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# A new image segmentation method based on multifractal detrended moving average analysis

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## HIGHLIGHTS

- A novel image segmentation method is proposed.
- Two rapeseed images of nutritional deficiency are used to test our method.
- The proposed method is superior to the other two multifractal segmentation methods.
- Some meaningful conclusions are obtained.

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ABSTRACT

In order to segment and delineate some regions of interest in an image, we propose a novel algorithm based on the multifractal detrended moving average analysis (MF-DMA). In this method, the generalized Hurst exponent $h(q)$ is calculated for every pixel firstly and considered as the local feature of a surface. And then a multifractal detrended moving average spectrum (MF-DMS) $D(h(q))$ is defined by the idea of box-counting dimension method. Therefore, we call the new image segmentation method MF-DMS-based algorithm. The performance of the MF-DMS-based method is tested by two image segmentation experiments of rapeseed leaf image of potassium deficiency and magnesium deficiency under three cases, namely, backward ($\theta = 0$), centered ($\theta = 0.5$) and forward ($\theta = 1$) with different $q$ values. The comparison experiments are conducted between the MF-DMS method and other two multifractal segmentation methods, namely, the popular MFS-based and latest MF-DFS-based methods. The results show that our MF-DMS-based method is superior to the latter two methods. The best segmentation result for the rapeseed leaf image of potassium deficiency and magnesium deficiency is from the same parameter combination of $\theta = 0.5$ and $D(h(-10))$ when using the MF-DMS-based method. An interesting finding is that the $D(h(-10))$ outperforms other parameters for both the MF-DMS-based method with centered case and MF-DFS-based algorithms. By comparing the multifractal nature between nutrient deficiency and non-nutrient deficiency areas determined by the segmentation results, an important finding is that the gray value's fluctuation in nutrient deficiency area is much severer than that in non-nutrient deficiency area.



## 1. Introduction

Image segmentation of key regions is one of hottest topics in image processing. As an important application field, intelligent agriculture relies greatly on the digital agricultural images analysis in modern society. In crop science, the key

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issue of diagnosing the nutritional deficiency of the studied crop by machine intelligence is how to acquire the valid features of leaf images and how to further locate key regions by these features [1]. The hard but interesting issue has attracted not only crop researchers but also mathematician and computer scholars, since it has become a cross-disciplinary problem. It is still difficult to solve the problem thoroughly, even though modern image processing technology has made great progress.

As a powerful mathematic tool, fractal theory initiated by Mandelbrot [2] in the 1960s has been widely applied to many areas of natural sciences. Since the simple iterative algorithm in the fractal theory can generate a variety of complex images and fractal dimension is considered as an effective measure of the complexity of the target object, there are some intrinsical connection between the fractal and complex image [3]. Currently, a mount of meaningful researches have been conducted to the image processing by the fractal analysis [4–7].

However, for most natural surfaces owing self-similarity or semi-similar, they are not only fractal but also multifractal. Hence, the fractal analysis is not enough for this case. Multifractal analysis (MFA) extended from the fractal analysis has been widely used to uncover the multifractal nature of the surface in the real world [8–12]. In the classic MFA, multifractal spectrum (MFS) is an important indicator which is usually used to describe singularity of the surface. Based on MFS, an image segmentation method was proposed to be applied in various image segmentation researches [13–15], of which Yu [13] used the MFS-based segmentation to segment the decayed CT images; Stojic [14] used this method to analyze the medical images. The large number of the empirical experiments indicates that the powerful MFS-based method is superior to traditional methods.

In 2002, Kantelhardt [16] introduced a new technology to uncover the multifractal nature of the object, which is the so-called multifractal detrended fluctuation analysis (MF-DFA). Compared with the MFA unable to analyze the non-stationary measure, the method of MF-DFA can well do this job. Not surprisingly, the MF-DFA was widely used to deal with non-stationary time series in various fields [17,18]. As a meaningful extension, two-dimensional (2D) MF-DFA [19] was proposed to analyze multifractal surface. Hereafter, some voluntary studies have been implemented for some specific image analysis by the 2D MF-DFA [20–23]. Furthermore, based on the 2D MF-DFA, Wang et al. [24] reported a novel image segmentation method to solve corn disease leaf image processing problem. The segmentation experiments show that the method is much better than the MFS-based method. Recently, a novel method, called multifractal detrended moving average analysis (MF-DMA) was extended by Gu [25] from the DMA [26], which was also able to estimate the generalized Hurst exponent accurately. Because the MF-DMA method can easily describe the multifractal nature of non-stationary series without any assumption, it is widely used in analysis of time series [27,28]. For the one-dimensional (1D) case, a mount of empirical studies unveil that the performance of the MF-DMA method is slightly superior to the MF-DFA method under some certain circumstances [29,30]. For the 2D case, by defining local generalized Hurst exponent by MF-DMA and MF-DFA, Wang et al. compared the performance of the local feature's identification of different textures between the two methods and also showed the former is better than the latter [31].

In this paper, we present a new image segmentation algorithm based on the 2D MF-DMA, which we call the MF-DMS-based method. Firstly, we consider three cases of position parameters in 2D MF-DMA to estimate generalized Hurst exponent for each pixel in an image, used as local texture descriptor. Then borrowing the ideas of the MFS-based and MF-DFS-based methods, multifractal detrended moving average spectrum function (MF-DMS) is defined as well as the MF-DMS-based segmentation algorithm is proposed. Finally, two rapeseed leaves of magnesium and potassium deficiency images are used to test the proposed method. The results show that our method is superior to the MFS-based and MF-DFS-based algorithms and can provide a precise location for the interest areas.

## 2. Methods

### 2.1. 2D MF-DMA

We first adopt the 2D MF-DMA methods proposed in Ref. [25], which is used to investigate possible multifractal properties of surfaces. It can be denoted by a two-dimensional matrix $X(i_1, i_2)$ with $i_1 = 1, 2, \ldots, N_1$ and $i_2 = 1, 2, \ldots, N_2$. The algorithm is described as follows.

**Step 1.** Calculate the sum $Y(i_1, i_2)$ in a sliding window with size $n_1 \times n_2$, where $n_1 - \lfloor (n_1 - 1)\theta_1 \rfloor \le i_1 \le N_1 - \lfloor (n_1 - 1)\theta_1 \rfloor$ and $n_2 - \lfloor (n_2 - 1)\theta_2 \rfloor \le i_2 \le N_2 - \lfloor (n_2 - 1)\theta_2 \rfloor$. The two position parameters $\theta_1$ and $\theta_2$ vary in the range [0, 1]. Specifically, for $\theta_1 = \theta_2 = 0$, which corresponds to backward moving average, we extract a sub-matrix $Z(u_1, u_2)$ with size $n_1 \times n_2$ from the matrix $X$, where $i_1 - n_1 + 1 \le u_1 \le i_1$ and $i_2 - n_2 + 1 \le u_2 \le i_2$. We can calculate the sum $Y(i_1, i_2)$ of $Z$ as follows,

$$Y(i_1, i_2) = \sum_{j_1=1}^{n_1} \sum_{j_2=1}^{n_2} Z(j_1, j_2). \tag{1}$$

**Step 2.** Determine the moving average function $\tilde{Y}(i_1, i_2)$. First, we extract a sub-matrix $W(k_1, k_2)$ with size $n_1 \times n_2$ from the matrix $X$, where $i_1 - \lceil (n_1 - 1)(1 - \theta_1) \rceil \le k_1 \le i_1 + \lfloor (n_1 - 1)\theta_1 \rfloor$, $i_2 - \lceil (n_2 - 1)(1 - \theta_2) \rceil \le k_2 \le i_2 + \lfloor (n_2 - 1)\theta_2 \rfloor$. Then we calculate the cumulative sum $\tilde{W}(m_1, m_2)$ of $W$

$$\tilde{W}(m_1, m_2) = \sum_{d_1=1}^{m_1} \sum_{d_2=1}^{m_2} W(d_1, d_2), \tag{2}$$