Article no. 30

THE CIVIL ENGINEERING JOURNAL 4-2017

STUDY ON DE-NOISING METHODS FOR SOIL COMPRESSIVE STRESS SIGNAL DURING VIBRATION COMPACTION

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ABSTRACT

The compressive stress signal of soil during vibration compaction is an unstable and transient saltation signal accompanied by broadband noise, and the spectra of the signal and noise always overlap. To extract the ideal original signal from noisy data, this paper studies several signal de-noising methods such as low-pass filtering, multi-resolution wavelet transform, spectrum subtraction and independent component analysis. Experiments show that the traditional low-pass filter is only applicable when the spectra of the signal and noise can be separated in the frequency domain. The multi-resolution wavelet transform can decompose the signal into different frequency bands and remove the noise efficiently by extracting useful the frequency band of the signal, but this method is not reliable when the signal to noise ratio (SNR) is low. Spectrum subtraction can remove strong background noise with stationary statistical characteristics even if the noise level is high and the spectrum of the signal overlaps with that of the noise. Independent component analysis can extract weak signals which are combined with heavy noise and can separate the noise from signal effectively when the independent channel hypothesis holds. These de-noising methods are of great importance for further analysing vibration signals in engineering.

KEYWORDS

Compressive stress signal, Low-pass filter, multi-resolution wavelet transform; spectrum subtraction; independent component analysis; de-noising methods

INTRODUCTION

Signals can be easily degraded by noise due to signal generators, sensors and other equipment during the acquisition and transmission process. In practical applications, most received signals are accompanied by noise. Processing the noisy signals directly will affect the feature recognition, classification and other subsequent steps [1]. Therefore, it is very important that signal de-noising is performed and the original signal information is preserved and extracted.

The soil compressive stress signal contains important physical information about the process of vibration compaction. It not only reflects the distribution of the compressive stress in each layer, but the distribution, absorption and transfer of the compaction energy in the soils. The compressive stress signal of soil during vibration compaction is an unstable transient saltation signal accompanied by broadband noise, and the noise and signal spectra always overlap [2]. In order to study the joint time-frequency property and the laws of distribution and transfer of the soil compressive stress signal in each layer, so as to reveal the vibration compaction mechanism, it is crucial to extract the ideal original signal from noisy data for further processing and analysis. In recent years, a large number of novel algorithms have appeared in the study of unstable and transient saltation signal de-noising [3-6]. Considering the soil compressive stress signal during vibration compaction, this paper discusses and studies the effect of de-noising methods on vibration signals; such methods include low-pass filters, multi-resolution wavelet transforms, spectrum subtraction and independent component analysis. A comparative analysis of the experimental results is presented and the applicability of the algorithms is discussed.

1. SOIL VIBRATION COMPACTION TEST

A soil vibration compaction test was implemented in the large soil tank of Key Laboratory for highway construction techniques and equipment of the Ministry of Education, Chang'an University. The test equipment used a custom-designed vibratory roller model [7]. The compaction test section length was 8 m, with a width of 1 m. Based on the test conditions and vibratory roller that used during vibration compaction, the nominal amplitude, vibration frequency and running speed of the roller are the main influencing factors in the test. An orthogonal experiment scheme of the 3 factors at 3 levels was implemented, resulting in nine tests that fully reflect the influence of various factors. For each condition, static compaction was first performed 2 times, then the vibration compaction was repeated for 12 times [8].

Before the test, turned loose soil to 35cm in soil tank by hand, and watering in order to achieve the appropriate moisture content. Then, three dynamic strain gauge pressure cells were placed on 3 layers under the soil at depths of 5cm, 15cm and 25cm, respectively. A DEWE-2010 data logger recorded the soil compressive stress signals of the pressure cells during the vibration compaction process, capturing stress signals on an oscilloscope in real time, as well as storing and processing data. The experimental setup is shown in Figure 1. The sampling frequency of the soil compressive stress signal in the test was 2000Hz.

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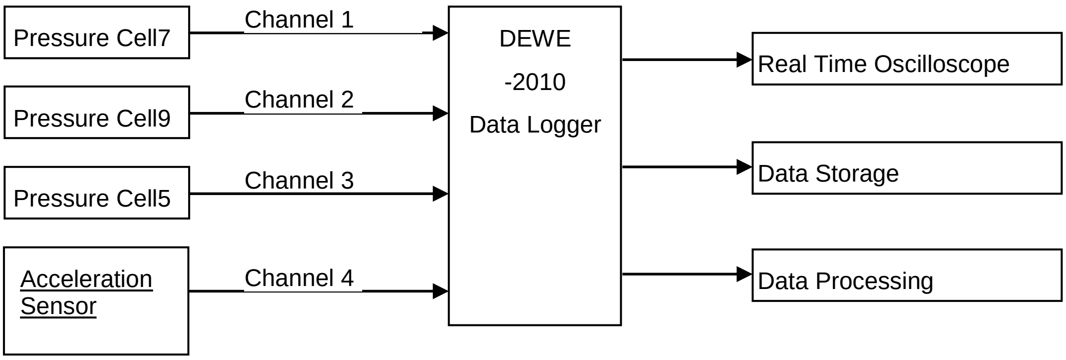


Fig.1 - Experimental setup

2. DE-NOISING METHODS OF COMPRESSIVE STRESS SIGNALS

This paper considers the case of the soil compressive stress signal, and assumes a signal S_1 with a low amount of noise and signal S_2 with heavy noise. Signal S_1 retains the waveform characteristics of stress signal generally, but due to the heavy noise, the waveform of signal S_2 has been distorted. The vibration compaction operating parameters in the test were: vibration frequency-- 30Hz, nominal amplitude-- 1.2mm, and running speed--1.12 km/h. According to the analysis, the ideal compressive stress signal is an unstable transient signal which has a peak value at the moment of impact, but is a stable signal with zero mean at other times.

2.1 Low-pass filtering

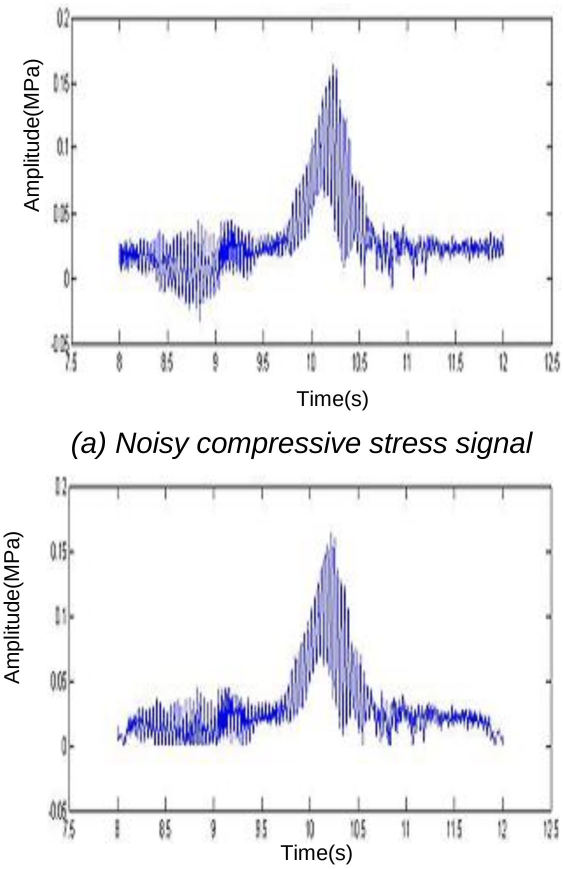
When the signal is band-limited and the signal and noise spectra can be separated in the frequency domain, a low-pass filter can filter out the noise spectrum by multiplying a window function in the frequency domain, thus separating the noise from signal through a purposedesigned filter [3, 9], as long as the cut-off frequency of the signal is known. Then, the de-noised signal can be obtained in the time-domain through the Inverse Fourier Transform.

By low-pass filtering signal $y(t)$, we can obtain the signal $x(t)$ as follows:

$$x(t) = IFFT(Y(\omega)W(\omega)) \qquad (1)$$

Where $W(\cdot)$ is window function.

The spectra of the signal and noise overlap in most cases. Low-pass filtering can remove high-frequency noise but low frequency noise is still mixed with the signal and is difficult to separate. The influence of the noise spectrum is more obvious when the SNR is low. Therefore, the de-noising effect of the low-pass filter degrades greatly with the decrease of the SNR.

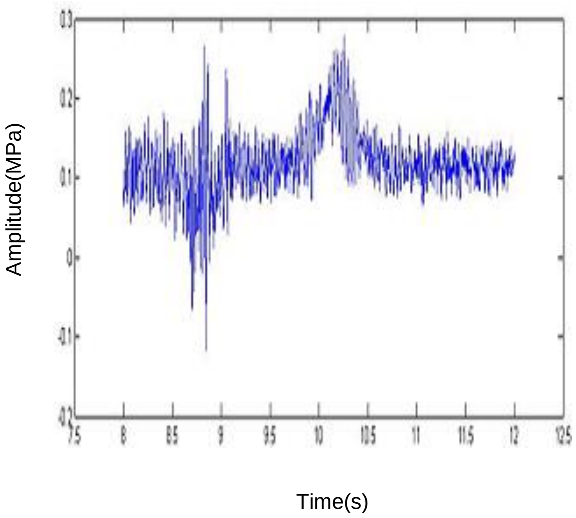


(a) Noisy compressive stress signal

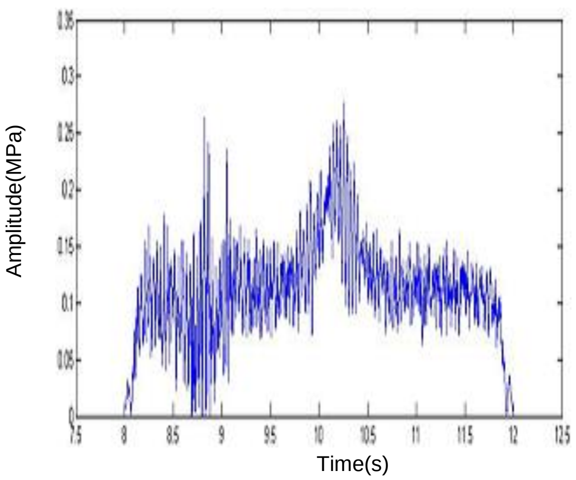
(b) Signal de-noised through frequency domain low-pass filtering

Fig. 2 - Low-pass filtering of noisy signal S1

DOI 10.14311/CEJ.2017.04.0030



(a) Noisy compressive stress signal



(b) Signal de-noised through frequency domain low-pass filtering
Fig.3 - Low-pass filtering of noisy signal S2

The vibration compaction operating parameters show that the main frequency of the signal is close to 30Hz. Therefore, the width of the pass-band of the low-pass filter applied was about 30Hz with a width of 35%. Figure 2(a) shows the compressive stress signal S_1 with small noise, Figure 3(a) shows compressive stress signal S_2 with heavy noise, Figure 2(b) and Figure 3(b) shows the de-noised signals S_1 and S_2 through the low-pass filter.

Comparing the de-noised result of Figure 2(b) with that of Figure 3(b), it can be seen that the de-noising effect is not significant when the noise is small, and we cannot reconstruct the ideal compressive stress signal through low-pass filtering when the noise level is high. This is because the compressive stress signal of the soil during vibration compaction is a mutation signal and contains high frequency information which is useful for signal processing. However, the low-pass filter filtered out the high frequency components over $1.35 * 30\text{Hz}$ as noise. Therefore, the low-pass filter cannot separate high frequency components of the signal from the noise effectively.

2.2 Multi-resolution wavelet transform

2.2.1 Signal analysis principle of wavelet transform [10]

The wavelet transform is a novel signal analysis method gaining popularity in recent years [4,11-13], and it is widely used in de-noising of transient saltation vibration signals accompanied by noise.

Let $\psi(t) \in L^2(R)$,and $\hat{\Psi}(\omega)$ be the result of the Fourier transform of $\psi(t)$. If $\hat{\Psi}(\omega)$ meets the admissibility condition: $C_\Psi = \int_{-\infty}^{\infty} (\left|\hat{\Psi}(\omega)\right|^2 \big/ |\omega|) d\omega < \infty$, then we consider $\psi(t)$ as a basic wavelet function, through the scale transformations and translations of which a group of wavelet functions can be obtained.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi((t-b)/a); a,b \in R, a \neq 0 \quad (2)$$

In Equation (2), '*a*' is the scale factor which controls the time window width of the wavelet function, and '*b*' is the displacement factor which controls the translation of the wavelet function on the time axis. The bigger |a| is, the wider the time window is and the narrower the frequency window is. It can be proved that the product of the time window width and the frequency window width of the wavelet function is constant.

The dyadic wavelet transform is used widely in practice. By letting $a = 2^j, b = 2^j \cdot k,$ a group of dyadic wavelet functions can be obtained.

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}} \psi(2^{-j} t - k); j,k \in Z \quad (3)$$

The wavelet transform of signal $f(t)$ is defined as:

$$W_f(j,k) = < f(t), \psi_{j,k}(t) > = \frac{1}{2^j} \int_{-\infty}^{\infty} f(t) \cdot \psi(2^{-j} t - k) dt \quad (4)$$

From the perspective of signal processing, changes in '*a*' are equivalent to a continuous change of the transmission bands of a band-pass filter and changes of '*b*' are equivalent to the band-pass filtering of the signal at different times. By varying '*a*', the signal can be observed through the wavelet transform on a wide time window (which corresponds to a narrow frequency window) at low frequency, but on a narrow time window (that is a wide frequency window) at high frequency. The local time-frequency characteristics of the wavelet transform are very suitable for the analysis of signals that change slowly at low-frequencies but rapidly at high-frequencies.

2.2.2 Wavelet transform principles for de-noising

The fundamental principle of wavelet transform for de-noising is to let some high-frequency components be zero selectively and retaining some useful frequency band, then reconstruct the signal through the wavelet reconstruction algorithm.

Mallat [4] proposed a multi-resolution wavelet transform based on a orthogonal wavelet basis. Let $\psi(n)$ be a wavelet function representing a band-pass filter, and $\phi(n)$ be a scaling function representing a low-pass filter. From the perspective of multi-resolution analysis, wavelet decomposition is equivalent to applying the low-frequency signal $c_{j-1,n}$ with scale $j-1$ through the band-pass filter $\psi(-k)$ and the low-pass filter $\phi(-k)$. Then, after downsampling, we can get a low-frequency signal $c_{j,n}$ and a high-frequency signal $d_{j,n}$ with scale j .The principle of multi-resolution wavelet decomposition is shown in Figure 4.

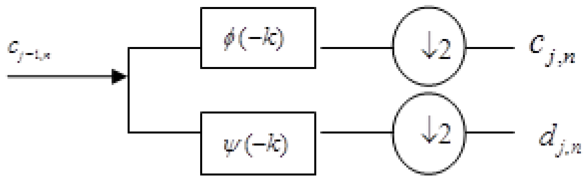


Fig.4 - Multi-resolution wavelet decomposition

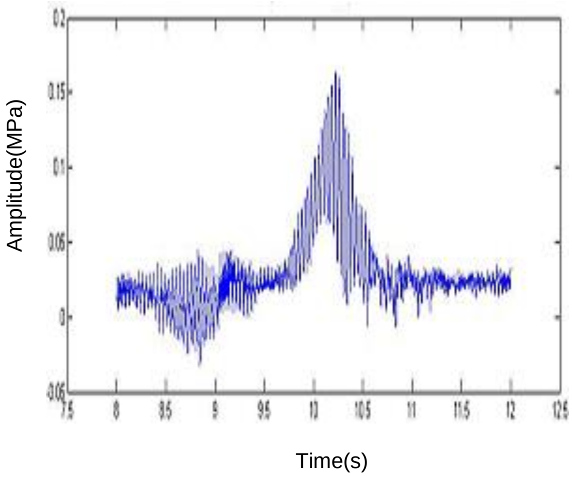
The low-frequency signal can be decomposed step by step using a multi-resolution wavelet transform. In every decomposition, the signal can be divided into a low-frequency band and a high-frequency band. Let the frequency band of the original signal be $[0, f_{\max}]$. Then, for the *k*-th wavelet decomposition, the signal can be divided into a low-frequency band and a high-frequency band with respective ranges $[0, f_{\max}/2^k]$ and $[f_{\max}/2^k, f_{\max}/2^{k-1}]$.

A signal can be decomposed into different frequency bands through multiple multi-resolution wavelet decompositions. By extracting the useful frequency band but suppressing the high-frequency band and applying the wavelet reconstruction algorithm, we can obtain the de-noised compressive stress signal.

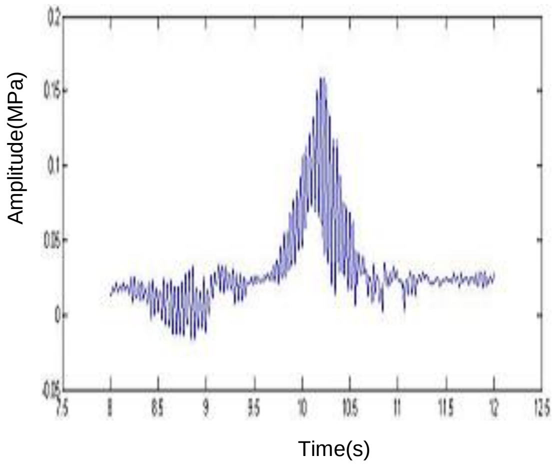
The vibration frequency of the vibratory roller was 30Hz in the test so, theoretically, the soil compressive stress signal should demonstrate a resonance peak value at about 30Hz. Therefore, the signal within this frequency band is useful and should be retained. In addition, because of the nonlinear characteristics of the vibration, the compressive stress signal not only includes the 30Hz frequency components, but other harmonic components such as those at 60Hz and 90Hz, etc, which should also be selectively retained. According to the sampling theorem, due to the fact that the sampling frequency of the stress signal in the test was 2000Hz, the frequency range analysed using the wavelet transform should be [0,1000Hz]. Thus, based on the frequency band segregation theorem of wavelet decomposition, the signal should be decomposed to 5 levels.

According to the above analysis, we decomposed the noisy compressive stress signal using the sym8 orthogonal wavelet function to 5 levels. The frequency of the low-frequency signal at the fifth level is [0,31.25Hz], which should be completely retained, and the frequency bands of high-frequency signals at the other levels are respectively $[1000/2^k, 1000/2^{k-1}]$ Hz. We can dispose of the high frequency coefficient at different levels by choosing soft thresholds using adaptive thresholding based on the estimated noise levels at each decomposition level. Thus, the signal can be reconstructed by disposing the high frequency coefficients and retaining the low-frequency signal at the fifth level.

DOI 10.14311/CEJ.2017.04.0030



(a) Noisy compressive stress signal



(b) Signal de-noised through the wavelet transform

Fig.5 - Signal S1 before and after application of the wavelet transform.

Figure 5(a) shows the noisy compressive stress signal S_1, while 5(b) shows the wavelet transform de-noising result. Compared with Figure 2, the de-noising effect using the wavelet transform is better than that obtained using the low-pass filter, and closer to the ideal stress signal. Because the wavelet transform can selectively retain some high frequency information, it is more effective in retaining the high frequency characteristics of signal.

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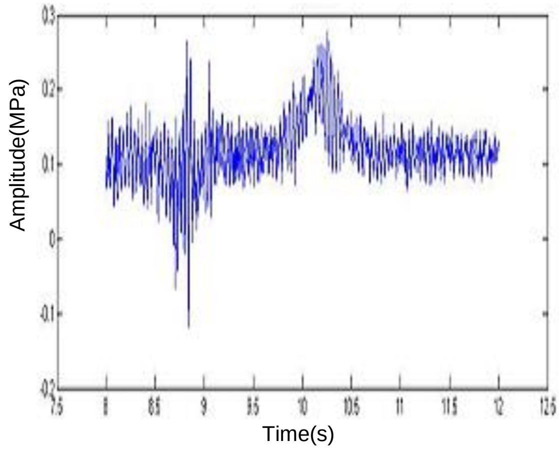
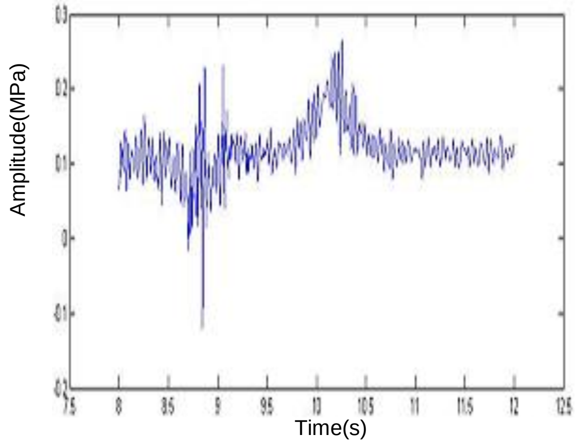


(a) Noisy compressive stress signal



(b) De-noised signal through wavelet transform

Fig.6 - Signal S2 before and after application of the wavelet transform

Figure 6 shows the wavelet transform de-noising result for signal S_2. It can be seen when noise levels are high, the wavelet transform can remove some noise but cannot reconstruct the ideal original signal. This is because the wavelet transform method is based on the assumption that the spectrum band of the noise and the signal can be separated in the multi-resolution decompositions; this is approximately correct only when the SNR is high. When the noise is of narrow spectrum, its influence can be ignored even its spectrum overlaps with that of the signal. However, when noise level is higher, the influence of the overlapping spectrum cannot be ignored. Therefore, the wavelet transform is only suitable for de-noising signals with a high SNR, as the result is not reliable when the SNR is low and the signal and noise spectra overlap.

2.3 Spectrum subtraction

The fundamental principle of spectrum subtraction is that we subtract the power spectrum of the noise from that of the signal in frequency domain, then obtain the power spectrum estimation of the de-noised signal [5,14-16]. It is essentially a modification of the amplitude of signal by subtracting from its power spectrum while retaining the original phase information. Then, the de-noised signal in the time-domain can be obtained through the Inverse Fast Fourier Transform (IFFT).

Suppose $s(n)$ is an ideal signal and $y(n)$ is an actual observation signal; then

$$y(n) = s(n) + d(n), \qquad (5)$$

DOI 10.14311/CEJ.2017.04.0030

where $d(n)$ is the additive noise.

When the signal and the noise are stationary random processes, the cross-correlation function $R(\tau)$ and power spectral density function $P(\omega)$ of the signal are related through the Fourier transform. In this case, the power spectrum of the signal is defined as the modular square of the Fourier transform of the signal, which represents its energy density, that is:

$$P_Y(\omega) = |Y(\omega)|^2 = |FFT(R_Y(\tau))|^2, \quad (6)$$

However, $R_Y(\tau) = E\big(Y(n)Y(n+\tau)\big) = E\big[\big(s(n)+d(n)\big)\big(s(n+\tau)+d(n+\tau)\big)\big]$.

If the noise is uncorrelated with the signal, it can be deduced that:

$$R_Y(\tau) = E[s(n)s(n+\tau)] + E[d(n)d(n+\tau)] = R_s(\tau) + R_d(\tau) \quad (7)$$

By applying the Fourier Transform to both sides of Eq. (7), it can be deduced that:

$$|Y(\omega)|^2 = |S(\omega)|^2 + |N(\omega)|^2 \quad (8)$$

The estimated value of the power spectrum of the signal can be obtained using power spectrum subtraction:

$$\left|\hat{S}(\omega)\right|^2 = |Y(\omega)|^2 - \left|\hat{N}(\omega)\right|^2 \quad (9)$$

Where $\hat{N}(\omega)$ is the estimated value of the power spectrum of the noise, which can be approximated using the variance of the noise.

It can be concluded from Eq. (9) that:

$$\left|\hat{S}(\omega)\right| = \left|Y(\omega)\right| \cdot (\sqrt{1-(|\hat{N}(\omega)|/|Y(\omega)|)^2}) \quad (10)$$

Suppose $G = \max(\varepsilon, \sqrt{1-(|\hat{N}(\omega)|/|Y(\omega)|)^2})$

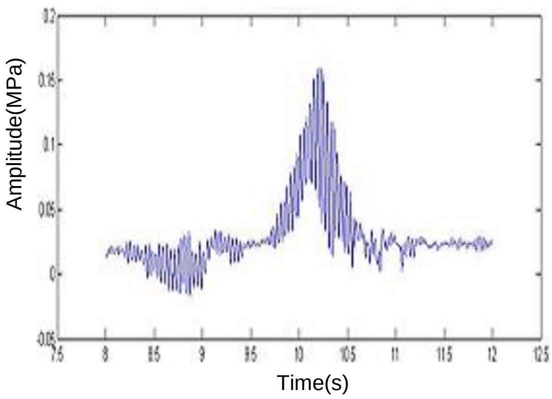
Where ε is a small positive constant. Then:

$$\left|\hat{S}(\omega)\right| = \left|Y(\omega)\right| \cdot G \quad (11)$$

The estimation of the reconstructed signal can be obtained through IFFT but retains the original phase information of signal, that is:

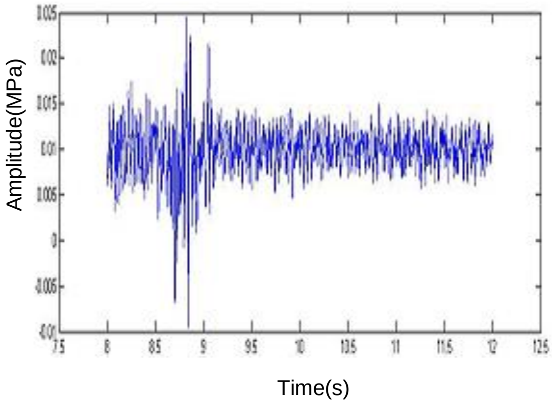
$$\hat{s}(n) = IFFT(\left|S(\omega)\right| \cdot e^{i\theta}) \quad (12)$$

where θ is the phase function of the original noisy signal. In practice, the compressive stress signal is non-stationary, but each signal segment can be regarded as stationary and can be reconstructed using spectrum subtraction by processing short-time windowing segments in the time-domain.



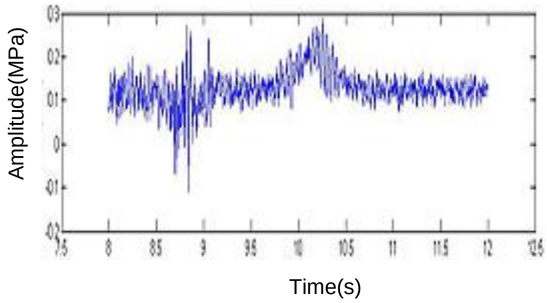
(a) Ideal compressive stress signal

Fig.7 - Ideal compressive stress signal and noise signal

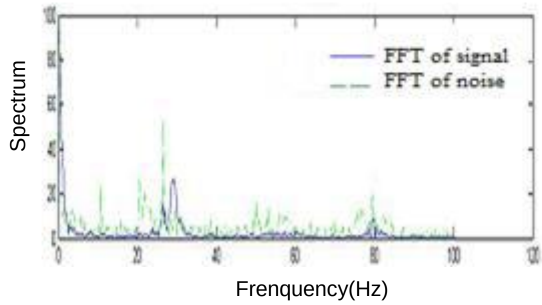


(b) Noise signal

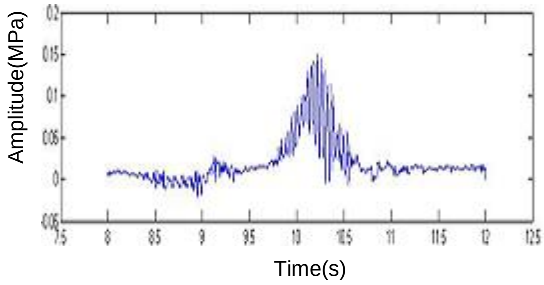
Fig.7 - Ideal compressive stress signal and noise signal



(a) Noisy compressive stress signal



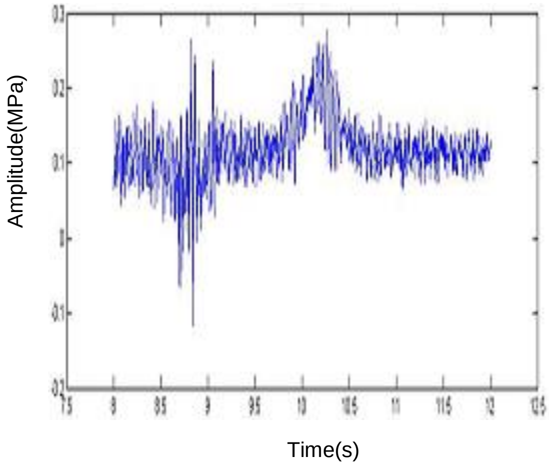
(b) Spectrum of signal and noise



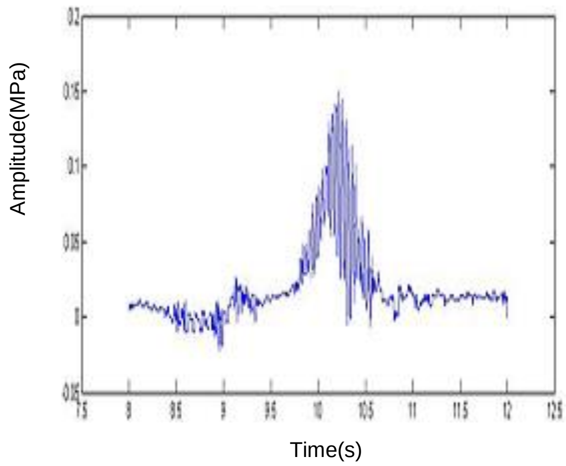
(c)Signal de-noised through spectrum subtraction

Fig.8 - The original signal, its spectrum and the signal de-noised through spectrum subtraction

The de-noising performance of spectrum subtraction is verified for a segment of a simulated signal. Suppose Figure 7(a) is an ideal compressive stress signal. After the addition of the noise signal shown in Figure 7(b), we obtain the noisy signal shown in Figure 8(a), whose waveform is distorted seriously because of the noise. Figure 8(b) shows the spectra of the signal and noise which overlap. Figure 8(c) shows the signal de-noised through spectrum subtraction, where it can be seen that the de-noised signal is very close to the ideal compressive stress signal. Therefore, spectrum subtraction performs well when removing strong background noise.



(a) Noisy signal



(b) Signal de-noised through spectrum subtraction

Fig.9 - De-noised signal of noisy signal S2 through Spectrum subtraction

Figure 9 shows signal S_2 de-noised through spectrum subtraction. The result shows that the de-noised signal has the characteristics of the compressive stress signal and is very close to its ideal form. Obviously, the de-noising results obtained through spectrum subtraction are superior to those obtained using the wavelet transform shown in Fig. 6. Therefore, when the SNR is lower, spectrum subtraction can be used to recover the ideal compressive stress signal even if the signal and the noise spectra overlap.

2.4 Independent component analysis (ICA)

ICA assumes that N source signals are statistically independent instantaneously, there is only one Gaussian-distributed signal at most in the source signals and that the received signal is a linear mixture of these N source signals. The ICA algorithm is essentially an optimization problem. The mixed signal is decomposed into independent components when the degree to which the

DOI 10.14311/CEJ.2017.04.0030

components are non-Gaussian reaches a maximum value. Every component obtained is a source signal [6,17-21].

Suppose $x = (x_1, x_2, \cdots, x_m)^T$ is the *m*-dimensional random observation signal vector, which is a linear combination of *n* independent source signals s_j in the source signal vector $s = (s_1, s_2, \cdots, s_n)^T$. Then, we can write

$$x = Hs = \sum_{j=1}^{n} h_j s_j, j = 1,2, \cdots n \quad (13)$$

In Eq. (13), H is an unknown $m \times n$ full-rank hybrid matrix. The ICA algorithm is used to estimate the separation matrix *W*, and the output that represents the source signal obtained by separating $x(t)$ using *W* is

$$y(t) = Wx(t) = WHs(t) = Gs(t) \quad (14)$$

The separation can be achieved by solving for the optimal G.

The central limit theorem of probability theory states that the probability distribution of sum of each independent random variable tends to be a Gaussian distribution. For the signal under consideration, the higher degree to which the components are non-Gaussian, the higher their mutual independence. Therefore, the signal is decomposed based on the non-Gaussianity measure of the resulting components. When the measure reaches a maximum, this indicates that each independent component has been completely separated. The non-Gaussianity measure can be represented using a probability density function $p(y)$ and the Kullback–Leibler divergence of the Gaussian distribution with the same covariance matrix, which is called negentropy. The negentropy of a random variable *y* is defined as:

$$N_g(y) = H(y_{Gauss}) - H(y) \quad (15)$$

where $H(y) = -\int p(x) \lg p(x) dx$ is the comentropy of *y*. $H(y_{Gauss})$ is the comentropy of a Gaussian distribution which has the same covariance matrix with *y*. According to information theory, the random variable of Gaussian distribution which has the same variance also has the maximum comentropy. The more non-Gaussian *y* is, the higher of the value of $N_g(y)$. The approximation equation of negentropy in practical applications is defined as follows:

$$N_g(y) = \sum_{i=1}^{P} k_i \{E[G_i(y)] - E[G_i(v)]\}^2 \quad (16)$$

where k_i is the constant greater than zero; v is the Gaussian random variable that obeys the *N* (0,1) distribution; and G_i is a non-quadratic function.

In order to maximize the upper equation, according to the Kuhn-Tucker condition, when $E[G(W^T x)^2] = \|W\|^2 = 1$, the optimal value should satisfy the following equation:

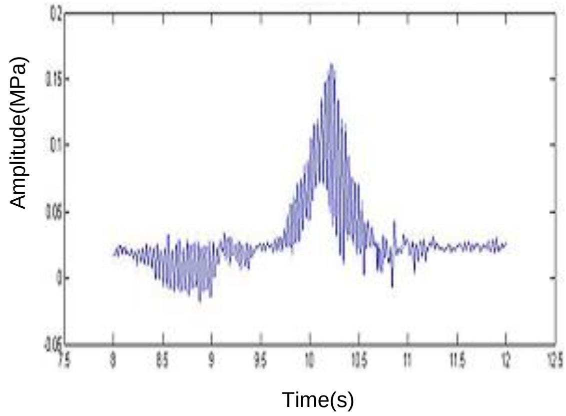
$$E[xg(w^T x) - \beta x = 0]. \quad (17)$$

Therefore, the recursion formula of the ICA algorithm can be obtained as follows:

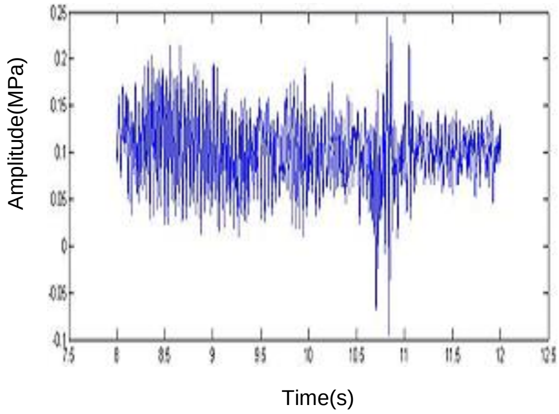
$$w^+ = w - \{E[xg(w^T x)] - \beta w\} / \{E[g'(w^T x)] - \beta\}$$
$$w_{new} = \frac{w^+}{\| w^+ \|} \quad (18)$$

where $\beta = E[w^T x g(w^T x)]$.

According to the principle of independent component analysis, when the observed data are a random mixture of real signal and noise, they can be separated using the ICA algorithm.

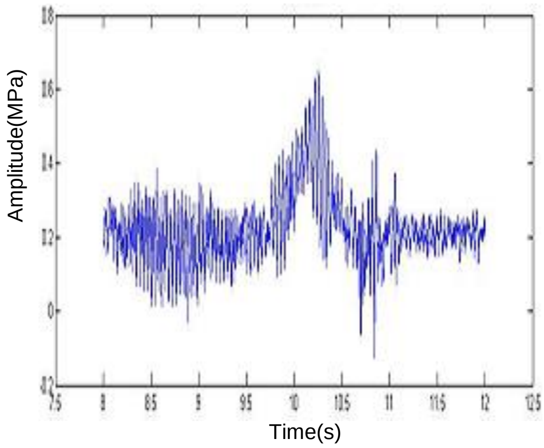


(a) Ideal compressive stress signal



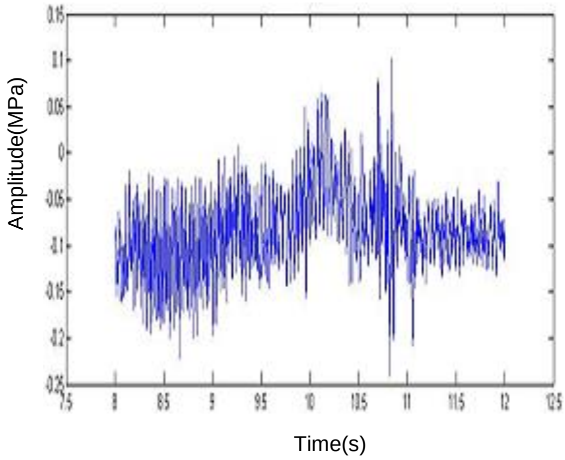
(c) Noise signal

Fig.10 - Ideal compressive stress signal and noise signal



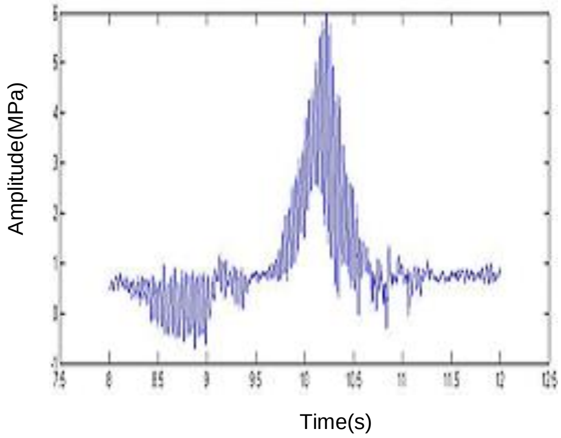
(a) Mixed-signal 1

Fig.11 - Two mixed-signals

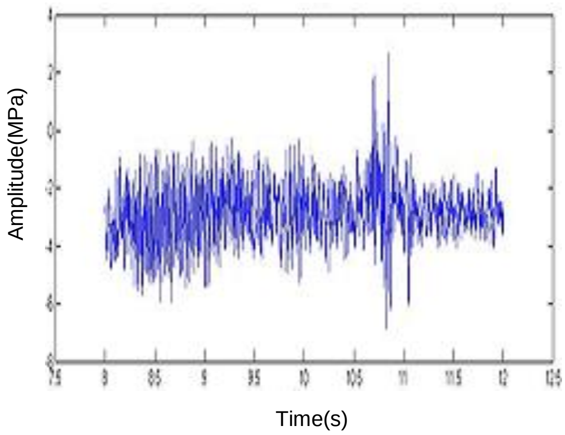


(b) Mixed-signal 2

Fig.11. Two mixed-signals



(a) Isolated stress signal



(b) Isolated noise

Fig.12 - Separation of signal and noise through ICA

Figure 10(a) shows an ideal compressive stress signal, while 10(b) shows a noise signal obtained by extracting and amplifying the time-domain signal from a real compressive stress signal during the stable period. If the noise is independent from the original signal, the signal received by the system is a random mixture of compressive stress signal and noise, as shown in Figure 11(a) and Figure 11(b), where the two signals are shown after being mixed randomly. Figure 12 shows the separation results of signal and noise obtained through the fast ICA algorithm. In Figure 12(a), it can be seen that the compressive stress signal was successfully separated from the two mixed-signals, and is close to the ideal compressive stress signal. Figure 12(b) shows the separation result of the noise signal.

3. CONCLUSION

This paper studied the principled and applicability of several de-noising methods for the soil compressive stress signal during vibration compaction, with applications on both low- and high-SNR signals. According to the above analyses, the following can be concluded:

1) Traditional low-pass filtering methods assume that the signal and noise are in different frequency bands, so using appropriately designed filters, noise can be removed while retaining the useful signal. When the noise level is low and the frequency band of noise does not overlap with that of the signal significantly, a low-pass filter can separate noise from the signal in frequency domain effectively. However, this method is not applicable when the spectrum of the signal overlaps with that of the noise.

2) The multi-resolution wavelet transform can decompose the signal into different frequency bands, and effectively remove the noise by extracting the signal from the useful frequency bands. However, these methods are based on the assumption that the spectrum band of noise and signal can be separated during the multi-resolution decompositions. This assumption does not hold when the SNR is lower and the spectrum of the noise and signal significantly overlap. In this case, the de-noised result is not reliable. Therefore, the wavelet transform is widely used for signals with a higher SNR.

3) Spectrum subtraction methods require that the noise is statistically stationary. Because spectrum subtraction takes full advantage of the statistical characteristics of the signal and the noise, it can remove the strong background noise. Spectrum subtraction can be applied to remove strong statistically stationary background noise, even in cases where the SNR is lower and the spectrum of the noise and signal overlap significantly.

4) ICA assumes that a multi-channel signal is a random mixture of N independent source signals. When the signal received is such a random mixture of the ideal signal and noise, the ICA algorithm can separate the noise from the signal accurately. In particular, if N independent observation channels received meet the assumption of instantaneous independence, the N-channel original signal can be directly extracted from N-channel noisy observation data through the ICA algorithm. ICA is applied in cases of broadband noise, low SNR and considerable spectrum overlap between signal and noise.

In conclusion, when the noise is small, using the multi-resolution wavelet transform can yield better de-noising results; when the noise level is high and the effect of spectrum overlapping between noise and signal cannot be ignored, spectrum subtraction or ICA algorithm should be used to remove the noise based on the specific signal processing system and the characteristics of the signal and the noise.

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