Ground Moving Target Detection With Seismic Fractal Features

Kangcheng Bin, Yun Long, Xunqian Tong, and Jun Lin

Abstract—**Due to the strong nonstationary characteristics of seismic signals, energy criteria-based methods are not robust for detecting moving targets, especially in data with low SNRs. To address this problem, we propose a new method for detecting ground moving target based on fractal dimension (FD) theory named FD-based support vector machine (FD-SVM). In this method, seismic signals are first measured by fractals, which can effectively extract seismic nonlinear features. These fractal features are then fed into an SVM to distinguish moving targets from noise. Two data sets are used to evaluate the proposed method. One is a set of seismic signals induced by wheeled and tracked vehicles. The other is a set of seismic signals generated by human footsteps. Experimental results demonstrate that the proposed FD-SVM algorithm achieves promising results on both data sets. Compared with the benchmark methods, the FD-SVM algorithm achieves a better precision rate, recall rate, and F1 score.**

Index Terms—**Detection, fractal dimensions (FDs), moving targets, seismic signals, support vector machine (SVM).**

I. Introduction

MOVING target detection with seismic sensing has been a research subject for a long time, and it can be widely applied in military and civil security/protection situations [1]. Moving targets can be of different types, such as humans, animals, various types of vehicles, and aircraft. It is vital to detect suspicious moving targets in sensitive areas because accurately and efficiently recognizing moving targets contribute to protecting restricted military zones and reducing illegal border crossings and illegal hunting [2]–[6].

Minimizing the false positive (FP) rate and maximizing the true positive (TP) rate are the main goals of detection problem. The established target detection methods using seismic sensing are mostly based on energy criteria, including four types: thresholding [3], [4], event isolation [5], cadence [6], and short/long time average (STA/LTA) ratio [7], [8]. The thresholding algorithm is the simplest and most intuitive detection method. It includes fixed thresholding and adaptive thresholding. A fixed threshold is an amplitude value that is set empirically. If the amplitude of the energy of the seismic signal exceeds a predetermined threshold, an abnormal event is confirmed. Otherwise, everything is deemed normal in the monitored areas [3]. The adaptive thresholding method usually takes the constant false alarm rate (CFAR) as the reference value. The CFAR has one more feedback adjustment module than the fixed threshold method, and the threshold can be dynamically adjusted according to external noise. Kalra *et al.* [4] proposed extracting the Renyi entropy from seismic signals in the time-frequency domain, and then inputting the Renyi entropy into a CFAR discriminator to detect moving targets. Event isolation is the second type of approach and is defined as the first-order second-moment of the signal. Clemente *et al.* [5] presented a fall detection method based on seismic sensing. The first-order second-moment of the seismic signal was used to detect footstep events in their work. Cadence can also be used to detect moving targets [6]. However, this method can only be used to detect footsteps. Its detection principle is based on the time interval between two adjacent footstep pulses. The delay is obvious in this frequency-based detection technique because it requires a series of footstep pulses to determine the signal period. The STA/LTA is a classic event detection method for seismic and microseismic signals [7], and is also widely used to detect moving targets. It is defined as the ratio of the energy of the short-term window to that of the long-term window of a signal segment. Mukhopadhyay *et al.* [8] compared the performances of the fixed thresholding, STA/LTA, and modified energy ratio (MER) methods in detecting moving targets. The experimental results showed that the MER method achieved the highest precision, but it took too much time. The detection precision of the STA/LTA method ranked second, and that of the fixed thresholding method was the worst. As a compromise, the authors ultimately chose the STA/LTA method. Although the above four types of methods have their strengths, most of them rely on seismic energy. Unfortunately, as the distance between the target and the sensor increases, the vibration energy propagated to the sensor rapidly diminishes [9]. Therefore, they are vulnerable to noises.

In this letter, a fractal dimension (FD)-based support vector machine (SVM) method is presented to improve the detection performance for ground moving targets. The FD theory can quantitatively describe the nonlinear behaviors of nonstationary signals, and has recently been successfully applied in heart rate detection and radar target detection [10], [11]. Inspired by these works, we study the effectiveness and advantages of the Hausdorff FD with linear SVM for detecting seismic signals generated by moving targets. Two data sets are used to evaluate the proposed method: seismic data induced by two types of military vehicles that were collected by

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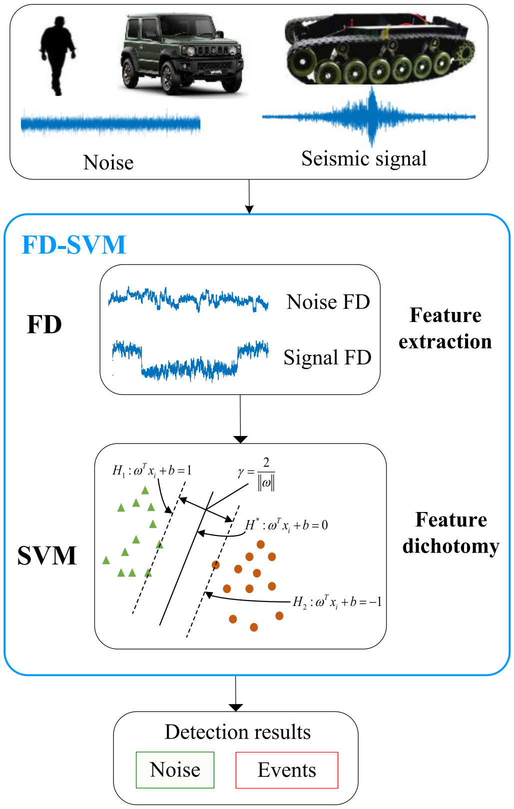


Fig. 1. Workflow of the fractal feature-based target detection method.

Defense Advanced Research Projects Agency's (DARPA's) SensIT project [15] and seismic data induced by human footsteps that were acquired by our self-developed seismic sensing apparatuses. The experimental results in these two case studies show that the proposed approach outperforms the benchmark methods.

II. Methodology

The workflow of the proposed method is illustrated in Fig. 1. It includes two steps: seismic feature extraction and feature discrimination. The seismic fractals are first calculated, and the seismic features of the moving targets are based on them. Then, the fractal features are input into an SVM to distinguish moving targets from noise.

A. FDs of Seismic Signals

Nonlinear dynamics and chaos theory can be used to describe irregular time-varying signals, which are universal in nonlinear dynamic systems [10]. FD technique is a phase–space dissimilarity measurement method based on chaos theory [12]. Its emergence provides a way for measuring how much space an object fills in a Euclidean space with a certain size. Dimensions in Euclidean space can only be integers, whereas in fractal geometry dimensions can be any positive real number.

FDs directly measure the complexity of a signal, which can be quantified by examining the dynamic behavior of the phase–space matrix. For any graph in Euclidean space, the relation holds

$$A \propto r^D \tag{1}$$

Algorithm 1 Pseudo-Code of Hausdorff Dimensions for Seismic Signals

1. Calculate the L using small circles with different radii.
2. Different segment lengths are generated.
3. Plot the series of data pairs (L_i, r_i) on a logarithmic coordinate system, where $(i = 1, 2, \ldots, n)$.
4. If all the (L_i, r_i) are roughly distributed along a straight line, the fractal dimension D can be obtained by the slope of the line.
5. Else, substitute the observed values (L_i, r_i) into equation (3) to obtain a linear regression model: $\lg L = (1 - D) \lg r$. D can be solved by a least square operation.

where A represents the quantity describing the graph (length, area, etc.) while r represents the measurement scale. D is the FD. Measure an irregular curve by a line segment of length r. The approximate length of the curve can be expressed as nr. n is the number of r. Hence, (1) can be converted to

$$nr \propto r^D. \tag{2}$$

For a seismic signal, its Hausdorff dimension is calculated and analyzed by the following: A self-affine curve can be obtained by the dimensionless graphical processing of a seismic signal. Cover a segment of the entire curve with a small circle of radius r. This curve is called a working window. Then, move the small circle along the curve. If n small circles can completely cover a curve segment, the length of the curve segment $L = nr$ can be defined. Based on (2), the Hausdorff dimension of the curve segment is obtained and can be formulated as

$$D = 1 - \lg(L)/\lg(r). \tag{3}$$

The total number of Hausdorff dimensions can be obtained by extending this calculation rule to the whole curve.

The calculation of the pseudo-code for seismic Hausdorff dimensions is described in Algorithm 1. It can be calculated that the FD of seismically quiet and active periods are different. Therefore, seismic fractal features can be used to discriminate between noise and effective signals.

B. Dichotomy of Seismic Fractal Features

The essence of moving target detection is to extract and locate the seismic signals in a long data segment. In other words, detecting a moving target is a dichotomy between seismic events and noise. The SVM model is an excellent dichotomy method. The basic SVM model is a linear classifier with the maximum interval defined in a feature space [13]. In our research, a linear SVM model is chosen as the classifier of seismic fractal features.

In linear SVM modeling, there is a data set $\{x_i, y_i\}_{i=1}^m$ with m samples and $y_i \in \{-1, 1\}$. A hyperplane $f(x) = 0$ is expected to separate the given data set into a positive class and a negative class. The hyperplane can be formulated as

$$f(x) = \omega^T x + b = \sum_{i=1}^{m} \omega^T x_i + b = 0 \tag{4}$$

where ω and b are the hyperplane parameters. To divide the samples into two classes, the hyperplane is subject to

$$y_i f(x_i) = y_i(\omega^T x_i + b) \geq 1, \quad i = 1, 2, \ldots, m. \tag{5}$$

Several training sample points closest to the hyperplane are called the support vectors. Support vectors satisfy the constraints in (5). A linear SVM model is supposed to insert a hyperplane between the positive and negative samples, and this operation is oriented by maximizing the margin $\gamma = 2/||\omega||$. Thus, the optimization objective of the linear SVM is expressed as

$$\begin{aligned}&\min_{\omega,b} \frac{1}{2}\|\omega\|^2 \\ &\text{s.t. } y_i(\omega^T x_i + b) \geq 1, \quad i = 1, 2, \ldots, m.\end{aligned} \tag{6}$$

III. Experiments

A. Evaluation Metrics

The metrics used for evaluation purposes are defined as follows: ground truths that are correctly detected are called TPs. Missed events are false negatives (FNs). Noise samples classified as events are called FPs. Metrics with statistical functions, including precision, recall, and the F1 score [14], are used to evaluate the detection performance of the proposed method. Precision is defined as: Precision $=$ TP$/($TP $+$ FP$)$. Recall represents the proportion of correctly detected events relative to the number of real events and is calculated by: Recall $=$ TP$/($TP $+$ FN$)$. The F1 score can evaluate the comprehensive performance of the algorithm. It represents the harmonic mean of precision and recall. Formally

$$F1 = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{7}$$

B. Case Study I

1) Description and Analysis of Data Sets: The seismic data collected from the third experiment (SITEX02) and organized by the DARPA's SensIT project [15] are used in our research. In SITEX02, 23 sensor nodes were distributed in an area of 900 $\times$ 300 m^2. The sensors acquired seismic data from two types of military vehicles, assault amphibious vehicles (AAVs) and dragon wagons (DWs), at a sampling rate of 4960 Hz. These data are sorted out and classified into three types in our work, which are AAVs, DWs, and noise segments. Then the FDs of these three types of sequences are calculated. Finally, a nonoverlapping window is employed to obtain detection samples.

To illustrate the seismic fractal features extracted from seismic signals, two seismic data segments generated by a DW and an AAV at the same sensor are processed. Their time domain forms are shown in Fig. 2(a) and (c). Data segments above background noise are marked by red dotted boxes. Two FDs are obtained from Fig. 2(a) and (c), and their results are shown in Fig. 2(b) and (d). It is easy to see that the noise FDs are larger while the signal FDs are smaller. When a vehicle signal is detected, the FD values drop rapidly. When the vehicle moves away from the sensor, the FD values increase rapidly. Therefore, the seismic fractal features can be used to distinguish signals from noise. We can also find from Fig. 2 that the average seismic energy of the DWs is approximately half that of the AAVs. The FDs of AAV seismic signals are relatively stable while the FDs of DW seismic signals have several pulses. This indicates that the FDs of AAV seismic signals are more ordered than those of DW seismic signals.

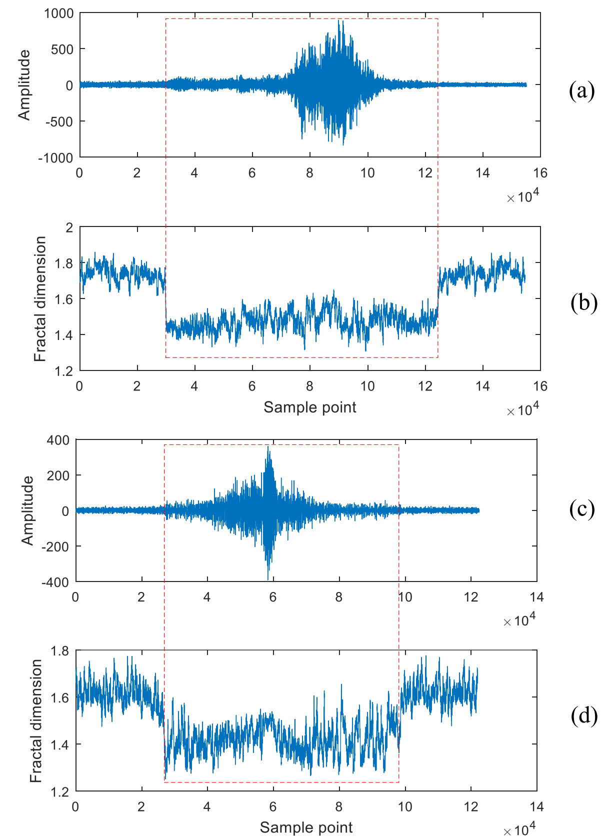
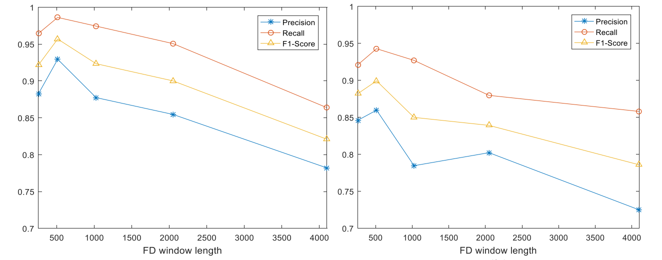


Fig. 2. Original seismic signals and seismic fractal features of two vehicles. (a) Seismic signals induced by an AAV. (b) FDs of (a). (c) Seismic signals induced by a DW. (d) FDs of (c).

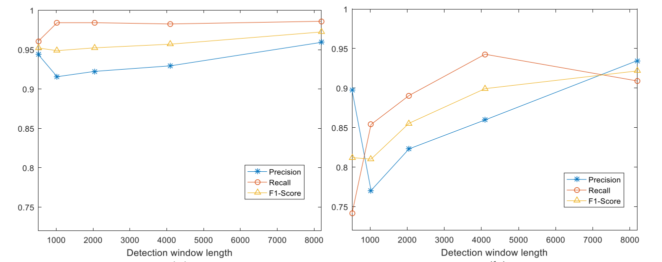
2) Determination of Model Parameters: Two parameters, the FD window length and detection window length, influence the detection results. The FD window length is the length of the working window for calculating Hausdorff dimensions. The detection window length is the number of fractal sample points input to the SVM. In this section, the optimal values of the two parameters are studied. For each parameter with different values, 10 repetitive trails are carried out. The mean value is employed to reduce the impact of random factors.

Detection windows longer than 1 second have little impact on the detection performance [8] while according to (3), the FD window length greatly influences the results. Hence, the length of the detection window is first fixed to 4096 ($\approx$1 s) to explore the optimal FD window length. The FD window length is increased from 256 to 4096, and the stride length is 2 to the power. Under different FD window lengths, the detection results for AAVs are shown in Fig. 3(a). The three statistical metrics all increase first and then decrease as the FD window length increases. When the FD window length is set to 512, the three metrics are at their highest values. The precision, recall, and F1 score are 0.929, 0.986, and 0.957, respectively. For the DWs, the overall results are similar to those of the AAVs, as shown in Fig. 3(b). However, the precision rate of the DWs fluctuates when the window length is 2048. When the



(a) (b)

Fig. 3. Results under different FD window lengths. (a) Detection results for AAVs. (b) Detection results for DWs.



(a) (b)

Fig. 4. Results under different detection window lengths. (a) Detection results for AAVs. (b) Detection results for DWs.

FD window length is 512, the precision, recall, and F1 score of the DWs are 0.860, 0.943, and 0.899, respectively.

The above experimental results demonstrate that the best detection performance is achieved when the FD window length is set to 512. Therefore, this FD window length is fixed to explore the lengths of the optimal detection windows. Under different detection window lengths, the results for the AAVs and DWs are shown in Fig. 4. When the detection window is small (512), the F1 scores of the AAVs and DWs are 0.952 and 0.812, respectively. When the detection window is set to 1024, the precision values of the AAVs and DWs begin to decline, but the recall values increase. To be more specific, the FD-SVM model detects more ground truths (i.e., TP) under this window length, but increases the FP detection at the same time (i.e., the model classifies more noise samples as events under this window length). The increase in FP is greater than that of TP under this new window length, leading to a decrease in the precision. When the size of the detection window increases from 1024 to 8192, all the detection metrics improve. The F1 score for the AAVs increases from 0.949 to 0.972, and the F1 score for the DWs increases from 0.810 to 0.922. We can also find that the influence of the detection window length on the DWs is greater than that on the AAVs, thereby indicating that appropriately increasing the detection window length can effectively improve the performance of the model for low-SNR signals. From Fig. 4(a) and (b), it is observed that the FD-SVM method performs better in detecting AAVs than DWs. This result is consistent with the previous analysis since the vibration energy of an AAV is higher than that of a DW.

It is worth noting that a time lag occurs when a long detection window is used, thus leading to a lag in the detection process. To achieve a relative balance between detection performance and computational efficiency, 512 is selected as the final FD window length and 4096 is selected as the detection window length.

3) Experimental Results: To evaluate the performance of the proposed method, the proposed FD-SVM method is compared with two benchmark methods, STA/LTA [8] and smooth and pseudo Wigner-Ville distribution (SPWVD) [4]. The STA/LTA is considered as the most popular method in seismic and microseismic detection tasks while the SPWVD is the state-of-the-art related detection method. The model parameters of the two benchmark methods are set according to the optimal values in the literature.

Fig. 5(a) shows the results achieved for the AAVs by the three methods. It is easy to find that the FD-SVM performs best because it achieves the highest value on all three evaluation metrics. For the F1 score, the FD-SVM has a value that is 8.2% higher than that of the STA/LTA and 7.5% higher than that of the SPWVD. In terms of the precision and recall rate, the recall rate of SPWVD is little higher than that of STA/LTA, but its precision is slightly lower than that of STA/LTA.

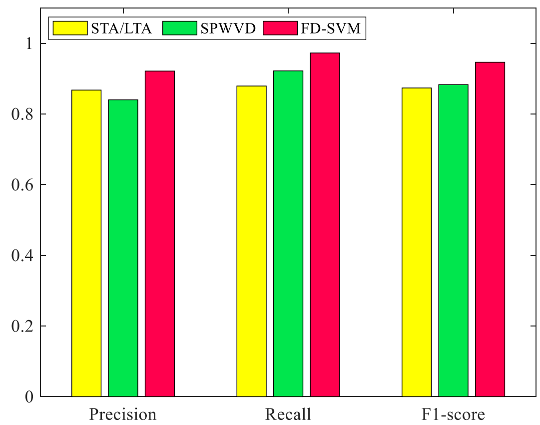
The results achieved for the DWs by the three methods are illustrated in Fig. 5(b). The FD-SVM achieves the highest precision, while the SPWVD achieves the highest recall rate. Although the SPWVD has the strongest ability to recall real events, its precision is the worst among the three methods. This means that the SPWVD is sensitive to both signals and noises. It is easy to classify noises as events, which results in a high false alarm rate (i.e., FP). In terms of the F1 score, the FD-SVM achieves the highest value, which is 0.901. The STA/LTA is ranked second (0.824) and the SPWVD is ranked third (0.766).

C. Case Study II

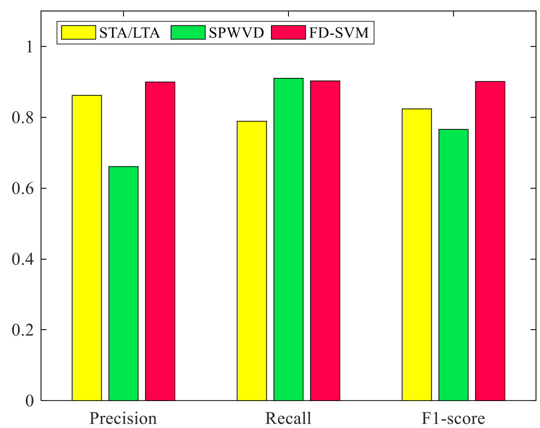
SITEX02 did not acquire seismic signals induced by human footsteps, which are the most common moving targets. Therefore, we developed a new data set in which the seismic signals generated by footsteps at different tracks were collected. This data set is used to evaluate the proposed method more comprehensively.

1) Description of Data Sets: Footstep signals from an adult male were acquired in a rural area of Changchun, China. The employed seismic sensors and data recording units were developed by Jilin University [16]. Their performances have reached industry-leading levels. The arrangement of the apparatuses and the trajectory of the moving target were as follows: Three seismic sensors were uniformly arranged in a circle with a radius of 1 m. The sampling rate was set to 1 kHz. An adult male weighing 82 kg walked counterclockwise 3–15 m [closest point of approach (CPA) [4]] from the center of the circle. The trajectories are circles with an increasing radius of 1 m. The recording time of each route was 60 seconds. Through this design, the acquired data attained different SNRs. According to the data preprocessing approach used in Case Study I, a total of 2340 signal samples were obtained. The logarithmic SNRs of these samples range from 0.2 to 1.4, and the numbers of samples with each SNR are nearly equal. Moreover, three apparatuses acquired noise data for 30 min, and 2770 noise samples were generated.

2) Experimental Results: The benchmark methods used on the footsteps data set are the same as in Case Study I. The detection results of the STA/LTA, SPWVD, and proposed



(a)



(b)

Fig. 5. Comparative results of the STA/LTA, SPWVD, and FD-SVM methods on the SITEX02 data set. (a) Results for the AAVs. (b) Results for the DWs.

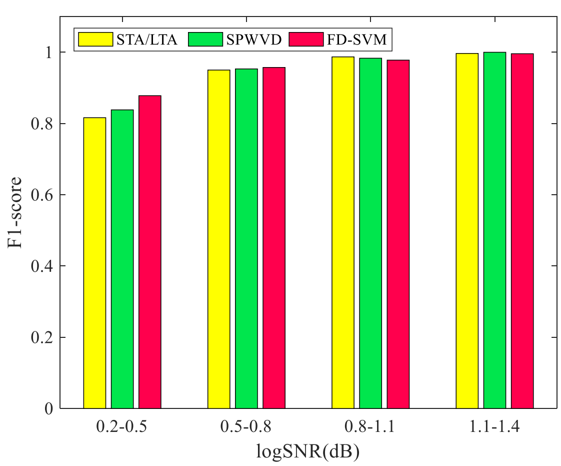


Fig. 6. F1 scores of the STA/LTA, SPWVD, and FD-SVM methods under different SNRs on the footsteps data set.

FD-SVM are shown in Fig. 6. The results of all three methods demonstrate that the higher the SNRs are, the better the F1 scores. Specifically, when testing the samples with high SNRs (0.5–1.4 dB), all the F1 scores achieved by three methods exceed 0.95, and the performance of the FD-SVM is very close to that of the two benchmark methods. However, when testing low-SNR samples (0.2–0.5 dB), the F1 score of the FD-SVM is 0.878, which is superior to that of the STA/LTA (0.816) and the SPWVD (0.838). In other words, the results of the three methods are approximate when testing high-SNR samples, while the FD-SVM method performs better when testing low-SNR samples, for which its F1 score is 6.2% and 4.0% higher than that of the STA/LTA and SPWVD method, respectively.

IV. Conclusion

In this letter, we present a novel method, called FD-SVM, for detecting ground moving target based on FD theory. Specifically, the Hausdorff dimension is first used to measure the complexity of seismic data, and it can effectively extract the nonlinear characteristics from signals and noises. Then, the seismic fractal features are input into the SVM to distinguish signals from noises. It has been observed that the FD-SVM method can offer good performance. The experimental results obtained on two data sets demonstrate that the FD-SVM model is superior to the benchmark methods. In future work, we will consider evaluating the performance of the proposed method for flying targets and mixed targets.

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