The combined algorithm of aluminum-electrolytic cell voltage collection based on Kalman filter

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Abstract: This paper proposes a combined cell voltage acquisition algorithm based on Kalman filtering, which is used to solve the problem of insufficient cell voltage acquisition and high delay in the current aluminum electrolysis process. This algorithm is based on Kalman filtering, and uses the mean square error of the data to represent the Gaussian white noise power of the collected and predicted values. It has strong tracking performance in the state of stable voltage. The voltage acquisition data out of the interval is complied to first-order inertial filtering, to replace the voltage sampling value, and then using the Kalman filtering algorithm to calculate the filtering gain, to ensure that the combined algorithm can filter out the influence of noise when the cell voltage fluctuates greatly, and in the stable process of electrolysis, the convergence of battery voltage can be tracked quickly. The simulation results show that compared with the first-order inertial filter, the improved Kalman filter reduces the root mean square error by 50% when the voltage is stable, and reduces the convergence time by 50% after the electrolytic cell regenerates needle vibration and swing.

1. Introduction

The electrolytic cell for aluminum electrolysis in industrial production is operated by a tank control machine. The tank makes various electrolytic operation by collecting and analysing datas, and then makes judgement of the electrolytic state. Therefore, in the aluminum electrolytic producing process, Data analysis algorithms are critical. Intensity is used as an auxiliary criterion for intelligent prediction of anode effect. The usage of filters with good performance can improve the reliability of judging the state of material balance (Al2O3 concentration) by using the tank voltage and predicting the anode effect. At the current stage of industrial production, a first-order inertial filtering algorithm is mainly deployed, and the tracking performance of the slot voltage acquisition is poor. Kalman filter algorithm has the advantages of strong tracking and fast speed, but the standard Kalman filter algorithm can only be used in linear systems, and in actual application process, it is difficult to have an accurate system model, which easily leads to filter divergence [1-4]. If it is a non-linear system, extended Kalman filtering [5-7] or Kalman filtering based on UT transformation [8-9] is mainly used; but these two filtering algorithms also need clear system calculation models and statistical characteristics of noise It is not applicable in the acquisition of tank voltage. In this paper, the traditional Kalman filtering method is optimized. Due to the short interval of sampling data, the predicted value is used as the system observation value, and the Kalman method is used to filter. The amplitude change threshold is set. First-order inertial filtering is performed on the collected data to replace the voltage sampling value, and then the Kalman filtering algorithm is used. The simulation results show that the improved filter algorithm has strong tracking ability in the stable state of the electrolytic cell, the ability of...
removing the interference of needle vibration and swing, also with better performance of extracting information from the cell resistance and the change in Al2O3 concentration.

2. Problem formulation

In the actual production process, the aluminum electrolytic cell control system can only collect the voltage and current of the electrolytic cell, because the calculated resistance value of the cell is very small, in order to be able to judge the change of the material balance in the electrolytic cell based on the resistance value of the electrolytic cell. The slot resistance can be linearly transformed into "normalized slot voltage", so that it has the same meaning as the slot resistance [10]:

\[ V_n(i) = R(i) \cdot I_b + F = \frac{V(i) - B}{I(i)} \cdot I_b + F \quad (1) \]

Where \( V_n(i) \) is Normalized tank voltage at \( i \) time (original value), \( I_b \) is reference current, \( F \) is the apparent back-EMF represents the part of the tank voltage that does not change with the change of the series current.

Commonly referred to as "cell resistance filtering" of aluminum electrolytic cells refers to low-pass digital filtering of the "normalized cell voltage" to remove the higher frequency components to avoid its relative impact on the pole pitch and Al2O3 concentration. In order to interfere with the judgment and control of the slowly time-varying state parameters, in order to achieve this purpose, a first-order recursive low-pass digital filter with inertial filtering performance is generally used. Its time domain expression is:

\[ y(i) = (1 - \varphi) y(i - 1) + \varphi x(i) \quad (2) \]

Where \( y(i) \) is the output of the filter (the filtered value), \( x(i) \) is the input of the filter (the sampled value), \( i \) represents the number, \( \varphi \) is filter coefficient. Because the fluctuating frequency of the normalized tank voltage is between 0.002 Hz and 0.04 Hz, and the fluctuating frequency of the aluminum liquid is about 0.03 Hz [11], in order to obtain a sufficiently narrow filtering bandwidth, it is generally used in the aluminum electrolytic industry.

3. Combined Kalman filter

3.1. Kalman filter basic equation

Let the discrete state equation and observation equation of the linear system be:

\[ X(i) = AX(i - 1) + BU(i) + G(i) \quad (3) \]
\[ Z(i) = H(i) + N(i) \quad (4) \]

Where \( X(i) \) is system status at time \( i \), \( U(i) \) is control amount of the system at time \( i \), \( A \) and \( B \) is system parameters, for multi-model systems, they are matrices, \( Z(i) \) is the measured value at time \( i \), \( H \) is the parameter of the measurement system. for multi-measurement systems, \( H \) is the matrix, \( G(i) \) and \( N(i) \) represent process noise and measurement noise.

Assuming that the process noise and measurement noise of the above systems are both Gaussian white noise, and their covariance matrices are represented by \( Q \) and \( R \), respectively, then the Kalman filter is the optimal information processor for the above system. The recursive equation of the Kalman filter can be obtained as:

\[ X(i|i - 1) = AX(i - 1|i - 1) + BU(i) \quad (5) \]
\[ P(i|i - 1) = AP(i - 1|i - 1)A^T + Q \quad (6) \]
\[ Kg(i) = P(i|i - 1)H^T (HP(i|i - 1)H^T + R)^{-1} \quad (7) \]
\[ X(i|i) = X(i|i - 1) + Kg(i)(Z(i) - HX(i|i - 1)) \quad (8) \]
\[ P(i|i) = (1 - Kg(i))P(i|i-1) \]  \hspace{1cm} (9)

Where \( X(i|i-1) \) is estimate the state at time \( i \), using time \( i-1 \), \( P(i|i-1) \) represents the single-step prediction covariance matrix time \( i-1 \) to time \( i \). \( Kg(i) \) is Kalman gain. \( X(i|i) \) is optimal estimation of system state at time \( i \). \( P(i|i) \) is updated estimated covariance matrix.

### 3.2. Establishment of equations of state and observations

The Kalman filter is an efficient recursive filter. The use of the Kalman filter requires the establishment of state equations and observation equations, but there is no clear state transition calculation equation for the aluminum electrolytic cell voltage. The voltage information obtained by filtering in this paper is used to reflect the two relatively slow time-varying state variables: anode pole distance and \( \text{Al}_2\text{O}_3 \) concentration. Under the current production technology, the dissolution time constant of \( \text{Al}_2\text{O}_3 \) is 10 min and the dissolution lag time is 2 min. Right and left, the concentration of \( \text{Al}_2\text{O}_3 \) in the electrolytic cell is maintained between 1% and 8%. The changes in the concentration of \( \text{Al}_2\text{O}_3 \) and the anode pole pitch are relatively slow, and the sampling frequency of the data is 1 Hz. Therefore, when using Kalman filtering, it can be determined as The predicted voltage value is the last filtered voltage value. So its equation of state can be expressed as:

\[ X(i) = X(i-1) + C(i) \]  \hspace{1cm} (10)

Where \( X(i) \) is the state of the system at time \( i \), \( C(i) \) is the mean square error of the first ten Kalman predictions. Here it is used to characterize the power of the system's white Gaussian noise.

\[ C(i) = 10^{-1} \left\{ \sum_{i=10}^{i=1} [X(i) - R]^2 \right\} \]  \hspace{1cm} (11)

Where \( R \) is the average of the first ten acquisitions.

Due to the problems of the aluminum electrolysis process, the cell voltage is not smooth and stable, and the cell also often fluctuates, leading to the instability of the cell voltage. When the anode effect occurs in the cell, the calculated cell voltage will also be huge. Variety. In order to reflect the real change of the slot resistance, and to maintain the filtering effect to quickly converge after the fluctuation is over, the applicable interval of the algorithm is divided according to the process requirements, the threshold is set to 70, and the return interval is set to \([60,80]\). When the calculated normalized tank voltage change exceeds the upper limit of the hysteresis interval, a first-order filtering will be applied to it. As the voltage change gradually stabilizes until the lower limit of the hysteresis interval is reached, the normal calculated value will be used, so the measurement The time domain expression of the equation is as follows:

\[
\begin{aligned}
Z(i) &= V_o(i) + D(i) \\
Z(i) &= 31/32Z(i-1) + 1/32V_o(i) + D(i) \\
V_o(i) - V_o(i-1) &< 40 \\
V_o(i) - V_o(i-1) &> 60
\end{aligned}
\]  \hspace{1cm} (12)

Where \( Z(i) \) is the measured value at time \( i \), \( V_o(i) \) is the calculated value of normalized tank voltage at time \( i \), \( D(i) \) is the mean square error of the first ten measurements, which is used to characterize the power of the system's white Gaussian noise.

### 3.3. Kalman filter error accumulation analysis and processing method

This article uses the previous filter resistance value instead of the current state value of the Kalman filter, so the filtering result will have errors due to inaccurate prediction. The time-domain expressions that cause errors due to inaccurate predictions are:

\[ E(i) = [1 - Kg(i)]\varepsilon(i) \]  \hspace{1cm} (13)

Where \( \varepsilon(i) \) is the \( K \)-th prediction error, \( E(i) \) is the error caused by inaccurate prediction in the \( k \)-th filtering result.

It can be known from equation (13) that if the prediction error increases or remains constant over
time, the Kalman filter gain decreases with time, which will cause the accumulation of errors, that is, if the system changes from stationary to linear monotonic increasing (decreasing), then will cause the accumulation of errors.

In this paper, the Gaussian white noise power of the prediction equation and the measurement equation are respectively characterized by the mean square error of the filtered value and the acquired value. When the system changes from a steady state to a linear monotonic increase (decreasing), the filtering gain cannot change according to the change in the slope. Large errors will be introduced and accumulated. If there is a sudden change in the calculated "normalized tank voltage", since the state value is the resistance value of the previous filtering, a larger prediction error will also be introduced at this time. In the process of aluminum electrolysis, the sudden change of voltage is caused by the unstable factors of the electrolysis process (such as bubbles and aluminum liquid fluctuations), and this interference needs to be filtered out in the process control, so that the oxidation in the electrolytic cell can be judged by the change in resistance. The concentration of aluminum changes, and the electrolytic cell is finally controlled. Therefore, the first-order filtering can be used to process the calculated value when the collected resistance changes suddenly, and then the Kalman filter is used. When the voltage is stable, the calculated value is used again as the voltage. Collecting values and recalculating the gain can prevent the accumulation of errors.

4. Analysis of results
The data used in the experiment are derived from the resistance values of aluminum electrolytic cells collected by an aluminum factory in Qinghai. The total number of data is 8053 and the sampling frequency is 1Hz. This experiment will use classical Kalman filtering, first-order filtering, and combined Kalman filtering to analyze and compare the data, intercept several waveforms, and observe the filtering results.

After calculating the “normalized tank voltage” with the same meaning as the tank resistance from the voltage and current signals collected by the aluminum factory, in order to facilitate data observation, the data is retained to three decimal places and multiplied by 1000, and then filtered. The filtering effect of several states of the electrolytic cell is compared. Because the filtering method adopted will eventually converge to the normalized cell voltage after the measurement of the voltage and current calculation, the initial value of the predicted value can be set to an arbitrary value. However, in order to speed up the convergence of the filtering algorithm, this paper sets the initial value to 4000.

Figure 1 shows the filter tracking trajectory in the steady state, and Table 1 shows the comparison of the root mean square error of the three filters in the steady state. From the comparison of the 40 collected data in Figure 1, it can be seen that when the electrolytic cell is relatively stable, the first-order inertial filter can barely reflect the trend of the tank voltage caused by the change in the concentration of AL2O3. It can also be seen from the root-mean-square error calculated in Table 1 that the root-mean-square error of the first-order inertial filter is 50% higher than the Kalman filter. Therefore, the first-order inertial filtering cannot track the value of the cell voltage well even when the electrolytic cell is relatively stable. The combined Kalman and classic Kalman have strong tracking performance when the cell voltage is stable. It can better reflect the change trend of the cell resistance, and can also track the true value of the cell voltage, so that the change in the AL2O3 concentration of the electrolytic cell can be judged more accurately by the voltage change.
Figure 1. Filtered graphics tracking trajectory in steady state

Table 1. Comparison of Root Mean Square Errors of Three Filtering Algorithms in Stationary State

| algorithm                  | Root mean square error |
|----------------------------|------------------------|
| First-order inertial filtering | 26.0572               |
| Combined Kalman filter      | 12.3710                |
| Classic Kalman filter       | 12.6336                |

Figure 2 shows the sampled voltage of the needle tank voltage. Figure 3 shows a graphical comparison of three filtering algorithms based on the sampling resistor. Table 2 shows a comparison of the convergence speed of the pin vibration, the convergence time of the classical Kalman filter is faster than the first-order inertial filter, but it is slower than the combined Kalman filter, because the classical Kalman also retains a strong strength when the pin vibration and swing occur in the electrolytic cell Tracking characteristics, and the filter gain is not reset after the needle vibration and swing occur; the combined Kalman filter first performs strong filtering on the signal, and then performs Kalman filtering on the signal, which can not only remove most of the interference, and can quickly converge after the waveform is re-stabilized, so the improved Kalman filter has the shortest convergence time after needle vibration and swing in the aluminum electrolytic cell; and when the cell condition is stable, the improved Kalman filter and classic Kalman filter The Mann filter also maintains strong tracking, which can provide more accurate information for the control of the aluminum electrolytic cell, so that it can better control the feeding amount and improve production efficiency.

Figure 2. Sampling value of the pin vibration resistance
Figure 3. Convergence comparison after needle vibration

Table 2. Convergence time comparison of three filtering algorithms

| Algorithm                        | Convergence time(s) |
|----------------------------------|---------------------|
| First-order inertial filtering   | 9                   |
| Classic Kalman filter            | 9                   |
| Combined Kalman filter           | 4                   |

Figure 4 is a filtering effect diagram of three filtering algorithms when an abnormal step occurs. The abnormal step is caused by the collapse of the material surface, the anode dropping, or the manual operation. From the filtering effect diagram in Fig. 4, it can be seen that the abnormal step of the narrow-band first-order inertial filtering in the electrolytic process will have a large lag. This will affect the tracking and control of the pole distance and the alumina concentration under artificial monitoring, and it will not help the computer to judge and process the collected data. The Kalman filter has faster tracking performance than the first-order inertial filter, and can adapt to the step of the voltage to ensure the accuracy of production control.

Figure 4. Convergence comparison when an abnormal step occurs

5. Conclusion

Based on the first-order inertial filtering method commonly used in the aluminum electrolytic industry at present, a combined Kalman filtering method is proposed, which can be used to collect the voltage of the aluminum electrolytic tank. The improved algorithm uses the previous filtering value as the state of the next calculation, and set an applicable filtering interval. When needle vibration and swing occur in the electrolytic cell, first-order inertial filtering is performed on the signal, and then Kalman filtering is performed. Simulation results show that the filtering effect and tracking performance of the algorithm are better than the first-order filtering. Compared with the classical Kalman filter, the method is less affected by the needle vibration and swing in the electrolytic cell, and its filtering effect is better.
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