Data-driven predictive control for the swing process of a cutter suction dredger

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Abstract. The working process of cutter suction dredger is complex, so it is difficult to establish accurate model by traditional physical modeling method. The final yield of cutter suction dredger is directly related to the density of the slurry in the pipeline, while the density is controlled by the swing process. Therefore, by analyzing the measured data of the dredger, it establishes the swing process mathematical model based on subspace theory. The algorithm is based on input–output data, simulation results show the algorithm is effective for the control application.

1. Introduction
The cutter suction dredger is a kind of ship widely used in the dredging project at present. The operation first cuts the sediment on the bottom of the river by the cutter, then the slurry is sucked into the pipeline by the submerged dredge pump, and finally the slurry is pumped by the cabin pump and the relay pump for long-distance transportation. The operation process includes the swing process, the cutting process and the pipeline transportation process. The traverse cutting process is the most frequent operation, and the swing speed is directly related to slurry density. However, the current swing speed is often adjusted by the operator based on the dredging experience, which makes the dredging inefficient and can easily lead to the blockage of the pipe. And because in the actual construction operation, faced with the complex construction environment, varied soil quality, uncertain working conditions, making the control of swing speed becomes particularly difficult.

Figure 1. Brief description of cutter suction dredger.
Therefore, it is very important to control the process of lateral movement with high efficiency, high precision and high automation. Some research has been done on swinging process in China, WEI Changyun\cite{1} applied predictive control to the lateral movement process based on the RBF-ARX theory, Zhu Wenliang\cite{2} proposed a modeling method of lateral movement process based on BP neural network, Song Dongpeng\cite{3} proposed lateral movement control system based on BP neural network. The above control system requires a large amount of historical data to model the swing system, and due to the uncertainty of the construction environment, soil quality and working conditions, it can’t achieve good control effect in the actual construction.

Based on the theory of subspace identification, this paper constructs the swing process model from dredging data, which can accurately predict the slurry density. After the prediction model is obtained, rolling optimization and feedback regulation are carried out. The swing process model established in this paper can predict the slurry density through the swing speed, which meets the requirements of the prediction model. Rolling optimization and feedback regulation can make the swing system continuously optimized during operation, thus solving the problem that the dredger construction cannot be kept optimal due to external factors.

2. Subspace identification method

\begin{align*}
\hat{Y}_f &= L_1 W_p + L_2 U_f \\
\min_{L_1, L_2} \left\| Y_f - (L_1 L_2) \begin{bmatrix} W_p \\ U_f \end{bmatrix} \right\|_F^2
\end{align*}

Where, $L = [L_1 \quad L_2]$ is the corresponding subspace matrix, for $L_1 \in \mathbb{R}^{(i \times N) \times ((i+m) \times N)}$, $L_2 \in \mathbb{R}^{(i \times N) \times (i \times N)}$, obtained by solving the following least squares problem.

Then use QR decomposition to solve the least squares problem. The best prediction of future output $\hat{Y}_f$ could be described as an orthogonal mapping from the column space $Y_f$ to the column spaces $W_p$ and $U_f$.

![Figure 2. The frame of subspace state-space identification.](image-url)
\[
\hat{Y}_f = Y_f / \begin{pmatrix} W_p \\ U_f \end{pmatrix} = L W_p + L_2 U_f 
\]

The solution for equation (3) could be found by performing a QR-decomposition:

\[
\begin{bmatrix} W_p \\ U_f \\ Y_f \end{bmatrix} = \begin{bmatrix} R_{11} & 0 & 0 \\ R_{21} & R_{22} & 0 \\ R_{31} & R_{32} & R_{33} \end{bmatrix} \begin{bmatrix} Q_1^T \\ Q_2^T \\ Q_3^T \end{bmatrix}
\]

Then:

\[
L = \begin{bmatrix} R_{31} & R_{32} \end{bmatrix} \begin{bmatrix} R_{11} & 0 \\ R_{21} & R_{22} \end{bmatrix}
\]

Where \( L = [L_1 \quad L_2] \), \( L_1 \) and \( L_2 \) could be denoted as follow:

\[
L_1 = L(\cdot, 1 : i(l + m))
\]

\[
L_2 = L(\cdot, i(l + m) + 1 : i(2l + m))
\]

Set the current time to \( k \), then the past input/output and future input data as shown below:

\[
\begin{bmatrix} u(k - i) \\ u(k - i + 1) \\ \vdots \\ u(k - 1) \end{bmatrix}, \begin{bmatrix} y(k - i) \\ y(k - i + 1) \\ \vdots \\ y(k - 1) \end{bmatrix}, \begin{bmatrix} u(k) \\ u(k + 1) \\ \vdots \\ u(k + i - 1) \end{bmatrix}
\]

Then the future output is shown as follows:

\[
\begin{bmatrix} \hat{y}(k) \\ \hat{y}(k + 1) \\ \vdots \\ \hat{y}(k + i - 1) \end{bmatrix} = L_1 \begin{bmatrix} u(k - i) \\ u(k - i + 1) \\ \vdots \\ u(k - 1) \end{bmatrix} + L_2 \begin{bmatrix} u(k) \\ u(k + 1) \\ \vdots \\ u(k + i - 1) \end{bmatrix}
\]

3. Model predictive control

In fact, MPC has been widely used in the dredging field, and the control effect is satisfactory\[^6\]. Model predictive control can be described as a process of minimizing the following cost functions\[^7\]:

\[
J = \sum_{k_r=1}^{N_p} (y_{r+k} - r_{r+k})^T W_Q (y_{r+k} - r_{r+k}) + \sum_{l=1}^{N_c} \Delta u_{r+l}^T W_R \Delta u_{r+l}
\]

Where \( N_p \) and \( N_c \) are the prediction and control horizon, \( y_t \) is the output at time \( t \), \( r_t \) is the setpoint at time \( t \), \( W_Q \) and \( W_R \) are weighting matrices, \( \Delta u_t \) is the incremental input.

The system output is predicted by the predictive model obtained from the subspace identification:

\[
\hat{Y}_f = l_1 W_p + l_2 U_f
\]

Where \( \hat{Y}_f = [\hat{y}_{t+1} \ \hat{y}_{t+2} \ \cdots \ \hat{y}_{t+N_p}] \), \( u_f = [u_{t+1} \ \ u_{t+1} \ \ \cdots \ \ u_{t+N_c}] \), then the cost function
can be redefined as below:

\[ J = \left( r_f - \hat{y}_f \right)^T W_Q \left( r_f - \hat{y}_f \right) + u_f^T W_R u_f \]  

(11)

By using the prediction equation (10) to minimize the cost function (11), the future input \( u_f \) can be obtained:

\[ u_f = \arg \min_{u_f} \left\{ \left( r_f - \hat{y}_f \right)^T W_Q \left( r_f - \hat{y}_f \right) + u_f^T W_R u_f \right\} \]  

(12)

Data-driven predictive control can be achieved by taking the first set of calculated data as input to the actual system and then cycling.

4. Experimental results and analysis

4.1 Results of subspace identification
The first step of data-driven predictive control is subspace identification. Only when the model identified in the subspace achieves good prediction results, the following predictive control can obtain accurate control results.

600 sets of data in the actual dredging process were selected, and the subspace identification was carried out with the swing speed as the input and the density as the output. After the identification, the output of the swing system model and the prediction errors as follows:

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

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

The prediction error rate is concentrated around 1%, and the MAPE(Mean Absolute Percentage Error) is 1.8771%. The prediction results are relatively accurate.

4.2 Predictive control results
There are 50 groups of data in the cycle control, and the data collection is 1 group in 2 seconds, and the total operation time is 100 seconds.

When the setpoint is a fixed value of 1.27(t/m3), the control results are as follows:
It can be seen from the control results that when the target value is fixed, the density after control quickly reaches the target value, and the swing speed also tends to be stable quickly.

When the target value is set as the optimal density calculated by the dredging data, that is, when the target value is dynamic fluctuation, the control results are as follows:

It can be seen from the control results that when the set value is changed, the value after predictive control can also reach the set value more accurately, and the change of swing speed is also stable.

5. Conclusion
This paper uses the method of subspace identification to build the prediction model of the swing system, and uses data-driven predictive control to skip the complicated traditional modeling and control the swing speed of the cutter suction dredger to make the slurry density reach the predetermined value. The experimental results show that the prediction model obtained by using the subspace identification has high accuracy and can achieve good control effect, which provides a new method for the control of the swing system of cutter suction dredger.
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