Application of Blind Deconvolution with Crest Factor for Recovery of Original Rolling Element Bearing Defect Signals

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볼 베어링 결함신호 복원을 위한 파고율을 이용한 Blind Deconvolution 의 응용

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Key Words : Rolling element bearing(구름 요소 베어링), Condition monitoring(상태감시), Blind deconvolution, Crest factor(파고율), Signal processing(신호처리), Vibration detection(진동감시)

Abstract

Many machine failures are not detected well in advance due to the masking of background noise and attenuation of the source signal through the transmission mediums. Advanced signal processing techniques using adaptive filters and higher order statistics have been attempted to extract the source signal from the measured data at the machine surface. In this paper, blind deconvolution using the eigenvector algorithm (EVA) technique is used to recover a damaged bearing signal using only the measured signal at the machine surface. A damaged bearing signal corrupted by noise with varying signal-to-noise (s/n) was used to determine the effectiveness of the technique in detecting an incipient signal and the optimum choice of filter length. The results show that the technique is effective in detecting the source signal with an s/n ratio as low as 0.21, but requires a relatively large filter length.

1. INTODUCTION

In order to remain profitable and competitive, it is often necessary to extend the production capability of the machine until symptoms of possible failure occurs. Continuous condition monitoring of the machine's health is therefore necessary. One of the major components in rotating machineries is the rolling element bearing, which provides rotating motion and at the same time carries heavy load over a small surface area.

Although the life of rolling element bearings can be calculated based on the load and the rotating speed, catastrophic failure of these bearings can occur prematurely due to unpredicted static and dynamic loading, geometry of the housing, shaft and bearing, pre-load and maintenance personnel [1]. Numerous techniques are now available to detect rolling element bearing failures but the suitability of the techniques varies from systems to systems.

Detection of an internal malfunction via vibration analysis is widely used, such as shock pulse, statistical analysis (crest factor, kurtosis and rms level) and frequency based detection techniques [2]. Unfortunately, vibration analysis based on

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frequency and time domain analysis can only be effectively applied when the signal-to-noise (s/n) ratio is high. Early detection of an incipient failure requires special sensors and advanced signal processing techniques to detect symptoms of imminent. With a small s/n ratio, the source signal from a defective component is severely attenuated through the machine components until its final detection by sensors on the machine surface.

This requires the noise component in the overall vibration signal to be severely attenuated with a consequential improvement to the signal to noise ratio. One of the earliest methods to suppress noise component is the application of adaptive filtering techniques, such as adaptive noise cancellation (ANC) [3,4]. Other applications of adaptive signal processing include identifying rotating machine fault is described in [5] and detecting of tool wear [6]. Recently other signal processing techniques to enhance an internal defect have been introduced, such as auto-regressive technique [7] and application of higher order moment spectra analysis [8,9]. Although auto-regressive techniques have the potential for early detection of component defects but the complexity of these techniques made them difficult to implement and the authors [8] concluded that they should not replace conventional methods but supplement them.

Blind deconvolution (equalization) (BD) is a technique used to recover the desired signals from a single received channel without any priory knowledge about the channel. The technique is widely used in network communication since 1980s [10]. In the past 20 years numerous techniques have been proposed to enhance signal based on single input in a variety of applications [11-12]. A major advantage of BD is that it does not require a training stage, which is essential in conventional equalization.

In this paper, BD is applied to recover a rolling element bearing signal at source by analyzing the transmitted signal via an unknown channel and corrupted by noise at a measurement point. The technique utilizes a blind equalizer based on Eigenvector Algorithm (EVA). A damaged bearing with an outer ring defect is pre-recorded and corrupted by simulated gear and shaft noise. The measured signals with varying signal-to-noise ratios were used to test the effectiveness of the technique in detecting an incipient failure. Crest factor (CF) is used as a criterion to determine the optimum filter length of the equalizer. The results show that for a large s/n ratio, a small number of filters were sufficient to extract the original signal. As the s/n ratio gets small, the filter length increases.

2. BLIND DECONVOLUTION THEORY

BD refers to the reconstruction of a source signal through an unknown system using only the measured (observed) signal alone. Convolution is the computation of an output signal $v(k)$, given the knowledge of both the input signal $d(k)$ and the impulse response $h(k)$ of the system. Deconvolution refers to the determination of the impulse response of the system $h(k)$ where the output of the system $v(k)$ is typically accessible and the knowledge of the input (source) signal $d(k)$ is unavailable. Since the process is performed "blindly" to estimate the input signal, it is called blind deconvolution.

The observed signal from measurement is given by:

$$v(k) = h(k) * d(k) + n(k) \tag{1}$$

The output of the blind equalizer is denoted by $x(k)$,

$$x(k) = e(k) * v(k) \tag{2}$$

$$x(k) = \sum_{k=1}^{L} e(l) v(k-l) \tag{3}$$

The objective is to derive a set of equalizer coefficients $e(k)$ of the blind equalizer from the received data to determine an inverse of the impulse response of the system. Higher rate of convergence has been achieved through the use of higher order statistics (HOS) for the estimation of the coefficients of the equalizer [15]. In [15] EVA method with kurtosis (4^{th} order cumulant matrices) was used to extract impacting signals from a measured signal. The criterion is to maximize the cross-cumulant of the output signals and reference signals.

2.1 Eigenvector Algorithm (EVA) Approach

The schematic of the EVA approach is shown in Fig. 1. The input signal is a non-Gaussian independent, identically distributed (i.i.d.) sequence of variables with zero mean, finite variance σ^2, a non-zero kurtosis and the transfer function is a causal stable system (channel) having impulse sequence $h(k)$. The system is corrupted by Gaussian noise $n(k)$ with variance σ^2. The output from the system is given by $v(k)$. The application of BD is to create an inverse filter with coefficients $e(k)$ from the maximization of the higher order cross-cumulant of the system output signal $x(k)$ and the reference signals $y(k)$.

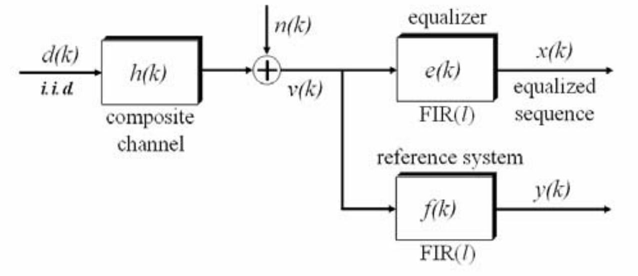


Fig. 1 Block diagram of the eigenvector approach

The reference Finite Impulse Response (FIR) filter $f(k)$ is introduced to generate an implicit sequence of training data with impulse response $f(k) = f(0), \ldots f(l)$ for subsequent use in the iterative process. The blind equalizer FIR has the same order of impulse response $e(k) = e(0), \ldots e(l)$. The equalization objective is to adjust the $(l+1)$ coefficients $e(k)$ so that the equalizer sequence $x(k)$ is as close as possible to the delay transmitted data $d(k-k_0)$ in the mean square error (MSE) sense [15].

$$MSE(e,k_0) \triangleq \sum \{|x[k]-d[k-k_0]|\}^2 \qquad (4)$$

where k_0 is the delay and l is the order of the FIR filter, the minimization of Eq. (4) leads to minimum mean square error, MMSE(l, k_0).

The solution to BD is based on a maximum cross-kurtosis quality function, similar to that shown in [12,14]. As the output from the equalizer $x(k)$ and reference FIR $y(k)$ can be only be derived from the observed signal $v(k)$, we may considered the two-dimensional fourth order cross-cumulant sequence as shown in [15]. Optimizing of the cross-cumulant leads to the well-known eigenvector solution,

$$C_4^{yv} e_{EVA} = \lambda R_{vv} e_{EVA} \qquad (5)$$

The coefficients of the equalizer vector $\mathbf{e}_{EVA} \triangleq [e_{EVA}(0), \ldots, e_{EVA}(l)]^T$ is obtained from the eigenvector of $\mathbf{R}_{vv}^{-1}\mathbf{C}_4^{yv}$ when the magnitude of the eigenvalue λ is at maximum.

3. SIMULATION STUDY

3.1 Experimental Rig

The machine faults simulated by this rig include a range of bearing faults, gear faults, unbalance and linear and angular misalignments. The variable speed motor has a speed range of up to 4000 rpm and the drive shaft through a belt drives the gearbox. The gear meshing frequencies can be varied by changing the dimensions of the shaft input pulley. Misalignment is generated by placing thin metal shims underneath the output-housing block.

In this study, an artificially damaged bearing with an outer race defect is installed in the housing block at the far end of the test-rig. With a rotating speed of 29.69 Hz and known dimensions of the test bearing, the impact frequency of rolling elements striking the defect produces an impulsive signal with an impact rate of 104.7 Hz. A pure defective bearing signal without machine faults in time domain and frequency domains are shown in Figs. 2 and 3, respectively. From Fig. 2 the impact periods are clearly visible but with varying amplitudes due to the non-linearity of the system. The frequency spectrum in Fig. 3 shows a number of prominent peaks relating to the fundamental damaged bearing frequency, f_b (104.5Hz) and higher harmonics (418Hz ($4\times f_b$), 525Hz ($5\times f_b$), 628Hz ($6\times f_b$)). The first peak at 60 Hz is caused by the motor noise and 88 Hz have not been investigated.

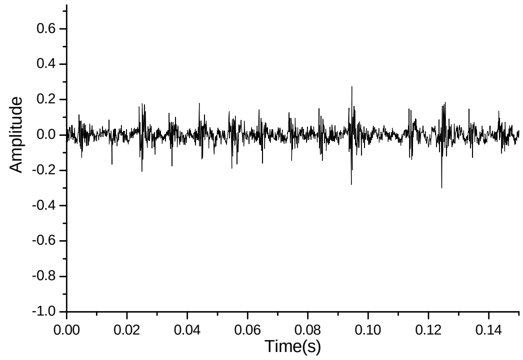


Fig. 2 Original damaged bearing signal

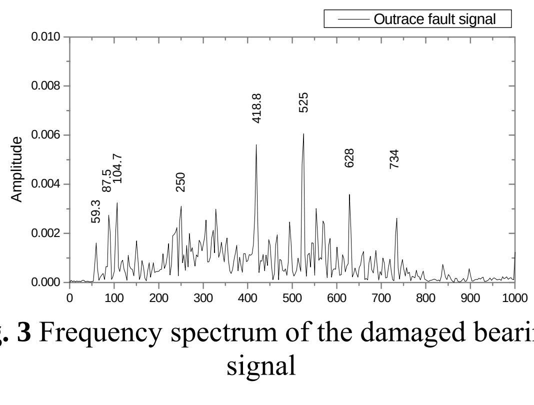


Fig. 3 Frequency spectrum of the damaged bearing signal

3.2 Simulation Model

The simulation model is to test the feasibility of using BD in recovering the source signal. A pure defective bearing impulsive signal was generated with a simulated defect on the bearing outer ring.

This signal represents the source signal $d(k)$ propagating through the unknown system (channel) $h(k)$ .The source signal is corrupted by a combination of periodic noise and instrumentation and cable noise to form a sequence of noise signal $n(k)$.

In this work it is assumed to have an unity impulsive response $h(k)$. The desired signal from the test-rig after passing through the A/D converter is stored in the computer. The convolution of the desired signal with the impulse response of the channel and the simulated noise are summed together to form the input $v(k)$ for the EVA process. The objective is to obtain an output signal $x(k)$ as close as possible to the original source signal.

4. APPLICATIONS

The EVA approach developed in [15] is chosen in this work for its simplicity and excellent performance. Proper choice of filter length is critical in the calculation of the eigenvectors.

In [15] it was shown that convergence rate strongly depends on the number of parameters to be updated that is the filter length of the equalizer. This is confirmed experimentally through simulation studies and a trial and error method to determine the optimum filter length [16].

This paper illustrates a practical approach in determining the optimum filter length using a computer simulation study. The EVA approach with crest factor as criteria for determining the filter number is compare to original signal`s crest factor. After initiating the fundamental parameters, the EVA algorithm will evaluate the coefficients of the equalizer and to use them to update the reference filter's coefficients.

At the end of the EVA process, the output results, for a particular filter length, from the equalizer will be compared with the known simulated source data. The initial Crest Factor, defined as the ratio of peak value over the root-mean-square (rms), before corrupted by simulated noise and the Crest Factor of the output results after EVA will be used as a feature for determining the optimum filter length. In this paper, the algorithm will be terminated if the output result is within 10% of the initial Crest Factor.

5. SIMULATION TEST

This study is to determine the effectiveness of BD techniques in detecting a source signal corrupted by noise. The source signal (shown in Fig. 3) is a known damaged bearing signal with a crest factor of 4.628 and an rms level of 0.0343v. The corrupting noise consists of a 50 Hz component and a 350 Hz component with two sidebands to represent an unbalance and a gear fault, respectively.

With a low level of corruption, it is obvious that damaged bearing signals are still visible. With a low s/n ratio, the bearing signals are totally buried in noise. The amplitudes of corrupted noise in relation to the bearing signals for the various s/n ratios are shown.

As the noise level increases, it becomes difficult to identify the periodic components of the damaged bearing. With the s/n ratios lower that 0.14, the damaged bearing component is totally buried in noise as shown in the frequency plots in Fig. 4.

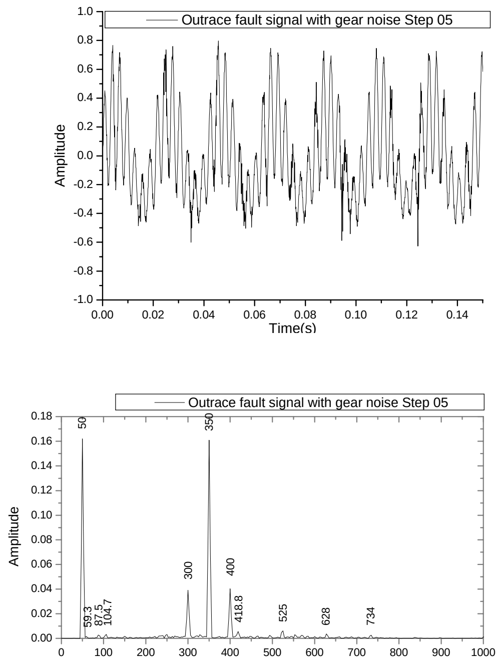


Fig. 4 Bearing signals corrupted by large level noise with s/n ratio = 0.1404

6. RESULT AND DISCUSSION

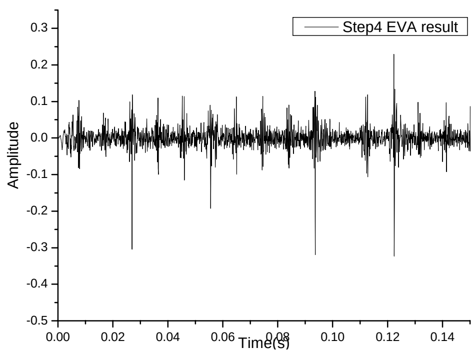
In this paper, crest factor is used as the target for determining the optimization of the blind equalizer filter length. As the CF hits the threshold level of ±10% of the original damaged CF, the program will terminate. A high s/n ratio needs a shorter filter length, while a low s/n ratio requires a larger filter length. For input signals with an extremely low s/n ratio (0.1404), the current test set up was not able to obtain an optimum filter length and the extraction of the original bearing signals. This reason for this could be due to insufficient filter length in the program or signal component is too low for the EVA to detect.

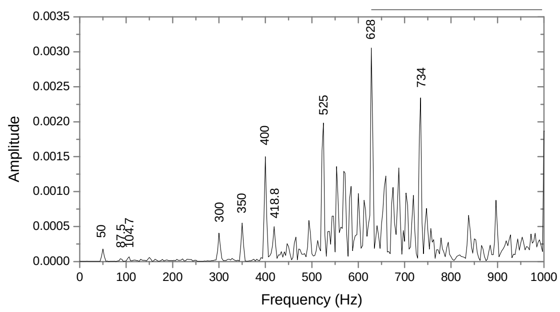
The original rms value of the damaged bearing signal is 0.0434. For higher s/n ratios the output rms levels were relatively consistence with the original value. However, as the s/n ratio gets smaller, the rms level started with a relatively high value, then dropped after some iteration and rose again to high values. This is probably the reason for the low CF values due to the high rms levels and small peaks. The result finally converges to the original CF and the rms value converges to the original rms value. For an extremely small s/n ratio, the result does not seem to converge to the original CF.

The EVA output results in time and frequency plots for the range of s/n ratios are shown in Fig. 5. All the time domain plots are identical to the original bearing signals shown in Fig. 3.

In the frequency plots show remnants of noise components after the EVA process, although are much smaller in amplitudes. These values do not seem to affect the time domain signal of the original damaged bearing signal. The original amplitudes (unfiltered) of the major frequency components and the amplitudes after the EVA process (filtered) are shown in Table 1.

A comparison of the unfiltered frequency components to those of filtered is shown in Tables 1 and 2. It can be seen that the 50Hz component in Step 1 (s/n = 4.2136) has a reduction of 0.5394/ 0.0167 and in Step 4 (s/n = 0.2105) has a reduction of 10.795/0.0176. This shows that the noise component has been severely suppressed. The amplitude reduction in Step 1 and Step 4 are 0.4457/0.0877 and 10.6921/0.00551, respectively. On the other, the original source signal has only a small fluctuation of the original amplitude. For example, the 628Hz component, the change in Step 1 and Step 4 are 0.3577/0.1244 and 0.3578/0.3054.





s/n ratio = 0.1404

Fig. 5 Results of EVA

7. CONCLUSION

Proper choice of EVA equalizer filter length in the blind deconvolution is critical in the recovery of the original signal corrupted by noise and the convolution of the signal with the channel during the transmission process. The results conclude that with a high signal-to-noise ratio (s/n = 4.2), a low level of corrupting noise and high signal, the EVA process needs only 14 coefficients of the filter length. As the noise level increases, with a consequential reduction of s/n ratio, the filter length increases. For an s/n ratio of 0.21 the filter length is 78. With an extremely low s/n ratio (s/n = 0.14), the EVA failed to recover the original signal for a filter length of up to 80 coefficients. Work is now in progress to apply the technique in enhancing real life bearing signal with an extended filter length to test the limiting s/n ratio for successful application of the technique.

Table 1 Amplitude ratios of major frequency components

Signal Frequency	Step 1		Step 2		Original Value
	Unfiltered	Filtered	Unfiltered	Filtered	
50Hz	0.5394	0.0167	3.2372	0.0840	0
59Hz	0.1625	0.0058	0.1625	0.0048	0.1611
87.5Hz	0.2740	0.0144	0.2740	0.0115	0.2742
104.7Hz	0.3245	0.0201	0.3245	0.0155	0.3245
300Hz	0.0682	0.0118	0.6700	0.0184	0.1584
350Hz	0.4457	0.0877	3.1348	0.0699	0.1475
400Hz	0.1467	0.0327	0.7979	0.0754	0.0884
418.8Hz	0.5613	0.1313	0.5613	0.0711	0.5613
525Hz	0.6044	0.1763	0.6044	0.2107	0.6049
628Hz	0.3577	0.1244	0.3578	0.2107	0.3578
734HZ	0.2622	0.1040	0.2622	0.2009	0.2622

Table 2 Amplitude ratios of major frequency components.

Signal Frequency	Step 3		Step 4		Original Value
	Unfiltered	Filtered	Unfiltered	Filtered	
50Hz	5.4065	0.0174	10.7950	0.0178	0
59Hz	0.1625	0	0.1625	0.0039	0.1611
87.5Hz	0.2740	0.0071	0.2740	0.0039	0.2742
104.7Hz	0.3245	0.0123	0.3245	0.0069	0.3245
300Hz	1.2040	0.0895	2.5571	0.0406	0.1584
350Hz	5.2938	0.0149	10.6921	0.0551	0.1475
400Hz	1.3126	0.1496	2.6841	0.1502	0.0884
418.8Hz	0.5613	0.0905	0.5613	0.0497	0.5613
525Hz	0.6044	0.2725	0.6044	0.1982	0.6049
628Hz	0.3578	0.2220	0.3578	0.3054	0.3578
734HZ	0.2622	0.1452	0.2622	0.2343	0.2622

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