2008 American Control Conference
Westin Seattle Hotel, Seattle, Washington, USA
June 11-13, 2008

Enhancement of the Signals Collected by Oil Debris Sensors

I. Soltani Bozchalooi, Ming Liang

Abstract—Oil condition data is a major source of information for machine condition monitoring. It contains information about the metallic particle content and thus reflects the level of wear and fatigue-induced damage in the mechanical system. Oil debris sensor is a popular measurement device used to collect oil condition data. This sensor generates an output signature with the passage of a metallic particle through the oil return lines. Analysis of the measured data leads to an estimate of the size and number of metallic particles present in the lubricating oil and consequently health state of the mechanical system. However, the signal measured through the oil debris sensor is severely tainted by various noises, e.g., the background noise present as well as the interferences caused by the vibrations of the structure where the sensor is mounted. These interferences affect the performance of the health assessment unit considerably. This will inevitably cause misleading maintenance decisions and hence premature machine failure as well as lost productivity. As such, this paper focuses on the enhancement of the signals acquired from oil-debris sensors. This is achieved by a two stage de-noising scheme. In the first stage the adaptive line enhancement (ALE) technique is applied to remove the vibration related interferences. Following this step, the partly purified signal is further enhanced using the wavelet decomposition based de-noising method to remove the background noise mainly caused by the wiring and measurement system flaws. The proposed approach has been validated using both simulated and experimental data.

I. Introduction

Machinery fault detection and diagnosis is a key step in preventive maintenance. Oil condition monitoring is one of the most important approaches to machinery fault detection and diagnosis. The oil condition data contain information about the size and quantity of metal debris in the oil and thus provide a direct perspective of the machine condition. In off-line oil analysis methods, oil samples are collected and later analyzed in laboratories. The analysis results can provide information about the health state of the mechanical components. Another approach uses a chip detector that utilizes magnetic collector to capture the metallic debris. An alarm system will then warn machine operators when the quantity of such debris reaches a predefined threshold [1, 2].

ODM (Oil Debris Monitor) 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. The operation of the ODM is based on sensing the electromagnetic disturbances caused by passing metallic particles [2]. This sensor generates a signature similar to a full period of a sine function 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.

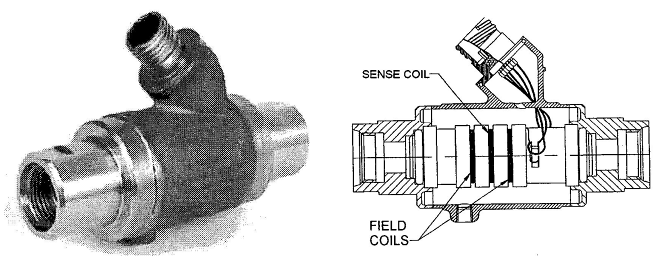
Figures 1a and b show a typical oil debris sensor. The output signature resulting from the passage of a metallic particle is shown in Figure 2. This signature is affected by the nature and size of the passing metallic particle. The phase of the signature depends on the nature (ferromagnetic or non-ferromagnetic) of the passing particle and the amplitude depends on the mass of the particle for ferromagnetic metals and on the surface area of the particle for the non-ferromagnetic metals [2]. Following the measurements using the sensor the built-in software counts the number of such signatures contained in the signal and estimates the size and nature of each particle through the corresponding amplitude and phase information. As a result, an estimate of the damage level could be obtained and if necessary an alarm regarding the health state of the machinery would provide time for scheduled maintenance and consequently reduce unplanned production delays or in-flight shut-downs in the aircrafts [2, 3]. The minimum detectable size particle depends on the sensor bore size. For the ½” sensors used in F119 engines this minimum size is 125 microns. This sensor has shown superior performance compared to the traditional magnetic chip collector. It is sensitive to non-ferromagnetic particles as well and requires no periodic inspection or cleaning as it does not block the passing metallic debris [2].

However, like many other measuring devices the performance of the sensor is affected by the noise and interferences that contaminate the signatures of interest. The interferences are due to vibrations of the structure where the sensor is mounted and manifest as addition of a combination of modulated sinusoidal signals to the sensor output. This masking effect leads to malfunction of the fault estimation system and causes false alarms or leaves existent faults

Ming Liang is with the Mechanical Engineering Department, 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 Mechanical Engineering Department, University of Ottawa, Ottawa, Ontario, Canada, K1N 6N5. (e-mail: isoltani@uottawa.ca).

undetected. Figure 3a shows the original output of an oil-debris sensor in response to the consecutive passage of two particles without any interference, sampled at 8000 Hz. Figure 3b displays the output of the system with added simulated vibration interference. As one can see it is not possible to detect the passage of metallic particles from the noisy signal.



(a) (b)

Fig. 1. (a) Oil debris sensor (b) Sensor cross section (Miller and Kitaljevich 2000)

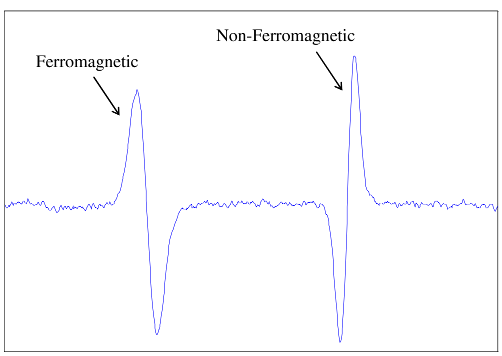


Fig. 2. Sensor output in response to the passage of a metallic particle

Though not as disturbing as the vibration related interferences, background noise due to the wiring and measurement system flaws also affects the performance of the system specifically in the case of the very small particles where the corresponding signatures can be easily masked by the corrupting noise.

One possible approach for removal of the vibration interferences is the adaptive noise cancellation (ANC) method. In this approach a reference signal correlated with the interfering signal is required. Such reference signal can be obtained by installing additional vibration sensors to the structure where the oil debris sensor is mounted. In this paper, a variation of the above noise cancellation scheme, adaptive line enhancement (ALE) technique, is used to enhance the oil debris output signal. The notion of adopting ALE will be explained in section 2. Following the ALE step, a wavelet decomposition based de-noising method is applied to remove the background noise. The proposed de-noising scheme is evaluated using the oil-debris signals with simulated vibration interferences as well as the signals measured from the sensor mounted on an electrodynamic shaker.

Hereafter, this paper is organized as follows: In section 2 we provide a brief introduction to Adaptive Line Enhancement (ALE) technique and its application in vibration interference removal. Section 3 explains the wavelet decomposition based de-noising method and applies it to further enhance the partly purified signal achieved through the ALE step. The proposed de-noising algorithm is evaluated on both simulated and experimental data in section 4. Section 5 concludes this paper.

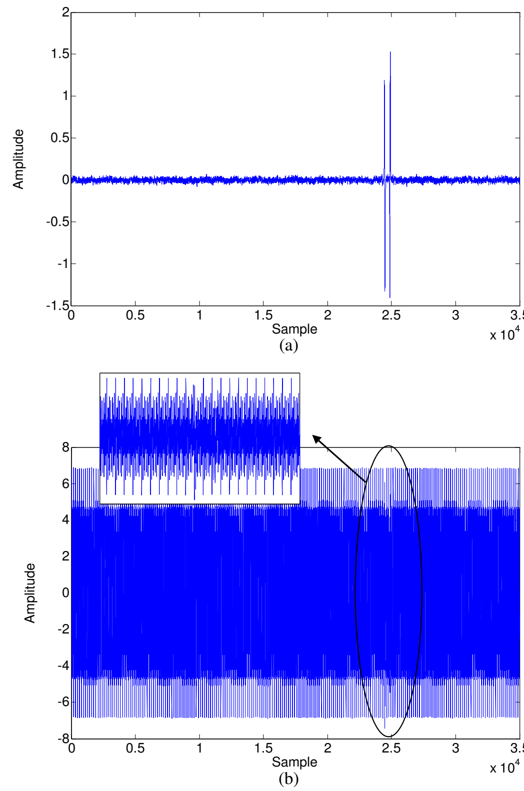


Fig. 3. (a) The output of the sensor due to two consecutive metallic particle passages (Particles: ferromagnetic, diameter = 175 µm and non-ferromagnetic, diameter = 508 µm) (b) Output Signal + $2\sin(1400\pi t)(1+\cos(900\pi t))+2\sin(2000\pi t)(1+\cos(700\pi t))$

II. Adaptive Line Enhancement and its Application in Vibration Interference Removal

A filtering process designed to eliminate the noise components and pass the signal components can lead to an estimate of the signal corrupted by noise. These filters can be either fixed or adaptive. A fixed filter can be designed when adequate prior knowledge about both signal and noise is available whereas an adaptive one works by adjusting certain parameters dynamically to compensate for the lack of such information.

The frequency content of the particle signals are mainly dependent on the speed in which the metallic particles pass through the sensor. This is associated with the lubricating oil flow speed. The vibration interferences on the other hand depend on the vibrations of the structure where the sensor is mounted. Accordingly, it is obvious that both signal and interference attributes are entirely dependent on the working conditions of the machinery and are unknown beforehand for the purpose of filter design. Consequently, an adaptive system capable of adjusting filter parameters according to the working conditions of the machinery is desirable.

Adaptive noise cancellation makes use of a reference input correlated with the corrupting noise. The reference input is filtered to find an estimate of the corrupting noise by minimizing the mean square error. Subtraction of this filtered signal from the primary input results in a signal with higher signal to noise ration (SNR). The block diagram of the ANC approach is shown in Figure 4.

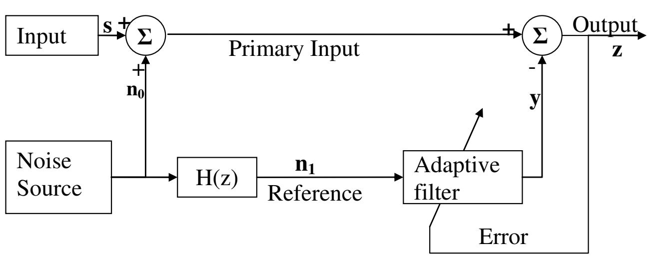


Fig. 4. Adaptive Noise Cancellation technique

Assume that s, n_0, n_1 and y are statistically stationary with zero means (Figure 4). Assume that s is uncorrelated with n_0 and n_1 but n_0 is correlated with n_1. The output z is then

$$z = s + n_0 - y$$

By squaring both sides of the equation and taking the expectation, we have [4]

$$E\left\{z^2\right\} = E\left\{s^2\right\} + E\left\{(n_0 - y)^2\right\} + 2E\left\{s(n_0 - y)\right\}$$
$$= E\left\{s^2\right\} + E\left\{(n_0 - y)^2\right\}$$

As the above equation shows, by minimizing $E\left\{z^2\right\}$ the signal power $E\left\{s^2\right\}$ remains unaffected and $E\left\{(n_0 - y)^2\right\}$ approaches zero by proper adjustment of the filter coefficients. As a result, filter output y represents an estimate of noise n_0 in the minimum mean square error sense.

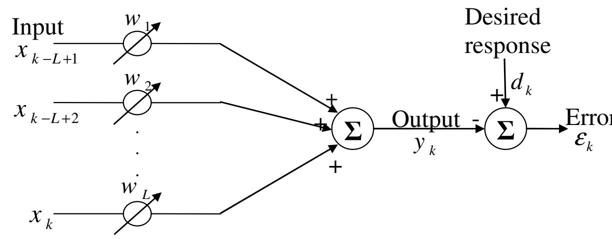


Fig. 5. Adaptive linear filter

Now let us consider the linear filtering process shown in the Figure 5 where x is the input vector, w the filter weight vector, y the filter output and d the desired output of the filter. The purpose of this filtering process is to find an estimate of a desired signal d in the minimum mean square error sense through linear filtering the signal x. Comparing this filtering process with the ANC method explained above, we see that in the ANC the primary input plays the role of the desired signal. Assuming linear filtering with weight vector W of length L, we can write [5]

$$E\left\{\varepsilon_k^2\right\} = E\left\{d_k^2\right\} + W^T E\left\{X_k X_k^T\right\}W - 2E\left\{d_k X_k^T\right\}W \qquad (1)$$

The performance surface given in (1) is a quadratic function of the weight vector W [6]. Here we take a stochastic gradient approach known as Least Mean Square method. In this approach the noisy gradient is calculated from a single realization of matrix X and ε by taking the derivative of (1) with respect to W. In other words at each iteration in the adaptive process, we have a gradient estimation of the form

$$\hat{\nabla}_k = -2\varepsilon_k X_k$$

The corresponding steepest descent algorithm for filter weight matrix W update is defined as

$$W_{k+1} = W_k - \mu\hat{\nabla}_k$$

where μ is a gain constant or learning rate regulating the speed and stability of adaptation.

To apply ANC for interference removal from the output signal of the oil debris sensors, we need a reference signal correlated with the vibrations of the structure where the sensor is mounted. However, this method requires a vibration sensor and related hardware, which would substantially complicate the system and thus should be avoided.

Adaptive line enhancement (ALE) is a variation of the above approach and was first applied to the classical detection problem of finding a sine wave in noise [5]. The block diagram of the method is illustrated in Figure 6. This approach becomes appealing mainly due to the fact that the method uses a delayed version of the primary input as the reference signal. It is based on the assumption that there is no correlation between the noise samples.

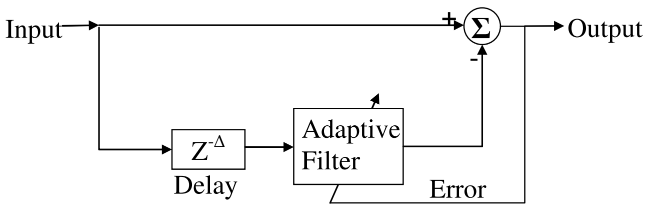


Fig. 6. Adaptive Line Enhancement technique

The same idea can be used in the oil debris sensor interference problem to avoid the use of extra sensors and associated hardware.

As the metallic particles pass through the sensor randomly, there would be no correlation between their signatures. On the other hand, it is reasonable to assume that the rate of change of the vibration nature of any mechanical system is sufficiently slower than the adaptation rate of the ALE algorithm. In other words a delayed version of the measured signal will be correlated with the original signal due to such vibration interferences. As a result, following the same idea as that of using the ALE technique for sine wave detection, it would be possible to detect and eliminate such interferences.

In contrast to other adaptive systems, in this case very high adaptation rate is undesirable whereas it may also cause the particle signatures to be distorted or eliminated. As the characteristics of these signatures (phase and amplitude) are later used to assess the damage level of the machinery components, it is very important that the adaptive algorithm leaves the particle signals intact. To prevent such distortions in the particle signatures, filter weight vector is updated following a number of iterations. The update value is then calculated by averaging the weight vector changes found in these iterations, analogous to the Block LMS algorithm [6]. It should be noted that this method is unable to remove the white Gaussian noise included in the signal while noise samples are also expected to be uncorrelated. Such noises will be tackled later in a separate step using a wavelet decomposition based de-noising method.

Figure 7a shows the mixture of the particle signal shown in Figure 3a and simulated interferences. The de-noised version of the same signal mixture using the ALE approach with L=100, Δ=300 and μ=0.05 is presented in Figure 7b. As one can see, the metallic particles can be easily detected from the de-noising result.

$$\left\langle f, \psi(2^{-j}t-n)\right\rangle = \frac{1}{\sqrt{2^{j}}}\int_{-\infty}^{\infty} f(t)\psi(2^{-j}t-n)dt \qquad (2)$$

where $\left\langle \psi(2^{-k}t-m), \psi(2^{-j}t-n)\right\rangle = 0$ for $m \neq n$ or $j \neq k$.

The orthogonal wavelet transform provides a non-redundant wavelet representation. Then

$$f = \sum_{j=-\infty}^{\infty}\sum_{n=-\infty}^{\infty}\left\langle f, \psi_{j,n}\right\rangle \psi_{j,n} \qquad (3)$$

where $\psi_{j,n} = \frac{1}{\sqrt{2^{j}}}\psi(2^{-j}t-n)$.

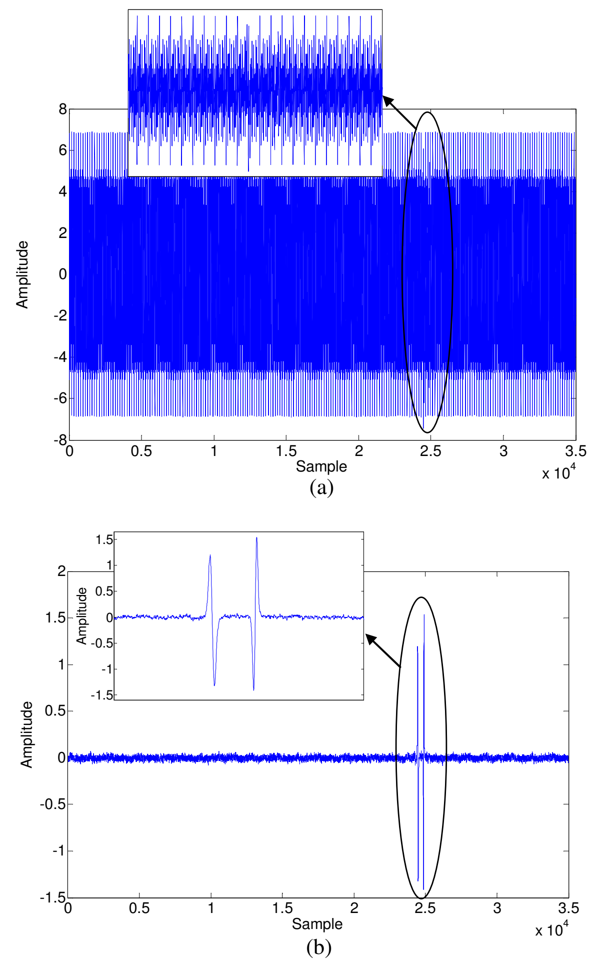


Fig. 7. a) Output Signal Shown in figure 3(a) $+2\sin(1400\pi t)(1+\cos(900\pi t))+2\sin(2000\pi t)(1+\cos(700\pi t))$

b) ALE result (Particles: ferromagnetic, diameter = 175 µm and non-ferromagnetic, diameter = 508 µm)

III. Wavelet Decomposition Based De-noising

Nevertheless, as mentioned above the proposed ALE method is unable to remove the white Gaussian background noise present in any measurement device since there is no correlation between such noise samples. To further enhance the signal achieved through the ALE step, a wavelet threshold de-noising scheme is proposed.

The wavelet transform is given by [7]

According to (3), the original function *f(t)* can be reconstructed using the wavelet coefficients given by (2). On the other hand, according to equation (2) the wavelet coefficients are the correlations of the function *f*(*t*) with the wavelet basis. With this interpretation, we expect to see higher wavelet coefficient values on the intervals where *f*(*t*) has higher correlation with the daughter wavelet or in other words where the wavelet describes the features of the function better. Bearing this concept in mind, it is possible to construct an approximation of the original function using the larger wavelet coefficients.

In the presence of noise, this approach is equivalent to hard threshold de-noising method. The thresholding function is defined as

$$\theta_T(x) = \begin{cases} x & \text{if } |x| \geq T \\ 0 & \text{if } |x| < T \end{cases}$$

where x is the wavelet coefficient and T is the threshold value. We have

$$\tilde{f} = \sum_{j=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \theta(\langle Z, \psi_{j,n} \rangle)\psi_{j,n}$$

where $Z = f + W$ and W is the white Gaussian noise.

As one can see, in this approach the wavelet coefficients larger than some threshold value are used for the reconstruction process and the rest of the coefficients are discarded.

Donoho and Johnston [8] proved that for the Gaussian corrupting noise, by applying the hard thresholding rule and using an appropriate threshold given below

$$T_j = \sigma_j \sqrt{2 \log_e N} \tag{4}$$

where N is the number of data points and $\sigma_j^{\,2} = E\left\{ \left| \langle W, \psi_{j,n} \rangle \right|^2 \right\}$, it is possible to have an estimation error that is within a factor of 2log2N of an ideal selection error. However, the noise variance σ_j should be known.

One possible approach for noise variance estimation would be to measure the system noise in the absence of any passing particles or structural vibrations. However, it should be noted that the system background noise characteristics may vary in accordance with the working conditions.

On the other hand, a variance estimator insensitive to large outliers in the data set was introduced as [7]:

$$\tilde{\sigma}_m = \frac{1}{0.6745} Med\left(\left| \langle W, \psi_{m,n} \rangle \right| \right)_{0 \leq n < \frac{N}{2^m}} \tag{5}$$

Following the same concept, for the signal containing particle signatures and white Gaussian noise, it is possible to consider the particle signatures as the outliers in the data set and use the above variance estimation method to calculate the threshold value. In this case no prior knowledge about the background noise is required.

In this study, we apply the hard thresholding method explained above to remove the background noises. The threshold value is calculated using (5) and Symlet 4 is chosen as the mother wavelet. As shown in Figure 8, applying the proposed wavelet threshold de-noising method to the partly purified signal shown in Figure 7b yields very clean particle signatures.

IV. Experimental Evaluation

To experimentally evaluate the proposed method, we acquired data using an oil debris sensor mounted on a shaker (Fig 9). A metallic particle embedded at the tip of a plastic catheter was manually passed through the sensor while the vibration was introduced by the shaker. Sampling frequency was set at 8000 Hz. The collected signal mixture is shown in Figures 10a. As the first step, the ALE was applied to enhance the signal. The ALE output is shown in Figure 10b. This result was then further enhanced using the proposed threshold de-noising scheme which leads to much cleaner result as plotted in Figure 10c. The passage of particle can be easily detected from the final de-noised result.

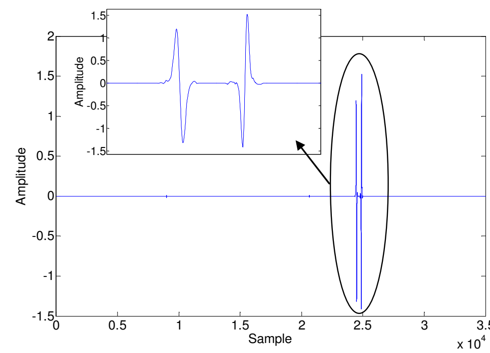


Fig. 8 Threshold de-noised version of the ALE result shown in fig. 7b (Particles: ferromagnetic, diameter = 175 µm and non-ferromagnetic, diameter = 508 µm)

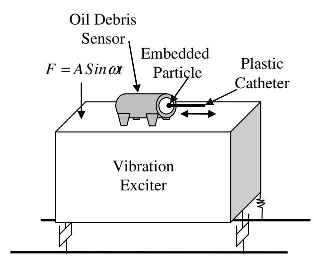
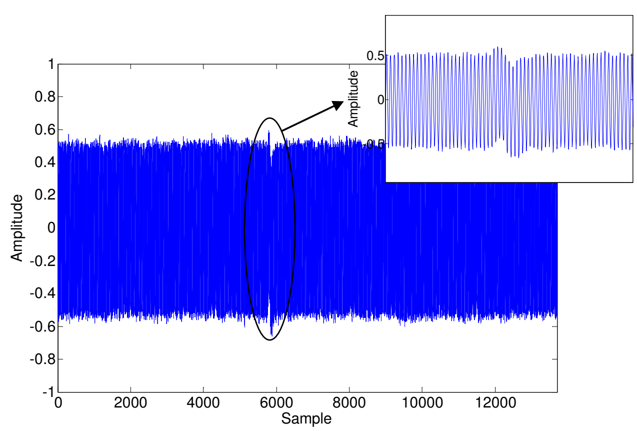
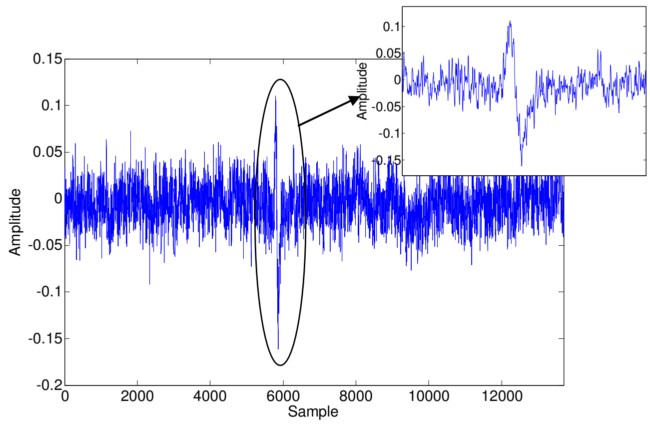


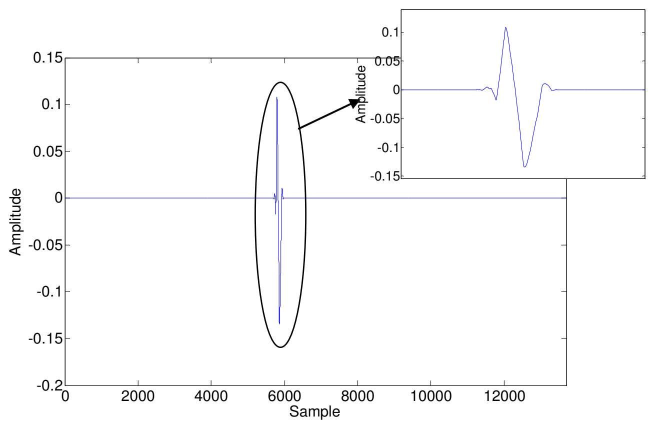
Fig.9 Schematic of test setup.



(a)



(b)



(c)

Figure.10 a) Measured signal mixture, b) Interference removal result obtained using ALE, and c) Result obtained after threshold de-noising the ALE output shown in part (b) (Particle: ferromagnetic, diameter =125 µm, shaker frequency = 500 Hz)

V. Conclusion

In this paper, a two-stage approach is proposed to enhance the detectability of metallic particles in the ODM signal. In the first stage, the ALE technique was applied to eliminate the vibration related interferences from the oil debris signal. The ALE method is well suited for interference elimination because: a) the passage of metallic particles holds a random nature and consequently there would be no correlation between the corresponding signatures, and b) the change rate of the vibration pattern of the mechanical system is much slower than the adaptation rate of the filter. As the ALE method is unable to remove the white Gaussian background noise caused by the wiring flaws and electrical interferences, wavelet hard threshold de-noising method is then applied following the ALE step. The proposed de-noising approach was evaluated using simulated and experimental data and performed very well in both cases.

References

[1] Dempsey, J. P., 2000, A comparison of vibration and oil debris gear damage detection methods applied to pitting damage. NASA report number: TM-2000-210371, Prepared for the 13th International Congress on Condition Monitoring and Diagnostic Engineering Management, Houston, Texas

[2] Miller, J. and Kitaljevich, D., 2000, In-line oil debris monitor for aircraft engine condition assessment, IEEE Aerospace Conference Proceedings, Big Sky, MT, USA, 6, 49-56.

[3] Industry Canada, 2007, http://strategis.ic.gc.ca/app/ccc/search/navigate.do?language=eng&portal=1&subPortal=&estblmntNo=123456056194&profile=completeProfile

[4] Widrow, B., Glover, J. R., McCool, J. M., Kaunitz, J., Williams, C. S., Hearn, R. H., Zeidler, J. R., Dong, E. and Goodlin, R. C., 1975, Adaptive noise cancelling: principles and applications. Proceeding of the IEEE, 63(12), 1692-1716.

[5] Widrow, B. and Stearns, S. D., 1985, Adaptive signal processing, (Englewood Cliffs, N.J.: Prentice-Hall).

[6] Haykins, S., 2002, Adaptive filter theory, (Upper Saddle River, N.J.: Prentice Hall).

[7] Mallat , S., 1998, A Wavelet Tour of Signal Processing, (San Diego: Academic Press).

[8] Donoho, D. L. and Jonestone, I. M., 1994, Ideal spatial adaptation via wavelet shrinkage. Biometrika, 81, 425-455.