Improved Random Load Processing Algorithm Based on Kalman Filter

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Abstract

This paper first analyses the reasons of the disturbance signal emerging in the process of weighing, and then selects an improved algorithm based on Kalman filter method to deal with the raw data. After the analysis and comparing the new results with the static weighing data, we finally verify the accuracy of the new algorithm.
Keywords: dynamic weighing; Kalman filter; parallel algorithm

1 Introduction

The design of dynamic weighing system is based on the principle of traditional weighbridge. When vehicles drive through the weighing platform, its internal pressure sensor converts the pressure signal to electric signal, and uses the data acquisition module to transmit data to the filter program. The data which is dealt with the algorithm is the effective weight of the vehicle[1]. Vehicles are affected by many signal factors in the process of driving, mainly including high frequency interference and low frequency interference.

High frequency interference is divided into two parts, the hardware of weighing system itself contains variety of electronic components (such as pressure sensor, etc.), they produce frequency of high frequency interference which is much higher than the effective signals generated by the weight of the vehicle itself; vehicle engine and electric device also can produce the high frequency interference in the process of driving, and its frequency is higher than that of the effective signal. For this part of the high frequency interference, we use low-pass filter to remove it. According to related literatures, the effective signal frequency is normally not greater than 25 Hz, here we set a cut-off frequency of low pass filter with 30 Hz, allowing the signal below the cut-off frequency to pass, but preventing the signal higher than cut-off frequency, thus obtaining the signal without high frequency interference.

Low frequency interference mainly results from the random vibration produced by vehicles driving through the uneven road, i.e. the random dynamic load. Due to the randomness of dynamic load, its frequency, phase and amplitude are not regular, and lower frequency leads to longer periodicity, so the full cycle low frequency interference signals can't be collected. When the vehicle is moving, the vibration of vehicle itself caused by the uneven road surface is vehicle's dynamic load. The amplitude of the vibration reaches around 10% of weight of the vehicle itself, the vibration frequency is generally 3-20 Hz. Through the analysis of the actual vehicle dynamic weighing data, we find that the dynamic load frequency of actual vehicle is generally lower than 5 Hz, and the dynamic load is one of the largest interference factors of vehicle dynamic weighing data. The forming principle of dynamic load is complex, and the vibration of vehicle is closely related to the formation extent of road surface. However it is difficult to achieve the purpose of eliminating dynamic load by leveling off the road surface, because the vehicle vibration which produces dynamic load is also closely related to the vehicle itself. On the other hand, the deformation of the tire leads to continuous vehicle vibration even on flat road, so the improvement of hardware can't completely eliminate the influence of dynamic load.

2 Analysis of the Random Dynamic Load Processing Method

Characteristics of the Dynamic Load. Dynamic load can't be filtered by using the conventional methods for the reason that the frequency of dynamic load is too low and often mixed with useful signal. We can also calculate the numerical value, assuming that the speed of the vehicle when passing through the dynamic weighing platform is 10 m/s. While the width of the weighing platform is equivalent to the diameter of the vehicle's tire, and the platform width is about 1 meter. Assuming that the dynamic load frequency is 5 Hz, time when vehicle passes through the platform is 0.1s. There is only half-cycle vibration of dynamic load during the time when vehicle passes through the platform, so the complete information about the vibration of dynamic load is not enough. In addition, the amplitude, phase and frequency of the dynamic load are random, all data above is only an estimate range, so the conventional way can't filter out the dynamic load. Through the above analysis, although lengthening the bearing plate of dynamic weighing platform and reducing the passing speed of vehicle can effectively lengthen sampling time and get enough information of the dynamic load. However, this improvement is contrary to the aim of dynamic weighing itself. Hence, a new algorithm must be found in order to reduce the dynamic load's influence on the results of dynamic weighing.

The Removing Method of Dynamic Load. Current studies show that the time-domain cancellation is more suitable to be applied to the filter process of low frequency noise of dynamic weighing signal. Its principle is mainly to use polynomial to fit the original signal. The amplitude, frequency, phase and other values of the low frequency signal can be obtained by least square method which can fit the coefficients of polynomial. Then the goal of eliminating low frequency interference can be achieved by subtracting the fitting vibration signal from the original signal. To distinguish the periodic interference according to dynamic weighing data within complete table periodic interference signal, we take advantage of dynamic weighing signal composition provided by dynamic weighing system's prior knowledge to analyze. Because the width of bearing plate of dynamic weighing system is about 1 meter, we could consider that the vehicle is moving at a constant speed on the bearing plate.

According to the principle of dynamics and the knowledge of signal decomposition, we can infer that dynamic weighing data mainly consists of three parts as follows:

(1) Static load: the static weight of the vehicle itself, the weight of the vehicle we need to obtain.

(2) Dynamic load: the vehicle vibration caused by the uneven road. The low frequency interference should be removed in this section.

(3) High frequency noise: the high frequency interference which is analyzed in the previous section.

For the dynamic load, we adopts the improved processing method based on extended Kalman filter[2].

3 Improved Processing Method Based on Kalman Filter

Kalman Filter Theory. For the dynamic system of random disturbance, the application of Kalman filter performs well .As the optimal state estimation, the conventional Kalman filter method is usually based on the mean square error, and our basic idea is using the state space model of signal and noise. Further, we then use the previous moment estimate and observed value of the current time to estimate of the updated state variables, and finally yield the value of the current moment.

Consider a deterministic control input { u_k }, i.e., the conventional linear/random uncertainty system, Assuming that the state space model is:

$$\begin{cases} x_{k+1} = A_k x_k + B_k u_k + \Gamma_k \xi_k \\ v_k = C_k x_k + D_k u_k + \eta_k \end{cases} \tag{1}$$

where A_k is system matrix, B_k is input control matrix, Γ_k is noise matrix , C_k is measurement matrix, D_k is input control matrix. Specifically, the above values are n×n, n×m , n×p, q×n, q×m order constant matrix (both are known), respectively, and 1≦m, p, q ≦n, { u_k } is m dimensional vector sequence, { ξ_k } and { η_k } are both known average values the variance and covariance in the statistics system and observation noise sequence, respectively.

Kalman filter algorithm process is characterized as follows:

$$\begin{cases} P_{0,0} = Var(x_0) \\ P_{k,k-1} = A_{k-1}P_{k-1,k-1}A_{k-1}^T + \Gamma_{k-1}Q_{k-1}\Gamma_{k-1}^T \\ G_k = P_{k,k-1}C_k^T(C_kP_{k,k-1}C_k^T + R_k)^{-1} \\ P_{k,k} = (I - G_kC_k)P_{k,k-1} \\ \hat{x}_{0|0} = E(x_0) \\ \hat{x}_{k|k-1} = A_{k-1}\hat{x}_{k-1|k-1} + B_{k-1}u_{k-1} \\ \hat{x}_{k|k} = \hat{x}_{k|k-1} + G_k(v_k - D_ku_k - C_k\hat{x}_{k|k-1}) \\ k = 1,2,\cdots \end{cases}$$

(2)

where $P_{k,k}$ is the estimating covariance matrix, is the variance matrix for random vector $\{\zeta_k\}$, Gk is the Kalman gaining matrix, and Q_k is the variance matrix for random vector$\{\eta_k\}$.

Extended Kalman Filter Parallel Algorithm. Linearization should be done first for nonlinear model, in the system equation of state estimation, we do real-time linear Taylor approximation to previous state estimate value, and do the same to the estimated position in the measurement equation of predicted estimates, that is the extended Kalman filter[3].

The nonlinear model[4] is:

$$\begin{cases} x_{k+1} = f_k(x_k) + H_k(x_k)\zeta_k \\ v_k = g_k(x_k) + \eta_k \end{cases}$$

(3)

The initial estimate is $\hat{x}_0 = E(x_0)$, predictive value is $\hat{x}_{1|0} = f_0(\hat{x}_0)$, when k=1,2, … ,use predictive value in turn, we can get $\hat{x}_{k+1|k} = f_k(\hat{x}_k)$, consider linear Taylor approximation of $f_k(x_k)$ at $\hat{x}_k$ and linear Taylor approximation of $g_k(x_k)$ at $\hat{x}_{k|k-1}$:

$$\begin{cases} f_k(x_k) \approx f_k(\hat{x}_k) + A_k(x_k - \hat{x}_{k|k-1}) \\ g_k(x_k) \approx g_k(\hat{x}_{k|k-1}) + C_k(x_k - \hat{x}_{k|k-1}) \end{cases}$$

(4)

Here and hereafter, for any vectorvalued function , the correction formula can be got according to the standard Kalman filter process:

$$\hat{x}_k = \hat{x}_{k|k-1} + G_k(w_k - C_k \hat{x}_{k|k-1}) = \hat{x}_{k|k-1} + G_k(v_k - g_k \hat{x}_{k|k-1}) \tag{5}$$

The extended Kalman filter's process is similar to standard kalman filter's. Due to the expansion by Taylor series and ignoring of higher order term, the truncation error is introduced inevitably which leads to the poorer performance of state estimation. So we introduce the parallel algorithm[5] (i.e. improved algorithm) which is more efficient, for nonlinear time-variable systems:

$$\begin{cases} \begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} F_k(y_k)x_k \\ H_k(x_k, y_k) \end{bmatrix} + \begin{bmatrix} \Gamma_k^1(x_k, y_k) & 0 \\ \Gamma_k^2(x_k, y_k) & \Gamma_k^3(x_k, y_k) \end{bmatrix} \begin{bmatrix} \xi_k^1 \\ \xi_k^2 \end{bmatrix} \\ v_k = [C_k(x_k, y_k)] \begin{bmatrix} x_k \\ y_k \end{bmatrix} + \eta_k \end{cases} \tag{6}$$

Improved Kalman filter algorithm includes two sub algorithms, its difference with the previous algorithm is that real-time linear Taylor approximation is not done at the previous estimate, it is calculated by the estimate in algorithm 1 based on the subsystem

$$\begin{cases} x_{k+1} = F_k(\tilde{y}_k)x_k + \Gamma_k^1(\tilde{x}_k, \tilde{y}_k)\xi_k^1 \\ v_k = C(\tilde{x}_k, \tilde{y}_k)x_k + \eta_k \end{cases} \tag{7}$$

These two algorithms run in parallel with the same initial estimates. Algorithm 1 (i.e. improved Kalman filter algorithm) produces estimate $\begin{bmatrix} \tilde{x}_k \\ \tilde{y}_k \end{bmatrix}$, the input $\tilde{x}_{k-1}$ is given by that its input by algorithm 2 (i.e. the standard Kalman filter algorithm of Eq. 7) , the synthesis of the two algorithms is called parallel algorithm (1 and 2).

Algorithm 1: let $\begin{bmatrix} \tilde{x}_0 \\ \tilde{y}_0 \end{bmatrix} = \begin{bmatrix} E(x_0) \\ E(y_0) \end{bmatrix}$, $P_0 = Var\left(\begin{bmatrix} x_0 \\ y_0 \end{bmatrix}\right)$, for k=1,2,…, we have

$$P_{k,k+1}=\left[\frac{\partial}{\partial\begin{bmatrix}x_{k-1}\\ y_{k-1}\end{bmatrix}}\begin{bmatrix}F_{k-1}(\tilde{y}_{k-1})\tilde{x}_{k-1}\\ H_{k-1}(\tilde{x}_{k-1},\tilde{y}_{k-1})\end{bmatrix}\right]P_{k-1}\left[\frac{\partial}{\partial\begin{bmatrix}x_{k-1}\\ y_{k-1}\end{bmatrix}}\begin{bmatrix}F_{k-1}(\tilde{y}_{k-1})\tilde{x}_{k-1}\\ H_{k-1}(\tilde{x}_{k-1},\tilde{y}_{k-1})\end{bmatrix}\right]^T$$

$$+\begin{bmatrix}\Gamma^1_{k-1}(\tilde{x}_{k-1},\tilde{y}_{k-1}) & 0\\ \Gamma^2_{k-1}(\tilde{x}_{k-1},\tilde{y}_{k-1}) & \Gamma^3_{k-1}(\tilde{x}_{k-1},\tilde{y}_{k-1})\end{bmatrix}\bullet Q_{k-1}\begin{bmatrix}\Gamma^1_{k-1}(\tilde{x}_{k-1},\tilde{y}_{k-1}) & 0\\ \Gamma^2_{k-1}(\tilde{x}_{k-1},\tilde{y}_{k-1}) & \Gamma^3_{k-1}(\tilde{x}_{k-1},\tilde{y}_{k-1})\end{bmatrix}^T \tag{8}$$

$$G_k=P_{k,k\text{-}1}\left[\frac{\partial}{\partial\begin{bmatrix}x_k\\ y_k\end{bmatrix}}C_k(\tilde{x}_{k|k-1},\tilde{y}_{k|k-1})\right]^T\left\{\left[\frac{\partial}{\partial\begin{bmatrix}x_k\\ y_k\end{bmatrix}}C_k(\tilde{x}_{k|k-1},\tilde{y}_{k|k-1})\right]\bullet P_{k,k\text{-}1}\left[\frac{\partial}{\partial\begin{bmatrix}x_k\\ y_k\end{bmatrix}}C_k(\tilde{x}_{k|k-1},\tilde{y}_{k|k-1})\right]^T+R_k\right\}^{-1}$$

$$\begin{bmatrix}\tilde{x}_k\\ \tilde{y}_k\end{bmatrix}=\begin{bmatrix}\tilde{x}_{k|k-1}\\ \tilde{y}_{k|k-1}\end{bmatrix}+G_k\left(v_k-C_k(\tilde{x}_{k|k-1},\tilde{y}_{k|k-1})\tilde{x}_{k|k-1}\right)$$

In the formula, $Q_k=Var(\begin{bmatrix}\xi_k^1\\ \xi_k^2\end{bmatrix}), R_k=Var(\eta_k)$, $\tilde{x}_{k|k-1}$ is obtained by algorithm 2 below.

Algorithm 2: let $\hat{x}_0=E(x_0), P_0=Var(x_0)$, for k=1,2,…, we have

$$P_{k,k-1}=\left[F_{k-1}(\hat{y}_{k-1})\right]P_{k-1}\left[F_{k-1}(\hat{y}_{k-1})\right]^T+\left[\Gamma^1_{k-1}(\hat{x}_{k-1},\hat{y}_{k-1})\right]Q_{k-1}\left[\Gamma^1_{k-1}(\hat{x}_{k-1},\hat{y}_{k-1})\right]^T \tag{9}$$

$$G_k=P_{k,k-1}\left[C_k(\tilde{x}_{k-1},\tilde{y}_{k-1})\right]^T\bullet\left[\left[C_k(\tilde{x}_{k-1},\tilde{y}_{k-1})\right]P_{k,k-1}\left[C_k(\tilde{x}_{k-1},\tilde{y}_{k-1})\right]^T+R_k\right]^{-1} \tag{10}$$

$$\hat{x}_k=\hat{x}_{k|k-1}+G_k(v_k-\left[C_k(\tilde{x}_{k-1},\tilde{y}_{k-1})\right]\hat{x}_{k|k-1}) \tag{11}$$

In the formula, $Q_k=Var(\xi_k^1), R_k=Var(\eta_k), (\tilde{x}_{k-1},\tilde{y}_{k-1})$ is obtained by algorithm 1.

The difference between improved Kalman filter algorithm (i.e. algorithm 1) and original Kalman filter is that the Jacobi matrix and the predicted value of (nonlinear) vector valued function $F_{k-1}(y_{k-1})x_{k-1}$ is estimated at the optimal estimate $\hat{x}_{k-1}$ in each moment. $\hat{x}_{k-1}$ is determined by the standard Kalman filter algorithm (algorithm 2).

4 The Simulation Analysis

We choose the weighing platform in Tianjin port for our experiment, the platform are divided into two parts including front axle and rear shaft, and the gross vehicle weight contains the two part values. First, we measures that the static value of vehicle weight is about 22800 kg, which can be as a benchmark data. Second, let the vehicle pass through the weight platform at a speed of 20 km/h, we can obtain the experiment results, and the data can be measured by a curve. Third, we use the improved and extended Kalman filter algorithm to deal with the data, and observe the filter effect by comparing it with the benchmark data. The detail processing steps are as follows:

System Initialization. Take the dynamic weighing system as a whole, and model the system later.Consider the stochastic system that contains unknown parameters θ:

$$\begin{cases} x_{k+1} = \begin{bmatrix} 1 & 1 \\ 0 & \theta \end{bmatrix} x_k + \xi_k , x_0 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\ v_k = \begin{bmatrix} 1 & 0 \end{bmatrix} x_k + \eta_k \end{cases} \tag{12}$$

We can see that the value of x will gradually become convergence as the Kalman filter works. For P, it cannot be equivalent to 0, otherwise it may make the Kalman filter algorithm mistaken the x0|0 that you given is the optimal one of the system, resulting that the algorithm can't be convergence. Hence, here we choose $x_{0|0}$ = 22800, $P_{0|0}$ = 22800.

MATLAB Simulation Experiment. We select the effective pieces of data to perform the experiment, i.e., to opt to the maximum value between the front axle and rear axle. Effective data selection: we select the data with smooth curve, and remove scale data which is up and down the steelyard, then take the sum of the total steady data. We deal with all effective data by using Kalman filter, and get the acquisition value of the optimal estimation, and finally estimate the data in turn. Consequently, we compare the actual benchmark data with the optimal estimating average values that processed by the improved and extended Kalman filter algorithm, then the conclusions follow.

Results Analysis. The acquisition data and algorithm processing results are shown in Figure 1, which are also the waveform data for the weight of trucks. Line 2, 3 are respective the load curve of front and rear axle. Line 1 is the synthetic weight curve, line 4 is the static load of the total vehicle axle, line 5 is the curve for the improved extended Kalman filter algorithm.

From the results, we can obtain very precise signal that processed by the Kalman filter, which is close to the real signals. The signal of the vehicle’s axle is easily obtained by choosing starting point and end point from the effective data segment. From Fig. 1, we can also find that the precision by using Kalman filter method is very high, which can reach the international standard range.

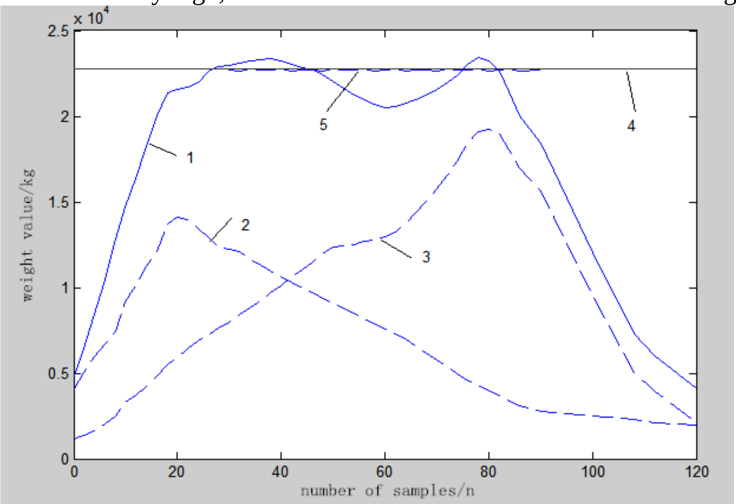

Fig. 1. The Acquisition Data and Algorithm Processing Results by Kalman Fiter Method

5 Summary

In this paper, we deal with the dynamic data by using a new improved and extended Kalman filter. Particularly, the weighting factor in this method can be adjusted dynamically, and it does not need a priori information of noise. Furthermore, though the method is easily implemented, it can still obtain high measuring accuracy with effective real-time performance. In addition, if we introduce the parallel algorithm into the extended Kalman filter method, one can effectively use the optimal estimate information repeatedly, and adjust the prediction covariance matrix to ensure that the algorithm has global convergence. Experiment results show that the method can effectively control the shaft weight measured in the international standard range, and the calculation results are approximately close to the real weight of the axle. Hence, the new method that we propose is a very effective and well-performing tracking method.

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