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## A Novel Adaptive Interference Canceller of Vibration Measurement Based on Empirical Mode Decomposition

Zhang Lanyong, Zhou Juncheng and Liu Sheng  
College of Automation, Harbin Engineering University, Harbin 150001, China

**Abstract:** A novel adaptive interference cancellation algorithm that was suitable for filtering non-stationary random signal was presented in the paper. An intelligent measurement system was designed for vibration signal measurement based on Empirical Mode Decomposition (EMD) analysis. At first, the complex vibration signal was decomposed to different intrinsic mode functions which represent signals with different frequency by the Empirical Mode Decomposition (EMD) method. An improved least mean square (LMS) algorithm was applied to the adaptive interference cancellation. Computer simulation and experimental results showed that the method had better noise cancellation capability than the traditional adaptive noise cancellation. At the same time, the novel adaptive interference cancellation improved the speed and precision of vibration measurement. So it can be introduced to the engineering application. Comparing with the other traditional apparatuses and the manual testing, the system increased the test efficiency and had good extensibility.

**Key words:** Vibration measurement, Empirical mode decomposition, Adaptive interference cancellation, Least mean square, filtering

### INTRODUCTION

With the extensive application of the mechanical equipment in the modern society, various vibration radiation had affected our life severely (Zhu *et al.*, 2011). Therefore vibration signal measurement of the mechanical equipment has become an urgent task. Because of the effect of environment noise from television, engineering, factory, earth-ionosphere cavity and so on, the measurement result includes severe ambient noise generally. The spectrum of vibration is mixed by various signal which is nonlinear and non-stationary, so the usual filtering method was invalid. Professor Robert presented a novel method to perform machine vibration measurements at an urban site polluted with ambient noise (Parhami *et al.*, 1999). It is a two channel system based on conventional coherent receivers carrying out the measurements in frequency domain. The receiver needs to step through the whole frequency range and consequently the measurement will take a lot of time depending on the frequency range to investigate and the desired accuracy as a consequence of the frequency resolution.

A novel adaptive noise canceller is used to suppress narrow-band interference nevertheless, it didn't interpret how to set the threshold in the adaptive filtering. This paper presents a novel adaptive interference canceller to eliminate vibration noise in the measurement. The mixed vibration signal with noise is decomposed to different

Intrinsic Mode Functions (IMF) by EMD. Thereby, some single-frequency signals is in place of the multi-frequency mixed signal. According to different character between useful signal and noise in the IMF, the improved LMS algorithm is applied to cancel the interference. Computer simulations and experiment show that the method has better noise cancellation capability compared to the traditional adaptive noise canceller.

### EMPIRICAL MODE DECOMPOSITION

EMD is an intuitive signal-dependent decomposition of a time series into waveforms modulated in both amplitude and frequency (Huang *et al.*, 1998). The iterative extraction of these components is based on the local representation of the signal as the sum of an oscillating component and a trend. The first iteration of the algorithm consists of extracting a component, referred to as the Intrinsic Mode Function (IMF), which represents the oscillations of the entire signal. Each IMF should satisfy two basic conditions (Gu and Zhou, 2011): (1) in the whole data set, the number of extreme and the number of zero crossing must be the same or differ at most by one and (2) the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is always zero.

By virtue of the IMF definition, the decomposition method can simply use the envelopes defined by the local maxima and minima separately. Once the extreme are

identified, all the local maxima are connected by a cubic spline line as the upper envelope. Repeat the procedure for the local minima to produce the lower envelope. The upper and lower envelopes should cover all the data between them. Their mean is designated as  $m_1$  and the difference between the data and  $m_1$  is the first component  $c_1$ :

$$x(t) - m_1 - h_1 \quad (1)$$

$$h_1 - m_{11} = h_{11} \quad (2)$$

$$h_{1(K-1)} - m_{1K} = h_{1K} \quad (3)$$

Then, it is designated as:

$$c_1 = h_{1K} \quad (4)$$

As described above, the process is indeed like sifting: to separate the finest local mode from the data first based only on the characteristic time scale. The sifting process, however, has two effects: (1) to eliminate riding waves and (2) to smooth uneven amplitudes.

The sifting process should be applied with care, for carrying the process to an extreme could make the resulting IMF a pure frequency modulated signal of constant amplitude. To guarantee that the IMF components retain enough physical sense of both amplitude and frequency modulations, we have to determine a criterion for the sifting process to stop. This can be accomplished by limiting the size of the standard deviation,  $e_{SD}$ , computed from the two consecutive sifting results as:

$$e_{SD} = \sum_{i=0}^1 \left[ \frac{|h_{i(p-1)}(t) - h_{i(p)}(t)|^2}{h_{i(p-1)}^2(t)} \right] \quad (5)$$

A typical value for  $e_{SD}$  can be set between 0.2 and 0.3.

Overall,  $c_1$  should contain the finest scale or the shortest period component of the signal. We can separate  $c_1$  from the rest of the data by:

$$x(t) - c_1 = r_1 \quad (6)$$

Since the residue,  $r_1$ , still contains information of longer period components, it is treated as the new data and subjected to the same sifting process as described above. This procedure can be repeated on all the subsequent  $r_j$ s and the result is:

$$r_1 - c_2 = r_2, \dots, r_{n-1} - c_n = r_n \quad (7)$$

The sifting process can be stopped by any of the following predetermined criteria: either when the component,  $c_n$  or the residue,  $r_n$ , becomes so small that it is less than the predetermined value of substantial consequence or when the residue,  $r_n$ , becomes a monotonic function from which no more IMFs can be extracted. Even for data with zero mean, the final residue can still be different from zero; for data with a trend, then the final residue should be that trend. By summing up Eq. 6 and 7, we finally obtain:

$$x(t) = \sum_{i=1}^n c_i + r_n \quad (8)$$

## IMPROVED ADAPTIVE INTERFERENCE CANCELLER

**Adaptive interference canceller:** Some of the earliest work in adaptive interference canceling was performed by Howells and Applebaum and their colleagues at General Electric Company between 1957 and 1960 (Klein *et al.*, 2006). They designed and built a system for antenna sidelobe canceling using a reference input derived from an auxiliary and a simple two-weight adaptive filter.

The basic principle of the adaptive interference canceller is that there is a single signal composed of the sum of the desired signal  $S_i$  and an uncorrelated undesired signal  $I_i$  as one input to the system (Xu and Sun, 2007). A second input reference signal  $I_r$  contains no desired signal  $S_i$  or is uncorrelated to it but is correlated to the undesired signal,  $I_i$ , in some manner. The reference should be proportional in order for an exact replica of the desired signal  $S_i$  to become possible (Kong *et al.*, 2009). The output from the measurement system is the original signal minus the reference signal. Figure 1 shows schematically the principle of a basic cancellation system where  $n_{0i}$  and  $n_{1i}$  are from a common origin. They are correlated with each other but uncorrelated with the Equipment under Test (EUT) vibration signal  $S_i$  (Parhami *et al.*, 1999).

As in Figure 1, we need two sensors to receive the vibration signal. The first one is placed near the EUT to receive the EUT vibration and the ambient interference noise. The other one is far away from the EUT just to receive the ambient interference noise for reference. Then EMD algorithm decomposes the multi-frequency signal into some single frequency signal (Zhu, 2011). The computing equations are as follows:

$$y = W \times (I_j + n) \quad (9)$$

$$D = S + I + n_0 \quad (10)$$

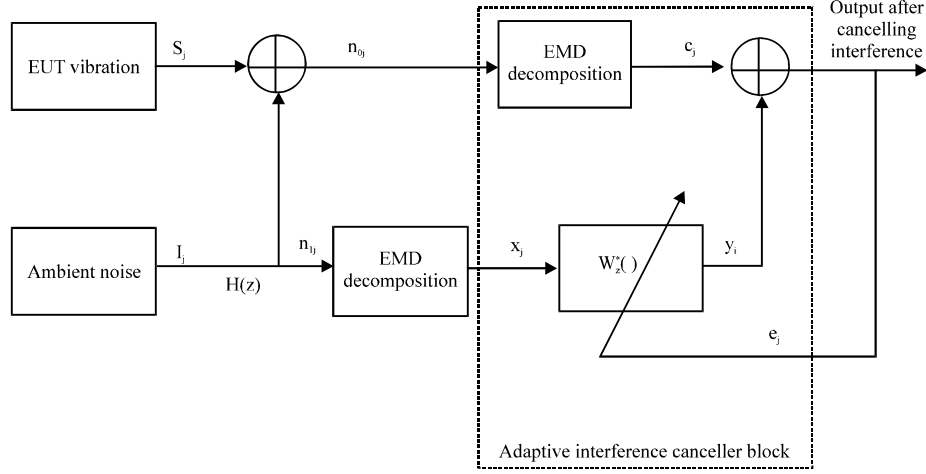


Fig. 1: Adaptive interference canceller flow block

$$V = d - y = S + I + n_0 - [W \times (I + n_i)] \approx S \quad (11)$$

If the right proportionality constant  $W$  is selected, the output becomes the desired signal  $S$  and the undesired noise signal is gone.

**Improved least mean square algorithm:** The iterative equations of the traditional LMS algorithm are as follows:

$$e(n) = d(n) - X^T W(n) \quad (12)$$

$$W(n+1) = W(n) + 2\mu_e(n)X(n) \quad (13)$$

where,  $X(n) = [x(n), x(n-1), x(n-2), \dots, x(n-L+1)]^T$  is the input signal in the time  $n$  which is composed of  $L$  samples.  $W(n) = [\omega_0(n), \omega_1(n), \dots, \omega_{L-1}(n)]^T$  is the weight vector of the adaptive filter at  $n$  and  $L$  is the steps of the adaptive filter. What is more,  $d(n)$  is expected output and  $e(n)$  is error signal, with  $\mu$  being the step coefficient which controls the stationary and convergence.

For being applied in the adaptive interference system better, an improved varying step size algorithm is presented. In the algorithm, the estimation of the LMS error modulate the adaptive varying step size, with deduction equations as follow (Zhu *et al.*, 2011):

$$W(n+1) = W(n) + \mu(n)e(n)X(n) \quad (14)$$

where,  $\mu(n)$  is step coefficient. The update equation as:

$$\mu(n+1) = \alpha\mu(n) + \gamma p^2(n) \quad (15)$$

$$P(n) = \beta p(n-1) + (1-\beta)e^2(n) \quad (16)$$

What is more:

$$\mu(n+1) = \begin{cases} \mu_{\max}, & \mu(n+1) > \mu_{\max} \\ \mu_{\min}, & \mu(n+1) < \mu_{\min} \\ \mu(n+1), & \text{else} \end{cases} \quad (17)$$

In the equations,  $0 < \alpha < 1$ ,  $\gamma > 0$ ,  $0 < \beta < 1$ .  $\gamma$  controls the convergence time and maladjustment of the algorithm.  $\beta$  is the exponent weight coefficient which controls the convergence time as well. As usual, the choice of  $\mu_{\max}$  is near the non-stationary step point of LMS algorithm for the fast convergence speed. However, in the stationary condition, a more appropriate range of  $\mu_{\max}$  is as follow:

$$0 < \mu_{\max} < \frac{2}{3\text{tr}(R)} \quad (18)$$

## THE SIMULATION AND EXPERIMENTAL ANALYSIS

**Computer simulation:** The vibration noise is nonlinear and non-stationary in the complicated environment and the spectrum of noise is colorful (Gu and Zhou, 2011). According to the power principle, the spectrum of low frequency has large energy (Widrow and Hoff, 1985). Therefore, the traditional suppose that noise is white Gaussian stationary is false and the corresponding processing method has problems (Shen *et al.*, 2008). However, EMD decomposes the non-stationary signal into some IMFs and distinguishes the signals doing to the different character (Fig. 2).

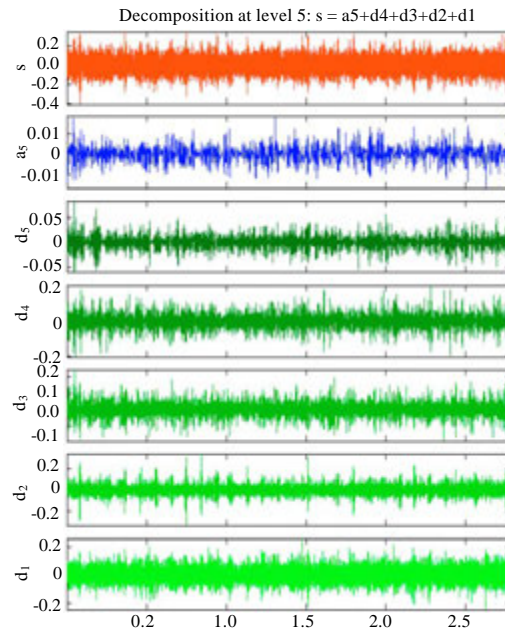


Fig. 2: The decomposition of non-stationary signal by EMD

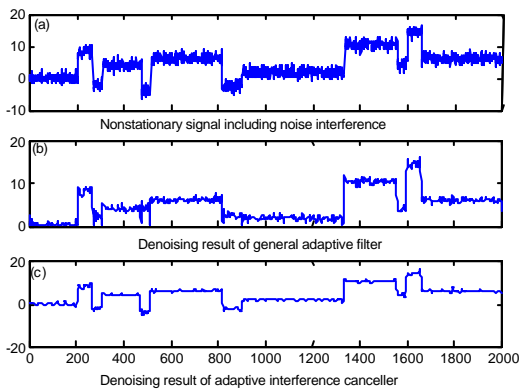


Fig. 3: Denoising results comparison

From the Fig. 3, red components (level 1 and level 5) include obvious noise, so the designed adaptive interference canceller can eliminate it efficiently.

Then compare the ability of processing complicated non-stationary signal between the common adaptive filter and improved adaptive interference canceller. The results is in Fig. 3.

In the Fig. 3, the first one is the original signal, while the middle one is the result of common adaptive filter processing and the below one is the denoising result of the improved adaptive interference canceller. The common adaptive filter can't eliminate the noise from the signal. What is more, there is some distortion and the curve isn't

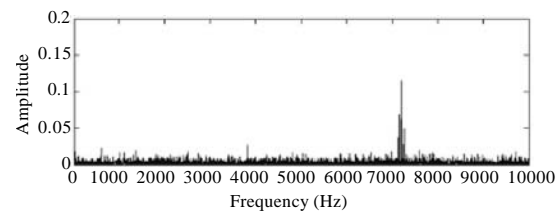


Fig. 4: The spectrum of the original vibration signal

smooth. Whereas, the improved adaptive interference canceller based on EMD eliminates the ambient noise and the signal is more smooth. The simulation shows that the improved algorithm has least mean square root error and peak error, so it is more adaptive.

**Experimental analysis:** The algorithm is applied to the vibration signal measurement system experiment to prove its feasibility. Figure 4 is the mechanic vibration signal of some equipment. The useful signal is submerged in the ambient interference noise, so we can't obtain the real amplitude.

Figure 5 shows the denoising result of the vibration signal by the improved adaptive interference canceller. Compared with Fig. 4, it is observed that the interference noise spectrum is suppressed by 40-50%, with the real noise of the equipment left. As we known in the last

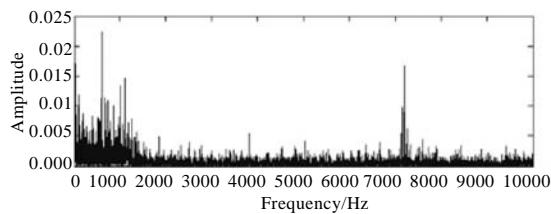


Fig. 5: The spectrum of processed signal

section, the traditional adaptive filter can't process the signal which is non-stationary efficiently.

### CONCLUSIONS

EMD is a novel analysis method for non-stationary in the past years. The method can decompose the non-stationary signal to a series IMFs from different frequencies adaptively without choosing basis function. The paper combines EMD with adaptive interference canceller to solve the problem of filtering non-stationary vibration signal. Computer simulation and experiment prove that the method has better noise cancellation capability compared with the traditional adaptive noise canceller. The computer controls several instrument automatically and coordinated and the testing results can be real-time showed. At the same time, the novel adaptive interference canceller improves the speed and precision of vibration signal measurement, so it can be introduced to the engineering application.

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