Research on Algorithm Based on Improved PID Controller

Gang Wu\textsuperscript{1}, Wanqiang Wu\textsuperscript{*}\textsuperscript{2}

\textsuperscript{1}Intelligent science and engineering, Shenyang University, Shenyang City, Liaoning Province, 110000, China
\textsuperscript{2}Information Engineering and Science, Shenyang University, Shenyang City, Liaoning Province, 110000, China

\textsuperscript{*} Corresponding author: 714653430@qq.com

Abstract. In order to solve the problem of noise and lag in the control system, which can not make the balance vehicle reach a fast and stable state, an improved PID closed-loop controller is proposed. The piecewise function is added to the closed-loop controller to weaken the integral, and the integral link is weakened in different states to make the system reach a stable state. The data collected by the sensor is processed, and the balance system reaches the steady state through Kalman filtering algorithm. The simulation results show that the improved PID control algorithm can effectively reduce the lag effect. At the same time, the environmental noise can be removed after Kalman filter processing, so that the balance car can reduce the jitter time and achieve stability quickly.

1. Introduction

In today's control field, the principle of PID control algorithm is simple and easy to implement, so PID control algorithm has become the most widely used controller \cite{1}. However, when using the PID controller, it is necessary to constantly adjust the parameters. Too large or too small will affect the final convergence, effect. Huang Jian et al. \cite{2} believe that small proportional parameters will affect the response speed, and large proportional parameters will produce low-frequency oscillation. Therefore, parameter debugging is very important. Lin Feng et al. \cite{3} believed that the traditional PID controller has defects, and the integral link in the PID controller will lead to large overshoot of the system. Chen Peng Zhan \cite{4} believed that the integral of the PID controller has cumulative error, so only the proportional coefficient and differential control quantity are introduced. Wang Yi Chen et al. \cite{5} thought that the position PID structure is clear and the parameter setting is clear, but there will be integral saturation zone. After entering the saturation zone, it takes a long time to exit from the saturation zone. Based on the above point of view, this paper proposes a PID control algorithm, which adds a piecewise function before the saturation zone and weakens the integral link when the control algorithm is close to the saturation zone, which can reduce the overshoot of the control system. Complex environment, noise and other factors will affect the stability of the balance system and the recovery time of the system. In the actual test, attitude and other related data will be mixed with noise. Wang Liang et al \cite{6} believe that external interference will also affect the accuracy of accelerometer measurement, resulting in large drift and distortion of data. In this paper, Kalman filter algorithm is proposed to remove the noise in the environment. After obtaining the attitude data, it is filtered to remove the noise in the data, so as to reduce the jitter of the balance system and quickly realize the stable state.
2. Design of control system

2.1. PID control algorithm

The main body of PID regulates the system through three links: proportion, integral, differential [7]. The main design idea of this method is to compare the system set value with the system output value through proportional, integral and differential calculation to form a deviation value, and control the system by calculating the difference [8]. The deviation value is obtained by comparing the feedback value with the target value, and then the system is adjusted through the proportional coefficient corresponding to the p-ring. However, when there is only p-ring in the system, there will be steady-state error, which will make the balance vehicle unable to maintain balance finally. Therefore, an i-ring is added on the basis of p-ring for control and adjustment. The i-loop will accumulate the deviation value in the control decision to determine the difference from the target value, which can reduce the steady-state error caused by a single P-loop and achieve the steady-state near the target value. However, after the introduction of P control and I control, the system is easy to cause oscillation, which will affect the steady-state speed and time. Therefore, the introduction of D-loop in the control system can adjust the system oscillation. After the introduction of D-loop, the continuous adjustment of D-loop parameters can reduce the system oscillation.

Establish a model, such as formula (1), where $K_p, K_i, K_d$ are the proportion, integral and differential in the PID controller, and $e(t)$ is the error in the balance system.

$$P_{out}(t) = K_p e(t) + K_i \sum e(t) + K_d (e(t) - e(t-1))$$  \hspace{1cm} (1)

2.2. Improved PID control algorithm

There is overshoot in the convergence process of the balance system, which will affect the balance system. By improving the traditional PID, segment near the specified output value and weaken the integral link to achieve the purpose of rapid convergence. When using piecewise PID and separating the integral under appropriate conditions, better control effect can be obtained. The reason is that when the steady-state error is about to meet the requirements, the system lag is eliminated, so the system overshoot will be significantly reduced. Improved PID controller for balance system $u(k) > u_{\text{max}}$, $e(k) > 0$, When the output value of the improved PID controller of the balance system has not reached the specified value, the integration will bring the overshoot effect, so the integration link will be weakened. When $u(k) < 0$, $e(k) < 0$, If the output value exceeds the specified value, further integration will also bring overshoot effect. Therefore, the weakening link is also carried out, as shown in formula (2).

$$\begin{cases} u(k) > u_{\text{max}}, e(k) > 0 \\
 u(k) < 0, e(k) < 0 
\end{cases}$$  \hspace{1cm} (2)

3. Kalman filter algorithm

In the case of 0-30db low noise, compared with other complementary filters, the detection error of Kalman filter is low. The difference between the angle fitting curve obtained by Kalman filter and the angle curve measured by attitude detection sensor is smaller than that by traditional complementary filter, and the fitting effect is better, which reduces the impact of low noise on the accuracy of dynamic inclination measurement [9].

The principle of Kalman filter is to use Kalman gain to modify the state prediction value to approximate the real value. Part of the derivation process is as follows.

It is assumed that the model of discrete linear dynamic system is as follows:

$$x_k = A x_{k-1} + B u_k + w_k$$  \hspace{1cm} (3)

$$z_k = H x_k + B u_k + w_k$$  \hspace{1cm} (4)
Where \( x_k \) is the system state matrix, \( z_k \) is the observed measurement (measured) of the state matrix, \( A \) is the state transition matrix, \( B \) is the control input matrix, \( H \) is the state observation matrix, \( w_k \) is the process noise, and \( u_k \) is the measurement noise.

Make the status prediction value \( \tilde{x}_k^- \) as:

\[
\tilde{x}_k^- = A \cdot \tilde{x}_{k-1}^- + B \cdot u_k
\]

(5)

Make the optimal state estimate \( \bar{x}_k \) as:

\[
\bar{x}_k = \tilde{x}_k^- + K (z_k - H \cdot \tilde{x}_k^-)
\]

(6)

The Kalman gain is \( K \), which actually represents the ratio of prediction error to measurement error in the optimal estimation process. The ratio of prediction error to measurement error ranges from 0 to 1. The closer the gain is to 0, the more the state value of the system depends on the prediction value. The closer the gain is to 1, the more the value of the system depends on the measurement value.

Substitute formula (4) into formula (6), and make a difference between both ends of the formula and the real value of the system to obtain formula (7).

\[
\tilde{x}_k - x_k = \tilde{x}_k^- - x_k + KH (x_k - \tilde{x}_k^-) + K u_k
\]

(7)

Let \( e_i^k = x_i - \tilde{x}_i^- \) and \( e_i = x_i - \bar{x}_i \), where \( e_i^- \) is a priori state error and a posteriori state error. Bring \( e_i \) into formula (7) to obtain a posteriori error. Formula (8) is as follows.

\[
e_i^k = (I - KH) \cdot e_i^- - K \cdot u_k
\]

(8)

Let \( P_k^- = E [e_i^- \cdot e_i^-^T] \), \( P_k^* = E [e_i^* \cdot e_i^*^T] \). Where \( P_k^- \) is the covariance between the real value and the predicted value, \( P_k^* \) is the covariance between the real value and the optimal estimated value, and \( R \) is the covariance of the measurement noise. The estimation error variance formula (9) can be obtained by simultaneous formula (8)

\[
P_k^* = E [e_i^* \cdot e_i^*^T]
\]

\[
= (I - KH) \cdot P_k^- \cdot (I - KH)^T + K \cdot R \cdot K^T
\]

\[
= P_k^- - KHP_k^- P_k^- H^T K^T + K (HP_k^- H^T + R) K^T
\]

(9)

In order to minimize the optimal state covariance, the partial derivative of (9) \( P_k^* \) in the formula is obtained to obtain formula (10), and the Kalman gain \( K \) can be obtained through the transformation and arrangement of formula (10).

\[
\frac{\partial P_k^*}{\partial K} = -2(P_k^- H^T) + 2K (H P_k^- H^T + R) = 0
\]

(10)

The Kalman gain matrix \( K \) under the observation optimal estimation condition of the state matrix is:

\[
K = P_k^- H^T (H P_k^- H^T + R)^{-1}
\]

(11)

Replace formula (11) with formula (9) and simplify to obtain the estimation error covariance matrix \( K \):

\[
P_k^- = (I - KH) \cdot P_k^-
\]

(12)

Given \( e_i^k = x_i - \tilde{x}_i^- \), formula (13) is obtained by combining \( e_i^k = x_i - \bar{x}_i \) and the model of discrete linear dynamic system.
Given $T_{k} = E[e_k^* e_k^T]$, formula (11) is combined with $P_k = E[e_k^* e_k^T]$ and $P_{k+1} = E[e_{k+1}^* e_{k+1}^T]$ to obtain formula (14), where $Q$ is the covariance of process noise.

Through the derivation process of the above formula, we get the formulas of the prediction process, which are formula (5) and formula (14) respectively, and the formulas of the update process, which are formula (6), formula (11) and formula (12) respectively. Kalman filter estimates the state at the current time (time k) according to the a posteriori estimate of the previous time, and obtains the a priori estimate of time $K$. The measured value at the current time is used to correct the estimated value at the prediction stage to obtain the a posteriori estimated value at the current time [10].

4. PID control algorithm simulation

Set the sampling time and transfer function in MATLAB, set the proportional, integral and differential parameters, and draw the waveform with plot function. The system simulation verification by MATLAB shows that when adjusting the proportional link and integral link, the proportional coefficient is small, the system is sensitive to the introduced differential and integral, and the integral term will cause overshoot. When the proportional coefficient is large, the integral link should not be too small, otherwise the adjustment time will be increased.

The traditional PID control algorithm and the improved PID control algorithm are simulated, as shown in Figure 2. It is found that the traditional PID control algorithm produces overshoot, and the PID control algorithm after piecewise weakening integral can effectively reduce the overshoot, and the controller system quickly enters convergence. Through MATLAB simulation, it is found that the overshoot of the system is significantly reduced and the adjustment time is also reduced a little. The reason is that we adopt the means of piecewise PID, which not only eliminates the steady-state error, but also weakens the lag effect caused by the integration link [11].
5. Kalman filter simulation

The Kalman filter is simulated. In the comparison after simulation, it is found that the Kalman filter can effectively remove the added noise in the data added with noise, so as to reduce the data fluctuation of PID controller system. Finally, the theoretical practice is carried out in the real object of the balance vehicle. The improved PID controller and Kalman filter algorithm can quickly achieve stability in the car system and reduce the occurrence of car body jitter.

Simulate in MATLAB software, generate a group of matrices with variance of 1 and standard deviation of 1 through randn, and accumulate the simulation data, as shown in Figure 3.

![Figure 3. Observation data](image)

Add noise to the simulation data for processing. The data added with noise is shown in Figure 4 below.

![Figure 4. Adding noise image](image)

After filtering, it is shown in Figure 5. Comparing Figure 5 with Figure 4, it is found that the noise in the data is filtered by the filtering algorithm, which effectively removes the noise contained in the data and reduces the impact of inaccurate data on the system.

![Figure 5. Image after Kalman filtering](image)

6. Conclusion

Through the simulation of the algorithm, it is confirmed that the improved PID control algorithm can effectively stabilize the system and Kalman filter can reduce the impact of noise. The improved PID parameters and Kalman coefficients are determined in the process of simulation and actual debugging. After Kalman filter algorithm and under the control of P-loop, i-loop and D-loop of improved PID, the balance system can reach the balance state, and the balance vehicle can keep running stably. At the same time, it also solves the problem that the balance vehicle is affected by noise.

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