Research on preprocessing method of tractor wheel speed signal based on wavelet transform

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Abstract. As one of the most important parameters in the measurement of tractor slip ratio, wheel speed signal must ensure its accuracy in order to accurately measure the tractor slip ratio. Noises make tractor wheel speed signal a significant fluctuation, which may cause control system failure. Fault points elimination method suitable for tractor wheel speed signal was determined based on the characteristics of tractor wheel speed signal during working process. Meanwhile, soft-hard compromise threshold function wavelet denoising method is designed according to the characteristics of tractor wheel speed signal and trials. We use Carsim simulation software to get actual tractor wheel speed signal, and add white noise which SNR (signal to noise ratio) is 60 to the original signal. From the results of several wavelet denoising methods we can conclude that the soft-hard compromise threshold function wavelet denoising method is better than any other ordinary wavelet denoising methods. The SNR of denoised signal is 56.440 and the MSE (mean square error) is 0.0042. The wavelet transform denoising method is feasible to remove noise from tractor driving wheel speed signal.

1. Introduction
Slip or travel reduction is of interest when agricultural tractors pull a drawbar load. Tractive efficiency and fuel economy of agricultural traction devices can be improved by cutting down wheel slip. In tractor system, it is very critical to appropriately process wheel angle speed [1]. The circuit of wheel speed sensor is an electronic system which is easily interfered by strong external electromagnetic field, and the wheel speed sensor often gets vibrating due to tractors’ bad working condition [2]. These two factors often cause many interference signals which almost overlap the real signal.

These interference signals generate randomly with complex frequency, so they can hardly be removed by traditional method based on mere frequency domain, such as Butterworth filter. Wavelet transform can easily handle spectrum overlap and information loss in time domain through adjustment of wavelet coefficient [3]. The purpose of signal preprocessing is to eliminate outliers exist in signals. The causes of abnormal data are electromagnetic interference, voltage variation, and vibration impact. There are also faults in measuring instruments and human errors. We designed a signal preprocessing method based on Pauta criterion to eliminate wrong points. Mean while, a wavelet transform denoising method based on soft-hard compromise threshold function is proposed to remove the noise from the wheel speed signal.

2. Methods for eliminating wrong points
Gross error refers to the error obviously beyond expected, which is inevitable in wheel speed signal. Before removing the wrong points, we must determine whether a sampling point is wrong point. General methods of determining wrong points are Pauta criterion, Chauvenel criteria, Grubbs criterion and Dixon criterion [4].

2.1. Grubbs criterion
This criterion holds that sampling point \( x_i \) corresponding to the maximum residual error \( |v_i| \) may be wrong point \( x_d \). If equation 1 is satisfied when significant level between 0.01 and 0.05, this sampling point can be identified as wrong point.

\[
|x_d - \bar{x}| / s \geq G(\alpha, n) \tag{1}
\]

Where, \( \alpha \) is significant level, \( G(\alpha, n) \) is Grubbs critical value.

2.2. Dixon criterion
We arrange sampling points in descending order to form a sequence: \( x_1, x_2, \ldots, x_n \). So the minimum value in sequence is \( x_1 \), and the maximum value is \( x_n \). Statistical parameters \( \gamma_y \) and \( \gamma'_y \) are calculated as follow:

If \( 3 \leq n \leq 7 \),

\[
\gamma_{10} = \frac{x_n - x_{n-1}}{x_n - x_1}, \quad \gamma'_{10} = \frac{x_2 - x_1}{x_n - x_1} \tag{2}
\]

If \( 8 \leq n \leq 10 \),

\[
\gamma_{11} = \frac{x_n - x_{n-1}}{x_n - x_2}, \quad \gamma'_{11} = \frac{x_2 - x_1}{x_n - x_1} \tag{3}
\]

If \( 11 \leq n \leq 13 \),

\[
\gamma_{21} = \frac{x_n - x_{n-2}}{x_n - x_2}, \quad \gamma'_{21} = \frac{x_3 - x_1}{x_{n-1} - x_1} \tag{4}
\]

If \( 14 \leq n \leq 30 \),

\[
\gamma_{22} = \frac{x_n - x_{n-2}}{x_n - x_3}, \quad \gamma'_{22} = \frac{x_3 - x_1}{x_{n-2} - x_1} \tag{5}
\]

First, selecting significance level \( \alpha \). Second, we calculate the critical value \( D(\alpha, n) \) and compare \( D(\alpha, n) \) with \( \gamma_y \). If \( \gamma_y > \gamma'_y \), \( \gamma_y > D(\alpha, n) \), we can conclude that \( x_n \) is wrong point, else there is no wrong point. Dixon criterion can be used multiple times to eliminate wrong points, each time the algorithm can be used to eliminate one wrong point.

2.3. Pauta criterion
This criterion can be used to eliminate wrong points when sampled signal has a large number of sampling points. The expression of this criterion is:

\[
|x_d - \bar{x}| / s \geq 3s \tag{6}
\]

Where, \( s \) is standard deviation of population sample calculated by Besar formula, \( x_d \) is doubtful point, \( \bar{x} \) is the average of all sampling points.
It is concluded that among the three methods above, Pauta criterion is the simplest and most commonly used method for eliminating wrong points. When sample points are more than 10, this method can be used directly without table look-up. Which method to use largely depends on the number of sampling points. When the number of sampling points \( n > 50 \), we should use Pauta criterion; When the number of sampling points \( 3 < n < 50 \), Grubbs criterion is better; When the number of sampling points \( 3 < n < 30 \), Dixon criterion is better. The number of sampling points in tractor wheel speed signal is greater than 50, Pauta criterion is best [5].

3. Wavelet theory

3.1. Basic theory of wavelet transform

Wavelet, as its name implies, is a small waveform. The so-called "small" means that it has attenuation; and "wave" is its volatility, which exhibits positive and negative fluctuations. Compared with Fourier transform and windowed Fourier transform, wavelet transform is the localization analysis of time or space frequency. Through the telescopic translation operations and multi-scale refinement to signal or function, it can ultimately realize time subdivision at high frequency points and frequency subdivision at low frequency points [6].

3.1.1. One dimensional continuous wavelet transform. Presume the function \( \psi(t) \in L^2(\mathbb{R}) \), if its Fourier transform \( \hat{\psi}(\omega) \) satisfies the admissibility condition below [7]:

\[
C_{\psi} = \int_{\mathbb{R}} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < \infty
\]  

(7)

Then it is called basic wavelet or mother wavelet function. A family of time-frequency atoms is obtained by scaling \( \psi(t) \) with \( a \) and translated by \( b \):

\[
\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right)
\]  

(8)

where, \( a \in \mathbb{R}_+ \) is a transformation scale factor, and \( b \) is a position factor in the equation.

The continuous wavelet transform of signal \( f(t) \in L^2(\mathbb{R}) \) is defined as:

\[
W_f(a,b) = \left( f, \psi_{a,b} \right) = |a|^{-1/2} \int_{-\infty}^{\infty} f(t) \overline{\psi}\left(\frac{t-b}{a}\right) dt
\]  

(9)

In which \( \overline{\psi} \) is the complex conjugate of \( \psi(t) \). As the inverse transform of wavelet transform, the continuous wavelet rebuild function of signal \( f(t) \) is:

\[
f(t) = \frac{1}{C_{\psi}} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} a^2 W_f(a,b) \psi\left(\frac{t-b}{a}\right) dadb
\]  

(10)

3.1.2. One dimensional discrete wavelet transform. Continuous wavelet transform has the character of self-similarity and redundancy in information expression, so another way called discrete wavelet transform is usually used in practical computing. The discrete function of transformation scale factor \( s \) and position factor \( u \) are: \( s = s_0^j \), \( u = k_0^ju_0 \), \( (s_0 > 0, s \neq 1, u_0 > 0, j \in \mathbb{Z}, k \in \mathbb{Z}) \).

3.2. The feasibility and necessity of wavelet transform denoising

Signal denoising is one of the classical problems in signal processing. Traditional denoising methods include linear filters and nonlinear filters. Linear filters such as high frequency and low frequency
filters are prefilters. In the process of filtering, they assume the noise and signal are separated, in fact the tractor wheel speed signal and noise often interfere with each other, degree of overlapping is high, at this moment these filters will not work [8].

Kalman filter, Wiener filter and other kinds of nonlinear filters are not good in dealing with noise signal of unknown statistical data, and it is not easy to obtain the mean and variance of noise in original signal. The disadvantages of traditional denoising methods are that the entropy of the signals were increased, and the signal is not stable. Traditional denoising methods can’t describe the nonstationarity of signals, nor the correlation between signals.

The wavelet transform has following characteristics:

- Low entropy: wavelet coefficients are sparse distribution, so that the entropy of the signal is low.
- Multi-resolution characteristics: wavelet transform can well characterize the stationary characteristics of signals, such as edges, spikes, breakpoints, etc.
- Decorrelation: correlation of signals can be removed, and the noise will be whitened after wavelet transform.
- Flexible choice of base functions: wavelet transform can select the base function flexibly, so we can choose appropriate wavelet according to the characteristics of the signal.

4. Wavelet analysis of tractor wheel speed signal

Tractor wheel speed signal is a serial of velocity values corresponding to the sample time, it can be approximate represented by one dimensional signal model with noise [9]:

$$f(t) = s(t) + n(t)$$

where, $f(t)$ is wheel speed signal with noise, and $s(t)$ is wheel speed signal without noise. We assume that $n(t)$ is Gauss white noise. The mean of Gauss white noise is 0, and variance is 1.

Wheel speed signal is a serial of continuous observation signals, so $f(t)$ can be discretized as:

$$w_f(j,k) = w_s(j,k) + w_n(j,k); j = 0,1,2,\cdots ; J; k = 0,1,2,\cdots , N$$

in which, $w_f(j,k)$ are wavelet coefficients of wheel speed signal with noise decomposed at $j$ th layer; $w_s(j,k)$ are wavelet coefficient of wheel speed signal without noise decomposed at $j$ th layer; $w_n(j,k)$ are wavelet coefficient of noise signal decomposed at $j$ th layer. Length of the signal is $N$. The total layers of discrete wavelet transform is $J$. We mark $w_f(j,k)$, $w_s(j,k)$, $w_n(j,k)$ as $w_f$, $u_{j,k}$, and $v_{j,k}$.

Tree diagram of tractor wheel speed 3 layers Multi-resolution decompose is illustrated in figure 1.

![Tree diagram of tractor wheel speed 3 layers Multi-resolution decompose.](image)

Figure 1. Tree diagram of tractor wheel speed 3 layers Multi-resolution decompose.

3 layers discrete wavelet decomposition diagram of tractor wheel speed signal is used to illustrate the decomposition process. The actual decomposition level of this paper is 5 layers. As shown in
In figure 1, we presume S is wheel speed signal with noise, S can be decomposed to low frequency information cA1 and high frequency detailed information cD1 at 1st layer, then the 2nd layer, and so on.

Because of different wavelet coefficient in high frequency domain, real signal and noises can be discriminated, so that noises can be eliminated and useful high frequency information cD1, cD2, cD3 can be retained. Then we can rebuild the denoised signal S with low frequency information and retained high frequency information:

\[ \bar{S} = cA3 + cD3 + cD2 + cD1 \] (13)

5. Analysis of tractor wheel speed signal denoising

5.1. Using wavelet decomposes wheel speed signal

We should choose the suitable wavelet base and determine the number of decomposition layer J. There are many kinds of wavelet bases, but 8 of them are frequently used. Harr wavelet series, Daubechies wavelet series (dbN), Biorthogonal wavelet series (biorNr.Nd), Coiflet wavelet series (coifN), Symlets wavelet series (SymN), Morlet wavelet series (morl), MexicanHat (mexh), Meyer wavelet series are included.

According to the characteristics of tractor wheel speed signal, this paper use Daubechies wavelet series dbN (N=1,3,5), which is compactly supported in time domain [10].

5.2. Threshold processing of high frequency coefficients of wavelet decomposition

Threshold processing can be divided into two parts: threshold estimation and threshold function selection. The effect of wavelet denoising depends on the estimation of threshold and the construction of threshold function. In this paper, we use threshold estimation formula [11]:

\[ \lambda(j) = \sigma_j \sqrt{2 \log(N) / \log(j + 1)} \] (14)

to estimate threshold \( \lambda(j) \). Where, \( N \) is number of sampling points, \( j \) is wavelet decomposition level, \( \sigma_j \) is standard deviation of noise signal in \( j \)th decomposition layer. The noise variance estimation formula is expressed as [9]:

\[ \hat{\sigma}_j = \frac{\text{median}(|w_{j,k}|)}{0.6745} \] (15)

where, median is calculating the median of high frequency coefficients \( w_{j,k} \) after \( j \) th layer decomposition.

A soft-hard threshold compromise threshold function was designed in this paper, it can be described as [12]:

\[ \hat{w}_{j,k} = \begin{cases} \text{sgn}(w_{j,k}) \left( |w_{j,k}| - \frac{b\lambda}{a|w_{j,k}| - b - 1} \right), & |w_{j,k}| \geq \lambda \\ 0, & |w_{j,k}| < \lambda \end{cases} \] (16)

In which, sgn is sign function, \( \lambda \) is threshold. \( w_{j,k} \) is wavelet coefficients of wheel speed signal with noise decomposed at \( j \)th layer, \( a > 1 \) and \( b > 1 \) are constants that can be adjusted according to different signals.

In order to determine the appropriate values of \( a \) and \( b \), we use a variety of threshold functions to denoise a signal with noise. The SNR of this signal is 6.8098:

\[ x = 30\sin(t) + 25\sin(2t) + \text{rand}(n) \] (17)
where, $x$ is signal with noise, $t$ is time, $\text{rand}(n)$ is white noise.

Denoising performances of different threshold functions are shown in table 1.

**Table 1.** Denoising performances of different threshold function.

| Threshold denoising function | SNR   | MSE   |
|-----------------------------|-------|-------|
| Soft threshold              | 6.9721| 0.82825|
| Hard threshold              | 7.6533| 0.42006|
| Soft-hard threshold compromise threshold $a=2000$, $b=13$ | 7.7321 | 0.38824|
| Soft-hard threshold compromise threshold $a=4000$, $b=13$ | 7.7336 | 0.38765|
| Soft-hard threshold compromise threshold $a=6000$, $b=13$ | 7.7341 | 0.38744|
| Soft-hard threshold compromise threshold $a=8500$, $b=13$ | 7.7345 | 0.38732|

As is shown in table 1, the higher SNR is, the better denoising performance is. The smaller MSE is, the better denoising performance is. In this paper, we choose $a=8500$, $b=13$.

5.3. **Wavelet reconstruction**

We can reconstruct signal according to the lowest frequency coefficient of wavelet decomposition and the high frequency coefficients of each layer.

6. **Wavelet denoising of tractor wheel speed signal**

In this paper, the vehicle dynamics simulation software Carsim8.1 is used to simulate the working situation of tractor plowing condition. Speed of the tractor is set to 10 km/h. The simulation time step (sampling interval) is 0.02 s.

In order to simulate the actual wheel speed signal measured by wheel speed sensor, we added noise to simulation signal. The SNR of added noise is 60. We can get noise signal by running the noise adding program in Matlab R2014a. The tractor wheel speed signal with noise is shown in figure 2.

![Figure 2. Comparison between wheel speed signal with and without noise.](image)

We can get denoising results of different kinds of threshold functions by running the denoise program in Matlab R2014a. Tractor wheel speed signal with noise is shown in figure 3. Wheel speed signal after soft threshold denoising is shown in figure 4.
7. Conclusions

It can be seen from figure 3 to figure 6 that the soft threshold function can reduce the amplitude of the signal with noise. The signal after denoising is smoother than before. However, it also leads to a large distortion compared with the noise free signal. Although the hard threshold function denoising preserves the small details of the original signal, such as the sudden bulge and the peak, but it reduces the amplitude of original signal. Soft-hard compromise threshold function combines the advantages of soft threshold function and hard threshold function. The signal distortion is small after denoising.

While running the Matlab denoising program, SNR and MSE of denoised signals were calculated. Calculation results are shown in table 2.

| Threshold denoising function                  | SNR  | MSE   |
|----------------------------------------------|------|-------|
| Soft threshold                               | 53.3701 | 0.0060 |
| Hard threshold                               | 54.3573 | 0.0053 |
| Soft-hard threshold compromise threshold     | 56.4400 | 0.0042 |

It can be obtained from table 2 that the SNR of the soft-hard compromise threshold function is biggest, and it is closest to 60. At the same time, the mean square error of the signal after denoising is
smallest. It has proved that the wavelet transform denoising method in this paper is feasible to remove the noise signal of tractor driving wheel.

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