OPTIMAL TERMINAL ITERATIVE LEARNING CONTROL FOR THE PARKING CONTROL SYSTEM OF MAGLEV TRAIN

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Abstract—This paper analyzes the parking process of maglev trains, establishes the corresponding mathematical model, based on the method of terminal iterative learning control(TILC), uses the stopping position error in the previous braking process to update the current control curve. In this paper, we select the initial braking position, initial speed or braking force or a combination thereof as the control input, and formulate the corresponding learning law. Finally, a line is simulated, and the traditional TILC method and the optimal TILC method are compared through simulation experiments, which verify that the latter has a faster convergence speed.

1. INTRODUCTION
Maglev train is a new type of rail vehicle that uses electromagnetic force to achieve suspension, guidance and drive, and is expected to become one of the main modes of transportation in the 21st century. Compared with traditional wheel-rail trains, maglev trains have the advantages of low vibration, low noise, small turning radius, easy maintenance, strong weather resistance and long life[1]. The operation control system(OCS) is the central system that guarantees the normal operation of the maglev train. Its main functions are operation command and safety protection. Operation control algorithm is one of the core technologies of OCS. However, the current maglev operation control system draws on Communication-Based Train Control System(CBTC), and there is no mature operation control algorithm. Therefore, it is of great significance to study the maglev train operation control algorithm and improve the maglev train operation control performance.

Different control methods are proposed to effectively improve the running performance of wheel-rail trains[2-3]. The traditional train dynamics model is improved, and the genetic algorithm is used to modify the drag coefficient under different operating conditions. By introducing a fractional PID controller into the train operation control, a better speed control effect is achieved and the control accuracy is improved[4]. In view of the repeatability of the train parking phase and the characteristics involving multiple objectives, iterative learning control (ILC) is introduced to improve the train parking accuracy and comfort[5]. However, the traction method of the maglev train is different from that of the traditional wheel-rail train, and its operation control method is quite different. The existing mature wheel-rail train operation control method is not suitable for the maglev train.

In recent years, research scholars have used ILC for repetitive job objects, using the information of previous iterations or cycles to continuously modify the current iteration or cycle controller output. As
the number of iterations increases, the system can accurately track the desired trajectory within a limited time[6-8]. The terminal iterative learning control method was first introduced into the train parking control field, and three TILC-based algorithms were proposed[9]. Considering that the stopping position and initial braking speed are selected as the system output and control input, respectively, an optimal terminal iterative learning control method is proposed[10].

2. DESCRIPTION OF THE PROBLEM OF THE OPERATION CONTROL OF THE MAGLEV TRAIN

According to Newton's law of motion, during the operation of the maglev train, the resultant force of the train is satisfied[10]:

\[ ma = u - f_{\text{air}} - f_{\text{eddy}} - f_i - f_r - f_e \]  

Where \( m \) is the mass of the train; \( a \) is the acceleration of the train; \( u \) is the traction or braking force of the train; \( f_{\text{air}} \) is the air resistance encountered during the train operation; \( f_i \) and \( f_r \) is the additional resistance of the ramp and the additional resistance of the curve; \( f_{\text{eddy}} \) is the eddy current resistance between the F rail of the line and the suspended electromagnet; \( f_e \) is the other resistance that the train receives.

During train operation, the air resistance is related to the maximum cross-sectional area of the train body, drag coefficient, air density and train speed, which can be expressed as:

\[ f_{\text{air}} = 2.8(0.53 + 0.3)N \]  

Where \( v \) is the train speed; \( N \) is the number of train marshalling vehicles.

Eddy current resistance mainly comes from the eddy current effect between the F rail on both sides of the line and the suspended electromagnet. The calculation formula is as follows:

\[ f_{\text{eddy}} = N(0.1v^{0.5} + 0.02v^{0.7}) \]  

When the maglev train passes the ramp line, the additional resistance is determined by the slope of the ramp, expressed as:

\[ f_i = Nmg \sin(\phi) \]  

Where \( i \) is the thousandth of the slope of the ramp; \( g \) is the acceleration of gravity. When \( \sin(\phi) > 0 \), \( f_i > 0 \), it means the train is uphill; when \( \sin(\phi) < 0 \), \( f_i < 0 \), it means that the train is downhill.

In addition, when the train is running on a curve line, the additional resistance of the curve can be expressed as:

\[ f_r = \frac{600}{R} Nmg \]  

Where \( R \) is the curve radius of the curve.

Consider the following mid-to-low speed maglev train dynamics model:

\[ \dot{x}(t) = v(t) \]

\[ m\dot{v} = u - f_{\text{eddy}}(v) - f_{\text{air}}(v) - f_i(v) - f_r(v) - f_e(v) \]

Where \( x \) is the displacement of the train.

\[ \dot{x}(v) = \frac{mv}{u - f_{\text{eddy}}(v) - f_{\text{air}}(v) - f_i(v) - f_r(v) - f_e(v)} \]

\[ x(0) = x_{ini} + \int_{v_{ini}}^{0} \frac{mv}{u - f_{\text{eddy}}(v) - f_{\text{air}}(v) - f_i(v) - f_r(v) - f_e(v)} dv \]

Where \( x_{ini} \) is the starting braking point, \( v_{ini} \) is the initial speed at the beginning of braking.

According to (9), the train parking process is a non-linear process, thus finding the relationship between the k-th stop and the k-1th stop:
\[ x_k(0) - x_{k-1}(0) = \int_{v_{i,ini}}^{0} \frac{mv}{u - f_{dab}(v) - f_{air}(v) - f_i(v) - f_r(v) - f_e(v)} dv \] \\
\[ - \int_{v_{i,ini}}^{0} \frac{mv}{u - f_{dab}(v) - f_{air}(v) - f_i(v) - f_r(v) - f_e(v)} dv \] 

(10)

According to the median theorem:
\[ x_k(0) - x_{k-1}(0) = (v_{k,ini} - v_{k-1,ini}) \theta_k \] 

(11)

Where \( \theta_k = \frac{m \xi_k}{-u + f_{dab}(\xi_k) + f_{air}(\xi_k) + f_i(\xi_k) + f_r(\xi_k) + f_e(\xi_k)} \), and \( \xi_k \in (v_{k-1,ini}, v_{k,ini}) \)

Define the parking error as
\[ e_k(0) = x_f(0) - x_k(0) \] 

(12)

Construct a cost function and substitute (12) into it
\[ J_k(0) = e_k(0)^2 + \lambda \left| \Delta v_{k,ini} \right|^2 \] 

(13)

\[ J_k(0) = (e_{k-1}(0) - (x_k(0) - x_{k-1}(0)))^2 + \lambda \left| v_{k,ini} - v_{k-1,ini} \right|^2 \] 

(14)

\[ J_k(0) = (e_{k-1}(0) - \theta_k (v_{k,ini} - v_{k-1,ini}))^2 + \lambda \left| v_{k,ini} - v_{k-1,ini} \right|^2 \] 

(15)

Let the cost function \( J_k(0) = 0 \), the solution is
\[ v_{k,ini} = v_{k-1,ini} + \rho \theta_k e_{k-1}(0) + \frac{\lambda + \theta_k^2}{2} \] 

(16)

According to the TILC method, estimate the parameter \( \hat{\theta}_k \):
\[ \hat{\theta}_k = \hat{\theta}_{k-1} + \eta \Delta v_{k,ini} (\Delta x_{k,ini} - \beta \hat{\theta}_{k-1}) \] 

(17)

The initial braking position, initial speed and braking force are used as control inputs, and corresponding learning laws are formulated to obtain
\[ v_{k,ini} = v_{k-1,ini} + \hat{L}_k e_{k-1}(0) \] 

(18)

Where \( L_k = \frac{\rho \hat{\theta}_k}{\lambda + \hat{\theta}_k^2} \) is the iterative gain.

During the simulation, \( f_e \) is equal to 0.

3. SIMULATION STUDY
The parameters of the line are set as follows:
- \( R_i = 0, i_1 = 0, -1000 \leq x \leq -800 \)
- \( R_2 = 1000, \alpha_2 = 0, -800 \leq x \leq -600 \)
- \( R_3 = 0, \alpha_3 = 0, -600 \leq x \leq -500 \)
- \( R_4 = 1000, \alpha_4 = 30\%, -500 \leq x \leq -300 \)
- \( R_5 = 0, \alpha_5 = 30\%, -300 \leq x \leq 0 \)

The line from the starting braking point to the stopping point includes a 200m straight line, a 200m radius arc line of 1000m, a 100m straight line, a 200m uphill line with a slope of 30, and a 300m straight line.

Assuming that the initial speed, starting braking position and braking force are the same during the 50-stop process, and there is no error from the preset value, the simulation results are as follows:
It can be seen that, under the same stopping error correction, the optimal TILC method has fewer iterations. And the final stopping error of the two control methods approaches zero.

It can be seen that the speed of the train changes through the simulated line.

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**Figure 1.** Variation of stopping error

**Figure 2.** Speed position curve comparison

**Figure 3.** Speed position curve details comparison
However, in the actual train parking process, there is no same parking process, so assuming that the initial speed, starting braking position and braking force of the 50 parking processes are all different from the preset values, the simulation results are as follows:

![Figure 4. Variation of stopping error with disturbance](image)

4. CONCLUSION

In this paper, the model of the maglev train parking process is established, and the iterative learning control method is used to consider the repeatability of the train parking process, and the current control curve is updated using the stopping position error during the previous braking process. We select the initial braking position, initial speed and braking force as control inputs, and formulate corresponding learning rules. The simulation compares the optimal TILC method with the traditional TILC method. The simulation was conducted under two hypothetical situations, one is that the initial speed, starting braking position and braking force are the same each time the parking process is in progress, and the other is that there is an error from the preset value. It is concluded that the optimized TILC method has a faster convergence speed.

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