A comparison of parameters optimized-type VMD methods used in bearing fault diagnosis

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Abstract. In the early fault stage of bearings, the impact component of the signal is easily submerged by strong noise. To solve this problem, some fault diagnosis methods have been developed based on the variational mode decomposition (VMD) with optimized parameters. In this paper, we compare the performance of three different VMD methods with parameters optimized by whale optimization algorithm (WOA), grey wolf optimization (GWO) and particle swarm optimization (PSO), respectively. The results show that under the same conditions, the performance of WOA-VMD is better than that of the other two optimized VMD methods.

1. Introduction

Rotating machinery has been widely employed in many places. Bearings are the important parts of rotating machinery and they are very easy to be damaged due to long-term operation under harsh conditions, resulting in heavy losses. Therefore, it is of great significance for the early fault diagnosis of bearings to ensure the reliable operation of the machine [1].

It is a crucial step to accurately extract fault features for early fault diagnosis of bearings. However, when the bearing is under the condition of early fault, the weak vibration signal is often disturbed by the strong noise, which makes it very difficult to obtain the fault characteristics from the original signals [2]. To solve above problems, variational mode decomposition (VMD) was developed by Dragomiretskiy et al., which could decompose the signal into several mode components [3]. The decomposition effect of VMD depends on the selection of its critical parameters (mode number \( K \) and penalty factor \( \alpha \)). If \( K \) is improperly selected, the phenomenon of over-decomposition or under-decomposition will occur. The improper selection of \( \alpha \) will affect the bandwidth of the mode component. Some scholars have conducted research on VMD parameters selection. Gu et al. developed a method based on VMD parameters optimized by grey wolf optimization, which was used to extract fault features successfully. Zhao et al. used single-objective salp swarm algorithm to obtain VMD parameters adaptively, which could reduce mode aliasing and kept the fidelity of complex vibration signals [4-7]. This paper mainly compares the performance of parameters optimized-type VMD methods in bearing fault diagnosis.
2. The Principle of three optimization algorithms

2.1. GWO algorithm
Grey wolf optimization (GWO) was proposed by Mirjalili et al., which simulated the predation behavior of grey wolves [8]. The initial population was generated in the optimization space, which was divided into four social levels, namely $\alpha$, $\beta$, $\delta$ and $\omega$.

In the grey wolf hunting process, we need to determine the distance $\vec{D}$ between the wolf pack and prey, and the grey wolf population position $\vec{G}(l + 1)$.

\[
\vec{D} = \left| \vec{h} \cdot \vec{G}_p(l) - \vec{G}(l) \right| \\
\vec{G}(l + 1) = \vec{G}_p(l) - \vec{A} \cdot \vec{D}
\]

where $\vec{G}_p(l)$, $\vec{G}(l)$ and $l$ represent the prey position, the current position of the wolf group, and the number of iterations, respectively.

In the above formulas, the coefficient $\vec{A}$ and coefficient $\vec{h}$ are calculated as follows:

\[
\vec{A} = 2\vec{a} \cdot \vec{n}_1 - \vec{a} \\
\vec{h} = 2 \cdot \vec{n}_2
\]

where the coefficient $\vec{a}$ decreases linearly from 2 to 0 during the optimization process, and $\vec{n}_1$ and $\vec{n}_2$ are random vectors in [0,1].

The distance between the remaining individuals and $\alpha$, $\beta$ and $\delta$ wolves is calculated as follows:

\[
\vec{D}_O = \left| \vec{h}_M \cdot \vec{G}_p(l) - \vec{G}(l) \right|
\]

The grey wolf population location is updated as follows:

\[
\vec{G}_M = \vec{G}_F - \vec{A}_M \cdot \vec{D}_O \\
\vec{G}(l + 1) = \frac{\vec{g}_1 + \vec{g}_2 + \vec{g}_3}{3}
\]

where $O = \alpha$, $\beta$, $\delta$ and $M = 1, 2, 3$.

2.2. WOA algorithm
Whale optimization algorithm (WOA) has certain advantages in global optimization because it simulates the predation behavior of humpback whales [9]. Whale algorithm mainly adopts bubble-net attack for hunting, and the model is as follows:

\[
\vec{G}(l + 1) = \vec{d} \cdot e^{bn} \cdot \cos(2\pi n) + \vec{G}_*(l) \\
\vec{d} = \left| \vec{g}_*(l) - \vec{G}(l) \right|
\]

where $\vec{G}_*(l)$ and $\vec{G}(l)$ represent the prey position and the current position of the whale group respectively, $b$ is a constant which can model the logarithmic spiral shape and $n$ is a random number between [-1, 1].

In order to simulate the simultaneous behavior of bubble-network attack, 50% probability is set to select one of the above mechanisms. The model is shown in Equation (10).

\[
\vec{G}(l + 1) = \begin{cases} 
\vec{g}_*(l) - \vec{A} \cdot \vec{d}, & \text{if } p < 0.5 \\
\vec{d} \cdot e^{bn} \cdot \cos(2\pi n) + \vec{G}_*(l), & \text{if } p \geq 0.5
\end{cases}
\]

where $p$ is a random number between [0, 1]. For more details, please see is shown in Reference [9].

2.3. PSO algorithm
Particle swarm optimization algorithm designs a massless particle to simulate the individual in the bird swarm [10]. The particles have only two attributes: velocity and position. The formulas for velocity and position are as follows:

\[
v(t + 1) = \omega v(t) + b_1 r_1 (p_{i}^{best}(t) - G_i(t)) + b_2 r_2 (g^{best}(t) - G_i(t)) \\
G_i(t + 1) = G_i(t) + v_i(t + 1)
\]

where $\omega$ is the inertia weighting factor, $b_1$ and $b_2$ are non-negative constants, and $p_{i}^{best}(t)$ and $g^{best}(t)$ are the best solutions of the current particle and global particle, respectively.
represent the current optimal value of the individual and the optimal value of the population, respectively. For more details, please see in Reference [10].

2.4. Performance verification of GWO, PSO and WOA
In order to compare the performance of the GWO, PSO and WOA, a standard test function is used as the test object, as shown in the following formula:

$$f(x) = \sum_{i=1}^{n} \left( x_i^2 - 10 \cos(2\pi x_i) + 1 \right)$$

(13)

Figure 1 shows the convergence curves of the GWO, PSO and WOA. It can be found that WOA algorithm has faster convergence speed and higher search accuracy than PSO and GWO algorithm under the same number of iterations. Therefore, the performance of WOA is better than that of PSO and GWO.

Figure 1. Performance comparison between PSO, GWO and WOA

3. Fault feature extraction process
Figure 2 shows the early fault feature extraction process based on GWO-VMD, WOA-VMD and PSO-VMD. In the optimization process, kurtosis ($KU$) values are calculated for all modes. When it is the maximum kurtosis value, then the corresponding ($K, \alpha$) is the optimal parameter combination.

Figure 2. Flowchart of fault feature extraction
4. Experimental verification

The experimental data comes from the Case Western Reserve University bearing data Center [11]. We select the outer ring data for analysis. The bearing fault size used in the experiment is 0.07”, the sampling frequency $f_s = 12000$ Hz, and the motor speed is 1797 r/min (rotating frequency $f_r = 29.95$ Hz). The fault characteristic frequency ($f_o$) is 107.36 Hz. In order to make the above raw data conform to the characteristic of early fault, we design the raw data to be an early fault signal by adding white Gaussian noise with signal-to-noise ratio of -5 into raw bearing signals. Figure 3 shows the time-domain waveform and frequency-domain waveform of designed signal. From Figure 3, we can see that it is very hard to directly obtain the fault characteristic frequency $f_o$ from the designed signal.

![Figure 3. Bearing outer ring signal](image)

Firstly, WOA-VMD is used to decompose the signal, and Figure 4 shows the convergence curve in the optimization process. From Figure 4, it can be seen that when the number of iterations is 3, the fitness value is -3.89. And the corresponding optimal parameters are obtained as (7, 557). The optimal parameters are substituted into VMD to decompose the signal.

![Figure 4. Convergence curve in optimization process](image)

Then, the PSO-VMD and GWO-VMD are also employed to decompose the signal of the bearing as shown in Figure 3. The maximum kurtosis values obtained by PSO-VMD, GWO-VMD and WOA-VMD are shown in Table 1. The modes with the largest kurtosis are selected for envelope analysis.

Figure 5 shows the envelope spectrum of these modes with the largest kurtosis obtained by the above three methods. We can find that all of three methods could effectively extract the characteristic frequency $f_o$. At the same time, the corresponding harmonics ($2f_o, 3f_o$ and $4f_o$) can also be accurately extracted. Moreover, it is mentioned that the amplitude of the characteristic frequency $f_o$ extracted by WOA-VMD is obviously larger than that extracted by GWO-VMD or PSO-VMD. Therefore, the
performance of WOA-VMD is better than PSO-VMD and GWO-VMD, when they are employed to extract the early fault characteristic frequencies.

Table 1. Maximum kurtosis obtained by three methods

|       | WOA-VMD | GWO-VMD | PSO-VMD |
|-------|---------|---------|---------|
| KU    | 3.89    | 3.82    | 3.56    |

Figure 5. The results obtained by PSO-VMD and GWO-VMD

5. Conclusions
This paper compares three parameters optimized-type VMD methods (GWO-VMD, PSO-VMD and WOA-VMD) for decomposing the early fault signal of bearing. From the results, we can see that WOA algorithm has faster convergence speed and higher search accuracy than PSO and GWO algorithm. Our results also show that all of three methods can extract the bearing early fault characteristic frequency. Moreover, the amplitude of the characteristic frequency extracted by WOA-VMD is obviously larger than that by GWO-VMD or PSO-VMD. Therefore, the performance of WOA-VMD is better than PSO-VMD and GWO-VMD, when they are employed to extract the early fault characteristic frequencies.

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