Rotating Machine Fault Detection based on Fuzzy Logic and Improved Adaptive Filter

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***Abstract*—The rotating machine contains the many rotating parts and one rotating part produces additional noise to the others. As a result, fault signatures of the rotating machine are turned out to be quite weak. This paper proposed an effective method to detect the fault signatures of rotating machines based on improved adaptive filter, fuzzy logic and spectrum analysis. An improved adaptive filter is used to remove the noises from the faulty signal. Since the performance of the adaptive filter depends on the step size, a new technique is proposed to select the step size effectively based on entropy and fuzzy logic. To determine the fault signature of rotating machines of vibration signals effectively, demodulation is often required. Both squared envelope and Hilbert based envelope analysis are performed to identify the fault signature accurately. The effectiveness of the proposed adaptive filter is shown by simulation. Performances of the improved adaptive are also verified by real experimental data. Experimental results show that the proposed method can effectively detect the fault signatures of the rotating machines.**

***Index Terms*—improved adaptive filter, entropy, Hilbert transform, squared envelope, fuzzy logic, SNR**

I. Introduction

In today's industries, the rotating machine is one of the major parts. Due to the hazardous location and installation issues, rotating machines fail sooner than the excepted lifetime. The unexpected failures of the rotating machine cause economic loss as well as human causality. Therefore, it is important to prevent the failure of rotating machines. As a result, fault detection of a rotating machine in the early stage is an important research field. Among the many other techniques, the signal-processing technique is most important in this research field. In this technique, signals that often contain the information are collected from different parts of the machine. There are thousands of methods have been proposed so far to detect the rotating machine fault in the early stage [1]-[3].

Sever background noise and measurement noise can distort the fault signal of rotating machines. Moreover, these sever noise can lead to the wrong calculation for the fault detection process. Therefore, it is obvious to reduce theses noise from the vibration signal. Many digital filters have been proposed so far. However, adaptive noise cancellation is widely used in this research [4]. It automatically updates the parameters based on the characteristics of noise [5]. The performance of the adaptive filter is mainly depending on the selection of the step size [6]. Many algorithms have been proposed to select the step size of the adaptive filter [7]-[9].

This paper proposed an improved adaptive filter to reduce the noises from rotating machine signals. A new technique is proposed to select the optimum step size of the adaptive filter based on wavelet entropy and fuzzy logic. The rest of the paper organized as follows: Literature review is given in section II. Section III describes the proposed mechanical fault detection method, Verification of Speed and WE based adaptive filter is described in section III and section IV presents the performance of the proposed method using real experimental data. Finally, conclusions are given in Section V.

II. Literature Review

A. Vibration Signal

For condition monitoring and diagnosis of rotating machine faults, vibration signal analysis is an effective method. Vibration signals can provide plentiful information about the system dynamics. Therefore, faults of the rotating machine can be easily detected from the vibration signal. It is the most common and widely used method to detect and diagnosing of rotating machine faults [10].

B. Envelope Spectrum Analysis

After reducing the noises from the vibration signal, spectrum analysis is used to detect the fault signature of the rotating machine. Envelope analysis is an efficient tool for a separating modulating signal from its carrier

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[11]. Fig. 1 shows the upper envelope (red line), E_{upp} and the lower envelope, E_{low} (green line). From this figure, the modulating signal, $m(t)$ and carrier signal, $c(t)$ can be calculated as follows:

$$m(t) = E_{upp} - E_{low} \tag{1}$$

$$C(t) = E_{upp} + E_{low} \tag{2}$$

In this paper, both the squared envelope and Hilbert based envelope are applied for spectrum analysis to determine the magnitude of the fault signatures.

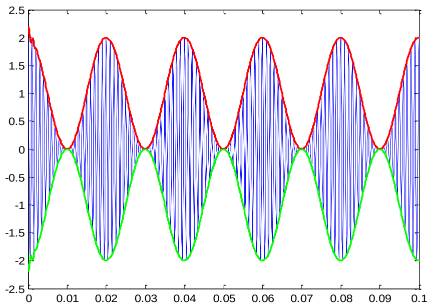

Figure 1. Envelope analysis [12].

i) Hilbert transform

Hilbert transform (HT) introduced by German mathematician David Hilbert is a widely used tool in many areas like edge detection, theory of modulation [13-15]. HT is a linear operator and defined for function f(x)

$$H(t) = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{f(x)}{t-x}dx \tag{3}$$

The analytic signal, X(t) can be constructed using Hilbert transform

$$X(t) = x(t) + j\mathrm{h}(t) \tag{4}$$

For constructing the analytic signals, the Hilbert transform is a well-known tool. For example, to obtain the envelope of a signal in the signal demodulation, amplitude modulation and so on. Hilbert transform is used in the demodulation process. Hilbert based envelope analysis can separate the fault signature properly from adjacent components.

ii) Squared envelope

Due to the existing random components during the envelope analysis, it is difficult to identify the fault signatures clearly. That why the signal to noise ratio plays a vital role here. However, this limitation can be overcome by using the squared envelope analysis. It is defined as a convolution of an analytic signal and its complex conjugate. The squared envelope provides a higher harmonic reduction [12]. It can calculate by the convolution process easily.

III. Proposed Mechanical Fault Detection Method

The main objective of this proposed method is to detect the fault signatures of the rotating machine effectively using the proposed adaptive filter. In this proposed approach, the faulty vibration signal is used. Since this vibration signal contains noise as well as the components from the other parts of the machine, adaptive filter this used to reduce noise and other effects. To select the proper step size of the adaptive filter, an entropy and fuzzy based new approach is proposed in this paper. Finally, squared envelope and Hilbert based envelope analysis are used to identify the fault signatures. The flow chart of the proposed method is shown in Fig. 2.

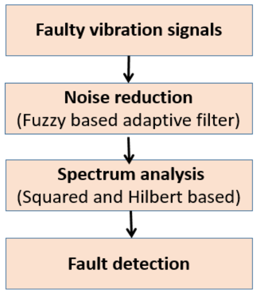

Figure 2. The proposed fault detection technique.

A. *Noise Reduction by the Proposed Adaptive Filter*

Magnitudes of the fault signatures of the rotating machines are quite weak when surrounded by strong noise. Additional random noise can be added to the fault signals if the rotating machine contains additional rotating parts. These noises should be reduced to detect the fault signatures accurately. Many noise reduction techniques have been proposed so far. Adaptive noise cancellation is widely used in this field. To design an adaptive filter, the step size of it plays an important rule. Because the step size of an adaptive filter governs the speed of tracking ability as well as the rate of convergence. Several methods have been proposed for choosing the step size of the adaptive filter [6, 9]. However, Noise has a great impact on the identification of the fault signatures accurately. A new technique has been proposed in this paper to select the optimum step size. To reduce the noise from the faulty vibration signal, entropy and fuzzy logic based step size of the adaptive filter is proposed.

i) Step Size selection using fuzzy and entropy

The entropy is defined as a measure of complexity and disorders of signal. If E_{jk} is wavelet energy spectrum at scale j and instant k, wavelet entropy can be defined as:

$$WE_j = \sum_k E_{jk}\log(E_{jk}) \tag{5}$$

The speed of the rotating machines may vary due to the fluctuation of loads even for driving forces. This speed variation can happen for constant speed machine. As a result, the dynamic behaviors of the vibration signal change accordingly. This behavior can be obtained by wavelet entropy. However, if the speed of the rotating machines changes dramatically, the magnitudes of the fault signatures are changed significantly. In other words, if the speed variation of the rotating machine is high, then the fault signatures change. In this situation, only wavelet entropy cannot determine the step size effectively. The effect of this high-speed variation is present in Table II. To solve this problem, fuzzy logic is applied along with the wavelet entropy to determine the step size of the adaptive filter.

ii) Fuzzy system

A fuzzy system is used along with wavelet entropy to determine the step size of the proposed adaptive filter. This fuzzy system contains one input and one output. Input is the speed of the machine while the output is the step size of the adaptive filter based on the entropy of the vibration signal. The membership function of input depends on the speed variation of the rotating machine while output membership functions are design based on wavelet entropy. The input variable 'speed' contains five membership functions very small (VS), small (S), normal (N), medium (M) and large (L) shown in Fig. 3. The output variable 'MU' also contains five membership functions shown in Fig. 4. Fig. 5 presents the relationship between the input and output variables.

The relationship between membership functions of input and membership function of output is define by following five rules:

Rule 1: IF *{speed is very small(VS)}* THEN*{step size is small(S)}*

Rule 2: *IF {speed is small(S)}* THEN*{step size is medium(M)}*

Rule 3: *IF {speed is normal(N)}* THEN*{step size is Wavelet entropy (WE)}*

Rule 4: *IF {speed is medium(M)}* THEN*{step size is large(L)}*

Rule 5: *IF {speed is large (L)}* THEN*{step size is very large(VL)}*

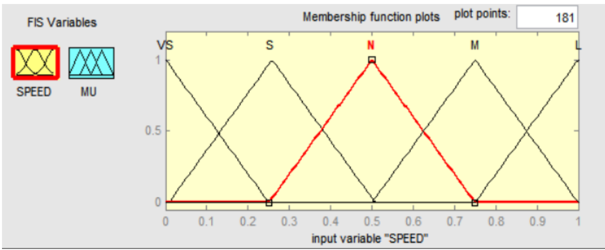

Figure 3. Membership function for input variable "speed".

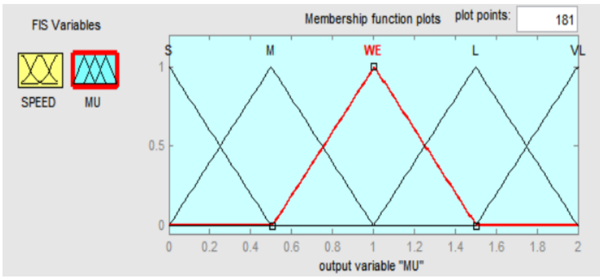

Figure 4. Membership function for output variable "mu" of the fuzzy system.

B. Spectrum Analysis

After reducing the noises from the faulty signal by applying proposed fuzzy based adaptive filter, both squared envelope and Hilbert based envelope are used to identify the fault signatures. The details of squared envelope and Hilbert based envelope are given in section II.

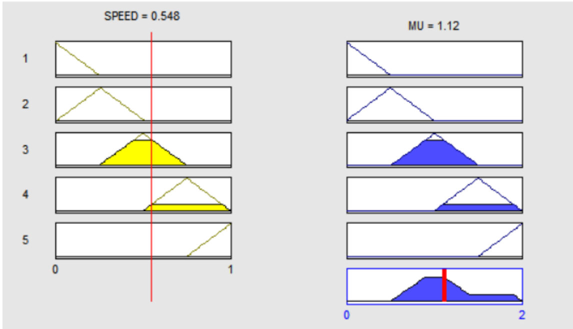

Figure 5. Relation between input and output of the membership function.

IV. Verification of the Proposed Adaptive Filter

This section presents the verification of the proposed new technique. Section III (A) shows the significance of the WE to select the proper step size. This section also shows the limitation of WE when the speed of the rotating machine varies. How fuzzy overcomes, this problem is presented in section III (B).

A. Benefits of WE Based Step Size

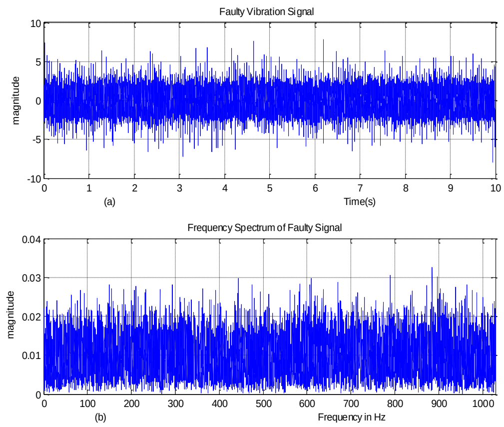

Figure 6. (a) Signal (time domain) from rotating machine, (b) frequency spectrum of the signal.

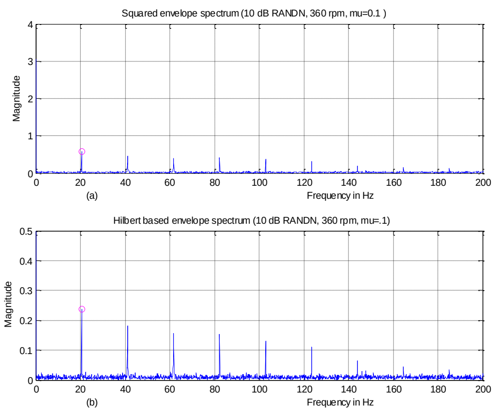

Figure 7. Fault signatures at 10 dB RANDN, 360 rpm and mu=0.1. (a) Squared envelope and (b) Hilbert based envelope.

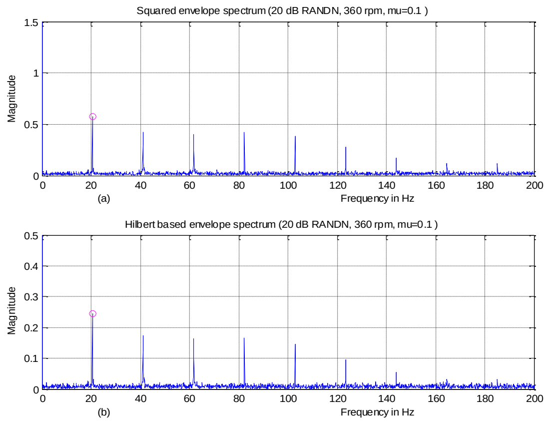

Figure 8. Fault signatures at 20 dB RANDN, 360 rpm and mu=0.1. (a) Squared envelope and (b) Hilbert based envelope.

Fig. 6(a) presents the vibration signal in the time domain and Fig. 6(b) shows the spectrum of the faulty signal. Unfortunately, no fault signature appears. The fault signature is visible in Fig. 7 where envelope analysis is used at 10 dB RANDN, 360 rpm and step size, mu=0.1. Magnitudes of the Fault signature are 0.5627 and 0.2346 for squared and Hilbert based envelope, respectively given in Table I. Fig. 8, Fig. 9 and Fig. 10 provide the fault magnitude with SNR 20 dB, 30 dB, and 40 dB respectively. From Table I, it can say that magnitudes of fault signature are change with SNR.

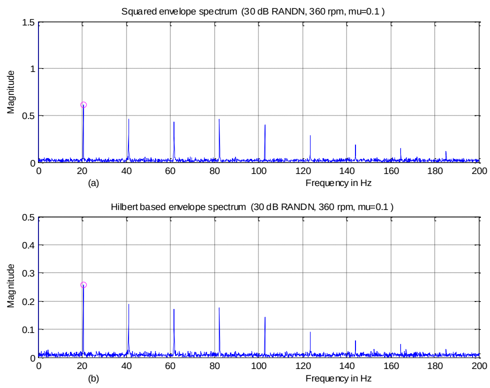

Figure 9. Fault signatures at 30 dB RANDN, 360 rpm and mu=0.1. (a) Squared envelope and (b) Hilbert based envelope.

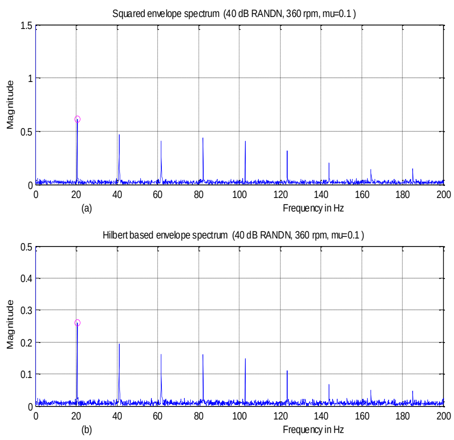

Figure 10. Fault signatures at 40 dB RANDN, 360 rpm and mu=0.1. (a) Squared envelope and (b) Hilbert based envelope.

TABLE I. MAGNITUDE OF FAULT SIGNATURES

	Mu=.1		Mu=.01		Mu=entropy	
dB	squared	Hilbert	squared	Hilbert	squared	Hilbert
10	.5627	.2346	.5619	.2350	4.1410	.6167
20	.5760	.2457	.5731	.2487	3.0220	.6071
30	.6097	.2589	.6037	.2542	2.7730	.5520
40	.6144	.2660	.6060	.2598	2.4710	0.5183

Now step size is considered 0.01. With 10 dB RANDN and 360 rpm, the frequency spectrum of the faulty signal is shown in Fig. 11. In this case, fault magnitudes are 0.5619 and 0.2350 for squared and Hilbert based envelope respectively. Fig. 12, Fig. 13 and Fig. 14 also show the fault magnitudes using the step size 0.01. It can conclude that when the size of the adaptive filter is changed, the fault magnitudes also are change. Therefore, to know the exact magnitude of the fault signature it is very important to select the proper value of step size.

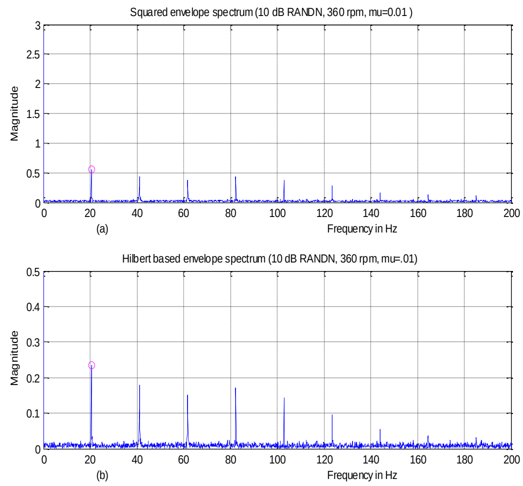

Figure 11. Fault signatures at 10 dB RANDN, 360 rpm and mu=0.01. (a) Squared envelope and (b) Hilbert based envelope.

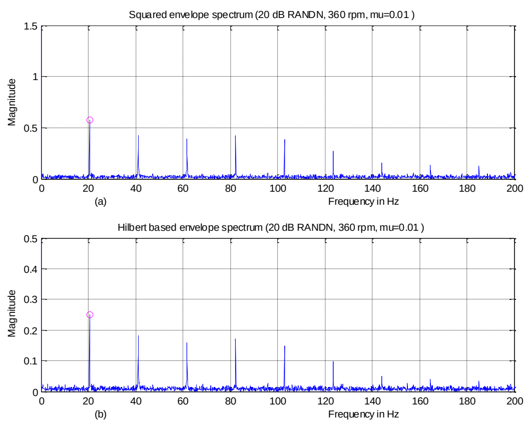

Figure 12. Fault signatures at 20 dB RANDN, 360 rpm and mu=0.01. (a) Squared envelope and (b) Hilbert based envelope.

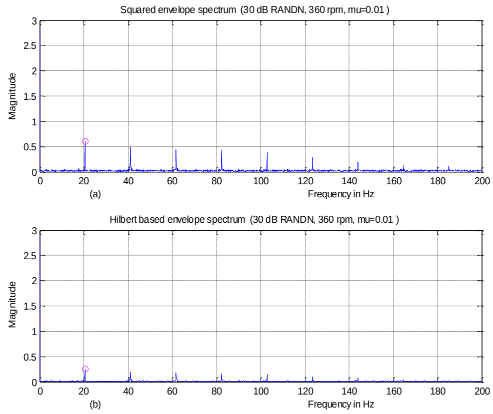

Figure 13. Fault signatures at 30 dB RANDN, 360 rpm and mu=0.01. (a) Squared envelope and (b) Hilbert based envelope.

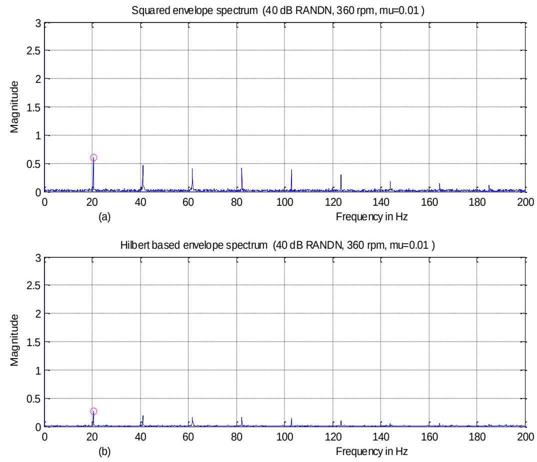

Figure 14. Fault signatures at 40 dB RANDN, 360 rpm and mu=0.01. (a) Squared envelope and (b) Hilbert based envelope.

Fig. 14, Fig. 15, Fig. 16 and Fig. 17 represent the magnitude of the fault signature using the entropy-based step size for the adaptive filter. Values of the fault magnitude are present in Table I. From Table I, it is clear that magnitudes of the fault signatures are higher than the fixed step size of 0.1 and 0.01. In other words, magnitudes of the fault signatures are more visible in this method.

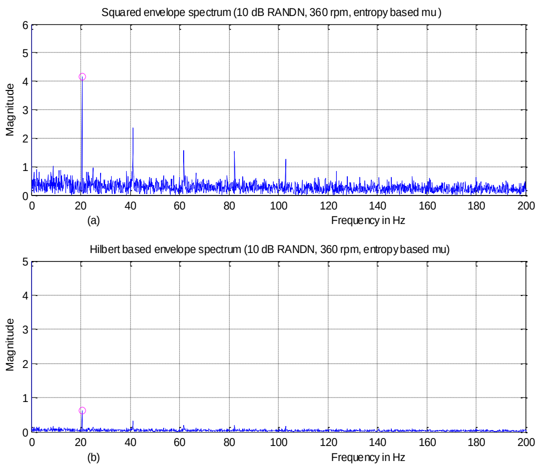

Figure 15. Fault signatures at 10 dB RANDN, 360 rpm and entropy based mu. (a) Squared envelope and (b) Hilbert based envelope.

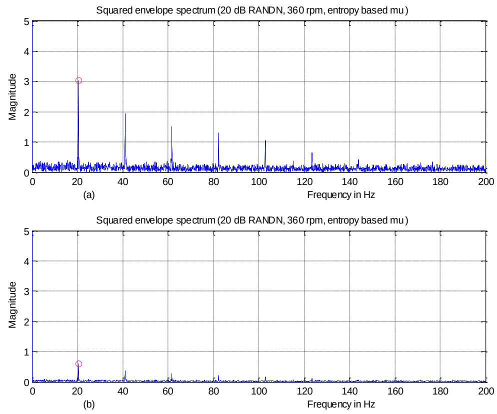

Figure 16. Fault signatures at 20 dB RANDN, 360 rpm and entropy based mu. (a) Squared envelope and (b) Hilbert based envelope.

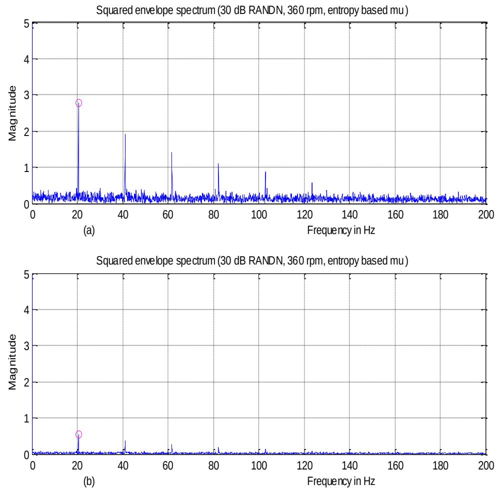

Figure 17. Fault signatures at 30 dB RANDN, 360 rpm and entropy based mu. (a) Squared envelope and (b) Hilbert based envelope.

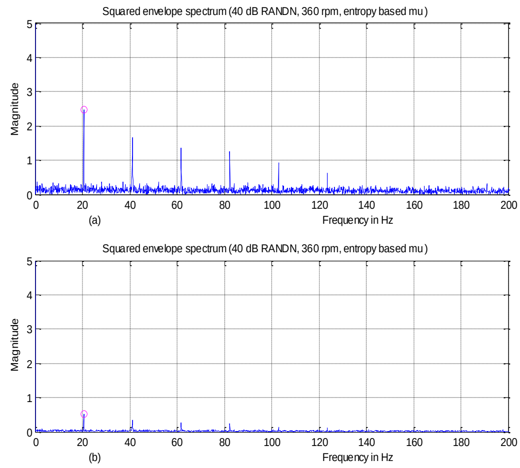

Figure 18. Fault signatures at 40 dB RANDN, 360 rpm and entropy based mu. (a) Squared envelope and (b) Hilbert based envelope.

B. Effect of Speed on Entropy

From the above section, magnitudes of the fault signature are maximized using entropy in the step size of the adaptive filter. However, speed variation has a great effect on the value of entropy. Fig. 19, Fig. 20 and Fig. 21 indicate the magnitudes of fault signature with a speed of 420 rpm, 480 rpm and 540 rpm respectively. Table II represents the faults magnitudes with different speeds of machine. If the speed of the machine is changed, magnitudes of the fault signature are changes. Therefore, it is important to select the value of entropy based on the speed of the machine. In this paper, fuzzy logic is used to choose the values of entropy based on machines speed.

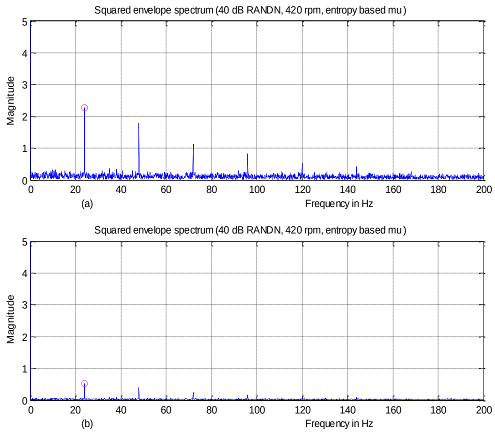

Figure 19. Fault signatures at 40 dB RANDN, 420 rpm and entropy based mu. (a) Squared envelope and (b) Hilbert based envelope.

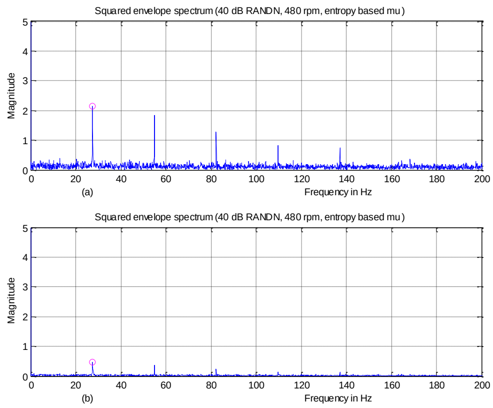

Figure 20. Fault signatures at 40 dB RANDN, 480 rpm and entropy based mu. (a) Squared envelope and (b) Hilbert based envelope.

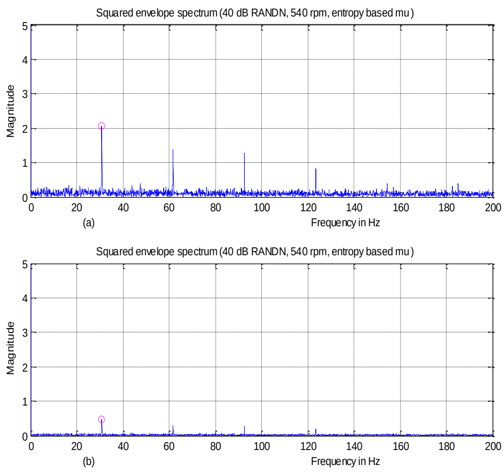

Figure 21. Fault signatures at 40 dB RANDN, 540 rpm and entropy based mu. (a) Squared envelope and (b) Hilbert based envelope.

TABLE II. MAGNITUDES OF FAULT SIGNATURES AT DIFFERENT RPM

Speed (rpm)	Magnitudes of fault signatures	
	Squared envelope	Hilbert based envelope
360	2.4710	0.5183
420	2.2750	0.5161
480	2.1340	0.4670
540	2. 0650	0.4599

V. EXPERIMENTAL VERIFICATION

Performance of the proposed presented in this section using experimental data. Outer race bearing fault of the induction motor is considered in this paper.

A. Experimental Data

To evaluate the performance of the proposed method, real experimental data [16] is used. The experimental setup for the induction motor is shown in Fig. 22. From this experiment, only bearing outer race (Fig. 22) vibration data is used in this paper. Three accelerometers are used to the motors in horizontal, vertical, and axial directions to collect the vibration signal from the faulty machine.

Figure 22. Test rig [16].

B. Performances of the Improved Adaptive Filter

Fig. 23 represents the frequency spectrum of the real experimental data without applying the proposed method. Here, bearing outer race fault signature is visible around 169 Hz. However, there is another frequency component with the same magnitude appear around 183 Hz. This is due to severe noise (at 10 dB) and not the fault signature. This noise is significantly reduced by the proposed adaptive filter.

After applying the proposed modified adaptive filter, only fault signature appears in Fig. 24 and no other frequency components appears in the spectrum significantly. In this figure, only the fault signature is dominant at 169 Hz. Therefore, it is obvious that the proposed adaptive filter can effectively reduce the noise from the vibration signal of low SNR. In other words, this proposed fault detection method detects the fault signatures accurately.

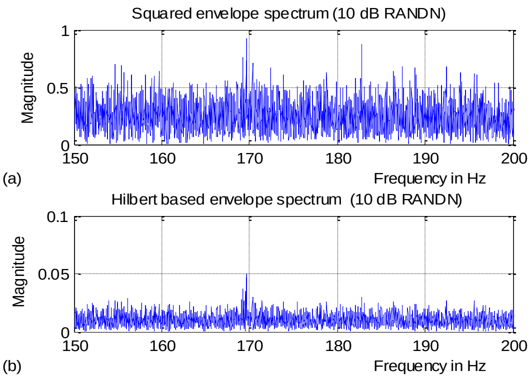

Figure 23. Fault signature for bearing outer race fault.

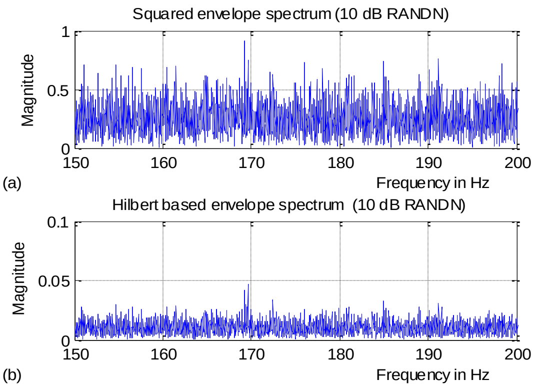

Figure 24. Fault signature for bearing outer race fault (10dB RANDN) using the proposed method.

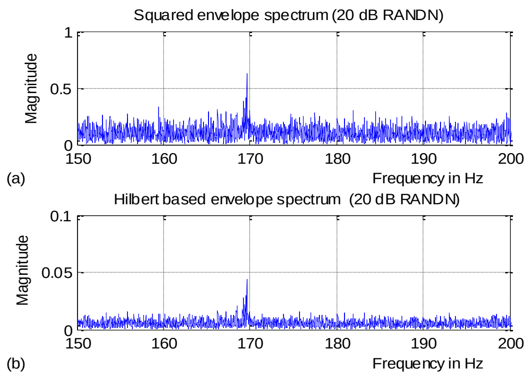

Figure 25. Fault signature for bearing outer race fault (20dB RANDN) using the proposed method.

When the SNR is getting higher, the fault signatures become more and more dominant. Fig. 25, Fig. 26 and Fig. 27 presents the magnitudes of the fault signature for 20 dB, 30 dB and 40 dB respectively. Fault signatures are clearly visible in these figures. Therefore, the outcomes of the proposed method indicate that it detects the fault signatures efficiently. As a result, it can conclude that the proposed adaptive filter reduces the noise from the vibration signal effectively.

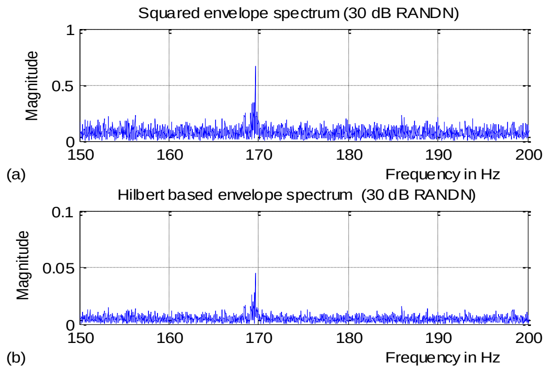

Figure 26. Fault signature for bearing outer race fault (30dB RANDN) using the proposed method.

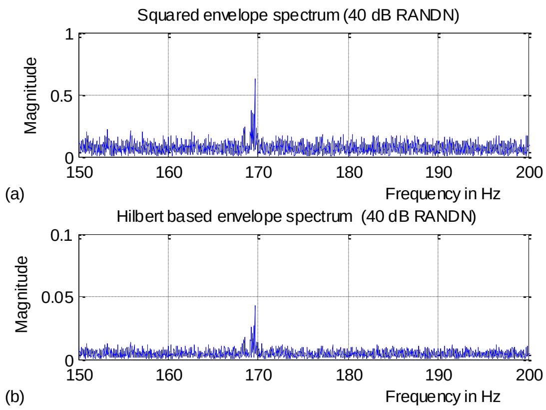

Figure 27. Fault signature for bearing outer race fault (40dB RANDN) using the proposed method.

VI. Conclusion

This paper presents a rotating machine fault detection method using an improved adaptive filter. A new technique has been proposed to determine the step size of the adaptive filter. The entropy and fuzzy based approach are used in this modified adaptive filter. Both squared envelope and Hilbert based envelope are used for spectrum analysis. The performance of the proposed method is verified by simulation and experimental data. Results show that by using the proposed adaptive filter, the fault signatures of the rotating machine are detected effectively even when the signal is surrounded by severe noise.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

M S Islam conceived and designed the topic and wrote the paper; U Chong refined the idea and revised the paper. All authors have read and approved the final manuscript.

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