Performance Comparisons Between MFDFA and EMD Using Neural Network and Support Vector Machine

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Abstract. Multifractal detrended fluctuation analysis (MFDFA) is a powerful tool for discovering dynamics hidden in complex data. Similarly, empirical mode decomposition (EMD) is a typical method for time-frequency analysis of nonstationary data. Many works have applied MFDFA and EMD to get insight into nature of machine vibration signals. However, comparisons of performance of MFDFA and EMD in feature extraction have rarely been performed so far. To fill this gap, this paper benchmarked the performance of MFDFA against EMD by neural network (NN) and support vector machine (SVM) using a group of gearbox vibration signals containing gear faults in different types and severity levels. In this way, five characteristic parameters were obtained using MFDFA. For comparison, an eleven-dimension feature vector was acquired using EMD. Following this, either of NN and SVM served to distinguish between gearbox conditions characterized by the features extracted above. The results indicated that MFDFA is comparable to EMD in discrimination between gearbox conditions. In addition, this paper demonstrated that the integration of MFDFA and SVM is promising in fault diagnosis of gearboxes.

Introduction

A gearbox generally brings about an important effect on transmission of machines[1]. When a gearbox breaks down, vibration data gathered from the gearbox usually exhibit nonlinear and nonstationary properties[2]. As a result, fault diagnosis of gearboxes is a challenging problem, especially when fault patterns of gearboxes are very similar. Multifractal detrended fluctuation analysis (MFDFA) is a powerful tool for discovering multifractal properties of complex data[3]. Recently, MFDFA has been introduced for investigating machine vibration data[4]. Currently, MFDFA has demonstrated the potential for feature extraction of machine vibration data[4]. In this case, it is beneficial to conduct a test for evaluating performance of MFDFA. Since widely used in time-frequency analysis of data, empirical mode decomposition (EMD) seems to be suitable as a benchmark for measuring performance of MFDFA. In this respect, this paper benchmarked the performance of MFDFA against EMD using neural network (NN) and support vector machine (SVM) by a group of gearbox vibration data containing similar gear faults[5, 6]. The results indicated that MFDFA is comparable to EMD in distinguishing between gearbox conditions. Moreover, this paper demonstrated that the integration of MFDFA and SVM is seemingly feasible for fault diagnosis of gearboxes.

A Brief Description of EMD

EMD can adaptively decompose a signal \( x(t) \) into a group of components and a trend [7]:

\[
x(t) = \sum_{i=1}^{N} a_i(t) + r(t)
\]
\[ x(t) = \sum_{i=1}^{k} c_i(t) + r \]  

Here, \( c_i(t) \) and \( r \) denote the \( i \)th component and the general trend of the signal \( x(t) \), respectively, and \( k \) represents the number of the components. In this paper, a \( k \)-dimension vector was constructed as a feature vector of the signal \( x(t) \), defined as

\[ e_j = c_j^2 \sqrt{\sum_{i=1}^{k} c_i^2}, \quad j = 1, \ldots, k \]  

### A Brief Description of MFDFA

The execution of MFDFA for a series \( x_n \) with length \( N \) comprises the next five steps[3]:

1. Construct a “profile” as

\[ Y(i) \equiv \sum_{k=1}^{i} [x_k - \langle x \rangle] \]  

2. Split the profile \( Y(i) \) into \( N_s = \text{int}(N / s) \) non-overlapping segments, each with the same length \( s \). To make full use of these data, the same procedure is carried out again in reverse order. Accordingly, altogether \( 2N_s \) data segments are obtained.

3. Apply the least-square algorithm to fit the local trend of each of the \( 2N_s \) segments. Define the variance as

\[ F^2(v, s) \equiv \frac{1}{s} \sum_{i=1}^{s} \{Y[(v-1)s + i] - y_v(i)]\}^2 \]  

for the \( v \)th segment, \( v = 1, \ldots, N_s \), and

\[ F^2(v, s) \equiv \frac{1}{s} \sum_{i=1}^{s} \{Y[N - (v - N_s)s + i] - y_v(i)]\}^2 \]  

for the \( v \)th segment, \( v = N_s + 1, \ldots, 2N_s \). Here, \( y_v(i) \) stands for the fitted polynomial trend in the \( v \)th segment.

4. Acquire the \( q \)th-order fluctuation function \( F_q(s) \) by averaging all of the \( 2N_s \) segments:

\[ F_q(s) = \left( \frac{1}{2N_s} \sum_{v=1}^{2N_s} [F^2(v, s)]^{q/2} \right)^{1/q} \]  

Here, it must be pointed out that the real number \( q \) can not be set as zero. For a different time scale \( s \), repeat steps 2~4. Consequently, the fluctuation \( F_q(s) \) can present itself as a function of variables \( q \) and \( s \).

5. Establish a power-law relation between \( F_q(s) \) and \( s \) for different \( q \):

\[ F_q(s) \sim s^{\alpha(q)} \]  

For \( q = 0 \),
A Performance Benchmark of MFDFA against EMD

A gearbox experiment sketched in Fig. 1 was carried out for generating desirable gearbox vibration data containing gear faults in different types and severity levels. The tooth numbers of gears 1-4 of the gearbox in Fig. 1 are 25, 40, 22 and 55, respectively. The frequency converter was employed to control an output speed of the three-phase asynchronous motor in Fig. 1. In this experiment, slight-scratch, medium-scratch and broken-tooth faults were individually fed into gear 1. Here, it must be emphasized that the slight- and medium-scratch faults are similar and tough to separate. From the housing close to gear 1, vibration data were collected by an acceleration transducer. For each gearbox condition, thirty-five pieces of data were collected, each piece with sample frequency 16384Hz and size 4096. Afterwards, fifteen pieces selected randomly served as training data and the remaining as testing data. Vibration data under running speed 1200 RPM (Revolutions Per Minute) are displayed in Fig. 2. To start with, MFDFA was adopted to analyze these gearbox vibration data and the results are demonstrated in Fig. 3. As demonstrated in Fig. 3, the multifractal spectra for the normal and broken-tooth conditions clearly differ from those for the scratch conditions in the positions of extreme points of the multifractal spectra. Also, the multifractal spectra for the slight- and medium-scratch conditions are different only in the shapes of the multifractal spectra. Consequently, the shapes and positions of the multifractal spectra enable different gearbox conditions to be separated. With the capabilities to almost determine the shapes and positions of the multifractal spectrum, five characteristic parameters: \( \alpha_{\text{max}} \), \( f(\alpha_{\text{max}}) \), \( \alpha_{\text{ext}} \), \( \alpha_{\text{min}} \) and \( f(\alpha_{\text{min}}) \), corresponding to coordinates of the left-end, right-end and extreme points of the multifractal spectrum, were extracted for describing a gearbox condition. Moreover, to benchmark the performance of MFDFA, EMD was applied to explore these gearbox vibration data. According to the results derived from EMD, the vibration data corresponding to each gearbox condition were uniformly decomposed into eleven components by EMD. Furthermore, according to Eq. 2, an eleven-dimension feature vector was established for EMD. Afterwards, NN and SVM were separately employed to classify the feature parameters derived from each of MFDFA and EMD. Consequently, comparisons of performance of MFDFA and EMD are shown in Table 1. As shown in Table 1, although using fewer characteristic parameters for describing gearbox conditions, MFDFA is comparable to EMD in feature extraction of gearbox vibration data. In addition, Table 1 reports that SVM performs better than NN in classification of features. It means that the method associating MFDFA with SVM shows the potential for fault diagnosis of the gearbox.

\[
F_v(s) = \exp \left\{ \frac{1}{4N_s} \sum_{v=1}^{2N_s} \ln[F^2(v,s)] \right\} \sim s^{H(0)}
\]  

(8)

Figure 1. A sketch map of gearbox experiment table.
Figure 2. Four types of gearbox vibration data, (a)–(d) for normal, slight-scratch, medium-scratch and broken-tooth conditions, respectively.

Figure 3. Multifractal spectra of four types of gearbox vibration data.

Table 1. Performance comparisons between MFDFA and EMD by NN and SVM in fault diagnosis of gearboxes.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Numbers of feature parameters</th>
<th>Success rates of fault diagnosis (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>NN</td>
</tr>
<tr>
<td>MFDFA</td>
<td>5</td>
<td>97.50</td>
</tr>
<tr>
<td>EMD</td>
<td>11</td>
<td>97.50</td>
</tr>
</tbody>
</table>

Summary

This paper compared the performance of MFDFA and EMD by applying them to study gearbox vibration data containing gear faults in different types and severity levels. The comparisons indicated that MFDFA is comparable to EMD in feature extraction of machine vibration data. Moreover, the results showed that SVM has an advantage over NN in classification of gearbox conditions. Consequently, this paper indicated that the method connecting MFDFA to SVM is seemingly hopeful for fault diagnosis of gearboxes.

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Reference


