for taking the uncertainties into account in a global as well as general manner at the planning stage.

The planned paths obtained based on only a nominal model of the camera and/or robot may not be fully traversable by the robot without violating certain constraints. In a recent work [9], Chesi proposed a planning approach to design a robust image trajectory that satisfies the required constraints not only for the nominal model but rather for a family of admissible models. In the proposed approach an uncertain model has been considered for image correspondence between the initial and desired images, and the camera's intrinsic parameters are assumed to be affected by some unknown random errors with known bounds. Given the above uncertain models, there are different admissible camera poses and consequently different camera trajectories rather than a common and robust one. A polynomial parametrization is proposed through which each camera trajectory is parameterized by a possible camera pose and by a design variable which is common to all admissible trajectories. So, the robust trajectory is computed through an optimization problem determining the common design variable that satisfies field of view limits and maximizes the distance of the image features from the boundary of image on all parameterized trajectories.

Although the results obtained through the above approaches in taking calibration uncertainty and measurement errors into account seem promising, more research needs to be done. Physical constraints, especially collisions and occlusions, are highly affected by the uncertainties in the modeling of the environment. Robot path planning considering uncertainties in modeling, localization, and sensing has been studied for decades within path planning community [40] yielded a number of promising approaches, e.g. [5], [30], [43], [48], [55]. Incorporating the research results achieved through these approaches into the visual servoing framework would be a promising future direction. Moreover, planning robust trajectories for visual servoing tasks in unknown or partially known environments remains an open research problem.

5 Conclusions

We provided a comprehensive review of existing path planning for visual servoing techniques aimed at making the visual servoing more robust in complex scenarios, especially in applications where the initial and desired views are distant. Considering the underlying path planning approach, the existing techniques have been divided into four categories: (1) Image space path planning, (2) Optimization-based path planning, (3) Potential Field-based path planning, and (4) Global path planning. We reported on the previous works pertinent to each category and for each technique we discussed the set of assumptions along with its benefits and drawbacks and its integration with the reactive visual servo controllers.

Recent works (discussed in Section 4) demonstrated the effectiveness of accounting for modeling/calibration uncertainties and measurement errors at the planning stage in generating robust trajectories for visual servoing scenarios where the available data are affected by uncertainties. Towards that aim, incorporating the results achieved on robot path planning under uncertainty within the path planning community is a promising direction to follow.

References

[1] Allotta B, Fioravanti D (2005) 3D motion planning for image-based visual servoing tasks. In: Proc. IEEE Int. Conf. Robot. Autom., pp 2173–8
[2] Baumann M, Dupuis D, Leonard S, Croft E, Little J (2008) Occlusion-free path planning with a probabilistic roadmap. In: Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst., pp 2151–56
[3] Bhattacharya S, Murrieta-Cid R, Hutchinson S (2007) Optimal paths for landmark-based navigation by differential-drive vehicles with field-of-view constraints. IEEE Trans Robot 23(1):47–59
[4] Borgstadt J, Ferrier N (2001) Visual servoing: path interpolation by homography decomposition. In: Proc. IEEE Int. Conf. Robot. Autom., pp 723–30
[5] Censi A, Calisi D, Luca A, Oriolo G (2008) A Bayesian framework for optimal motion planning with uncertainty. In: Proc. IEEE Int. Conf. Robot. Autom., pp 1798–805
[6] Chaumette F (1998) Potential problems of stability and convergence in image-based and position-based visual servoing. In: Kriegman D, Hager G, Morse A (eds) Confluence of Vision and Control, Springer Berlin / Heidelberg, pp 66–78
[7] Chaumette F, Hutchinson S (2006) Visual servo control Part I: Basic approaches. IEEE Robot Autom Mag 13(4):82–90
[8] Chaumette F, Hutchinson S (2007) Visual servo control Part II: Advanced approaches. IEEE Robot Autom Mag 14(1):109–18

[9] Chesi G (2009) Desigining image trajectoris in the presence of uncertain data for robust visual servoing path planning. In: Proc. IEEE Int. Conf. Robot. Autom, pp 1492–7
[10] Chesi G (2009) Visual servoing path planning via homogeneous forms and LMI optimizations. IEEE Trans Robot 25(2):281–91
[11] Chesi G, Hung Y (2007) Global path-planning for constrained and optimal visual servoing. IEEE Trans Robot 23(5):1050–60
[12] Chesi G, Malis E, Cipolla R (2000) Automatic segmentation and matching of planar contours for visual servoing. In: Proc. IEEE Int. Conf. Robot. Autom., pp 2753–8
[13] Chesi G, Hashimoto K, Prattichizzo D, Vicino A (2004) Keeping features in the field of view in eye-in-hand visual servoing: a switching approach. IEEE Trans Robot 20(5):908–14
[14] Chesi G, Prattichizzo D, Vicino A (2007) Straight line path-planning in visual servoing. Trans ASME, J Dyn Syst Meas Control 129(4):541–3
[15] Comport A, Marchand E, Pressigout M, Chaumette F (2006) Real-time markerless tracking for augmented reality: the virtual visual servoing framework. IEEE Trans Vis Comput Graphics 12(4):615–28
[16] Corke P, Hutchinson S (2001) A new partitioned approach to image-based visual servo control. IEEE Trans Robot Autom 17(4):507–15
[17] Cowan N, Weingarten J, Koditschek D (2002) Visual servoing via navigation functions. IEEE Trans Robot Autom 18(4):521–33
[18] Deguchi K (1998) Optimal motion control for image-based visual servoing by decoupling translation and rotation. In: Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst., pp 705–11
[19] Deng L, Janabi-Sharifi F, Wilson W (2005) Hybrid motion control and planning strategies for visual servoing. IEEE Trans Ind Electron 52(4):1024–40
[20] Espiau B (1994) Effect of camera calibration errors on visual servoing in robotics. In: Proc. 3rd Int. Symp. Exp. Robot., pp 182–92
[21] Espiau B, Chaumette F, Rives P (1992) A new approach to visual servoing in robotics. IEEE Trans Robot Autom 8(3):313–26
[22] Espiau B, Chaumette F, Rives P (1992) A new approach to visual servoing in robotics. IEEE Trans Robot Autom 8(3):313–26
[23] Faugeras O (1993) Three-Dimensional Computer Vision: A Geometric Viewpoint. MIT Press, Cambridge, MA
[24] Gans N, Hutchinson S (2007) Stable visual servoing through hybrid switched-system control. IEEE Trans Robot 23(3):530–40
[25] Gans N, Hutchinson S, Corke P (2003) Performance tests for visual servo control systems, with application to partitioned approaches to visual servo control. Int J Robot Res 22(10-11):955–81
[26] Hartley R, Zisserman A (2003) Multiple View Geometry in Computer Vision, 2nd edn. Cambridge University Press, Cambridge, UK
[27] Hashimoto K, Noritsugu T (2000) Potential problems and switching control for visual servoing. In: Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst., pp 423–8

[28] Hayet J, Esteves C, Murrieta-Cid R (2009) A motion planner for maintaining landmark visibility with a differential drive robot. In: to be published in Algorithmic Foundations of Robotics VIII

[29] Hosoda K, Sakamoto K, Asada M (1995) Trajectory generation for obstacle avoidance of uncalibrated stereo visual servoing without 3d reconstruction. In: Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst., pp 29–34

[30] Huang Y, Gupta K (2008) RRT-SLAM for motion planning with motion and map uncertainty for robot exploration. In: Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst., pp 1077–82

[31] Hutchinson S, Hager G, Corke P (1996) A tutorial on visual servo control. IEEE Trans Robot Autom 12(5):651–70

[32] Kazemi M, Gupta K, Mehrandezh M (2009) Global path planning for robust visual servoing in complex environments. In: Proc. IEEE Int. Conf. Robot. Autom, pp 326–32

[33] Khatib O (1986) Real-time obstacle avoidance for manipulators and mobile robots. Int J Robot Res 5(1):90–8

[34] Kirkpatrick S, Gelatt Jr C, Vecchi M (1983) Optimization by simulated annealing. Science 220(4598):671–80

[35] Kuffner J, LaValle S (2000) RRT-connect: an efficient approach to single-query path planning. In: Proc. IEEE Int. Conf. Robot. Autom, pp 995–1001

[36] Kyrki V, Kragic D, Christensen H (2004) New shortest-path approaches to visual servoing. In: Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst., pp 349–54

[37] Kyrki V, Kragic D, Christensen H (2006) Measurement errors in visual servoing. Robot Auton Syst 54(10):815–27

[38] Lang O, Graser A (1999) Visual control of 6 DOF robots with constant object size in the image by means of zoom camera. In: Proc. Conf. IEEE Ind. Electron. Society, pp 1342–7

[39] Latombe JC (1991) Robot Motion Planning. Kluwer Academic Publishers, Norwell, MA, USA

[40] LaValle S (2006) Planning Algorithms. Cambridge University Press, Cambridge, U.K.

[41] LaValle S, Gonzalez-Banos H, Becker C, Latombe JC (1997) Motion strategies for maintaining visibility of a moving target. In: Proc. IEEE Int. Conf. Robot. Autom., pp 731–6

[42] Lopez-Nicolas G, Bhattacharya S, Guerrero J, Sagues C, Hutchinson S (2007) Switched homography-based visual control of differential drive vehicles with field-of-view constraints. In: Proc. IEEE Int. Conf. Robot. Autom., pp 4238–44

[43] Lozano-Perez T, Mason M, Taylor R (1984) Automatic synthesis of fine-motion strategies for robots. Int J Robot Res 3(1):3–24

[44] Mahony R, Hamel T, Chaumette F (2002) A decoupled image space approach to visual servo control of a robotic manipulator. In: Proc. IEEE Int. Conf. Robot. Autom., pp 3781–6

[45] Malis E (2004) Visual servoing invariant to changes in camera-intrinsic parameters. IEEE Trans Robot Autom 20(1):72–81

[46] Malis E, Chaumette F (2000) 2 1/2 D visual servoing with respect to unknown objects through a new estimation scheme of camera displacement. Int J Comput Vis 37(1):79–97
[47] Malis E, Chaumette F, Boudet S (1999) 2-1/2-D Visual servoing. IEEE Trans Robot Autom 15(2):238–50
[48] Melchior N, Simmons R (2007) Particle RRT for path planning with uncerat-inty. In: Proc. IEEE Int. Conf. Robot. Autom., pp 1617–24
[49] Mezouar Y, Chaumette F (2002) Path planning for robust image-based control. IEEE Trans Robot Autom 18(4):534–49
[50] Mezouar Y, Chaumette F (2003) Optimal camera trajectory with image-based control. Int J Robot Res 22(10-11):781–803
[51] Michel P, Scheurer C, Kuffner J, Vahrenkamp N, Dillmann R (2007) Planning for robust execution of humanoid motions using future perceptive capability. In: Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst., pp 3223–8
[52] Morel G, Liebezeit T, Szewczyk J, Boudet S, Pot J (2000) Explicit incorporation of 2D constraints in vision based control of robot manipulators. In: Proc. 6th Int. Symp. Exp. Robot., pp 99–108
[53] Morel G, Zanne P, Plestan F (2005) Robust visual servoing: bounding the task function tracking errors. IEEE Trans Control Syst Technol 13(6):998–1009
[54] Park J, Chung M (2003) Path planning with uncalibrated stereo rig for image-based visual servoing under large pose discrepancy. IEEE Trans Robot Autom 19(2):250–8
[55] Pepy R, Lambert A (2006) Safe path planning in an uncertain-configuration space using RRT. In: Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst., pp 5376–81
[56] Salaris P, Belo F, Fontanelli D, Greco L, Bicchi A (2008) Optimal paths in a constrained image plane for purely image-based parking. In: Proc. IEEE/RSJ Int. Conf. on Intell. Robot. Syst., pp 1673–80
[57] Sauvee M, Poignet P, Dombre E, Courtial E (2006) Image based visual servoing through nonlinear model predictive control. In: Proc. IEEE Conf. Decis. Control, pp 1776–81
[58] Schramm F, Morel G (2006) Ensuring visibility in calibration-free path planning for image-based visual servoing. IEEE Trans Robot 22(4):848–54
[59] Sharma R, Hutchinson S (1997) Motion perceptibility and its application to active vision-based servo control. IEEE Trans Robot Autom 13(4):607–17
[60] Sharma R, Sutanto H (1997) A framework for robot motion planning with sensor constraints. IEEE Trans Robot Autom 13(1):61–73
[61] Tarabanis K, Tsai R, Kaul A (1996) Computing occlusion-free viewpoints. IEEE Trans Pattern Anal Mach Intell 18(3):279–92
[62] Yao Z, Gupta K (2007) Path planning with general end-effector constarints. Robot Auton Syst 55(4):316–27
[63] Zhang H, Ostrowski J (2002) Visual motion planning for mobile robots. IEEE Trans Robot Autom 18(2):199–208