APPLICATION OF SOME ADVANCED SIGNAL PROCESSING TECHNIQUES FOR ROLLING ELEMENT BEARING FAULT DETECTION

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Summary

Vibration response of rotating machines is typically mixed and corrupted by a variety of interfering sources and noise, leading to the necessity for the isolation of the useful signal components. A relevant frequently encountered industrial case is the need for the separation of the vibration responses of the same type of bearings inside the same machine. For this purpose, a Blind Source Separation procedure is applied, based on the maximization of the information transferred in a neural network structure. As has been proven, this approach is quite effective in separating signals with super-Gaussian distributions, as it is the case of the vibration response of defective rolling element bearings. The role of the non-linear sigmoid function used in the neural network of the method is discussed and the Kullback-Leibler information divergence is considered as a tool to adapt this non-linearity to the bearing distributions considered. The effectiveness of the method is demonstrated in an experimental application, where a class of optimum non-linear functions is compared to the classical logistic function.

Key words: defective rolling element bearings, blind source separation, neural networks.

ZASTOSOWANIE ZAAWANSOWANYCH METOD ANALIZY SYGNAŁU W WYKRYWANIU USZKODZEŃ ELEMENTÓW TOCZNYCH ŁOŻYSK

Streszczenie

Sygnał drganiowy maszyn wirujących jest zazwyczaj zakłócony przez interferujące z nim sygnały innych źródeł oraz zakłócenia, co prowadzi do potrzeby ekstrachowania użytecznych składowych takiego sygnału. Często spotykanym w praktyce przemysłowej przypadkiem jest potrzeba separacji sygnałów drganiowych pochodzących od łożysk tego samego typu znajdujących się w tej samej maszynie. Do tego celu zastosowano procedurę ślepej separacji sygnałów wykorzystującą maksymalizację informacji przenoszonej przez strukturę sieci neuronowej. Zostało udowodnione, że w przypadku analizy sygnału wibroakustycznego generowanego przez uszkodzony element łożyska tocznego, takie podejście do separacji sygnałów może być efektywne przy założeniu ich super-gaussowskiego rozkładu.

Rozważono możliwość adaptacji nieliniowej funkcji sigmoidalnej i dywergencji informacji Kullback-Leibler'a jako narzędzi wykrywania nieliniowości w sygnałach. W celu dostosowania nieliniowości do rozkładów sygnałów łożysk wykorzystywano nieliniową funkcję sigmoidalną oraz rozbieżność informacji Kullback-Leibler'a. Efektywność przedstawionej metody została zaprezentowana na przykładzie, w którym klasa optymalnych nieliniowych funkcji jest porównywana z klasycznymi funkcją logistyczną.

Słowa kluczowe: diagnostyka łożysk, ślepa separacja sygnałów, sieci neuronowe.

INTRODUCTION

Although condition monitoring and fault diagnosis of rotating machines based on their vibratory and acoustical response has emerged to a dominating industrial practice, many practical problems are still encountered, since the vibration and especially the acoustical response is usually corrupted by other interfering sources and noise. In this case, methods for the decomposition of the measured signals into a number of independent components are quite important, so that the individual signal sources can be analyzed separately. In source separation the problem is to recover a set of independent sources when only a set of measurements are available, in which the sources have been mixed by an unknown channel (Blind Source Separation, BSS). The Blind Source Separation methods first emerged as an extension to the well-known Principal Component Analysis (PCA) by Comon [1]. In this approach, first, PCA is used to achieve independence up to second-order statistics, and then higher order cumulants are calculated, such as the third and fourth order cumulants.

Since then, several other alternative procedures have been proposed [2-9]. Due to their effectiveness and generality, BSS approaches have found in the recent years a number of applications in rotating machinery condition monitoring [9-14].

In this paper, the problem of separating vibration signals generated by defective rolling element bearings under simultaneous defects, especially of the same type mounted inside the same machine, is addressed, using the infomax algorithm, proposed by Bell-Sejnowski [3] . This method results to an unsupervised learning algorithm, based on entropy maximization in a single-layer feed forward neural network.

First, the basic theoretical principles of the method applied in this paper, are briefly reviewed. Then, the role of the non-linear sigmoid function used in the neural network is discussed and the Kullback-Leibler information divergence is considered as a tool to adapt this non-linearity to the bearing distributions considered. Finally, a class of optimum non-linear functions is compared to the classical logistic function in an experimental application.

1. REVIEW OF BASIC THEORETICAL CONCEPTS

The simplest BSS model involves N unknown, statistically independent source signals $s_i(t)$, i=1,N, which are assumed to be instantaneously mixed by an unknown linear NxN matrix A, resulting to N observation (measured) signals $x_i(t)$, i=1,N:

$$x(t)=As(t) \tag{1}$$

$$s(t)=[s_1(t), \dots , s_N(t)]^T \tag{2}$$

$$x(t)=[x_1(t), \dots , x_N(t)]^T \tag{3}$$

The goal of the Blind Source Separation in this case is to find a linear NxN separating matrix W without any prior knowledge of the matrix A and the probability distribution of the source signals $s(t)$, such that the components of the reconstructed signals:

$$u(t)=Wx(t) \tag{4}$$

$$u(t)=[u_1(t), \dots , u_N(t)]^T \tag{5}$$

are mutually independent and approximate as close as possible the source signals $s(t)$.

The source separation criterion focuses on finding the spatial diversity of the measured signals $x(t)$. Since the distribution of a sum of independent random variables tends towards to a more Gaussian distribution than any of the original random variables, the goal of the BSS methods is to find a way to maximize the nongaussianity of $W \cdot x(t)$, in order to extract each one of the independent components. As a consequence, the sources, except one, must be non-Gaussian.

In order to measure the the nongaussianity of the signals in Eq (4), several methods theoretically equivalent have been proposed [8], such as higher order statistics (e.g. kyrtosis), negentropy (including simplified approximations of it), mutual information, maximimum likelihood, etc. The BSS method proposed by Bell and Sejnowski [3], presented graphically in Fig. 1, maximizes the mutual information $I(y,x)$ that the output y of a neural network contains about its input x:

$$I(y,x)=H(y)-H(y/x) \tag{6}$$

where H(y) is the entropy of the output, the conditional entropy H(y|x) is the amount of the entropy contained in the output which is not derived by the input, and g() is the nonlinear sigmoid function used in the neural network:

$$y=g(Wx+w_0) \tag{7}$$

The method results to a self-organizing algorithm which, in the case of the assymetric generalized logistic sigmoid [3],

$$y'=dy/du=y^p(1-y)^r \tag{8}$$

updates the weights of the neural network (elements of the unmixing matrix W) according to the following rules:

$$\Delta W \propto [W^T]^{-1}+p(1-2y)x^T \tag{9}$$

$$\Delta w_0 \propto p(1-2y) \tag{10}$$

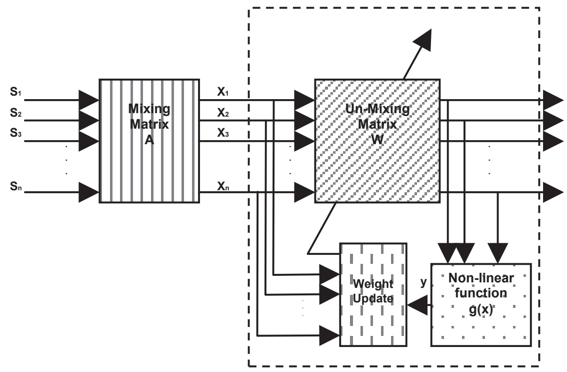


Fig. 1. Block diagram of Bell-Sejnowski approach [3] to BSS

The effectiveness of the method lies is the fact that when the inputs are processed by a sigmoid function, maximum information transmission is achieved when the slopping part of the sigmoid is optimally lined up with the high density parts of the inputs. Thus, the approach converges when the high density part of the probability density function of the input data *x* is aligned with the highly sloping parts of the function *g(x),* and the slope of *g(x)* is matched to the variance of *x*. Hence, the sigmoid function *g(x)* should be monotonically increasing, must have sloping sections and should be adapted to fit the data.

2. EFFECT OF THE SIGMOID FUNCTION

The typical probability density functions of the vibratory response of defective bearings are sharply peaked and have long tails. It is well known [15] that the kurtosis of these probability density functions is greater than zero and thus, they are classified as super-Gaussian. Hence, proper forms of non-linearities have to be additionally evaluated in this specific problem.

One way to do this, is to adapt the flexible sigmoid described by the differential equation (8), as close as possible, the distribution of the input signals emitted by defective bearings. The integration of Eq. (8) for various coefficients p and r produces a series of sigmoid functions, which can be suitable for the input cumulative distributions. The values of the coefficients p and r, which are subsequently considered to be equal since no skew is allowed in the distributions, are chosen via an optimization process.

For this reason, it is necessary to use a performance measure, which will be minimized. Such a suitable measure is the Kullback-Leibler information divergence, used to estimate a pseudo-distance among the stimulus' pdf and the slope of the sigmoid. The Kullback-Leibler information divergence represents the relative entropy and can be expressed by the following equation,

$$KLD(p_x // p_y) = \int p_x(s) \log[p_x(s)/p_y(s)]\, ds \qquad (11)$$

where p_x is the stimulus' statistical distribution and p_y is the slope produced by the chosen sigmoid. The smaller the relative entropy, the more similar the distribution of the two variables, and conversely. Since the measure is asymmetrical, the difference between KLD(p_x//p_y) and KLD(p_y//p_x) is used to estimate the minimum mismatch measure which can detect if the sigmoid slope fits the bearing vibration distributions.

3. EXPERIMENTAL APPLICATION

A characteristic case of two defective rolling element bearings of the same type with an outer and inner race fault respectively, mounted on the same shaft, is examined. The measurements were conducted on a machine fault simulator carrying a ½ HP DC motor whose rotation speed could be varied up to 4,000 rpm. The DC motor rotates via belt a rotor whose platform is fixed on the motor base. The rotor structure consists of a shaft, two bearings of SKF 7303 BEP type, and two rotor disks. The laboratory test bench is indicated in Fig. 2.

The measuring device is based on a Pentium II/266 MHz portable computer, equipped with a PCMCIA 6024E data acquisition card. Two accelerometers are mounted vertically on the top of the bearing housings A and B respectively (Fig. 2). Parallel, two B&K accelerometers, are mounted vertically on the points C and D of the motor base. All the measured signals were recorded simultaneously by the accelerometers on the points A, B, C and D. Each measured signal is 8,192 samples long and recorded with sampling rate of 10 KHz. The shaft rotation speed during the measurement was around 2,125 rpm (=35.4 Hz).

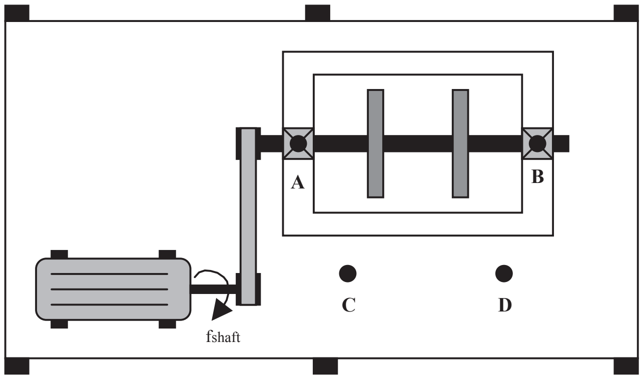
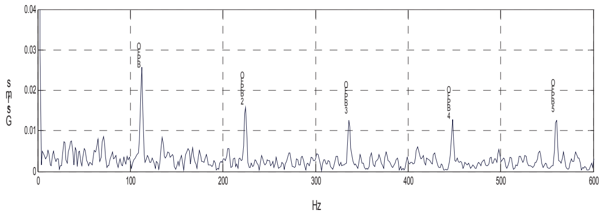


Fig. 2. Sketch of the test bench and the measurement points

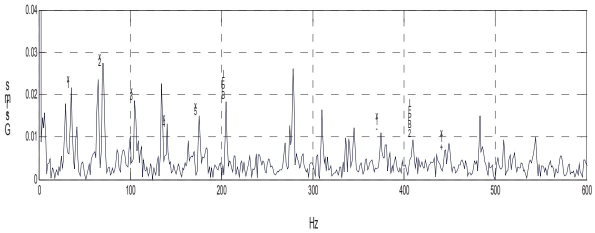
The monitored bearing in the housing B corresponds to an outer race fault. The characteristic defect frequency is estimated to 3.47 times the shaft rotation speed, leading to a theoretical estimation of the BPFO frequency around 123 Hz. The measured bearing defect frequency BPFO is equal to 112.30 Hz. The envelope analysis of the measured signal is presented in figure 3(a), confirming a typical bearing outer race fault.

The kurtosis of the signal, acquired by the sensor mounted on position B, is equal to 0.7 and its pdf is illustrated in figure 4(a). The signal can be classified as super-Gaussian due to the fact that the kurtosis is greater than zero.

Furthermore, an inner race wear has artificially introduced at the monitored bearing in the housing A. The theoretical estimation of the characteristic defect frequency BPFI is evaluated to 5.53 times the shaft rotation speed, leading to a value around 196 Hz.

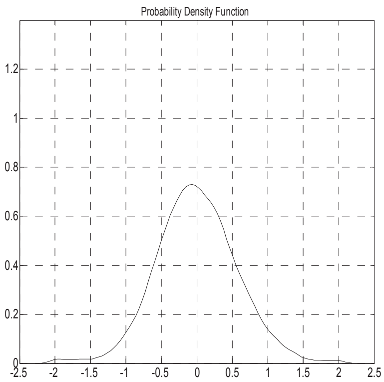


(a)

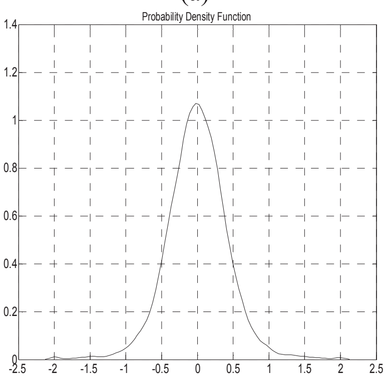


(b)

Fig. 3. Envelope analysis of (a) the first source signal measured on B with an outer race fault and (b) the second source signal measured on A with an inner race fault



(a)



(b)

Fig. 4. Probability density functions (pdf) of the source signals measured on positions (a) B and (b) A

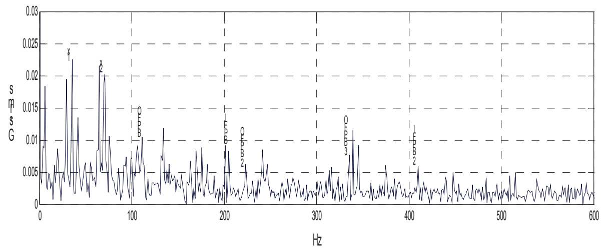
The spectrum of the envelope of the second source signal, shown in figure 3(b), is characterized by two spectral line families: a) the shaft rotational frequency component and its harmonics, and b) the defect frequency BPFI (=205.00 Hz) and its second harmonic. The presence of the bearing inner race defect frequency (BPFI), the shaft speed frequency and their harmonics reveals and confirms the inner race fault.

This measured signal can be characterized as super-Gaussian, since its kurtosis is equal to 2.3. The pdf plot of the signal is shown in figure 4(b).

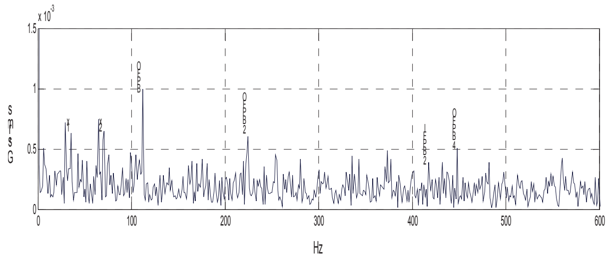
It should be clarified that the above signals were measured as close as possible on each source in order to be used as an priori knowledge about the sources.

The source separation procedure can be viewed as a pre-processing step that improves the diagnosis in the case where we cannot obtain measurements close enough to the bearings of the same type that are mounted inside the same machine, or even on the same shaft. According to this scenario, two accelerometers are placed on the points C and D on the motor platform and measure mixtures of all the sources. Hence, the contribution of each damaged bearing is received by each sensor.

Figure 5 displays the spectra of the envelopes observed signals. Not any specific filtering procedure is used in the demodulation process. The interpretation of the frequency domains produced by the demodulation process is indeterminate. Thus, it is impossible to detect and distinguish the type of damage of each individual bearing, since both bearings are of the same type and mounted on the same shaft. The defect frequencies BPFO and BPFI and other frequency components, such as shaft rotation speed and its harmonics, govern both frequency domains.



(a)



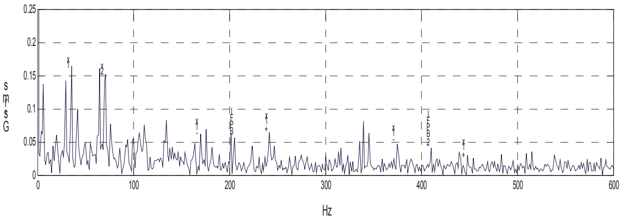
(b)

Fig. 5. Envelope analysis of (a) the first observed signal measured on point C and (b) the second observed signal measured on point D

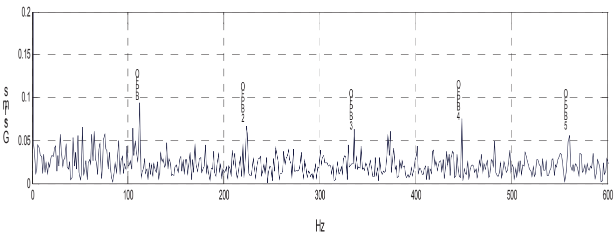
Additionally, the kurtosis of the observations measured by the accelerometers on positions C and D are equal to 1.2 and 0.6, respectively. Both signals are classified as super-Gaussian.

Then, the measured signals are processed by the proposed BSS approach using the logistic transfer function. The unmixed signals produced by the source separation process are post-processed using envelope analysis.

The spectrum produced by the demodulation process of the second unmixed signal [fig. 6(b)] is governed by the defect frequency BPFO and its harmonics. Thus, it is clear that the bearing in the housing B has a defect in the outer race. The envelope analysis of the other unmixed signal [fig. 6(a)] is dominated by the shaft speed frequency, the defect frequency BPFI and their harmonics.



(a)



(b)

Fig. 6. Envelope analysis of (a) the first unmixed signal and (b) the second unmixed signal

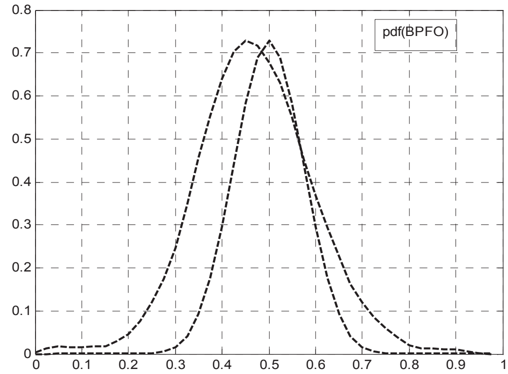
Thus, the method using the logistic function is able to separate the source signals in a set of mixed observations.

Then, the Kullback-Leibler information divergence algorithm is used to detect the optimum non-linearity that can approximate the cumulative distributions of both source signals.

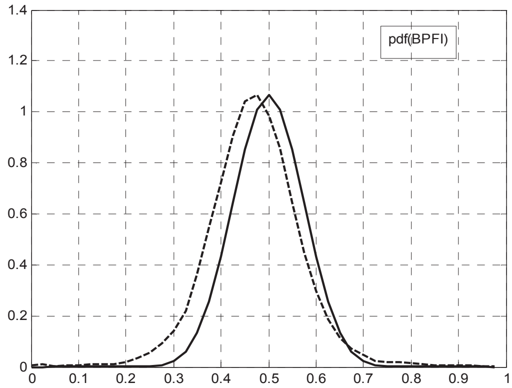
The optimum form of the non-linearity has to be selected for this specific application in order to validate if the algorithm can work more trustworthily and effectively. The coefficient p is estimated equal to 22.

Figure 7 illustrates the pseudo-distance among the distributions of the source signals and the slope produced by the optimum non-linearity. Then the neural network using this non-linearity, which has been constructed for p=22, tries to align its sigmoid function to the stimulus' pdf.

The results of the output of the algorithm for this optimum non-linearity are similar to the ones, where the sigmoid was the logistic function. Additionally, the Bell-Sejnowski algorithm has been implemented for several coefficients p, but the results remained unaltered.



(a)



(b)

Fig. 7. Probability Density Functions of the source signals (solid line) and slope of the resulting optimal sigmoid (dotted line) for p=21. (a) First source signal, (b) Second source signal

CONCLUSION

The applied infomax algorithm addressed successfully the problem of separating simultaneous fault signals generated by defective rolling element bearings in the experimental application. This is due to the fact that the matching neurons used, are able to cope to the super-Gaussian distributions of the measured signals. As additionally concluded from the experimental results, some further enhancements to the method are useful, in order to compensate certain effects of the transmission path. For example, although enveloping has been successfully applied in this case, other alternative procedures could be also followed, such as the usage of BSS methods based on a more complex mixing model.

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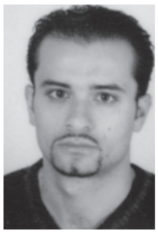

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