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ALGORITHM OF THE DYNAMIC VEHICLE WEIGHING SYSTEM

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АЛГОРИТМ СИСТЕМИ ДИНАМІЧНОГО ЗВАЖУВАННЯ ТРАНСПОРТНИХ ЗАСОБІВ

Purpose. To develop a stable and high-precision algorithm of the dynamic vehicle weighing.

Methodology. The model of the dynamic vehicle weighing system was created. Several kinds of noise that affect the accuracy during measuring were analyzed. The new algorithm of WIM (Weight-In-Motion)was suggested. High-frequency noise signals were eliminated by Butterworth low-pass digital filter, and then fitted by least squares method based on Levenberg-Marquardt optimization algorithm. This allowed the separation of dynamic load and calculation of the static axle.

Findings. The results of application of the algorithm for dynamic vehicle weighing system have proved that the proposed algorithm is of high accuracy and steadiness. Based on the analysis of weighing results we adopted the algorithm of the WIM systems.

Originality. The optimization algorithm method has been designed, which can improve the measurement accuracy and reduce the restrictions of weighing.

Practical value. The suggested dynamic vehicle-weighing algorithm may allow controlling the vehicle overload and overrun.

Keywords: *WIM, data processing, dynamic load, optimization algorithm, Butterworth, squares method*

Introduction. With the rapid development of the economy, the cargo capacity rises sharply, which results in a very serious overweight phenomenon in domestic road transportation. Over weight is the main cause of road damage [1]. Roads are severely damaged, which leads to frequent incidences of vicious traffic accidents and affects traffic safety. Vehicle weight detection includes static weighing and dynamic weighing methodology [2]. Although static weighing is more precise, in practice the results are easy to get only when the system is stable. Dynamic weighing can weigh moving vehicles, in which cars do not have to stop during weighing. Thus, traffic flow could be ensured smoothly and the axle load could be measured separately as needed. Furthermore, because of the smaller weighing platform, the dynamic weighing system is easy to install and is costless. However, due to the lower accuracy of the system than that of the static system, the speed of the vehicle to be weighed should be limited [3].

The dynamic weighing system can be traced back to the fifties of the twentieth century. The first study of the dynamic weighing system was conducted by the United States for a period of 16 years. First patented capacitive weighing sensor was patented by South Africa in 1968. In the late 60's early 70's the patent right on vehicle dynamic weighing system was acquired by France. In the mid 80's of the twentieth century, American Streetre and British Golden River companies adopted advanced electronic technology, which was based on the dynamic capacitance-weighing sensor, and improved the performance of the dynamic weighing system significantly. In the 90's, with the rapid development of transportation, the urgent requirement of the weighing system met the requirements of practical application. The System Research Laboratory of the European Union highway (FEHRI) in 1992 in accordance with the EU Transport Commissions (ECTD) framework worked out the COST323 plan, namely the dynamic weighing system for a period of 30 months of actual application test [4]. Along with the development of science and technology and strengthening of economy, a large number of dynamic systems have been put into use. China's independent research and development played an important role in the fields of highway automation, toll by weight, axle load limit detection, law enforcement and others.

The overload, speeding and overweight in mining provinces is a serious problem; the phenomenon of overloading is misrepresented as legal norms. Study on the vehicles weighing system in domestic research institutions have never been interrupted. The representative of the product in the national "the eighth five-year plan" period [5], Chongqing Highway Research Institute under the Ministry of Transportation, successfully developed the dynamic vehicle weighing system. This system is used for dynamic vehicle weighing of fixed type, can simultaneously detect one to four lanes the axle load, the error is less than 10%, the confidence level is 95%. Although our dynamic weighing technology has been developed rapidly, compared with the advanced countries in the world, there is still a certain gap. There are aspects that are not fully mature, such as the accuracy of weighing system, cost of the system. Low cost, high efficiency, high accuracy of weighing system is the last to develop technology priority.

The accuracy of the current dynamic weighing system, of which we only took simple digital filtering process in signal weighing, is difficult to improve greatly because of the lack of further signal processing techniques. In this paper, we establish the model of the system. Dynamic Weighing Systemmodeling combined with the actual situation, so that the results will weigh more in line with the actual situation, may improve the accuracy of the weighing results. We are introducing the optimization algorithm method to improve the measurement accuracy and reduce the restrictions of weighing.

The principle of the dynamic weighing system. ***The designing of the system.*** In this section, we designed a weighing system to detect the weights of the vehicles on the road to determine whether they were overloaded, manage and monitor all of them. Thus, the number of overloaded vehicles could be reduced effectively. Fig.1 shows the diagram of the system's design.

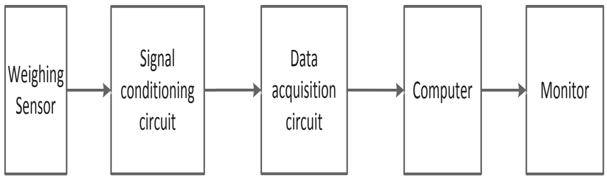

Fig.1. The system's design diagram

The hardware platform composition of the system.

(1) Weighing System.

The weighing system is composed of a weighing platform and a weighing sensor. Weighing platform is a metal plate embedded in the well-paved road, it must be ensured that only one weighing axle is on it while weighing. The weighing sensor adopts high-precision strain sensor.

(2) Data acquisition system.

To collect the data and send the collection signal to the computer system.

(3) Computer system.

The computer system is used to preprocess data for the inputted discretized electric signals. Then signals will be processed with an algorithm to produce the output of the dynamic weighing results.

(4) External weighing indicator.

The total weight of the vehicle will be displayed on the external weighing indicator. Fig.2 shows the dynamic weighing platform.

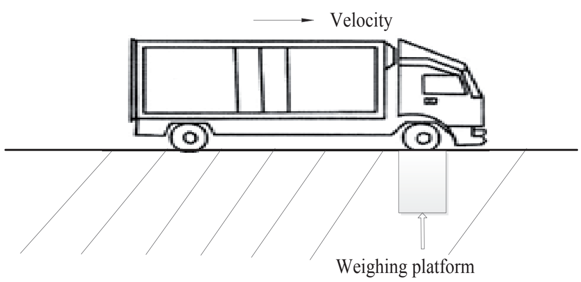

Fig.2. Dynamic Weighing Platform

The software platform composition of the system. After the weighing data had been converted, sampled and filtered, the dynamic weighing software completed signal preprocessing and weighing result calculation. Because the design of the software is related to the algorithm which is used, for hardware system, the gross process of the software is broadly divided into the following steps:

1. The process to signal noise. Low-frequency part mainly comes from the vibration signal of the system, including bearing plate, bearing shaft and sensor, which is the main signal to be processed in the dynamic weighing signals. Intermediate-frequency part mainly comes from the interference generated by the rotation of the vehicle itself. High-frequency part mainly comes from the measurement interference generated by the detection system itself. It is very convenient for further signal processing that minimizes the impact on the low-frequency signal during filtering the medium-frequency noise and high-frequency noise.

2. The process to low frequency interference. In the dynamic weighing signals, the useful signal in the low-frequency section contains a kind of interference factors, which have a great influence on the weighing results, i.e. low-frequency interference. The vehicle vibration and the uneven road are the reasons causing the low-frequency interference. The frequency of the low-frequency interference generally ranges 0–30 Hz, and the variation of amplitude can reach the 10% of the static load, which is the weight when the vehicle is under the stationary state. So the accuracy of the weighing results cannot be guaranteed if low-frequency interference was not eliminated. Furthermore, low-frequency interference and useful signals are mixed in one frequency band, which determines that the conventional filtering methods cannot filter out low-frequency interference. Therefore, the methods to filter out low-frequency interference are different from those to filter out high-frequency noise. The common method is to fit out the amplitude, frequency and phase of low-frequency interference using least square method followed by filtering out the interference then.

3. Acquiring the real axle load of the vehicle.

Dynamic weighing system model. According to the decomposition knowledge of the dynamic principle and signals, the dynamic weighing data is mainly composed of the following three parts [6]:

1. Static loads: Static loads are the static weights of vehicles, which are the important data that we need to get.

2. Low-frequency interference: Vehicle vibration caused by the uneven pavement, which is the dynamic loads we need to filter out.

3. High-frequency noise: Measurement interference cause by the detection system, i.e. the high-frequency interference.

So the weighing data can be expressed as follows

$$Y(t) = W + A_0 \sin(w_0 t + \varphi_0) + \sum_i A_i \sin(w_i t + \varphi_i), \qquad (1)$$

where $Y(t)$ is a vehicle weight signal; W is a static load, which is the actual weight of vehicle; A_0 is a vibration amplitude of low-frequency interference; w_0 is an angular frequency of low-frequency interference; φ_0 is an oscillation phase of low-frequency interference; A_i is a vibration amplitude of the i-th noise componentt; w_i is an angular frequency of the

i-th high-frequency noise component; φ_i is an oscillation phase of the i-th high-frequency noise component.

Fig.3 shows the waveform when vehicle tire passing by the weighing platform.

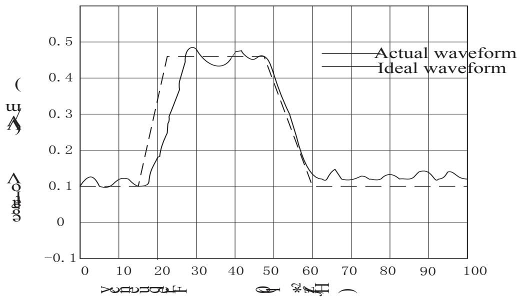

Fig.3. The waveform when vehicle tire passing by weighing platform

The car passes through the weighing platform with a certain speed and it is weighed. In the forces the car acts on the platform, many other factors interfere the result except for the real car weight. Due to the presence of confounding factors, the real car weight is submerged in interference, which seriously affects the weighing accuracy. Let us analyze the impacts of dynamic load and driving speed on the vehicle dynamic weighing. There are many reasons causing the vehicles vibration when cars run [7]. The reasons can mainly be divided into the three categories as follows:

1. Vibrations caused by various factors of the car itself. It mainly refers to the vibration caused by the tread pattern of tire, the eccentric rotation of the car engine, the instability of driver's operations (including speed change, braking, and steering, etc.) and the non-uniform combustion of gasoline, etc.

2. Vibrations caused by the uneven road. Because the road surface has a certain degree of unevenness, a big or small displacement of vehicles will appear which causes vehicle vibrations. Especially on the uneven and undulating roads, the displacement of the car wheels is more serious, and so is the vibration. It belongs to those caused by unevenness that the vibrations caused by cracks and the joints between roads and bridges.

3. Vibrations caused by the coupling between vehicles and roads. When cars are running on the road, they will apply external force on the road. Under the action of external force, the road will produce vibrations, which will react on the cars above and result in coupled vibrations.

After the elimination of low-frequency interference by the low-pass filtering and optimized algorithms, the weighing signals should not contain the interference theoretically. However, a large number of experiments showed that in dynamic weighing system, the vehicle speed, at which the car passes through the weighing platform, has a great impact on the weighing accuracy. Because in the front of the weighing process and the rear axles do not pass through the weighing platform at the same time, so the heights of gravity center and air resistance point are different [8]. When the car accelerates, the focus will shift backward. While the car decelerates, the focus will move forward. It can be seen that the vibration caused by the vehicle itself and the unevenness of the road is one of the key factors affecting the weighing ac-curacy. The real axle load signal is submerged in a variety of complex vibration signals. In order to obtain the real axle load signal, we must eliminate or mitigate these vibrations according to causes to minimize the impact on the weighing accuracy.

Filtering of the high-frequency noise. It is the main task of filtering technique to remove the noise. According to the implementation platforms, filtering techniques are generally divided into two major categories, i.e. hardware filtering technology and software filtering technology. In hardware filtering, people need to design the hardware circuit and make a circuit board. It is expensive and difficult to up-date the algorithm on the original circuit board, which draws the main drawbacks. The most commonly used method for filtering is software filtering. In the high-frequency filtering, we usually make algorithms by designing a low-pass filter. The production cost of software filtering is low, and the improvements of algorithms turn flexible. Meanwhile, the filtering can be divided into digital filtering and simulated filtering. The reason why the digital filtering is chosen in this paper is that it is more precise, stable, and flexible than that of simulated filtering, and the non-essential requirement for impedance matching and some special filter functions that cannot be implemented by simulation filtering. The digital filter cannot fully implement ideal functions. It cannot implement the mutation from one frequency band to another frequency band. Only a transitional zone can be set between the two frequency bands. The bandstand and bandstand are not strictly 1 or 0, but to tolerant a narrow range. According to the transfer functions, the categories of low-pass filters can be divided into several types, namely Butterworth filter, Kuibyshev Type I and Kuibyshev Type II, etc. The amplitude-frequency curve of Butterworth filter, also known as "the flatest" amplitude-frequency response filter, is monotonically decreasing in both bandstand and bandstand. Chebyshev filter is generated by Chebyshev polynomials to design the filter, where Chebyshev Type I shows equiripple vibration within the passband and descends monotonically within the stop band while Chebyshev Type II is just the opposite.

In order to facilitate the subsequent data processing and to reduce the impact of high-frequency signals on the results with consideration of filter passband stability, we have chosen the Butterworth low-pass digital filter in this research. However, this simple method cannot eliminate two kinds of errors, one of which is the impact of tire stiffness on weighing accuracy and the other of which is the impact of vehicle vibrations on weighing accuracy [9]. Because the main signals frequencies are mainly in the low-frequency part, if the-re is a ripple in the filter, it will produce a serious impact on the results. The main consideration we should take during selection is to filter out high-frequency interference and maintain the main low-frequency signals just the same as unfiltered before.

Since it is almost clear that the vibration signals distribute at different frequencies and the noise sources from different frequencies, we can use a more accurate model to express thesenoises [9]. Specifically, we can obtain the following rules by physical observation.

The signals in (1), of which the frequencies are higher than 200 Hz, come from the noise caused by wheel rotation and the detection system. They should be completely filtered out.

The signals in (2), of which the frequencies are between 60–200 Hz, come from the vibration of the detection system itself. They should be filtered out too.

The signals in (3), of which the frequencies are lower than 60 Hz, can be divided into two parts. One in linear term (to be retained) is caused by steady-state load when the vehicles' wheels are passing through the bearing plate. The other one is the periodic vibrations (known as low-frequency cycle interference hereinafter), of which the frequency is about 30 Hz caused by dynamic tire load. Fig.4 shows the relationship of voltage and frequency.

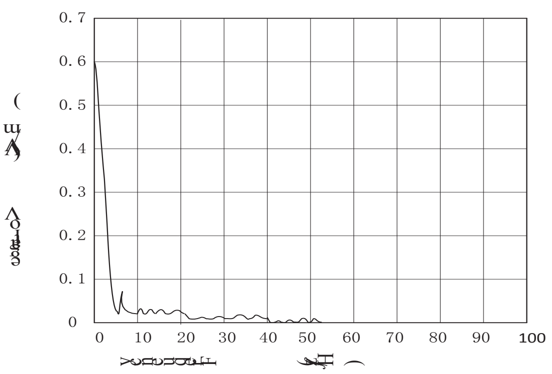

Fig.4. The relationship of voltage and frequency

Cut-off frequency is the most important parameters when designing the low-pass digital filters. The cut-off frequency is the frequency when the signal attenuates to 0.707 time of the original. According to the spectral analysis of the signal, the frequencies of the wheel load signals are between 0–60 Hz. Thus, the cut-off frequency is 60 Hz. Performance indicators of digital filters are provided as follows. The frequency of passband boundary is 60 Hz. The attenuation R_p of passband is less than 1dB. The frequency of stopband boundary is 100 Hz. The attenuation R_s of stopband is greater than 15dB. The sampling frequency is 200 Hz. According to the rules above, we finally designed the Butterworth low-pass digital filter. Fig.5 shows the Amplitude-frequency characteristics of Butterworth low-pass filter and fig. 6 shows the phase-frequency characteristics of Butterworth low-pass filter.

The transfer function of the filter is shown as follows

$$H(z) = (1.25*10^{-5} + 6.26*10^{-5} z^{-1} + 1.25*10^{-4} z^{-2} + \\ + 1.25*10^{-4} z^{-3} + 6.26*10^{-5} z^{-4} + \\ + 1.25*10^{-5} z^{-5}) / (1 - 4.28 z^{-1} + 7.36 z^{-2} - \\ - 6.37 z^{-3} + 2.77 * z^{-4} - 0.48 * z^{-5}) . \quad (2)$$

After eliminating the high-frequency noise by filtering out the high-frequency noise in the weighing signals with the Butterworth low-pass digital filter mentioned above, the reconstruction function of the formula (1) is

$$Y(t) = W + A_0 \sin(w_0 t + \varphi_0). \quad (3)$$

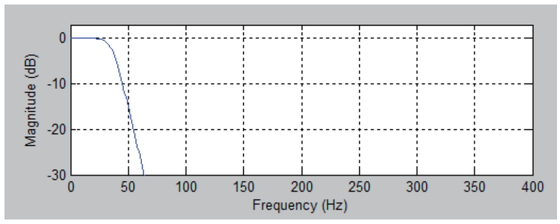

Fig.5. Amplitude-frequency characteristics of Butterworth low-pass filter

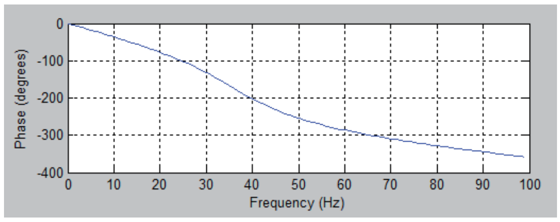

Fig.6. Phase-frequency characteristics of Butterworth low-pass filter

Elimination of the low-frequency random vibration interference. Nowadays, the main method to eliminate the low-frequency interference is to employ the digital moving average filtering, which is to average the dynamic random vibrations in the range of measurement ideally by the digital average method. In order to achieve more accurate filtering, the signal acquisition time must be greater than twice of the period of interference. However, this common method is ineffective to the periodic interference of low frequency in the weighing signals. This is because the main factor affecting the accuracy of the vehicles dynamic weighing system is the interference from the dynamic load generated by running vehicles. The weight signals collected by the weighing platform can be seen as signals consisting of the static axle load and the dynamic load. Dynamic load can be seen as composed of a plurality of signal, the frequencies of which are generally within the 30 Hz, and the amplitudes and the frequencies of which are different. So the dynamic load can be approximated by the superposition of a number of trigonometric functions. According to the accurate mathematics model of the formula (1), we can suppose that: if the point on the scale and the point off the scale are chosen properly, during the brief weighing process, the high-frequency noise is eliminated, formula (1) can be expressed as

$$Y(t) = A_0 t + \sum_{i=1}^{n} A_i t \sin(2\pi f_i t + \phi_i), \quad (4)$$

where $Y(t)$ is the ideal low-frequency weighing signal; A_0 is the slope generated by the static load move on the weighing platform; A_i is the change rate of different frequencies' amplitude of the dynamic load with the time; f_i is the frequency

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of different frequencies; φ_i is the initial phase of different frequencies; n is the number of the different frequency components contained in the periodic interference generated by the moving vehicles dynamic load. (Actually, the signal interference suppression ratio can be greater than 30–40 dB when $n \le 3$. Because even though there was a high frequency component, the usual filtering method in preprocessing can effectively inhibit it).

The above model can be fitted out according to the detected data. In order to eliminate the noise, it can be used to obtain the linear term $A_0 t$ by the method of least squares to fit out the ideal low-frequency signal. Obviously, this is a nonlinear fitting problem. At present, there are many optimization algorithms to solve nonlinear least squares problems. In this research, the Levenberg-Marquardt optimization algorithm was used to solve the nonlinear least squares problems with the least squares fitting. With the method of increasing the periodic oscillation items of variable amplitude one by one based on the residuals, the linear regression was estimated.

Finally, we got the stationary random sequence of residuals. In actual fitting, when the number of periodic vibrations is no more than 2, the extracted parts of low-frequency and the residuals of the fitting model tend to be smooth data. Using the inferior check criteria in application, namely

$$\sqrt{\frac{N}{2}}\,\frac{\delta_{n-1}^2-\delta_n^2}{\delta_n^2}<C,$$

where δ_{n-1}^2 is a variance of model residual before adding one periodic oscillation item, and δ_n^2 is the variance of model residual after adding one period oscillation item [10]. After estimation of the parameters of each sub-model, they can be used as initial values to make entire parameters estimation for the whole portfolio model. The nonlinear optimization algorithm was used repeatedly in the estimation process.

In fitting process, the objective function is taken as

$$\min F(x)=\min\sum_{i=1}^{m} f_i^2(x)=\sum_{i=1}^{m}[y(t)-Y(t)]^2. \qquad (5)$$

In (5), $x=[A_0, A_1, f_1, \phi_1 \ldots A_n, f_n, \phi_n]^T$, $y(t)$ is the test data, and m is the data sampling points.

Levenberg-Marquardt optimization algorithm is shown as follows:

(1) Give the initial point $x^{(0)}$, the maximum allowed number of iterations M, and the accuracy ε which the results meet.

(2) Start calculating. Set $k=0, \lambda_0=10^4$ to ensure that λ_0 is large enough. Calculate the value of $\nabla f(X^{(k)})$.

(3) Judge $\nabla f(X^{(k)})$. If $\|\nabla f(X^{(k)})\|<\varepsilon$, then $X^{(k)}$ is the extreme point and stop the iteration. If it does not meet, go to step (4).

(4) If the number of iterations $k>M$, stop the iteration. If not, go to step (5).

(5) Calculate $p^{(k)}=-[\nabla^2 f(X^{(k)})+\lambda_k I]^{-1}\nabla f(X^{(k)})$ and $X^{(k+1)}=X^{(k)}+p^{(k)}$.

(6) If $f(X^{(k+1)})<f(X^{(k)})$, go to step (7). If not, go to step (8).

(7) $\text{Deviation}=\dfrac{\sum_{i=0}^{N}\left|y_i(t)-G(t)\right|}{\sum_{i=0}^{N} y_i(t)}*100\%$, in this function, $y_i(t)$ is the reconstructed dynamic weighing signals after a low-pass denoising, and $G(t)$ is the fitting result data. Then go to step (4).

(8) $\lambda_{k+1}=2\lambda_k, k=k+1$, then go to step (4).

This optimization algorithm is simple and has the decreasing feature, which converges rapidly to the minimum point and there is no need to do the one-dimensional search. The actual calculation shows that this algorithm is more efficient. Let us discuss the calculation process in detail below.

Take the objective function as $F(x)=\sum_{i=1}^{m} f_i^2(x)$, and then solve $\min F(x)$. Get the optimal solution $x^*=[x_1^*,\ldots,x_n^*]^T$ of the undetermined function.

If $f(x)=\begin{bmatrix} f_1(x)\\ \ldots\ldots \\ f_m(x)\end{bmatrix}$, then $f(x)$ is an m-dimensional vector function based on x as the independent variable. Least squares problem could be abbreviated as

$$\min F(x)=\min f(x)^T f(x)=\min\|f(x)\|^2 \qquad (6)$$

in virtue of $\dfrac{\partial F(x)}{\partial x_j}=2\sum_{i=1}^{m} f_i(x)\dfrac{\partial f_i(x)}{\partial x_j}, (j=1,\ldots,n)$;

$$\nabla F(x)=\begin{bmatrix}\dfrac{\partial F(x)}{\partial x_1}\\ \ldots\ldots\ldots \\ \dfrac{\partial F(x)}{\partial x_n}\end{bmatrix}=m\begin{bmatrix}\dfrac{\partial f_1(x)}{\partial x_1}\dfrac{\partial f_2(x)}{\partial x_2}\cdots\dfrac{\partial f_m(x)}{\partial x_1}\\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \dfrac{\partial f_1(x)}{\partial x_n}\dfrac{\partial f_2(x)}{\partial x_n}\cdots\dfrac{\partial f_m(x)}{\partial x_n}\end{bmatrix}\begin{bmatrix} f_1(x)\\ \ldots\ldots \\ f_m(x)\end{bmatrix} \qquad (7)$$
$$=2J(x)^T f(x)$$

Among them,

$$J(x)=[J_{ij}(x)]_{m*n}, J_{ij}=\frac{\partial f_i(i)}{\partial x_j}, i=1,\ldots,m;\ j=1,\ldots,n.$$

In formula (7), $J(x)$ is used to represent the gradient of the objective function $F(x)$ in the form of sum of squares. Expand $f_i(x)$ at the point $x^{(k)}$ to the first degree according to Taylor's formula

$$f_i(x)\approx f_i(x^{(k)})+\nabla f_i(x^{(k)})^T(x-x^{(k)})\equiv l_i^{(k)}(x). \qquad (8)$$

Obtain the approximate function $F(x)$ based on the above formula $L^{(k)}(x)$.

$$F(x)=\sum_{i=1}^{m} f_i^2(x) \approx \sum_{i=1}^{m}[l_i^{(k)}(x)]^2 \equiv L^{(k)}(x)\,. \qquad (9)$$

Since $l_i^{(k)}(x)$ is a linear function, $L^{(k)}(x)$ is a quadratic function.

$$\frac{\partial^2 F(x)}{\partial x_i \partial x_j} \approx \frac{\partial^2 L^{(k)}(x)}{\partial x_i \partial x_j} = 2\sum_{r=1}^{m} J_{ri}(x^{(k)}) J_{rj}(x^{(k)})\,.$$

There is

$$\nabla^2 F(x^{(k)}) \approx 2J(x^{(k)})^T J(x^{(k)})\,. \qquad (10)$$

Bring formulas (7) and (10) into the direction searching formula in the algorithm optimization process (5), then we obtain the Levenberg-Marquardt iterative formula

$$x^{(k+1)} = x^{(k)} - [J(x^{(k)})^T J(x^{(k)}) + \lambda_k I]^{-1} \times \times J(x^{(k)})^T f(x^{(k)}). \qquad (11)$$

Verify the performance of optimization algorithm about the inhibition of the periodic interference, and the simulation data is generated by $y(t)=s(t)+n(t)$, where $s(t)$ is the signal, and $n(t)$ is the noise. The specific process is to be explained as follows.

Signal:

$s(t)=20t$

Noise:

$n(t)=6t\sin(2\pi*6t+3\pi/2)+4t\sin(2\pi*8t+0)$

Data for simulations:

$y(t)=20t+6t\sin(2\pi*6t+3\pi/2)+4t\sin(2\pi*8t+0)$

Because the model is complex and during the fitting process the initial value of periodic items parameter will af-fect the calculation efficiency of the nonlinear least squares method, before adding a periodic item each time, it should be made a preliminary determination for A_i, f_i, φ_i according to the characteristics of residual data. Treat them as the initial values, and then do the fitting. The choice of the initial values determines the amount of calculation and the reliability of the results.

(1) Determine the initial frequency. Determine the first maximum point and the first minimum point of the reconstructed function after low-pass filtering. Then obtain the number of points n between two points. Calculate the initial frequency $f=f_s/(2*n)$.

(2) Determine the initial phase. Determine the number of points n_1 between the first data point and the first extreme point, and the nature of the first extreme point, that whether the first extreme point is the maximum value or the minimum value. When the extreme point is the maximum value, $\varphi=\frac{\pi}{2}-\frac{n_1}{n}\pi$. When the extreme point is a minimum value, $\varphi=-\frac{\pi}{2}-\frac{n_1}{n}\pi$.

Fig.7 shows the simulated signal, fig.8 shows the signals after removing one periodic interference items, fig.9 shows the signals after removing two periodic interference items.

SNR of the simulated signals is

$$SNR1 = 10\lg\left(\frac{\text{Energy of the signal}}{\text{Noise energy}}\right) = 10\lg\left(\frac{\sum_{i=1}^{m} s^2(t)}{\sum_{i=1}^{m} n^2(t)}\right)(dB). \qquad (12)$$

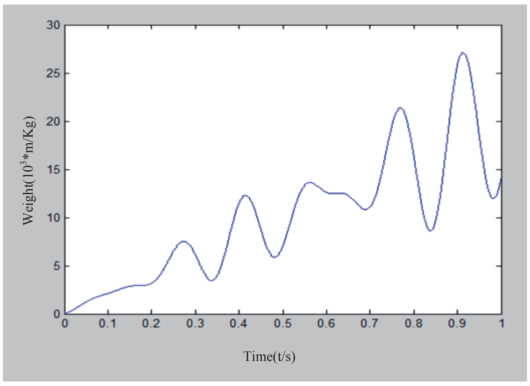

Fig. 7. Simulated signal

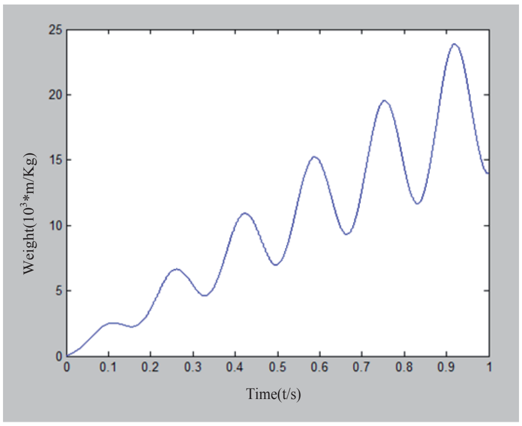

Fig. 8. The signals after removing one periodic interference items

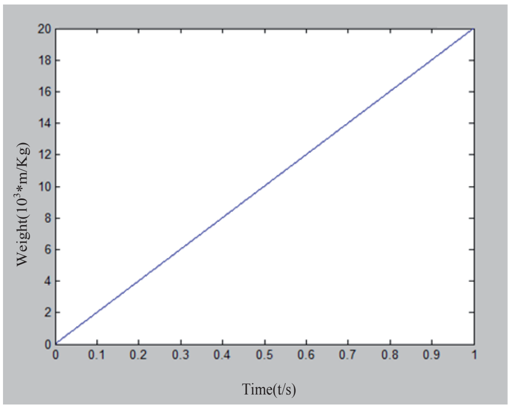

Fig. 9. The signals after removing two periodic interference items

After eliminating the noise signals by the above method, $s\ (t) = A\ t$ can be obtained and now SNR is

$$SNR2 = 10\lg\left(\frac{\sum_{i=1}^{m} s^2(t)}{\sum_{i=1}^{m}[s(t) - s^*(t)]^2}\right)(dB) . \qquad (13)$$

A large number of simulation calculations were carried out by adjusting the SNR [9], the frequency of periodic interference signal, and the phase. Finally, the signals need to be kept the linear term $A_0 t$ at the end of the fitting process.

Experimental results and analysis. In order to test the measurement accuracy of the vehicle dynamic weighing algorithm proposed in this paper, an experiment was conducted on the dynamic weighing system. In the experiment, we used a two-axle truck vehicle. In the static case, the front axle weight of the truck was 5620 kg, the rear axle weight was 8953 kg, and the whole vehicle weight was 14573 kg. Table shows the test data received in the experiment.

Table

Dynamic Experimental Data and Analysis

NUMBER	1	2	3	4
Speed (km/h)	10	20	30	40
FrontAxleWeight (kg)	5527	5530	5694	5513
FrontAxleError (%)	-1.7	-1.6	+1.3	-1.9
Rear AxleWeight (kg)	8799	8825	9112	8798
Rear AxleError (%)	-1.7	-1.4	+1.8	-1.7
TotalWeight (kg)	14326	14355	14806	14311
OverallError (%)	-1.7	-1.5	+1.6	-1.8
Speed (km/h)	50	60	70	80
FrontAxleWeight (kg)	5711	5723	5548	5724
FrontAxleError (%)	+1.6	+1.8	-1.3	+1.9
Rear AxleWeight (kg)	9080	9097	8821	9111
Rear AxleError (%)	+1.4	+1.6	-1.5	+1.7
TotalWeight (kg)	14791	14820	14369	14835
OverallError (%)	+1.5	+1.7	-1.4	+1.8

After experimental data analysis, the rate of the overall weighing error of the dynamic vehicle-weighing algorithm designed in this project appeared less than ±2% when the speed of vehicles is lower than 80 km/h. The measurement accuracy reached a higher level.

Conclusions. In our country, although some relevant departments designed and developed a variety of WIM systems, their performances have not been improved to be good enough. The reason is that the traditional design method of static balance has been still used in the design of the WIM systems. A deep research on the weighing measurement methods and the signals processing methods were not carried out. When measuring the weight of the running vehicle, because the weighing signal contains the low-frequency random interference, and the sampling signal is too short to get the stable weighing signals, it is necessary to figure out new weighing measuring and data processing methods. In this article, we started from the analysis of the dynamic loads of vehicles to solve these problems. We made deep researches on the design principles of the highway dynamic weighing system, the filtering of the high-frequency signal, the method of inhibiting the periodic random interference of short course signal, and so on.

Specific to the dynamic detection characteristics of the WIM system, the basic design principles of the system was proposed based on the analysis on the characteristics of dynamic loads of the WIM weighing. The correctness of the design criteria was proved through the experimental research on the dynamic characteristics of the system. This method may greatly reduce the production and the cost of the highway system, which is significant to guide the structural design of highway dynamic weighing system.

For the same digital filter, the frequency responses of the analog filter corresponding to the different sampling frequencies are different, and vice versa. The high sampling frequency will increase the degree and the amount of calculation of the filters with the same performance. In order to solve this problem and reduce the amount of design work, that a plurality of filters during frequency division, we designed the Butterworth low-pass filter according to the spectrum characteristics of weighing signals in the signal preprocessing. It is able to eliminate the high-frequency noise signals and implement the preprocessing of the weighing signals.

According to the analyses of the dynamic loads of vehicles, during weighing, the dynamic loads act as the low frequency noise interference in the weighing signals, of which the initial phases, frequencies, and amplitudes are random. When raising the speed of the vehicle passing the weighing system, the interference signals contained in the weighing signals are too short to be inhibited effectively by the normal filtering methods. In order to solve this problem, we established the ideal weighing signal model using the Levenberg-Marquardt optimization algorithm in least squares fitting, figured out the optimal solution, and inhibited the low frequency periodic random interference of the short course signals.

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Мета. Розробка стабільного й високоточного алгоритму динамічного зважування транспортних засобів.

Методика. Створена модель системи динамічного зважування транспортних засобів. Проаналізовані деякі види перешкод, що знижують точність зважування. Запропоновано новий алгоритм зважування в русі (WIM). Високочастотні перешкоди були усунені за допомогою цифрового фільтра низьких частот Баттерворта, а потім оптимізовані методом найменших квадратів на основі алгоритму Левенберга-Марквардта, що дозволило розділяти динамічне навантаження та обчислювати статичну вісь.

Результати. У результаті застосування алгоритму системи динамічного зважування транспортних засобів його стабільність і точність була підтверджена. На підставі аналізу результатів зважувань алгоритм зважування в русі (WIM) був схвалений.

Наукова новизна. Був розроблений оптимізаційний алгоритм, що дозволяє підвищити точність вимірювання та скоротити обмеження по зважуванню.

Практична значимість. Запропонований алгоритм динамічного зважування транспортних засобів дозволить запобігати перевищенню нормального навантаження.

Ключові слова: *динамічне зважування, обробка даних, оптимізаційний алгоритм, Баттерворт, метод найменших квадратів*

Цель. Разработка стабильного и высокоточного алгоритма динамического взвешивания транспортных средств.

Методика. Создана модель системы динамического взвешивания транспортных средств. Проанализированы некоторые виды помех, снижающих точность взвешивания. Предложен новый алгоритм взвешивания в движении (WIM). Высокочастотные помехи были устранены с помощью цифрового фильтра низких частот Баттерворта и затем оптимизированы методом наименьших квадратов на основе алгоритма Левенберга-Марквардта, что позволило разделять динамическую нагрузку и вычислять статическую ось.

Результаты. В результате применения алгоритма системы динамического взвешивания транспортных средств его стабильность и точность были подтверждены. На основании анализа результатов взвешиваний алгоритм взвешивания в движении (WIM) был одобрен.

Научная новизна. Был разработан оптимизационный алгоритм, позволяющий повысить точность измерения и сократить ограничения по взвешиванию.

Практическая значимость. Предложенный алгоритм динамического взвешивания транспортных средств позволит предотвращать превышение нормальной нагрузки.

Ключевые слова: *динамическое взвешивание, обработка данных, оптимизационный алгоритм, Баттерворт, метод наименьших квадратов*

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