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Sliding mode adaptive neural network control for hybrid visual servoing of underwater vehicles

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ABSTRACT

In this paper, a hybrid visual servo (HVS) controller is proposed for underwater vehicles, in which a combination of the vehicle's 3-D Cartesian pose and the 2-D image coordinates of a single feature is exploited. A dynamic inversion-based sliding mode adaptive neural network control (DI-SMANNC) method is developed for tracking the HVS reference trajectory generated from a constant target pose. A single hidden-layer (SHL) feedforward neural network, in conjunction with an adaptive sliding mode controller, is utilized to compensate for dynamic uncertainties. The adaptation laws of neural network weight matrices and control gains are designed to ensure the asymptotical stability of tracking errors and the ultimate uniform boundedness (UUB) of neural network weight matrices. The main advantage of the proposed DI-SMANNC over conventional sliding model neural network controllers lies in the fact that the knowledge of the bounds on system uncertainties and neural approximation errors is not required to be previously known. Simulation results are presented to validate the effectiveness of the developed controller, especially the robustness with respect to dynamic modeling uncertainties and camera calibration errors.

1. Introduction

Visual servoing, also known as vision-based control, uses a camera system to provide feedback signals for a robotic system, such that a set of visual features moves through the image frame to reach a desired configuration (Chaumette and Hutchinson, 2006, 2007). Visual servoing methods fall into three categories based on the type of information used in the feedback signals: (1) Position-based visual servoing (PBVS), where feedback is defined in terms of the relative 3-D Cartesian information reconstructed from obtained images, (2) Image-based visual servoing (IBVS), where feedback is directly defined in terms of image feature coordinates, and (3) Hybrid visual servoing (HVS), also called 2.5-D visual servoing, where a combination of partially reconstructed 3-D Cartesian information and 2-D image-space information is used in the feedback control design.

Over the past few decades, visual servoing has gained a lot of research interests with applications in industrial, aerial, and wheeled robots. This technology is applied to dynamic positioning (DP) or station keeping of underwater vehicles operated near the seafloor or subsea facilities since the 2000s (Sørensen, 2011). For an underwater vehicle, visual servoing uses low-cost visual features rather than acoustic beacons, and inherently has the advantage of higher resolution and update-rate compared to acoustic positioning systems. Lots et al. (2000) applied an HVS technique to maintain the position of an underwater vehicle with respect to a fixed planar target. The dynamic controller was simplified by using a steady thrust mapping with saturation. In another paper, Lots et al. (2001) introduced an IBVS technique with a proportional-integral-derivative (PID) controller to solve a similar station-keeping problem, where only the surge and sway degrees-of-freedom (DOF) were considered. Silpa-Anan et al. (2001) designed and implemented a positioning controller for an underwater vehicle using a standard computed torque method, based on the position and velocity feedback provided by a binocular camera system. Caccia et al. (2007) estimated the motion of near-seafloor vehicles using a laser-triangulation sensor with optical correction, and designed and implemented high-precision motion control using a gain-scheduling PI controller. Bechlioulis et al. (2013) described a PBVS system to stabilize an underwater vehicle, where the state vector was estimated using an extended Kalman filter (EKF). Heshmati-alamdari et al. (2014) employed self-triggered model predictive control (MPC) in a PBVS approach based on a kinematic model for an underactuated underwater vehicle, in which the vehicle pose was estimated using a

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visual system. Hua et al. (2014) proposed a homography-based visual servoing approach to stabilize a fully-actuated vehicle by exploiting the homography matrix containing the transformation information between the current and desired camera coordinates. Li et al. (2015) proposed a visual docking method for an underwater vehicle using two cameras at the nose. A two-layer control system composed a homing controller and an attitude tracking controller was designed. The authors (Gao et al., 2016a) proposed a hierarchical IBVS control architecture for underwater vehicles, composed of a nonlinear model predictive kinematic controller and an adaptive neural network dynamic controller. In a recent work (Gao et al., 2016b), we designed a PBVS controller for underwater vehicles to track a time-varying reference trajectory based on the estimated pose by an unscented Kalman filter with visual measurements.

In summary, the PBVS approach, which is mostly employed for underwater vehicles, simplifies the controller design, but relies heavily on exact camera calibration to reconstruct the vehicle's 3-D pose by fusing visual and motion information. The aforementioned IBVS and HVS controllers use only visual information from multiple features for feedback control and orientation reconstruction, as those applied to robot manipulators. In a real underwater environment, light is highly attenuated by the water mass and scattered by suspended particles; which make it hard to identify and locate multiple features with low-quality images. The orientation reconstructed from images by a conventional HVS approach is sensitive to image noises and camera calibration errors. Another drawback of IBVS and classical HVS algorithms lies in that only local asymptotic stability can be obtained (Chaumette and Hutchinson, 2006, 2007), because the dimension of visual feedback is greater than the number of system DOFs.

In practice, different to a robotic manipulator that uses only cameras for motion detection, a work-class underwater vehicle is also equipped with various motion sensors, including a depth sensor, an altimeter, an attitude and heading reference system, and a Doppler velocity log to provide position, orientation, and velocity information for feedback control. In this paper, motivated by this fact, we propose a novel HVS approach by integrating the visual information of a single point-like feature and the global pose information into the system state (Gao et al., 2016c).

An underwater vehicle is a highly nonlinear, heavily coupled system with uncertain hydrodynamic parameters and suffering from environmental disturbances, which makes the control task challenging (Shi et al., 2017). Various nonlinear control methods have been developed, including sliding mode control (SMC) (Zhu and Sun, 2013; Zhang and Chu, 2012; Cui et al., 2016), robust adaptive control (Fischer et al., 2014; Zool et al., 2016; Soylu et al., 2016), neural network (NN) control (Zhang et al., 2009; Du et al., 2013; Chu et al., 2016; Peng and Wang, 2017), model predictive control (Shen et al., 2016b; Shen et al., 2017), energy-based control (Valentinis et al., 2015), and active disturbance rejection control (Shen et al., 2016a). In particular, neural network-based mode reference adaptive control (MRAC) (Johnson and Kannan, 2005) has showed an excellent performance even in the presence of uncertainties through comprehensive simulations and in-water tests (Proctor, 2014). In NN-based adaptive controllers, linearly parameterized radial basis function (RBF) and nonlinearly parameterized single hidden-layer (SHL) neural networks are widely employed as adaptive elements to model continuous nonlinear dynamics as well as all uncertainties in the plant. An RBF NN acts as a universal approximator only for suitably chosen basis functions, and the number of required basis functions increases dramatically with the dimension of input vectors. By conducting a detailed comparison of these two NNs in the flight control of unmanned aerial vehicles, Anderson et al. (2009) indicated that an RBF NN controller has a slower update rate than an SHL one, and is more susceptible to overfitting errors and improper learning.

Conventionally, the closed-loop stability of an NN-based control system is restricted to ultimate uniform boundedness (UUB) because of residual NN approximation errors (Johnson and Kannan, 2005; Lewis, 1999). A direct method for removing the inherent error is to integrate a robustifying term, such as SMC, into the NN-based adaptive control law (Wai and Muthusamy, 2013). Patre et al. (2008) incorporated a robust integral of the sign of the error (RISE) feedback term with an NN-based feedforward compensator to achieve semi-global asymptotic tracking for uncertain dynamic systems. However, the asymptotical stability of control systems still relies on the assumption that the upper bounds of ideal network weights and approximation errors are previously known, especially for nonlinear SHL NNs.

To remove this assumption, Sun et al. (2011) designed an RBF NN-based sliding mode adaptive controller for trajectory tracking of robot manipulators. The enhanced asymptotical convergence of tracking errors was achieved by incorporating an SMC-like time-varying robustifying term with adaptive gains driven by error signals. Unfortunately, this approach cannot be directly applied to nonlinear SHL NN-based adaptive controllers.

In this paper, motivated by the adaptive SMC designed by Li and Xu (2010), we present a dynamic inversion-based sliding mode adaptive neural network controller (DI-SMANNC) for the HVS control of underwater vehicles to handle vehicle dynamic uncertainties, including external disturbances. Compared with the existing underwater visual servo systems, the main contributions of the proposed approach are two-folds.

(1) This proposed HVS scheme is more robust and practical than conventional visual servoing approaches of underwater vehicles, because only a single visual feature is required, which reduces the system complexity and computational load of image processing. The orientation directly obtained by motion sensors are more reliable than those reconstructed from images in a classic HVS system.
(2) The control gains in the proposed DI-SMANNC are updated online to ensure asymptotical stability without any knowledge of the upper bounds on uncertainties and neural network weights, which simplifies the controller design. This method is also valid for other nonlinear robotic systems, e.g., manipulators as presented in Wai and Muthusamy (2013) and Sun et al. (2011).

The remainder of this paper is organized as follows. Section 2 describes the mathematical formulation of the HVS problem, including the models for an underwater vehicle and a downward-looking visual system. Section 3 details the DI-SMANNC development for HVS of underwater vehicles. The asymptotical stability of visual servoing errors and the boundedness of neural network weight matrices are proven by a Lyapunov method. In Section 4, simulation studies with a six DOF underwater vehicle are presented to illustrate the performance of the proposed controller, and test the robustness with respect to dynamic modeling uncertainties and camera calibration errors. Finally, some concluding remarks are provided in Section 5.

Notations. Let $\mathbb{R}$ denote the real number, $\mathbb{R}^n$ the real n-vectors, and $\mathbb{R}^{m\times n}$ the real $m \times n$ matrices. $\mathbf{0}_{m\times n}$ is an $m \times n$ zero matrix consisting of all 0 s, and $\mathbf{I}_n$ is an $n \times n$ identity matrix. Superscript "T" indicates matrix transposition. We use the notation $\|\mathbf{x}\| = \sqrt{\mathbf{x}^{\mathrm{T}}\mathbf{x}}$ to indicate the 2-norm of vector $\mathbf{x}$ for any $\mathbf{x} \in \mathbb{R}^n$. Given $\mathbf{A} = [a_{ij}]$, the Frobenius norm is defined by $\|\mathbf{A}\|_F^2 = \mathrm{tr}(\mathbf{A}^{\mathrm{T}}\mathbf{A}) = \sum a_{ij}^2$ with $\mathrm{tr}(\cdot)$ being the trace operation.

2. Problem formulation

2.1. Modeling of underwater vehicles

This section describes the underwater vehicle model presented by Fossen (2002) for control design and simulations. The kinematic and dynamic equations of an underwater vehicle is developed with the