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A Study of Hydraulic Signals Denoising Based on Morphological Filter and Ensemble Empirical Mode Decomposition

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Abstract — According to some inherent shortcomings of traditional denoising algorithms, a new algorithm based on the morphological filter and Ensemble Empirical Mode Decomposition (EEMD) is presented. In this algorithm, firstly, preprocess the noisy signals with the combined morphology filters which are composed of *open-close* and *close-open* operations; secondly, decompose the noisy signals with EEMD algorithm, extract the IMF components based on the setting threshold; finally, recombine the extracted IMF components to get the denoising signals. The application verifies the feasibility and validity of the algorithm proposed in this paper, and the new method will have a good application prospect in hydraulic signals denoising.

Keywords — Morphological filter; Ensemble Empirical Mode Decomposition; Hydraulic signals; Denoising

1. Introduction

The PT fuel system, which is the patent of USA Cummins Engines Company, is widely used in mostly engines of large-scale machinery. As the core component of the diesel, the dynamic characteristics of fuel system directly affect the performance of the diesel. It is important to study the dynamic characteristics of the fuel system. The commonly used methods are to do experiment on the test bench, collect the signals of pressure, flow and rotation rate along with the time, then summarizes the characteristic curve of the fuel system through some kinds of signal processing algorithm.

In the signals collecting process, the feature information of the signals is often covered with noise because of the complex industrial environment conditions and numerous powerful interfering sources. In order to reduce the influence of the noise, enhance signals characteristics and improve the accuracy of the status monitoring and dynamic characteristics analysis, the preprocessing of denoising is essential.

Traditional denoising algorithms generally include Fourier transform, Wavelet decomposition, Empirical Mode Decomposition (EMD) time-frequency analysis and so on. The Fourier transform suits for processing stationary signals whose frequency spectrum is obvious different from the noise's [1]. The wavelet decomposition has the characteristic of time-frequency analysis and it can filter the non-stationary signals, but it has the difficulty to select the wavelet function and the decomposition level [2-4]. EMD is a new method of adaptive signal processing proposed by Norden E. Huang, and it is considered as the great breakthrough in the stationary spectrum analysis based on the Fourier transform [5], it is widely used in image denoising and mechanical fault diagnosis [6,7]. Related researches have proved that the illusive Intrinsic Mode Function (IMF) components (which is also called as the phenomenon of mode mixing) would produce during the EMD [8], especially the low frequency illusive IMFs, and the reference [9] describes the phenomenon in detail.

In order to overcome the mode mixing problems of EMD, Ensemble Empirical Mode Decomposition (EEMD) was proposed by WU through using noise [10]. The IMFs, which are decomposed by the EEMD, partial reflect the character of signals and partial are noise. In this paper, the denoising algorithm which is firstly filter the noisy signals by the Mathematical Morphology (MM), then select the IMFs (decomposed by the EEMD) through the adaptive threshold was proposed, and application verifies the validity and practicability of the algorithm.

2. Basic Principle of Morphological Filter

2.1 Basic Principle

Mathematical morphology (MM) is a theory and technique for the analysis and processing of geometrical structures, based on set theory, lattice theory, topology, and random functions. MM is most commonly applied to digital images, but it can be employed as well on graphs, surface meshes, solids, and many other spatial structures. The basic idea of the MM is to design a "probe" which is called structural element, when shifting in the signals it can match the signals, it can meet the propose of extracting features, preserving details and restraining noise of the signals [11].

The fundamental morphological operators of MM are *erosion, dilation, open and close* [12]. The morphological transform can be generally concluded as dual-value morphological transform and multi-value transform. As the signals of the hydraulic are one-dimension, only the one-dimension morphological filter was introduced in this paper. The fundamental morphological operators are defined as follows.

Assumed that original signal $x(n)$ is a discrete function, and the variable $n = 0,1,..., N-1$. The structural element $g(n)$ is defined as a discrete function too, the variable $n = 0,1,..., M-1$, $N \geq M$. The *erosion* and *dilation* operations for the set of $x(n)$ about the structural element $g(n)$ are defined as:

$$(x\Theta g)(n) = \min[x(n+m) - g(m)] \quad (1)$$

$$(x \oplus g)(n) = \max[x(n-m) + g(m)] \quad (2)$$

Where $m = 0,1,..., M-1$.

The *open* and *close* operations for the set of $x(n)$ about the structural element $g(n)$ are defined as:

$$(x \circ g)(n) = (x\Theta g \oplus g)(n) \quad (3)$$

$$(x \bullet g)(n) = (x \oplus g\Theta g)(n) \quad (4)$$

The symbol $\circ$ and $\bullet$ represents *open-close* operation and *close-open* operation respectively.

In order to restrain the noise of the signals effectively, the cascade of *open* and *close* operations are used to construct *open-close* and *close-open* combination morphology filters. In this paper, the combined filter discussed in the reference [13] was induced.

$$y(n) = \frac{1}{2}[(x \circ g \bullet g)(n) + (x \bullet g \circ g)(n)] \quad (5)$$

2.2 Selection of Structural Element

According to the combination of the calculating mode, the choice of structural element has great effect on the result of signals processing. Generally speaking, the more complex the shape of structural element is, the better the effect of denoising, but also more time will be spent. The commonly used structural elements are circular, triangle, regular curve, flat and the combination of them. The choice of the structural element is determined by the shape of the processing signals, and should make the structural element and the signals as close as possible. Relative theories have proved that the triangular structural element has good filtering effect on pulse noise [14].

3. Denoising Algorithm based on MM and EEMD Adaptive Threshold

3.1 Pretreatment of the Signals based on MM

Due to the interference of environmental noise and electromagnetic impulse, the signals collected often have some very tip “peak” and very low “valley”. In order to eliminate the “peak” and “valley” produced by the interference, the combined morphological filter based on formula 5 was used to preprocess of the signals. As the triangular structural element has good filtering effect on impulse noise, the triangular structural element whose hemline is 7 and height is 0.0001 is chosen to filter the collected signals in this paper.

3.2 Adaptive Threshold Selection Algorithm

In reference [15,16], it is reported that when the white Gaussian noise is decomposed by EMD, the multiplication of energy density and average period of IMF components is constant. The formula is described as follows:

$$E_n \overline{T_n} = const \quad (6)$$

In which E_n is the *n*th IMF energy density, $E_n = \frac{1}{N}\sum_{j=1}^{N}[C_n(j)]^2$, C_n is the *n*th IMF component, $\overline{T_n} = \frac{2N}{O_n}$ is the *n*th IMF average period and O_n is the total extreme points of IMF components.

For the white noise which is normal distribution, the const of formula 6 is 1, and then the formula 6 can be described as follows:

$$\ln E_n + \ln \overline{T_n} = 0 \quad (7)$$

If the energy density deviates from the formula 7 greatly, it indicates that the IMF components contain useful information, not pure noise. Extract and recombinant the IMF components which contain useful information will get the signals de-noising. The algorithm consists of the following steps [17]:

(1) Decompose the noisy signals with EEMD algorithm, get the *k*th IMF components and residual r;

(2) Calculate the energy density E_n and average period T_n of *n*th IMF components C_n (n=1,2,3,…,N);

(3) Extract the IMF components which $\left|\ln E_n + \ln \overline{T_n}\right| / \ln \overline{T_n} \geq a$;

(4) Process the IMF components extracted in steps 3 based on selected threshold. The threshold can refer to Donoho's filter function describe in reference [18].

$$\tau_n = \hat{\sigma}_n / \sqrt{2\ln(N)} \quad (8)$$

$$\hat{\sigma}_n = MAD_n / 0.6745 \quad (9)$$

Where $\hat{\sigma}_n$ is the noise level of *n*th IMF component, which is also called as the Modified Absolute Difference (M. MAD). MAD_n represents the absolute difference of *n*th IMF component which is describe as follows:

$$MAD_n = Median\{|C_n(t) - Median\{C_n(t)\}|\} \quad (10)$$

Where $Median()$ is the mean-value function.

The IMF components after processing are described as follows:

$$\hat{C}_n(t) = \begin{cases} sign(C_n(t))(|C_n(t)| - \tau_n) & if \quad |C_n(t)| \geq \tau_n \\ 0 & if \quad |C_n(t)| < \tau_n \end{cases} \quad (11)$$

Lots of experiments show that the denoising algorithm mentioned above have a much better result for the high-frequency IMF components, while, it may induce deviation for the low-frequency components. The low-frequency IMF components often remained or processed with other method, such as wavelet threshold denoising in practice.

(5) Get the denoised signals after recombining the processed IMF components and residual.

The filtering effect is related to the value of a. Simulation results showed that the filtering effect is stable when the value of a is between 0.25 and 0.3 [17]. The flowchart of MM-EEMD denoising algorithm is shown in figure 1.

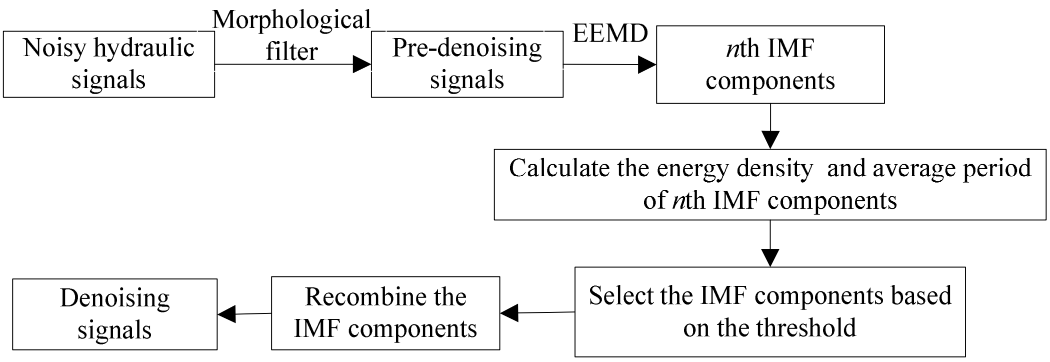


Figure 1. Denoising Algorithm flowchart of MM-EEMD

4. Application of the Algorithm

4.1 Evaluation Indicator

In order to compare the denoising effects of various algorithms accurately, the Signal to Noise Ratio (SNR) and Mean Square Error (MSE) are selected as the evaluation indicator, the definition of them are described as follows:

$$SNR = 10\log\left(\frac{\sum_{i=1}^{N} f_i^2}{\sum_{i=1}^{N}(f_i - s_i)^2}\right) \quad (12)$$

$$MSE = \frac{\sum_{i=1}^{N}(f_i - s_i)^2}{N} \quad (13)$$

Where $i = 1,2,...,N$, s_i and f_i are original signals and denoising signals respectively, and N is the length of signals.

The value of SNR reflect the denoising ability, and it is proportional to the denoising effects. The value of MSE reflect the amplitude difference degree of the denoising signals and the original signals, and it is inversely proportional to the denoising effects [19]. As mentioned above, the larger of the SNR value and the smaller of the MSE value is, the higher the similarity of the denoising signals and the original signals is, and the better the denoising effect is.

4.2 Application of the Algorithm

In order to validate the feasibility and validity of the denoising algorithm proposed in this paper, the hydraulic signals of outlet of the PT pump test bench is selected as the research object. The test bench is self-developed by the research group, and the type is JCPS01. The testing principle is shown in figure 2 [20].

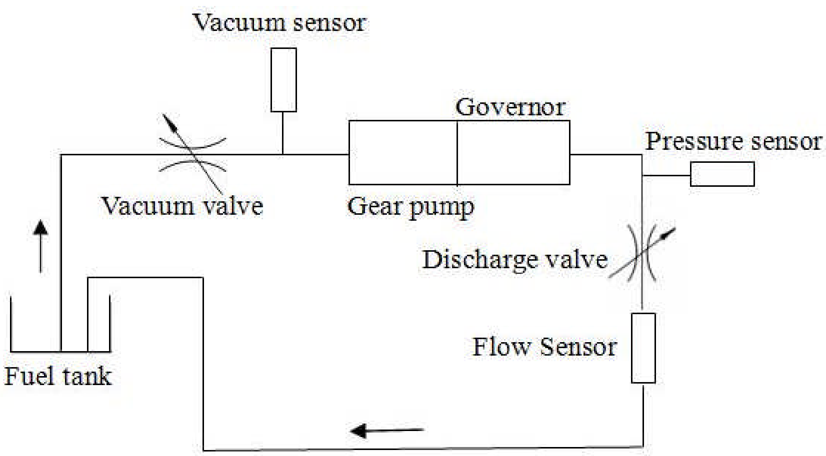


Figure 2. The graph of testing principle

The principles of the PT pump are discussed in detail in reference [21], and the structure of PT fuel system is shown in figure 3.

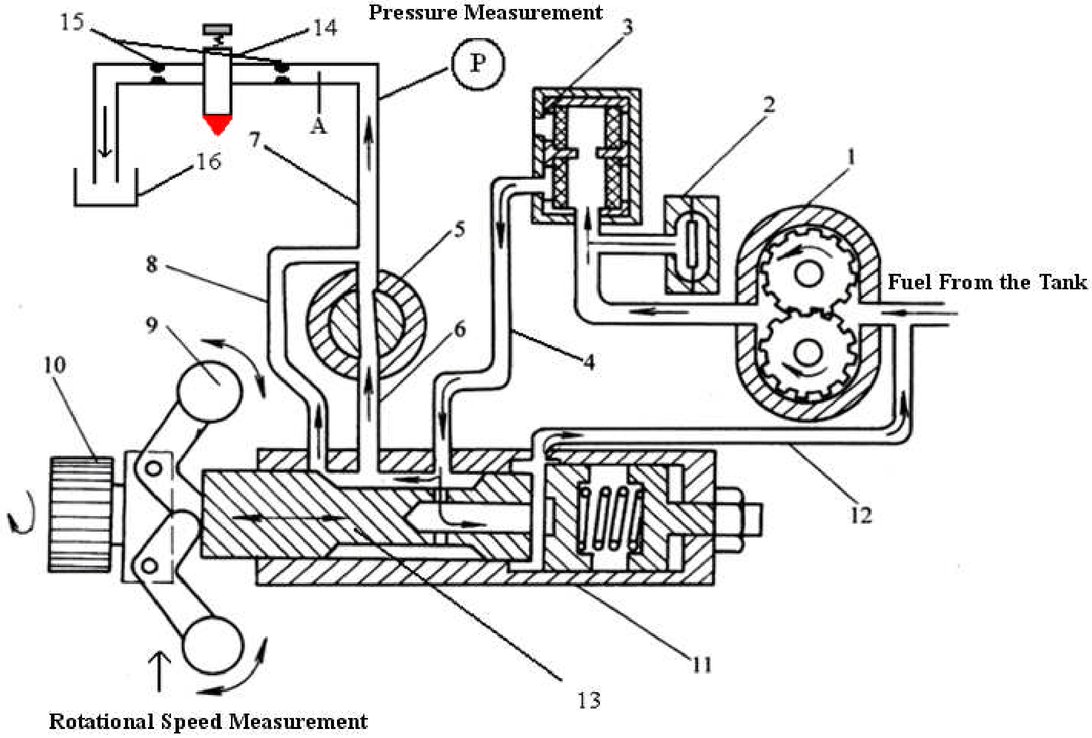


Figure 3. Structure of PT fuel system

1- oil pump 2-manostat 3-oil filter 4-oil-entering pipe 5-throttle valve 6-main oil gallery 7-outlet of the fuel 8-idling oil gallery 9-fly ball 10-driving gear 11-PT speed governor 12-discharge oil gallery 13-valve core 14-injector 15-throttle 16-tank

Rotating speed of the motor rises gradually from 0 to 2180r/min during the signals acquisition. The pressure sensor records the signals of the outlet of the PT pump, the sample frequency is 500Hz and the signal length is 2048, the complete pressure control process of PT pump was recorded. Electrical equipments such as high power transducer, three-phase motor and electromagnetic brake were installed in the narrow space of the test bench, and the kilo-volt pulses formed powerful electromagnetic interference during the working process, so there are many clutters (pulse components) in figure 4.

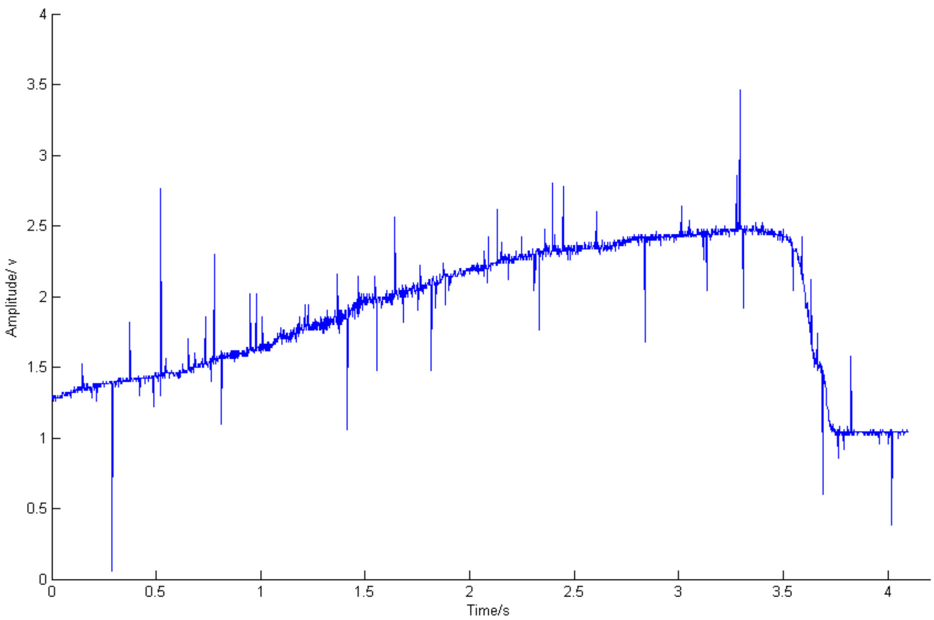
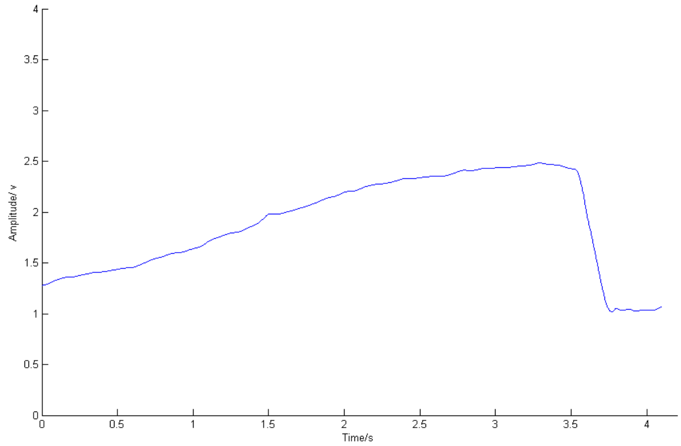
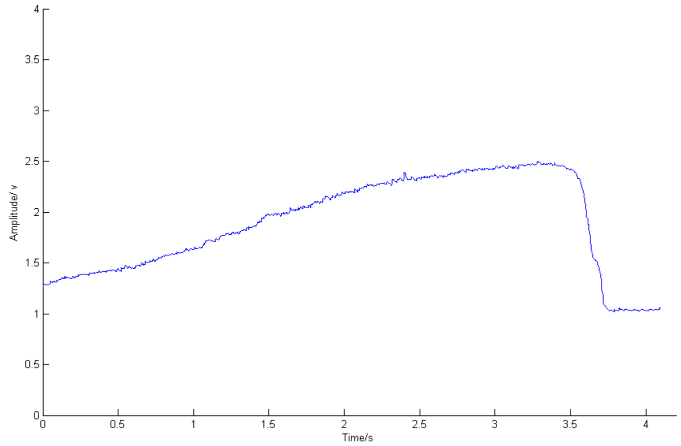


Figure 4. Collected signals

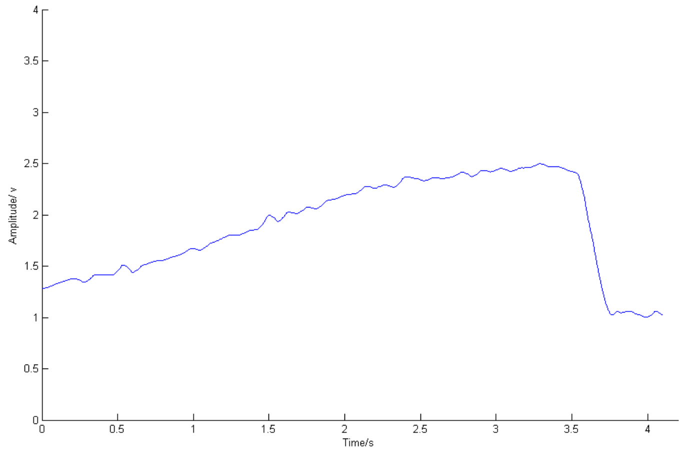
The original signals and denoising signals processed with different algorithm were shown in figure 5, and the value of evaluation indexes were shown in table 1.



(a)



(b)



(c)

Figure 5. Comparison of the different denoising algorithm
(a) Algorithm proposed in this paper
(b) Algorithm of mathematical morphology
(c) Adaptive EMD threshold algorithm

Table 1. Comparison of the evaluation indexes

Denoising algorithm	SNR/dB	MSE
MM-EEMD	27.9241	0.0061
Adaptive EMD threshold algorithm	26.6169	0.0075
Algorithm of Mathematical morphology (the structural element is triangle)	27.3925	0.0069

As is shown in figure 5 and table 1, the algorithm proposed in this paper has better denoising effect, the value of the SNR is largest and the value of the MSE is smallest, the denoising signals can clearly reflect the dynamic performance of the PT pump. The signals denoised by the mathematical morphology is not smoother than other algorithms, this is mainly because of the morphological operators of *open* and *close*. The greatest advantage of mathematical morphology filtering is that it can sharpen the “peak” and filled the “valley” which is decided by the cascade of *open* and *close* operations. If the noisy signals contain continuous “peak” or “valley”, the denoising algorithm of mathematical morphology will take partial noise as useful signals, and this will lead to few small amplitude noise can not be wipe off. The denoising signals based on the algorithm of adaptive EMD threshold are anamorphic, and the signals obviously have hackles, this is not according with the characteristic of the actual signals.

5. Conclusions

The denoising algorithm based on the MM and EEMD is proposed in this paper. Firstly, filter the noisy signals with mathematical morphology; secondly, decompose the noisy signals with EEMD algorithm, extract the IMF components based on the setting threshold; finally, recombine the extracted IMF components to get the denoising signals. Practical application shows that the algorithm has better denoising effect through comparison of other methods, and it provides a new denoising method for the hydraulic signals.

Acknowledgements

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