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Research Article

Fractal Dimension Based on Morphological Covering for Ground Target Classification

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Seismic waves are widely used in ground target classification due to its inherent characteristics. However, they are often affected by extraneous factors and have been found to demonstrate a complicated nonlinear characteristic. The traditional signal analysis methods cannot effectively extract the nonlinear features. Motivated by this fact, this paper applies the fractal dimension (FD) based on morphological covering (MC) method to extract features of the seismic signals for ground targets classification. With the data measured from test field, three different schemes based on MC method are employed to classify tracked vehicle and wheeled vehicle in different operation conditions. Experiment results demonstrate that the three proposed methods achieve more than 90% accuracy for vehicle classification.

1. Introduction

Detecting the moving ground targets has two ways. One way is active detection technology, including sonar and radar. Due to large volume and wave launch, this kind of detection equipment is not fit to be used in battlefield surveillance. Another way called passive detection technology, which applies sensors to record signals produced by targets, is cheaper and safer than the former one. For the passive detection method, seismic waves are more employed in ground target detection than acoustic, image, and infrared signals which are sensitive to Doppler effects, noises introduced from various moving parts of vehicles, and atmospheric and terrain variations [1, 2].

However, seismic waves have their own defects. They are often affected by some factors such as field conditions, noises, speeds, and types of vehicles. Thus, the seismic waves have been found to demonstrate a complicated nonlinear characteristic [3]. The traditional signal analysis methods cannot effectively extract the nonlinear features.

Fractal geometry theory is an effective method to analyze complex nonlinear signals, and it has been applied in many fields successfully [4–9]. Fractal dimension (FD) is an important parameter to measure the complexity of signal. It can also be used to analyze the motion states of the ground target, so as to improve the recognition ability of ground target. At present, there are many methods to estimate the FD of signal. The box-counting (BC) method is the most widely used because it is simple to be implemented by the computer and easy to be understood [5, 10–13]. However, the BC based algorithm has been proved to have low accurate rate in fractal estimations due to its intrinsically regular partition [14, 15]. An alternative approach is FD based on the morphological covering (MC) method. Different from the BC method which transforms one-dimension signal to two-dimension images to divide the grids, the FD of morphology uses one-dimension morphological coverage; therefore, it has higher computational efficiency. Furthermore, the morphological operations do not need to divide the grids; this means that the calculation would not be affected by the amplitude range and the rotation of the signals, so the estimated results are more stable and accurate. At present, the fractal dimension of morphology is broadly applied to image segmentation, image description, target detection, acoustic signals processing, and medical signal processing [7, 8, 14, 16]. And, in the field of one-dimension vibration signal analysis, the generalized

dimension based on MC method can effectively extract the features of mechanical fault through the analysis of the vibration signals [17, 18]. However, to our knowledge, the FD based on MC method has never been used for processing the vibration signals of ground target.

In this paper, we have first investigated the application of FD based on MC method for characterizing and classifying the seismic waves generated by tracked vehicle and wheeled vehicle. The experiment results demonstrate that the proposed method performs more than 90% accuracy in three different feature extraction forms.

In Section 2, the computation of FD based on MC method is detailed. In Section 3, the presented scheme is applied to extract and classify the seismic waves acquired from the tracked vehicle and wheeled vehicle. And the conclusions of this investigation are summarized in Section 4.

2. FD Based on MC Method

2.1. Generalized Fractal Dimension Based on MC Method. In the area of self-similar fractal, a fractal object can be characterized by a single FD. However, the description of the uniform FD is too simple for most of the physical phenomenon in the real world. The behavior of some complex systems is mainly determined by the spatial distribution of a certain physical phenomenon. The seismic waves do not have ideal self-similarity and their statistical distribution is inhomogeneous, so a single FD is not enough to represent the complexities of the signals.

Derived from relative difference BC method [19], the generalized fractal dimension (GFD) based on MC method uses morphological cover to replace the regular box cover.

Let f be the discrete one-dimension signal, let g be the structural elements (SE), and let ε be the size of the SE; we can define the distribution function $u_i(\varepsilon)$ which reflects the partial metric used by MC method as

$$u_i(\varepsilon) = \frac{f \oplus \varepsilon g(n) - f \Theta \varepsilon g(n)}{\sum_{n=1}^{N} \left[f \oplus \varepsilon g(n) - f \Theta \varepsilon g(n) \right]}, \tag{1}$$

where $\oplus$ denotes the operator of dilation and Θ denotes the operator of erosion [17, 18]. The dilation and erosion operators are defined as

$$\begin{aligned} (f \oplus g)(n) &= \max_{x \in G} \{ f(n-m) + g(m) \}, \\ (f \Theta g)(n) &= \min_{x \in G} \{ f(n+m) - g(m) \}. \end{aligned} \tag{2}$$

Thus, the q-order measurement $K_q(\varepsilon)$ [20] on scale ε can be defined as

$$K_q(\varepsilon) = \alpha \cdot \frac{\ln \sum_{i=1}^{N} [u_i(\varepsilon)]^q}{(1-q)}. \tag{3}$$

The parameter α can be calculated by

$$\alpha = \frac{\log \left[A_g(\varepsilon) / \varepsilon^2 \right]}{\log (N(\varepsilon))}. \tag{4}$$

Here $A_g(\varepsilon)$ is the morphological covering area and $N(\varepsilon)$ is the length of the signal.

As a multifractal metric, the exponential relationship between $K_q(\varepsilon)$ and ε must be satisfied as follows:

$$K_q(\varepsilon) \propto \varepsilon^{-D_q} \quad -\infty < q < +\infty. \tag{5}$$

Then the GFD can be calculated by

$$D_q = \lim_{\varepsilon \to 0} \frac{\ln K_q(\varepsilon)}{\ln(\varepsilon)}. \tag{6}$$

In actual calculation, we can obtain the estimation of the GFD by the least square linear fitting of $\ln[K_q(\varepsilon)]$ versus $\ln(\varepsilon)$. It can be proved that when $q = 0$, the GFD degenerates into single FD based on mathematical morphology.

2.2. Multiscale Fractal Dimension Based on MC Method. The GFD takes into account the nonstrict self-similarity of the signal in space; we can also extract features of a signal with its nonstrict self-similarity on scale. The multiscale fractal dimension (MFD) based on MC method calculates the FD on different scale to provide more information of the signal for higher classification rate [17].

As mentioned above, $A_g(\varepsilon)$ is the morphological covering area which is calculated by

$$A_g(\varepsilon) = \sum_{n=1}^{N} \left[f \oplus \varepsilon g - f \Theta \varepsilon g \right](n). \tag{7}$$

Then we can get the FD by [21]

$$D = \lim_{\varepsilon \to 0} \frac{\log \left(A_g(\varepsilon) / \varepsilon^2 \right)}{\log(1/\varepsilon)}. \tag{8}$$

If the analyzing scale $\varepsilon = [\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_L]$, the local FD on scale ε_i can be calculated by the least square linear fitting of $\ln[A_g(\varepsilon)/\varepsilon^2]$ versus $\ln(1/\varepsilon)$ over the moving window $[\varepsilon_i, \varepsilon_{i+1}, \ldots, \varepsilon_{i+w-1}]$, where w is the width of the window. Moving the window from scale ε_1 in turn, we can get $L-w+1$ FDs.

2.3. Multiscale Generalized Fractal Dimension Matrix Based on MC Method. The GFD and MFD obtain a more comprehensive and accurate description of the signal structure from its nonstrict self-similarity in spatial distribution and size distribution, respectively. The multiscale generalized fractal dimension matrix (MGFDM) based on MC method, which considers the local characteristics of the signal in both distributions, has been employed to extract the features of seismic waves. The calculation method is detailed as follows.

For each parameter q, we estimate multiple FDs of the signal at each local scale range $[\varepsilon_i, \varepsilon_{i+1}, \ldots, \varepsilon_{i+w-1}]$ instead of single global FD. It means that, for each signal, we can obtain a FD matrix. Compared with GFD and MFD, the MGFDM contains more information.

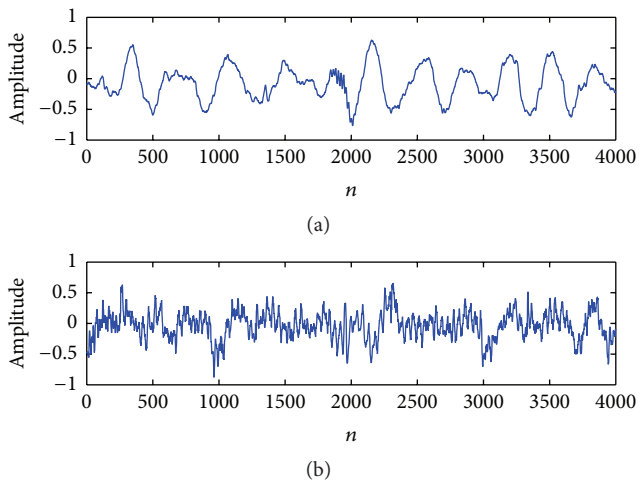

Figure 1: Waveform of seismic waves of two kinds of targets: (a) tracked vehicle and (b) wheeled vehicle.

3. Application to Target Classification

3.1. Experiment Equipment. The seismic waves of the tracked vehicle and wheeled vehicle in this paper are measured by DZ-CDJ—Z/P60, a kind of vertical geophone made by Odd Instrument Co., Beijing. The collected signals are transformed into electrical signals by the sensor to store. The sample frequency is 4000 and the sample number 4000 points. For the reason that the initial unit of amplitude is voltage value and it is a little big, we normalize them in order to facilitate processing. The experiment is carried out on the same test field where geological condition is hard soil under same climate conditions in two different operating conditions. In one operating condition, the two targets are driving at a uniform speed of 20 km/h. In another operating condition, the driving speed is 40 km/h equably. Twenty samples are collected for each target in each state. Thus, totally 80 samples were collected. Figure 1 demonstrates the waveform of seismic waves of tracked vehicle and wheeled vehicle.

3.2. Feature Extraction. In this section, the GFD, MFD, and MGFDM are employed to extract the nonlinear features of the seismic waves measured from tracked vehicle and wheeled vehicle. It should be mentioned that there is no criterion to select the analyzing scales. For reflecting the periodic characteristic of the signal, the maximum analyzing scale should not exceed half-length of main shock period of the signal. Thus, we set the sizes ε to be [1, 2, 4, 8, 16: 16: 256] and the width w of the moving window as 6.

Figure 2 demonstrates the GFD calculation results of the signals. Each target under different operating conditions gives four samples, respectively. It can be observed that the multifractal characteristics of the target signals are obvious. With the change of parameters q, the fractal dimensions of the signals have a certain dynamic range, which offers more information than the single fractal dimension for distinguishing the targets.

In Figure 3, we compare the MFD of the target signals in different speed and the MGFDM result is shown in Figure 4.

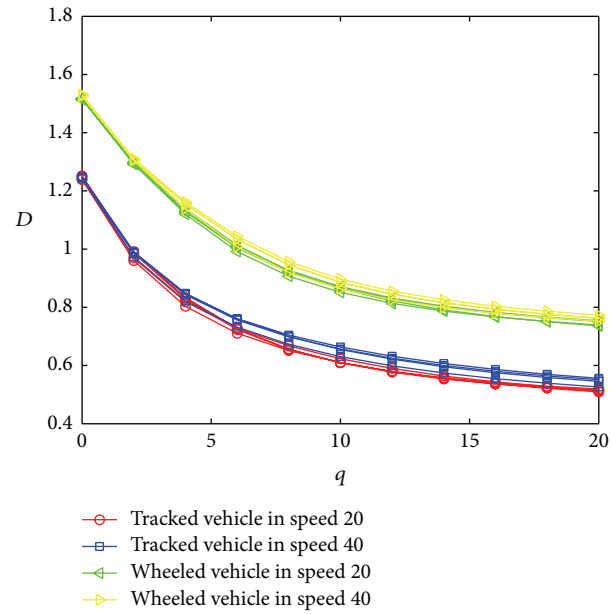

Figure 2: GFD of tracked vehicle and wheeled vehicle.

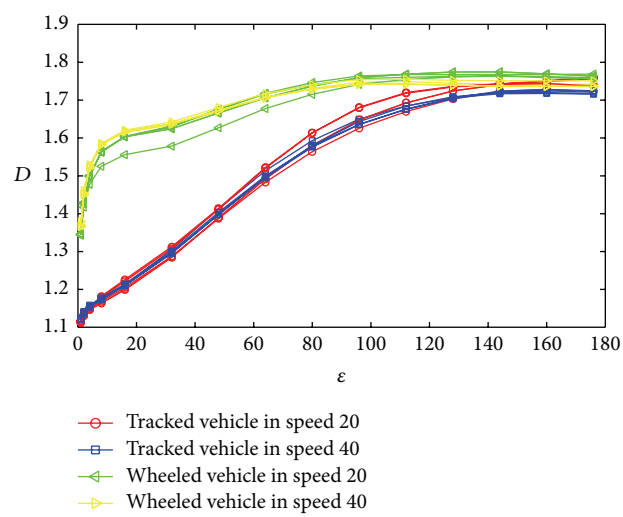

Figure 3: MFD of tracked vehicle and wheeled vehicle.

Clearly, the MGFDM method shows the best ability to extract features. The MFD method also presents satisfactory discriminative power. We can also observe that the FD of the signals in the three schemes is relatively close with same target under two different operating conditions. Moreover, the FD of the wheel vehicle signals is larger than tracked vehicle signals'.

3.3. Target Classification. In this section, the FD estimated by GFD, MFD, and MGFDM methods are employed as feature vectors for classifying tracked vehicle and wheeled vehicle. The support vector machine (SVM) [22] is employed as the classifier and the parameters of the SVM are optimized by cross-validation method. The SVM type and kernel function are C-SVM and radial basis function. As mentioned above, 80 samples are collected in the experiment: 40 samples for

Table 1: Target classification accuracy of GFD, MFD, MGFDM, and BC methods.

Methods	Classification rates (%)
GFD	90.3
MFD	93.5
MGFDM	97.3
BC	85.8

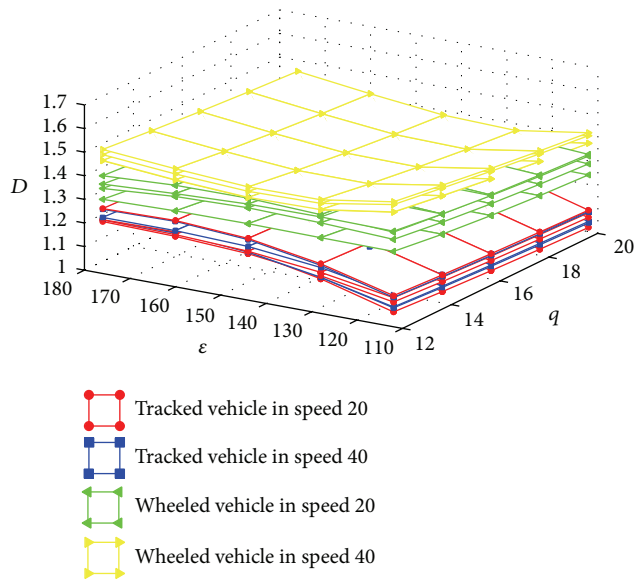

Figure 4: MGFDM of tracked vehicle and wheeled vehicle.

the tracked vehicle and 40 samples for the wheel vehicle. We select 20 samples randomly of each target as the testing dataset and other 20 samples as the training dataset. Thus, we obtain 40 testing samples and 40 training samples in total. We did this segmentation randomly for 10 times to get more robust evaluation results. For each time we can obtain a set of classification rates for different methods and average the 10 times data, we can get the final classification accuracy. The dimension of feature vectors of the three methods is 11, 15, and 165, respectively.

Since the GFD, MFD, and MGFDM methods are developed based on BC method algorithm, the generalized dimension based on BC method is used as a comparison. The size of the box used for BC method is set to be [1, 2, 4, 8, 16: 16: 256]. The dimension of feature vectors of the BC method is 11.

The classification accuracies of GFD, MFD, MGFDM, and BC method are listed in Table 1. We can find that the proposed three schemes achieve consistent better classification rate than the BC method. The MGFDM demonstrates the best performance for target classification. The results of GFD and MFD are also satisfactory.

4. Conclusion

This paper has applied FD based on MC method to extract features of seismic waves for ground targets. The main difference between the MC method and the BC method is the utilization of the morphological cover to replace the regular box cover. Based on MC method, three schemes for estimating the FD are employed to extract features of tracked vehicle signals and wheeled vehicle signals in two different speeds. Experiment results reveal that the GFD, MFD, and MGFDM can effectively distinguish the two targets in different operation conditions. Furthermore, the GFD, or MFD, or MGFDM of the same target is relatively close and speed conditions have little effect on it.

The classification accuracy of GFD, MFD, MGFDM, and BC methods has also been evaluated by SVM. Experiment results demonstrate that the three proposed algorithms based on MC method obtain a significant improvement over the BC method. The MGFDM method presents the best discrimination ability and the performance of GFD and MFD is also satisfactory.

There are two aspects to be improved. First, there is no criterion to select the analyzing scales and the width of the moving window. Second, more types of targets in different speeds and observation distances should be studied in future works.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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