Cutting Process Model Design of Cutter Suction Dredger Based on Auto Regressive eXogenous and Radial Basis Function model

Huan Zhang1, Menghong Yu2 and Wei Yuan1*

1 College of Electronic Information, Jiangsu University of Science and Technology, Zhenjiang, Jiangsu, 212100, China
2 Ocean Equipment Research Institute, Jiangsu University of Science and Technology, Zhenjiang, Jiangsu, 212003, China
*Corresponding author’s e-mail: 192030011@stu.just.edu.cn

Abstract. The dredging operation of the strander dredger is complex, and the mathematical model established according to its key equipment characteristics is not possible to describe such a system having time degeneration and non-linear. Therefore, based on the analysis of mud formation process of dredger, RBF-ARX model is used to model the cutting process, and mud concentration is taken as the output. This modeling method is a combination model based on the theory of Auto-Regressive eXogenous (ARX) model and Gauss radial basis function (Radial Basis Function) neural network (RBF). The comparison between the simulation results and the actual data shows that the model can accurately describe the dynamic characteristics of cutter suction dredger in the cutting process.

1. Introduction

In the dredging operation, the cutter suction dredger first cuts the soil through the during dredging operation, and then the mud is sucked into the pipe by the mud pump and transported to the designated area through the long pipe. The whole dredging operation includes the swing process, cutting process, pipeline transportation process and other major processes, and these processes have mutual influence and interaction. This makes the dynamic characteristics of the dredging process of cutter suction dredger become complicated and changeable, resulting in the dredger construction efficiency in the actual construction process is greatly affected by the external, so it is particularly necessary to model the dredging system of cutter suction dredger and its automatic control.

In foreign countries, the model and automatic control of the dredging process have been studied since the 1990s [1-2], and many domestic studies have also been done in related areas. Ni[3] studied the dynamic characteristics of sediment transport system. Bi[4] studied the process control of pipeline mud concentration conveying system based on the mud concentration process, and the online dynamic optimization of working condition points. Wei[5] researched the predictive control system of the cutter suction dredger's lateral movement process. For cutting parts, Zhang[6] established a mathematical model of the soil cutting and mud formation process through the analysis of the cutter cutting process. These studies have laid a certain foundation for the subsequent research on the capacity and energy consumption of dredgers, but these researches are based on a certain operating point and cannot reflect the dynamic characteristics of the cutting process during dredging operations.

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In order to reflect the dynamic characteristics of cutting process in the process of dredging, according to the principle of RBF-ARX model, in the case of no need to know the mathematical relationship between the parameters of the cutting process, through the method of parameter identification, the dredger cutting process model is established, and the established model is compared and verified.

2. Analysis of dredger cutting process

In the dredging construction of the cutter suction dredger, the steel pile trolley positioning horizontal excavation method is adopted. With the main positioning pile as the center, the cutter installed at the front end of the bridge is putted into the bottom, and the soil is layered cutting by moving the cutter about horizontally. The mud concentration in the pipeline can be calculated by the following formula:\cite{6}:

\[ C = \frac{4V_n}{\pi d^2 v} \]  

\( d \) is the inner diameter of the pipeline, \( v \) is the mud flow rate, \( V_n \) is the volume of sand entering the pipeline per unit time: \( V_n = kV_c \), \( k \) is the cutter excavation coefficient, \( V_c \) is the volume of the soil cut by the cutter during the cutting process, which is related to the cutting width \( h \) and depth \( d_c \) of the cutter and the swing speed \( v_s \) of the cutter: \( V_c = h_d v_s \). Since not all the cut soil can be mixed with water to form silt into the pipeline, it is necessary to calculate the volume of silt that can be formed by the degree of soil pulverization, and the degree of pulverization is related to the thickness of the cut mud per unit time and the properties of the soil:

\[ d_s = \frac{60v_s}{Z_c n} \]  

In the formula, \( Z_c \) is the number of arms of the cutter, and \( n \) is the rotation speed of the cutter.

The above analysis illustrates the influence of cutter parameters on mud concentration during cutting. In fact, there are many more factors that affect production during cutting, but there is no good model to explain the relationship between these effects. Therefore, based on the actual construction data of cutter suction dredger, this paper takes cutter speed and swing speed as input, takes the mud concentration formed by cutting as output, and obtains the dynamic model of cutting process based on RBF-ARX principle.

3. Cutting process model of RBF-ARX model

3.1 The basic structure of the RBF-ARX model

The RBF-ARX model is a composite model that combines the RBF neural network and the linear autoregressive ARX model to achieve local linearization and global non-linearization. The cutting process model of the cutter suction dredger based on RBF-ARX is as follows:

\[
C_n(t) = \phi_0(w(t-1)) + \sum_{i=1}^{n} \phi_i(w(t-1))C_n(t-i) + \sum_{i=1}^{n} \phi_{ij}(w(t-1))a(t-i) + \xi(t)
\]

\[
\phi_0(w(t-1)) = c_0^w + \sum_{k=1}^{n} c_k^w \exp\left(-\|w(t-1) - z_k\|_{L_2}^2\right)
\]

\[
\phi_i(w(t-1)) = c_i^w + \sum_{k=1}^{n} c_k^w \exp\left(-\|w(t-1) - z_k\|_{L_2}^2\right)
\]

\[
w(t-1) = \begin{bmatrix} \omega(t-1)^T & \omega(t-2)^T & \cdots & \omega(t-n)^T \end{bmatrix}^T
\]

\[
z_{jk} = \begin{bmatrix} z_{j1}^T & z_{j2}^T & \cdots & z_{jK}^T \end{bmatrix}^T, j = C_n, u, v
\]

\[
\omega(t-l) = [C_n(t+\tau-l), u_l(t-l), v_l(t-l)], l = 1, 2, K, n
\]
In the formula, $C_{w}(t)$ is the mud concentration, $n_s$ is the cutter speed, $p_s$ is the swing speed, and $\tau$ is the lag time. In order to cause the process variable combination to change the operating point of the system state, $\{\xi(t) \in \mathbb{R}^{n_c}\}$ represents the white noise sequence $n_{w}, n_{h}, n_{e}$ are the model order, $\phi_{h}(w(t-1))$ and $(k = 1, 2, \ldots, h; j = y, u, v)$ are the state-dependent function coefficients, where $h$ and $n_{w}$ are the model order; $Z_{jk}$ $(k = 1, 2, \ldots, h; j = y, u, v)$ is the RBF network center; $\lambda_{jk}$ $(k = 1, 2, \ldots, h; j = y, u, v)$ is the scale factor of the RBF network; $c_{jk}^{0}$ $(k = 1, 2, \ldots, h; j = y, u, v)$ and $c_{jk}^{l}$ $(k = 1, 2, \ldots, h; j = y, u, v)$ are the linear weights of the RBF network; $\|\|_{2}$ represents the quadratic norm of the vector; $\lambda_{N} = \text{diag}(\lambda_{1}^{2}, \lambda_{2}^{2}, \ldots, \lambda_{\text{dim}(x)}^{2})$, $\lambda_{t} = \lambda \lambda_{1}^{2} \lambda_{2}^{2} \cdots \lambda_{\text{dim}(x)}^{2}$ are the scaling factors.

3.2 Parameter identification of RBF-ARX model

In this paper, nonlinear parameter optimization method (SNPOM) is used to estimate the parameters of RBF-ARX model, which has the characteristics of fast calculation speed and high precision. It combines linear least square method (LSM) for linear parameter estimation and Levenberg-Marquardt method (LMM) for nonlinear parameter estimation, and divides the model parameters into nonlinear parameter subspaces and linear weighty subspaces. The solution process about the entire model is as follows:\[7].

The determination of the model order can be calculated using the AIC information criterion:

$$AIC = N \log V + 2d$$ (4)

Among them, $V$ is the covariance of the model, $N$ is the length of the observation data, and $d$ is the sum of all the parameters that need to be identified. Before choosing the final model, it is necessary to repeat the experiment several times under different model orders according to the above-mentioned model parameter estimation method, and compare the value of AIC under different orders. The smaller the AIC, the higher the model fitting accuracy will be. Under normal circumstances, $h$ take $1 \sim 2$, take 1 in the paper, and compare the value of AIC through calculation of data, and finally determine the order of the model is $n_{w} = 2$, $n_{h} = 4$, $n_{e} = 2$.

Rewrite formula (3) as:

$$C(t) = \phi(\theta_{N}, w(t))^{T} \theta_{k} + \xi(t)$$ (5)

$\theta_{N}$ is the vector of all the non-linear parameters in formula (3), $\theta_{k}$ including the vector of all linear weights. The initial value of the proportional coefficient needs to be calculated by the following formula:

$$\lambda_{0}^{0} = \max_{i=1}^{\text{max}} \left| w(t-1) - Z_{i} \right|$$ (6)

Among them, $\epsilon = [0.1: \ 0.00001]$, in the subsequent calculations in this article, $\epsilon$ take 0.0001. Use the LSM algorithm to calculate the initial value of the linear parameter subspace:

$$\theta_{k}^{0} = \left[ P(\theta_{k}^{0}) \right]^{-1} P(\theta_{k}^{0})^{T} Y$$ (7)

After the parameter initialization is completed, in order to further optimize the parameters, define the objective function

$$R(\theta_{k}, \theta_{e}) \leq \frac{1}{2} \left\| F(\theta_{k}, \theta_{e}) \right\|_{2}^{2}$$ (8)

Thus, the parameter optimization problem is transformed into the following formula:

$$(\theta_{k}, \theta_{e}) = \arg \min_{\theta_{k}, \theta_{e}} R(\theta_{k}, \theta_{e})$$ (9)
The key to using the SNPOM algorithm for parameter optimization calculations is to search for the k-th iteration $\theta_N^{k+1}$. The nonlinear parameters $\theta_N^{k+1}$ have the following update strategies:

$$\theta_N^{k+1} = \theta_N^k + \beta_k p_k$$  \hspace{1cm} (10)

Where $\beta_k$ is the step length and $p_k$ is the search direction, which can be solved by the following formula:

$$
\begin{bmatrix}
J(\theta_N^k) & J(\theta_N^k) + \gamma_k I
\end{bmatrix}
\begin{bmatrix}
p_k
\end{bmatrix} = -J(\theta_N^k)F(\theta_N^k, \theta_N^k)^T \\
J(\theta_N^k) = \left\{ \frac{\partial F(\theta_N^k, \theta_N^k)}{\partial \theta_N^k} \right\}^T
$$

(11)

After $\theta_N^{k+1}$ determining, update the linear weight with LSM:

$$\theta_L^{k+1} = \left[ P(\theta_N^{k+1})^T P(\theta_N^{k+1}) \right]^{-1} P(\theta_N^{k+1})^T \bar{y}$$  \hspace{1cm} (12)

it needs $R(\theta_L^{k+1}, \theta_N^{k+1}) < R(\theta_L^k, \theta_N^k)$ to be guaranteed to be true, otherwise the parameter identification process will be terminated.

4. Experimental and result analysis of cutting process model

In order to reflect the dynamic information of reamer cutting process in dredging process as much as possible, the field data collected by cutter suction dredger were selected to analyze the data in each pile changing period as a group of parameters. In a real dredger, the sensor for measuring the concentration is generally installed at the stern of the ship, and there is a certain distance from the cutter device, causing the measured mud concentration to have a certain lag compared to the change of the working state of the cutter. According to the measured data of the mud flow rate and the distance between the concentration meter and the cutter device, the lag time is taken as 24s.

Choose the coefficient of determination $R^2$ as the evaluation index to intuitively reflect the accuracy of the model's output results. The value of the coefficient of $R^2$ determination is between $[0 \sim 1]$, and the larger the value, the closer to 1, indicating the better fitting degree of the model.

4.1 Identification of cutting process parameters and result analysis

After the identification of the above steps is completed, the output result of the cutting process model is shown as follows:

![Figure 1. Comparison between actual density and predicted density.](image1)

![Figure 2. Mean Absolute Percentage Error.](image2)
It can be seen that the established model reflects the change of mud concentration during the dredging process. The prediction error is roughly normally distributed, and the error is concentrated in between $[-3\%,3\%]$, indicating that the model output value has a high degree of coincidence with the measured data. After calculation, the coefficient of determination reaches 0.986, which also proves that the model output results have a higher degree of fit with the measured data. But at the same time, some problems can be seen from the graph. When the mud concentration is at its maximum value, the error of the model is relatively large. This is due to the limited input selected and cannot fully reflect the factors affecting the mud concentration during the entire dredging process.

4.2 Verification and comparative analysis
In order to verify the predictive ability of the established model, another set of data is used to verify the model, and the results are as follows:

![Figure 3. Comparison between actual density and predicted density.](image1)

![Figure 4. Mean Absolute Percentage Error.](image2)

The results shown in the figure above show that the model still has a good prediction effect after changing the data. It reflects the RBF-ARX model in the cutting process of superior performance, not only high fitting accuracy and good stability and reliability.

5. Conclusion
The dredging operation of the stranded dredger boat is an extremely complex and multi-change process, which can affect the factors of dynamic characteristics. The relationship between the interaction between related factors is also different. This paper uses the RBF-ARX model theory to model the important process-cutting process in the dredging operation of the mud boat, using the actual construction data, to establish a global model to describe its dynamic characteristics.

The simulation results show that the model can describe the dynamic performance of the system well. But in this paper, only cutter speed and swing speed are used as control inputs. In the future, factors such as mud flow rate and mud pump speed can be incorporated into the model establishment process to make the model more accurate. At the same time, it lays the foundation for the next step of designing the predictive controller of the system.

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