2009 American Control Conference
Hyatt Regency Riverfront, St. Louis, MO, USA
June 10-12, 2009

Oil Debris Signal Analysis Based on Empirical Mode Decomposition for Machinery Condition Monitoring

I. Soltani Bozchalooi, Ming Liang

Abstract—Analysis of lubricating oil is a direct and reliable approach to machinery condition monitoring. An estimate of the amount of fatigue induced metallic debris in the lubricating oil of a mechanical system can help us plan maintenance schedules. A reliably designed preventive maintenance system can reduce lost productivity and prevent catastrophic failures by timely replacement or maintenance of mission critical mechanical components. Oil-debris sensors can provide the required information on the amount of metallic debris in oil return lines. These sensors generate a signal signature similar to a single full period sine wave with the passage of a metallic particle. As such, the output of these sensors can be analyzed and an estimate of the health state of mechanical system can be obtained. However, these sensors are sensitive to vibrations of the structure where the sensor is mounted. This sensitivity leads to the distortion of the signal output. Such signals are difficult to interpret and could be misleading. As such, an imperative step towards successful machinery fault detection is signal enhancement. In this paper, we apply empirical mode decomposition (EMD) technique to extract particle signatures from the output of oil-debris sensors contaminated with vibration induced signal components. To reduce the computational burden, the acquired signal is lowpass filtered prior to the application of the EMD. The proposed algorithm has been tested using both simulated and experimental data and has shown to be effective.

I. Introduction

The advantages in preventive maintenance techniques have been a strong impetus for a large body of research in the field of machinery condition monitoring. Preventive maintenance not only enables us to preclude disastrous consequences of failure of mission critical mechanical components, but also helps us to prevent unwanted production delays.

Vibration signals and oil condition data are two dominant sources of information currently used for health assessment of mechanical systems. Especially, with the recent development in digital signal processing methods, vibration data analysis has received much attention during the past few decades. Vibration signals are information rich as the health condition in one way or another affects the vibration nature of a mechanical system. Gear wear/fatigue cracks or roller bearing spalls, shaft misalignment etc all create some form of featuring vibration signatures which can be detected through vibration signal analysis.

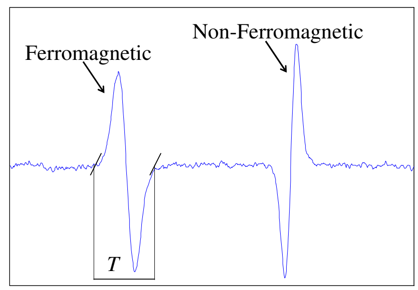

Fig. 1. Sensor output in response to the passage of a metallic particle

However, it is very difficult to properly extract such featuring signatures due to the large number of components in a mechanical system, each contributing to the overall vibration signal captured by a sensor. As a result, the fault induced vibration signal components are often masked by strong vibration interferences from other mechanical components. This is the main challenge when the detection of incipient faults is of great importance whereas the corresponding fault signatures are very weak comparing to noise and interferences.

Furthermore, fault severity estimation based on vibration analysis is usually very difficult. Even when the extraction of fault related vibration signal component is successful, it could still be an intricate task to relate such signatures to the severity of the fault because of the non-linearility of a mechanical system.

The above difficulties in vibration-based methods give rise to the analysis of oil condition data. A majority of mechanical systems are oil lubricated. The metallic debris content in the lubricating oil provides a direct perception on the health state of mechanical systems. Furthermore, the metallic particle size and count can be directly related to the severity of the faults. Accordingly, machinery condition monitoring based on oil condition data is preferred in many applications.

In off-line oil analysis methods, oil samples are collected and then analyzed in laboratories. Another approach uses a chip detector that utilizes magnetic collector to capture the

Ming Liang is with the Department of Mechanical Engineering, University of Ottawa, Ottawa, Ontario, Canada, K1N 6N5. (phone: 613-562-5800 ext. 6269; fax: (613) 562-5177; e-mail: liang@genie.uOttawa.ca).
I. Soltani Bozchalooi, is with the Department of Mechanical Engineering, University of Ottawa, Ottawa, Ontario, Canada, K1N 6N5. (e-mail: isoltani@uottawa.ca).

978-1-4244-4524-0/09/$25.00 ©2009 AACC

metallic debris. An alarm system will then warn machine operators when the quantity of such debris reaches a predefined threshold [1, 2].

Oil Debris Monitor (ODM) is an on-line oil condition monitoring device. It is installed on the oil return lines and provides a full flow passage way for the lubricating oil. It can detect the metallic particles that pass through it [2, 3]. The ODM was first developed for monitoring the F22 Advanced Tactical Fighter engine. This sensor generates a signature very much like a full period of a sine wave with each metal particle passing. By processing the output signal it is possible to find an estimate of the level of fatigue-induced material deterioration of the mechanical components.

Figure 1 illustrates distinct output signatures of ODM in response to the passage of ferromagnetic and non-ferromagnetic particles. As one can see from this figure, the phase of the output signature depends on the nature (ferromagnetic or non-ferromagnetic) of the metallic particle. The amplitude of this signature is affected by the particle mass for ferromagnetic material and by particle surface area for non-ferromagnetic metals [2]. The period of this signature denoted by T in Figure 1 depends on the particle passing speed.

Consequently, from the output of the sensor the number of metallic particles contained in lubricating oil, as well as size and nature (through amplitude and phase of each signature output) of each can be determined. As a result, an estimate of the damage level could be obtained and if necessary maintenance can be scheduled to reduce production loss or in-flight shut-downs of aircrafts [2, 3].

However, this sensor like many other measuring devices suffers from noise and interferences. Due to the sensitivity of the sensor to vibrations, in addition to the intrinsic background noise caused by wiring flaws and electrical interferences, the signal output of the sensor may be mixed with interferences caused by vibrations of the structure where the sensor is mounted. These interferences appear as a mixture of modulated sinusoidal signals. As mentioned before and also shown in Figure 1, the particle signature is similar in shape to a full period sine wave. As such, interferences could be mistakenly interpreted by the health assessment unit as passage of numerous consecutive metal particles of the same nature. In addition, the original particle signature masked with interferences would remain undetected.

Figure 2(a) illustrates the output of an ODM in response to the passage of a ferromagnetic particle in the absence of any vibration interferences. Figure 2(b) shows the signature of the same particle passing through the sensor when the ODM was subject to vibrations introduced by an electromagnetic shaker. Apparently, this signal in its current form practically provides no clue to the machine condition.

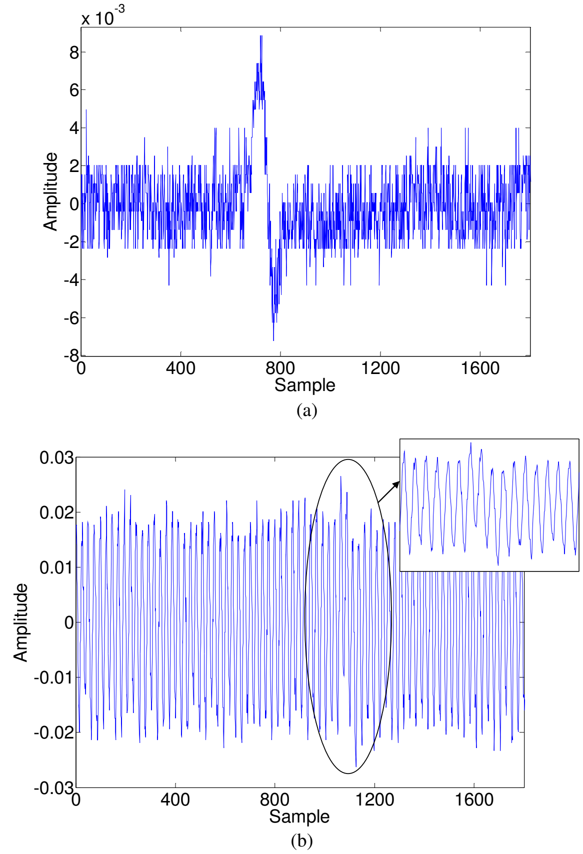

Fig.2. ODM Sensor output measured at 4000Hz sampling rate with the passage of a ferromagnetic metallic particle a) in the absence of vibration interferences and, b) with vibrations introduced by a shaker.

Accordingly, a pre-processing step is required in order to extract the particle signatures from such a signal and interference mixture. The extracted signal components can then be used for health assessment.

II. Empirical Mode Decomposition and its Application in Enhancing an Oil-Debris Sensor

In this section we elaborate on EMD application to extracting particle signatures from a mixture of particle signatures and vibration interferences. EMD is a relatively new approach for analyzing stationary and non-stationary signals. This method was originally proposed by Haung et al. [4, 5]. In this paper we do not deliberate on the conceptual details of this method as plenty of information is available from the literature [4-6].

This method decomposes a signal into a finite number of intrinsic mode functions. In the following, the steps involving the extraction of intrinsic mode functions known as the sifting process are explained:

Given the signal $X(t)$:

1) Find all the local minima and local maxima in the signal.
2) Connect all the local maxima by a cubic spline to form the upper envelope.

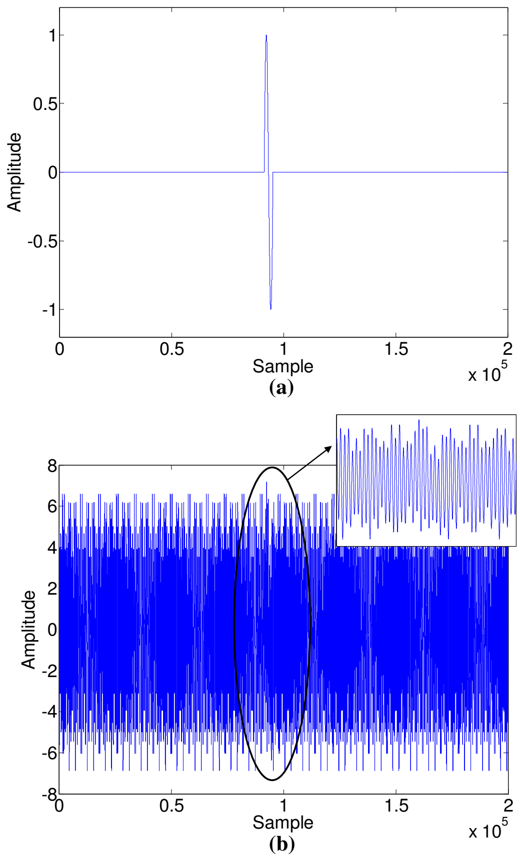

Fig. 3 (a) A single simulated particle signature and, (b) signature of part (a) mixed with simulated vibration interference $2\sin(400\pi t)\cos(1300\pi t)+5\cos(2000\pi t)$

3) Repeat step 2 for all the local minima to form lower envelope.
4) Find the mean of upper and lower envelopes at every instant t and subtract this mean $m(t)$ from signal $X(t)$: $h(t) = X(t) - m(t)$.
5) $h(t)$ is an intrinsic mode function (IMF) if it satisfies the conditions:
   I. The number of extrema and the number of zero crossings must be either equal or differ at most by one.
   II. At every instant the mean of upper and lower envelopes should be equal to zero.

Otherwise, repeat steps 1 to 4 but this time for $h(t)$ instead of $X(t)$ until one intrinsic mode function can be extracted.

6) Subtract the extracted IMF from $X(t)$ to find the signal residue $R(t)$. Apply steps (1) to (6) on $R(t)$ to extract an additional IMF.
7) Continue the sifting process until the residue $R(t)$ is less than a predetermined threshold value or in other words the residue is not of any significance.

Now let us consider a single simulated particle signature as shown in Figure 3(a). As one can see from this figure, a particle signature satisfies the requirements of an IMF, namely zero mean envelope with three zero crossings and two extrema (the difference between the number of zero crossings and extrema is equal to one). In other words, application of the sifting process may be a simple approach for the extraction of particle signatures from a mixture of particle signature and vibration interferences.

To illustrate, the simulated particle signature of Figure 3(a) is mixed with simulated vibration interferences as shown in Figure 3(b) where the passage of metallic particle can not be detected and further processing is required.

We then apply the sifting process on the simulated signal mixture. The extracted IMFs are shown in Figures 4(a), 4(b) and 4(c). The signature of the passing particle is extracted as a distinct IMF (Figure 4(c)). The original simulated particle signature is superposed on the extracted IMF in red dotted line. The difference is unnoticeable.

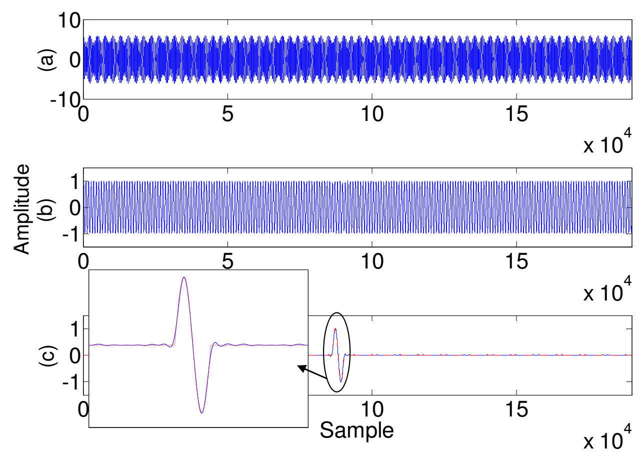

Fig. 4. Extracted Intrinsic Mode Functions

According to this observation, the EMD method can be successfully applied to extract particle signatures from a mixture of signal and vibration interferences. The flowchart of the proposed algorithm is shown in Figure 5.

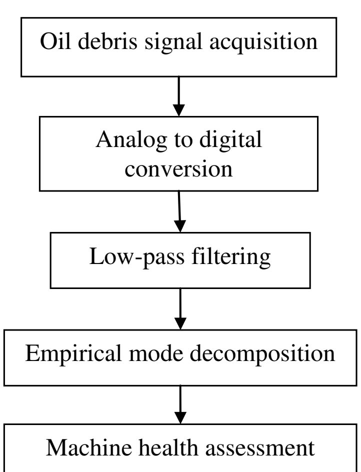

Fig. 5. Flowchart of the proposed algorithm.

However, in addition to the capability of the EMD technique to extract oil-debris particle signals, the computational complexity of the method should also be considered. This is mainly because in this specific application the EMD technique is applied as a pre-processing step in an on-line health monitoring system. As such, the processing time is of great importance.

However, the computational complexity of the EMD method depends on the number of extrema in the signal. Consequently, presence of high frequency noise and interferences may slow down the process significantly. As mentioned before, the frequency content of the particle signature corresponds to the passage speed of the metallic particle. Therefore, we can specify a frequency limit beyond which no frequency components associated with the particle signature can be found. Accordingly, we can lowpass filter the measured signal to remove all the high frequency noise and interference, while leaving the signals of interest intact. This step should be applied to the acquired signal prior to the EMD steps. The experimental work is presented in the following section.

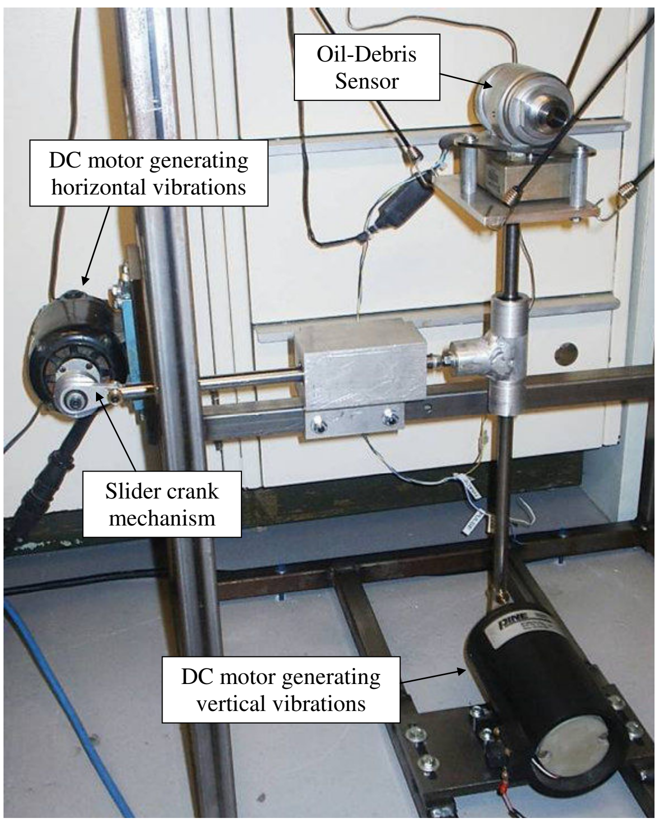

Fig. 6. Experimental setup.

III. Experimental Evaluation

To evaluate the performance of the proposed method, a bi-axial vibration exciter is used to shake an ODM sensor in both vertical and horizontal directions at the same time (Figure 6).

As shown in Figure 6, in each direction (horizontal or vertical) a DC motor drives a slider-crank mechanism and vibrates the ODM sensor. Two separate DC motor speed controllers are used to adjust the rotational frequency of individual DC motors.

While the sensor is subject to such vibrations we manually pass very small metallic particles through the sensor. These particles as shown in Figure 7 are embedded at the tip of a plastic catheter.

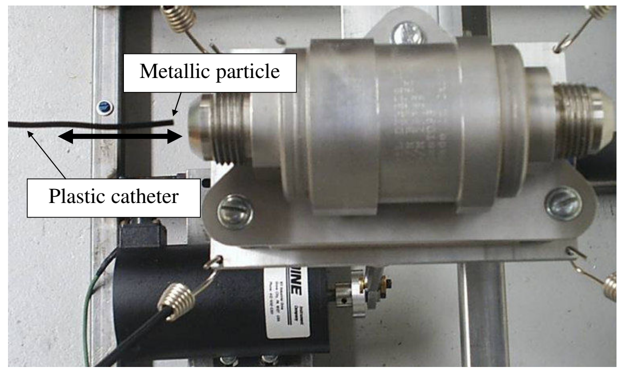

Fig. 7. A metallic particle embedded at the tip of a plastic catheter is manually passed through the sensor.

The output of the sensor was fed to an NI AT-MIO-16DE-10 DAQ card and then collected through LabVIEW. The signal processing was done using MATLAB on a Pentium® 4 PC with 2.52 GHz speed.

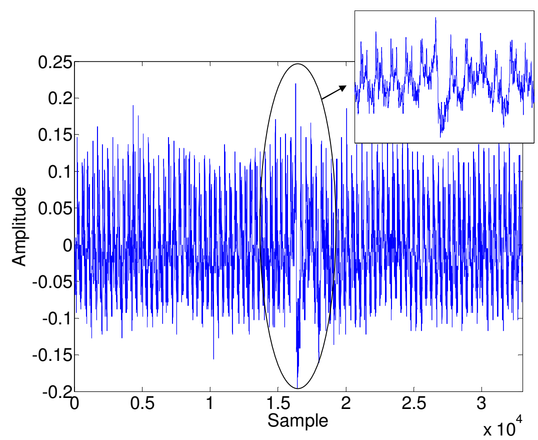

Fig. 8. Signal measured from the vibrating ODM at 20 KHz sampling rate, when a Titanium particle was manually passed through the sensor.

In the first experiment, the rotational speed of the DC motor associated with vertical vibrations is set to 3250 rpm and the one associated with horizontal vibrations to 30 rpm. A small Titanium (45~150µm in diameter) particle is passed through the sensor. The output of the sensor is sampled at 20 KHz. A portion of the measured signal is shown in Figure 8. As one can see, the particle signature is immersed in large amplitude vibration interferences. The measured signal is lowpass filtered with the cutoff frequency of 1KHz (The lowpass filter is designed based on Parks-McClellan method

[7]).

It should be noted that for a particle signature to have a significant spectral content over 1KHz we should have $T<0.001s$ (see Figure 1). Hence, the corresponding particle passage speed would be approximately over 50 m/s which is not the case in this experiment. Similarly, it is possible in most of the practical cases to define an upper limit for the passage speed of the particle and accordingly design a lowpass filter. When the cut off frequency of the low pass filter is significantly higher than the upper limit of $1/T$, the filtering would not distort the particle signature.

The lowpass filtered signal is then decomposed to 6 intrinsic mode functions as shown in Figure 9. The particle signature is successfully extracted using the EMD method.

In another experiment the rotational speed of the DC motors associated with vertical and horizontal vibrations were set to 3500 and 50 rmp respectively. A fine Nickel particle (11~65μm in diameter) is passed through the sensor. The sampling frequency is set to 50 KHz. A portion of the measured signal is plotted in Figure 10.

Following the same procedure illustrated above, the measured signal is lowpass filtered and then decomposed using EMD to 6 intrinsic mode functions. The extracted IMFs are illustrated in Figure 11. Similar to the previous experiment, the EMD is also effective in extracting this particle signature from the raw signal mixture measured by the sensor.

It is important to note that in the above two experiments the particle signatures are detected visually. In practice however, an automatic approach is needed to detect the IMF in which the particle signature resides. Hence, only that specific IMF will be analyzed for condition monitoring. This is not elaborated in this paper and is under investigation.

In addition, one should note that all the limitations of the EMD technique are inevitably inherited by the proposed signature extraction algorithm. It is very difficult to guarantee reliable results in all circumstances. In practice, the vibration interferences can be very complicated in nature which can affect the performance of the EMD. Background noise characteristics on the other hand can also influence the decomposition results. These are some other concerns which need to be addressed through further research.

IV. CONCLUSION

In this paper we proposed a simple yet effective method for the extraction of particle signatures when the ODM sensor is subject to intense vibrations. It was shown that in such circumstances the output of the sensor is a mixture of particle signatures and unwanted vibration interferences. Empirical Mode Decomposition technique was used to extract the particle signature and remove the vibration interference. As the computational complexity of EMD technique depends on the intensity of high frequency noise and interferences, the measured signal was lowpass filtered prior to the application of EMD. This step has made the EMD process much less computation-demanding and thus suitable for on-line applications. The proposed algorithm was validated using the simulated as well as experimental data acquired from an ODM subject to vibrations.

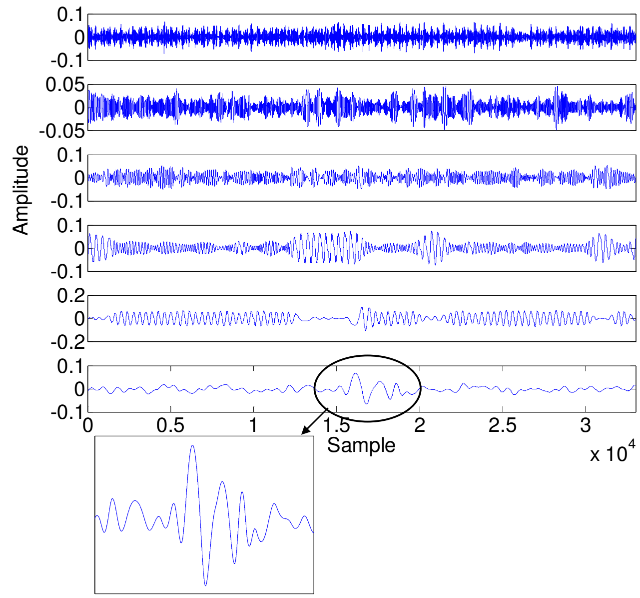

Fig. 9. The EMD result of the lowpassed version of the signal shown in Figure 8.

ACKNOWLEDGEMENT

This work is supported in part by the Natural Science and Engineering Research Council. The authors are grateful to GasTOPS, Ltd for providing the sensor for the experimental work.

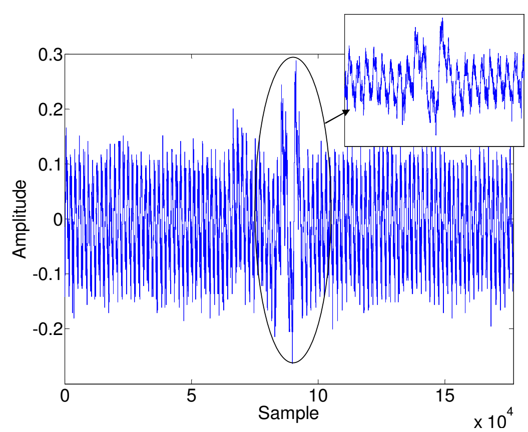

Fig. 10. Signal measured from the vibrating ODM at 50 KHz sampling rate, when a Nickel particle was manually passed through the sensor.

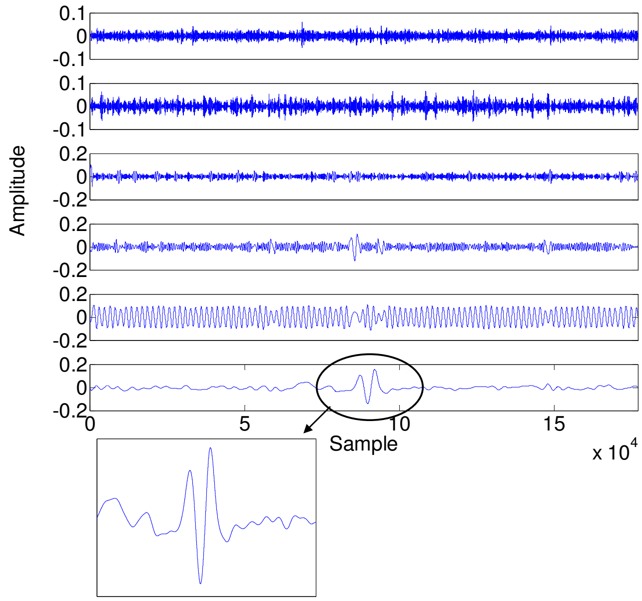

Fig. 11. The EMD result of the lowpassed version of the signal shown in Figure 10.

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