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VIBRATION-BASED CAVITATION DETECTION IN CENTRIFUGAL PUMPS

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Abstract
Cavitation is a common cause of failure in centrifugal pumps. Because of interaction of several mechanical parts and fluid, the vibration signal of a centrifugal pump is complicated. In this paper, the vibrations of a transparent-casing centrifugal pump are studied. Three states are studied experimentally: no cavitation, limited cavitation and developed cavitation. Each case was also confirmed by visually inspecting the cavitation bubbles. The vibrations of the pump was acquired by using an accelerometer that was attached to the casing. Discrete wavelet transform (DWT) analysis and empirical mode decomposition (EMD) are used to extract classification features from the acquired signals. Using these features, an artificial neural network (ANN) successfully diagnosed the cavitation condition of the pump. Finally, EEMD is also implemented. The results showed the success of EMD and DWT in cavitation diagnosis. The output of EEMD does not show significant change comparing to EMD.

Keywords: Cavitation Severity, Centrifugal Pump, Vibration Analysis, EEMD, EMD, DWT

1. INTRODUCTION

Centrifugal pumps are rotating machinery which transfer liquid by using a rotating impeller and face failures related to liquids. They may fail during their operating conditions because of the liquid-related problems such as cavitation, or failures in solid parts such as impeller, shaft and bearing. There are thirteen well defined fault modes of centrifugal pumps. A number of them can be detected using vibration monitoring[1].

One of the most common causes of failure of centrifugal pumps is cavitation. Cavitation is the formation of vapor bubbles in low pressure region of the pump (it happens if absolute pressure is less than vapor pressure). If the bubbles move with fluid to the downstream, they implode in the higher pressure region of the pump and generate intense shock waves. The effects of cavitation within centrifugal pumps can have some unwanted outcomes such as deterioration of the hydraulic performance, pitting and erosion of the pump internal parts caused by cavity collapse, violent structural vibration and emitted noise [2]. Therefore, it is necessary to detect this type of fault at its early stages. The commonly used cavitation detection methods in centrifugal pumps are, determination of the net positive suction head (NPSH) at a constant speed and flow rate, visualization of the flow by an in-pump impeller eye, paint erosion testing of impeller blades and shrouds, static pressure measurement within the flow or on the volute-casing wall, vibration measurement of the pump structure and measurement of ultrasound or sound pressure of the pump in audible range [3].

Vibration analysis has been widely used in condition monitoring of centrifugal pumps. Using this method, fault detection is possible by conducting a comparison between the vibration signals of faulty and healthy conditions. In the previous research studies, the occurrence of cavitation has been detected by analyzing vibration signals of the pump and comparing them with the signals acquired from normal conditions. Wang and Chen [4] applied wavelet transform to extract the cavitation detection features from the vibration signal of a centrifugal pump. The obtained features then were fed to an ANN for detection of health condition of the pump. Their results showed the success of wavelet transform in processing the signals generated by cavitation. Other signal processing techniques are also applicable. The envelope analysis have been applied as a powerful signal processing technique for fault diagnosis of bearings and gears. As a new application, it was used for cavitation detection by Tan and Leong [5]. Sakthivel et al. [6] used a number of statistical time-domain features and a decision tree in order to detect cavitation. Cernetic and Cudina [7] studied the influence of uncertainties on vibration-based cavitation detection in centrifugal pumps. Muralidharan and Sugumaran [8] also applied wavelet transform tree for cavitation detection of centrifugal pumps, but they combined it with a decision for obtaining better results. McKee et al. [1] extracted time and frequency-domain features from vibration signals of a pump for cavitation detection. Azizi et al. [9] used EMD to decompose the vibration signal and then extracted the necessary features for cavitation detection. In summary, several signal processing techniques have been applied in this field.

In the previous studies, despite of the superiorities of EEMD, it has not been used for cavitation detection. It does not have the shortcoming of mode mixing of EMD and has been successfully applied to, rotors, ball bearings and gearboxes diagnosis, before [10-13]. Moreover, in the available literature, mostly the presence and absence of cavitation has been studied. The level of cavitation determines the type of action and its urgency. Therefore, it is necessary to determine the severity of cavitation. In this study, the limited and developed cavitation are distinguished. The raw vibration signals acquired from experiments in three conditions, including no cavitation, limited cavitation and developed cavitation, are decomposed using discrete wavelet transform and EMD. The detailed coefficients level one to three and approximation coefficient level three are used for further analysis. In the case of EMD, the first four IMFs are used for further analysis. Five statistical features are extracted from four sub-bands of DWT and first four IMFs. For each analysis method, the 20 extracted features are inputted to the generalized regression neural network (GRNN) to intelligently classify the fault severity. The first IMFs of EMD and EEMD are compared in order to examine possible improvements by EEMD.

2. EMD AND EEMD

The empirical mode decomposition, is a signal processing technique which is used to decompose any signal x(t) into a number of intrinsic mode functions [14, 15]. Each of these IMFs can be amplitude modulated and (or) frequency modulated. They have to satisfy the following two terms [16, 17]:

a) In each IMF, the difference between the number of extrema and the number of zero-crossings has to be less than two.
b) At any point of any IMF, the mean value of the envelope obtained by local maxima and the envelope obtained by the local minima has to be zero.

Based on the definition, EMD decomposes any signal x(t) as follows:

Pick out the local maxima of the whole data, then fit a cubic spline to them and produce the upper envelope.

Repeat all the steps for the local minima in order to produce the lower envelope.

Compute the mean value of the two envelopes, $m_1(t)$.

Compute the difference between the original signal, x(t), and m1 to obtain the first component, h_1:

$$h_1 = x(t) - m_1 \tag{1}$$

If h_1 satisfies the conditions of an IMF, then it is the first component of x(t) and is defined as c_1.

If h_1 is not an IMF, replace original signal, x(t), with h_1 and repeat steps one to four:

$$h_{11} = h_1 - m_{11} \tag{2}$$

which, m_{11} is the mean value of upper and lower envelope of h_1. Repeat the described steps for k times, until h_{1k} becomes an IMF. This so-called sifting process is repeated until size of the standard deviation (SD) computed from the two consecutive sifting results is less than a predetermined value. SD is defined as follows:

$$SD = \sum_{t=0}^{T} \left[\frac{\left| (h_{1(k-1)}(t) - h_{1k}(t)) \right|^2}{h_{1(k-1)}^2(t)} \right] \tag{3}$$

where T is the size of the signal. An appropriate value for SD is a number between 0.2 and 0.3. In Eq. (3), h_{1k} is the first IMF and is defined as c1:

$$c_1 = h_{1k} = h_{1(k-1)} - m_{1k} \tag{4}$$

Subtract c1 from x(t) and compute residue, r1:

$$r_1 = x(t) - c_1 \tag{5}$$

Assume r1 as original signal and repeat the above process to obtain the second component of x(t). By repeating the process for n times, the total number of obtained IMFs of x(t) is n and the remaining IMFs can be shown as:

$$\begin{cases} r_2 = r_1 - c_2 \\ \vdots \\ r_n = r_{n-1} - c_n \end{cases} \tag{6}$$

The decomposition process is stopped when r_n has at most two extrema. The relation between original signal and its IMFs is expressed as follow:

$$x(t) = \sum_{i=1}^{n} c_i + r_n \tag{7}$$

The IMFs c_1, c_2 , . . . and c_n include different frequency bands ranging from high to low.

Although the EMD technique is applicable to most of the diagnosis studies, it has the weak point of mode-mixing. This shortcoming has been mostly resolved through the improvements achieved in EEMD method.

EEMD is an improved version of EMD method which is based on adding a limited-amplitude white noise to the signal. The major steps of EEMD algorithm are [18]:

1) Add a white noise to the original signal.
2) Find the desired number of IMFs of the noise-added signal (e.g. *N* IMFs).
3) Repeat the first two steps for m times.
4) The results will be *N* *m*-member groups of IMFs.
5) The final IMFs of this method are the ensemble average of each group of IMFs.

In most of the cases the IMFs of EEMD method are better than EMD if the ensemble number and the level of the white noise are selected appropriately. More discussion on the implementation of EEMD and setting its parameters will be provided in the following sections.

3. DISCRETE WAVELET TRANSFORM

Discrete wavelet transform is a multi-resolution signal processing method that uses digital filters to exhibit a typical time-frequency description of a signal. DWT decomposes any signal into some frequency sub–bands as described below [19]:

At first, it uses a low-pass filter to pass frequency components lower than the cutoff frequency (half of the maximum frequency being in the original signal) and attenuate components with frequencies higher than the cutoff frequency. This process is repeated with a high-pass filter to attenuate low frequency components. Therefore, the original signal divides into two frequency bands as shown in figure 1. The low-passed signal is denoted as approximation coefficients, A, and the high-passed signal is denoted as detail coefficients, D. The high-pass and low-pass filtering processes can repeated for low-passed signals in several levels.

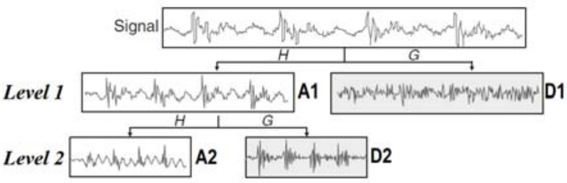

Fig. 1. Signal decomposition process using DWT in two levels

4. TESTS

For the purpose of cavitation severity detection in a centrifugal pump, a laboratory closed-loop system is used (figure 2). In this system, water is pumped from a 20 litter water tank, placed on top of the bench, and delivered to it again (in a closed circuit). A motor with a speed range of 100 to 4200 rpm is used to drive the pump. The pump is directly connected to the drive unit through an elastic coupling. An accelerometer mounted on delivery side of the pump casing is used to measure the vibrations of the pump. This accessory kit is made up of a single stage centrifugal pump with three blades, a ball valve and pressure indicator in the intake of the pump and pipes. The transparent plastic pump housing provides a view into the interior of the pump during operation. This allows cavitation to be observed when it occurs.

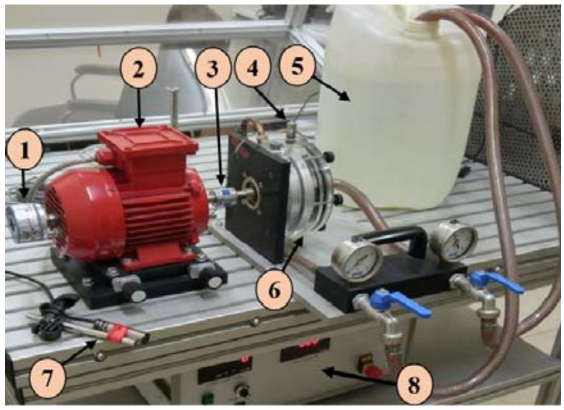

Fig. 2. The test setup: (1) Encoder, (2) Motor, (3) Elastic coupling, (4) Accelerometer sensor, (5) Water tank, (6) Centrifugal pump, (7) Optical sensor, (8) speed controller

Before getting started, it is necessary to bleed the pump. Therefore, after removing the bleed screw, the pump is filled with water until no more water remains in the housing. Then, the screw is closed again. Motor is turned off. Then it is switched on with the ball valves closed and run up to the desired speed. After that, first the ball valve on the suction side, and then the ball valve on the delivery side are opened.

The test was repeated 10 times and vibration signals were measured using an accelerometer mounted on the delivery side of the pump. The vibration signals were measured from the pump working under normal condition at a constant rotating speed of 2900 rpm. Having measured the normal condition, the inlet valve was partially closed to reduce the pressure at suction side of the pump until cavitation started, and acceleration data was collected until gradually the cavitation bubbles appeared in the pump eye area. This condition was denoted as limited cavitation. After that, the inlet valve was closed a little more and pressure at inlet of the pump was reduced more, and data was continuously collected until cavitation bubbles filled the pump housing. This condition was denoted as developed cavitation. Figures 4-6 show interior of the pump at this three conditions.

The collected data from each test consists of three parts, namely: 1) without cavitation, 2) limited cavitation and 3) developed cavitation. An optical sensor was used to separate these three parts. The signal obtained from this sensor has zero amplitude, except for the initiation of cavitation and initiation of the developed cavitation. In these two moments, the amplitude of the output of the optical sensor is increased to 5 volts by taking an object in front of the optical sensor, manually. Fig. 6 shows a sample of vibration signals and signal measured by the optical sensor. The sampling frequency was 20 kHz for all the tests.

Fig. 3. The pump at normal condition

Fig. 4. The pump at limited cavitation

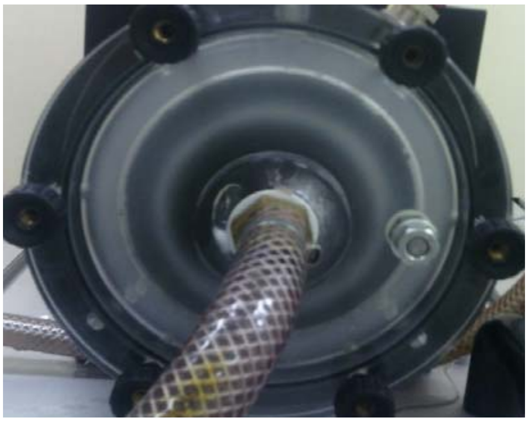

Fig. 5. The pump at developed cavitation

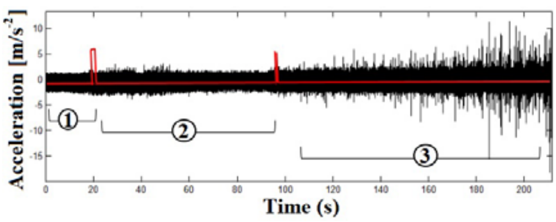

Fig. 6. The vibration signal (black color) and optical sensor output (red color) during three stages: (1) Without cavitation, (2) Limited cavitation, (3) Developed cavitation

4. RESULTS

The vibration signals acquired from experiments are used to perform fault diagnosis. Signal collected from each test is divided into three classes and each class divided into four parts with 7000 samples. Therefore, there are 120 vibration signals of length 7000 (40 signal for each class). The 120 vibration signals are analyzed using EMD and DWT. Five statistical features, namely root mean square, kurtosis, skewness, mean and standard deviation, are extracted from the first four IMFs. In the case of DWT, decomposition is performed in three levels, using the Daubechies (db9) wavelet function as the mother wavelet, and then five statistical features are extracted from the first to the third detailed coefficients levels and the third approximation coefficient level.

In each signal processing case, there is a feature set with 20 members for each vibration signal. The extracted features are fed to a generalized regression neural network to intelligently classify the fault modes. GRNN as a non-iterative neural network, performs one pass training to reduce computational time. The design parameter of this network is spread factor, which is set to be 1.0 in this paper. The input of the network is the features vector extracted from processed signals and the output is a prediction of the pump condition. There are 40 samples for each class that are divided in two parts: 28 samples for training the classifier and other samples for testing. Correct classification rate of GRNN with features extracted from IMFs as input vector is 98.33% and features extracted from DWT sub-bands is 97.5%.

To have a better insight, the obtained results for the applied techniques are summarised in Table1. In this table, the rates of success in diagnosis of the fault type are written for each technique.

Table 1. The total and separate rate of diagnosis success for different techniques that are applied in this research.

data / analysis	No cavitation (%)	Limited cavitation (%)	Developed cavitation (%)	Total (%)
Raw signals	77.5	77.5	90	81.67
EMD	95.0	100	100	98.33
DWT	92.5	100	100	97.5

The results of Table 1 shows the lowest performance in the case of no cavitation and limited cavitation. It also presents a significant decrease in the diagnosis (classification) success in the case of extracting the time-domain features from the raw vibration signals.

In the next step, the extracted IMFs obtained from EMD are compared with EEMD. In order to make a comparison, the first five IMFs are extracted for two conditions of severe cavitation and no cavitation. In Fig. 7a and Fig. 7b, the first five IMFs extracted from EMD method are displayed for no cavitation and severe cavitation conditions, respectively. The difference between

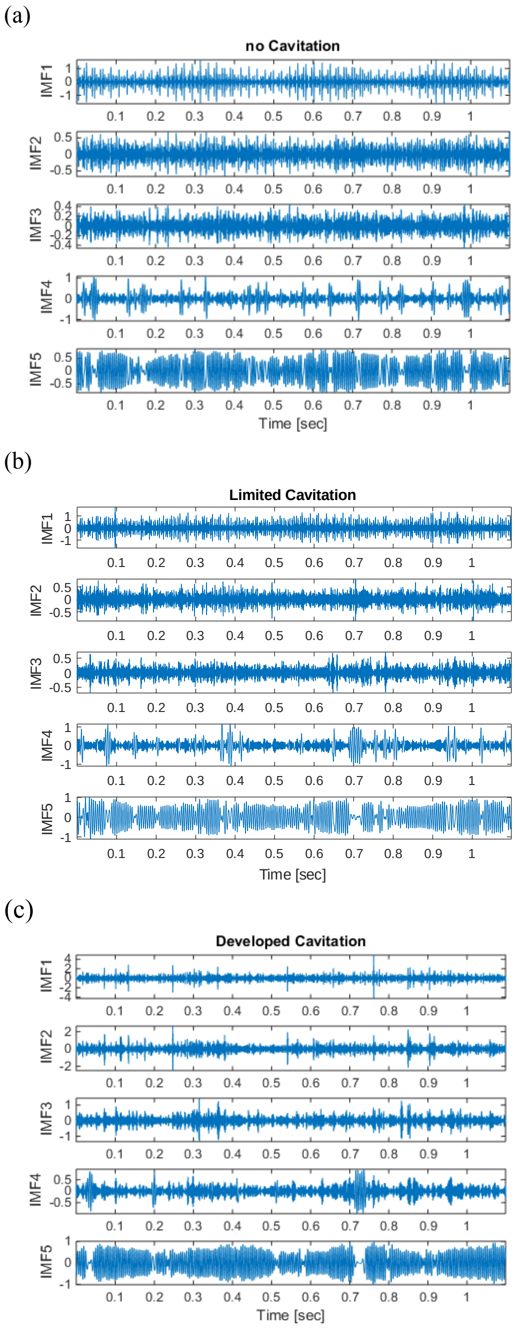

Fig. 7. The first five IMFs extracted from EMD method: a) No cavitation. b) Developed or severe cavitation

the waveform of the IMFs in those two conditions are quite obvious, especially for the first two IMFs the difference is observed both in amplitude and frequency contents. In Fig. 8a and Fig. 8b, the first five IMFs extracted from EEMD method are shown. In EEMD algorithm, the ensemble number was set to 100. The ratio of the added noise standard deviation to the standard deviation of the signal were also set to 0.2. The IMFs of EEMD method show no significant change or improvement comparing to EMD. It can be because of the random nature of the cavitation signals. The added white noise cannot help in separating the IMFs.

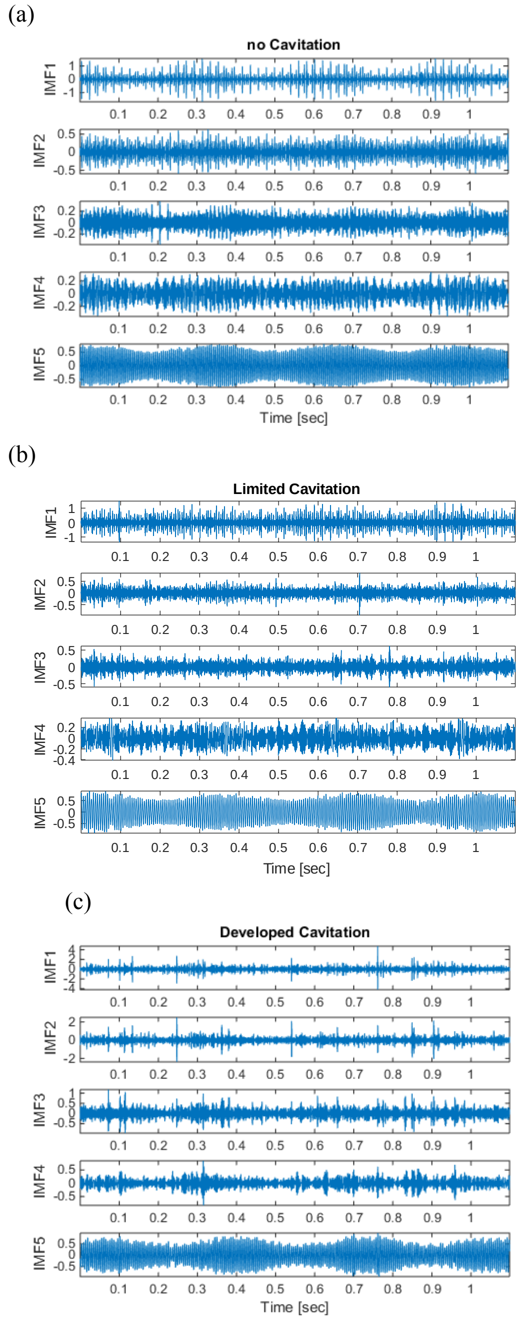

Fig. 8. The first five IMFs extracted from EEMD method: a) No cavitation. b) Developed or severe cavitation

The outputs of DWT that is used for decomposing the vibration signals in three levels are shown in Fig. 9. The obtained components are three vectors of detail coefficients and one vector of approximation coefficients for each fault condition. The fault pattern is hardly observable in the diagrams, but the extracted features give enough ability to the ANN to diagnose successfully to an acceptable level.

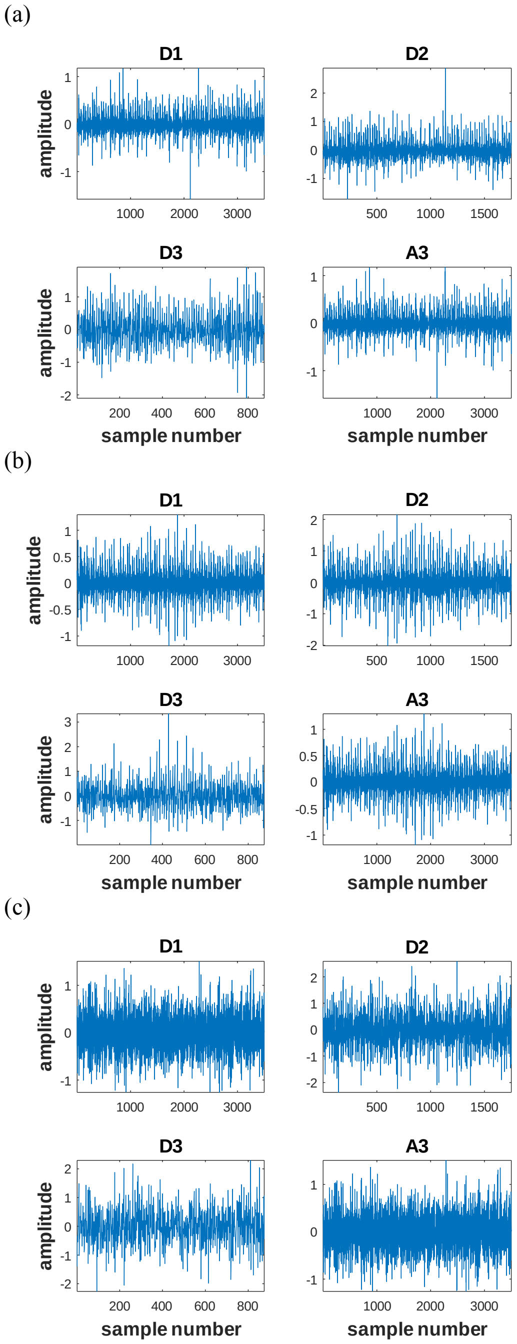

Fig. 9. The outputs of DWT: a) No cavitation. b) Limited cavitation. c) Developed cavitation

To sum up, the obtained table and graphs show that although identification of each condition based on the obtain graphs from EMD, EEMD and DWT is not easy, the ANN can perform this task with an acceptable performance. The level of confidence for the limited cavitation depends on the applied techniques, but it is acceptable by considering a narrow margin.

4. CONCLUSIONS

A procedure was proposed for cavitation severity detection in centrifugal pumps. Vibration signals acquired from experiments were decomposed using empirical mode decomposition and discrete wavelet transform. Five statistical features were extracted from first four IMFs and DWT sub-bands. GRNN was used for fault classification. The results showed that the EMD and DWT techniques are both effective methods in signal processing for detection of cavitation severity this type of fault, DWT was significantly faster than EMD in signal decomposition. Likewise the ability of GRNN in classification and its fast training could be seen. Plotting the extracted IMFs showed that the first two IMFs represent the most significant changes in case of occurance of cavitation. By applying EEMD to the vibrations signals of the pump and comparing the resulting IMFs showed no advantage or improvement comparing to EMD. For future works, it is advised that output of frequency-domain methods on the IMFs be investigated for detecting occurrence of cavitation.

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