WIM Optimization Algorithm Based on Euler-Bernoulli Beam Model

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Abstract: The non-stop weighting mode of heavy vehicles is a method that can significantly improve the capacity of toll stations. However, due to its model, the existing dynamic weighing technology (WIM) cannot guarantee the weighing accuracy when heavy vehicles are driving at high speed. Aiming at the above problems, a piezoelectric quartz load cell is used, combined with parameter estimation experiment and nonlinear fitting algorithm, an optimization algorithm based on Euler-Bernoulli beam model is proposed. The system was tested based on the Ha Tong Expressway East Toll Station. The results show that within the 95% confidence interval, the average deviation between the dynamic weighing result and the static measurement is 1.99%, and the corrected average deviation is 1.78%, both of which are in line with the Class 2, Level 2 standard specified in the national JJG907-2006. The weighing accuracy is not related to the linearity of the vehicle speed. This indicates that the dynamic weighing system constructed by the proposed algorithm has high precision and strong robustness and can accurately measure the vehicle weight under the condition of vehicle shifting motion. The system can effectively solve the congestion problem of highway toll stations, reduce the queuing time, and provide a certain theoretical basis for the realization of the truck non-stop weighting and charging system.

1. Introduction

In recent years, with the development of China's social economy, the construction of transportation infrastructure has also developed rapidly. By the end of 2017, the total mileage of highways in China reached 4,773,500 kilometers. However, due to the emergence of road diseases, the maintenance mileage reached 4,746,600 kilometers, accounting for 97.9% of the total road mileage. Overloading of transport vehicles is an important factor leading to the emergence of diseases [1-2]. To this end, since 2000, many provinces in China have carried out the work of over-limit overloading. Jiangsu, Henan and other places have successively implemented highway weighting, but most of the methods used are static weighing, but their traffic efficiency is low. It often leads to large-scale congestion of toll stations, and WIM has gradually become an effective technical means for the highway management department to overload and implement the toll collection [3].

Since its introduction, the dynamic weighing system has been widely concerned and studied by many scholars. The Wang Xuan cang team of Chang'an University [4] aimed to increase the traffic capacity of toll stations by using computer technology to integrate the weighing and charging system of passing vehicles. Based on system identification and variable bandwidth filtering, Michal Meller [5] extended and compared two dynamic weighing methods. Shandong Delutai Company developed a double-station dynamic weighing truck scale and its model and algorithm, but the effect of putting it into use is not satisfactory, because the model used is linearly related to the driving state of the vehicle [6]. Gustavo Garcia Otto [7] extended the Dynamic Weighing (WIM) sensor response model based on road stress and deflection. In 2016, Wang Lei et al[8]. proposed an array layout scheme with wide plates and multiple quartz sensors to improve the weighing accuracy, but the stability of the whole system needs to be improved. Based on the above problems, based on the previous research [9-10], an improved algorithm based on the Euler-Bernoulli beam pavement interaction model is proposed. The nonlinear pavement algorithm is used to decouple the average pavement response. Extract, and then combine the estimated test to obtain the model parameters, and then get the weight of the whole vehicle. After testing, the heavy truck passed the system at 30km/h with an accuracy of ±3% or less, thus solving the problem of low weighing accuracy of heavy vehicles under high-speed driving conditions, and solving the problem of truck towing and jumping, from the algorithm. The abnormal driving state such as the call is called, and the robustness of the model is good after correlation research. This is of great significance for improving the efficiency of charging stations and reducing the queue time. It also provides technical support for the highway management department to effectively control over-limit overload behavior, extend the service life of roads and bridges, and ensure safe driving.

2. WIM system estimation process

In order to improve the weighing accuracy and reduce the systematic error, the Euler-Bernoulli pavement interaction model optimization algorithm is adopted to obtain the model parameters through parameter estimation and nonlinear fitting algorithm. Firstly, the signal processing is performed, and the received sensor signal is passed through two moving average filters to obtain the average road surface response of the heavy vehicle. Then the nonlinear fitting algorithm proposed in this paper is used to decouple and extract the response of each axle $a_i(t)$, combined with the estimation test. Then, the road surface interaction model is used to obtain the axle weight under the motion state, thereby obtaining the vehicle weight. The truck weighing algorithm framework is shown in Figure 1.

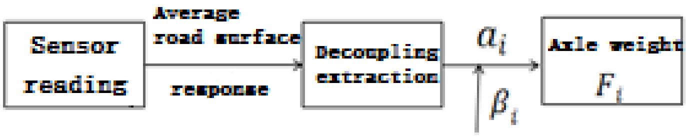

Figure 1 Block diagram of the load estimation process

3. WIM algorithm based on Euler-Bernoulli beam model

3.1 Model building

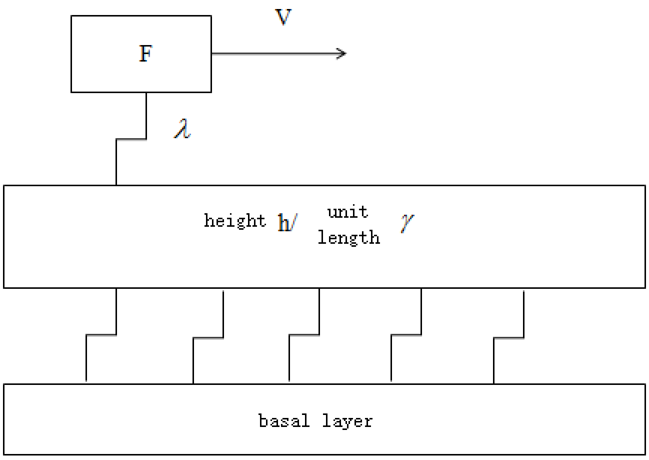

Figure 2 Euler-Bernoulli beam pavement interaction model

The Euler-Bernoulli beam model is proposed for vehicle-road interaction, as shown in Figure 2. In this model, the road surface is considered to be an elastic foundation one-dimensional beam. Because the axle is in an oscillating state, the axle is modeled as a dynamic load, and its magnitude changes with time. Rajagopal [11] obtained a closed solution of a partial differential equation of a control system by modeling. Assuming that the influence of the vehicle suspension system is ignored(Setting $\rho_0 = 0$), the solution can be expressed as follows:

$$y(t) = F\xi^{-1}\varphi(t) \tag{1}$$

In the formula, $y(t)$ is the vertical displacement or road surface deflection, $\varphi(\cdot)$ and ξ depending on the structure and material properties of the road surface, ,$\xi^{-1}\varphi(t)$ is the road surface response of the unit load traveling at unit speed. As can be seen from equation (1), the model is linearly related to F and $\varphi(\cdot)$ is a function of time, measured by vehicle speed v.

The shape of the road surface displacement curve is approximately similar to the Gaussian function[12], and in general the shape of the sensor response depends on the speed of the vehicle v and the suspension frequency. Then the road displacement $y(t)$ can be expressed as:

$$y(t) = F\xi^{-1}\varphi(t) = F\mu e^{-\frac{v^2t^2}{2\sigma_0{}^2}}\varphi(\cdot) \tag{2}$$

In the formula, μ is the amplitude, σ_0 is the standard deviation of the Gaussian response when the unit load is traveling at unit speed.

Assuming $\sigma = \frac{\sigma_0}{v}$, the above equation can be expressed as:

$$y(t) = F\mu e^{-\frac{t^2}{2\sigma^2}} \tag{3}$$

Both μ and σ_0 depend on the characteristics of the road. Since the measured data obtained by the sensor is acceleration rather than displacement, So in order to make the model more suiTable, you can make the following conversion:

$$a(t) = -F\mu\frac{v^2}{\sigma_0{}^2}\left(1-\frac{t^2}{\sigma^2}\right)e^{-\frac{t^2}{2\sigma^2}} \tag{4}$$

let $\phi(t) = -\left(1-\frac{t^2}{\sigma^2}\right)e^{-\frac{t^2}{2\sigma^2}}$, $\alpha = F\mu\frac{v^2}{\sigma_0{}^2}$,we can get:

$$a(t) = \alpha\phi(t,\sigma) \tag{5}$$

Known by the definition of α:

$$F = \frac{\sigma_0{}^2}{\mu}\frac{\alpha}{v^2} = \beta\frac{\alpha}{v^2} \tag{6}$$

$$y(t) = \alpha\frac{\sigma_0{}^2}{v^2}e^{-\frac{t^2}{2\sigma^2}} \tag{7}$$

3.2 Parameter estimation

The unknown parameters α and σ can be calculated from the measured acceleration, but β depends on the road performance and material properties [13] and can be measured by a set of pre-weighed trucks.

Assume that N trucks are used to measure β, $\hat{f}_i^n$ is the load estimation of the i-th axis of the n-type truck. v_n means speed, T_n is the corresponding road surface temperature, α_i^n is related to fitting parameter α_i^*. e_i^n is the error associated with load estimation. The optimal β_i can be calculated by minimizing the mean square error of the load estimate as follows:

$$f_i^n = \beta_i \frac{\alpha_i^n}{v_n^2} \lambda(T_n) \quad (8)$$

$$e_i^n = \beta_i \frac{\alpha_i^n}{v_n^2} \lambda(T_n) - f_i^n \quad (9)$$

$$\beta_i^* = \arg\min_{\beta} \frac{1}{N} \sum_{n=1}^{N} (e_i^n)^2 \quad (10)$$

$$\beta_i^* = \arg\min_{\beta} \sum_{n=1}^{N} \left(\beta \frac{\alpha_i^n}{v_n^2} \lambda(T_n) - f_i^n \right)^2 \quad (11)$$

$$\hat{f}_T^n = \sum_{i=0}^{N} \hat{f}_i^n \quad (12)$$

3.3 Nonlinear fitting algorithm

For a K-axis truck, when the i-th axis passes the sensor and a force F_i is applied to the sensor at time η_i, the response can be viewed as a superposition of the single axle response $a_i(t)$,which is:

$$a_i(t) = \alpha_i \phi(t - \eta_i, \sigma_i) \quad (13)$$

$$a(t) = \sum_{i=1}^{N} \alpha_i \phi(t - \eta_i, \sigma_i) \quad (14)$$

Using a nonlinear fitting algorithm, you can estimate α_i, η_i and σ_i for each axle.

Firstly, the two moving average filters with the number of taps S and 2S are used to smooth the measurement signal, and the average response $\alpha_m^i(t)$ of the k-th sensor is obtained. The number of sensors located directly under the tire is represented by M, and the average acceleration of the road surface $a_m(t)$ is passed through the equation. Calculated by the formula (15):

$$a_m(t) = \frac{1}{M} \sum_{i=1}^{M} \alpha_m^i(t) \quad (15)$$

Since the speed of the vehicle is high and the shaft spacing is relatively short, it is necessary to decouple and extract the response $a_i(t)$ of each axle from $a_m(t)$ and implement it by a nonlinear fitting algorithm.

Use $a(t)$ to indicate the simulated response of the k-axis truck. The calculation method is as shown in equation (13). Let $\delta(t)$ be the error between the measured response and the simulated response of the truck at time t, ie $\delta(t) = a_m(t) - a(t)$. Therefore the measured response is:

$$a_m(t) = a(t) + \delta(t) = \sum_{i=1}^{N} \alpha_i \phi(t - \eta_i, \sigma_i) + \delta(t) \quad (16)$$

Minimize the mean squared errors i and e to estimate the unknown parameters $\{\alpha_i\}_{i=1}^n$, $\{\sigma_i\}_{i=1}^n$

and $\{\eta_i\}_{i=1}^{n}$.

$$\{\alpha_i^*,\sigma_i^*,\eta_i^*\}=\arg\min_{\alpha_i,\sigma_i,\eta_i}\int_{-\infty}^{+\infty}\left[a_m(t)-a(t)\right]^2 dt \tag{17}$$

$$\{\alpha_i^*,\sigma_i^*,\eta_i^*\}=\arg\min_{\alpha_i,\sigma_i,\eta_i}\int_{-\infty}^{+\infty}\left[a_m(t)-\sum_{i=1}^{N}\alpha_i\phi(t-\eta_i,\sigma_i)\right]^2 dt \tag{18}$$

Once the response of a single axle is estimated, each axis can be processed separately to estimate the remaining variables, such as a single axle load F_i and road displacement $y(t)$, ie:

$$F_i=\beta_i\frac{\alpha_i}{v^2} \tag{19}$$

$$y(t)=\alpha_i\sigma_i^2 e^{-\frac{(t-\eta_i)^2}{2\sigma^2}} \tag{20}$$

The vehicle weight calculation method is as follows:

$$F=\sum_{i=0}^{n}F_i \tag{21}$$

4. Experimental verification

4.1 Experimental program

According to the optimization algorithm proposed in this paper, the Harbin East Toll Station of Ha Tong Expressway was tested. The sensor uses a piezoelectric quartz load cell, and the test vehicle is a three-axle truck. The average speed of a single measurement is 0~30km/h. On the basis of the previous research, the sensors are arranged in a parallel four rows as shown in Figure 2, and the pitch is set to 480 mm and the width is 500 mm [10].

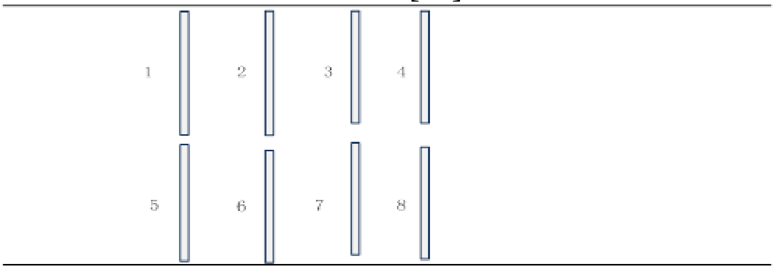

Figure 2 Sensor layout

First, measure the weight of the heavy vehicle when it is at rest, record it as G_0, then pass the heavy vehicle through the sensor 5 times at 5, 15, 20, 25, 30km/h, weigh it and take the average $\overline{G_i}$, calculate it. average error ERR_i:

Firstly, the test vehicle is calibrated, and then the sensors are used to measure the weight at 0, 5, 15, 20, 25, 30 km/h, and each speed point is run 10 times, averaged, and compared with the standard value. Using the accuracy of the average error to describe, the expression is:

$$ERR_i=\overline{G_i}/G_0-1 \tag{22}$$

To reduce the measurement error, correct the measured value:

$$DEV_i=\overline{G_i}/G_{AVG}-1 \tag{23}$$

In the formula: DEV_i is the deviation of n measurements, $\overline{G_i}$ is the nth measurement, and G_{AVG} is the measurement average.

4.2 Analysis of results

Table 1 Quantitative test data

Dynamic weight(t)	Average speed (km/h)	average error (%)	Correction error (%)
14.217	0	1.47	1.42
14.133	4.96	0.4	0.35
14.096	11.07	0.63	0.49
14.121	14.97	1.08	1.04
14.211	20.22	1.99	1.71
14.475	24.96	1.68	1.56
14.104	30.24	1.04	0.86

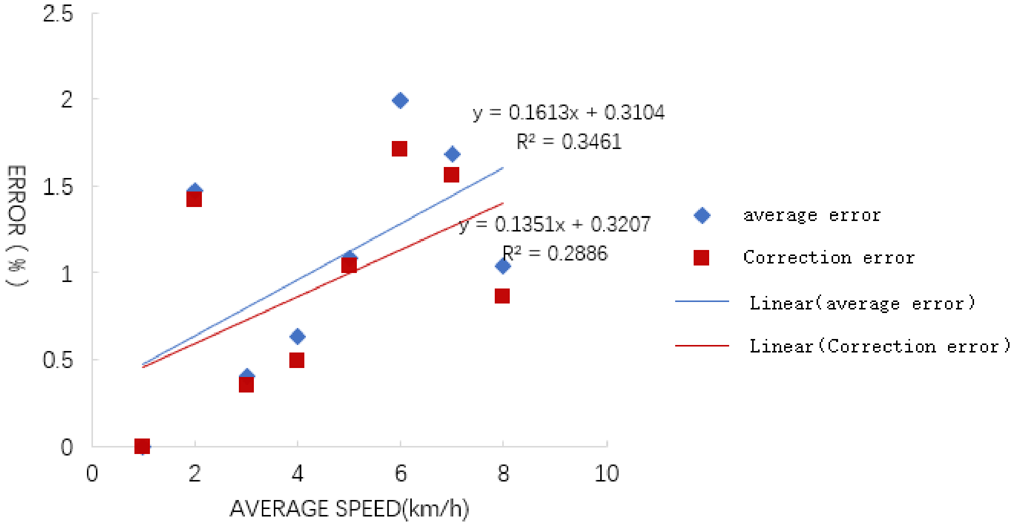

Figure 3 Correlation between error and average speed

It can be seen from the data in Table 1 that the system with the new model has a maximum initial error of 1.99%, and the corrected error is 1.87%, which is in line with the Class 2 and Level 2 standards specified in the national JJG907-2006. The correlation coefficient between vehicle speed and average error is only 0.35, and the correlation coefficient with correction error is only 0.2886. Therefore, the data is linearly uncorrelated and has a discrete type, which indicates that the system is robust, each data has sporadicity, and the system error is small.

5. Conclusion

(1)The algorithm is optimized based on the Euler-Bernoulli beam model. When the heavy truck is driven at a higher speed, its weighing accuracy is greatly improved. At the same time, the weighing value is not related to the linearity of the vehicle speed, which improves the robustness of the system and significantly improves the congestion problem of highway toll stations.

(2)The road surface response obtained by the optimization algorithm is an accumulated result, which avoids the error caused by the change of the single instantaneous response value, and thus can solve the abnormal form problems such as the vehicle call, jump, and s-bend, and the overload management of the highway management department. Provides an effective method

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