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Robots visual servo control with features constraint employing Kalman-neural-network filtering scheme

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A B S T R A C T

This paper presents an image-based servo control approach with a Kalman-neural-network filtering scheme for robots manipulation in uncalibrated environment. The image Jacobian on-line identification problems are firstly addressed by introducing the state estimation techniques, which have been incorporated neural network assists Kalman filtering (NNAKF). In fact, this is, the neural network (NN) can serve to play exactly the role of the error estimator, has the task of compensate the errors of Kalman filtering (KF). Then, by employing the NNAKF scheme, the proposed image-based servo control approach has guaranteed the robustness with respect to destabilized system attached dynamic noises, as well as the image features are constrained in field-of-view (FOV) of the camera. Furthermore, it is without requiring the intrinsic and extrinsic parameters of the camera during visual servoing tasks. To demonstrate further the validity and practicality of proposed approach, various simulation and experimental results have been presented using a six-degree-of-freedom robotic manipulator with eye-in-hand configurations.

1. Introduction

It is necessary that guaranteed the robust stability along with feature points kept within the FOV of the camera to successful robot manipulation by visual servo control. The visual-sensor-based robot manipulation is depends mainly on visual feedback to control the positioning or motion of a manipulator [1], [2]. There are two general categories, may be due to the difference definition of the feedback information [3], are position-based visual servoing (PBVS), image-based visual servoing (IBVS), and their hybrid visual servoing [4–10].

The visual sensors used in PBVS are to provide 3D position to regulate the pose of robot's end-effector relative to the object in the Cartesian space. This method is suitable for most industrial robotic manipulators owe to its characteristic of the global asymptotic stability [11]. However, this servo system is inevitably associated with the "hand-eye" calibration model. In consequence, the PBVS be more sensitive, in practical, with respect to the calibration errors and the depth information of the object [12], further with the possibility that the image features disappear from FOV [13–15].

In IBVS, there is direct control of the feature points on the image plane for robot manipulation, and the image Jacobian matrix is used for the description of the differential relationship between image features and end-effector moving [2]. This characteristic has simplified the computation of PBVS, therefore, the IBVS has been catch more attention in recently [6–8]. While, there is, the most pressing of issues presented in uncalibrated IBVS is the calculation of image Jacobian matrix, which as a local and linear approximation to this nonlinear and highly coupled mapping between visual-motor spaces.

As far as the image Jacobian matrix calculation is concerned, some existing works actually considered it as a dynamic parameters identification problem, the solution for this issue are broadly with on-line techniques, such as Broyden-based method and the family of Broyden updating formulas can be defined to estimates the Jacobian matrix [16], [17], and in [18] the exponentially weighted recursive least square update method is used for Jacobian matrix estimation. However, these techniques may actually depend on the system configurations or the tasks to be accomplished, and ill-suited for dealing with the dynamic noises of servo system. While a statistically robust M-estimator is proposed in [19], this method uses visual-motor memory to gradually increase the quality of the Jacobian estimate, which does not require the system model parameters. In [20], it was presented a method for local calculation of the image Jacobian through training without the need for depth estimation. And in recent years, the literature with Kalman–Bucy filter (KBF) for Jacobian matrix estimation is proposed in [21]. This KF-based method assumes that the filtering parameters are known and the

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constructed system with the observed states of Jacobian elements is unvaried. However, this assumption unsuited to some unknown dynamic noises environments, especially the situation with serious changing of observation and state models. As an improvement, the [22] investigated the application of KF in the state space model with variable noise parameters. In [23], an iterative adaptive extended Kalman filter (EKF) is proposed by integrating mechanisms for noise adaptation and iterative-measurement linearization in visual servoing tasks. In [24], the transition matrix of the KF is adjusted to address the problem of where the system model is unavailable, and then the performance of this adaptive KF predictor has been evaluated on a visual servoing application.

The famous Kalman filtering structure is a minimum-variance state estimator for ideal linear dynamic systems with strongly Gaussian white noises [25], which is widely used for real-time state estimation, and parameter identification under the least squares condition [26], [27]. In most practices, however, the processing noises and the observation noises of visual sensors rather than the simple Gaussian white noises. In this case, the limitation to the use of KF for state estimation is the suboptimum, meanwhile the filter will be easy divergent. Some solutions to the nonwhite noise handling have been presented, among which include the dimension extension of KF [28], LMS-based adaptive filtering [29], wavelet-based adaptive Wiener filtering [30]. In recently, many works shed new light on adaptive KF approaches by introduction the concept of neural network [31–35]. In [31], The KF gain was replaced by a feed-forward neural network, the filter with robust capability for estimating the states of the plant in a stochastic environment without knowledge of noise statistics. In [32], it was thinking that the estimation accuracy of the tracking Kalman filter (TKF) is degraded due to the uncertainties which can't be expressed by the linear state-space model, and then presents a method for improving the TKF's estimation accuracy by using a multilayered neural network. In [33], the KF with backpropagation network was proposed to track the maneuvering targets, which the inaccuracies in model were corrected by the neural network and the tracking accuracy can be improved.

As mentioned above, those KF-based techniques have the same properties as recursive-least-squares-based estimation processing, which rely on “known” noise statistics, and good approximation of linear state-space model. Deviations from such assumptions usually lead to degraded Jacobian matrix estimation during visual servoing, that failure to have end-effector positioning in cases of large displacement between the initial and desired poses, and the image features out of FOV is also a risk, *i.e*. the results are only accurate in a small subspace of robot workspace, and non-robustness with respect to destabilized system model attached dynamic noise.

In this paper, we present a robust NNAKF state estimator for image Jacobian on-line identification, without requiring the intrinsic and extrinsic parameters of the camera and the depth information of the target, and then a new image-based servo control approach based on NNAKF is proposed for model-free robot manipulation. In practices, the KF for Jacobian matrix estimation was often suboptimum, in that the traditional KF lacks the adaptive ability to the maneuvering model and the dynamic feature of noises. Thus there are at least two error-elements should be taken into account to improve the KF for best state-estimation: (1) modeling error, due to the perturbation of robot visual servoing system, it is equivalent that the linear time invariant observation model and state model intrinsic contains the nonlinear approximation errors. (2) Statistics error, the precise statistic knowledge of processing noise and observation noise is difficult to be definitely determined in actual environment, since the covariance of those noises may be dynamic changing. So in our considering, a NN was adopted to play exactly the role of the error estimator for assisting the KF algorithm, experiments showed that the proposed NN could improve the robustness of KF for dynamic noises and uncertainty of the system model, and then the NNAKF could construct a robust state estimator for image Jacobian on-line identification with high precise. Finally, we have design a new IBVS framework by employing NNAKF. In our finding, the image Jcobian matrix is dynamic estimated with nothing to do with the camera calibration error and target's 3D-modeling errors. In additional, the proposed IBVS is different from the traditional PBVS methods, with the merits of robust stability no matter the system destabilized with odious dynamic noises, also the servo controller could guaranteed the image features are constrained on the FOV of the camera in global workspace of the robotics.

The rest of the paper is organized as follows: the background of the visual servoing for model-free robot manipulation is represented in the next section. The image Jacobian identification problem with state estimation techniques is presented in Section 3. The NNAKF algorithm and a new IBVS scheme based on NNAKF are proposed in Sections 4 and 5, respectively. The simulation and experimental results are discussed in Section 6, followed by conclusions in Section 7.

2. Visual servo control for robot manipulation

First, we given an eye-in-hand robotics configuration system, the goal of image-based visual servoing is to drive the end-effector from the current pose, to the desired pose. Herein, let us define a image error $\mathbf{e}_s(t)(\mathbf{e}_s(t) \subset \Re^n)$, according to

$$\mathbf{e}_s(t) = \mathbf{S}\left(p_i(t), C\right) - \mathbf{S}'\left(p_i'(t), C\right) \tag{1}$$

where $\mathbf{S}(t)$, $\mathbf{S}'(t)$ are belong to n-dimensional current image features and desired image features, respectively. $p_i(t)$, for $i=1,2,3,\ldots,\ n$ represents a set of 3D position of n feature points of the object in the camera frame, and $p'_i(t)$ denote the 3D coordinates of desired feature points. The coefficient $\boldsymbol{C}$ has includes the calibration parameters of the camera and the depth information of the feature points.

In order to conduct the robot finishes one manipulation task by visual feedback, the visual servo system needs employing a control law $\mathbf{U}(t)$ $(\mathbf{U}(t) \subset \Re^m)$, to minimize the cost function as follows:

$$F(t) = \frac{1}{2}\mathbf{e}_s(t)^{\mathbf{T}}\mathbf{e}_s(t) \tag{2}$$

Generally, a slightly location movement of end-effector will lead to the nonlinear complex change of many features on image plane. There is a practical solution for describing the change-relationship between the image features and the pose of end-effector, by adopting an image Jacobian matrix which was original proposed in [2]. The association of the time change of the image error $\mathbf{e}_s(t)$ with the time derivative of end-effector's spatial velocity $\mathbf{V}_e(t)$ $(\mathbf{V}_e(t) \subset \Re^m)$ is done assuming linearity through the Jacobian matrix $\mathbf{J}_t$, as follows:

$$\dot{\mathbf{e}}_s(t) = \mathbf{J}_t(\mathbf{S}(t), \mathbf{V}_e(t))\dot{\mathbf{V}}_e(t) \tag{3}$$

where $\dot{\mathbf{V}}_e(t) = [\dot{v}(t), \dot{w}(t)]^{\mathbf{T}}$, $v(t)$ and $w(t)$ are the linear velocity and angular velocity of the end-effector, respectively. Considering the desired image feature $\mathbf{S}'(t)$ is constant parameter due the fixed goal pose, then substituting Eq. (1) into Eq. (3), we have

$$\dot{\mathbf{S}}(t) = \mathbf{J}_t\mathbf{S}(\mathbf{S}(t), \mathbf{V}_e(t))\dot{\mathbf{V}}_e(t) \tag{4}$$

where the $\mathbf{J}_t$ is defined by

$$\mathbf{J}_t(\mathbf{S}(t), \mathbf{V}_e(t)) = \left[\frac{\partial \mathbf{S}(t)}{\partial \mathbf{V}_e(t)}\right]_{m \times n} \tag{5}$$

Above Eq. (5) denotes that the camera's parameters and the depth information of target have been implied in $\mathbf{J}_t$, due to $\mathrm{S}(t)$ is the