[[1]](#footnote-1)

Design and experimental validation of an adaptive sliding mode observer based fault tolerant control for underwater vehicles

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*Abstract*—Cost and other practically related reasons can mean that velocity sensors are not available on an underwater vehicle. For such cases, the results in this paper are developed on an observer based fault tolerant control for underwater vehicles in the presence of external disturbances and unknown thruster faults. An adaptive sliding mode observer is developed to achieve finite-time convergence where, in comparison to a high-gain based design for the observer, a nonlinear feedback is constructed based on the position estimation error. Unlike alternatives, a discontinuity term in the developed fault tolerant controller is avoided and the stability of the controlled dynamics is characterized using Lyapunov theory. Finally, these new results are supported by both a simulation based study and experimental verification.

*Index Terms*—Underwater vehicles, fault tolerant control, finite-time estimation, sliding mode observer, validation results

# Introduction

Applications for autonomous and remotely operated underwater vehicles (AUVs and ROVs respectively) include inspection of underwater structures, exploration of underwater resources, pipeline tracking and target searching, see, e.g. [1, 2]. In the complex and unknown ocean environment, tracking control is critical to ensure that these vehicles follow as closely as possible a specified or planned-online trajectory. This task is always challenging due to the underlying nonlinear dynamics and the presence of external disturbances.

An increasing trend in the control of these vehicles is to use state feedback action based on position and velocity information measured directly by onboard sensors [3]. In this area, GPS cannot be directly used to determine the vehicles current position due to short wave attenuation effects [4]. This has led to the use of acoustic instruments, such as acoustic long baseline (LBL) and acoustic ultrashort baseline (USBL) to measure position and attitude with respect to the inertial frame using a compass module.

To measure velocity, the Doppler velocity log and fibre optic gyroscope are one option to obtain translational and angular velocities with respect to the body-fixed frame. However, the cost of implementation and other practical reasons mean that some of these vehicles do not carry velocity measurement sensors. In such cases, a simple method to obtain approximate velocities for the vehicle is based on numerical differentiation, but this is often not feasible due to measurement noise in the position sensor measurements [3].

To implement trajectory tracking control without velocity measurements for these vehicles, observer based control schemes have been considered, see, e.g., [3, 5-7]. Of the possible structures, high-gain observers have been applied to estimate velocities. In, e.g., [8] nonlinear model based state estimation experiments on a Jason2 ROV using a high-gain observer and extended Kalman filter, respectively, are reported. Also in [9] results from full-scale sea trials based on an output feedback control system that combines a three term (proportional plus integral plus derivative) controller with a high-gain observer for an ROV are reported.

High-gain observer stability analysis, see, e.g., [5], shows that the associated estimation error can only achieve asymptotic convergence. Moreover, to converge quickly with acceptable estimation performance, a large gain is needed but the result could be ‘quick’ changes (or chattering) in the estimation error, tracking error and control output in the early stages of the system output. Finite-time convergent observer design offers advances in convergence speed, disturbance rejection and robustness to uncertainty and a natural step is to investigate the possible benefits of this approach in the underwater vehicles area.

A terminal sliding mode observer was used in [10] to guarantee that all estimated states of an AUV converge in a finite time and hence a thruster fault can be reconstructed in time. In [3], a nonlinear observer with finite-time convergence was constructed to estimate an AUV’s translational velocities where the observer used was based on a fractional order signature function to estimate the position error without considering the external disturbance. To estimate an underwater vehicle’s unmeasured states, another adaptive terminal sliding mode observer was developed in [5] that uses the derivative of the position estimation error.

Observer/controller design for underwater vehicles requires a model of the dynamics in most cases. Due to the highly coupled multivariable nonlinear dynamics and the external disturbance, any model will be subject to potentially significant uncertainties. Also during operation faults, such as entanglement and impairment, can occur in the thrusters, see, e.g., [11] and this increases the uncertainty in the model and makes trajectory tracking more challenging. In this area, a suitably designed neural network has been applied to approximate the unknown model or the general uncertainty term in underwater vehicle research, as discussed next.

In [12] an adaptive sliding mode tracking control design for underwater vehicles was developed where a radial basis function based neural network was applied to mimic the equivalent control. Moreover, in [13], the unknown thruster fault, model uncertainty and external disturbance are treated as a general uncertainty term, which is approximated by a neural network. Designs such as these must counteract the neural network’s estimation error and the effects of the neglected higher-order terms resulting from use of the Taylor series expansion.

Existing methods using this approach assume that the upper bound of the neural networks estimation error and the neglected higher-order terms is known a priori. This assumption is very strict (with consequences for controller design), since it is very difficult to select the upper bound for underwater vehicles subject to external disturbances, which includes effects from waves and the ocean current. An alternative is to directly estimate the upper bound of the term involved, i.e., an adaptive rate in the framework of Lyapunov theory. Such a method does not need to know this upper bound a priori but it introduces a discontinuous term into the control law.

Safety is one of key issues for underwater vehicles [14, 15]. This paper investigates fault tolerant control design without velocity measurement for underwater vehicles with the presence of ocean current disturbances and unknown thruster faults, where a recurrent neural network is used to approximate the unknown function in the dynamics.

The main new contributions are as follows: (a) An adaptive sliding mode observer based fault tolerant control design is developed to estimate quickly the underwater vehicle’s unmeasured velocity states, with the advantage that the estimation error converges to zero in finite time compared with a design based on a high-gain observer. In contrast to the designs in [16, 17], a new sliding mode observer is constructed by combining a linear function, signature function, integral function and a fractional order function of the position estimation error to keep the discontinuous term as small as possible. (b) A method to counteract the neural network estimation error and the higher-order term caused by truncating a Taylor series expansion is developed. In alternative approaches [5, 13], the bound on this term is assumed to be known a priori or is directly estimated based on an adaptive rate. In the new approach in this paper the term involved is split into two parts: an unknown function and the sliding surface. Then the unknown function is estimated based on an adaptive rate and thereby avoids introducing a discontinuous term into the control law. (c) Based on the developed observer and compensation method, a fault tolerant control law is designed using the integral sliding mode technique. In the process of constructing an integral sliding surface, the estimation error is also included.

Results from simulation studies and pool experiments are given to demonstrate the effectiveness of the new design.

# Modeling and Problem Specification

The nonlinear vehicle model considered in the presence of ocean current disturbances and thruster faults is

  (1)

where if denotes the number of degrees of freedom, is the position and orientation vector with respect to the inertial frame. Also if *m* denotes the number of thrusters, the vector *u* is the control vector applied through the thrusters and

 

  (2)

where, *B* is the thruster configuration matrix. Also *K* is a diagonal matrix with entries that specifies the loss of the *i*th thruster effectiveness,where *kii*=0 denotes the *i*th thruster is healthy and *kii*=1 denotes the case when the thruster has completely failed. The remainder of the notation is specified in **Appendix 1**.

**Assumption 1**: *It is assumed that G is exactly known and that is unknown but with a known structure.*

Let *ui* denote an entry in *u*. Then it is assumed that such an entry satisfies  where and , respectively, denote the minimum and maximum available thrust.

In this paper, a recurrent neural network is used to estimate the term , where the output of a recurrent neural network with one hidden layer can be written as

  (3)

In this representation *x* is the network input and *W*, *α*, *β*, *γ* are weighting matrixes and the output of an entry in the hidden layer is expressed as

 

 (4)

where *Q*(*x*, *α*, *β*, *γ*)(*i*) denotes the *i*th entry of *Q*(*x*, *α*, *β*, *γ*); and *α*(*i*), *β*(*i*), *γ*(*i*), respectively, are the *i*th rows of *α*, *β*, *γ* and , , are, respectively, the last instantaneous values of the output of the hidden and output layers.

By standard neural network theory, there exist ideal weighting matrices, denoted by *W\**, *α\**, *β\**, *γ\**, such that

  (5)

where is the minimum error arising from an insufficient number of neurons in the hidden layer. Hence the approximation error can be written as

  (6)

where , , ,are the estimates of *W\**, *α\**, *β\**, *γ\**. For ease of presentation, the dependence of, e.g., *Q* on *x*, *α*, *β*, *γ* is suppressed. Also and and is the estimate of by this recurrent neural network, i.e., .

Using a Taylor series expansion for , the approximation error can be written as

  (7)

where , , ，, , , and denotes the higher order Taylor series terms.

In the absence of sensors to measure the underwater vehicle’s velocity, an observer with finite-time convergence is first designed in the analysis that follows in this paper. Next, based on the estimated states, an integral sliding surface is designed by adding the observer estimation error and the neural network based control design is developed. Then a new robust compensator is designed to attenuate the term , denoted as *ψ*. Finally, the stability of the controlled system is established and simulation and experimental verification results are given.

# Sliding Mode Observer Design

Introduce the state variables, and set . Also introduce the state transformation [17], with

 

where *I* and 0 denote the identity and null matrices, respectively, of compatible dimensions and *T*2 is a diagonal matrix with positive entries *αi*, . Hence

  (8)

where



The sliding mode observer structure is

  (9)

where the superscript *e* denotes an estimated quantity,, and

  (10)

where

 , 

and ,, , are positive constants, , ,where is a positive constant, *l*1*i*, *l*2*i* are constants and will be selected below, the block diagonal matrix *P* = diag(*P*1, *P*2) will be selected below, where *P*1, *P*2 are symmetric positive definite matrixes, the superscript -1 denotes the inverse matrix,  and denotes replacing the entries in a vector by their absolute values.

If the term  is not present in the observer structure, finite time stability, established later in the paper, requires to be chosen sufficiently large. This means that the magnitude of the discontinuity will also be large and hence more control action would be required. Hence this is the reason why this term is included in the second observer equation.

Using (8) and (9), the observer estimation error dynamics are given by

  (11)

with estimation error vector  and .

**Assumption 2:** *It is assumed that there exists a known parameter σ >0 such that [10, 17]*

  (12)

**Proposition 1**: *The observer (9) is finite-time convergent if the following conditions hold*

  (13)

  (14)

  (15)

 ,  (16)

*where, , Qo is a symmetric positive definite matrix, ,*  *and are positive constants (specified below) and*

 

***Proof:***To establish finite-time convergence of the observer, the route is to first establish that the resulting estimation error is bounded and then establish the required property.

As shown in **Appendix 2**, the estimation error Δis bounded under the conditions given by (13)-(14). Given this fact, the finite-time convergence of Δ1 and Δ2 is established by first introducing  and hence from (11)

  (17)

where

 

Moreover, since Δ is bounded and is a combination of a linear function and a fractional order function of Δ, it is routine to establish that this latter function is also bounded, i.e., , where . Also it is routine to show that Δ1 and are finite-time convergent to zero under the conditions of (15)-(16), similar to the proof in [18]. Also given this property for these two variables ensures, also occurs in a finite time by the second entry in (17).

It remains to prove that Δ2 = 0 also occurs in finite time, where in **Appendix 2** it is shown that

  (18)

Also since the position estimation error Δ1 converges to zero in finite time, then

  (19)

where *λ*min(*Qo*) denotes the minimum eigenvalue of *Qo*.

Suppose to the contrary that Δ2 converges to a non-zero constant in finite time. Then this assumption plus (19) means that Δ2 is still decreasing. Hence the observer converges in finite time.

The matrix *P* in (13) can be obtained by the following Linear Matrix Inequality (LMI) for a given

  (20)

with *C*=[*I*, 0];.

# Sliding Mode Based Fault Tolerant Control

To ensure that *η* converges to the desired trajectory , a second-order reference model is used, i.e.,

  (21)

where is the reference state vector and and *ξ* are positive constants. Also define the tracking error

  (22)

and hence the error dynamics can be written as

  (23)

The fault tolerant controller is designed based on sliding mode theory but the estimation error is added to the sliding surface, resulting in

  (24)

where, Λ > 0 is a constant and , (from (8)) is given by

  (25)

Prior to deriving the control law, it is necessary to counteract the effects of *ψ* in such a way that an upper bound on this term is not needed and a discontinuity does not occur in the control law. In contrast to existing methods, the term *ψ* is split into two parts in what follows, i.e.,

  (26)

***Assumption 3****: At low speeds, it is assumed that h(s) varies slowly and hence there exists a constant vector Hb such that .*

Let denote the estimated value of *h*(*s*) and hence the estimate of *ψ* is . In this paper, a fractional order expression is used to adjust and since the sliding surface cannot converge exactly to zero in application, a boundary technique is also included, i.e.,

  (27)

where for ease of notation the dependence of on *s* is omitted,  is a positive definite diagonal matrix; and is the boundary term to be selected. Also it can be shown [16] that .

***Proposition 2****: Consider an underwater vehicle subject to an unknown thruster fault as described in Section II. Suppose also that the control law u applied results in tracking error dynamics described by (23). Suppose also that the fault tolerant controller defined by (24)-(27) is applied. Then the following control law and recurrent neural network updating structure guarantee that the tracking error e*1*exponentially converges to a known region.*

  (28)

  (29)

  (30)

  (31)

  (32)

*where k > 0, are constants, , , and are positive definite diagonal matrices, and the superscript + denotes the pseudo inverse, x is the input of the neural network, described in Section II.*

***Proof:***This proof is based on the Lyapunov function

  (33)

  (34)

where , = diag(*ς*) where *ς* is selected below.

Differentiating *V*2 with respect to time gives

  (35)

where Ξ = Δ2 + *T*2Δ1 and since Δ1 and Δ2 converge to zero in finite time both Ξ and also have this property.

Next, perform the following steps, i) substitute (23) into (35), ii) then introduce the control law (28) and iii) substitute (29)-(32) to give after extensive, but routine, manipulations

  (36)

Two cases now arise: **Case I** . In this case, (36) can be written as

  (37)

where *ς* is selected such that . Hence the sliding surface is bounded and will be inside the specified boundary after a finite period of time has elapsed.

**Case II** . In this case the sign of is not certain and it has been shown in [19] that inside the designed boundary the stability property of is indefinite. If the sliding surface *s* exceeds the designed boundary, i.e., , (37) again holds and as detailed in [19], *s* will be attracted to inside the boundary. Hence the sliding surface *s* converges to the designed boundary under the applied control system.

After a certain time, say *t*0, the sliding surface satisfies with zero estimation error. Hence there exists a constant vector satisfying and by the definition of the sliding surface (see (24))

  (38)

Next, apply the following sequence of operations, i) multiply (38) by , ii) integrate the result from *t*0 to *t*, iii) divide the result by . Then since , it follows that

  (39)

Also since

  (40)

and using (38) and (39) it follows that

  (41)

and hence the tracking error *e*1 exponentially converges to the domain given by the right-side of this last equation.

# Experimental and Simulation Results

## Experimental results for an ROV

The Beaver 2 ROVcan be used for underwater observation by carrying different sensors. The results are given in this section are for tracking of the yaw angle, where by design this vehicle has weak coupling between axes. This ROV has dimensions 0.8m×0.5m×0.4m and its dry weight is 50 kg. It is also slightly positively buoyant with thrusters on the left and right-hand sides to provide the force inputs and the yaw angle is measured by a HMR3000 digital compass [20].

Two desired yaw angles are considered, i.e.,

 ,  (42)

An incipient thruster fault is considered, which is widely used in the subject area. The fault is specified as

  (43)

where *f* [0, 1] denotes the magnitude of the thruster fault,

Consider the case when the left-hand side thruster has an incipient fault with *f* = 0.3, i.e., the effectiveness of the thruster output is gradually reduced to 70% of its input after 20 seconds. Also consider the following choices for the design parameters:

*σ* = 2, = 2, = 3; *ξ* = 0.8, *T*2 = *I*, *P*1 = 1.1546*I*, *P*2 = 1.4845*I*,

*ρ*1 = 2*P*1, *ρ*2 = 2*I*, = 3*I*, = 4/5, *L*1 = 2.5*I*, *L*2 = -0.222*I*,

 = (*T*2 - *L*1 + 0.3*I*), *αϖ* = *I*, *Λ* = 5,  = 5/7, *k* = 5, = 12/5,

 = =  = = 0.2*I*, = 0.2*I*, *φ* = 0.02*I*

Moreover, *σ*, *ρ*1,, *αϖ*  must be selected according to experimental results, since it is difficult to determine the values of *σ*, and .

Computing the control law (28) and applying it to the vehicle generated the experimental results shown in Fig. 1 for the first desired yaw and Fig. 2 for the second under the incipient thruster fault. From Figs. 1 and Fig. 2, the tracking performance is satisfactory for the new design, showing the effectiveness of the design for the ROV without velocity measurement.



(a)



(b)

Fig. 1 Experimental results for the first desired yaw.

(a) Yaw angle. (b) Tracking error.



(a)



(b)

Fig. 2 Experimental results for the second desired trajectory.

(a) Yaw angle. (b) Tracking error.

## AUV simulation results

The center gravity for an open-frame AUV can be adjusted to be lower than its center of buoyancy and also the pitch and roll angles have only small values, fluctuating near zero, during operation. In such cases, the interaction between the horizontal and vertical planes can be neglected. In this paper, therefore, the horizontal plane is considered.

For the ODIN underwater vehicle, the following model matrices are used

 

 

 

 , 

 , , 

 (44)

where *v* and *vr* denote, respectively, the vehicle’s absolute and relative, velocities with respect to the ocean current in the body-fixed frame. Also the ocean current is simulated as in [20], and its direction is assumed be of fixed value π/4 with respect to the inertial frame.

This vehicle has four identical thrusters in the horizontal plane with configuration matrix

  (45)

with *θ* = 1/4π; *R*z = 0.508. Also the initial position and velocity vectors

 *η*(0) = [0.05, 0.05, 0.01]*T*, (0) = 0 (46)

In the reference trajectory model (21), = 3 and *ξ* = 0.8. And the neural network (3) has 6 hidden layers and the input vector *x* formed from and. The number of outputs is 3 and all weights are randomly selected in the range [0, 0.5].

In the sliding mode observer, *T*2 = *I* and then an LMI solver is used to compute *P*, *L*1 and *L*2 from (20). Then the rest of the parameters are selected based on (13)-(16). Moreover the term  ensures that *αϖ* do not need to be large.

The parameters used in the simulation results are

*σ* = 2, = 2, *L*1 = 2.5*I*, *L*2 = -0.222*I*, *P*1 = 1.1546*I*,

*P*2 = 1.4845*I*, = 4*P*1, = 50*I*, = 20.5*I*, = 4/5,

 = (*T*2 - *L*1 + 0.3*I*), *αϖ* = 0.125*diag*(1, 1, 0.4).

Moreover, *σ*, *ρ*1, *κα* , *αϖ*  must be selected according to simulation results, since it is difficult to determine the values of *σ*, and .

The control law and the adaptive estimation are constructed using

*Λ* = 5, = 5/7, *k* = 5, = 12/5,

 = =  = = 0.5*I*, = 150*I*, *φ* = 0.01*I*

In simulation, the incipient thruster fault of (43) is considered again, where it is assumed that the fault occurs in the first thruster with *f* = 0.3. Also the desired trajectory is an “8” type, given by

 , 

 ,  (47)

To provide a comparison, designs based on a high-gain observer and a terminal sliding mode observer, respectively, are also considered. In the first of these two cases, the final control law is again of the form and the structure of the law developed in this paper and the parameters in the neural network are not changed. Hence in this case

 

 

  (48)

where *L*1 = *L*2 = *diag*(2, 2, 10), = [6, 3, 7.5]*T* and the saturation function sat(s) is given by

  (49)

Similarly, the terminal sliding mode observer based controller is given by

 

 ,  (50)

where, *T*2 = *I*, *L*1 = 2.5*I*, *L*2 = -0.222*I*, = 0.5, = 2.5, = 0.1 and the sliding surface is again given by the third entry in (48).

In the case of the incipient fault, Fig. 3 gives the simulation results for the new design in this paper and Fig. 4 and Fig. 5, respectively, show the results for the high-gain observer based controller and the terminal sliding mode observer based controller. These results show that the new controller has distinct advantages in terms of tracking error, energy consumption and chattering reduction.



(a)



(b)

Fig. 3 Simulation results for the new design.

(a) Tracking error. (b) Control output.



(a)



(b)

Fig. 4 Simulation results for the high-gain observer-controller.

(a) Tracking error. (b) Control output.



(a)



(b)

Fig. 5 Simulation results for the terminal sliding mode observer.

(a) Tracking error. (b) Control output.

From Figs. 3-5, among these three methods, the estimation based on high-gain observer is worst in the early stage, and the chattering phenomenon in the control output in this stage is most pronounced. In high-gain observer based controller, satisfactory tracking performance requires the gain in the observer to be large, but such a gain would also cause serious chattering in the control output. In the terminal sliding mode observer based controller, although it avoids large gain in the observer and has good performance in the early stage compared with the high-gain observer based controller, the signature function in the feedback of the observer leads to the discontinuity of the control law, resulting in the largest energy consumption and chattering value among these three methods. Experimental validation is the next step as further research.

# Conclusion

This paper has developed new results on the fault tolerant control problem for underwater vehicles without velocity measurement. An adaptive sliding mode observer based fault tolerant control has been developed where the estimation error of the constructed observer converges to zero in a finite time. Also Lyapunov stability analysis has been used to show that the sliding surface converges in a well defined sense in a finite time and that the tracking error exponentially converges in the same sense. Experiment results on a Beaver 2 ROV in yaw angle tracking confirm the effectiveness of the new design. The new design has also been applied to the ODIN AUV and compared with two alternative designs. The results show that the new design can deliver better performance in the early stages and has superior tracking precision. It also requires less energy and has less chattering of the designs considered. Future research will include the pool experiment verification on the AUV and then lake tests.

Appendix 1

The following notation is used throughout the paper. *J* is the transformation matrix from the inertial frame to the body frame;; and *Vc* is the ocean current vector with respect to the body frame;  is the mass matrix including added mass effects described in the inertial frame;  is the rigid-body Coriolis and centripetal matrix described in the inertial frame;  is the hydrodynamic Coriolis and centripetal matrix described in the inertial frame;  is the drag matrix described in the inertial frame;  is the vector of gravity and buoyancy forces and moments.

Appendix 2

The proof is based on the following Lyapunov function

  (51)

Taking the derivative of *V*1 and making use of Young’s inequality (where both *X* and *Y* are column vectors of the same dimension and is a positive scalar) plus extensive, but routine, manipulations gives

  (52)

Hence there exists a positive constant, say *R*, such that when , , and therefore the estimation error Δ is bounded.

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