Adhesion Control of Electric Locomotives Based on Machine Learning Rail Surface State Recognition

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ABSTRACT

The key to traction control in locomotive systems is adjusting the axle traction torque through adhesion control. In traditional adhesion control systems, due to the inability to detect the peak adhesion coefficient of the rail surface in real-time, locomotives are prone to spinning and sliding phenomena under different rail surface conditions. This reduces the utilization of adhesion and can even lead to irreversible damage such as tread detachment and rail wear. Therefore, this paper proposes a machine learning-based rail surface recognition method to identify the rail surface condition online and set the peak adhesion coefficient for different rail surfaces. The output torque of the traction motor is dynamically adjusted based on the set reference peak adhesion point to fully utilize the current adhesion force between the rail surface and wheels. A locomotive multi-axis adhesion control model is established to validate the effectiveness of the rail surface recognition algorithm. The results show that the improved adhesion control method effectively prevents wheel spinning, improves the stability of locomotive operation, and reduces the loss of adhesion utilization.

Keywords: Machine learning, rail surface recognition, peak adhesion coefficient, adhesion control model

1. Introduction

The key to the operation of railway transportation systems lies in adjusting the adhesion between the wheels and the tracks, which is influenced by the conditions of the track surface and the wheel surface. Meanwhile, the adhesion is also affected by the creepage ratio between the track and the wheelset, and the maximum adhesion can only be fully utilized at the peak adhesion point corresponding to the optimal creepage ratio. The target creepage ratio of railway transportation systems is usually a fixed value, but the optimal creepage ratio varies for different road surfaces. Therefore, traction transmission systems with a fixed creepage ratio as the control target cannot achieve the maximum traction/braking force when operating on different road surfaces. Only by setting the current road surface's optimal creepage ratio as the target can the current adhesion conditions be maximally utilized. This requires real-time recognition of the current road surface during locomotive operation.

In the field of rail surface recognition, there is limited literature or research available, with most studies focusing on road surfaces. Literature [1] indirectly identified road surface conditions by extracting temporal and frequency domain statistical features from radial and lateral acceleration signals and using dimensionality reduction and classification algorithms. Based on the Burckhardt tire-road mathematical model, Literature [2] designed six ranges of variation for typical road surface peak adhesion coefficients for road surface recognition. Literature [3] introduced the concept of "road surface feature factor" and provided threshold values and intervals for seven typical road surfaces to identify the current road surface state of a vehicle. Literature [4] established the relationship between different slip ratios, road surface utilization adhesion coefficients, and road surface peak adhesion coefficients by constructing different road surface peak adhesion coefficient surfaces in three-dimensional space, indirectly obtaining road surface conditions. Literature [5] proposed a road surface recognition algorithm based on analogical characteristics, which can calculate the peak adhesion coefficient of the current road surface in real-time.

There are significant differences between rail surface recognition in railway transportation systems and road transportation systems. For example, the contact area between locomotive wheelsets and tracks is relatively small, making the changes in track surface conditions have a greater impact on adhesion. The operating environment is complex, including high temperatures, high humidity, and extreme cold, which can affect the condition of the track surface. The high-speed operation requires the recognition algorithm to have high real-time performance. Moreover, the accuracy of the rail surface

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recognition algorithm needs to be sufficiently high to ensure the safety and operational efficiency of the railway transportation system. Therefore, this paper designs a rail surface recognition algorithm that considers both real-time performance and accuracy. The effectiveness and feasibility of the algorithm are validated through the establishment of a locomotive multi-axis adhesion control model using Simulink, demonstrating its practical engineering application value.

2. Adhesion Calculation Model

The adhesion coefficient represents the ability of a locomotive to transmit traction/braking forces[6]. The adhesion coefficient is defined as the ratio of locomotive adhesion force to equivalent axle load:

$$\mu = \frac{f_u}{W} \tag{1}$$

The typical adhesion characteristic curve shown in Figure 1 indicates that the adhesion force between the wheel and rail is always constrained by an adhesion limit due to the presence of creepage. This adhesion limit is represented by the maximum adhesion coefficient μ_m and the corresponding optimal creepage rate λ_m. Before reaching the maximum adhesion coefficient μ_m, the adhesion coefficient μ and the creepage rate λ are positively correlated. After reaching μ_m, they become negatively correlated. Therefore, based on this maximum adhesion point, the adhesion characteristic curve can be divided into two parts: the creepage region and the spin region.

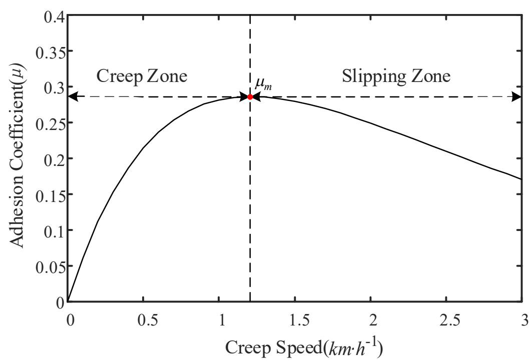


Figure 1: Typical Adhesion Characteristic Curve

When the torque provided by the traction drive system is excessive and exceeds the maximum available adhesion force that the wheel-rail can withstand, the locomotive adhesion state crosses the maximum adhesion coefficient point and enters the spin region. The excess torque is then converted into wheel slip force, further damaging the wheel-rail adhesion state. In severe cases, this can damage the surface of the track and affect the safety of locomotive operation. Therefore, in practice, spin detection methods aim to timely and accurately detect situations where the locomotive adhesion state is about to or has just entered the spin region, in order to identify spin occurrence and prevent further deterioration[7].Due to the complex nature of the track surface, the adhesion coefficient exhibits a dispersed random characteristic. Therefore, it is difficult to establish a mathematical relationship between the creepage velocity and the adhesion coefficient. At the same time, the adhesion coefficient is often difficult to measure directly. However, domestic and foreign researchers have derived empirical calculation formulas for the adhesion coefficient through a large number of experiments and summarized an empirical curve of creepage velocity and adhesion coefficient, known as the adhesion characteristic curve. This curve can reflect the corresponding adhesion state and thus judge the condition of the track surface. The relevant empirical formula [8] is as follows:

$$\mu = c \cdot e^{-aV_s} - d \cdot e^{-bV_s} \tag{2}$$

In this formula, v_s represents the creepage velocity, while a, b, c, and d are coefficients representing the condition of the track surface. These coefficients may vary depending on the differences in locomotive operation conditions.

3. Adhesion control strategy based on track surface identification

3.1 ECOC-SVM Algorithm

SVM is a machine learning algorithm used for classification problems [9]. It separates data of different classes by finding a hyperplane in the data space and maximizing the margin between the support vectors and the hyperplane to find the optimal solution.ECOC-SVM (Error Correcting Output Coding-SVM) is a multi-class support vector machine algorithm [10]. It solves the multi-class classification problem by utilizing models of individual binary classifiers, encoding each class into multiple coding vectors using a set of binary weight vectors.

The first step in ECOC-SVM is to encode each class C_i in the target variable into a binary vector $c_i = (c_{i1}, c_{i2}, \cdots, c_{il})$, where the value of l is 3.Next, an ECOC matrix is used to determine the sub-problems handled by each binary classifier. The ECOC matrix consists of k rows and l columns, where each element can be {-1, 1, 0}. Each column in the ECOC matrix corresponds to a binary encoding vector C_i. For each C_i, a unique binary encoding vector $b_l = \{b_{11}, b_{12}, \cdots, b_{lk}\}$ needs to be determined. In the lth classifier, all vectors associated with $c_{ij} = 1$ will be classified as positive, while all vectors with $c_{ij} = -1$ will be classified as negative. Table 1 shows the ECOC matrix for three different rail surface conditions (dry, wet, icy).

Table 1: ECOC Matrix for Three rail surface Conditions

	Classifier1	Classifier2	Classifier3
Dry rail surface	1	1	0
wet rail surface	-1	0	1
icy rail surface	0	-1	-1

For each binary tuple (x_i, y_i), we map the tuple to a $2l$ -dimensional feature vector. This feature vector includes l SVM+ classifiers representing all the +1/-1 predictions and l SVM- classifiers representing all the +1/-1 predictions, each represented by a corresponding list. Finally, the predicted result for class C is the one with the minimum error correction distance, where the error correction distance refers to the number of binary differences (Hamming Distance) between the predicted result and the true result.

3.2 Locomotive adhesion control strategy

The overall process of the online identification of the locomotive track surface proposed in this chapter is shown in Figure 2. It mainly includes the track surface online identification module, the full-dimensional state observer, the creep speed estimation module, the optimal adhesion point setting module, the motor torque control module, and the vehicle dynamics model.

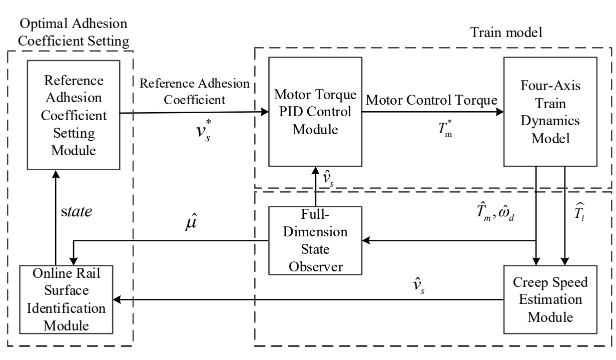


Figure 2: Schematic diagram of optimal adhesion control.

The full-state observer in the diagram estimates the current adhesion coefficient, denoted as $\hat{\mu}$ of the track surface by continuously observing the motor torque and wheel speed of the quadricycle's dynamic model. This estimation is one of the inputs to the track surface identification module. The other input is the estimated creep speed, denoted as $\hat{u}_s$, obtained through the creep speed estimation module using the Kalman filtering algorithm. The track surface identification module utilizes the adhesion coefficient and creep speed as inputs and calls the ECOC-SVM model, which has been trained offline, to output the real-time track surface state. The track surface state, denoted as 'state' is then input to the reference adhesion coefficient search module to obtain the current optimal adhesion coefficient v_s. The PID control method is employed to adjust the motor torque based on the difference between the desired adhesion coefficient v_s^* and the estimated adhesion coefficient $\hat{v}_s$, thereby forming a closed-loop adhesion control system for the quadricycle.

4. Analysis of Simulation Results

In this paper, we used MATLAB as the development environment to train the ECOC-SVM model using offline data. We selected 300 sets of data for each of the dry track, wet track, and icy track as the dataset. The ratio of training set to test set is 8:2, with 60 sets of data used as the test data for each type of track.

Since the different track conditions depend on the adhesion coefficient and creep speed, the adhesion coefficient and creep speed are used as input features, and each set of data has a two-dimensional input. The label 1 represents the dry track, 2 represents the wet track, and 3 represents the icy track.

The ECOC-SVM classification boundary plot based on the test set is shown in Figure 3. It can be observed that the classification of the three types of tracks is effective, with a prediction accuracy of 96.67%. However, before the creep speed reaches 0.2 km/h, there are partially overlapping regions in the two-dimensional plane due to the features of the three types of tracks, leading to some classification prediction errors at this point, which affects the accuracy. However, locomotives rarely operate in this region during actual operation, so it does not affect the accuracy of real-time simulation classification.

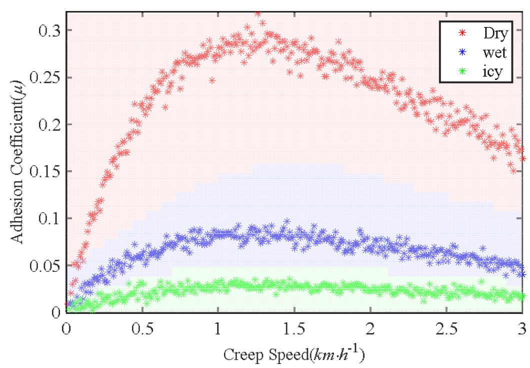


Figure 3: ECOC-SVM Classification Boundary of the Test Set

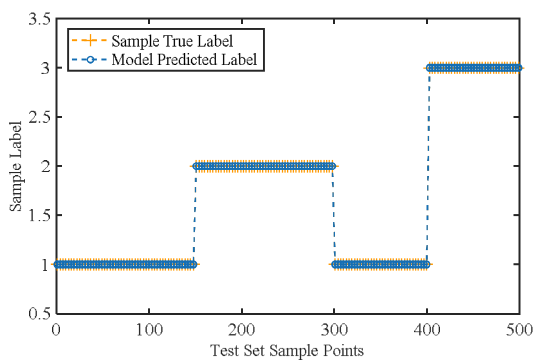


Figure 4: Classification Results of the Locomotive Dynamics Model

To simulate the locomotive dynamics model in Simulink, the locomotive runs on a dry track from 0 to 15 seconds, on a wet track from 15 to 30 seconds, back to a dry track from 30 to 40 seconds, and switches to an icy track from 40 to 50 seconds. A step size of 0.1 is chosen, and the data points in the format of 500*2 [vt vs] are imported into the pre-trained

ECOC-SVM training model. Real-time identification of the locomotive's current track condition is performed online, and the classification results are shown in Figure 4, with an accuracy of 100%. Both real-time performance and accuracy are well guaranteed.

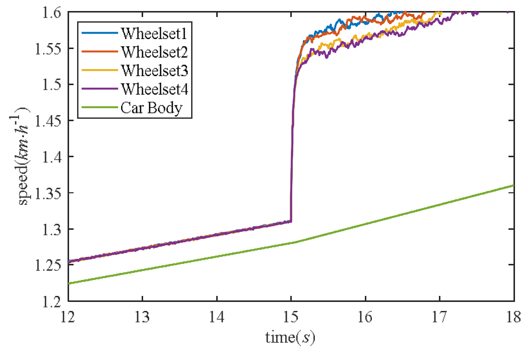
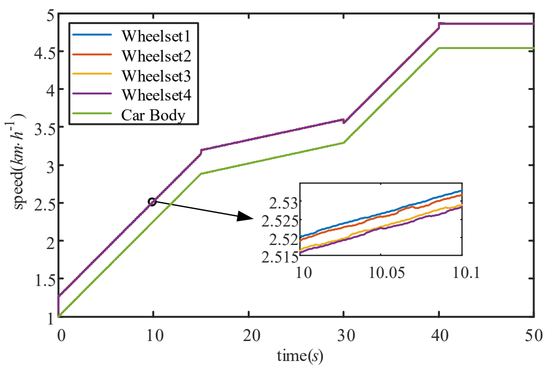
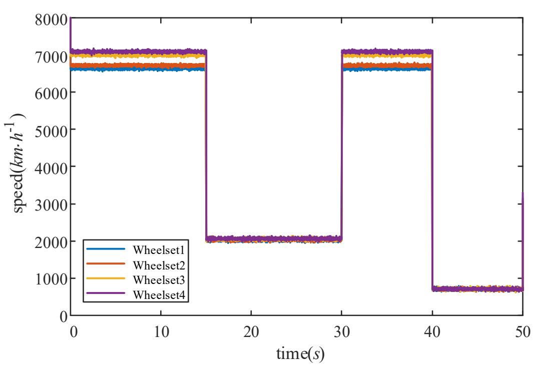


Figure 5: Simulation results of Each Wheelset and Vehicle Body without adhesion control system.

A traction torque of 1600N is applied to each wheelset. From the Figure 5, it can be observed that initially, all four wheelsets operate with a small amount of creep speed. At 15 seconds, the locomotive switches to a wet track condition, and the speeds of the four wheelsets rapidly increase along with a significant increase in creep speed, indicating a deterioration of the wheel-rail adhesion condition.



(a) Speed of Each Wheelset and Vehicle Body



(b) Traction Motor Output Torque for Each Wheelset

Figure 6 Simulation Results under Adhesion Control System

After adding the adhesion control system, the simulation results are shown in Figure 6. Figure 6(a) shows the simulation graph of the line speed of each wheelset and the vehicle speed. It can be seen that the locomotive runs under different track conditions at 15, 30, and 40 seconds. The line speed of all four wheelsets can track the vehicle speed well and operate at the optimal creep speed. Figure 6(b) shows the output torque of the traction motors for the four wheelsets. From the graph, it can be observed that during the three track condition transitions of the locomotive, the traction control system can quickly adjust the output torque of the traction motors based on the track identification results. This ensures that all four wheelsets can maintain the optimal adhesion utilization point for the current track condition, achieving the goal of fully utilizing the adhesion between the wheels and the rails.

5. Conclusions

In this study, the ECOC-SVM algorithm was used for online identification of the track surface state. This method utilizes the real-time output of the track surface state based on the adhesion coefficient and creepspeed obtained from the observer. The optimal creep parameter is adjusted according to different road conditions. Additionally, the validation of the track surface online identification was conducted using the multi-axis electric locomotive adhesion control model. Compared to the traditional single-wheel model, this model can monitor the situation of each wheel pair in real-time, providing a comprehensive reflection of the dynamic performance during locomotive operation. The simulation results demonstrate that the track surface identification module based on the ECOC-SVM algorithm accurately and rapidly identifies the current track surface condition. By adjusting the locomotive control parameters based on different track surface identification results, the probability of wheel slip can be effectively reduced, thereby improving the adhesion utilization and overall traction performance of the locomotive in the presence of continuously changing track surfaces.

Acknowledgement

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