



# Photovoltaic Power Station Electromagnetic Environment Complexity Evaluation Utilizing Logarithmic Morphological Gradient Spectrum

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In this paper, a feature extraction method for evaluating the complexity of the Electromagnetic Environment (EME) of the photovoltaic power station is presented by using logarithmic morphological gradient spectrum (LMGS) based on the mathematical morphological theory. We use LMGS to evaluate electromagnetic environment signals. We also explored the impact of structure element (SE) on the MS, MGS, and LMGS. Three types of SE, mean the line SE, square SE and diamond SE, are utilized and compared for computing the LMGS. EME signals with four complexity degrees are simulated to evaluate the effectiveness of the presented method. The experimental results have shown that the feature extraction scheme proposed in this paper is a reasonable method to classify the complexity of EME.

**Keywords:** electromagnetic environment, photovoltaic power station, mathematical morphological spectrum, evaluation, feature extraction

## INTRODUCTION

With the rapid development of photovoltaic power generation technology and power electronics technology in the 21st century, photovoltaic power generation technology is becoming more and more mature. Human beings have built many large photovoltaic power stations on a large scale and use pollution-free green electric energy. On the other hand, the power of photovoltaic power stations is constantly expanding. Various electronic devices in photovoltaic power stations will produce electromagnetic radiation and form a complex and changeable electromagnetic environment. This will have an important impact on the efficiency of electronic equipment. Therefore, it is of great significance to study the complexity of the electromagnetic environment in photovoltaic power stations (Christoforidis et al., 2013; Wang et al., 2013; Salinas, 2018).

There are few related studies on the electromagnetic environment analysis of photovoltaic power stations, but there are many pieces of research on battlefield electromagnetic environment analysis, which can be used for reference to the electromagnetic environment analysis of photovoltaic power stations.

Tetley et al. proposed the analysis and prediction method of electromagnetic environment based on the mathematical model for the first time and gave the basic model of the electromagnetic environment from the point of view of mathematical analysis (Tetley, 1961). To classify the electromagnetic environment in different complexity degrees, feature extraction of

electromagnetic environment signal is a key step. In the past research, diverse features, such as spatial coverage, spectrum occupancy, time occupancy, energy domain average power density spectrum, and so on, have been developed and widely used to evaluate the electromagnetic environment in different complexity degrees (Chen et al., 2010; Zou et al., 2018; Liu et al., 2019; Fu, 2020). Dong and Li (2008) proposed a complexity assessment method of electromagnetic environment based on the Analytic Hierarchy Process (AHP), which refined the evaluation index, defined the evaluation standard parameters, and determined the scaling criterion. Wang and He (2008) introduced multivariate connection number to construct a comprehensive evaluation method of electromagnetic environment complexity, and the weight was set according to the principle of equal distribution. Li et al. (2017) provided a method to evaluate the complexity of electromagnetic environment based on generalized S-transform and probabilistic neural network (PNN), which used generalized S-transform to analyze the interfered sample signals in the electromagnetic environment, extracted signal parameters to train PNN, and classified them. (Li et al., 2013) proposed a new fractal dimension evaluation method based on morphological coverage to evaluate the complexity of the electromagnetic environment. (Li et al., 2019) proposed a method based on S-transform to simultaneously calculate timeshare, frequency share and energy share in the time-frequency domain and used the extreme learning machine to evaluate the environmental complexity. (Yin et al., 2019) proposed an electromagnetic environment assessment algorithm based on Fast S-transform and time-frequency space model. The time complex number, frequency complex number, and energy complex number were calculated at the same time, and F norm and root mean square were selected as evaluation indexes.

As a multi-scale analysis method based on mathematical morphology, mathematical morphological spectrum has been widely used in the field of image processing and feature extraction of mechanical vibration signals (Gao et al., 2015). The main idea is to filter the research object with structural elements of different scales and shapes to express the internal information of the research object.

Mathematical morphological spectrum is a very effective method to deal with image granularity and shape features proposed by Matheron (Matheron, 1975). Its vitality is strong, and it is widely used in image shape and texture feature description, image segmentation, image restoration, image denoising, and other fields. The main idea is to use sieves of different sizes and shapes to filter the image to understand its morphological characteristics. However, the traditional mathematical morphological spectrum is defined based on morphological open operation and difference operator, which is very effective in the analysis of binary images. In the past research, mathematical morphological spectrum has been applied to mechanical fault diagnosis, electronic device fault diagnosis and other fields (Song et al., 2018; Gao, 2019). (Zhao et al., 2018) proposed a method for Fault damage degree Identification based on high-order differential morphology gradient spectral entropy.

(Zhao et al., 2020) proposed a performance degradation prediction (HMEPEM) method based on high-order differential mathematical morphology gradient spectral entropy, phase space reconstruction, and limit learning machine, and applied it to predict the performance degradation trend of rolling bearings. (Lv et al., 2014) applied the theory of multi-scale mathematical morphological spectrum and morphological spectral entropy to the vibration fault diagnosis of water pump, which could achieve the purpose of fault diagnosis.

However, previous studies have found that the traditional mathematical morphological spectrum is not very effective in analyzing complex electromagnetic environment signals.

Therefore, the purpose of this paper is to study the application of the mathematical morphological spectrum method in the extraction of characteristic parameters of complex electromagnetic environment signals and to improve the original calculation method of the mathematical morphological spectrum. In this work, we discussed the influence of different types of structural elements and methods on the representation ability of mathematical morphological spectrum, verified the method with a variety of standard signals and electromagnetic environment signals, and compared various morphological spectrums.

The paper is organized as follows. In *Logarithmic Morphological Gradient Spectrum*, we introduce the mathematical morphological spectrum feature extraction method and support vector machine classification method used in this paper. In *Experimental Results*, the electromagnetic environment information is simulated, and the signal is tested by the method in *Logarithmic Morphological Gradient Spectrum*. The experiments are described and commented on in *Conclusion*.

## LOGARITHMIC MORPHOLOGICAL GRADIENT SPECTRUM

### Mathematical Morphological Spectrum

The main idea of the mathematical morphological spectrum is to use structural elements of different scales and shapes to filter the research object, to represent the internal information of the research object. Mathematically, the mathematical morphological particle analysis is defined in the form of set  $Y = \{\Psi_\lambda\}_{\lambda \geq 0}$ , that is, a series of transformational  $\Psi_\lambda$  sets.  $\Psi_\lambda$  is defined as:

$$\Psi_\lambda(X) = X \circ \lambda g$$

Where “ $\circ$ ” is the morphological operation symbol,  $\lambda$  is a scale parameter whose value is not less than 0, and  $g$  is a unit structural element,  $\lambda g$  represents the structural element under a certain scale  $\lambda$ , and its expression is as follows:

$$\lambda g = \underbrace{g \oplus g \cdots \oplus g}_\lambda$$

In the formula, “ $\oplus$ ” is the symbol of morphological dilation operation.

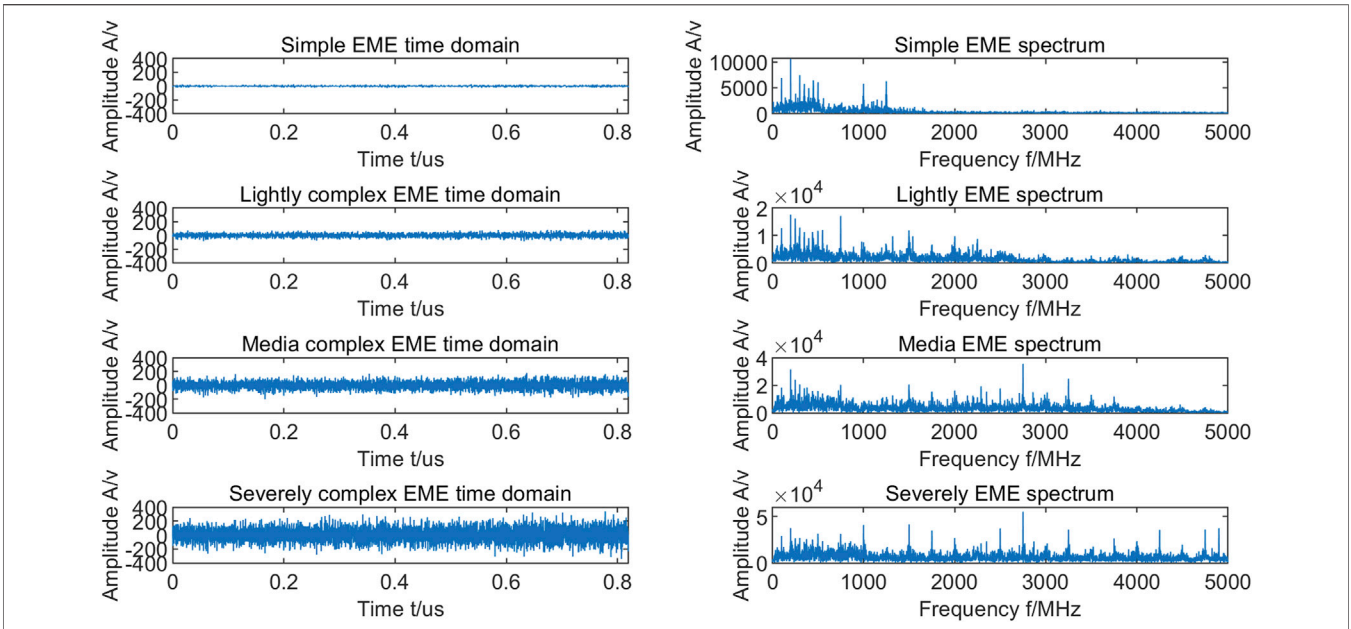


FIGURE 1 | Simulation for EME signal.

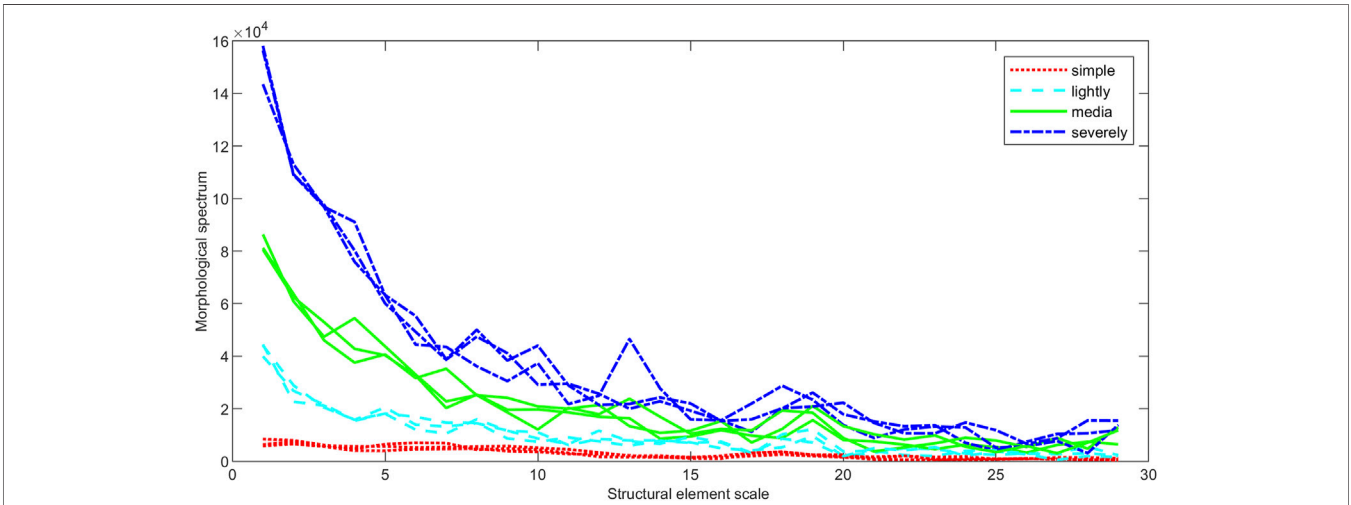


FIGURE 2 | MS analysis result of line SE.

Set a continuous-time domain function  $f(n)$ , structure-function  $g(m)$ , then the mathematical morphological spectrum expression of the function  $f(n)$  is as follows:

$$MS(f, \lambda, g) = \begin{cases} \frac{dS(f \circ \lambda g)}{d\lambda} & \lambda \geq 0 \\ -\frac{dS(f \cdot (-\lambda)g)}{d\lambda} & \lambda < 0 \end{cases}$$

In the formula,  $\lambda$  represents the scale of the structural element,  $S = \int f(x)dx$  represents the measure of  $f(x)$  in the definition domain, and the umbra area of the gray value signal is taken. The

scale of structural elements can be taken as a continuous integer value when analyzing the morphological particle distribution of the one-dimensional discrete signal. The morphological spectrum in the combination formula below simplifies the morphological spectrum of the open operation and closed operation of the one-dimensional discrete signal respectively:

$$MS_+(\lambda, g) = S[f \circ \lambda g - f \circ (\lambda + 1)g], \quad 0 \leq \lambda \leq \lambda_{max}$$

$$MS_-(\lambda, g) = S[f \cdot (-\lambda)g - f \cdot (-\lambda + 1)g], \quad \lambda_{min} \leq \lambda < 0$$

In the form,  $S = \int f(x)dx$ . The mathematical morphological spectrum reflects the distribution of signal morphological

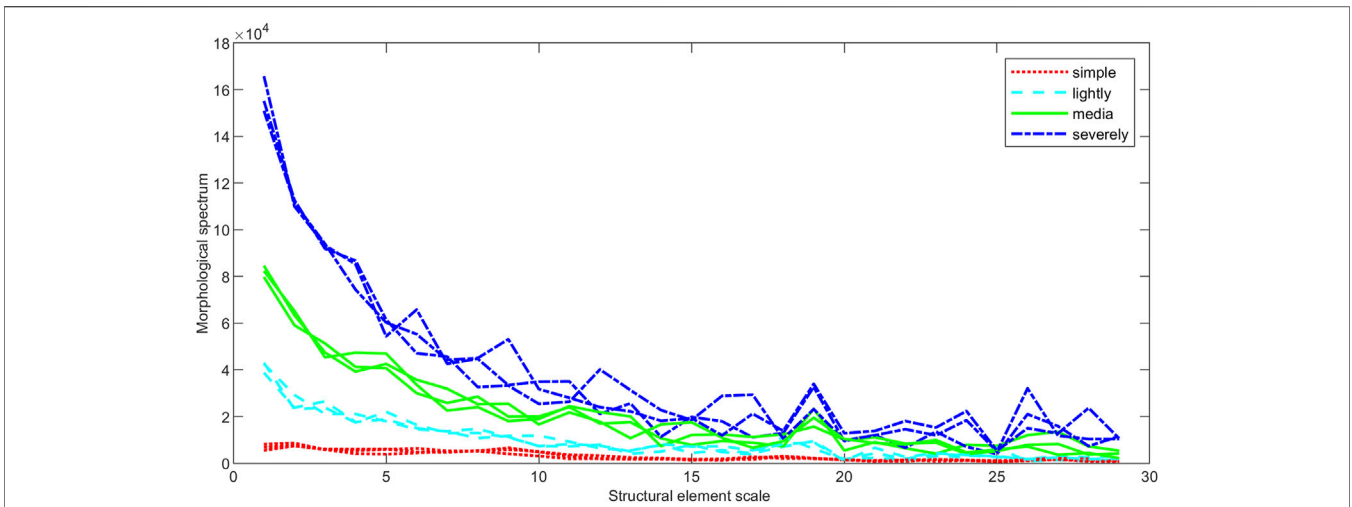


FIGURE 3 | MS analysis result of square SE.

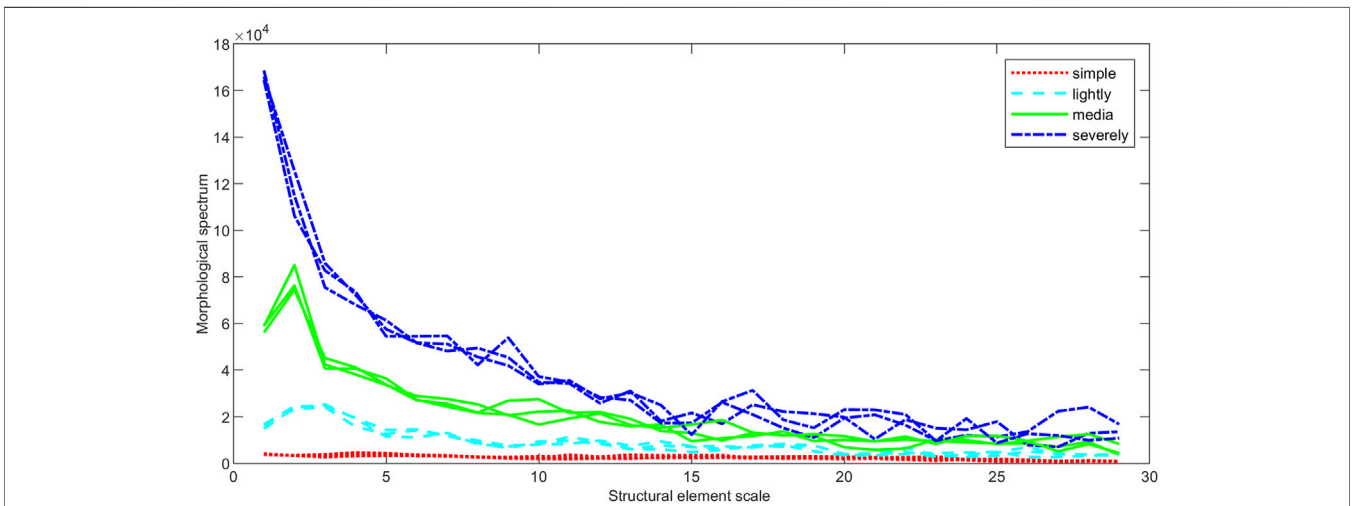


FIGURE 4 | MS analysis result of diamond SE.

characteristics at different structural element scales. For the structural element  $\lambda g$  under a certain scale, the more morphological structural components corresponding to the signal, the larger the spectral line value in the signal mathematical morphological spectrum, on the contrary, the less the structural component, the smaller the corresponding spectral line value (Zhang et al., 2013).

The mathematical morphological spectrum can be simplified to the open operation morphological spectrum at scale  $\lambda \geq 0$  and the closed operation morphological spectrum at scale  $\lambda < 0$ . The open operation morphological spectrum reflects the structural characteristic information of the signal itself, while the closed operation morphological spectrum reflects the corresponding background information (Li et al., 2015).

### Mathematical Morphological Gradient Spectrum

The difference of the function  $f(n)$  after the expansion and erosion of the structural element  $g(m)$  forms the concept of the function morphological gradient. When processing the signal, the morphological gradient not only considers both the positive and negative pulse information of the signal but also can efficaciously extract the morphological features of the signal (Liu et al., 2016). The morphological gradient operator expression is as follows:

$$Gard(f) = f \oplus g(m) - f \ominus g(m)$$

Introducing the concept of morphological gradient into the mathematical morphological spectrum in formula above, the

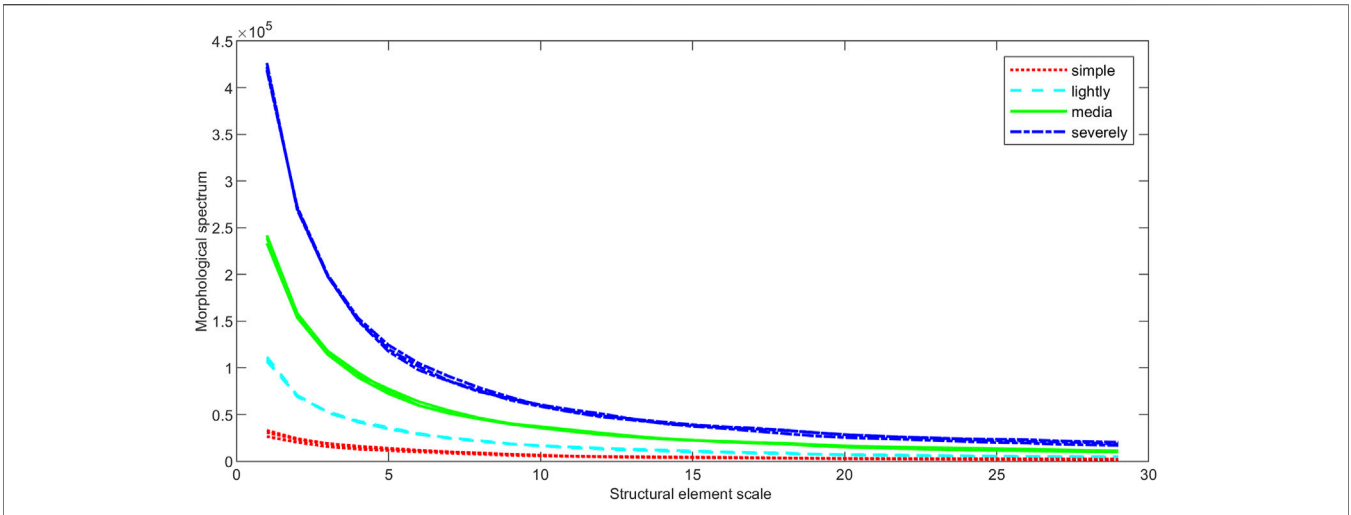


FIGURE 5 | MGS analysis result of line SE.

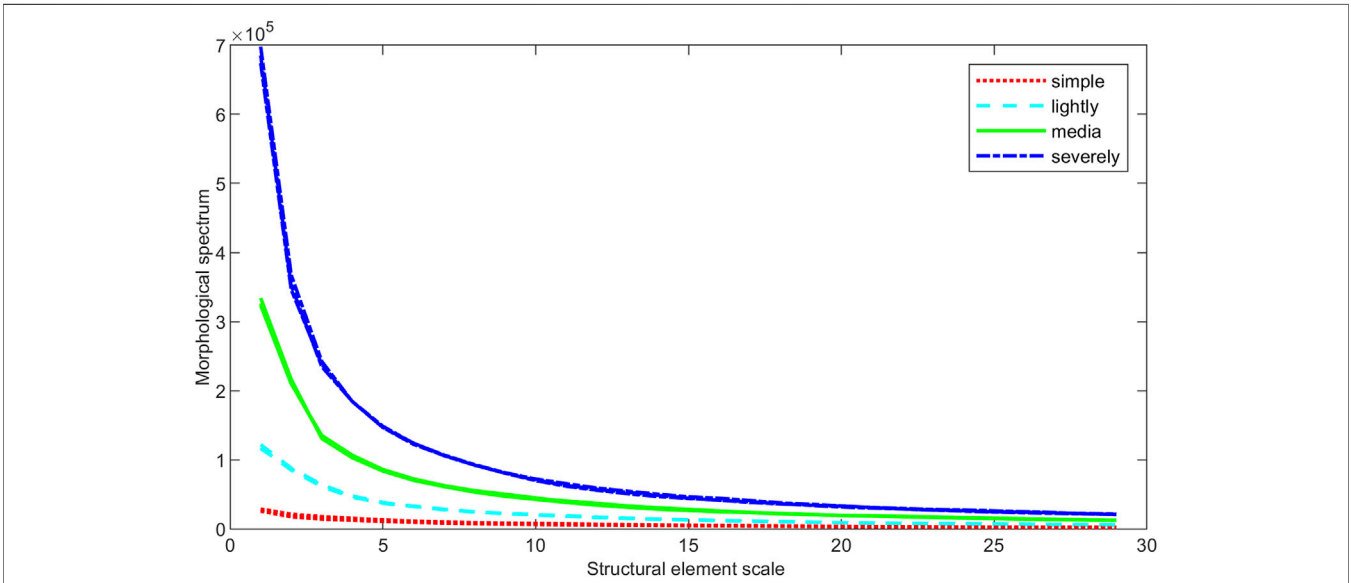


FIGURE 6 | MGS analysis result of square SE.

concept of mathematical gradient spectrum (MGS) is obtained (Zhang et al., 2013):

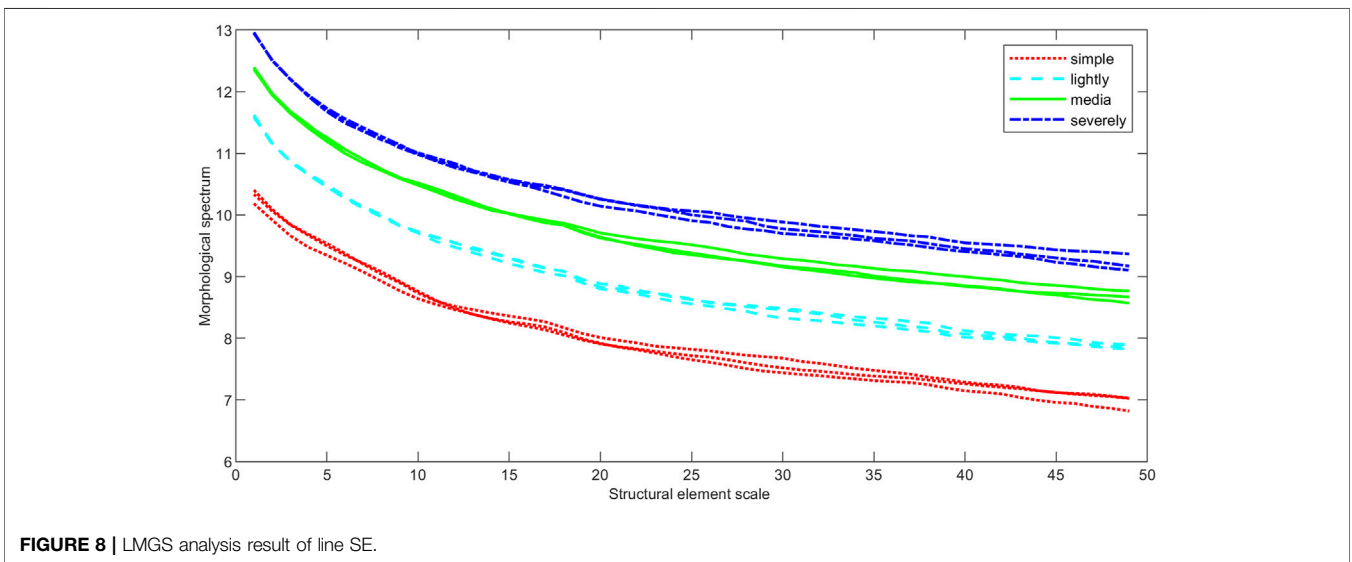
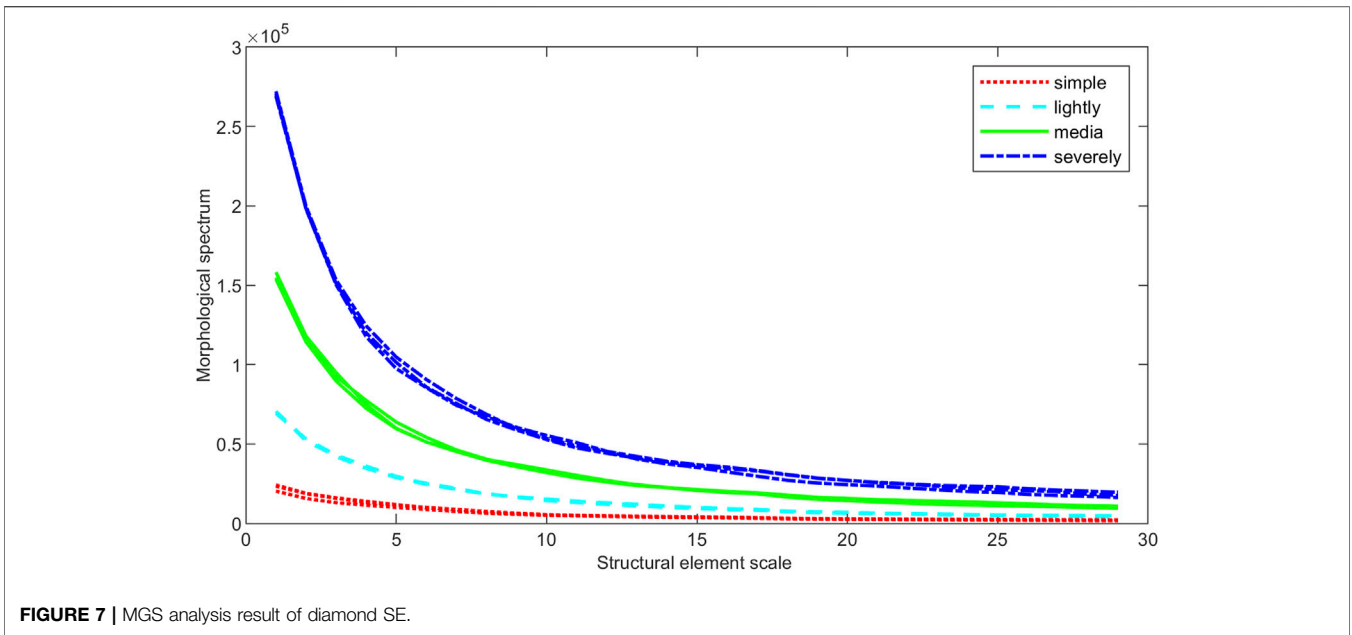
$$MGS(f, \lambda, g) = \begin{cases} \frac{dS(f \oplus \lambda g - f \ominus \lambda g)}{d\lambda} & \lambda \geq 0 \\ \frac{dS(f \ominus (-\lambda)g - f \oplus (-\lambda)g)}{d\lambda} & \lambda < 0 \end{cases}$$

For the one-dimensional discrete signal, considering the extension of the morphological gradient operator, the morphological gradient spectrum can be simplified as follows:

$$MGS_+(f, \lambda, g) = S[f \oplus (\lambda + 1)g - f \ominus (\lambda + 1)g - (f \oplus \lambda g - f \ominus \lambda g)]$$

$$MGS_-(f, \lambda, g) = S[f \ominus (-\lambda + 1)g - f \oplus (-\lambda + 1)g - (f \ominus (-\lambda)g - f \oplus (-\lambda)g)]$$

In the formula, the dilate and erode morphology gradient spectrum of  $S(f) = \sum f(n)$ ,  $MGS_+(f, \lambda, g)$ , and  $MGS_-(f, \lambda, g)$  respectively reflect the shape change law of the signal under different structural element scales in the positive and negative intervals. It can be seen from the duality of dilate and erode operations that these two kinds of morphological gradient spectrum are essentially the same structure when describing the morphological complexity of objects.



### Logarithmic Morphological Gradient Spectrum

Although both mathematical morphology spectrum and mathematical morphology gradient spectrum describe the change law of signal shape at different scales, it is found that the discrimination between EME signal spectral lines with different complexity is very poor by extracting the mathematical morphology spectrum characteristics of EME signal at different scales. The morphological gradient spectral curves calculated at different scales can distinguish EME signals with different complexity, but the distinguishing effect is poor. In

this section, the morphological gradient spectrum is logarithmically processed, and the feature extraction method based on the logarithmic mathematical morphological gradient spectrum is adopted. Combined with the properties of logarithmic function and expansion corrosion morphology gradient spectrum, the expansion corrosion morphology gradient spectrum is processed logarithmically. The expression of the logarithmic morphological gradient spectrum on the positive interval is obtained.

$$LMGS_+ = \log(MGS_+(f, \lambda, g) + 1), \lambda \geq 0$$

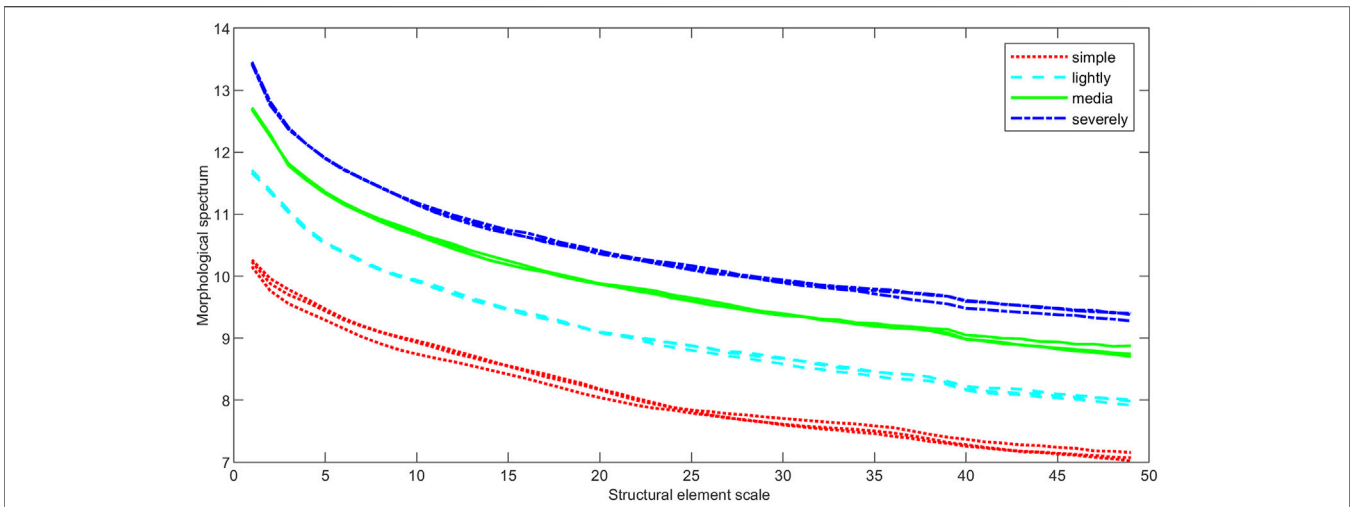


FIGURE 9 | LMGs analysis result of square SE.

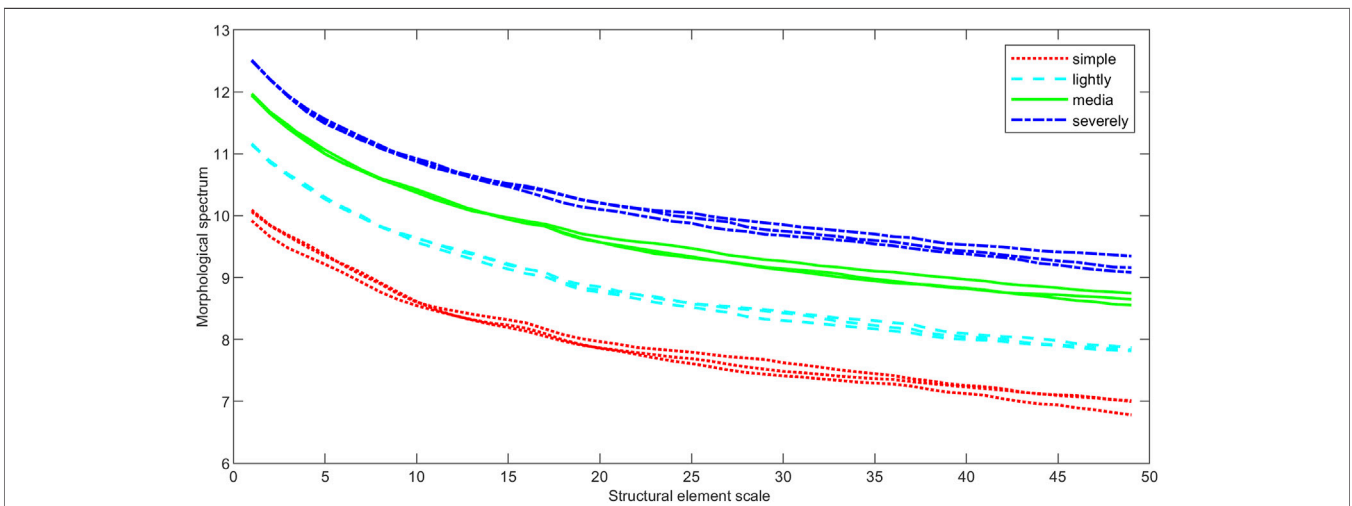


FIGURE 10 | LMGs analysis result of diamond SE.

TABLE 1 | Classification accuracy.

Accuracy	Line (%)	Square (%)	Diamond (%)
MS	84.5	83.6	85.2
MGS	90.3	89.8	92.1
LMGS	96.7	95.2	97.1

## EXPERIMENTAL RESULTS

### EME Simulation

Photovoltaic Power Station mainly consists of control devices and solar panel area (Wang et al., 2013). The control devices include the inverter cabinet, DC voltage regulator cabinet, DC control cabinet, AC control cabinet and so on. And there are lots of thin-

film solar panels of different power in the solar panel area. These devices will produce a variety of electromagnetic signals with different frequencies and amplitudes when they are working, and these devices may not work at the same time, so the occurrence time of electromagnetic signals is not consistent. These various electromagnetic signals constitute the complex electromagnetic environment of photovoltaic power stations together.

Base on this, we simulate a variety of electromagnetic environment signals with different frequencies and apply these signals to construct the electromagnetic environment under the condition of random time and amplitude of the signals. According to the number of signals used, we construct four kinds of electromagnetic environment signals with simple, slight, moderate and severe complexity.

The generated electromagnetic environment signal is shown in Figure 1. The time-domain waveform and spectrum of simple, slightly

complex, moderately complex, and severely complex electromagnetic environment signals are arranged from top to bottom.

## Feature Extraction

### Mathematical Morphological Spectrum

Similar to the filter window in digital signal processing, the scale and shape of SE have an important influence on the calculation results. In this experiment, the line, square and diamond structure elements are used to verify the influence of different shape structure elements on the mathematical shape spectrum.

The mathematical morphological spectrum curves of different electromagnetic environment signals are calculated. The results are shown in **Figures 2–4**.

As the results show, the MS curve fluctuates up and down, and when the scale of the structural elements tends to 20, the curves are interlaced with each other. The morphological spectrum values calculated by the MS method cannot well distinguish the four kinds of EME signals when they are used as features.

### Mathematical Morphological Gradient Spectrum

The mathematical morphological gradient spectrum curves of different electromagnetic environment signals are calculated. The structural elements are selected as line, square and diamond. The results are shown in **Figures 5–7**.

As the results show, the trend of the four MGS curves is the same, they all decrease monotonously, and the differentiation is certain when the scale is small, but with the increase of the scale, the differentiation of the four curves decreases.

### Logarithmic Mathematical Morphological Gradient Spectrum Feature Extraction

The mathematical morphological gradient spectrum curves of different electromagnetic environment signals are calculated. The structural elements are selected as line, square and diamond. The results are shown in **Figures 8–10**.

The LMGS curves of four kinds of complexity EME signals are distinct and have the same trend, and their spectral values all decrease monotonously with the increase of the scale, they are well differentiated.

## SVM Classification

The data samples used are all from the feature matrix extracted by mathematical morphological spectrum, mathematical morphological gradient spectrum, and logarithmic mathematical morphological gradient spectrum. After training the SVM through the training data, the test data is classified to obtain classification accuracy. The process is repeated 50 times, and the average classification accuracy of different types of support vector machines is shown in **Table 1**.

Through support vector machine classification, the classification effect obtained by LMGS is the best, and the

classification effect obtained by MS and MGS is worse than LMGS. For line, square, and diamond structure elements, the results have shown that the diamond SE acquires the best performance on distinguishing the four EME complexity degrees.

## CONCLUSION

This work has proposed an effective feature extraction method by using the logarithmic morphological gradient spectrum for evaluating the EME complexity degree of the photovoltaic power station. The EME signals with four complexity degrees are simulated to verify the effectiveness of the presented method. We use MS, MGS, and LMGS to evaluate electromagnetic environment signals. The experimental results have shown that LMGS can effectively distinguish the complexity of EME and show better performance than MS and MGS.

We also explored the effects of the structure elements, mean line, square, and diamond on distinguishing the EME complexity degrees. Results have shown that the diamond SE acquires the best performance in distinguishing the four EME complexity degrees. Our research has shown that the feature extraction method of logarithmic morphological gradient spectrum is an ideal technique to evaluate the complexity of electromagnetic radiation of photovoltaic power stations.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

## AUTHOR CONTRIBUTIONS

HX contributed to conceptualization, data curation, methodology, and writing—original draft. BL contributed to formal analysis, visualization, and resources. WM, XX, and YW wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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