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Research article

An adaptive stochastic resonance method based on grey wolf optimizer algorithm and its application to machinery fault diagnosis

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ABSTRACT

Stochastic resonance (SR) is widely used as an enhanced signal detection method in machinery fault diagnosis. However, the system parameters have significant effects on the output results, which makes it difficult for SR method to achieve satisfactory analysis results. To solve this problem and improve the performance of SR method, this paper proposes an adaptive SR method based on grey wolf optimizer (GWO) algorithm for machinery fault diagnosis. Firstly, the SR system parameters are optimized by the GWO algorithm using a redefined signal-to-noise ratio (SNR) as optimization objective function. Then, the optimal SR output matching the input signal can be adaptively obtained using the optimized parameters. The proposed method is validated on a simulated signal detection and a rolling element bearing test bench, and then applied to the gear fault diagnosis of electric locomotive. Compared with the conventional fixed-parameter SR method, the adaptive SR method based on genetic algorithm (GA-SR) as well as the well-known fast kurtogram method, the proposed method can achieve a greater accuracy. The results indicated that the proposed method has great practical values in engineering.

1. Introduction

Rotating machinery are widely used in the fields of aerospace, energy, transportation and chemical industry, etc. However, their key components including bearings and gears are prone to some failures due to the harsh working conditions, and the failures may lead to the breakdown of whole mechanical system and even serious accidents [1]. Consequently, the machinery condition monitoring and fault diagnosis is a front-burner engineering problem.

Vibration based time-frequency analysis has become the most commonly and successfully used approaches in machinery fault diagnosis [2]. In engineering practice, the fault features in vibration signals are usually buried by strong background noises. Therefore, it is necessary to extract fault features through filtering or some other means for final fault diagnosis. Various methods have been developed for this issue, such as wavelet transform (WT) [3], wavelet packet transform (WPT) [4], local mean decomposition (LMD) [5] and signal sparse decomposition etc. However, WT and WPT need to select basic function and decomposition level, which partly restricts their application. LMD is affected by mode-mixing and end effects. For signal sparse decomposition method including matching pursuit (MP) [6], orthogonal matching pursuit (OMP) [7] and basis pursuit (BP) [8], a severe challenge is the storage and computation capacity of computers. Most importantly, these methods are based on signal filtering and will inevitably result in deterioration of useful signal energy while suppressing noise.

In contrast, stochastic resonance (SR) is a kind of noise-assisted or enhanced weak signal detection method, which describes a phenomenon where adding white noise to the signal can boost a signal that is normally too weak to be detected [9]. It is precisely because of the ability to greatly improve signal-to-noise ratio (SNR), SR method has received extensive attention since proposed by Benzi et al. [9] in 1981. In the field of machinery fault diagnosis, various applications of SR-based vibration signal analysis methods have been reported. For instance, Leng et al. [10] designed a large parameter SR called re-scaling frequency SR method to solve the problem that classical SR can only analyze small parameter signals and demonstrated the effectiveness through engineering application of electromotor monitoring and fault diagnosis. Hu et al. [11] used SR method to diagnosis the rub-impact fault of rotor system and found that this fault diagnosis method is simple, robust and reliable. He et al. [12] proposed a cascaded bistable SR method for metal cutting vibration signal analysis and rolling bearing fault diagnosis. Tan et al. [13] developed a frequency-shifted and re-scaling SR method for milling machine tool fault diagnosis. Li et al. [14] proposed a multi-stable SR method for gearbox fault

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diagnosis. Lu et al. [15] researched the enhanced rotating machine fault diagnosis based on time-delayed feedback SR. In [10–15], the SR system parameters are determined based on experience and convenience. This action based on experience greatly limits the performance of SR and may cause inaccurate analysis results. Therefore, choosing appropriate system parameters is a critical problem to signal analysis using SR method. Li et al. [16,17] proposed a parameter-adaptive SR method, in which two parameters are optimized independently. However, they neglected the interaction of the two parameters, and the algorithm would easily trap in local optimization. Even though some adaptive SR methods [18–20] based on optimization algorithms have been proposed which can optimize the two parameters concurrently, the performance of SR is still constrained by the limited global optimization capacity (see [21–24]) of the optimization algorithms (i.e., genetic algorithm (GA), particle swarm optimization (PSO) and grid search method) used in these methods. Consequently, the global optimization capacity of optimization algorithms would directly influence the performance and efficiency of adaptive SR methods.

Grey wolf optimizer (GWO) algorithm is a novel nature-inspire optimization algorithm which mimics leadership hierarchy and hunting mechanism of grey wolves in nature. In [25,26], GWO demonstrated its advantages compared to popular optimization algorithms including GA, PSO and gravitational search algorithm (GSA), as it is simple, flexible, robust, high performance in terms of approximating global optimum, and is easy to implement. Due to these advantages, GWO algorithm has been successfully used in many engineering problems such as optimal reactive power dispatch problem [27] and optimal control of DC motor [28].

Based on the above introduction, this paper proposes an adaptive SR method based on GWO algorithm to improve performance of SR method for machinery fault diagnosis. The rest of this paper is organized as follows. The proposed method, basic theory of bistable SR as well as the GWO algorithm are introduced in Section 2. Numerical simulation is carried out in Section 3. Experimental investigation and engineering application as well as the comparisons with other methods are conducted in Section 4. Finally, the conclusions are drawn in Section 5.

2. Adaptive SR method based on GWO

2.1. Basic theory of bistable stochastic resonance

SR describes a method for improvement of output SNR by increasing input noise in nonlinear systems [9]. The SR system consists of a: (1) nonlinear system; (2) weak input signal; (3) and noise that is inherent or that adds to the input signal. Generally, in study of SR, bistable system is the most commonly used nonlinear system [29–31]. Nonlinear effect of noise is expected in bistable systems. In addition, research findings for bistable systems can be easily extended to other multi-stable systems or other more complex systems. In our study, a bistable system is also selected as the signal-processing unit. Classical bistable SR model is presented in Fig. 1. The bistable system subjected to noise and external periodic driving force can be described by the following Langevin equation:

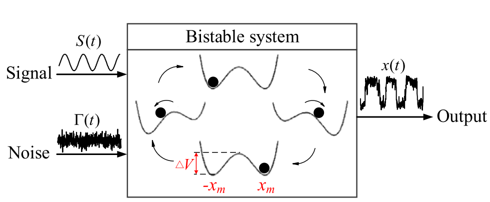

Fig. 1. Structure diagram of classical bistable SR.

$$\dot{x} = -V'(x) + S(t) + \Gamma(t) \tag{1}$$

where $\dot{x}$ is derivative of the system output, and $V'(t) = dV(x)/dx$, $V(x)$ is potential function of bistable system, $S(x)$ and $\Gamma(x)$ are input simulation signal and white Gaussian noise respectively, $V(x)$, $S(x)$ and $\Gamma(x)$ are described by Eqs. (2)-(4) respectively.

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

where a and b are system parameters greater than 0, and x is output signal.

$$S(x) = A\cos(2\pi ft) \tag{3}$$

where A and f are amplitude and frequency of input signal respectively, and t represents time.

Noise $\Gamma(x)$ needs to meet the requirement in Eq. (4).

$$E[\Gamma(t)\Gamma(t-\tau)] = 2D\delta(t-\tau) \tag{4}$$

where D, δ and τ are noise intensity, impulse function and time constant respectively.

The following Langevin equation can be obtained by substituting Eq. (2) into Eq. (1).

$$\dot{x} = ax - bx^3 + S(t) + \Gamma(t) \tag{5}$$

Eq. (5) essentially describes the over damping motion of unit particles in a double potential well, when synchronously driven by external forces and noise. From Eq. (2), two stable solutions for the potential function of bistable systems are $x_m = \pm\sqrt{a/b}$, and barrier height is $\Delta V = a^2/4b$. The double-well potential and barrier height can be seen in Fig. 1.

When unit particles are driven only by the input signal $S(x)$, they cannot stride cross the barrier, and only undergo a local periodic motion along one side of the potential well. When these unit particles are synchronously driven by input $S(x)$ and noise $\Gamma(x)$, noise will transfer some energy to the signal. Then, unit particles will cross the barrier and undergo periodic motion at the signal frequency between the two potential wells. Accordingly, output signal can be amplified by noise assistance, namely SR phenomenon (see Fig. 1). Hence, one can see that barrier height ΔV is an important parameter for occurrence of SR, and value of barrier height ($\Delta V = a^2/4b$) is determined by system parameters a and b. Thus, there exists an optimal set of parameters a and b to obtain the best SR effect matching the input signal, which motivates the following research.

2.2. Grey wolf optimizer algorithm

GWO is a novel meta-heuristic optimization algorithm, which imitates leadership hierarchy and hunting mechanism of grey wolves [25]. Grey wolves are social animals, and are considered as apex predators. In population, they have a strict social hierarchy which can be divided into four layers: α, β, δ and w (see Fig. 2). This social hierarchy plays a vital role in hunting process. Leaders,

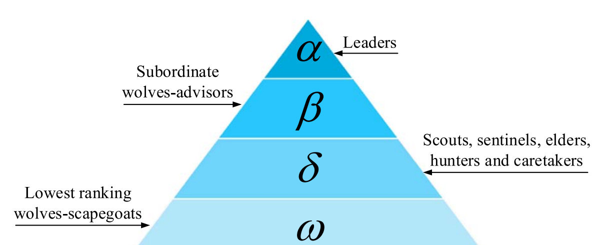

Fig. 2. Hierarchy of grey wolf population.

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