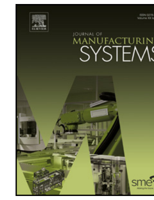
Journal of Manufacturing Systems 32 (2013) 529–535

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys



Technical paper

Dual-scale cascaded adaptive stochastic resonance for rotary machine health monitoring

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ARTICLE INFO

Article history:
Received 29 April 2013
Accepted 15 May 2013
Available online 21 June 2013

Keywords:
Weak signal detection
Noise-assisted method
Adaptive strategy
Frequency resolution

ABSTRACT

Effective extraction of weak signals submerged in strong noise that are indicative of structural defects has remained a major challenge in fault diagnosis for rotary machines. Unlike traditional techniques that focus on noise filtering and reduction, stochastic resonance (SR) takes a noise-assisted approach to detecting weak signals. This paper presents a new adaptive method for weak signal detection, termed Dual-scale Cascaded Adaptive Stochastic Resonance (DuSCASR), which can quantify the frequency content of a weak signal without prior knowledge. Simulations and experiments have confirmed the effectiveness of the method in bearing fault diagnosis at the incipient stage, with high precision and robustness.

1. Introduction

The importance of reconfigurable, condition-based machine health monitoring and fault diagnosis has been increasingly recognized to prevent unexpected machine failure, minimize costly down time, and reduce maintenance cost [1–3]. Because of the inherent link between machine operation and vibration, vibration signal analysis has been extensively investigated for defective component identification and localization. Considering the complex structural coupling among various components within a machine, representative features that are indicative of machine defects are often times submerged under strong noise as a *weak* signal, making machine health monitoring and fault diagnosis a significant challenge. The term 'weak signal' refers to a signal whose S/N ratio is so low that traditional frequency analysis is unable to identify the existence of the signal [4], and the challenges arise from the masking of the weak but useful signal component by the noise [5]. Traditionally, noise is considered an undesirable disturbance and source of signal contamination, and much research effort has been focused on removing noise for improved signal detectability. A general drawback of such filtering methods is that useful signal components may also be attenuated during the process. In recent years, noise-assisted data processing has been increasingly investigated as a viable method for weak signal detection [6,7], with stochastic resonance (SR) as a typical representative. The general idea for such techniques is to leverage the energy associated with noise to enhance weak but periodic components within the signal [8], which reflect the periodic operation nature of rotating machines, for improved signal detection.

The concept of SR was first introduced in the 1980s to describe the periodicity associated with the Earth's ice ages in climatology [9]. Essentially, SR refers to a process in which noise contained in a signal is utilized to enhance the response of a nonlinear and multistable system to a weak, external driving signal, thereby amplifying (or identifying) the effect of the weak input. Over the past two decades, SR has been found applications in the design of ring lasers, Schmitt triggers, bistable magnetic systems, and optical or chemical systems [10,11].

There are two limitations restricting the application of SR to weak signal detection. First, classic SR can only deal with a periodic signal with a low frequency (e.g. below 1 Hz) [12,13]. To ease this restriction, various algorithms have been proposed, e.g. by developing frequency re-scaling techniques that transform high frequency signals to a low frequency range (e.g. below 1 Hz) [14,15]. Other methods focused on integrating frequency modulation with frequency re-scaling [16]. Also, system parameter tuning techniques based on scale normalization have been proposed [17]. Recently, a multi-scale noise tuning technique was developed to overcome the small parameter restriction of stochastic resonance [18].

The second limitation is the selection of system parameters to generate SR. Since the intensity of noise associated with measured data cannot be altered to drive SR's generation, modifying system parameters that determine the distribution and amount of potential energy to produce SR is the only option. For this purpose,

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http://dx.doi.org/10.1016/j.jmsy.2013.05.009

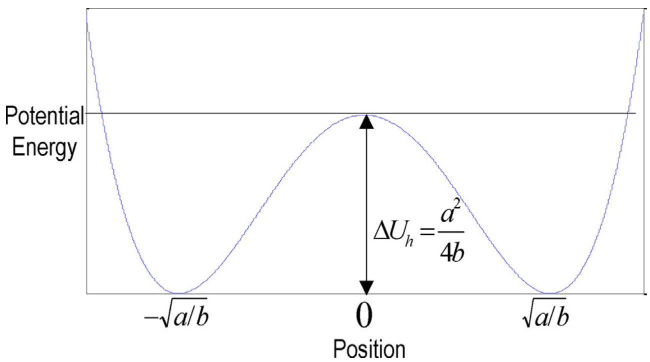

Fig. 1. Potential function $U(x)$.

adaptive SR algorithm has been developed in the past decade [7,10,19–23] to adaptively identify system parameters to produce SR. These adaptive techniques focused on constructing the criterion to determine the appropriate system parameters to produce SR. To ensure accurate and efficient selection of these parameters, the optimization index, as the criterion for the evaluation of SR performance, must indicate whether SR occurs or not. Most of the indices are based on the signal-to-noise ratio (SNR) [7,10,20,21]. Approximate entropy (ApEn) was also proposed as a measure for quantifying SR performance [22]. In [23], a weighted kurtosis index was constructed to realize an adaptive SR scheme. While these prior efforts have improved the effectiveness in weak signal detection, one common drawback is that they all need prior knowledge about the input signal, such as the frequency composition. In real-world applications, however, such prior knowledge may not be available in advance; often times, it represents the unknown information to be obtained itself. Such a situation motivates the development of a new adaptive stochastic resonance strategy that does not require a priori knowledge of the periodic component within the signal, which reflects the defect characteristic.

The rest of the paper is arranged as follows. After introducing the theoretical framework of SR in Section 2, the new adaptive SR scheme for weak signal detection is presented in Section 3. In Section 4, performance evaluation of the new signal processing method is performed by means of numerical simulations and experimental study. Finally, concluding remarks are drawn in Section 5.

2. Theoretical framework

Stochastic Resonance can be regarded as a characteristic nonlinear phenomenon of stochastic relaxation in a modulated bistable or multistable system. When a periodic signal with additive noise is fed into a nonlinear system, the interaction among the signal, the noise and the nonlinear system has shown to possibly improve the S/N ratio in the output [9]. Intuitively, the phenomenon of SR can be illustrated by the motion of a particle in a double well, a quartic potential $U(x)$, which can be defined as:

$$U(x) = \frac{-(ax^2)}{2} + \frac{(bx^4)}{4} \tag{1}$$

where a and b are real-value parameters. As shown in Fig. 1, the potential has two stable stationary points at $x = \pm\sqrt{a/b}$ and an unstable one at $x = 0$ with a barrier height given by:

$$\Delta U_h = \frac{a^2}{4b} \tag{2}$$

The motion of the particle in the double well can be modeled as a function of the frictional force, $-\gamma\dot{x}$, a potential force, $-\dot{U}(x)$, and a random force, $\varepsilon(t)$, representing noise [12] as:

$$m\ddot{x} = -\gamma\dot{x} - \dot{U}(x) + \varepsilon(t) \tag{3}$$

where x describes the one-dimensional displacement of the particle. By rescaling the time variable from t to γt, $\gamma\dot{x}$ and $m\dot{x}$ become $\dot{x}$ and $(m/r)\ddot{x}$ respectively, and adding a periodic modulation force representing a periodic and interesting signal, Eq. (3) can be rewritten as:

$$\frac{m}{r}\ddot{x} = -\dot{x} - \dot{U}(x) + \varepsilon(t) + A\sin(\omega t) \tag{4}$$

where A is the signal amplitude, and ω is the periodic signal frequency.

To simplify Eq. (4), the limit of large damping is considered so that the second derivative of x can be neglected. Then, the following equation can be arrived at:

$$\dot{x} = -\dot{U}(x) + \varepsilon(t) + A\sin(\omega t) \tag{5}$$

Furthermore, the noise $\varepsilon(t)$ is assumed as a zero-mean, Gaussian white noise, i.e. $\varepsilon(t) = \sqrt{2D}\xi(t)$, where D denotes the noise intensity, which is defined as the variance of the white noise, and $\xi(t)$ is a unit variance Gaussian white noise. Representing $U(x)$ and $\varepsilon(t)$ leads to:

$$\dot{x}(t) = ax(t) - bx^3(t) + A\sin(\omega t) + \sqrt{2D}\xi(t) \tag{6}$$

which is the general model for SR [8,24]. Accordingly, the existence of noise can cause particle hopping between two potential wells at $x = \pm\sqrt{a/b}$, with the Kramer's rate defined as [25,26]:

$$T_K = \left(\frac{\sqrt{2}\pi}{a}\right)\exp\left(\frac{\Delta U_h}{D}\right) \tag{7}$$

If the mean passage time between the two wells is equal to half the period of the periodic forcing applied to the particle, a statistical synchronization between noise-induced transition and the weak periodic forcing occurs. The condition for such a synchronization to occur through matching of the time scales can be quantified as:

$$T_K = \frac{1}{(2T_s)} = \frac{\pi}{\omega} \tag{8}$$

where T_s is the period of the periodic forcing function. Therefore, if the relationship between T_K and T_s matches Eq. (8), the representation of the periodic signal can be enhanced by the presence of noise, and as a result, SR occurs. In Eq. (8), the value of T_K is affected by the system parameters a and b, and the noise intensity D. This means that three basic requirements need to be met in order for SR to occur:

- A bistable or multistable system;
- A periodic signal, which may be weak in magnitude, as input to the system;
- Noise which is inherent in or can be mixed with the weak signal to form the input to the system.

3. Signal detection scheme

3.1. Adaptive strategy

In the presented study, a new adaptive stochastic resonance scheme has been developed by combining the highest spectral peak location graph (HSPLG) and the variances of the constructed residual signals (VCRS). The basic idea behind the strategy is a direct identification of the frequency value of a periodic component submerged in a high intensity noise, neglecting the selection of optimal system parameters. The term *location* refers to where the frequency value assumes the highest value in the output power spectrum of SR. Generally, the system parameters a and b do not necessarily guarantee that SR will occur when the system is excited by a weak, periodic forcing function, which represents the defect-induced component and is thus the objective of diagnosis. Consequently, the