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An Online State and Parameter Estimation of Dynamic State Space Model of High Speed Train

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Abstract

In this paper, the state space model of high speed train is established to describe its nonlinear dynamic characteristics, whose parameters are disturbed by noise with an arbitrary distribution, and an online state and parameter identification method is proposed based on a parameters set by employing Bayesian theory and Particle Filter (PF). Firstly, the priori probabilities of all of the possible parameters are set to be equal, and the predicted states with different parameters are estimated using PF. Then the posterior probabilities of the parameters are updated by analyzing the characteristic of the measurement noise using Bayesian theory. Finally, the system sate and parameter are estimated by weighted summing all of the parameters and predicted states. The simulation results indicate that the proposed method can estimate the states and parameters of high speed train online and adaptively.

***Keywords**: High speed train, Parameter identification, Particle filter, Bayesian theory*

1. Introduction

High speed train (HST) has dramatically expanded around the world, especially in China as its superiority of high efficiency, environmental protection and energy saving. To ensure the safety and stability of high speed train, an accurate dynamic model of train is crucial. However, model parameters which are foundation of system control are usually hard to detect and vary from the type of trains 00.

Considerable efforts on states and parameters estimation have been made for high speed train during the past decades. For example, system identification of the electric train braking model in urban rail transit was studied 000. Based on monitoring data, the running states of key components about air springs and lateral damper of high speed train were estimated 0. The Rao Blackwellised particle filter was used in the estimation of parameters of a stochastic linear state space model0. A heuristic nonlinear creep model was used to derive the nonlinear coupled differential equations of motion of a high speed train traveling on a curved track 0. The method of parameter estimation based on Rao Blackwellised particle filter (RBRF) was developed in reference 0, which can solve the nonlinear problems caused in augmenting the state vector of the performance parameters of high speed train. Based on the braking characteristics of train station parking in urban rail transit, two simplifications about the train dynamics equation were made. Furthermore, the online learning algorithm for updating the models' parameters was developed to overcome the influence by the nonlinear factors in

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parking to increase the parking accuracy 0, *etc*. Admittedly, the above research have important significance for building the dynamic model of high speed train and ensuring the safety. Meanwhile, because of the complex nonlinear relationship between the force of traction, braking, resistance, the speed and acceleration of train, the existed research mainly focused on the off line parameter estimation methods for the dynamic model with Gaussian noise.

However, the running states of high speed train are disturbed by stochastic factors such as wind, rain and railroad. Obviously, the assumption which approximates the noise by Gaussian noise is not appropriate. Besides, the running states and model parameters may vary with the type of trains and some running state, so the off line methods are not suitable for an actual train control system. In view of these problems, this paper aims at proposing an online states and parameters estimation for the nonlinear dynamic model of high speed train, which is affected by the noise with arbitrary distribution, not limited to Gaussian noise.

The remainder of this paper is organized as follows. Section 2 presents the modeling process of high speed train (HST) and problem statement. In Section 3, the states estimation and parameters identification of the HST system is developed. Furthermore, the effectiveness and practicability of method is verified by numerical simulation in Section 4. Lastly, this paper concludes with Section 5.

2. Model and Problem Statement

In this section, the dynamic model of high speed train is established, and the problem of states and parameters identification of high speed train is presented as follows.

2.1. The Dynamic Model of High Speed Train

For convenience of description, a reasonable assumption is stated as that the length of the train is much less than the length of railroad, so the train can be regarded as a mass point. Then according to Newton's law its motion equation can be established as follows:

$$\frac{ds}{dt} = v \tag{1}$$

$$\frac{dv}{dt} = \xi\left(f\left(v\right) - W\left(v\right)\right) \tag{2}$$

where s is the position of the train (km), v is the speed of the train (km/h), ξ is acceleration coefficient, $f\left(v\right)$ and $W\left(v\right)$ represent the traction(or braking) force and running resistance (kN/t), respectively. The unit running resistance $W\left(v\right)$ exists consistently during train operation, mainly consisting of aerodynamic drag and rolling mechanical resistance, which is given by the Davis formula according to the Regulations on Railway Train Traction Calculation (RRTTC). Namely, the train resistance can be described as

$$W\left(v\right) = c_0 + c_1 v + c_2 v^2 \tag{3}$$

where c_0, c_1, c_2 represent resistance coefficients. The first two terms represent the rolling mechanical resistance coefficients, which are proportional to the train speed. The third term is the aerodynamic drag coefficient which is proportional to the square of the speed, and its influence on the train's dynamic behavior becomes increasingly significant as the train speed increases. In practice, as the train speed increases, the aerodynamic drag, *i.e.* the third term in the right of Eq.(3), will become the major part of the total running resistance 000.

The model of train (Eq. 1-2) is continuous, which need to be discretized in order to be implemented in a computer system. Meanwhile, due to nonlinearity of high speed train system, an analytical discretization form of the equation (2) cannot be obtained. Therefore, the forward difference method is adopted to approximate the discretization model as follows,

$$\frac{ds}{dt} \approx \frac{s_{k+1} - s_k}{T} \tag{4}$$

$$\frac{dv}{dt} \approx \frac{v_{k+1} - v_k}{T} \tag{5}$$

where T denotes sampling period (s), usually T =1s.

During the running of high speed train, its speed is disturbed by several factors such as weather condition, curves, ramps and vehicles. In order to accurately describe the dynamic behavior of the running process of high speed train, the method of state space model is employed, where the state is set as $x_k = [s_k, v_k]^T \in R^2$, and the observation $y_k = s_k \in R$. Namely, the vector state x_k consists of position and speed of the train, *i.e.* $x_{1k} = s_k$, $x_{2k} = v_k$; the input u_k represents the unit traction or braking force $f(v_k)$, and the observation y_k means the position, *i.e.* $y_k = s_k$. Based on above analysis, the stochastic discrete state space model of high speed train can be described as,

$$x_{k+1} = \begin{bmatrix} x_{1k} + Tx_{2k} \\ x_{2k} + \xi T\left(u_k - c_0 - c_1 x_{2k} - c_2 x_{2k}^2\right) \end{bmatrix} + w_k \tag{6}$$

$$y_k = [1\ 0]\, x_k + e_k \tag{7}$$

where $w_k \in R^2, e_k \in R$ are mutually independent identically distributed processes, representing the state noise and measurement noise. They influence the changing of state (*i.e.* position and speed) and measuring accuracy. Their probability distribution functions are denoted by $p_w(\cdot)$ and $p_e(\cdot)$ respectively, which may be Gaussian or non-Gaussian forms.

2.2. Problem Statement

Regarding the nonlinear model of high speed train (Eq. 6-7), the unknown parameters represented as $\theta = \{c_0, c_1, c_2\}$ are key elements to build the dynamic model, and usually vary with the performance differences, performance degradation and types of trains. Therefore, an online estimation of states and parameters is indispensable for obtaining an accurate dynamic model of HST. However, due to the following main reasons:

(1) the nonlinear relationship between the resistance and speed of train (Eq.3 and Eq. 6);

(2) the states of trains are usually affected by stochastic noise (*i.e.* $w_k \in R^2, e_k \in R$ in Eq. 6 and Eq. 7) which usually can't be described by Gaussian distribution;

(3) the parameters (*i.e.* $\theta = \{c_0, c_1, c_2\}$) are unknown.

The widespread used methods such as Kalman-based and Guassian sum-based filtering methods no longer apply. According to our knowledge, there were no achievements on the online states and parameters estimation of nonlinear state space model with Non-Gaussian noise at present.

In this paper, an online states and parameters estimation method for nonlinear dynamic model of high speed train with an arbitrary noise distribution is proposed. Although state and parameter estimation for nonlinear systems is a quite complex thing, fortunately, the existing high speed trains in the word (or in a country) are only limited types, and the empirical knowledge of model parameters of existing trains is extremely useful, which is adopted to estimate the states and parameters. Firstly, a reasonable assumption is that, the number of train types is n , and the parameters of all types of trains can be represented as a parameter set $\Omega = \{\theta_l, l = 1, \ldots, n\}$. Therefore, although the real parameter θ of one type of trains is unknown, it certainly belongs to the parameter set Ω, *i.e.* $\theta \in \Omega$. Based on the analysis above, in this paper, we consider the state and parameters identification problem as follows.

In general, the dynamic model of high speed train is described as

$$x_{k+1} = f_k\left(x_k, u_k, w_k; \theta\right) \tag{8}$$

$$y_k = h_k\left(x_k, e_k; \theta\right) \tag{9}$$

where $f_k(\cdot)$ and $h_k(\cdot)$ correspond to the mapping relation as Eq. 6 and Eq. 7. Correspondingly, the have the same meanings on x_k, y_k, u_k, w_k, e_k. The empirical knowledge is expressed by $\Omega = \{\theta_l, l = 1,\ldots,n\}$, where n is the types number of existing high speed train (in China), and the real parameter $\theta \in \Omega$. Thus what we need to do is identifying the real parameter θ from the parameter set Ω.

A solution to this problem is proposed in this paper by the method based on particle filter, and described in detail in the following sections.

3. State Estimation and Parameter Identification

For the train model (Eq. 6-7), we consider the situation that precise information on θ is unknown, and the process noise w_k and measurement noise e_k are assumed to be stochastic and uncertain, which coincides with engineering actuality. To address the identification problem, the particle filter is employed to estimate the states firstly. Then the posterior probabilities of each group of parameters are calculated according to the realtime output of the model (*i.e.* y_k) and update the weight of each group of parameters in the parameter set Ω. The real parameter will be identified as its weight close to one finally. Therefore, at first, the sequential Monte Carlo algorithm will be introduced. The following content will provide a sufficient condition for the parameter identification strategy of high speed train.

3.1. Particle Filter and State Estimation

The sequential Monte Carlo approach will now be employed in order to compute approximations of the real state. The main idea underlying the particle filter is to approximate the filtering probability density function (PDF) of a random variable x_k using a collection of M samples x_k^i (so called particles), *i.e.*

$$p\left(x_k \mid y_{1:k}\right) = \sum_{i=1}^{M} \omega_k^i \delta\left(x_k - x_k^i\right) \tag{10}$$

where each particle x_k^i has an importance weight ω_k^i, and satisfies $\sum_i \omega_k^i = 1$. The weight denotes the importance of every particle in constituting the probability distribution function (PDF) of state x. The function $\delta\left(x_k - x_k^i\right)$ denotes the delta Dirac function located at x_k^i.

By the theory of Strong Law of Large Numbers (SLLN), the general integral representation of the filtering PDF is approximated by a finite sum.

$$\int g\left(x_k\right) p_\theta\left(x_k \mid y_{1:k}\right) dx_k \approx \frac{1}{M}\sum_{i=1}^{M} g\left(x_k^i\right)\omega_k^i \tag{11}$$

where the convergence is with probability one $M \to \infty$. The function $g\left(x_k\right)$ denotes an arbitrary PDF of x_k. Then, the respective weights of the particles are computed according to,

$$\omega_k^i = \omega_{k-1}^i \frac{p\left(y_k \mid \tilde{x}_k^i\right) p\left(\tilde{x}_k^i \mid x_{k-1}^i\right)}{q\left(\tilde{x}_k^i \mid x_{k-1}^i, y_{1:k}\right)} \tag{12}$$

In this formulation, $p\left(y_k \mid \tilde{x}_k^i\right)$ is the likelihood function of the measurements y_k, and $q\left(\tilde{x}_k^i \mid x_{k-1}^i, y_{1:k}\right)$ is the proposal density function. In general, the standard particle filter uses the transition prior $p\left(\tilde{x}_k^i \mid x_{k-1}^i\right)$ as a proposal density. Except for initialization, the algorithm mainly contains four steps: sampling, weight calculation, output, resampling [00] **Error! Reference source not found.**. A basic form of particle filter is given as follows.

- *Initialization*: at $k=1$, M sample points $\left\{x_1^i\right\}_{i=1}^M$ are picked up from prior probability $p\left(x_1\right)$, and initial weights of $\left\{x_1^i\right\}_{i=1}^M$ are set as,

$$\omega_1^i = 1/M, i = 1, \ldots, M;$$

- *Sampling phase*: new particles $\tilde{x}_k^i\left(i=1,\ldots,M\right)$ are sampled from the proposal distribution, which is presented as

$$q\left(\tilde{x}_k^i \mid x_{k-1}^i, y_{1:k}\right) = p\left(\tilde{x}_k^i \mid x_{k-1}^i\right);$$

- *Weight calculation and normalization*: particle weights are calculated as the formula,

$$\tilde{\omega}_k^i = \omega_{k-1}^i \frac{p\left(y_k \mid \tilde{x}_k^i\right) p\left(\tilde{x}_k^i \mid x_{k-1}^i\right)}{q\left(\tilde{x}_k^i \mid x_{k-1}^i, y_{1:k}\right)} = \omega_{k-1}^i p\left(y_k \mid \tilde{x}_k^i\right).$$

The weight is normalized as:

$$\omega_k^i = \tilde{\omega}_k^i \Big/ \sum_{i=1}^M \tilde{\omega}_k^i;$$

- *Output phase*: this step is to estimate state $\hat{x}_k$ according to

$$\hat{x}_k = \sum_{i=1}^M \tilde{x}_k^i \omega_k^i;$$

- *Resampling phase*: new particles $(x_k^i, 1/M)$ are sampled from particles $(\tilde{x}_k^i, \omega_k^i)$ and this step is to solve particle degradation problem;
- $k \rightarrow k+1$, if continuing identifying, go to sampling phase; otherwise, algorithm ends.

This derivation of particle filter is presented here, so that the reader can fully appreciate the rationale and approximating steps. This is important since they are key aspects underlying the estimation methods derived in the next sections.

3.2. The parameter Estimation based on the Posterior Probabilities

The following parts derive the process of the posterior probabilities based parameter identification for the high speed train. Because the parameter set can be obtained in advance, and the output of system y_k is observed online, the particle filter is applied to estimate the realtime state with each group of parameters in the parameter set Ω. The posterior probability of every parameter can be calculated according to the probability density function of observation noise e_k. Then the weight of each group of parameters can be updated according to the corresponding posterior probability. Finally the probability of real parameter will tend to one. The parameter estimation algorithm based on this idea is called the posterior probabilities based online identification.

Since different types of high speed train correspond to different model parameters, the analysis about the type of high speed train should be made. Note that the resistance exists consistently during train operation. So in this paper, the parameters needed to be identified are chosen as the resistance coefficients, *i.e.* $\theta=\{c_0,c_1,c_2\}$. The resistance coefficients of part of existing China Railway High-speed (CRH) are listed in Table 1.

Table 1. Resistance Coefficients of Different Types

Type \ Parameter	c_0	c_1	c_2
CRH1	0.53	0.0026	0.000069
CRH2	0.88	0.0074	0.000114
CRH3	0.79	0.0064	0.000115
CRH5	0.69	0.0063	0.000146
$SS_1/SS_3/SS_4$	2.25	0.0190	0.000320
SS_7	1.40	0.0038	0.000348
SS_8	1.02	0.0035	0.000426
DF	2.93	0.0073	0.000271
$DF_4/DF_{4B}/DF_{4C}/DF_{7D}$	2.28	0.0293	0.000178
DF_8	2.40	0.0022	0.000391
DF_{11}	0.86	0.0054	0.000218
ND_5	1.31	0.0167	0.000391
ND_2	2.98	0.0202	0.000033
DFH_3	2.40	0.0095	0.000673
Xian Feng	1.65	0.0001	0.000179
Star EMU Central Plains	1.28	0.0012	0.000195
China Star	1.16	0.00534	0.000182

In the case of parameters set are known, the state $\hat{x}_k^l$ of each group of parameters $\theta_l\left(l=1,2,\ldots,n\right)$ at time k can be estimated by particle filter. Furthermore, the system output y_k are obtained directly, so the posterior probability G_k^l of $\theta_l\left(l=1,2,\ldots,n\right)$ is calculated at time k according to probability density function of the measurement noise $p_e(\cdot)$, *i.e.*

$$G_k^l = p_v\left(\hat{x}_k^l \mid y_k\right) \tag{13}$$

Then according to Bayesian theory, the weight $q_k^l\left(l=1,2,\ldots,n\right)$ of each group of parameters is updated according to the following formula

$$q_k^l = \frac{q_{k-1}^l \cdot G_k^l}{\sum_{j=1}^{n} q_{k-1}^j \cdot G_k^j}. \tag{14}$$

The whole process of the identification method is showed in Table 2.

Table 2. The Procedure of State and Parameter Estimation

State A: The Calculation of Real Parameter
(1) Calculate the real parameter directly according to the formula

$$\theta=\sum_{l=1}^{n} q_k^l \cdot \theta_l \text{ ;}$$

(2) Optional calculation method.
If the weight of parameter q_k^l is bigger than 0.9 for a certain period of time τ (chosen as 0.3 times of the operation time *N*, *i.e.* $\tau=0.3N$), the parameter θ_l corresponding to the weight q_k^l is regarded as the real parameter, *i.e.*

$$\theta=\theta_l \text{ ;}$$

Else
the real parameter is calculated according to

$$\theta = \sum_{l=1}^{n} q_k^l \cdot \theta_l \ .$$

State B: The Identification Algorithm

(1) *Model*: establish the model of the high speed train system, *i.e*. the state space model

$$\begin{array}{l} x_{k+1} = f_k\left(x_k, u_k, w_k; \theta\right) \\ y_k = h_k\left(x_k, e_k; \theta\right) \end{array};$$

(2) *Parameter set*: obtain parameter set $\Omega = \{\theta_l, l = 1, \ldots, n\}$ and initialize the weights of each parameter with $q_1^l = 1/n \left(l = 1, \ldots, n\right)$;

(3) *output*: obtain the realtime output of system y_k ;

(4) *State estimation*: estimate the current state $\hat{x}_k^l$ of system according to the particle filter;

(5) *Posterior probability*: calculate the posterior probability G_k^l of each parameter $\theta_l\left(l = 1, 2, \ldots, n\right)$ at time *k*;

(6) *Update* the weight q_k^l of each parameter $\theta_l\left(l = 1, 2, \ldots, n\right)$;

(7) *Calculation of real parameter*: If there is a weight of parameter q_k^l is bigger than 0.9 for a certain period of time τ , the identification ends; otherwise, *k*→ *k*+1, return to step 3);

(8) The real parameter θ is identified.

4. Numerical Simulation

To verify the effectiveness of the proposed method, two numerical simulations about CRH3 with eight vehicles are conducted in this section. Four vehicles are trailer coaches (T) and the rest are motor coaches (M), which are arranged in the order as T+ M+ M+ T+ T+ M+ M+ T. The dynamic model is the same as Eq.6-7. The total mass of the train is Mt=500t. The resistance coefficients simulated may be any value in the following vectors, *i.e*. $c_0 \in \left[0.1, 4\right]$, $c_1 \in \left[0.0001, 0.03\right]$, $c_2 \in \left[0.00001, 0.0008\right]$, respectively, which covers a wide class of trains including CRH and SS series 0. The initial position and speed of high speed train are $x_{11} = s_1 = 0\text{km}$, $x_{21} = v_1 = 0\text{km/h}$. In the next parts, the problems about the estimation of system states and parameters with two kinds of stochastic noise are considered. In all cases the number of particles is set as *M*=100.

Case 1. In this case, considering the system is disturbed by Gaussian noise with the distribution characteristics of noise as

$$w_k \sim N\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}0.02 & 0\\ 0 & 0.05\end{bmatrix}\right), \ e_k \sim N\left(0, 5\right).$$

The parameter set is chosen as

$$\Omega = \begin{Bmatrix}\theta_1\\ \theta_2\\ \theta_3\end{Bmatrix} = \begin{Bmatrix} 2.25 & 0.019 & 0.000320\\ 0.79 & 0.0064 & 0.000115\\ 1.02 & 0.0035 & 0.000426\end{Bmatrix}$$

where $\theta_1, \theta_2, \theta_3$ are the resistance coefficients of SS_1, CRH3, and SS_8, respectively. The real parameter of CRH3 is the second group θ_2 . The simulation results are presented in Figure 1-4.

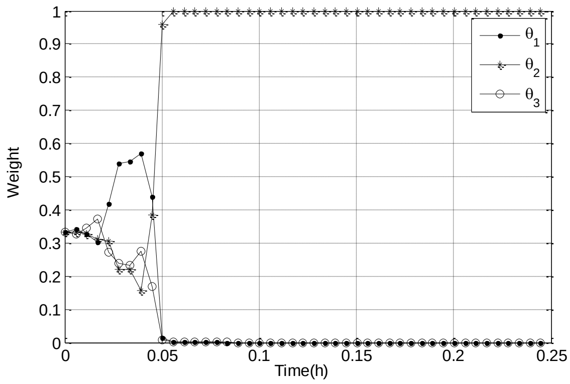

Figure 1. The Evolution Curves of the Weighs of Each Group Parameter

The evolution of the weights of each group is shown in Figure 1. It is obviously that when k=0.05h, the probability denoted by line plotted with '*' nearly reached one, which means that the real parameter is the second group.

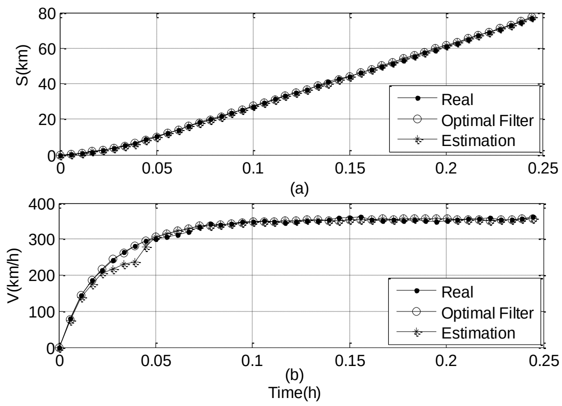

Figure 2. The Comparison of Real State and Estimate of State

The real and estimated train position and speed versus time (s-k and v-k) are as shown in Figure 2. We can observe that the estimate and optimal filter value can well track the real value at the whole operation process. From Figure 2(a), we can see that the position gradually increases over time. The speed curve is plotted in Figure 2(b). From k=0h to k=0.11h, the speed increases from 0km/h to 350km/h. After k=0.11h, the speed stabilizes on a constant value 350km/h.

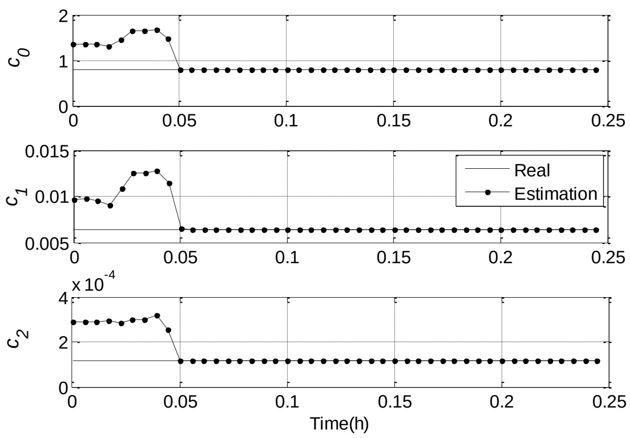

Figure 3. The Evolution Curves of Each Parameter

Figure 3 depicts the evolution curves of each parameter which shows that the real parameters can be obtained at k=0.05h. It is confirmed that the parameter identification schemes lead to fairly good performance.

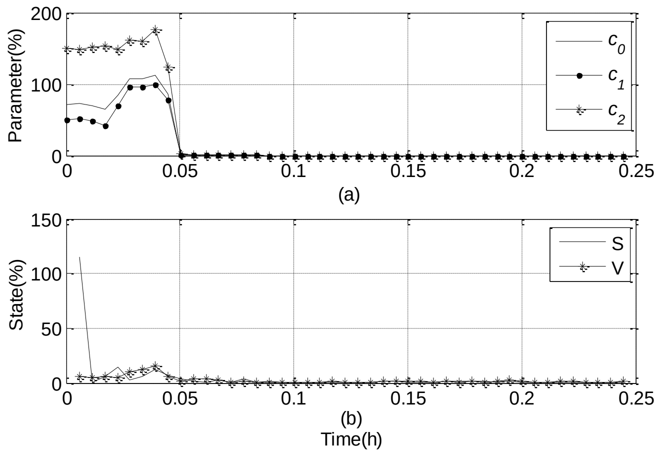

Figure 4. The Relative Errors of Parameters and States

Figure 4 shows the relative errors of parameters and states. From Figure 4(a), the relative errors of parameters were over 150% at the start stage. But after k=0.05h, the relative errors dropped into the range of ±5%. Similarly, the Figure 4(b) is the relative errors of states. We can see that the relative errors of states were over 100% firstly, and dropped to near zero soon.

Case 2. In this case, considering that the system is disturbed by Gamma noise with the distribution characteristics of noise as

$$w_k \sim \Gamma\left(\begin{bmatrix} 0.02 \\ 0.1 \end{bmatrix}, \begin{bmatrix} 0.1 & 0 \\ 0 & 0.05 \end{bmatrix}\right),\ e_k \sim \Gamma(0.5, 0.2).$$

The parameter set is chosen as

$$\Omega = \begin{Bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{Bmatrix} = \begin{Bmatrix} 0.53 & 0.0026 & 0.000069 \\ 0.79 & 0.0064 & 0.000115 \\ 0.69 & 0.0063 & 0.000146 \end{Bmatrix}$$

where $\theta_1, \theta_2, \theta_3$ are the resistance coefficients of CRH1, CRH3, and CRH5, respectively. That is, the real parameter of CRH3 is θ_2 .The simulation results are shown in Figure 5-8.

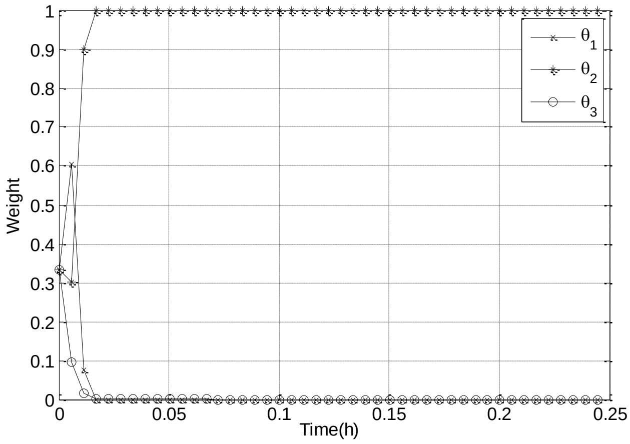

Figure 5. The Evolution Curves of the Weighs of Each Group Parameter

According to Figure 5, it is interesting to note that as the time k increases, the weight of second group, *i.e*. the line plotted with '*', gradually approaches one at time k=0.02h, whereas the rest group parameters tend to zero. It means that the second group is the real parameter.

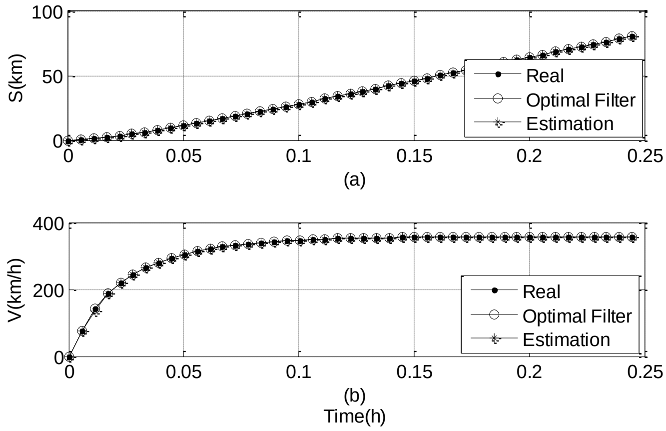

Figure 6. The Comparison of Real State and Estimate of State

The change curves of position and speed by applying particle filter to identify parameter of high speed train CRH3 are depicted in Figure 6, in which the line plotted with '*' denotes the estimate of state, *i.e*. position or speed, and the line plotted with 'o' is the optimal filter value. It is obvious that the estimate of state is not only quite close to the optimal filter value, but also can track the real state rapidly and accurately. The steady state speed reaches 350km/h at time k=0.11h which is consistent with the actual situation according to Figure 6(b).

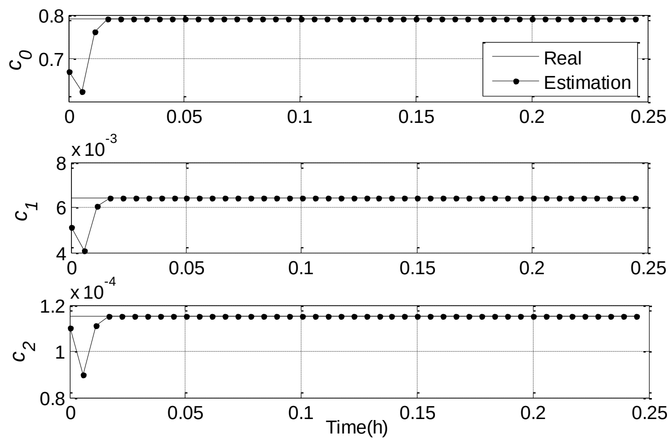

Figure 7. The Evolution Curves of Each Parameter

The evolution curves of each parameter are shown in Figure 7, in which the line plotted with '.' represents the estimated value, and the solid line corresponds to the real value. From Figure 7, we find that the deviation between the real value and the estimated value decreases with the increase of time over the interval [0h, 0.02h]. The real parameters are obtained at time k=0.02h.

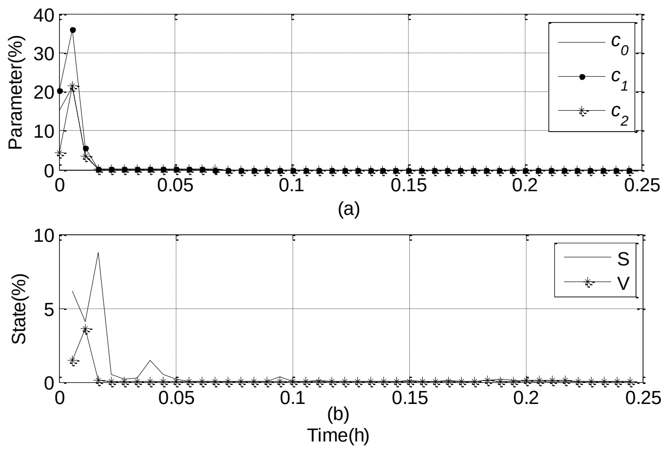

Figure 8. The Relative Errors of Parameters and States

Figure 8 depicts the relative errors of parameters and states. The relative errors of parameters are shown in Figure 8(a). At the initial stage, the relative errors are about 40%, but along with more information (observable output) are obtained, when k=0.02h, the relative errors nearly dropped to zero. Similar tendency to the relative errors of states are shown in Figure 8(b), *i.e*. the relative errors change to nearly zero after k=0.06h.

The simulations confirmed the effectiveness of proposed method in this paper. The disturbance to the motion of high speed train is effectively suppressed. By comparing case 1 and case 2, we can find that well identification performance is obtained under different noises. It means that the proposed method is not only suitable for Gaussian noise, but also appropriate for non-Gaussian noise.

5. Conclusion

In this paper, the discrete time state space model of the dynamic characteristics of high speed train has been established. Then considering the uncertainty of the parameters, and the model disturbed by stochastic noise with an arbitrary probability distribution function, an online parameters and states identification method was proposed based on the Bayesian theory and particle filter. Specifically, the problem of parameter identification was transformed to the calculation of the weights of prior parameters. The real parameter was obtained along with the evolution of the weights. The attraction feature of the proposed method lies in its simplicity and low computation in design and implementation, which enables the parameters to be obtained online. The simulation results indicate that the proposed method can effectively estimate the parameters of high speed train system. Additionally, the parameter identification of high speed train by considering the curve resistance and gradient resistance will be investigated in our future work.

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References

[1] Q. Song, Y. D. Song, T Tang and B Ning, “Computationally inexpensive tracking control of high speed trains with traction/braking saturation”, IEEE Transactions on Intelligent Transportation Systems, vol.12, no.4, **(2011)**, pp.1116–1125.

[2] Q. Song and Y. D. Song, “Data-based fault-tolerant control of high-speed trains with traction/braking notch nonlinearities and actuator failures”, IEEE Transactions on Neural Networks, vol.22, no.12, **(2011)**, pp.2250-2261.

[3] C. Gao and D. Chen, “Study on ATO braking model identification based on model selection and optimization techniques”, Journal of the China Railway Society, vol.33, no.10, **(2011)**, pp.57-60.

[4] Z. Y. Yu and D. W. Chen, “Modeling and system identification of the braking system of urban rail vehicles”, Journal of The China Railway Society, vol.33, no.10, **(2011)**, pp.37-40.

[5] H. G. Guo and K. M. Xie, “Hammerstein model and parameters identification of EMU braking system”, Journal of The China Railway Society, vol.36, no.4, **(2014)**, pp.48-53.

[6] L. Y. Liu, W. D. Jin and Z. B. Yu, “Running state estimation of high-speed train based on wavelet analysis”, Application Research of Computers, vol.30, no.10, **(2013)**, pp.2948-2950.

[7] P. Li, R. Goodall and V. Kadirkamanathan, “Estimation of parameters in a linear state space model using a Particle filter”, IEE Rao-Blackwellised Proceedings Control Theory and Applications, vol.151, no.6, **(2004)**, pp.727-728.

[8] Y. Cheng, S. Lee and H. Chen, “Modeling and nonlinear hunting stability analysis of high-speed railway vehicle moving on curved tracks”, Journal of Sound and Vibration, vol.324, issue. 1-2, **(2009)**, pp.139-160.

[9] J. M. Ding, J. H. Lin, H. Wang, C. G. Huang and J. Zhao, “Performance parameter estimation method of high-speed train based on Rao-Blackwellised particle filter”, Journal of Traffic and Transportation Engineering, vol.14, no.3, **(2014)**, pp.52-57.

[10] D. W. Chen, T. Tang, C.H. Gao and R.Q. Mu, “Research on the Error Estimation Models and Online Learning Algorithms for Train Station Parking in Urban Rail Transit”, China Railway Science, vol.31, no.6, **(2010)**, pp.122-127.

[11] C. D. Yang and Y.P. Sun, “Mixed H2/H1 cruise controller design for high speed train”, Int. J. Control, vol.74, no.9, **(2001)**, pp.905-920.

[12] H. R. Dong, B. Ning, B. G. Cai and Z. S. Hou, “Automatic train control system development and simulation for high-speed railways”, IEEE Circuits Syst. Mag, vol.10, no.2, **(2010)**, pp.6-18.

[13] S.K. Li, L.X. Yang, K.P. Li and Z.Y. Gao, “Robust sampled-data cruise control scheduling of high speed train”, Transportation Research Part C, vol.46, **(2014)**, pp.274-283.

[14] T. Zhang, S. M. Fei and X D. Li, “Tracking algorithm based on color correlogram using particle filter”, Journal of System Simulation, vol.21, no.17, **(2009)**, pp.5423-5426.

[15] M. S. Arulampalam, S. Maskell and N. Gordon, “A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking”, IEEE Transactions on Signal Processing, vol. 50, no.2, **(2002)**, pp.174-188.

[16] Z. Wang, Z. Liu, W. Liu and Y. Kong, “Particle filter algorithm based on adaptive resampling strategy”, International Conference on Electronic & Mechanical Engineering and Information Technology; Harbin, Heilongjiang, China, **(2011)**, pp.3138-3141.

[17] R. Zhong, “Train traction calculation”, Beijing: China Railway Press, **(2005)**.

