Robust Sampling-Based Planning for Vision-Based Control in Unstructured Environments

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Abstract— **We propose a robust planning algorithm to reject visual-motor outliers and address uncalibrated visual servoing in unstructured settings. The proposed framework is built on the success and efficiency of the sampling-based planners while incorporating robustness to outliers in both planning and control.**

I. Introduction

Planning for vision-based robot control in unstructured environments is an open challenging problem, because models are not known a priori and sensor measurements contain outliers. The planner should be efficient, while building *robustly* on raw sensory-motor data.

Path planning has been applied to address some classic problems in *visual servoing* [1], the real-time motion control of robots using visual feedback (see Kazemi *et al.* [2] for a recent survey). Most existing path planning approaches in visual servoing improve the convergence of the visual servo for distant goals by avoiding visual, physical, or joint constraints. However, they usually consider calibrated robot/cameras with known scene/target models. These strong assumptions are not realistic for operation in unstructured environments. Only a handful of papers consider an uncalibrated robot/camera system without using the 3D target model [3]–[5]. Early approaches [3] are limited and cannot be generalized to more realistic unstructured environments. Other methods [4], [5] rely on partial scene reconstruction or homography interpolation, which are ill-posed problems with an unknown scene model. Sampling-based planning is a fairly new approach to improve visual servoing performance [6]–[8]. However, they rely on having an accurate model of the obstacle. In addition, none of these methods consider noise and outliers in visual measurements.

We consider a manipulator with an eye-in-hand configuration, planar points on the target object, and planar points on the obstacle environment *without* using their geometric model. We propose a new algorithm built on the Rapidly-Exploring Random Tree (RRT) planner. Our proposed algorithm works in the visual-motor space to avoid visual occlusions of the target by the obstacle that might occur during servoing. In addition, the visual-motor planner avoids joint and field-of-view (FOV) constraints. A unique property of the planner is that it works directly with the raw data and is able to reject outliers online. The raw visual-motor data is used for both planning and control purposes. Both the robustness to outliers and the algorithmic efficiency are favorable properties for vision-based planning and control in unstructured environments.

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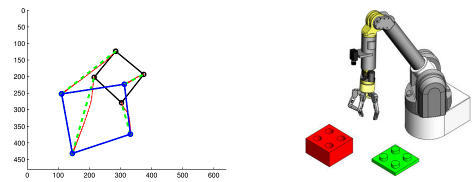

Fig. 1. (Right) A Barrett WAM with in-hand camera configuration. Since the camera is on the elbow, 4 DOFs are controllable: $N = 4$. The flat object (green) is the target with 4 point features $M = 8$. The box (red) is the obstacle that might visually occlude the target. (Left) Initial and desired images of the feature points, the desired trajectory (dotted line) and the actual trajectory are shown for the case without visual occlusion.

II. Uncalibrated Visual Servoing

Uncalibrated Visual Servoing (UVS) studies vision-based motion control of robots without calibration or modeling assumptions [9], [10]. *In particular, the uncalibrated approach makes no use of the camera intrinsic parameters, the robot-to-camera calibration, or the geometric object/scene models.* These assumptions are desired for operation in unstructured environments, but impose theoretical and practical burdens. The UVS control law should be defined without the need to reconstruct the depth or other 3D parameters.

Let $\mathbf{F} : \mathbb{R}^N \rightarrow \mathbb{R}^M$ be the mapping from configuration $\mathbf{q} \in \mathbb{R}^N$ of a robot with N joints, to the visual feature vector $\mathbf{s} \in \mathbb{R}^M$ with M visual features (see Figure 1). The visual-motor function of such vision-based robotic system can be written as $\mathbf{s} = \mathbf{F}(\mathbf{q})$. The time derivative of the visual-motor function leads to $\dot{\mathbf{s}} = \mathbf{J_u}(\mathbf{q})\,\dot{\mathbf{q}}$, where $\mathbf{J_u} = \partial\mathbf{F}(\mathbf{q})/\partial\mathbf{q}$ is the visual-motor Jacobian. With a local estimate $\widehat{\mathbf{J}}_{\mathbf{u}}(\mathbf{q})$ for $\mathbf{J_u}(\mathbf{q})$, the discrete-time form of the above can be written as $\Delta\mathbf{s} \simeq \widehat{\mathbf{J}}_{\mathbf{u}}(\mathbf{q})\,\Delta\mathbf{q}$. Similar to the Image-Based Visual Servoing (IBVS) control law [1], the approximate visual-motor Jacobian, $\widehat{\mathbf{J}}_{\mathbf{u}}$, appears in the uncalibrated control law: $\dot{\mathbf{q}} = -\lambda\widehat{\mathbf{J}}_{\mathbf{u}}^{\dagger}(\mathbf{s} - \mathbf{s}^*)$, where $\widehat{\mathbf{J}}_{\mathbf{u}}^{\dagger}$ is the Moore-Penrose pseudoinverse of $\widehat{\mathbf{J}}_{\mathbf{u}}$. The visual-motor Jacobian may be approximated from local least-squares estimation or using a statistically robust M-estimation technique to reject outliers [11]. A numerical estimate of Jacobian matrix can be further updated by the Broyden update rule [10], [12]. This formulation is general to both eye-in-hand and eye-to-hand systems.

There are two main reasons for the failure of the visual servo: (a) visual constraints such as field of view (FOV) and occlusions, and (b) configuration/physical constraints such as kinematic singularity, joint limits, and obstacles. Image-based methods can handle modeling uncertainties, however, they have a local controller and not safe to use for distant goals [9]. In addition, the visual features may leave the FOV, which leads to system failure. Another failure is due to the singularity of the interaction matrix or the kinematic Jacobian during servoing. Some of these shortcomings can be resolved by path planning [2].

III. Robust Uncalibrated RRT

In a realistic robotic application, outliers in the visual-motor space are unavoidable. In our previous work [11], we have demonstrated the need for robust Jacobian estimation algorithms and proposed a statistically robust one.

To follow any planned path using the UVS controller, the visual-motor Jacobian estimates along the path are needed.

Our proposed sampling-based planning algorithm is based on the Bidirectional RRT (BiRRT) algorithm [13] with a modified data structure that incorporates the sensory input from the cameras. The standard configuration space would only allow us to model the joint limits, kinematic singularities, and other physical constraints (but not the visual constraints). Our problem requires modeling the sensory constraints in addition to the physical/joint constraints. We augment the configuration space with the visual measurements to construct the *visual-motor space*. A typical data point in this space can be represented by a vector of joint values and visual measurements. This data structure can improve the tree extension routine to avoid visual constraints.

As the robot senses the environment and collects new data points, a robust estimate of the visual-motor Jacobian is calculated and kept for later use. When a new random point is sampled, we can simultaneously estimate the robust visual-motor Jacobian at the sample and label it as inlier or outlier. This helps with building robustness into the tree extension algorithm of the proposed RRT-based planner, as follows. We can replace the outlier by a neighboring inlier and extend the tree to the neighbor, if such exists or discard the randomly sampled point otherwise. This ensures robustness to outliers by tree construction. In the absence of enough neighboring data to estimate the Jacobian, the robot can perform exploratory orthogonal motions to estimate it.

In this framework, visual, physical, and joint constraints are labeled as *occupied space*. Inclusion of the joint and the FOV constraints in the occupied space are straightforward. Visual occlusion is found by applying projective geometry of plane intersections. Since visual occlusion is determined entirely in the image space, there is no need for an explicit 3D model of either the target or the obstacle objects. The planning is performed on the rest of the visual-motor space, the *free space*.

For the typical setup shown in Figure 1, we consider the initial and goal states, for which visual servoing without planning fails due to visual occlusions. In Figure 2, the free and occupied space, and the planned path are depicted. The visual-motor space has $M + N = 12$ dimensions

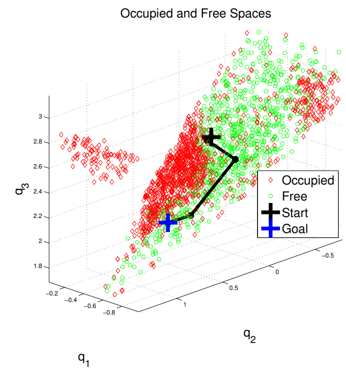

Fig. 2. Approximate visualization of the free and occupied configuration spaces. The occupied space corresponds to visual occlusion (by an obstacle different from the target) and FOV violations. The isolated data labeled as occupied, correspond to visual constraints due to outliers or the 4th dimension. The final path avoids the constraints with a tunable safety margin.

(only 3 dimensions can be visualized). The proposed planner produces a path that goes around the visual occlusion, while avoiding other constraints and handling visual-motor outliers.

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