Thrusters under the Disabled Velocity
 Information Condition

Xiu-lian Liu, Li-dong Guo, Li-xin Yang, Jian-wei Zhu, Qi-qi Shen
 Abstract[—]Under the time-varying ocean current</sup> sliding mode control [8, 9], the fuzzy trol Model for AUV
Disabled Velocity
Condition
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 $\gamma_{\text{resaarch, including the neural network control [6, 7], thesiding mode control [8, 9], the fuzzy control [10], theinversion control [11], the adaptive control [12] and so on.inerthodes in comparison results show that those proposed by$ IAENG International Journal of Applied Mathematics

A Fault Tolerant Control Model for AUV

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environment, the path tracking control is extremely complex i **EXECTS CITENT (STEP)**
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environment, the path tracking control is extr **information Condition**

Xiu-lian Liu, Li-dong Guo, Li-xin Yang, Jian-wei Zhu, C
 Abstract—Under the time-varying ocean current sliding mode control [11], t

when the path tracking control is extremely complex inversion **control method, a fault tolerant control method was proposed to**
 control methods are search, including the neural method. The path tracking control is extremely complex

when the AUV thruster faults or thruster saturat Xiu-lian Liu, Li-dong Guo, Li-xin Yang, Jian-wei Zhu,
 Abstract—Under the time-varying ocean current sliding mode control

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when the AUV XIU-IIan LIU, L1-dong Guo, L1-XIN Yang, Jian-wei Zhu,
 charact—Under the time-varying ocean current sliding mode control

environment, the path tracking control is externely complex investion control [11],

when the AUV *research***, including the environment, the path tracking control is extremely complex sidding mode control environment, the path tracking control is extremely complex inversion control [11] oveur. Different from the exist** *Abstract***—Under the time-varying ocean current sliding mode control environment, the path tracking control is extremely complex inversion control [11] wecur. Different from the existing models with the inverse methods c Abstract—Under** the time-varying ocean current sliding mode control [8, when the AUV thruster faults or thruster sturration constraints when the AUV thruster faults or thruster sturration onstraints occur. Different from **Abstract—Under the time-varying ocean current** siding mode control [8, 9]
 and the sensor in the sensor of the sensor faults or thruster saturation constraints Extensive simulation results
 corur. Different from the e **Extensive** the time-varying ocean current sincing control is, the path tracking control is extremely complex inversion control [11], the when the AUV thruster faults or thruster sturation constraints Extensive simulation When the AUV thruster failures with the pair unceraing control on the active in the AUV thruster failurs of thruster staturation constraints methods can compensate control method, a fault tolerant control method was propos weit the AUV thus term is the measurement and the and connect the AUV and the different control method, a fault tolerant control method was proposed to the ocean compensate the AUV thrusters while its velocity information occur. Dinerent from the existing models
control method, a fault tolerant control metho
AUV thrusters while its velocity information
Considering the difficulty in constructin
dynamic model for the AUV and the cha
character *I* Musters with unitation was not available. However, it is

mannic model for the AUV and the changes in dynamic methods are base

aracteristics caused by thruster failures, a adaptive which means that

resoft the dynamic dynamic model for the AUV and the changes in dynamic
characteristics caused by thruster failures, a adaptive
vision neural networks was used to estimate those unknown
arts of the dynamic model. Meanwhile, to solve the unkn characteristics caused by thruster failures, a accept
regression neural networks was used to estimate those un
parts of the dynamic model. Meanwhile, to solve the un
AUV velocity information caused by the measurement
and t Franchischer and continue that the unknown

and caused by the measurement noise

a silding-mode observer was designed for

the daptive rate and control law

in the Lyapunov stability theory. Finally,

ing simulation was co

marine environment, Finally discussed the anti-

marine environment parameter and the Expansion was conducted on the

the AUV path tracking simulation was conducted on the

thruster failures. At this in

the AUV path track the AUV path tracking simulation was conducted on the

thruster failures.

thruster failures.
 Index Terms—AUV (autonomous underwater vehicle); Fault

incorrect velocity information

tolerant control; Sliding mode observ thruster failures.
 *Index Terms—*AUV (autonomous underwater vehicle); Fault

incorrect velocity information of

toerant control; Sliding mode observer; Ocean current;

Thruster saturation constraints

Thruster saturation *Index Terms—*AUV (autonomous underwater vehicle); Fault
tolerant control; Sliding mode observer; Ocean current;
tolerant control performance. For ex-
mode method can achieve
formation. But its control performance through *Index Terms*—AUV (autonomous underwater vehicle); Fault

folerant control; Sliding mode observer; Ocean current;

Thruster saturation constraints

Thruster saturation constraints

I. INTRODUCTION

I. INTRODUCTION

I. INTR tolerant control; Sliding mode observer; Ocean current; $\frac{1}{2}$ consequence through the information. But its contractive to the interval of the intervals of the cocity of the statement of the engineering series of the th For sturation constraints

For formance through the meas

Information. But its control outp

I. INTRODUCTION

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I. Under the Solution of AUV) are currently **1.** INTRODUCTION
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 1. Control methods (AUV) are currently the faults in the velocity

marine environment, resource exploratio Fraction (Figure 13, 2023; revised November 7, 2024)

Manuscript received November 13, 2023; revised November 2, 2024

Manuscript received November 13, 2023; revised November 7, 2024.

This work was supported in part by Sc This work was supported in part of China under Western To avoid the net vironment, AUV displays the highly nonlinear and the maintaining high transference and the maintaining high transference cause of this, the path track strong coupling characteristic between multi-freedom system. have

Because of this, the path tracking control of AUV has always et al

been a hot research field of marine engineering [4, 5].

For improving the AUV's tracki

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Qi-qi Shen is an Assistant of Huzhou Vocational & Technical College,

velocity information caused by the measurement noise

sensors generally contains signevelocity variables, a sidding-mode observer was designed for

exceptre velocity variables, and the daptive rate and control law

underw in existor haust, a shump-induce observer was usigned or

velocity variables, and the adaptive rate and control law

behavior chromous measurement principles

the diversity parameter principles

ter failures.

ter failures trol Model for AUV
Disabled Velocity
Condition
Yang, Jian-wei Zhu, Qi-qi Shen
research, including the neural network control [6, 7], the
sliding mode control [8, 9], the fuzzy control [10], the
inversion control [11], the **Disabled Velocity**
 Condition

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sliding mode control [8, 9], the fuzzy control [10], the

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Yang, Jian-wei Zhu, Qi-qi Shen

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Extensive simu Yang, Jian-wei Zhu, Qi-qi Shen
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Extensive sim rang, stan wer zma, Qr qr snen
research, including the neural network control [6, 7], the
sliding mode control [8, 9], the fuzzy control [10], the
inversion control [11], the adaptive control [12] and so on.
Extensive simu research, including the neural network control [6, 7], the sliding mode control [8, 9], the fuzzy control [10], the inversion control [11], the adaptive control [12] and so on. Extensive simulation results show that those research, including the neural network control [6, 7], the sliding mode control [8, 9], the fuzzy control [10], the inversion control [11], the adaptive control [12] and so on. Extensive simulation results show that those research, including the neural network control [0, /], the sliding mode control [8, 9], the fuzzy control [10], the achive control [12] and so on. inversion control [12], the adptive control [12] and so on. Extensive simul silaing mode control [8, 9], the fuzzy control [10], the
inversion control [11], the adaptive control [12] and so on.
Extensive simulation results show that those proposed
methods can compensate the external disturbances inversion control [11], the adaptive control [12] and so on.
Extensive simulation results show that those proposed
methods can compensate the external disturbances caused by
the ocean current and achieve better tracking a Extensive simulation results show that those proposed
methods can compensate the external disturbances caused by
the ocean current and achieve better tracking accuracy.
However, it is worth noting that most of those contro methods can compensate the external disturbances caused by
the ocean current and achieve better tracking accuracy.
However, it is worth noting that most of those control
methods are based on the overall measurable states o the ocean current and achieve better tracking accuracy.
However, it is worth noting that most of those control
methods are based on the overall measurable states of AUV,
which means that the position and speed requirements However, it is worth noting that most of those control
methods are based on the overall measurable states of AUV,
which means that the position and speed requirements can be
directly obtained. In the practical applications methods are based on the overall measurable states of AUV,
which means that the position and speed requirements can be
directly obtained. In the practical applications, it has been
found that the velocity information obtai which means that the position and speed requirements can be
directly obtained. In the practical applications, it has been
found that the velocity information obtained by velocity
sensors generally contains significant nois directly obtained. In the practical applications, it has been
found that the velocity information obtained by velocity
sensors generally contains significant noise, especially for
the doppler relocity log (DVL) sensors. Re from the dopler velocity information obtained by velocity
sensors generally contains significant noise, especially for
the doppler relocity log (DVL) sensors. Restricted by the
dopler measurement principles, DVL is prone t sensors generally contains significant noise, especially for
the doppler velocity log (DVL) sensors. Restricted by the
doppler measurement principles, DVL is prone to significant
measurement errors through external environ the doppler velocity log (DVL) sensors. Restricted by the doppler measurement erriors through external environmental imfluences. At this moment, when the velocity sensor malflunctions and applies to the control algorithm, doppler measurement principles, DVL is prone to significant
measurement errors through external environmental
influences. At this moment, when the velocity sensor
malfunctions and applies to the control algorithm, the
inco Examement errors through external environmental
fluences. At this moment, when the velocity sensor
alifunctions and applies to the control algorithm, the
correct velocity information will lead to a deterioration of
ortrol influences. At this moment, when the velocity sensor
malfunctions and applies to the control algorithm, the
incorrect velocity information will lead to a deterioration of
control performance. For example, the neural networ mailuncluons and applies to the control algorithm, the
incorrect velocity information will lead to a deterioration of
control performance. For example, the neural network sliding
proformance through the measured position a meorrect velocity information will lead to a deterioration of
control performance. For example, the neural network sliding
mode method can achieve depth control and good tracking
performance through the measured position a Autonomous underwater robots (AUV) are currently the
marine of the thruster. Therefore, it is of meaningful to
marine environment, resource exploration, and underwater
webocity information is unavailable.

operations [1-3]. Under the time-varying ocean current To avoid the need 1
environment, AUV displays the highly nonlinear and the maintaining high trackin
strong coupling characteristic between multi-freedom system. have p environment, AUV displays the highly nonlinear and the maintaining high tracking
strong coupling characteristic between multi-freedom system. have proposed state observed
Because of this, the path tracking control of AUV h org coupling enatacteristic octevech initial encoder system. The case of this, the path tracking control of AUV bas always to the AUV output feed of method based on obselligent control methods have been shown in current ou Because of this, the path tracking control of AUV has always

been a hot research field of marine engineering [4, 5]. the AUV output feedb

For improving the AUV's tracking accuracy, a variety of

intelligent control metho been a hot research field of marine engineering [4, 5]. the AUV output feed

For improving the AUV's tracking accuracy, a variety of method based on obse

intelligent control methods have been shown in current output fieed Ligent control methods have been shown in current

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02145975, and High Leve Manuscript received November 13, 2023; revised November 7, 2024.

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Murelian Liu is a Lectur This work was supported in part by Scientific Research of Zhejiang

Province Education Department of China under Grant Y202249223 and High Level Talents Projects of Huzhou Vocational and most observers req

Technical Colle 02145975, and High Level Talents Projects of Huzhou Vocational and Intost Observers ieq

Nincal College under Grant 2022GY20 and 2022GY02.

Xiu-lian Liu is a Lecturer of Huzhou Vocational & Technical College, characterist control performance. For example, the neural network sliding
mode method can achieve depth control and good tracking
performance through the measured position and velocity
information. But its control output mutation pheno mode method can achieve depth control and good tracking
performance through the measured position and velocity
information. But its control output mutation phenomenon is
extremely serious if there is large measurement nois performance through the measured position and velocity
information. But its control output mutation phenomenon is
extremely serious if there is large measurement noise and
faults in the velocity sensor, which influences th information. But its control ouplut mutation phenomenon is
extremely serious if there is large measurement noise and
faults in the velocity sensor, which influences the
performance of the thruster. Therefore, it is of mean extremely serious it inter is large measurement noise and
faults in the velocity sensor, which influences the
performance of the thruster. Therefore, it is of meaningful to
research the AUV path tracking control problem wh reading to the threading conductions of the divendence of the diventure control or exerce to the AUV path tracking control problem when the velocity information is unavailable. To avoid the need for AUV speed information w performance of the thruster. Therefore, it is of meaningful to
research the AUV path tracking control problem when the
velocity information is unwaviable.
To avoid the need for AUV speed information while
maintaining high research the AUV path tracking control problem when the
velocity information is unavailable.
To avoid the need for AUV speed information while
maintaining high tracking accuracy, many literatures [13-16]
have proposed stat velocity information is unavailable.

To avoid the need for AUV speed information while

maintaining high tracking accuracy, many literatures [13-16]

have proposed state observer based the control problem based on

the AU To avoid the need for AUV speed information while
maintaining high tracking accuracy, many literatures [13-16]
have proposed state observer based the control methods. Su
et al. [16] discussed the set-point control problem maintaining nigh tracking accuracy, many interatures [13-16]
have proposed state observer based the control methods. Su
tel al. [16] discussed the set-point control problem based on
the AUV output feedback and proposed an nave proposed state observer based the control methods. Su

et al. [16] discussed the set-point control problem based on

the AUV output feedback and proposed an inversion control

method based on observer. Wang et al. [17 et al. [16] discussed the set-point control problem based on
the AUV output feedback and proposed an inversion control
method based on observer. Wanget al. [17] showed an AUV
output feedback control method based on the equ the AUV output reedback and proposed an inversion control
method based on observer. Wang et al. [17] showed an AUV
output feedback control method based on the equivalent
output injection method. Reference [18] studied a
fa method based on observer. wang et al. [1/] showed an AUV
output feedback control method based on the equivalent
output injection method. Reference [18] studied a
fault-tolerant control method of AUV thrusters and adopted a output recaback control method based on the equivalent
output injection method. Reference [18] studied a
fault-tolerant control method of AUV thrusters and adopted a
faate observer to obtain the velocity information for th ourput injection method. Keterence [18] studied a
fault-tolerant control method of AUV thrusters and adopted a
state observer to obtain the velocity information for the
ummeasurable conditions. In summary, it has been foun affectively increases and adopted a state observer to obtain the velocity information for the monesariable conditions. In summary, it has been found that most observers require accurate AUV dynamic models. However, due to the observer to obtain the velocity information for the measurable conditions. In summary, it has been found that sost observers require accurate AUV dynamic models. and the nonlinearity, the strong coupling aracteristics, unmeasurable conditions. In summary, it has been found that
most observers require accurate AUV dynamic models.
However, due to the nonlinearity, the strong coupling
characteristics, and the disturbance of time-varying oce

Internigent controf methods have been shown in currer

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thrusters on account of adaptive neural network model $M_{\eta}(\eta)$ is known while the finversion, of which can solve the AUV path tracking control
problems in unknown and com **IAENG International Journal of Applied Mathems**
thrusters on account of adaptive neural network model $M_{\eta}(\eta)$ is known while the inversion, of which can solve the AUV path tracking control
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thrusters on account of adaptive neural network model $M_{\eta}(\eta)$ is known while the inversion, of which can solve the AUV path tracking control
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thrusters on account of adaptive neural network model $M_{\eta}(\eta)$ is known while
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thrusters on account of adaptive neural network model $M_{\eta}(\eta)$ is known while the fo
inversion, of which can solve the AUV path tracking control
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thrusters on account of adaptive neural network model $M_{\eta}(\eta)$ is known while the
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thrusters on account of adaptive neural network model $M_{\eta}(\eta)$ is known while the
problems in unknown and complex ocean current environments where the velocity information **IAENG International Journal of Applied Mathematics**
thrusters on account of adaptive neural network model $M_{\eta}(\eta)$ is known while the force
problems in unknown and complex ocean current B . Problem Description
environ **IAENG International Journal of Applied Mathen**
thrusters on account of adaptive neural network model
inversion, of which can solve the AUV path tracking control
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thrusters on account of adaptive neural network model inversion, of which can solve the AUV path tracking control
problems in unknown and complex ocean current B . *Problem* thrusters on account of adaptive neural network model $M_{\eta}(\eta)$ is known while the
inversion, of which can solve the AUV path tracking control
problems in unknown and complex ocean current B . Problem Description
enviro thrusters on account of adaptive neural network model $M_{\eta}(\eta)$ is known while the force
inversion, of which can solve the AUV path tracking control
environments where the velocity information is unavailable,
environment thrusters on account of adaptive neural network model $M_{\eta}(\eta)$ is known while the formulation in unknown and complex ocean current B . *Problem Description* environments where the velocity information is unavailable, S Infusters on account of adaptive neural neuvors modes
in $M_{\eta}(q)$ is known while the formation in subset to a DUV path tracking control
problems in unknown and complex ocean current B . Problem Description
environments mversion, or which can solve the AUV paint tracking control

environments where the velocity information is unavailable,

environments where the velocity information is unavailable,

thruster faults occur, and thruster sa problems in unknown and complex ocean current

environments where the velocity information is unavailable,

thruster faults occur, and thruster staturation constraints exist.

Considering the difficulty in obtaining the ac environments where the velocity mormation is unavailable,

thruster faults occur, and thruster statuation constraints exist.

Considering the difficulty in obtaining the accurate dynamic

model and the accurate representat thruster raults occur, and thruster saturation constraints exist.

model: For those AUV dyr

considering the difficulty in obtaining the accurate dynamic characteristics caused by the AUV thruster faults, an

adaptive regr Considering the actrice of Ally in obtaining the accurate dynamic

model and the accurate representation of the changes

dynamic characteristics caused by the AUV thruster failus, an

dynamic components, thus achieving th model and the accurate representation of the characteristics caused by the AUV thruster faults, and
dataptive regression neural network is adopted to estimate conditions. The impl
date tracking throust constrained those un IVe regression neural neuvork is adopted to esume

unknown dynamic components, thus achieving thruster

tolerant control without the need for AUV dynamic

elses not rely on the

elses and thruster fault diagnosis. This pap fault-tolerant control without the need for AUV dynamodels and thruster fault diagnosis. This paper proposesliding mode observer to estimate the unavailable spinformation in response to the significant measurement er of AU by models and thruster fault diagnosis. This paper proposes a

druster faults on the over

dig mode observer to estimate the unavailable speed

AUV speed state variables and the control problem caused

the unavailability sliding mode observer to estimate the unavailable speed
of AUV speed state variables and the control problem casue measurement error
of AUV speed state variables and the control problem caused
by the unavailability of spe information in response to the significant me
of AUV speed state variables and the control
by the unavailability of speed variables v
sensor fails. And that the adaptive rate and
neural networks are deduced through the Ly ount of adaptive neural network model

of an solve the AUV path tracking control

the can solve the NUV path tracking control

mknown and complex ocean current *B. Problem*

or the velocity information is unavailable,

tr won and complex ocean current *B. Problem Description*
won and complex ocean current *B. Problem Description*
he velocity information is unwarialable, Brief description of the expansion
und thruster statution constraints is where the velocity information is unavailable,

is occur, and thruster sturation constraints exist.

is occur, and thruster sturation constraints exist.

the cacurate dynamic Eq. (3), a fault-tolerant control mo

the a observer to estimate the unavailable speed

it response to the significant measurement error

istate variables and the control problem caused

in state variables and the control problem caused

METHOI

ilability of speed by a since the significant measuring unitarial compensate for the

unitrol without the need for AUV dynamic

uster fault diagnosis. This paper proposes a

exponse to the significant measurement error

tate variables and t diagnosis. This paper proposes a

be significant measurement error

les and the control problem caused

speed variables when the speed

speed variables when the speed

seed through the Lyapunov stability

celect through t *M n* dynamic components, thus achieving thruster
 A control without the need for AUV dynamic
 I compensate
 I thruster fault diagnosis. This paper proposes a thruster fault
 In response to the significant measu *M* thruster fault diagnosis. This paper proposes a coherever to estimate the unavailable speed
 M change observer to estimate the unavalable speed
 M change in espects to estimate the unavalisable speed
 M change t bserver to estimate the unavailable speed

zesponse to the significant measurement error

zate variables and the control problem caused

d that the daptive rate and control law of A. Control System Framew

are deduced thr are variables and the control problem caused

bility of speed variables when the speed

that the adaptive rate and control law of A. Control System

are deduced through the Lyapunov stability

the application effect is va

In the data the adaptive rate and control law of
\norks are deduced through the Lyapunov stability
\nally, the application effect is validated through
\ntacking simulations on the "ODIN" AUV.
\nATHEMATICAL MODEL DESCRIPTION
\n*l* parameter
\n*u* operator model
\n
$$
u = J(\eta)v
$$
\n
$$
Mv + C_{RB}(v)v + g(\eta) + C_A(v_r)v_r +
$$
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D_A(v_r)v_r = Basat(u) - BKsat(u)
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u > u_{max}
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u < u_{max}
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u < u = \begin{cases} u_{max} & u > u_{max} \\ u & u < u_{max} \end{cases}
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u < u = \begin{cases} u_{max} & u < u_{max} \\ u & u < u_{max} \end{cases}
$$

given by
\n
$$
\vec{\eta} = J(\eta) \vec{v}
$$
\nnetworks is also d
\nWhen using ne
\nAUV path track
\n $M\vec{v} + C_{RB}(\vec{v})\vec{v} + g(\eta) + C_A(\vec{v}_r)\vec{v}_r +$ \n
$$
D_A(\vec{v}_r)\vec{v}_r = Basa(u) - BKsa(u)
$$
\nother interference
\nthe velocity info
\nobserver is design
\n
$$
sat(u) = \begin{cases}\nu_{\text{max}} & u > u_{\text{max}} \\
u & u_{\text{min}} < u < u_{\text{min}} \\
u_{\text{min}} & u < u_{\text{min}}\n\end{cases}
$$
\n(2) velocity elements
\n(2) are detailed in the literature [21,22].
\nThe physical meanings of each variable in Eq. (1) and Eq. networks, the un-
\nstate model is expressed as:
\n $\vec{\eta} = G(\eta) \cdot sat(u) + F(\eta, \vec{\eta})$ \n(3) literature [19,23-2
\nThe network of
\n $G(\eta) = M_\eta(\eta)^{-1}J^{-T}B$
\n $F(\eta, \dot{\eta}) = -M_\eta(\eta)^{-1}\Big[C_{RB\eta}(\eta, \dot{\eta})\dot{\eta} + C_{A\eta}(\eta, \dot{\eta}_r)\dot{\eta}_r +$ \n(4)
\n
$$
D_\eta(\eta_r, \dot{\eta}_r)\dot{\eta}_r + g_\eta(\eta) - J^{-T}BKsa(u)\Big]
$$
\nwhere: Q is hidden-layer ne
\n $M_\eta(\eta) = J^{-T}MJ^{-1}, \eta_r = \eta - V_c$ is the input vector

$$
\ddot{\eta} = G(\eta) \cdot sat(u) + F(\eta, \dot{\eta}) \tag{3}
$$

$$
G(\eta) = M_{\eta}(\eta)^{-1} J^{-T} B
$$

\n
$$
F(\eta, \dot{\eta}) = -M_{\eta}(\eta)^{-1} \Big[C_{R B \eta}(\eta, \dot{\eta}) \dot{\eta} + C_{A \eta}(\eta_r, \dot{\eta}_r) \dot{\eta}_r + (4)
$$

\n
$$
D_{\eta}(\eta, \dot{\eta}) \dot{\eta} + C_{R B \eta}(\eta) = I^{-T} B K_{R B \eta}(\eta) \Big]
$$
 Where: Q is

$$
\boldsymbol{D}_{\eta}(\boldsymbol{\eta}_r,\dot{\boldsymbol{\eta}}_r)\dot{\boldsymbol{\eta}}_r+\boldsymbol{g}_{\eta}(\boldsymbol{\eta})-\boldsymbol{J}^{-T}\boldsymbol{B}\boldsymbol{K} sat(u)
$$

$$
B_{A}(v_{r})v_{r} = B_{M}(u) = D_{R,M}(u)
$$
\nthe velocity information and the pos-
\n*sat(u)* =
$$
\begin{cases}\n w_{\text{max}} & u > u_{\text{max}} \\
 u & u_{\text{min}} & u < u_{\text{min}}\n\end{cases}
$$
\n
$$
S_{B} = \begin{cases}\n 2x + u_{\text{max}} & u > u_{\text{min}} \\
 2x + u_{\text{min}} & u < u_{\text{min}}\n\end{cases}
$$
\n
$$
S_{B} = \begin{cases}\n 2x + u_{\text{max}} & u > u_{\text{min}} \\
 2x + u_{\text{min}} & u < u_{\text{min}}\n\end{cases}
$$
\n
$$
S_{B} = \begin{cases}\n 2x + u_{\text{max}} & u > u_{\text{min}} \\
 2x + u_{\text{min}} & u > u_{\text{min}}\n\end{cases}
$$
\n
$$
S_{C} = \begin{cases}\n 2x + u_{\text{max}} & u > u_{\text{min}} \\
 2x + u_{\text{min}} & u > u_{\text{min}}\n\end{cases}
$$
\n
$$
S_{D} = \begin{cases}\n 2x + u_{\text{max}} & u > u_{\text{min}} \\
 2x + u_{\text{min}} & u > u_{\text{min}} \\
 2x + u_{\text{max}} & u > u_{\text{min}} \\
 2x + u_{\text{max}} & u > u_{\text{min}} \\
 2x + u_{\text{max}} & u > u_{\text{max}} \\
 2x + u_{\text{max}} & u > u_{\text{max}}\n\end{cases}
$$
\n
$$
S_{D} = \begin{cases}\n 2x + u_{\text{max}} & u_{\text{max}} \\
 2x + u_{\text{max}} & u_{\text{max}} \\
 2x + u_{\text{max}} & u_{\text{max}} \\
 2x + u_{\text{max}} & u_{\text{max}}\n\end{cases}
$$
\n
$$
S_{D} = \begin{cases}\n 2x + u_{\text{max}} & u_{\text{max}} \\
 2x + u_{\text{
$$

Where V_c is vector of the ocean current in the Reference

If of Applied Mathematics
 $M_{\eta}(\eta)$ is known while the force matrix $F(\eta, \eta)$ is unknown.
 B. Problem Description

Brief description of the expected objectives of the control

model: For those AUV dynamic models giv **pplied Mathematics**
is known while the force matrix $F(\eta, \eta)$ is unknown.
coblem Description
description of the expected objectives of the control
For those AUV dynamic models given in Eq. (1) and
a fault-tolerant contro is unknown.

is unknown.

i Eq. (1) and **of Applied Mathematics**
 B. Problem Description

B. Problem Description

Brief description of the expected objectives of the odel: For those AUV dynamic models given in Eq. (3), a fault-tolerant control model for AUV **Solution Contrigoral Mathematics**

For $\eta(\eta)$ is known while the force matrix $F(\eta, \eta)$ is unknown.

B. Problem Description

Brief description of the expected objectives of the control

odel: For those AUV dynamic model **al of Applied Mathematics**
 $M_{\eta}(\eta)$ is known while the force matrix $F(\eta, \eta)$ is unknown.
 B. Problem Description

Brief description of the expected objectives of the control

model: For those AUV dynamic models giv **al of Applied Mathematics**
 $M_{\eta}(\eta)$ is known while the force matrix $F(\eta, \eta)$ is unknown.
 B. Problem Description

Brief description of the expected objectives of the control

model: For those AUV dynamic models giv **al of Applied Mathematics**
 $M_{\eta}(\eta)$ is known while the force matrix $F(\eta, \eta)$ is unknown.
 B. Problem Description

Brief description of the expected objectives of the control

model: For those AUV dynamic models giv **al of Applied Mathematics**
 $M_{\eta}(\eta)$ is known while the force matrix $F(\eta, \dot{\eta})$ is unknown.
 B. Problem Description

Brief description of the expected objectives of the control

model: For those AUV dynamic models g **all of Applied Mathematics**
 $M_{\eta}(\eta)$ is known while the force matrix $F(\eta, \dot{\eta})$ is unknown.
 B. Problem Description

Brief description of the expected objectives of the control

model: For those AUV dynamic models **Applied Mathematics**
 M_n(*n*) is known while the force matrix $F(\eta, \eta)$ is unknown.
 B. Problem Description

Brief description of the expected objectives of the control

model: For those AUV dynamic models given in $M_{\eta}(\eta)$ is known while the force matrix $F(\eta, \dot{\eta})$ is unknown.
 B. Problem Description

Brief description of the expected objectives of the control

model: For those AUV dynamic models given in Eq. (1) and

Eq. (3), $M_{\eta}(\eta)$ is known while the force matrix $F(\eta, \dot{\eta})$ is unknown.
 B. Problem Description

Brief description of the expected objectives of the control

model: For those AUV dynamic models given in Eq. (1) and

Eq. (3), μ ¹.^{*G*} is known while the force matrix μ (μ , μ) is unknown.
 B. Problem Description

Brief description of the expected objectives of the control

model: For those AUV dynamic models given in Eq. (1) and
 Brief description of the expected objectives of the control model: For those AUV dynamic models given in Eq. (1) a Eq. (3), a fault-tolerant control model for AUV thrusters established when considering ocean current interf odel: For those AUV dynamic models given in Eq. (1) and

[. (3), a fault-tolerant control model for AUV thrusters is

tablished when considering ocean current interference,

custer failures and unavailable velocity informa Eq. (3), a fault-tolerant control model for AUV thrusters is
established when considering ocean current interference,
thruster failures and unavailable velocity information
conditions. The implementation of the established

METHOD

RB R **A** *R* **Examples through the speed variables when the speed that the adaptive rate and control law of** *A. Control System F***

Examples through the Lyapunov stability** Since accurate Ale application effect is val Matureots and the contour product and the the column of the speed variables when the speed

aliability of speed variables when the speed

the adeptive rate and control law of A. Control System Framew

1s, the application *ss.* And that the adaptive rate and control law of A. Control System Framework
works are deduced through the Lyapunov stability is ince accurate AUV dynamic
mally, the application effect is validated through obtain from *i* application effect is validated through the Lyapunov stability

since accurate AUV dy

simulations on the "ODIN" AUV.

traditional model inversion

1ATICAL MODEL DESCRIPTION

the fault-tolerant control of

the fault-t established when considering ocean current interference,
thruster failures and unavailable velocity information
conditions. The implementation of the established method
does not rely on the dynamic characteristic and can
c thruster failures and unavailable velocity information
conditions. The implementation of the established method
does not rely on the dynamic characteristic and can
compensate for the ocean currents disturbance and the
thru conditions. The implementation of the established method
does not rely on the dynamic characteristic and can
compensate for the ocean currents disturbance and the
thruster faults on the overall system.
III. OBSERVER-BASED does not rely on the dynamic characteristic and can
compensate for the ocean currents disturbance and the
thruster faults on the overall system.
III. OBSERVER-BASED PATH TRACKING CONTROL
METHOD
A. Control System Framework
 compensate for the ocean currents disturbance and the
thruster faults on the overall system.
III. OBSERVER-BASED PATH TRACKING CONTROL
METHOD
A. Control System Framework
Since accurate AUV dynamic models are difficult to
o thruster faults on the overall system.

III. OBSERVER-BASED PATH TRACKING CONTROL

METHOD

A. Control System Framework

Since accurate AUV dynamic models are difficult to

obtain from the strong coupling characteristics am III. OBSERVER-BASED PATH TRACKING CONTROL

METHOD

A. Control System Framework

Since accurate AUV dynamic models are difficult to

obtain from the strong coupling characteristics among the

working condition, the load and III. OBSERVER-BASED PATH TRACKING CONT

METHOD

A. Control System Framework

Since accurate AUV dynamic models are diffice

obtain from the strong coupling characteristics amon

working condition, the load and the AUV syst METHOD

Control System Framework

Since accurate AUV dynamic models are difficult to

tain from the strong coupling characteristics among the

orking condition, the load and the AUV system sate, the

ditional model inversi A. Control System Framework

Since accurate AUV dynamic models are difficult to

obtain from the strong coupling characteristics among the

working condition, the load and the AUV system sate, the

traditional model invers Example in the strong coupling characteristics among the obtain from the strong coupling characteristics among the working condition, the load and the AUV system sate, the traditional model inversion control methods can no Since accurate AOV dynamic models are difficult to
obtain from the strong coupling characteristics among the
working condition, the load and the AUV system sate, the
traditional model inversion control methods can not real obtain from the strong coupling characteristics among the working condition, the load and the AUV system sate, the traditional model inversion control methods can not realize the fault-tolerant control of AUV. Benefiting f

usually required. However, due to the measurement noise and
other interference signals, as well as the time delay between ATICAL MODEL DESCRIPTION

fraditional model inver

fodel

ante system, an AUV dynamic model

saturation constraints [21, 22] can be

saturation constraints [21, 22] can be

saturation constraints [21, 22] can be

luxp AUV thrusters of which can estimate the unmeasurable velocity elements through a sliding mode observer. Example the physical meanings of each variable in Eq. (1) and Eq. (1) are detailed in the literature When using neural network
 $\vec{n} = J(\vec{n})v$

When using neural network

AUV path tracking control,
 $M\vec{v} + C_{RB}(v)v + g(\vec{n}) + C_A(v_r)v_r +$
 $D_A(v_r)v_r = Basat(u) - BKsat(u)$

other interference signals, as we

the velocity information and the refer *Mation*
 Mates
 *Matesystem, an AUV dynamic model

<i>Inknown* elements in the model involvent
 Lyapunov stability theory, the intervents is the model involvent
 Where using neural networks
 Why and tracking control $\eta = J(\eta)$
 $M\dot{v} + C_{R\beta}(v)v + g(\eta) + C_A(v, v, v, +$
 $D_A(v, v, v, B_{R\beta}(u))$
 $\eta = B_{S\alpha f(u)} - B_{R\beta g(u)}$
 $\eta = \int_{\eta}^{U_{\text{max}}} u > u_{\text{max}}$
 $\eta = \int_{\eta}^{U_{\text{max}}} u \cdot \frac{U_{\text{max}}}{\eta}$
 $\eta = \int_{\eta}^{U_{\text{max}}} \frac{U_{\text{max}}}{\eta} \cdot \frac{U_{\text{max}}}{\eta}$
 $\eta = \int_{\eta}^{U_{$ *s I*(*η*)*v* When using neural netw
 NUV path tracking contracting contracting the
 D_A(*v_r*)*v_r* = *Bsat*(*u*) - *BKsat*(*u*) subserver is designed for fail of the velocity information and observer is desi working condition, the load and the AUV system sate, the traditional model inversion control methods can not realize the fault-tolerant control of AUV. Benefiting from nonlinear approximation ability of neural networks [19 traditional model inversion control methods can not realize
the fault-tolerant control of AUV. Benefiting from nonlinear
approximation ability of neural networks [19, 23-25], an
adaptive regression neural networks is appli the rault-tolerant control of AUV. Benefiting from nonlinear
approximation ability of neural networks [19, 23-25], an
adaptive regression neural networks is applied to estimate the
unknown elements in the model inverse pro *B.* Adaptive regression neural networks is applied to estimate the unknown elements in the model inverse process. Through the Lyapunov stability theory, the adaptive rate of neural networks is also derived.

When using ne known elements in the model inverse process. Through the
apunov stability theory, the adaptive rate of neural
tworks is also derived.
When using neural network model inversion method for
DV path tracking control, the veloc Lyapunov stability theory, the adaptive rate of neural
networks is also derived.
When using neural network model inversion method for
AUV path tracking control, the velocity information is
usually required. However, due to networks is also derived.

When using neural network model inversion method for

AUV path tracking control, the velocity information is

usually required. However, due to the measurement noise and

other interference signa When using neural network model inversion method for
AUV path tracking control, the velocity information is
usually required. However, due to the measurement noise and
other interference signals, as well as the time delay work model inversion method for
trol, the velocity information is
, due to the measurement noise and
as well as the time delay between
and the position information, an
fault-tolerant control model of the
can estimate the twork model inversion method for
trol, the velocity information is
r, due to the measurement noise and
as well as the time delay between
and the position information, an
fault-tolerant control model of the
h can estimate

B. Adaptive Neural Network Estimation

 $B_A(v) = B_{\delta a}(u) - BK_{\delta u}(u)$
 $D_A(v_r)v_r = B_{\delta a}(u) - BK_{\delta a}(u)$
 $S_{\delta a}(u) =\begin{cases} u_{\text{max}} & u > u_{\text{max}} \\ u & u_{\text{min}} < u < u_{\text{min}} \end{cases}$
 $u_{\text{min}} \neq u \cdot u_{\text{min}}$
 $u_{\text{min}} \neq u \cdot u_{\text{min}}$
 $u_{\text{min}} \neq u \cdot u_{\text{min}}$

(2) velocity idenents through a sli *RB_R* (*R*, *i*) $\hat{\theta}$ *RBR* (*R*, *i*) $\hat{\theta}$ *RBR* (*R*) *RBR* (*R*) *RBR* (*R*) *RBR* (*R*) *RBR* (*R*) *RBRR* (*R*) *RBRR r* $P_B(y) = B_{\text{tot}}(x) = B_{\text{tot}}(x) = B_{\text{tot}}(x) = B_{\text{tot}}(x) = -M_{\eta}(y) - \int_{0}^{1} (P_{\text{R}}(y) - \int_{0}^{1} P_{\text{R}}(y) - \int_{0}$ *F* = $J(\eta)$
 F = $J(\eta)$ = $J(\$ *D_A*(v_r) v_r *Bsat*(u) - *BAsat*(u)
 $d(u) =\begin{cases} u_{\text{max}} & u > u_{\text{max}} \\ u & u_{\text{min}} & u < u \leq u_{\text{min}} \end{cases}$ (2) velocity information *a*

dother interference signals, the velocity information *a*

dother interference signals, $Mv + C_{RS}(v)v + g(\eta) + C_A(v, v, v, +$ (1) usually required. However, the to the measurement noise
 $D_A(v, v, v, = Basa(u) - BKsau)$ where velocity information, the velocity information and the position information,
 $(u) = \begin{cases} u_{\text{max}} & u > u_{\text{max}} \\ u$ AUV path tracking control, the velocity information is
usually required. However, due to the measurement noise and
other interference signals, as well as the time delay between
the velocity information and the position inf usually required. However, due to the measurement noise and
other interference signals, as well as the time delay between
the velocity information and the position information, an
observer is designed for fault-tolerant c other interference signals, as well as the time delay between
the velocity information and the position information, an
observer is designed for fault-tolerant control model of the
AUV thrusters of which can estimate the e velocity information and the position information, an
server is designed for fault-tolerant control model of the
JV thrusters of which can estimate the unmeasurable
locity elements through a sliding mode observer.
Adapt *B. Adaptive Neural Network Estimation*
By using the nonlinear identification ability of neural
networks, the unknown force matrix is constructed based on
an adaptive regression neural network. Compared with
feed-forward By using the nonlinear identification ability of neural
networks, the unknown force matrix is constructed based on
an adaptive regression neural network. Compared with
feed-forward neural networks, and it can describe the ion information, an
control model of the
e the unmeasurable
e observer.

n ability of neural
constructed based on
the manufacture of the time
ariables, the physical
6) are detailed in the
1.
as:

 (x, β, γ) (6)
e activ *e* delay between
information, an
ol model of the
e unmeasurable
server.
bility of neural
ructed based on
Compared with
seribe the time
les, the physical
e detailed in the
detailed in the
 (6)
ivation function
 $= 1/(1 + \$

$$
f_o(N) = WQ(\mathbf{x}, \alpha, \beta, \gamma) \tag{6}
$$

<u>ja saaraa ka saaraa saaraa sa</u> are the weighting coefficients. an adaptive regression neural network. Compared with
feed-forward neural networks, and it can describe the time
series information from input to output variables, the physical
meanings of each variable in Equation (6) are is the input vector of the input layer node; α , β , γ and W and *W* reed-rorward neural networks, and it can describe the
series information from input to output variables, the phy
meanings of each variable in Equation (6) are detailed in
literature [19,23-26], as shown in Figure 1.
The n

Through the neural network, the unknown $F(\eta, \eta)$ can b
determined by the optimal network weight value
 $W^*, \alpha^*, \beta^*, \gamma^*$ and given by:
 $F = W^*Q(\zeta, \alpha^*, \beta^*, \gamma^*) + \varepsilon_f$
Where: ε_f is the reconstruction error caused by the

$$
\boldsymbol{F} = \boldsymbol{W}^* \boldsymbol{Q} (\boldsymbol{\zeta}, \boldsymbol{\alpha}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*) + \boldsymbol{\varepsilon}_f \tag{7}
$$

For describing the unava

Fig. 1. Adaptive regression neural networks

or describing the unava

determined by the optimal network weight value

determined by the optimal network weight value
 $W^*, \alpha^*, \beta^*, \gamma^*$ and given b network. Fig. 1. Adaptive regression neural networks

rough the neural network, the unknown $F(\eta, \dot{\eta})$ can be

termined by the optimal network weight value

, $\alpha^, \beta^*, \gamma^*$ and given by:

, $\alpha^, \beta^*, \gamma^*$ and given by:

F = W^* Fig. 1. Adaptive regression neural networks

Through the neural network eight value

determined by the optimal network weight value
 $W^*, \alpha^*, \beta^*, \gamma^*$ and given by:
 $W^*, \alpha^*, \beta^*, \gamma^*$ and given by:
 $F = W^*Q(\zeta, \alpha^*, \beta^*, \gamma^$ here: ε_f is the reconstruction error caused by the quantity

neures in the hidden and semantic layers of the neural

through the state transformat

twork.

(3) can be described as:
 $\dot{\zeta} = A\zeta + \overline{F}(\zeta_1)$,
 $\dot{F}_$ determined by the optimal network weight value
 $W^*, \alpha^*, \beta^*, \gamma^*$ and given by:
 $F = W^*Q(\zeta, \alpha^*, \beta^*, \gamma^*) + \varepsilon_f$ (7) $\zeta_1 = \eta$

Where: ε_f is the reconstruction error caused by the quantity

of neures in the hidden and $W^*Q(\zeta, \alpha^*, \beta^*, \gamma^*) + \varepsilon_f$ (7) $\zeta_1 = \eta$,

astruction error caused by the quantity

in and semantic layers of the neural
 $\overline{\zeta} = [\zeta_1^T$
 $\overline{\zeta} = [\zeta_1^T$
 \therefore Through the state tr

the estimate F, the estimated =*W Q*(*5, a*, *B*, *y*) + ε_f

construction error caused by the quantity

den and semantic layers of the neural

(3) can be described

(3) can be described

(3) can be described
 $\zeta = [\zeta_1]$
 $\hat{F}_1 = \hat{W}Q(x, \hat{\alpha},$

$$
\hat{F}_1 = \hat{W}Q(x, \hat{\alpha}, \hat{\beta}, \hat{\gamma})
$$
\n(8)

value.

$$
\forall \tilde{Q} = Q^* - \hat{Q}, \quad \tilde{W} = W^* - \hat{W}
$$

$$
\tilde{F} = F - \hat{F}_1 = W^* \tilde{Q} + \tilde{W} \hat{Q} + \varepsilon_f
$$
 (9) B

 $\hat{F}_1 = \hat{W}Q(x, \hat{\alpha}, \hat{\beta}, \hat{\gamma})$ (8)

Where \hat{W} , and $\hat{\alpha}, \hat{\beta}, \hat{\gamma}$ are the estimated values of each weight

value.

According to Eq. (7) and Eq. (8), the estimation error of the

unknown elements $F(\eta, \hat{\eta})$ can b

$$
\vec{F}_1 = \vec{W}Q(x, \hat{\alpha}, \hat{\beta}, \hat{\gamma})
$$
\n
$$
\vec{F}_2 = \vec{A}\vec{\zeta} + \vec{F}(\zeta_1, \zeta_2)
$$
\n
$$
\vec{F}_3 = \vec{W}Q(x, \hat{\alpha}, \hat{\beta}, \hat{\gamma})
$$
\n
$$
\vec{F}_4 = \vec{W}Q(x, \hat{\alpha}, \hat{\beta}, \hat{\gamma})
$$
\n(8)\nWhere \vec{W} , and $\hat{\alpha}, \hat{\beta}, \hat{\gamma}$ are the estimated values of each weight value.\n\nAccording to Eq. (7) and Eq. (8), the estimation error of the unknown elements $F(\eta, \eta)$ can be described as:\n
$$
\vec{G} = \begin{bmatrix} \mathbf{I}_3 & 0 \\ -\mathbf{I}_2 & \mathbf{I}_3 \end{bmatrix}, \quad \vec{T}_2 = \text{diag}
$$
\n
$$
\vec{G} = \begin{bmatrix} \mathbf{I}_3 & 0 \\ -\mathbf{I}_2 & \mathbf{I}_3 \end{bmatrix}, \quad \vec{F} = \vec{G}(\zeta_1, \zeta_2)
$$
\n(9)\n\nHowever, $\vec{F} = \vec{F} - \hat{F}_1 = W^* \vec{D} + \vec{W} \vec{D} + \varepsilon_f$ \n
$$
\vec{G} = \begin{bmatrix} 0 \\ 0 \\ -\zeta_2 \end{bmatrix}, \quad \zeta = T\overline{\zeta}, \quad a_i \in \mathbb{R}
$$
\n(15), the sliding constructed and given by:\n\nBy conducting the Taylor expansion on the variable \vec{Q} ,
\nthen:\n
$$
\vec{Q} = \begin{bmatrix} \frac{\partial Q}{\partial(\alpha \zeta)} \end{bmatrix}^T \vec{\alpha} \zeta + \begin{bmatrix} \frac{\partial Q}{\partial(\beta (N-1))} \end{bmatrix}^T \vec{\beta} Q(N-1) +
$$
\n
$$
\begin{bmatrix} \frac{\partial Q}{\partial(\gamma F(N-1))} \end{bmatrix}^T \vec{\gamma} F(N-1) + O_n
$$
\n(10)\nWhere: \vec{P} is the inverse matrix matrix matrix P , and the other variables a
\nsubstituted Eq. (10) into Eq. (9), the higher-order term and
\nthe reconstruction error can be defined as:\n
$$
\
$$

$$
\Psi = \tilde{W}\tilde{O} + W^*O_{\alpha} + \varepsilon_{\epsilon} \tag{11}
$$

Applied Mathematics
Based on the adaptive methods, the estimation value can
iven by $\hat{\Psi}$ in Eq. (11). Combine the output of the
ssion neural network with the adaptive estimation value
the estimation of the unknown pa **al of Applied Mathematics**
Based on the adaptive methods, the estimative given by $\hat{\Psi}$ in Eq. (11). Combine the our
regression neural network with the adaptive estinct to form the estimation of the unknown part F is
i **In Eq.** (11). Combine the output of the enducation value can
in Eq. (11). Combine the output of the
network with the adaptive estimation value
tion of the unknown part F in the model
extends, through adaptive neural netw **regression** the adaptive methods, the estimation value can
be given by $\hat{\Psi}$ in Eq. (11). Combine the output of the
regression neural network with the adaptive estimation value
to form the estimation of the unknown par **the extra form 10** and the estimation of Applied Mathematics

Based on the adaptive methods, the estimation value can

be given by $\hat{\Psi}$ in Eq. (11). Combine the output of the

regression neural network with the adapti **increase 3**
 in of Applied Mathematics

Based on the adaptive methods, the estimation value can

be given by $\hat{\Psi}$ in Eq. (11). Combine the output of the

regression neural network with the adaptive estimation valu **Example 10 In the model can be given** by $\hat{\Psi}$ in Eq. (11). Combine the output of the regression neural network with the adaptive estimation value to form the estimation of the unknown part F in the model inverse. Th Based on the adaptive methods, the estimation value can
given by $\hat{\Psi}$ in Eq. (11). Combine the output of the
gression neural network with the adaptive estimation value
form the estimation of the unknown part F in the m Based on the adaptive methods, the estimation
be given by $\hat{\Psi}$ in Eq. (11). Combine the our
regression neural network with the adaptive estint
to form the estimation of the unknown part F is
inverse. Therefore, through the estimation value can
mbine the output of the
daptive estimation value
own part F in the model
ve neural networks, the
can be represented as
 $(\hat{\beta}, \hat{y}) + \hat{\Psi}$ (12)
error can satisfy the
 $\vec{\xi}_2 - \hat{\vec{\xi}}_2$ (13) **EXECUTE:**

Five methods, the estimation value can

q. (11). Combine the output of the

ork with the adaptive estimation value

of the unknown part F in the model

ough adaptive neural networks, the

n the model can be re to form the estimation of the this
theorem part F in the model
inverse. Therefore, through adaptive neural networks, the
unknown part $F(\eta, \dot{\eta})$ in the model can be represented as
 $\hat{F} = \hat{W} \Theta(\zeta, \hat{\alpha}, \hat{\beta}, \hat{\gamma}) + \hat{\Psi}$

$$
\hat{\mathbf{F}} = \hat{W}\Theta(\zeta, \hat{\alpha}, \hat{\beta}, \hat{\gamma}) + \hat{\Psi}
$$
 (12)

$$
\|\boldsymbol{F} - \hat{\boldsymbol{F}}\| \le \sigma \|\bar{\zeta}_2 - \hat{\zeta}_2\| \tag{13}
$$

C. Sliding Mode Observer

For describing the unavaila

adaptive neural network slidir

evaluate the speed status of

vork, the unknown $F(\eta, \dot{\eta})$ can be

the thruster.

In all network weight value

by:
 $\int F^*Q(\zeta, \alpha^*,$ *C.* Sliding Mode Observer
 C. Sliding Mode Observer

For describing the unavai $\hat{F} = \hat{W} \Theta(\zeta, \hat{\alpha}, \hat{\beta}, \hat{\gamma}) + \hat{\Psi}$ (12)

Assuming that the estimation error can satisfy the

llowing conditions:
 $||F - \hat{F}|| \le \sigma ||\bar{\zeta}_2 - \hat{\zeta}_2||$ (13)

here: σ is the normal number.

Sliding *Mode Observer*

For $\hat{F} = \hat{W} \Theta(\zeta, \hat{\alpha}, \hat{\beta}, \hat{\gamma}) + \hat{\Psi}$ (12)

Assuming that the estimation error can satisfy the

following conditions:
 $\left\|F - \hat{F}\right\| \le \sigma \left\|\bar{\zeta}_2 - \hat{\zeta}_2\right\|$ (13)

Where: σ is the normal number.
 C. Sliding Mod Assuming that the estimation error can satisfy the

following conditions:
 $||\mathbf{F} - \hat{\mathbf{F}}|| \le \sigma ||\vec{\zeta}_2 - \hat{\vec{\zeta}}_2||$ (13)

Where: σ is the normal number.

C. Sliding Mode Observer

For describing the unavailable velo Assuming that the estimation error can satisfy the
following conditions:
 $\|\mathbf{F} - \hat{\mathbf{F}}\| \le \sigma \|\overline{\zeta}_2 - \hat{\zeta}_2\|$ (13)
Where: σ is the normal number.
C. Sliding Mode Observer
For describing the unavailable velocity Following conditions:
 $||\mathbf{F} - \hat{\mathbf{F}}|| \le \sigma ||\bar{\zeta}_2 - \hat{\zeta}_2||$

Where: σ is the normal number.

C. Sliding Mode Observer

For describing the unavailable velocit

adaptive neural network sliding mode of

evaluate the s $||\mathbf{F} - \hat{\mathbf{F}}|| \le \sigma ||\bar{\zeta}_2 - \hat{\zeta}_2||$ (13)

here: σ is the normal number.

Sliding *Mode Observer*

For describing the unavailable velocity information, an

uptive neural network sliding mode observer is used to

ul Where: σ is the normal number.

C. Sliding Mode Observer

C. Sliding Mode Observer

For describing the unavailable velocity inform

adaptive neural network sliding mode observer is

evaluate the speed status of the AUV $||\mathbf{F} - \hat{\mathbf{F}}|| \le \sigma ||\langle \overline{\zeta}_2 - \overline{\zeta}_2 ||$ (13)

he normal number.

ode Observer

ing the unavailable velocity information, an

al network sliding mode observer is used to

speed status of the AUV, and the obtained

var Figure 1.1 The unavailable velocity information, an

work sliding mode observer is used to

status of the AUV, and the obtained

bles could realize fault-tolerant control of

mediate variables for the unknown model
 $\overline{\$ by point in the unavailable velocity information, and
twork sliding mode observer is used to
1 status of the AUV, and the obtained
ables could realize fault-tolerant control of
mediate variables for the unknown model
 \overline $\hat{F} = \hat{W}\Theta(\zeta, \hat{\alpha}, \hat{\beta}, \hat{\gamma}) + \hat{\Psi}$ (12)

aat the estimation error can satisfy the

tions:
 $||F - \hat{F}|| \le \sigma ||\bar{\zeta}_2 - \hat{\zeta}_2||$ (13)

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 $||\mathbf{F} - \hat{\mathbf{F}}|| \le \sigma ||\bar{\zeta}_2 - \hat{\zeta}_2||$ (13)

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ditions:
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bing the unavailable velocity information, an
ral network sliding mode observer is use For describing the unavailable velocity information, an
aptive neural network sliding mode observer is used to
aluate the speed status of the AUV, and the obtained
locity status variables could realize fault-tolerant cont adaptive neural network sliding mode observer is used t
evaluate the speed status of the AUV, and the obtaine
velocity status variables could realize fault-tolerant control of
the thruster.
Firstly, the intermediate varia formal number.
 Observer

the unavailable velocity information, an

network sliding mode observer is used to

dd status of the AUV, and the obtained

raibles could realize fault-tolerant control of

ermediate variable

$$
\zeta_1 = \eta, \quad \overline{\zeta}_2 = \dot{\eta}
$$
\n
$$
\overline{\zeta} = \begin{bmatrix} \zeta_1^T & \overline{\zeta}_2^T \end{bmatrix}^T, \quad \zeta = \begin{bmatrix} \zeta_1^T & \zeta_2^T \end{bmatrix}^T
$$
\n(14)

$$
\dot{\zeta} = A\zeta + \overline{F}(\zeta_1, \zeta_2) + \overline{G}u \tag{15}
$$

$$
\begin{array}{ll}\n\text{We have} & \mathbf{F} - \hat{\mathbf{F}} \Big[\pm \sigma \Big| \vec{\xi}_2 - \hat{\vec{\xi}_2} \Big] & (13) \\
\text{We have} & \mathbf{F} - \hat{\mathbf{F}} \Big[\pm \sigma \Big| \vec{\xi}_2 - \hat{\vec{\xi}_2} \Big] & (13) \\
\text{where: } \sigma \text{ is the normal number.} \\
\text{Lattice regression neural networks & adaptive neural network. Stiding Mode } \text{Observe: } \sigma \text{ is the normal number.} \\
\text{Equation: } \mathbf{F} \text{ is the normal number.} \\
\text{Equation: } \mathbf{F} \text{ is the normal number.} \\
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\text{Equation: } \mathbf{F} \text{ is the normal number.} \\
\text{Equation: } \mathbf{F} \text{ is the normal number.} \\
\text{Equation: }
$$

$$
\vec{G} = \begin{bmatrix} 0 \\ G(\zeta_1) \end{bmatrix}, \ \zeta = T\vec{\zeta}, \ a_i \in R^+
$$

\nBased on Eq. (15), the sliding mode observer can be
\nconstructed and given by:
\n
$$
\dot{\hat{\zeta}}_1 = T_2 \hat{\zeta}_1 + \hat{\zeta}_2 - L_1 A + \bar{F}_1 \varsigma_1
$$
\n
$$
\dot{\hat{\zeta}}_2 = -T_2^2 \hat{\zeta}_1 - T_2 \hat{\zeta}_2 + F(\zeta_1, \hat{\zeta}_2) + (17)
$$
\n
$$
G(\zeta_1)u - L_2 A + \bar{F}_3 \varsigma_1
$$
\nWhere: \vec{P} is the inverse matrix of the positive-definite
\nmatrix P , and the other variables are:

Where: \overline{P} is the inverse matrix of the positive-definite

Volume 54, Issue 12, December 2024, Pages 2816-2823

1AENG International Journal of Applied Mathematics
\n
$$
L_1 = \begin{bmatrix} I_{11} & 0 & 0 \ 0 & 0 & 0 \end{bmatrix}, L_2 = \begin{bmatrix} I_{21} & 0 & 0 \ 0 & 0 & 0 \end{bmatrix}
$$
\n
$$
\overline{P} = \begin{bmatrix} \overline{P_1} & \overline{P_2} \\ \overline{P_3} & \overline{P_4} \end{bmatrix}, A = \hat{C}_1 - \hat{C}_1
$$
\n
$$
\overline{P} = \begin{bmatrix} -\frac{\sqrt{P_1}}{P_2} & \overline{P_2} \\ \overline{P_3} & \overline{P_3} \end{bmatrix}, A = \hat{C}_1 - \hat{C}_1
$$
\n
$$
\overline{P} = \begin{bmatrix} -\frac{\sqrt{P_1}}{P_2} & \overline{P_3} \\ 0 & 0 & |A| \end{bmatrix} = 0
$$
\n
$$
\begin{aligned}\n\overline{P} = \begin{bmatrix} -\frac{\sqrt{P_1}}{P_3} & \overline{P_2} \\ 0 & 0 & |A| \end{bmatrix} = 0 \\
\overline{P} = \begin{bmatrix} -\frac{\sqrt{P_1}}{P_3} & \overline{P_3} \\ 0 & 0 & |A| \end{bmatrix} = 0\n\end{aligned}
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\n
$$
\begin{aligned}\n\overline{P} = \begin{bmatrix} -\frac{\sqrt{P_1}}{P_3} & \overline{P_3} \\ 0 & 0 & |A| \end{bmatrix} = 0\n\end{aligned}
$$
\n
$$
\begin{aligned}\n\overline{P} = \begin{bmatrix} \overline{P_1} & \overline{P_2} \\ \overline{P_3} & \overline{P_4} \end{bmatrix}, A = \hat{C}_1 - \hat{C}_1 - \hat{C}_1 - \hat{C}_1 = 0\n\end{aligned}
$$
\n
$$
\begin{aligned}\n\overline{P} = \begin{bmatrix} \overline{P_1} & \overline{P_2} \\ 0 & 0 & |A| \end{bmatrix} = 0\n\end{aligned}
$$
\n
$$
\begin{aligned}\n\overline{P} = \begin{bmatrix} \overline{P_1} & \overline{P_2} \\ 0 & 0 & |A| \end{b
$$

$$
\zeta_1 = \begin{cases}\n\cdot & \text{if } \|\mathbf{A}\| = 0 \\
0 & \|\mathbf{A}\| = 0\n\end{cases}
$$
\nWhen, the equivalent variable is defined as $\Delta_2 = \hat{\zeta}_2 - \zeta_2$, Eq. *D. Model Invers*
\n2) can be obtained:
\n
$$
\Delta_1 = (T_2 - L_1)\Delta_1 + \Delta_2 + P_1^{-1}\zeta_1
$$
\n
$$
\Delta_2 = -(T_2^2 + L_2)\Delta_1 - T_2\Delta_2 + \text{if } \mathbf{A} = \begin{cases}\n\hat{r}(\zeta_1, \hat{\zeta}_2) - F(\zeta_1, \bar{\zeta}_2) + P_3^{-1}\zeta_1 \\
\vdots \\
\Delta_p = \begin{bmatrix}\nT_2 - L_1 & I_3 \\
-T_2^{-1} + L_2 & T_3\n\end{bmatrix}\n\end{cases}
$$
\n
$$
\begin{cases}\n\text{Meanwhile, a matrix variable is defined as:} \\
A_o = \begin{bmatrix}\nT_2 - L_1 & I_3 \\
-T_2^{-2} + L_2 & T_2\n\end{bmatrix}\n\end{cases}
$$
\nWhen $\hat{\zeta}_1$ is the

$$
\rho \|P\|_{\text{||A||}}^{\text{||A||}} \|A_{\parallel} \| \neq 0
$$
\n
$$
M = [M_1 \ M_2]^1 =
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M = [M_1 \ M_2]^1 =
$$
\nWe have:\n
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M_1, M_2
$$
\n
$$
M_1 = [M_1 \ M_2]^1 =
$$
\nWhere:\n
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M_1, M_2
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M_2
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M_3
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M_4
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M_1 = [M_1 \ M_2]^1 =
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\nWhere:\n
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M_1, M_2
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M_1 = [M_1 \ M_2]^1 =
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M_1 = [M_1 \ M_2]^1 =
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\nWhere:\n
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M_1 = [M_1 \ M_2]^1 =
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M_8
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$$
M_9
$$
\n<

Where: M_1, M_2 are also the diagona

Then, the equivalent variable is defined as $\Delta_2 = \xi_2 - \xi_2$, Eq. D. Model Inverse Control

(Different from the traditional

ontrol [28, 29], this section utilizes
 $\lambda_2 = (T_2 - L_1)\lambda_$ A_0 can turn into the Hurwitz matrix [27]. To any positive- $\Delta_2 = -(T_2^2 + L_2)\Delta_1 - T_2\Delta_2 +$ (19) information is not available
 $\hat{F}(\zeta_1, \hat{\zeta}_2) - F(\zeta_1, \bar{\zeta}_2) + P_3^{-1}\zeta_1$ First the chosen sliding

feanwhile, a matrix variable is defined as:
 $A_o = \begin{bmatrix} T_2 - L_1 & I_3 \\ - (T_2^2 + L_2) &$ $\hat{F}(\zeta_1, \zeta_2) - F(\zeta_1, \zeta_2) + P_2$

Meanwhile, a matrix variable is defined as:
 $A_o = \begin{bmatrix} T_2 - L_1 & I_3 \\ -(T_2^2 + L_2) & -T_2 \end{bmatrix}$
 $\varphi = diag\{0_3 \ \varepsilon_o \sigma^2 I_3\}, T_2 < L_1, \ \varepsilon_o$

Through designing the diagonal matrix L_1, L_2 $\hat{F}(\zeta_1, \overline{\zeta_2}) - F(\zeta_1, \overline{\zeta_2}) + P_3^{-1} \zeta_1$

trix variable is defined as:
 $s = \hat{e} +$
 $T_2 - L_1$ I_3
 $-(T_2^2 + L_2) - T_2$
 $(s = \sqrt{\alpha} \cos \theta)$
 $\hat{g} = \frac{1}{2}$ (20)
 $\hat{g} = \frac{1}{2}$ (20)
 $\hat{g} = \frac{1}{2}$ (20)
 $\hat{g} = \$ Meanwhile, a matrix variable is defined as:
 $A_o = \begin{bmatrix} T_2 - L_1 & I_3 \\ -(T_2^2 + L_2) & -T_2 \end{bmatrix}$
 $\varphi = diag\{0_3 \ \varepsilon_o \sigma^2 I_3\}, T_2 < L_1, \ \varepsilon_o \in R$

Through designing the diagonal matrix L_1, L_2 , th
 A_0 can turn into the Hurwit Fix variable is defined as:
 $T_2 - L_1$ I_3
 $-(T_2^2 + L_2) - T_2$
 T_3
 $T_4 = (T_2^2 + L_2) - T_3$
 $T_5 = (T_2^2 + L_3)$, $T_2 < L_1$, $\varepsilon_o \in R^+$
 $T_5 = (T_1^2, T_2^2, T_3^2)$, $T_6 = (T_1^2, T_3^2, T_4^2)$
 $T_7 = (T_1^2, T_2^2, T_3^2)$
 T $\varphi = diag\{0_3 \ \varepsilon_0 \sigma^2 \mathbf{I}_3\}$, $\mathbf{T}_2 < \mathbf{L}_1$, $\varepsilon_0 \in \mathbb{R}^+$ (17), the model can be given by

Through designing the diagonal matrix \mathbf{L}_1 , \mathbf{L}_2 , the variable
 $\hat{\mathbf{H}} = \hat{\xi}_2 + \hat{\xi}_3$

can turn into the $\psi = diag\{0_3 \quad \varepsilon_0 \quad 1_3\}, \quad 1_2 < L_1, \quad \varepsilon_0 \in R$

Through designing the diagonal matrix L_1, L_2 , the variable A_0 can turn into the Hurwitz matrix [27]. To any positive

definite matrix Q_0 , existing a positive-def e diagonal matrix L_1, L_2 , the variable

urwitz matrix [27]. To any positive-

The virtual control

isting a positive-definite symmetric
 $A_o^T P + \frac{1}{\varepsilon_o} PP + \varphi = -Q_o$ (21)

Where: k is also the

Theorem. If the

environ Where: Λ is the norr
 $\left[-(T_2^2 + L_2) - T_2\right]$ (20) $\hat{\eta}$ can be obtained by
 diag $\left[0_3 \ \varepsilon_0 \sigma^2 I_3\right]$, $T_2 < L_1$, $\varepsilon_0 \in R^+$ (17), the model can be

the Hurwitz matrix [27]. To any positive-

the Hurwitz ma igning the diagonal matrix L_1, L_2 , the variable
to the Hurwitz matrix [27]. To any positive-
 Q_0 , existing a positive-definite symmetric
lize
 $PA_0 + A_0^T P + \frac{1}{\varepsilon_0} PP + \varphi = -Q_0$ (21)
or
 $P A_0 + A_0^T P + \frac{1}{\varepsilon_0} PP + \varphi$ lesigning the diagonal matrix L_1, L_2 , the variable

into the Hurwitz matrix [27]. To any positive-

rix Q_0 , existing a positive-definite symmetric

realize
 $PA_0 + A_0^T P + \frac{1}{\varepsilon_0} PP + \varphi = -Q_0$ (21) Where: k is also
 $A_o = \begin{bmatrix} r_2 - r_1 & r_3 \\ -(r_2^2 + L_2) & -r_2 \end{bmatrix}$ (20) $\hat{\vec{\eta}}$ can
 $\varphi = diag\{0, \varepsilon_o \sigma^2 I_3\}, T_2 < L_1, \varepsilon_o \in R^+$ (17),

signing the diagonal matrix I_1, L_2 , the variable

into the Hurwitz matrix [27]. To any positive-

x Let $\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & \cos^2 2 \\ 0 & 0 & 0$ diagonal matrix L_1, L_2 , the variable
witz matrix [27]. To any positive-
ing a positive-definite symmetric
 ${}^{T}P + \frac{1}{\varepsilon_o}PP + \varphi = -Q_o$ (21) Where: k i
Theorem
nov function and constructing the fault-toleran
estimating
 $A_o = \begin{bmatrix} r_2 - r_1 & r_3 \\ -(r_2^2 + L_2) & -r_2 \end{bmatrix}$ (20)
 $\varphi = diag\{0_3 \ \varepsilon_o \sigma^2 I_3\}, T_2 < L_1, \ \varepsilon_o \in R^+$

designing the diagonal matrix L_1, L_2 , the variable

i into the Hurwitz matrix [27]. To any positive-

rix Q_o , existi (20)
 $\varphi = diag\{0_3 \ \varepsilon_o \sigma^2 1_3\}, T_2 < L_1, \ \varepsilon_o \in R^+$ (17), the model can be given

designing the diagonal matrix L_1, L_2 , the variable

into the Hurwitz matrix [27]. To any positive-

realize
 $PA_o + A_o^T P + \frac{1}{\varepsilon_o} PP + \var$ be diagonal matrix L_1, L_2 , the variable

lurwitz matrix [27]. To any positive-

lurwitz matrix [27]. To any positive-

disting a positive-definite symmetric
 $A_o^T P + \frac{1}{\varepsilon_o} PP + \varphi = -Q_o$ (21) Where: k is also the

more esigning the diagonal matrix *L*₁, *L*₂, the variable

into the Hurwitz matrix [27]. To any positive-
 $\mathbf{z} \mathbf{A}_0$, existing a positive-definite symmetric

calize
 $\mathbf{P}A_0 + A_0$ ^T $\mathbf{P} + \frac{1}{\varepsilon_0}$ $\mathbf{P} \math$

$$
PA_o + A_o^T P + \frac{1}{\varepsilon_o} PP + \varphi = -Q_o \qquad (21) \qquad \text{Wl}
$$

Prove.

$$
V_1 = \Delta^{\mathrm{T}} P \Delta, \quad \Delta = \begin{bmatrix} \Delta_1^{\mathrm{T}} & \Delta_2^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}
$$
 (22)

*A*₀ can turn into the Hurwitz matrix [27]. To any positive-
definite matrix
$$
Q_0
$$
, existing a positive-definite symmetric
matrix *P A*₀ + *A*₀^T*P* + $\frac{1}{\varepsilon_0}$ *P P* + $\varphi = -Q_0$ (21)
Prove.
Prove.
By reselecting a Lyapunov function and constructing the
integration variable as:

$$
V_1 = A^T P A
$$
, $A = \begin{bmatrix} A^T & A^T \end{bmatrix}^T$ (22)

$$
V_1 = A^T P A
$$
, $A = \begin{bmatrix} A^T & A^T \end{bmatrix}^T$ (22)
observer, the impact of
independent *Q*₀ is the *Q*₀ is the *Q*₁ is the *Q*₁ and *Q*₂ is the *Q*₂ is the *Q*₁ and *Q*₂ is the *Q*₂ is the *Q*₁ and *Q*₂ is the *Q*₂ and *Q*₂ is the *Q*₁ and *Q*₂ is the *Q*₁ and *Q*₂ is the *Q*₂ and *Q*₂ is the *Q*₁ and *Q*₂ is the *Q*₁ and *Q*₂ is the *Q*₂ and *Q*₂ is the *Q*₂ and *Q*₂ is the *Q*₂

$$
F(t) \text{ relative}
$$
\n
$$
P_0 + A_0^T P + \frac{1}{\varepsilon_0} PP + \varphi = -Q_0
$$
\n
$$
P_1 + A_0^T P + \frac{1}{\varepsilon_0} PP + \varphi = -Q_0
$$
\n
$$
P_2 = 0.55^T s + 0.5tr(\tilde{W}λW - 0.504) = 0.5F(s) + 0.5tr(\tilde{W}λW - 0.544) = 0.5F(s) + 0.5F(s) +
$$

Error A is able to converge to zero, which means that the

Denoting $\hat{k}_1 = -\lambda_a Q_a \hat{W}^T s \zeta^T$, $\hat{A} = -\lambda_a Q_a \hat{W}^T s \zeta^T$, $\hat{A} = -\lambda_a Q_a \hat{W}^T s \zeta^T$, $\hat{B} = -\lambda_a Q_a \hat{W}^T s \zeta^T$, $\hat{B} = -\lambda_a Q_a \hat{W}^T s \zeta^T$, $\hat{B} = -$ Combining with the Young's inequality and the assumed

condition, Eq. (23) can be converted to:
 $\forall : 2X^T Y \leq \frac{1}{c} X^T X + cY^T Y$ By selecting the Lyapun
 $\forall i \leq A^T (A_o^T P + PA_o) A + \frac{1}{c_o} A^T PP A +$ (24)
 $\epsilon_o \sigma^2 \Delta_2^T \Delta_2 - 2\rho$ Combining with the Young's inequality and the assumed

condition, Eq. (23) can be converted to:
 $\forall: 2X^T Y \leq \frac{1}{\varepsilon} X^T X + \varepsilon Y^T Y$ By selecting the Lyapuno

estimation can be given by:
 $\dot{V}_1 \leq \Delta^T (A_o^T P + PA_o) \Delta + \frac{1$ condition, Eq. (23) can be converted to:
 \forall : $2X^T Y \leq \frac{1}{\varepsilon} X^T X + \varepsilon Y^T Y$
 $\dot{V}_1 \leq \Delta^T (A_o^T P + PA_o) \Delta + \frac{1}{\varepsilon_o} \Delta^T P$
 $\varepsilon_o \sigma^2 \Delta_2^T \Delta_2 - 2\rho ||P|| ||\Delta|| \leq \Delta^T$

In viewpoint of Eq. (24), it can be know

error Δ

equivalent to solve a feasible element $P > 0$ to realize

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\n
$$
P, L_1, L_2
$$
 can be determined. The solution process is
\nequivalent to solve a feasible element $P > 0$ to realize
\n
$$
\begin{bmatrix}\nPA_0 + A_0^T P - MC - C^T M^T + \varphi & P \\
P & -\varepsilon_0 I_6\n\end{bmatrix} < 0
$$
\n
$$
M = [M_1 \quad M_2]^T = P \begin{bmatrix} L_1^T & L_2^T \end{bmatrix}^T, C = [I_3 \quad 0_3]
$$
\nWhere: M_1, M_2 are also the diagonal matrix.
\n, Eq. *D. Model Inverse Control*
\nDifferent from the traditional model-based inversion
\ncontrol [28, 29], this section utilizes the adaptive regression
\nneural network and sliding mode observer mentioned above

national Journal of Applied Mathematics
 *P.L.***,** *L***₂ can be determined. The solution equivalent to solve a feasible element** $P > 0$ **to \begin{bmatrix} P A_0 + A_0^T P - M C - C^T M^T + \varphi & P \\ P & -\varepsilon_0 & M = [M_1 \ M_2]^T = P \begin{bmatrix} L_1^T & L_2^T \end{bmatrix** information is not available for AUV thrusters. *M* = $[M_1 \t M_2]^T$ = $P \begin{bmatrix} L_1^T \\ L_2^T \end{bmatrix}$

ined as $\Delta_2 = \hat{\xi}_2 - \xi_2$, Eq. *D. Model Inverse Control*

Different from the tradition

control [28, 29], this section utili

neural network and sliding mode

to achieve *L₁, L₂* can be determined. The solution process is
uivalent to solve a feasible element $P > 0$ to realize
 $\begin{bmatrix} P A_0 + A_0^T P - MC - C^T M^T + \varphi & P \\ P & -\varepsilon_0 I_6 \end{bmatrix} < 0$
 $M = [M_1 \ M_2]^T = P \begin{bmatrix} L_1^T & L_2^T \end{bmatrix}^T, C = [I_3 \ 0_3]$ equivalent to solve a feasible element $P > 0$ to realize
 $\begin{bmatrix} P A_0 + A_0^T P - MC - C^T M^T + \varphi & P \\ P & -\varepsilon_0 I_6 \end{bmatrix} < 0$
 $M = [M_1 \ M_2]^T = P \begin{bmatrix} L_1^T & L_2^T \end{bmatrix}^T, C = [I_3 \ 0_3]$

Where: M_1, M_2 are also the diagonal matrix.

D $\begin{bmatrix} P A_0 + A_0^T P - M C - C^T M^T + \varphi & P \\ P & -\varepsilon_0 I_6 \end{bmatrix} < 0$ (25)
 $M = [M_1 \quad M_2]^T = P \Big[L_1^T \quad L_2^T \Big]^T, C = [I_3 \quad 0_3]$

Where: M_1, M_2 are also the diagonal matrix.

D. Model Inverse Control

Different from the traditional $\begin{bmatrix} P A_0 + A_0^T P - MC - C^T M^T + \varphi & P \\ P & -\varepsilon_0 I_6 \end{bmatrix} < 0$ (25)
 $M = [M_1 \quad M_2]^T = P \Big[L_1^T \quad L_2^T \Big]^T, C = [I_3 \quad 0_3]$

Where: M_1, M_2 are also the diagonal matrix.

D. *Model Inverse Control*

Different from the traditional $\begin{bmatrix} P A_0 + A_0 \cdot P - MC - C \cdot M^+ + \varphi & P \\ P & -\varepsilon_0 I_6 \end{bmatrix} < 0$ (25)
 $M = [M_1 \quad M_2]^T = P \Big[L_1^T \quad L_2^T \Big]^T, C = [I_3 \quad 0_3]$

Where: M_1, M_2 are also the diagonal matrix.

D. *Model Inverse Control*

Different from the traditional $\mathbf{L}_1, \mathbf{L}_2$ can be determined. The solution process is
uivalent to solve a feasible element $P > 0$ to realize
 $\begin{bmatrix} P A_0 + A_0^T P - M C - C^T M^T + \varphi & P \\ P & -\varepsilon_0 \mathbf{I}_6 \end{bmatrix} < 0$
 $M = [M_1 \quad M_2]^T = P \begin{bmatrix} L_1^T & L_2^T \end{bmatrix}^T, C$ Where: M_1, M_2 are also the diagonal matrix.

D. Model Inverse Control

Different from the traditional model-based inversion

control [28, 29], this section utilizes the adaptive regression

neural network and sliding m $\begin{aligned}\n &\text{if } \pm \varphi \quad P \ -\varepsilon_0 \mathbf{I}_6 \end{aligned} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} < 0$ (25)

 $\mathbf{L}_2^T \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$

al matrix.

model-based inversion

set adaptive regression

bserver mentioned above

of when the velocity

V *D. Model Inverse Control*

Different from the traditional model-based inversion

control [28, 29], this section utilizes the adaptive regression

neural network and sliding mode observer mentioned above

to achieve fault Different from the traditional model-based inversion
control [28, 29], this section utilizes the adaptive regression
neural network and sliding mode observer mentioned above
to achieve fault-tolerant control when the velo whilizes the adaptive regression
utilizes the adaptive regression
ode observer mentioned above
control when the velocity
or AUV thrusters.
face is given by:
 $+\Lambda^2 \int e dt$ (26)
nber, $e = \eta_R - \eta$, $\hat{e} = \dot{\eta}_R - \dot{\eta}$, and
ing **Example 1** *n***₂** *n***₂ ***n***₂** *n***₂ ***n***₂** *n***₂** *n***₂ ***n***₂** *n***₂ ***n***₂** *n***₂** *n***₂ ***n***₂** *n***₂** *n***₂** *n***₂** *n***₂** *n***₂** *n***₂** *n***₂ ***n n***₂** *n n n* the traditional model-based inversion
is section utilizes the adaptive regression
sliding mode observer mentioned above
tolerant control when the velocity
vailable for AUV thrusters.
liding surface is given by:
 $= \hat{e} + 2$

$$
s = \hat{\dot{e}} + 2\Lambda e + \Lambda^2 \int e \, \mathrm{d}t \tag{26}
$$

 (17) , the model can be given by: η can be obtained by the sliding mode observer given in Eq. Where: Λ is the normal number, $e = \eta_R - \eta \hat{e} = \dot{\eta}_R - \hat{\eta}$, and formation is not available for AUV thrusters.

First the chosen sliding surface is given by:
 $s = \hat{e} + 2\Lambda e + \Lambda^2 \int e dt$ (26)

here: Λ is the normal number, $e = \eta_R - \eta, \hat{e} = \hat{\eta}_R - \hat{\eta}$, and

can be obtained by the slid Where: *A* is the normal number, $e = \eta_R - \eta$, $\hat{e} = \dot{\eta}_R - \hat{\eta}$, and
 $\hat{\eta}$ can be obtained by the sliding mode observer given in Eq.

(17), the model can be given by:
 $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

The virtual con

$$
\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1 \tag{27}
$$

$$
\ddot{\eta}_{cmd} = \ddot{\eta}_R + \Lambda^2 e + 2\Lambda \dot{e} + k s \tag{28}
$$

Theorem. If the AUV dynamic model in a current environment can be given by Eq. (1) and (3), the proposed $\dot{A} = (T_2 - L_1)A + A_2 + P_1^{-1}S_1$ neural network and sliding mode c
 $\dot{A}_2 = -(T_2^2 + L_2)A - T_2A_2 +$ (19) information is not available for AU
 $\dot{F}(\zeta_1, \hat{\zeta}_2) - F(\zeta_1, \bar{\zeta}_2) + P_3^{-1}S_1$ First the chosen sliding surface faults on path tracking control can be compensated, which inte symmetric

(21) Where: k is also the norma

Theorem. If the AUV

environment can be given

onstructing the

fault-tolerant control model

estimating the AUV veloci

observer, the impact of cu

(22) ensures the AUV po $\varphi = diag\{\theta_3 \ \ \epsilon_o \sigma^{-1} \mathbf{1}_3\}, \ \ T_2 < \mathbf{1}_1, \ \epsilon_o \in \mathbb{R}\}$

A designing the diagonal matrix $\mathbf{I}_1, \mathbf{I}_2$, the variable
 $\hat{\mathbf{I}} = \hat{\epsilon}_2 + T_2 \hat{\epsilon}_1$

and into the Hurwitz matrix [27]. To any positive-
 $\hat{\mathbf{I}} = \hat{\$ $P = \text{diag} \left[0, \frac{1}{2} \sum_{i=1}^{n} \frac{1}{2} \sum_{j=1}^{n} \frac{$ interior and constructing the fault-tolerant control model can be

estimating the AUV velocity sta

observer, the impact of current

faults on path tracking control can be
 $\begin{bmatrix} 4^T & 4^T \end{bmatrix}^T$ (22) ensures the AUV p mere: A is the normal number, $e = \eta_R - \eta$, $e = \eta_R - \eta$, and
can be obtained by the sliding mode observer given in Eq.
7), the model can be given by:
 $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)
The virtual control instructions can be gi $\hat{\eta}$ can be obtained by the sliding mode observer given in Eq.

(17), the model can be given by:
 $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

The virtual control instructions can be given by:
 $\eta_{cmd} = \eta_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

Whe (17), the model can be given by:
 $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

The virtual control instructions can be given by:
 $\hat{\eta}_{cmd} = \hat{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

Where: k is also the normal number.
 Theorem. If the AUV dynami $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

The virtual control instructions can be given by:
 $\hat{\eta}_{cmd} = \hat{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

Where: k is also the normal number.
 Theorem. If the AUV dynamic model in a current

environment $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

The virtual control instructions can be given by:
 $\vec{\eta}_{cmd} = \vec{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

Where: k is also the normal number.
 Theorem. If the AUV dynamic model in a current

environment **Faulti Altertian** intertions can be given by:
 Faulti Control instructions can be given by:
 Faulti Alternal intertions can be given ky (28)

Where: k is also the normal number.
 Theorem. If the AUV dynamic model i The virtual control instructions can be given by:
 $\vec{\eta}_{cmd} = \vec{\eta}_R + \Lambda^2 e + 2\Lambda \dot{e} + k s$ (28)

Where: *k* is also the normal number.
 Theorem. If the AUV dynamic model in a current

environment can be given by Eq. (1) and $-q_R + N e + 2\pi e + 8S$ (26)

rmal number.

UV dynamic model in a current

en by Eq. (1) and (3), the proposed

del can be expressed as Eq. (29). By

locity state through a sliding mode

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cont an be given by:
 $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

atrol instructions can be given by:
 $\vec{\eta}_{cmd} = \vec{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

the normal number.

the AUV dynamic model in a current

be given by Eq. (1) and (3), the propose $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

1 control instructions can be given by:
 $\vec{\eta}_{cmd} = \vec{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

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If the AUV dynamic model in a current

can be given by Eq. (1) and (3), the proposed $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

structions can be given by:
 $= \hat{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

rmal number.

IV dynamic model in a current

en by Eq. (1) and (3), the proposed

del can be expressed as Eq. (29). By

locity s a control instructions can be given by:
 $\vec{\eta}_{cmd} = \vec{\eta}_R + \Lambda^2 e + 2\Lambda \dot{e} + k s$ (28)

also the normal number.

If the AUV dynamic model in a current

can be given by Eq. (1) and (3), the proposed

t control model can be expr det can be given by:
 $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

al control instructions can be given by:
 $\hat{\eta}_{cmd} = \hat{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

s also the normal number.

If the AUV dynamic model in a current

t can be given by Eq $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

al control instructions can be given by:
 $\vec{\eta}_{cmd} = \vec{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

salso the normal number.

1. If the AUV dynamic model in a current

t can be given by Eq. (1) and (3), the p *Q* instructions can be given by:
 $\ddot{\eta}_{cmd} = \ddot{\eta}_R + \Lambda^2 e + 2\Lambda \dot{e} + k s$ (28)
 Q enormal number.
 e AUV dynamic model in a current
 e given by Eq. (1) and (3), the proposed
 D model can be expressed as Eq. (29). B $\vec{\eta}_{cmd} = \vec{\eta}_R + \Lambda^2 e + 2\Lambda \dot{e} + k s$ (28)

also the normal number.

If the AUV dynamic model in a current

t can be given by Eq. (1) and (3), the proposed

t control model can be expressed as Eq. (29). By

the AUV velocity $\ddot{\eta}_{cmd} = \ddot{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)
the normal number.
the AUV dynamic model in a current
be given by Eq. (1) and (3), the proposed
rol model can be expressed as Eq. (29). By
JV velocity state through a sliding mode
ac d by the sliding mode observer given in Eq.

in be given by:
 $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

trol instructions can be given by:
 $\hat{\eta}_{cmd} = \hat{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

the normal number.

the AUV dynamic model in a curre $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

trol instructions can be given by:
 $\hat{\eta}_{cmd} = \hat{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

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the AUV dynamic model in a current

be given by Eq. (1) and (3), the proposed

trol model can $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

al control instructions can be given by:
 $\vec{\eta}_{cmd} = \vec{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

s also the normal number.

I. If the AUV dynamic model in a current

t can be given by Eq. (1) and (3), the $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

control instructions can be given by:
 $\hat{\eta}_{cmd} = \hat{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

lso the normal number.

If the AUV dynamic model in a current

an be given by Eq. (1) and (3), the proposed

on $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

control instructions can be given by:
 $\vec{\eta}_{cmd} = \vec{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

lso the normal number.

If the AUV dynamic model in a current

can be given by Eq. (1) and (3), the proposed

c control instructions can be given by:
 $\vec{\eta}_{cmd} = \vec{\eta}_R + \Lambda^2 e + 2\Lambda \dot{e} + k s$ (28)

also the normal number.

If the AUV dynamic model in a current

can be given by Eq. (1) and (3), the proposed

control model can be expresse $\hat{\eta} = \hat{\zeta}_2 + T_2 \hat{\zeta}_1$ (27)

instructions can be given by:
 $_{nd} = \hat{\eta}_R + \Lambda^2 e + 2\Lambda e + k s$ (28)

oormal number.

AUV dynamic model in a current

iven by Eq. (1) and (3), the proposed

of current environment and thruster
 i. The Act v uyaramic mode. In a Current of the proposed

it can be given by Eq. (1) and (3), the proposed

it control model can be expressed as Eq. (29). By

the AUV velocity state through a sliding mode

he impact of cu *s* and the view when the set of the proposed
control model can be expressed as Eq. (29). By
AUV velocity state through a sliding mode
impact of current environment and thruster
tracking control can be compensated, which
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 V dynamic model in a current

by Eq. (1) and (3), the proposed

1 can be expressed as Eq. (29). By

ity state through a sliding mode

current environment and thruster

ntrol can be compensated, which

error in be given by Eq. (1) and (3), the proposed
ontrol model can be expressed as Eq. (29). By
AUV velocity state through a sliding mode
mpact of current environment and thruster
tracking control can be compensated, which
V p is also the hormain number.
 m. If the AUV dynamic model in a current

ent can be given by Eq. (1) and (3), the proposed

aant control model can be expressed as Eq. (29). By

g the AUV velocity state through a sliding m

Exponential form of a given by Eq. (1) and (3), the proposed fault-tolerant control model can be expressed as Eq. (29). By estimating the AUV velocity state through a sliding mode observer, the impact of current environment and thruster faults on path tracking control can be compensated, which ensures the AUV position error converge to zero.

\n
$$
u = G(\eta)^+ (\ddot{\eta}_{cmd} - \hat{F}(\eta, \dot{\eta}))
$$
\n
$$
\dot{W} = -\lambda_W s \hat{Q}^T, \quad \dot{\beta} = -\lambda_\beta Q_\beta \dot{W}^T s Q (N-1)^T
$$
\n
$$
\dot{\alpha} = -\lambda_\alpha Q_\alpha \dot{W}^T s \zeta^T, \quad \dot{\gamma} = -\lambda_\gamma Q_\gamma \dot{W}^T s f (N-1)^T
$$
\n
$$
\dot{\hat{h}} = -\lambda_\beta s, \quad \Psi = hs
$$
\n**Prove.**

\nBy selecting the Lyapunov function, the velocity estimation can be given by:

\n
$$
V_2 = 0.5 s^T s + 0.5 \text{tr}(\tilde{W} \lambda_W^{-1} \tilde{W}^T) + 0.5 \text{tr}(\tilde{\alpha}^T \lambda_\alpha^{-1} \tilde{\alpha}) + 0.5 \text{tr}(\tilde{\beta}^T \lambda_\beta^{-1} \tilde{\beta}) + 0.5 \text{tr}(\tilde{\gamma}^T \lambda_\gamma^{-1} \tilde{\gamma}) + 0.5 \tilde{h}^T \lambda_\beta^{-1} \tilde{h}
$$
\n(30)

Prove.

$$
V_2 = 0.5s^{\mathrm{T}}s + 0.5tr(\tilde{W}\lambda_W^{-1}\tilde{W}^{\mathrm{T}}) + 0.5tr(\tilde{\alpha}^{\mathrm{T}}\lambda_{\alpha}^{-1}\tilde{\alpha}) +
$$

0.5tr(\tilde{\beta}^{\mathrm{T}}\lambda_{\beta}^{-1}\tilde{\beta}) + 0.5tr(\tilde{\gamma}^{\mathrm{T}}\lambda_{\gamma}^{-1}\tilde{\gamma}) + 0.5\tilde{h}^{\mathrm{T}}\lambda_{h}^{-1}\tilde{h} (30)

Volume 54, Issue 12, December 2024, Pages 2816-2823

1AENG International Journal of Applied Mathematics
\n
$$
\vec{v}_2 = tr(\vec{W} \lambda_W^{-1} \vec{W}^T)^0 \cdot Str(\vec{\hat{\alpha}}^T \lambda_\alpha^{-1} \vec{\alpha}) + s^T \vec{s} +
$$
\nis $\eta = [0.05, 0.05, 0.01]^T$, and the home velocity is $\dot{\eta} = [0.0, 0]^T$
\n $0.5tr(\vec{\hat{\beta}}^T \lambda_\beta^{-1} \vec{\hat{\beta}}) + 0.5tr(\vec{\hat{\alpha}}^T \lambda_\alpha^{-1} \vec{\alpha}) +$
\n $= tr(\vec{W} \lambda_W^{-1} \vec{W}^T)^0 \cdot Str(\vec{\hat{\alpha}}^T \lambda_\alpha^{-1} \vec{\alpha}) +$
\n $0.5tr(\vec{\hat{\beta}}^T \lambda_\beta^{-1} \vec{\hat{\beta}}) + s^T (\vec{\hat{\alpha}} + 2\lambda \vec{\hat{\alpha}} + \lambda^2 \vec{\hat{\alpha}}) +$
\n $0.5tr(\vec{\hat{\beta}}^T \lambda_\beta^{-1} \vec{\hat{\beta}}) + s^T (\vec{\hat{\alpha}} + 2\lambda \vec{\hat{\alpha}} + \lambda^2 \vec{\hat{\alpha}}) +$
\n $0.5tr(\vec{\hat{\beta}}^T \lambda_\beta^{-1} \vec{\hat{\beta}}) + 0.5\vec{h}^T \lambda_h^{-1} \vec{\hat{\beta}} +$
\n $0.5tr(\vec{\hat{\beta}}^T \lambda_\beta^{-1} \vec{\hat{\beta}}) + 0.5tr(\vec{\hat{\alpha}}^T \lambda_\alpha^{-1} \vec{\hat{\alpha}}) +$
\n $\vec{V}_2 = s^T (\vec{\eta}_R - \vec{\eta} + 2\lambda \vec{\hat{\alpha}} + \lambda^2 \vec{\hat{\alpha}} - 2\vec{\hat{\alpha}}) -$
\n $tr(\vec{W} \lambda_W^{-1} \vec{W}^T) - 0.5tr(\vec{\hat{\alpha}}^T \lambda_\alpha^{-1} \vec{\hat{\alpha}}) -$
\n $0.5tr(\vec{\hat{\beta}}^T \lambda_\beta^{-1} \vec{\hat{\beta}}) - 0.5tr(\vec{\hat{\beta}}^T \lambda_\beta^{-1} \vec{\hat{\gamma}}) - 0.5\vec{\hat{\beta}}^T \lambda_\beta^{-1} \vec{\hat{\beta}})$
\nWhere $\$

$$
0.5tr(\hat{\beta}^{T}\lambda_{\beta}^{-1}\hat{\beta}) + s^{T}(\hat{e} + 2\Lambda\hat{e} + \Lambda^{2}e) +
$$
\n
$$
0.5tr(\hat{\gamma}^{T}\lambda_{\gamma}^{-1}\hat{\gamma}) + 0.5\hat{h}^{T}\lambda_{h}^{-1}\hat{h}
$$
\nWhere: V_{c} is the ampli
\n
$$
V_{2} = s^{T}(\vec{\eta}_{R} - \vec{\eta} + 2\Lambda e + \Lambda^{2}e - \Xi - \Xi) -
$$
\nwith a mean value of -1.
\n
$$
\dot{V}_{2} = s^{T}(\vec{\eta}_{R} - \vec{\eta} + 2\Lambda e + \Lambda^{2}e - \Xi - \Xi) -
$$
\n
$$
tr(\tilde{W}\lambda_{W}^{-1}\hat{W}^{T}) - 0.5tr(\hat{\alpha}^{T}\lambda_{\alpha}^{-1}\hat{\alpha}) -
$$
\n
$$
0.5tr(\hat{\beta}^{T}\lambda_{\beta}^{-1}\hat{\beta}) - 0.5tr(\hat{\gamma}^{T}\lambda_{\gamma}^{-1}\hat{\gamma}) - 0.5\hat{h}^{T}\lambda_{h}^{-1}\hat{h}
$$
\nWhere $\Xi = (\Delta_{2} + T_{2}\Delta_{1})$, and it has been proven in section 3.3
\nthat this term will converge to zero.
\nSubstituting Eq. (3), (28), and (29) into Eq. (32), then
\n
$$
\dot{V}_{2} = s^{T}(\vec{\eta}_{R} - (f + (\vec{\eta}_{R} + \Lambda^{2}e + 2\Lambda\hat{e} - \hat{f}(\eta, \hat{\eta}))) +
$$
\n
$$
2\Lambda e + \Lambda^{2}e - s^{T}(\Xi + \Xi) - tr(\tilde{W}\lambda_{W}^{-1}\hat{W}^{T}) -
$$

0.3*tr*(*p*
$$
\lambda_{\beta}
$$
 p) + 0.3*tr*(*p* λ_{β} *p*) + 0.5*tr*($\vec{\alpha}^T \lambda_{\alpha}^{-1} \vec{a}$) + 0.5*tr*($\vec{\beta}^T \lambda_{\beta}^{-1} \vec{a}$) - 0.5*tr*($\vec{\beta$

$$
V_2 = s^r (η_R - η + Σ(λe + Λ2e – θ – θ – θ)\n
$$
tr(W̄λW^{-1}W̄†Y+0) – 0.5r(α̇†λα-1ᾱ) – 0.5r(α̇†λα-1ᾱ) – 0.5r(α̇†λα-1ᾱ) – 0.5r(α̇†λα-1α̇) – 0.5r(α̇†λα-1α̇) – 0.5r(α̇†λα-1α̇) – 0.5r(ᾱ†λα-1α̇) – 0.5r(α̇†λα-1α̇) – 0.5r(α̃†λα-1α̇) – 0.5r(α̃†λα-1α̇) – 0.5r(α̃†λα-1α̇) – 0.5r(α̃†λα-1α̇) – 0.5r(α̇πλα-1α̇) – 0.5r(α�
$$
$$

$$
\dot{V}_2 \le 0\tag{35}
$$

 $\frac{1}{2}tr(\beta^1 \lambda_{\beta}^{-1}\beta) - \frac{1}{2}tr(\gamma^1 \lambda_{\gamma}^{-1}\gamma)$ $T_2 = diag(1.2,1.2,1)$
 $\frac{1}{2}\tilde{h}^T\lambda_h^{-1}\dot{h} - s^T(\Xi + \dot{\Xi})$
 $\hbar = Q_{\alpha}^T\tilde{\alpha}\zeta + Q_{\beta}^T\tilde{\beta}Q(N-1) + Q_{\gamma}^T\tilde{\gamma}f(N-1)$
 $\Delta_2 = diag(-2.0383)$
 $\hbar = Q_{\alpha}^T\tilde{\alpha}\zeta + Q_{\beta}^T\tilde{\$ $\frac{1}{2} \tilde{h}^T \lambda_h^{-1} \hat{h} - s^T (\Xi + \dot{\Xi})$
 $\hbar = Q_\alpha^T \tilde{\alpha} \zeta + Q_\beta^T \tilde{\beta} Q(N-1) + Q_\gamma^T \tilde{\gamma} f(N-1)$
 $\hbar = Q_\alpha^T \tilde{\alpha} \zeta + Q_\beta^T \tilde{\beta} Q(N-1) + Q_\gamma^T \tilde{\gamma} f(N-1)$

When the update rate is substituted into Eq.(34), and

The initial $\frac{1}{2}h^1\lambda_h^{-1}h - s^1(\Xi + \Xi)$
 $h = Q_a^T\tilde{a}\zeta + Q_\beta^T\tilde{\beta}Q(N-1) + Q_\gamma^T\tilde{\gamma}f(N-1)$
 $L_2 = diag(0, 0, 0)$

When the update rate is substituted into Eq.(34), and The initial components

combining with the sliding observer error $h = Q_{\alpha} T \tilde{\alpha} \zeta + Q_{\beta} T \tilde{p} Q(N-1) + Q_{\gamma} T \tilde{r} f(N-1)$

When the update rate is substituted into Eq.(34), and The initial components are de

combining with the sliding observer error proof mentioned

above, thereby:
 \dot When the update rate is substituted into Eq.(34), and

When the update rate is substituted into Eq.(34), and

The

combining with the sliding observer error proof mentioned

above, thereby:
 $\dot{V}_2 \le 0$ (35)

Stem from t update rate is substituted into Eq.(54), and Ine in
th the sliding observer error proof mentioned
y:
 $V_2 \le 0$ (35)
the Lyapunov stability theory, the effects of
interference and unknown thruster faults can be
ompensated Example the Uyapunov stability theory, the effects of

Stem from the Lyapunov stability theory, the effects of
 $\vec{V}_2 \le 0$ (35)

Stem from the Lyapunov stability theory, the effects of

earn current interference and unk Stem from the Lyapunov stability theory, the effects of
 $\vec{V}_2 \le 0$ (35)

Stem from the Lyapunov stability theory, the effects of

ocean current interference and unknown thruster faults can be

effectively compensated b $V_2 \le 0$ (35)

Stem from the Lyapunov stability theory, the effects of

ocean current interference and unknown thruster faults can be

effectively compensated based on the proposed observer

based AUV path tracking contr Stem from the Lyapunov stability theory, the effects of

ocean current interference and unknown thruster faults can be

effectively compensated based on the proposed observer

based AUV path tracking control method, and c Stem from the Lyapunov stability theory, the effects of

scribted based on the proposed observer

ed AUV path tracking control method, and can make the

ed AUV path tracking control method, and can make the

In the ocean

clearly.

is $\mathbf{\eta} = [0.05, 0.05, 0.01]^{T}$, and the home velocity is $\mathbf{\eta} = [0, 0, 0]^{T}$. **al of Applied Mathematics**

is $\boldsymbol{\eta} = [0.05, 0.05, 0.01]^T$, and the home velocity is $\boldsymbol{\dot{\eta}} = [0, 0, 0]^T$.

By using first-order Gaussian Markov process to describe the

ocean currents [22], the model can be given by:
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is $\boldsymbol{\eta} = [0.05, 0.05, 0.01]^T$, and the home velocity is $\boldsymbol{\eta} = [0, 0, 0]^T$.

By using first-order Gaussian Markov process to describe the

ocean currents [22], the model can be given by:

$$
\dot{V}_c + \mu V_c = \omega \tag{36}
$$

V V c c (36) Where: V_c is the amplitude of the ocean current in the **is the amplitude of the amplitude of the amplitude of the coefficient of the coefficient of the ocean current in the ordinate system;** ω **is the Gaussian white noise value of -1.5 and a variance of 1; the constant to 3; and of Applied Mathematics**

is $\eta = [0.05, 0.05, 0.01]^T$, and the home velocity is $\dot{\eta} = [0, 0, 0]^T$.

By using first-order Gaussian Markov process to describe the

ocean currents [22], the model can be given by:
 $\dot{V$ is $\eta = [0.05, 0.05, 0.01]^T$, and the home velocity is $\dot{\eta} = [0, 0, 0]^T$.
By using first-order Gaussian Markov process to describe the
ocean currents [22], the model can be given by:
 $\dot{V}_c + \mu V_c = \omega$ (36)
Where: V_c is t is $\eta = [0.05, 0.05, 0.01]^T$, and the home velocity is $\dot{\eta} = [0, 0, 0]^T$.
By using first-order Gaussian Markov process to describe the
ocean currents [22], the model can be given by:
 $\dot{V}_c + \mu V_c = \omega$ (36)
Where: V_c is is $\eta = [0.05, 0.05, 0.01]^T$, and the home velocity is $\dot{\eta}$
By using first-order Gaussian Markov process to cocean currents [22], the model can be given by:
 $\dot{V}_c + \mu V_c = \omega$
Where: V_c is the amplitude of the ocean cur $\eta = [0.05, 0.05, 0.01]^{\dagger}$, and the home velocity is $\dot{\eta} = [0, 0, 0]^{\dagger}$.

v using first-order Gaussian Markov process to describe the

ean currents [22], the model can be given by:
 $\dot{V}_c + \mu V_c = \omega$ (36)

here: V_c i velocity is $\vec{\eta} = [0,0,0]^T$.

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the controller are set as
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follows:

$$
\frac{2\pi}{6} \int \frac{1}{3} \pi \int_{\pi}^{\pi} \int_{\theta}^{\pi} \int_{-\pi}^{\pi} \int_{-\pi}^{\pi}
$$

and the velocity information estimated from the sliding mode observer. The hidden-layer nodes is 6, and the output layer nodes is 3. The initial value of each of the weight variables is $A = \begin{bmatrix} 5 & 1 \ 5 & 5 \end{bmatrix}, \lambda_{\Psi} = \begin{bmatrix} 5 & 1 \ 5 & 5 \end{bmatrix}$ (37)
 $\lambda_{\alpha} = \lambda_{\beta} = \lambda_{\gamma} = \lambda_{\Psi} = \begin{bmatrix} 0.5 & 0.5 \ 0.5 & 0.5 \end{bmatrix}$

The input layer nodes is set to 4, which responds to the heading angle information measured by $A = \begin{bmatrix} 5 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 5 & 0 \end{bmatrix}$, $\lambda_{\psi} = \begin{bmatrix} 5 & 0 & 0 \\ 0.5 & 0 & 0 \\ 0.5 & 0 & 0 \end{bmatrix}$ (37)
 $\lambda_{\alpha} = \lambda_{\beta} = \lambda_{\gamma} = \lambda_{W} = \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix}$

The input layer nodes is set to 4, which responds to the $A = \begin{bmatrix} 5 \\ 5 \end{bmatrix}, \lambda_{\Psi} = \begin{bmatrix} 5 \\ 15 \end{bmatrix}$ (37)
 $\lambda_{\alpha} = \lambda_{\beta} = \lambda_{\gamma} = \lambda_{W} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$

The input layer nodes is set to 4, which responds to the heading angle information measured by the navigation sensor $\lambda_{\alpha} = \lambda_{\beta} = \lambda_{\gamma} = \lambda_{W} = \begin{bmatrix} 0.5 \\ 0.5 \\ 0.5 \end{bmatrix}$

The input layer nodes is set to 4, which responds to the ading angle information measured by the navigation sensor of the velocity information estimated from the sl $\lambda_{\alpha} = \lambda_{\beta} = \lambda_{\gamma} = \lambda_{W} = \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix}$

The input layer nodes is set to 4, which responds to the heading angle information measured by the navigation sensor and the velocity information estimated fro $\begin{bmatrix} 5 \ 5 \end{bmatrix}$, $\lambda_{\Psi} = \begin{bmatrix} 0.5 \ 0.5 \end{bmatrix}$
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S is set to 4, which responds to the

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Let the velocity information estimated from the string mode server. The hidden-layer nodes is 6, and the output layer des is 3. The initial value of each of the weight variables is virtually selected from [0, 0.5].

\nBy using the LMI toolbox, the parameters involved in the ding mode observer can be given by:

\n
$$
T_2 = diag(1.2, 1.2, 1.2)
$$
\n
$$
L_1 = diag(3.7122, 3.7122, 3.7122)
$$
\n
$$
L_2 = diag(-2.0383, -2.0383, -2.0383)
$$
\n
$$
\rho = diag(0.2, 0.2, 0.2)
$$
\nThe initial components are described as:

\n
$$
\hat{\zeta}_1 = [0, 0, 0], \quad \hat{\zeta}_2 = [0, 0, 0]
$$
\n
$$
\begin{bmatrix} 0.9760 & 0 & 0 & -0.6078 & 0 & 0 \\ 0.0 & 0.0 & 0 & 0 & -0.6078 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 &
$$

nodes is 3. The initial value of each of the weight variables is
arbitrarily selected from [0, 0.5].
By using the LMI toolbox, the parameters involved in the
sliding mode observer can be given by:

$$
T_2 = diag(1.2, 1.2, 1.2)
$$

 $L_1 = diag(3.7122, 3.7122, 3.7122)$
 $L_2 = diag(-2.0383, -2.0383, -2.0383)$
 $\rho = diag(0.2, 0.2, 0.2)$
The initial components are described as:
 $\hat{\zeta}_1 = [0, 0, 0], \ \hat{\zeta}_2 = [0, 0, 0]$
 $\hat{\zeta}_1 = [0, 0, 0], \ \hat{\zeta}_2 = [0, 0, 0]$
 $P = \begin{bmatrix} 0.9760 & 0 & 0 & -0.6078 & 0 & 0 \\ 0 & 0.9760 & 0 & 0 & -0.6078 & 0 \\ 0 & 0 & 0.9760 & 0 & 0 & 0.6078 \\ 0 & 0 & 0.11705 & 0 & 0 \\ 0 & -0.6078 & 0 & 0 & 1.1705 & 0 \\ 0 & 0 & -0.6078 & 0 & 0 & 1.1705 & 0 \\ 0 & 0 & -0.6078 & 0 & 0 & 1.1705 & 0 \\ 0 & 0 & -0.6078 & 0 & 0 & 1.1705 & 0 \\ 0 & 0 & -0.6078 & 0 & 0 & 1.1705 & 0 \\ 0 & 0 & -0.6078 & 0 & 0 & 1.1705 & 0 \\ 0 & 0 & -0.6078 & 0 & 0 & 1.1705 & 0 \\ 0 & 0 & -0.6078 & 0 & 0 & 1.1705 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1.1705 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.11705 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.11705 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.11705 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.11705 & 0 \\ 0 & 0 & 0$

$$
\eta_d = [x_d, y_d, \phi_d], \ x_d = 2\sin(0.5t) \ny_d = -2\cos(0.25t), \ \phi_d = 0.1t
$$
\n(40)

 $P = \begin{bmatrix} 0 & 0 & 0.9760 & 0 & 0 & -0.6078 \\ -0.6078 & 0 & 0 & 1.1705 & 0 & 0 \\ 0 & -0.6078 & 0 & 0 & 1.1705 & 0 \\ 0 & 0 & -0.6078 & 0 & 0 & 1.1705 \end{bmatrix}$

In the ocean current environment, the ideal tracking path is

an "8" shaped path and express F $\begin{bmatrix} 0.6078 & 0 & 0 & 1.1705 & 0 & 0 \\ 0 & -0.6078 & 0 & 0 & 1.1705 & 0 \\ 0 & 0 & -0.6078 & 0 & 0 & 1.1705 \end{bmatrix}$

In the ocean current environment, the ideal tracking path is

an "8" shaped path and expressed as:
 $\eta_d = [x_d, y_d, \phi_d], x_d =$ In the ocean current environment, the ideal
an "8" shaped path and expressed as:
 $\eta_d = [x_d, y_d, \phi_d]$, $x_d = 2 \sin \phi_d = -2 \cos(0.25t)$, $\phi_d = 0$.
Assuming that the first thruster occurs a
ramp fault at the 20th second, and the faul

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\n
$$
k_{11} = \begin{cases}\n0 & t < 20 \\
0.5(1 - e^{-(t-20)/4}) & t \ge 20\n\end{cases}
$$
\n(41)
\n50% thrust loss ramp fault occurs, Figure 2 to
\nnow the simulation results.
\n
$$
\sum_{t=1}^{250} \frac{100}{50} = 100
$$
\n(42)
\n
$$
\sum_{t=1}^{250} \frac{100}{50} = 100
$$
\n(43)
\n
$$
\sum_{t=1}^{250} \frac{100}{50} = 100
$$

Changes in thruster faults, the tracking ability of the AUV
decreases, making it difficult to track the required path.
However, the proposed method can modify the reference
output path to meet the saturation constraint of decreases, making it difficult to track the required path. $\begin{array}{|c|c|c|}\n\hline\n-1 & 0.9 & 0.06 & 0.08 \\
& & \times \text{direction(m)} & & & 1.5 & 0.08 \\
& & \times \text{direction(m)} & & & & 0.1 & 0 \\
& & & \times \text{direction(m)} & & & & 0.1 & 0 \\
& & & \times \text{direction(m)} & & & & 0.1 & 0 \\
& & & \times \text{direction(m)} & & & & 0.1 & 0 \\
& & & \times \text{direction(m)} & & & & 0.1 & 0 \\
& & & \times \text{cross} & & & & 0.1 & 0 \\
& & & \times \text{cross} & & & & 0.1 & 0 \\$ Fig. 2. AUV horizontal path to meet the saturation constraint of the thruster.

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-150
 $\frac{1}{2200}$
 $\frac{1}{220}$
 $\frac{1}{220}$
 $\frac{1}{20}$
 $\frac{1}{13}$
 $\frac{1}{1$ observer, the AUV velocity can be well estimated in the -250
 -250
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although there are significant variations between the velocity and the real values in the initial stage, the relative To achieve highly reliative errors would reduce to zero **EXENT International Journal of Applied Mathem**
although there are significant variations between the velocity
estimation and the real values in the initial stage, the relative
errors would reduce to zero quickly (about 3 **IAENG International Journal of Applied M**
although there are significant variations between the velocity
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errors would reduce to zero quickly (about 3 secon

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 $+1.5$
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Time(s)

Fig. 5. State estimation parameters and actual values

Through the comparison results obtained from the [13] Li, J., *

aconditions of no thruster faul

Example:

V. CONCLUSION

v reliable AUV path tracking control

ocean current interference and thruster

s conditions, a fault-tolerant control of Applied Mathematics

V. CONCLUSION

To achieve highly reliable AUV path tracking control

then considering the ocean current interference and thruster

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V. CONCLUSION

To achieve highly reliable AUV path tracking control

when considering the ocean current interference and thruster

saturation constraints conditions, a fault-tolerant control

method for AUV **Saturation Constraints Constraints**
Saturation considering the ocean current interference and thruster
saturation constraints conditions, a fault-tolerant control
method for AUV thrusters without velocity feedback is
prop **10 of Applied Mathematics**

V. CONCLUSION

To achieve highly reliable AUV path tracking control

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V. CONCLUSION

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V. CONCLUSION

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V. CONCLUSION

To achieve highly reliable AUV path tracking control

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To achieve highly reliable AUV path tracking control
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when considering the ocean current interference and thruster
saturation constraints conditions, a fault-tolerant control
method for AUV thrusters without velocity feedba when considering the ocean current interference and thruster saturation constraints conditions, a fault-tolerant control method for AUV thrusters without velocity feedback is proposed. Besides, the adaptive regression neur saturation constraints conditions, a fault-tolerant control
method for AUV thrusters without velocity feedback is
proposed. Besides, the adaptive regression neural networks is
used to estimate the unknown AUV dynamic model method for AUV thrusters without velocity feedback is
proposed. Besides, the adaptive regression neural networks is
used to estimate the unknown AUV dynamic models, which
avoids the changes in dynamic characteristics cause proposed. Besides, the adaptive regression neural networks is
used to estimate the unknown AUV dynamic models, which
avoids the changes in dynamic characteristics caused by the
thruster faults and the limitations of tradit used to estimate the unknown AUV dynamic models, which
avoids the changes in dynamic characteristics caused by the
thruster faults and the limitations of traditional model inverse
control methods. Meanwhile, the proposed m EVALUATE THE PAIR THE PAIR THE PAIR THE PAIR THE PAIR THE AUTY velocity' state, thereby effectively compensating
for the impact of thruster faults. Through the path reference
output and the thruster output signal, the prop v that the sliding mode observer can accurately estimate
AUV velocity' state, thereby effectively compensating
the impact of thruster faults. Through the path reference
ut and the thruster output signal, the proposed metho AUV velocity` state, thereby effectively
he impact of thruster faults. Through the
ut and the thruster output signal, the pre-
adjust the reference path to achieve path t
r saturation constraint of the thrusters.
EFERENCES for the impact of thruster faults. Through the path reference
output and the thruster output signal, the proposed method
can adjust the reference path to achieve path tracking control
under saturation constraint of the thr It and the thruster output signal, the proposed method
adjust the reference path to achieve path tracking control
r saturation constraint of the thrusters.
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