

Measuring Axle Weight of Moving Vehicle Based on Particle Swarm Optimization

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Abstract: The dynamic tire forces are the important factor influencing weigh-in-motion of vehicle. This paper presents a method to separate the dynamic tire forces contained in axle-weight signal. On the basis of analyzing the characteristic of axle-weight signal, the model of axle-weight signal and the objective function are constructed. After introducing the principle of particle swarm optimization (PSO), an improved PSO is employed to estimate the unknown parameters of the objective function. According to the obtained estimates of parameters, the dynamic tire forces contained in axle-weight signal are reconstructed. Subtract the reconstructed dynamic tire forces from the axle-weight signal, and get the estimate of axle weight of moving vehicle. Simulation and field experiments are conducted to demonstrate the performance of the proposed method.

Keywords: weigh-in-motion, dynamic tire forces, particle swarm optimization

I. Introduction

Weigh-in-motion (WIM) can be defined as scaling the axle weight and total weight of a moving vehicle. Compared with traditional static measurement, WIM has high measurement efficiency and little influence on traffic. With the rapid development of traffic and transportation, the increasing phenomenon of overload in freight transportation has become a serious problem. The overload vehicles have caused the various harms^[1], such as reducing the lifespan of road and bridge, causing the traffic accident and losing a considerable amount of road toll. Accordingly, WIM technology is widely employed in traffic management, weight enforcement, and road toll.

It is important to process the WIM signal for improving the performance of the WIM systems. Infinite impulse response filter and average filter are often used in WIM signal process. System identification method^[2] models the weighing system as a second-order system, and deduces an auto-regressive (AR) model with unknown parameters, and use the least square method to get the estimations of unknown parameters. The estimation of axle weight is calculated with the estimations of the unknown parameters. Empirical mode decomposition^[3] (EMD) is a good method for measuring the axle weight in theory, which can decompose the axle weight signal into a collection of intrinsic mode functions (IMFs, which denote the dynamic components contained in the axle weight signal) and a residual (which corresponds to the signal of static axle weight). The average value of the residual is regarded as the estimation of real axle weight. In practice, end effect and pseudo-IMF influence the performance of EMD method. When the decomposed signal is short and has few extreme points, end effect will result in serious distortion of IMF. Zhou et al.^[4] present an AR model prediction method to extend signal and correlation coefficient method to judge pseudo-IMF, and then use the improved EMD to decompose the axle weight signal. Neural network method^[5] uses the strong nonlinear mapping performance to establish the mapping network between the axle weight signal and the real axle weight. The connection weights between neurons can be obtained by the sample training. The performance of neural network mainly depends on the sample number and sample types. It is difficult and costly to get enough axle weight signal samples in practice. The displacement integral method is first proposed by H.Yoshikawa^[6], which accumulates the integrals of the axle weight signal along the time direction. This method essentially averages axle weight signal. When the axle weight signal is short and contains the incomplete-cycle dynamic components, displacement integral method will fail to work well.

There exist various factors^[7] influencing the weighing accuracy and efficiency. The dynamic tire forces contained in the axle weight signal are the main factor. In this paper, the method based on particle swarm optimization^[8] (PSO) is presented to separate the dynamic tire forces. In the following sections, the model of axle weight signal is constructed and the characteristic of the dynamic tire forces is analyzed; the objective function based on axle weight signal model and sampled signal is set up; the algorithm of PSO is introduced and an improved PSO is presented; the simulation and field experiments are conducted to evaluate the performance of the proposed method.

II. Axle Weight Signal

For a static vehicle, the tire force exerted on the ground is equal to the static axle weight (which is regarded

as the real axle weight in practice). For a moving vehicle, the tire force exerted on the ground contains the dynamic tire forces besides the static axle weight. Consequently, the axle weight signal from the WIM system consists of dynamic tire forces and static axle weight. The quarter-car model [9] is often used to study the dynamic tire forces.

Referencing the approach described in Appendix B of [8], we can simulate the vehicle response to road roughness. The axle weight signal consists of dynamic tire forces and static axle weight, and the dynamic tire forces vary with road roughness, vehicle speed, vehicle load, suspension stiffness and tire stiffness. The max amplitude of the dynamic tire forces can reach 30% of the real axle weight [9, 11], and the lowest frequency of the dynamic tire forces can reach 1.5 Hz [9, 11]. As the width (direction of vehicle driving) of weighing platform is limited, it is impossible to acquire any complete cycles of the low frequency dynamic tire forces. For example, when the width of weighing platform is 760 mm, the available width is about 490 mm taking account of the tire-pavement contact area. When the vehicle runs through the weighing platform at 10 km/h, the valid sampling time is 178 ms and only 0.54 multiple cycles for the 3 Hz dynamic tire force.

If we assume that the dynamic tire forces are the superposition of sine signals [12], then the axle weight signal obtained from the weighing platform can be described as

$$f(t) = w + \sum_{i=1}^n A_i \sin(2\pi f_i t + \varphi_i), \quad (1)$$

where t is the sampling time, w is the static axle weight, n is the number of the dynamic tire forces, A_i , f_i , and φ_i are the amplitude, frequency and initial phase of the i -th dynamic tire force respectively.

For example, let $f(t) = 1 + 0.2\sin(2\pi 2t + \pi/3) + 0.15\sin(2\pi 5t + \pi/5) + 0.1\sin(2\pi 10t + \pi/6)$ is the axle weight signal, where three sine functions denote the dynamic tire forces contained in the axle weight signal and 1 denotes the static axle weight. The dotted lines denote the acquired signals from the different sampling time segments in Fig.1. If the average value of the sampled signal is regarded as the estimation of the real axle weight, then the measurements corresponding to t_1 and t_2 sampled signals will be less and more than the real axle weight, respectively, and the measurement corresponding to t_3 sampled signal will be about equal to the real axle weight. So, the acquired measurements will fluctuate above and below the real axle weight depending on the magnitudes, frequencies and initial phases of the dynamic tire forces. The dynamic tire forces contained in the axle weight signal, especially the incomplete-cycle dynamic tire forces, are the important factor influencing the axle weight measurement.

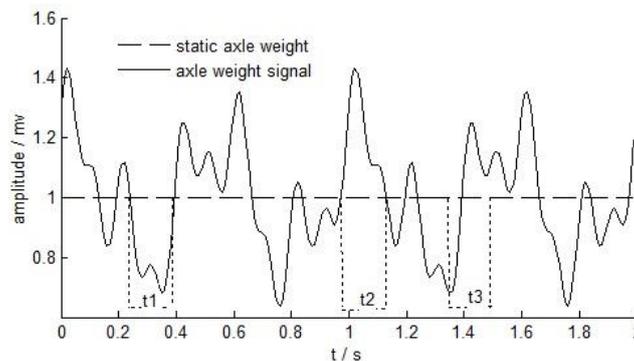


Fig.1 Simulation for the axle weight signal

III. Particle Swarm Optimization

Inspecting equation (1), if we can acquire the optimal estimations of unknown parameters to make $f(t)$ and the real axle weight signal $y(t)$ as close as possible, then we can reconstruct the dynamic tire forces and separate them from the axle weight signal. The objective function can be described as

$$G(\mathbf{X}) = \min \sum_{i=1}^n (f(iT) - y(iT))^2, \quad (2)$$

Where T is the sampling interval, n is the sample number of the real axle weight signal $y(t)$, $\mathbf{X} = [w, A_i, f_i, \varphi_i | i=1, 2, \dots, n]^T$ is the parameter vector. To reconstruct the dynamic tire forces, we must get

the optimal estimation $\hat{X} = [\hat{w}, \hat{A}_i, \hat{f}_i, \hat{\phi}_i \mid i=1, 2, \dots, n]^T$ to minimize $G(X)$. The problem of measuring the axle weight of moving vehicle is changed into looking for optimal estimations for unknown parameters.

Particle swarm optimization (PSO) is a global optimization method firstly proposed by J.Kennedy and R.C.Eberhart [13] in 1995. PSO searches the optimal solution by simulating the behavior of bird flock looking for food, and has been widely used to solve nonlinear, non-differentiable, multi-modal problems. PSO is initialized with a group of random particles, each of which represents a potential solution to a problem. The performance of each article is assessed by the fitness function previously constructed. Each particle adjusts its flying according to its own flying experience and its companions' fly experience in solution space. In every generation particle swarm, each particle tracks two best values. The first one is the optimal solution found by particle own so far. The second one is the optimal solution found by whole particle swarm so far. By iteration research, the optimal solution can be obtained.

Let a population consisting of M particles are flying at definite velocity in a D -dimensional space, the state of the i th ($1 \leq i \leq M$) particle at t time can be described as following.

$$\text{Position is } x_i^t = (x_{i1}^t, x_{i2}^t, \dots, x_{id}^t)^T, \quad x_{id}^t \in [L_d, U_d] \quad (1 \leq d \leq D),$$

where L_d and U_d denote the lower limit and upper limit of solution space, respectively.

$$\text{Velocity is } v_i^t = (v_{i1}^t, v_{i2}^t, \dots, v_{id}^t)^T, \quad v_{id}^t \in [v_{\min,d}, v_{\max,d}],$$

where v_{\min} and v_{\max} denote the minimum and maximum velocity.

$$\text{Individual optimal position is } p_i^t = (p_{i1}^t, p_{i2}^t, \dots, p_{id}^t)^T.$$

$$\text{Global optimal position is } p_g^t = (p_{g1}^t, p_{g2}^t, \dots, p_{gd}^t)^T.$$

The velocity and position of particle are manipulated at the $t+1$ time according to the following equation

$$v_{id}^{t+1} = v_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 (p_{gd}^t - x_{id}^t), \quad (3)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1}, \quad (4)$$

where c_1 and c_2 are two positive constants (usually $c_1=c_2=2$), r_1 and r_2 are two random numbers in the range $[0, 1]$. The equation (3) is used to calculate the particle's new velocity according to its previous velocity and the distances of its current position from its own best position and the group's best positions. The equation (4) is employed to calculate the particle's new position according to its previous position and its current velocity.

For improving the performance of PSO, a weight is introduced in practice. The velocity equation of standard PSO can be modified as [14]

$$v_{id}^{t+1} = \alpha v_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 (p_{gd}^t - x_{id}^t), \quad (5)$$

where α is a weight which affects the proportion of the particle's previous velocity in current velocity. If the valuate of α is large, then the global search performance of PSO is good and the local search performance is bad, and vice versa. A good weight will improve the performance of PSO and reduce the iteration times.

For a good balance between global optimization and local optimization of PSO, an inertia weight [15] is presented as following

$$\alpha = \alpha_{start} - \frac{\alpha_{start} - \alpha_{end}}{\tau_{max}} \times \tau, \quad (6)$$

where τ_{max} is the maximum iteration number, τ is the current iteration number, α_{start} and α_{end} are the initial weight and final weight, respectively. At beginning, a large weight is good for global optimizing and fast search the region containing the optimal solution. The weight becomes small and small with iteration and the local searching performance of PSO is gradually improved, the global optimal solution can be obtained at last.

IV. Simulation

Given the signal shown in fig.1 is the axle weight signal, where 1 denotes the static axle weight and three sine functions denote the dynamic tire forces. The sampling interval is 0.001 s and sampling time is 0.2 s. For the dynamic tire force $0.2 \sin(2\pi 2t + \pi/3)$, only 0.4 multi cycles can be acquired in 0.2 sampling time. The average value of signal $y(t)$ is regarded as the estimation of the real axle weight. The average value of $y(t)$ is 1.1131, which means the weighing error is 11.31%.

With the increasing of number of the unknown parameters, PSO algorithm becomes more complicated.

Therefore, it is reasonable to reduce the number of the estimated parameters. In this paper, the spectrum of the axle weight signal is employed to estimate the frequency components contained in the axle weight signal. Due to the axle weight signal containing incomplete-cycle dynamic tire forces, Fast Fourier Transform (FFT) fails to identify all the frequency components of the axle weight signal. Here, multiple signal classification (MUSIC)^[16] method is presented to estimate the frequencies of the axle weight signal. Compared with FFT, MUSIC can identify all the frequency components when the inspected signal contains incomplete-cycle frequency content.

The frequencies obtained by spectrum analysis are regarded as the frequency components of the dynamic tire forces. According to the axle weight signal model (1), the amplitudes and initial phases of the dynamic tire forces and the static axle weight can be regarded as the unknown parameters. Combining the sampling signal with the axle weight signal model (1), the objective function (2) is constructed. The population size is 100, and maximum iteration is 600, and convergence accuracy is 0.00001. The inertia weight (6) is used, and initial weight is 0.9, and final weight is 0.4. The objective function is employed as the fitness function to assess the particles. Fig.2 shows the process of error convergence. According to the estimations acquired, the axle weight signal is reconstructed in Fig.3. Subtracting the reconstructed dynamic tire forces from the sampling signal, the static component of axle weight signal can be obtained. The average value of the static component is 0.9954, which means the error is 0.46%. Compared with 11.31%, the weighing accuracy is improved greatly.

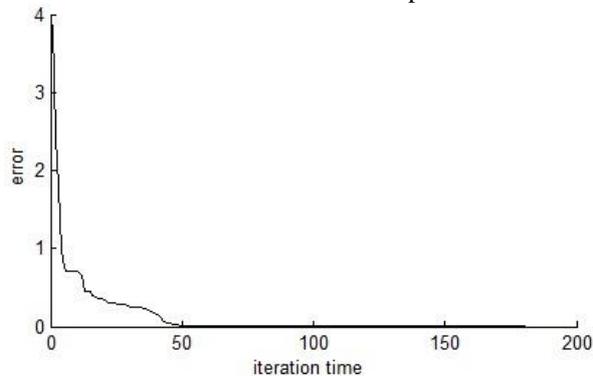


Fig. 2 process of error convergence

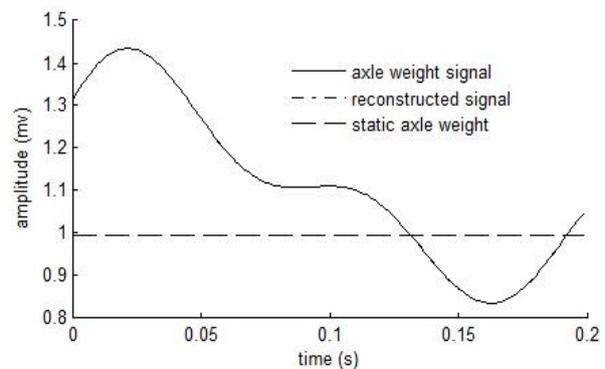


Fig. 3 simulation of dynamic tire forces separation

V. Field experiments

Fig. 4 shows the experiment field in this research. The weighing platform is 3.00 m in length and 0.75 m in width. The sampling frequency is 10 kHz. The experiment truck passes through the weighing platform at 10 km/h, 15 km/h and 20km/h, respectively. A low-pass filter is employed to preprocess the sampled signal. Fig. 5 shows the filtered signal at 10km/h. The first maximum point of the ascent segment denotes tire has entirely entered the weighing platform and the first maximum point of the descent segment denotes tire is going to leave the weighing platform. The data segment between the two maximum points is selected as the valid signal. The dashed lines depict the selection for valid axle weight signal in Fig. 5. In experiments, 18 axle weight signals at 10km/h, 18 axle weight signals at 15km/h and 18 axle weight signals at 20km/h are used to inspect the performance of the proposed method.

MUSIC method is employed to analyze the frequencies contained in the axle weight signals. Five frequencies selected from every axle weight signal are regarded as the frequency components of the dynamic tire forces. According to equation (1), the axle weight signal model is constructed. In the axle weight signal model, the amplitudes and initial phases of the dynamic tire forces and the static axle weight are the unknown parameters. The objective function similar to equation (2) is constructed. The size of particle swarm is 150, and the maximum iteration number is 400, and the error tolerance is 0.002. PSO algorithm is used to estimate the unknown parameters of the objective function. With the estimations, we can reconstruct the axle weight signal and the dynamic tire forces.

The performances of dynamic tire forces separation are shown in Fig.6, Fig.7 and Fig.8, where *axle weight signal* denotes the valid axle weight signal selected from the sampled signal shown in Fig.5, *reconstructed signal* denotes the reconstructed axle weight signal with the estimations and frequencies, and *residual signal* denotes the residue obtained by subtracting the reconstructed dynamic tire forces from the axle weight signal. The average value of the residual signal is regarded as the estimation of the real axle weight. Fig.9 shows the 54 axle weight estimations. The max measurement errors of axle weight are 5.37%, 4.07% and 13.13% at 10 km/h, 15 km/h and 20 km/h, respectively.



Fig. 4 field experiment site

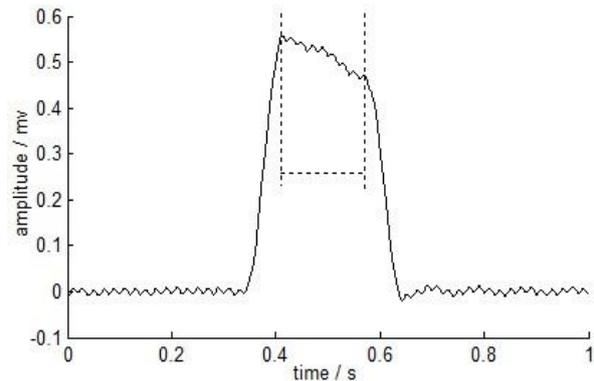


Fig. 5 filtered sampling signal at 10km/h

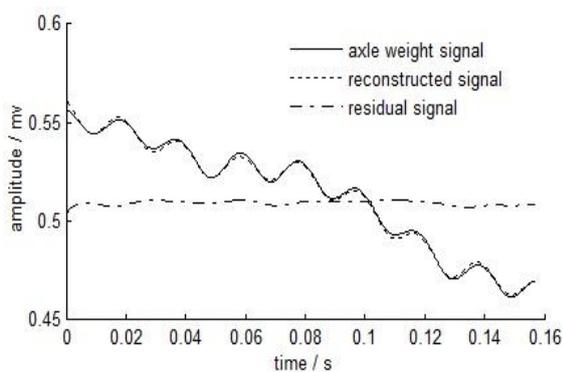


Fig. 6 estimating axle weight at 10 km/h

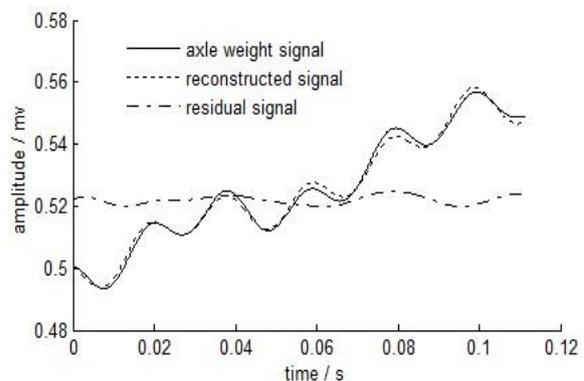


Fig. 7 estimating axle weight at 15 km/h

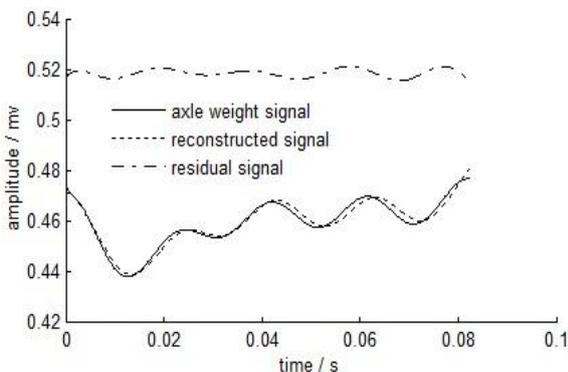


Fig. 8 estimating axle weight at 20 km/h

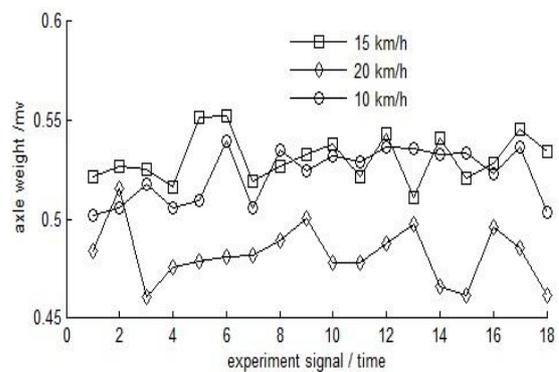


Fig. 9 fifty-four axle weight estimations

VI. Conclusions

The dynamic tire forces, especially incomplete-cycle dynamic tire forces, are the main factor that influences axle weight measurement of moving vehicles. This paper presents a dynamic tire forces separation method for scaling the axle weight of moving vehicles. The proposed method can be described as:

- (1) Analyzing the frequency spectrum of axle weight signal, and selecting several frequencies as the frequency components of the dynamic tire forces;
- (2) Constructing the axle weight signal model on the basis of the obtained frequency components, and constructing the objective function by combining the axle weight signal model with the sampled axle weight signal;
- (3) Employing the improved PSO algorithm to calculate the optimal estimations of the unknown parameters contained in the objective function, then reconstructing the dynamic tire forces according to the frequency components and the obtained optimal estimations;
- (4) Subtracting the reconstructed dynamic tire forces from the sampled axle weight signal, then acquiring the residual signal and calculating the average valued of the residual signal as the estimation of real axle

weight.

The simulation and field experiments are conducted to illustrate the performance of the proposed method. Referring to ASTM E1318-94^[17] standard specification, the measurement accuracy is superior to III class (axle load measurement error $\pm 15\%$) permissible accuracy.

VII. Acknowledgment

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REFERENCES

- [1.] J. F. Wang, M. G. Wu. An overview of research on weigh-in-motion system[C]. Proceeding of the 5th World Congress on Intelligent Control and Automation Hangzhou' 2004: 5241-5244.
- [2.] Xu Guanghua, Zhang Jijun, Qu Liangsheng. A Dynamic Weighing Method for Vehicle Scales Based on System Identification [J]. [China Mechanical Engineering](#), 2002, 13(8): 682-685(in Chinese).
- [3.] Norden E. Huang, Zheng Shen, Steven R. Long, Manli C. Wu, Hsing H. Shih, Qunan Zheng, et al., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," Proceedings of Royal Society, London, 1998, pp.903-995.
- [4.] Zhou Zhi-feng. Weigh in Motion Based on Dynamic Tire Force Separation [C]. Advances in Intelligent and Soft Computing, Proceedings of the 2011 International Conference on Informatics, Cybernetics, and Computer Engineering (ICCE2011) November 19-20, 2011, Melbourne, Australia: Volume 1: Intelligent Control and Network, 521-529
- [5.] S.M.T.Almodarresi Yasin and N.M.White. Application of artificial neural networks to intelligent weighing systems [J]. IEE Proc-Sci.Meas,Technol. 1999, 146(6):265-269
- [6.] Cai Zhengping, Zou Bingyi, Shi Changyan. Dynamic axle weight scale[C]. The Latest Development of Electronic Weighing Technology and Force Measurement-Conference Papers of 10th International Measurement Confederation Symposium on Measurement of Force and Mass. Beijing: China Metrology Publication House, 1986:182-186. (in Chinese)
- [7.] F. Scheuter. Evaluation of factors affecting WIM system accuracy[C]. Second COST323 WIM conference, Lisbon, 1998, P1216: 0-9.
- [8.] Li Li, Niu Ben. Particle Swarm Optimization [M]. Beijing: Metallurgical Industry Press, 2010 (in Chinese)
- [9.] D. Cebon. Interaction between Heavy Vehicles and Roads [J]. SAE Trans 930001, 1993: 1-80.
- [10.] Anon, 'Proposals for generalised road inputs to vehicles.' ISO/TC 108/WGp draft No.3e, 1972.
- [11.] G. Genta. Motor Vehicle Dynamic Modeling and Simulation [M]. Torino: World Scientific Publishing, 1997: 392-407.
- [12.] Toshiro ONO. On Dynamic weighing of Highway Vehicles in Motion[C]. SICE Annual Conference, Fukui, 2003: 2108-2114.
- [13.] J.Kennedy, R.C. Eberchart. Particle Swarm. Optimization [C]. Proceeding of the IEEE International Conference on Neural Networks, Perth, Australia, 1942-1948, 1995
- [14.] Y.Shi, R. Eberhart, C. Empirical. 2000. Study of Particle Swarm Optimization [C]. Proceeding of World Multiconference on Systemics, Cybernetics and Informatics, Orlando, FL: 1945-1950.
- [15.] Y.Shi, R.C.Eberhart. 1998. A Modified Particle Swarm Optimizer [C]. Proceedings of the IEEE World Congress on Computational Intelligence: 69-73
- [16.] Zhang Xianda. Modern signal processing [M]. Beijing: Tsinghua University Press, 2002: 126-146(in Chinese).
- [17.] ASTM Committee Standard specification for highway weigh-in-motion (WIM) systems with user requirements and test method. ASTM designation E1318-94, 1994.