Robust Identification Algorithm for Unmanned Underwater Vehicles Dynamics Model Parameters

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Abstract—As the exploration of marine resources continues to deepen, the Unmanned Underwater Vehicles (UUV) have gradually become the focus of industries such as military, fishery, seabed prospecting and marine platform monitoring. At present, the identification technology of the dynamic model parameters of the UUV is not mature yet, and the robustness is poor. In order to solve the problem that the identification algorithm is susceptible to underwater noise when the robot is navigating underwater, this paper integrates the Huber loss function into the recursive least square method, and proposes a robust identification algorithm to improve the control of the underwater robot Accuracy. Finally, the dynamic model of the underwater vehicle is simulated in Simulink to obtain a reasonable input signal, and then this algorithm is used to simulate and identify the model under Gaussian noise with ‘outliers’. The simulation results show that the algorithm has strong robustness while ensuring the identification accuracy.

1. Introduction

In recent decades, as countries around the world continue to increase resource exploitation, land non-renewable resources are facing depletion. Therefore, in order to explore the mysterious ocean and exploit its rich resources, Unmanned Underwater Vehicles (UUV) [1] have gradually become the focus of industries such as military, fishery, seabed prospecting and ocean platform monitoring, rising, while getting more and more practical applications.

Although the application of UUV is becoming more and more extensive, the identification technology for the parameters of the dynamic model of UUV is not mature and the robustness is poor.

There have been relevant researches in this area at home and abroad, and more achievements have been achieved. Because the least squares model is simple and converges quickly, many identification algorithms of the parameters of the dynamic model of underwater robots are based on the least square method. Martin S.C. et al. used the ordinary least squares method and the overall least squares method to identify the parameters of the dynamic model of the underwater robot [2]. You et al. used the state variable filter and the least square method to realize the online identification of the parameters of the dynamic model of the underwater robot [3].
Although the least squares method is relatively widely used, it also has the disadvantage that it is easily affected by sudden ‘outlier’ noise, and the robustness is deteriorated. Therefore, many other new algorithms have also appeared in the parameter identification of underwater robot dynamics model. Such as the diagnostic network combining wide convolutional neural network (WDCNN) and extreme learning machine (ELM) [4], the identification method based on Adaptive interval type-2 fuzzy control [5], the lossless Kalman filter [6] and other methods. However, due to the relative complexity of such algorithms and the high identification cost, their applications are not mature at present.

This paper proposes to use the least squares method with simple model and rapid convergence as the basis, and introduces the Huber loss function to improve the robustness of the identification algorithm, and at the same time uses the improved recursive least squares method to improve the ‘anti-data saturation’ ability of the identification algorithm, forming a recursive least squares method based on Huber loss function with strong robustness and fast convergence, which is of great significance for improving the anti-interference ability and accuracy of the parameter identification of the dynamic model of underwater robots.

2. UUV Dynamics Model

Underwater robots are subjected to very complex forces during underwater navigation. According to Jiang et al., underwater robots are mainly subjected to gravity, buoyancy, propeller thrust, hydrodynamic force, interference caused by umbilical cables, and interference caused by manipulator operations. Dynamics and the action of various moments related to these forces [7].

The dynamic model of the underwater robot can be established according to the Newton-Euler equation as [8]:

\[
\begin{align*}
M \ddot{v} + C(v)v + D(v)v + g(\eta) &= \tau \\
\dot{\eta} &= f(\eta)v
\end{align*}
\]

(1) (2)

In the formula, \( M \) is the mass and inertia matrix, which includes the rigid body mass and inertia matrix \( M_{RB} \), the hydrodynamic additional mass matrix \( M_A \); \( \dot{v} \) is the linear acceleration and angular acceleration vector; \( v \) is the linear velocity of the underwater robot in the motion coordinate system and Angular velocity vector; \( C(v) \) is the total Coriolis and centripetal force matrix; \( D(v) \) is the fluid resistance matrix; \( g(\eta) \) is the restoring force (moment) vector generated by gravity and buoyancy; \( \tau \) is the resultant force and moment vector of the thruster and the underwater robot disturbed by the water; \( f(\eta) \) is the conversion between the fixed coordinate system and the moving coordinate system matrix.

In addition, the dynamic model of the underwater robot is simplified according to the actual characteristics of the underwater robot.

Since the physical shape structure of the underwater robot is symmetrical about the three tangent planes, and its center of gravity is the origin of the motion coordinate system, the rigid body mass and inertia matrix \( M_{RB} \) and hydrodynamic additional mass matrix \( M_A \) can be simplified as:

\[
\begin{align*}
M_{RB} &= \text{diag}\{m \ 0 \ m \ 0 \ 0 \ I_x\} \\
M_A &= \text{diag}\{X_u \ 0 \ Z_w \ 0 \ 0 \ N_r\}
\end{align*}
\]

(3) (4)

where \( I \) is the inertia term of the robot.

Since the speed of the underwater robot is relatively slow, which is within 1 knot, the Coriolis and centripetal force can be directly discarded. Therefore, \( C(v) = 0 \), the dynamic model is simplified as

\[
\begin{align*}
M \ddot{v} + D(v)v + g(\eta) &= \tau
\end{align*}
\]

(5)

On the basis of model simplification, the dynamic model of underwater robot [9] discards the Coriolis and centripetal force matrices and is simplified to Equation (5), the single-degree-of-freedom dynamic simplified model of the underwater robot is summarized and described as follows [8, 9]:

\[
m_\xi \ddot{\xi} + k_\xi \dot{\xi} + k_{\xi|\xi|} \xi |\xi| = \tau_\xi
\]

(6)

where \( m_\xi \) is the inertia coefficient, \( \dot{\xi} \) is the one-dimensional acceleration of the degree of freedom, \( \xi \) is the one-dimensional velocity of the degree of freedom, \( k_\xi \) is the primary resistance coefficient, and \( k_{\xi|\xi|} \) is the secondary resistance coefficient, \( \tau_\xi \) is the force torque generated by the thrust
generated by the propeller in the degree of freedom.

The single-degree-of-freedom simplified model is used as the simulation model, and after substituting the true value of the parameter [9] and adding noise, the dynamic model of the heading degree-of-freedom is obtained as

\[ 30.04 \dot{\xi} + 2.57 \dot{\xi} + 10.0 |\dot{\xi}| + v = \tau \]

where \( v \) is the noise signal.

3. Robust Identification Algorithm

The recursive least squares method has been able to overcome to a large extent that the ordinary least squares method is greatly affected by the type of noise. However, when there are ‘outliers’ (noise outliers) with a large standard deviation in the interference noise, it will affect the estimation accuracy of the recursive least squares method, resulting in inaccurate estimation. In this case, Huber proposed the Huber loss function in his introduction to M-estimation [10] to distinguish the influence of different noises on the estimated value.

Therefore, in order to improve the robustness of the algorithm, the Huber loss function is introduced into the algorithm of this paper, and K-times before estimation criterion functions of the following RLS estimation method are considered.

\[ J_{k}^{RLS}(\hat{\theta}) = \min_{\hat{\theta}} \sum (y_k - x_k \hat{\theta})^T w_k (y_k - x_k \hat{\theta}) \]

Therefore, its recursive form is:

\[ J_{k}^{RLS}(\hat{\theta}) = J_{k-1}^{RLS}(\hat{\theta}_{k-1}) + (y_k - x_k \hat{\theta}_{k-1})^T w_k (y_k - x_k \hat{\theta}_{k-1}) \]

Note, \( e_k = W_k^{1/2} (y_k - x_k \hat{\theta}_{k-1}) \) then \( \dot{e}_k \cdot e_k \) is the k-th estimated residual. then there are:

\[ J_{k}^{RLS}(\hat{\theta}) = J_{k-1}^{RLS}(\hat{\theta}) + \sum \rho(e_k) \]

In the formula, \( \rho(e_k) \) is the Huber loss function, and its specific form is as follows:

\[ \rho(e_k) = \begin{cases} 
\frac{e_k^2}{2}, & |e_k| \leq \delta \\
\delta (|e_k| - \frac{\delta}{2}), & |e_k| > \delta 
\end{cases} \]

In the formula, \( \delta \) is the adjustment parameter. Differentiating Equation (10), the influence function can be obtained as:

\[ \phi(e_k) = \frac{\partial \rho(e_k)}{\partial e_k} = \begin{cases} 
1, |e_k| \leq \delta \\
\delta \cdot \text{sign}(e_k), & e_k > \delta 
\end{cases} \]

To find its minimum value, we have:

\[ \sum \phi(e_k) \cdot \frac{\partial e_k}{\partial \hat{\theta}} = 0 \]

Let

\[ u(e_k) = \frac{\phi(e_k)}{e_k} = \begin{cases} 
1, |e_k| \leq \delta \\
\delta / |e_k|, & |e_k| > \delta 
\end{cases} \]

\[ \Lambda = \text{diag}[u(e_k)] \]

From equations (13), (14) and (15) can be deduced:

\[ \sum \phi(e_k) \cdot \frac{\partial e_k}{\partial \hat{\theta}} \cdot \Lambda \cdot e_k = 0 \]

So solved:

\[ \hat{\theta} = [X_k^T (W_k^{1/2})^T \cdot \Lambda \cdot W_k^{1/2} X_k]^{-1} X_k^T (W_k^{1/2})^T \cdot \Lambda \cdot W_k^{1/2} y_k \]

After deriving the weighted estimation formula that introduces the Huber loss function, integrate it
into the recursive formula of the recursive least squares gain, and then the recursive least squares method based on the Huber loss function (Huber Recursive Least Squares, H_RLS) can be obtained. robust gain as follows:

$$K_{\text{Huber}}(k) = \frac{P(k-1)x(k)}{u(e_k) + x^T(k)P(k-1)x(k)}$$

(18)

Where $u(e_k)$ is the robustness factor of Huber’s method.

The Huber loss function and the adjustment parameter $\delta$ in the robust factor are the key to the robust estimation of the Huber method. When $\delta \to \infty$, the Huber recursive least squares method evolves into the ordinary recursive least squares method; when $\delta \to 0$, The Huber recursive least squares method evolved into the absolute value estimation method. Usually, when the noise model is Gaussian, taking $\delta = 1.345$ can get a relative efficiency of 95% [10].

4. Model Identification Simulation Experiment

4.1. Simulation of the Input Signal

This paper adopts the form of simulation research. Therefore, in the following introduction of this section, a simplified dynamic model of the bowing degree of freedom of an underwater robot [9] is selected for simulation.

In order to obtain a suitable input signal for the system, consider the system of equation (6), and transform the system into the following linear system at $\xi_0$:

$$m_\xi \dot{\xi} + (k_\xi + 2k_\xi|\xi_0|)\dot{\xi} = \tau_\xi + k_\xi|\xi_0|\xi_0$$

(19)

The time constant of this linear system is:

$$t_0 = \frac{m_\xi}{k_\xi + 2k_\xi|\xi_0|}$$

(20)

It can be seen from the relevant system identification knowledge that to identify the system shown in Eq. (19), the optimal angular frequency of the input is:

$$w_{\text{opt}} = \frac{1}{\sqrt{3}} t_0$$

(21)

When calculating the time constant of the linearization system of the heading degree of freedom dynamic model, the control voltage is taken as 10V, and the input torque is 3.44N·m. Then, the Runge-Kutta method is used to solve the differential equation (7), and in the obtained solution, take one-dimensional angular velocity stable value $\xi_0 = 0.4719 \text{ rad/s}$. Substitute into equations (20) and (21) to calculate the time constant and the optimal angular frequency as:

$$t_0 = \frac{30.04}{2.57 + 2 \times 10.0 \times |0.4719|} = 2.50 \text{ s}$$

$$w_{\text{opt}} = \frac{1}{\sqrt{3} \times 2.50} = 0.23 \text{ Hz}$$

(22)

In order to ensure that the propeller of the underwater robot will not suddenly reverse during the sailing process, when the input is the optimal frequency, the input voltage is set to have the following form:

$$V = 10 + 5 \sin 0.23t$$

(23)

If the sampling interval is set to 1 s, the output thrust curve is shown in Figure 1.
The system shown in equation (7) is simulated in Simulink with the thrust signal shown in Fig. 1 as the input. In order to observe the direct and construction aspects, the simulation system is directly built by the integrator, and the Simulink simulation system of the heading degree of freedom dynamic model is shown in Figure 2. The dynamic model of heading degree of freedom is simulated by SIMULINK, and the next-dimensional velocity and one-dimensional acceleration curves of thrust input shown in Fig.1 are shown in Figure 3.

4.2 Parameter Identification Simulation under Gaussian Noise with ‘Outliers’
In order to observe the effect of Huber’s method in the identification of noise models with ‘outliers’, this simulation adds ‘outliers’ noise to ordinary Gaussian noise. That is, a noise outlier signal with a standard deviation of 300 is added to the noise signal with a noise amplitude below 0.1.

Figure 4, Figure 5 and Table 1 show the identification and simulation results of the dynamic model of an underwater robot’s heading DOF under the interference of Gaussian signals with ‘outliers’.
Table 1 Identification results of heading dynamics model (Gaussian noise with outliers)

| Identification parameters | m/\text{kg} \cdot \text{m}^2 | k/\text{Nms} \cdot \text{rad}^{-1} | k_{\xi\xi}/\text{Nms}^2 \cdot \text{rad}^{-2} |
|----------------------------|-----------------|-----------------|-----------------|
| Parameters of the true value | 30.04 | 2.57 | 10.00 |
| RLS Estimated value | 35.2890 | 8.8655 | -1.6301 |
| Error $\Delta/%$ | 17.4734 | 244.9611 | -116.3010 |
| H_RLS Estimated value | 29.8287 | 2.5792 | 9.9555 |
| Error $\Delta/%$ | -0.7034 | 0.3580 | -0.4450 |

5. Analysis of simulation results

From the simulation results of the heading dynamics model of the underwater robot in two noise environments of ordinary Gaussian noise and Gaussian noise with ‘outliers’ in Section 4, it can be seen that: in the Gaussian noise environment with ‘outliers’, the identification results of the two algorithms, RLS and H_RLS, are quite different. The parameter estimation of the RLS algorithm cannot converge within the set number of simulations, and the absolute error of the estimation is also divergent. In contrast, the H_RLS algorithm shows its superiority in robustness in this noise environment. Near the value, the absolute error of the estimate also tends to 0 rapidly, and the relative error of the final estimate is still within $\pm 2\%$.

6. Conclusion

In view of the low control accuracy of underwater robots, the common identification algorithm is greatly affected by the type of noise, and prone to ‘data saturation’ and other problems, the Huber loss function is introduced into the recursive least squares estimation, and a robust method is proposed. The Huber recursive least squares method is used to simulate and identify the heading dynamics model of the underwater robot. The main conclusions are as follows:

1) The proposed algorithm can better solve the problem that the traditional identification algorithm is greatly affected by the type of noise and is prone to ‘data saturation’.

2) The identification results show that the proposed algorithm has high identification accuracy, the relative error is within $\pm 1\%$.

3) Under the influence of ‘outlier’ Gaussian noise, the proposed algorithm can still be identified stably and has strong robustness.

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