Detection of small-sized insect pest in greenhouses based on multifractal analysis

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\section*{ABSTRACT}
A new application of multifractal analysis for the detection of small-sized pests (e.g., whitefly) from leaf surface images in situ is proposed in this paper. Multifractal analysis was adopted for segmentation of whitefly images based on the local singularity and global image characters with the regional minima selection strategy. According to the multifractal dimension, the candidate blobs of whiteflies were initially defined from the leaf image. The regional minima were utilized for feature extraction of candidate whitefly image areas and the performance was compared to that of the fixed threshold. Subsequently, most false alarms from leaf veins were decreased by consideration of the size and shape of the whiteflies. Experiments were conducted with field images in a greenhouse. Detection results were compared with other adaptive segmentation algorithms. Values of $F$ measuring precision and recall scores were higher for the proposed multifractal analysis (86.6\%) than for conventional methods such as Watershed (60.2\%) and Efficient Graph-based Image Segmentation (EGBIS; 42.8\%). The true-positive rate of multifractal analysis was 86.9\% and the false-positive rate was at the minimum level of 8.2\%. Overall, the detection of small-sized pests is most feasible with the proposed multifractal analysis under greenhouse conditions.

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\section*{1. Introduction}
Pest damage is a primary factor leading to severe crop losses in an agriculture setting. Pest damage results in economic production losses to the agricultural industry, estimated as 28.2\% in Europe, 31.2\% in North America, 36.2\% in Oceania, and up to 50\% in Asia and Africa [1]. For many years, pesticides have been considered a primary way of increasing crop yield. Because of the drawbacks of pesticide misuse (e.g., non-target and adverse effects, pest resistance), agricultural scientists have initiated an alternative approach to pest control, i.e., integrated pest management (IPM), a program dating back to the late 1960s, when agricultural investigators from different disciplines began working together to search for better methods of pest control than the use of chemical pesticides.

Pest dispersal is critical, especially in a greenhouse environment, considering that the plants are cultivated in highly condensed concentrations in a closed, homogeneous environment [2]. Efficient control of pests is desired for the proper economic management of agricultural practices. Minimal use of pesticides is also required for the safety of cultivators and for the minimization of chemical residues in agricultural products and the environment [3]. Consequently, accurate localization of pests followed by on-site spraying of pesticides on the target pests is a prerequisite for achieving successful pest management.

As science and technology develop, image-processing technologies and robotics (e.g., harvesting and pesticide-spraying robots) are becoming more widely used in agriculture to reduce farmers' workload and save work time [4]. Automatic pest-detection methods have been examined along with development of imaging devices for the detection of insects on grain or crop fields to cope with the challenge of localizing pests. Computational techniques related to identification of agricultural pests and microorganisms have been tested in various environmental conditions. Vision-based detection for identification of pests on grain was reported by Ridgway et al. [5] and Neethirajan et al. [6]. Additionally, Zayas and Flinn [7] introduced a machine vision technique that uses multivariate analysis to detect insects in crop background images. The extraction of small spots from biological images was first reported by Olivo-Marín [8], an alternative solution for detection of crop
insects. Singh et al. [9] reported on the use of near-infrared (NIR) hypersonpectral imaging systems to detect wheat kernels damaged by insects.

Under greenhouse conditions, whiteflies (Genus Bemisia) have been regarded as a primary pest in Asian countries [10,11]. The insect is very harmful to plants, not only causing direct damage, but also transmitting potential vectors of plant disease (e.g., cucumber yellows virus) [12]. Conventionally, one of the most common methods for adult pest collection in greenhouses is sampling by the sticky traps. Due to the difficulty of analyzing the image data, however, counting the number of insects on sticky traps has primarily relied on visual judgment, which is tedious and time-consuming. Moreover, accuracy is frequently affected by intrinsic variability in identification skills as well as fatigue of investigators, especially concerning the small-sized insects commonly found in greenhouses (e.g., whiteflies, thrips). The most problematic issue regarding detection of the pest insects under field conditions is the small size of the pests and challenge in extraction of the target images from the background images. The length of whitefly adult is only approximately 2 mm, and thus, the specimens are difficult to identify with the naked eye.

Due to challenges of on-site detection, most early studies of pest detection methods relied on the scanning of sticky traps (or plant leaves) under highly controlled light conditions. Since the small images were strongly affected by the variable illumination conditions, high-resolution images (e.g., 1600 × 1200 pixels or higher) were required for detection. Various methods have been proposed for identifying and counting small-sized insects in laboratory conditions. Cho et al. [13] reported on an automatic pest-detection method that could identify small pests including whiteflies, aphid, and thrips based on the characteristic color and size of the species. Martin and Thonnat [14] reported on a cognitive-vision approach, which adjusts parameters for segmenting pests out of leaf backgrounds by an optimization algorithm. By employing computer vision and knowledge-based techniques, Martin and Thonnat [14] reported on a multidisciplinary cognitive-vision approach based on Watershed segmentation, which was applicable for segmenting whiteflies out of roses in situ.

Vision-based insect detection demonstrated high performance on scanned images under laboratory conditions. However, disadvantages in image scanning include the light requirements and its time-consuming nature [15]. Consequently, fully automatic in situ detection of pests is a more desirable technique over image scanning. Recently, many studies regarding in situ pest-detection have been proposed based on the observation of sticky traps under greenhouse conditions. Solis Sánchez et al. [16] introduced the application of machine-vision techniques using the Otsu algorithm [17] for scouting whitefly image segmentation from the sticky traps captured in the field. An upgraded version of insect monitoring has also been implemented using a scale-invariant approach for the scouting and identification of pests [18]. Along with in situ pest-detection, online pest-monitoring systems have been also proposed. Several prototypes of continuous pest-monitoring systems in greenhouses were devised, and these consisted of sticky traps, real-time observation cameras, and image recognition and recording software [19–21].

Here, we focused on detecting small-sized insect pests (whiteflies) from leaf images captured by an agricultural robot under greenhouse conditions based on multifractal analysis. Multifractals are considered to be an extension of fractals with multiple scales [22–25], introduced for numerous applications in pattern recognition, including image feature extraction [26,27]. Notably, multifractals are effective in combination with other algorithms, such as wavelet, are robust in their handling of environmental changes (e.g., scale and rotation), and are efficient in preserving abundant image information (e.g., textures) [28]. The performance of pest detection from the method based on multifractal analysis with regional minima is compared with three methods including two well-known adaptive segmentation algorithms in early studies: Watershed [29] and Efficient Graph-based Image Segmentation (EGBIS) [30], and multifractal analysis with fixed thresholds.

The report is organized as follows: Section 2 introduces the theory and principles of multifractal image analysis. Next, our pest detection method is proposed in Section 3. The experimental procedure is described in detail in Section 4, while experimental results are discussed in Section 5. Finally, the conclusions are provided in Section 6.

2. Multifractal image analysis

Self-similar objects and phenomena can be described by a non-integer dimension called the fractal dimension to show the irregular structure of objects [22]. The fractal dimension measures the degree of irregularity and complexity of an object. The multifractal dimension has been proposed as an extension of fractal dimension to describe more sophisticated, structured objects on different scales. Local and global characters of the object are concurrently measured to extract data features [31].

2.1. Basics of multifractal theory

The following equation, defined [30] as

$$l_{i,j,n} = \left[ \frac{i}{v_n}, \frac{i+1}{v_n} \right] \times \left[ \frac{j}{v_n}, \frac{j+1}{v_n} \right]$$

where, \(v_n\) is an increasing sequence of positive integers, and \(\mu\) is a measure of probability of a domain defined as \([0,1] \times [0,1]\), considering that

$$\tau_{\alpha}(q) = \frac{1}{\log v_n} \log \sum_{i,j} \mu(l_{i,j,n})^q$$

where, \(\sum_{i,j}\) presents the summation of \(\mu(l_{i,j,n})\), except \(\mu(l_{i,j,n}) = 0\). When the limit of \(\tau_{\alpha}(q)\) exists, then

$$\lim_{n \to \infty} \tau_{\alpha}(q) = \alpha(q).$$

The Legendre transform of \(\alpha(q)\) is defined as

$$f_{\alpha}(\alpha) = \inf_{\alpha \in \mathbb{R}} \alpha(q) - \tau_{\alpha}(q).$$

Considering the sets

$$E_{\alpha} = \{ (x,y) \in [0,1] \times [0,1] \mid \lim_{x \to \infty} \frac{\log \mu(l_{x,y})}{\log v_n} = \alpha \}$$

where, \(l_{x,y} = \{ l_{i,j,n} \mid (x,y) \in l_{i,j,n} \}\), \(\alpha\) is the local Hölder exponents, and \(f_{\alpha}(\alpha)\) is defined as the Hausdorff dimension of \(E_{\alpha}\). Consider the following double limit,

$$f_{\alpha}(\alpha) = \lim_{\epsilon \to 0, \alpha \to \alpha_{\epsilon}} \frac{\log N_{\alpha,\epsilon}(\alpha)}{\log v_n}$$

where, \(N_{\alpha,\epsilon}(\alpha) = \text{card} \{ l_{i,j,n} \mid \alpha_{\epsilon}(l_{i,j,n}) \in [\alpha - \epsilon, \alpha + \epsilon] \}\). The symbol \(\alpha_{\epsilon}\) is the coarse-grained Hölder exponent of \(\mu\) at \(l_{i,j,n}\). defined as

$$\alpha_{\epsilon}(l_{i,j,n}) = \frac{\log \mu(l_{i,j,n})}{\log v_n}$$

In multifractal theory, the central issue is to select and compare the three descriptions of the singularities of the measure, namely, the “spectra” \((\alpha, f_{\alpha}(\alpha)), (\alpha, f_{\alpha}(\alpha)), (\alpha, f_{\alpha}(\alpha))\). The latter, \(f_{\alpha}(\alpha)\), is usually much easier to generate than the other spectra, \(f_{\alpha}(\alpha)\) and \(f_{\alpha}(\alpha)\), which are more complex in computation, since the computation of a Hausdorff dimension is typically highly involved. In general, the relationship of the three spectra is \(f_{\alpha}(\alpha) > f_{\alpha}(\alpha) > f_{\alpha}(\alpha)\).
For certain special classes of measures, $f_h(\alpha) = f_\ell(\alpha) = f(\alpha)$, the special function is simply noted as $f(\alpha)$. A detailed mathematical description can be found in other literature\[22,23,31\]. The Hausdorff dimension, $f_h(\alpha)$, is used for feature extraction.

2.2. Multifractal analysis in image processing

The Hölder exponent $\alpha$ identifies singularities for each image pixel, which describes the local regularity of the image object. If multifractal analysis is applied to analyze an image object, the calculation of the Hölder exponent at point $(x, y)$ is represented as:

$$\alpha(x, y) = \lim_{i \to 0} \frac{\log[\mu[V(i)]]}{\log(i)} , \quad i = 2^n + 1, \ n = 0, 1, \ldots \quad (8)$$

where, $\mu[V(i)]$ is the measure of the area $V(i)$. $V(i)$ is a square of $i \times i$ area centered at a point on the image with a current of intensity $I(x, y)$. Different measures of $\mu[V(i)]$ may be used for estimating $\alpha$. Some of the most frequently used measures\[31,32\], known as capacity measures, are represented as follows:

Maximum : \[\mu[V(i)] = \max_{[x,y] \in V(i)} I(x, y) \quad (9)\]

Minimum : \[\mu[V(i)] = \min_{[x,y] \in V(i)} I(x, y) \quad (10)\]

Sum : \[\mu[V(i)] = \sum_{[x,y] \in V(i)} I(x, y) \quad (11)\]

where, $V(i)$ is a set of all nonzero pixels within a measure domain and $I(x, y)$ is a gray-scale intensity at point $(x, y)$. After this step, an $\alpha$ image is obtained in such a way that each $\alpha$ value presents the local singularity of a corresponding pixel in the initial grayscale image.

The multifractal dimension $f(\alpha)$ was subsequently calculated to represent the global singularity of the image based on the $\alpha$ values. First, maximal value $\alpha_{\text{max}}$ and minimal value $\alpha_{\text{min}}$ were determined from the $\alpha$ image. Next, $\alpha_r$ was obtained by dividing $\alpha$ into different values according to a constant value, $R$, within $[\alpha_{\text{min}}, \alpha_{\text{max}}]$:

$$\alpha_r = \alpha_{\text{min}} + (r - 1)\Delta \alpha_r, \quad r = 1, 2, \ldots, R$$

and

$$\Delta \alpha_r = \Delta \alpha = (\alpha_{\text{max}} - \alpha_{\text{min}})/R$$

where, $r$ is defined as an index to determine the sub-range of $\alpha_r$. If the $\alpha$ value falls in a sub-range indicated by $r$, the value will be replaced by $\alpha_r$. Therefore, the $\alpha$ image will be covered by a regular grid of boxes with integer box sizes $j = 1, 2, \ldots$. The number of boxes containing at least one $\alpha_r$ value is represented by $N_j(\alpha_r)$. The Hausdorff dimension is consequently calculated as follows:

$$f_j(\alpha_r) = -\frac{\log N_j(\alpha_r)}{\log(j)}, \quad j = 1, 2, \ldots$$

From a set of discrete points in bi-logarithmic diagram of $\log N_j(\alpha_r)$ vs. $-\log(j)$, the multifractal spectrum $f(\alpha)$ is estimated from linear regression, in a similar manner as in the case of estimation of $\alpha$.

3. Pest detection based on multifractal analysis

The leaf images with whiteflies on the surface were obtained by a camera installed on an autonomous agricultural robot. The flowchart for whitefly detection is displayed in Fig. 1.

3.1. Image pre-processing

For improving the correct rate of whitefly detection and the computational speed, the non-leaf regions of captured images are considered as background and removed by applying a Mahalanobis distance. Mahalanobis distance, $D$, is considered to assess pixel color similarities, which is defined as

$$D = \sqrt{(x_{\text{rgb}} - \mu_m)^T S^{-1}(x_{\text{rgb}} - \mu_m)}$$

where $\mu_m$ and $S$ represent the multivariate mean and covariance matrix of sampled vegetation pixels prepared in advance, respectively. $x_{\text{rgb}}$ is the vector of a pixel of captured images from agricultural robot in RGB color space, and $T$ denotes the transpose. Mahalanobis distance was chosen in this study since the distance is feasible for implementation in image processing and is efficient in segmentation of vegetation pixels from natural backgrounds against light changes at a certain range\[33\]. Each sample pixel is a 3-dimensional feature vector in R, G, B channels. In our study the multivariate mean and covariance of a known tissue type, referred to as the reference, is estimated from various of vegetation images in greenhouse. As the criteria for identifying vegetation pixels, Mahalanobis distance between each sample pixel and the mean of references (vegetation pixels) is generated for a given image obtained by the agricultural robot. If the distance of sample pixel is larger than a suitable threshold we set, the sample pixel is considered as a background (non-leaf region) and removed, whereas pixels with Mahalanobis distance less than the suitable threshold are identified as vegetation pixels. The suitable threshold value for segmentation of vegetation pixels is determined after testing various images before our experiments.

Opening and closing operations are the basic operations of morphological image processing, which are widely used in noise removing of image process. After Mahalanobis distance is calculated for each pixel, there are also minute noises on the binary image obtained after Mahalanobis distance calculation. Subsequently, opening operation followed by closing operation with a cross structuring element are utilized to remove them.

3.2. Procedure of small-sized pest detection

After an image pre-processing step, most of the non-leaf regions in the captured leaf image are removed. The leaf images with whitefly on the leaf surface after background removal are used as input for calculating $\alpha$ image and $f(\alpha)$ image. As an example, an $\alpha$ image (Fig. 2b) and $f(\alpha)$ image (Fig. 2c) is generated from a sample leaf image (Fig. 2a) by applying the minimum measure (Eq. (10)) since minimum measure suits to describe local image regularity to
enhance small light details [32]. After calculating the $\alpha$ image, the areas containing a significant local change in intensity (e.g., whitefly regions) have higher $\alpha$ values against the black background (e.g., leaf regions). Subsequently, the multifractal dimension $f(\alpha)$ is calculated by the box-counting method to represent the global singularity of the image based on the $\alpha$ values. It must be pointed out that according to the box size (i) of $V(i)$ (Eq. (8)), whitefly areas present different patterns on the $f(\alpha)$ image. As the box size increases, the whitefly areas show larger. The values of $f(\alpha)$ image vary according to the degree of homogeneity in the images. The points located in the homogenous area represent high $f(\alpha)$ values, while whitefly and leaf vein regions represent low $f(\alpha)$ values. In our study, the multifractal dimension showing nonsingularity is calculated with a larger box with size 5 pixels to make the whitefly areas be easily distinguished from noise in the $f(\alpha)$ image. By considering the size and shape of regions, the whitefly regions can easily be distinguished from vein regions in the $f(\alpha)$ image.

Two schemes are presented for extracting candidate whitefly regions. First, a sub-range of $f(\alpha)$ is generated by analyzing the multifractal spectrum (Fig. 2d) to examine the border of objects, and the proper threshold values, such as $f(\alpha) < 0.4$, were used to detect small objects based on preliminary studies. A small threshold would result in loss of information about the whiteflies, while a large threshold would generate more noise. Fig. 3 displays the multifractal segmentation results for $f(\alpha)$ in different sub-ranges. This procedure is referred to as MF_TH in this paper.

In order to improve the detection rate, we calculated a regional minimum to filter the candidate area of whitefly images instead of a fixed threshold. The regional minima of the $f(\alpha)$ image is extracted using the extended-minima transform [34], since the method is efficient at dealing with image contrast and brightness. The $f(\alpha)$ image variables were normalized across the different images used for test (0 to 255). Subsequently, regional minima values are extracted as the candidate whitefly regions from the gray value $f(\alpha)$ image. Here, the procedure using regional minima instead of the fixed threshold is termed Multifractal Minima (MF_MIN).

The size and shape of whitefly are additionally used for further selection of whiteflies from segmented images. The whitefly is presented as a fixed pixel size for the camera distance to the leaf when image captured. The candidate area with in-locked aspect ratio is considered a whitefly, while the area with a slender shape is considered a leaf vein. The whitefly extraction, in consideration of size and shape, is shown in Fig. 4.

### 3.3. Evaluation of detection results

In order to evaluate performance via multifractal analysis, two well-known adaptive segmentation algorithms, Watershed and EGBIS, are applied to the detection of pest images [29,30]. The precision and recall analysis is utilized as an evaluation method after detection of whiteflies [35]. Precision refers to the percentage of correctly identified whitefly images from the total extracted results. A high-precision value indicates that the detection results contain a high percentage of useful information (true positives) and a low
The robot control system is programmed with the VC++. Multifractal analysis is developed based on the Fraclab library (http://fraclab.saclay.inria.fr), while Watershed and EGBIS were conducted by the functions provided by Matlab 2008a.

5. Results and discussions

Through multifractal analyses, the whiteflies were accordingly detected and marked with star symbols (Fig. 4). The TPR percentages generated by all algorithms, except EGBIS, were over 80% (Table 1). The Watershed method in particular displayed the highest TPR at 89.7%. The multifractal and EGBIS algorithm displayed lower TPR percentages at 86.9% and 44.3%, respectively.

All of these algorithms generate false alarms. Notably, FPR was found in the low range of the multifractal algorithms, ranging from 8.2% to 10.8%. MF_MIN showed a remarkably low FPR of 8.2%. The Watershed and EGBIS algorithms showed FPRs of 49.8% and 45.5%, respectively.

Although a trade-off was observed between the two algorithms (i.e., higher TPR in watershed and lower FPR in multifractal), the overall performance of multifractal algorithm was observed when precision and recall score were considered. The detection results by multifractals, Watersheds, and Otsu algorithm according to the $F$ measure are displayed in Table 1. The $F$ measure generated by MF_MIN was the maximal at 0.886, whereas the $F$ value generated by MF_TH was 0.868. The Watershed EGBIS $F$ values were 0.602 and 0.428, respectively.

Light reflection and complex texture of leaf under greenhouse conditions were the primary source of noise that hinders the accurate detection of target insects. False alarms were generated in vision-based pest detection in situ by misrecognition of noises (Table 1). In order to cope with this complex problem in image detection of small-sized insects, this study demonstrated that multifractal analysis is a feasible algorithm in dealing with noise interference to the trap images under greenhouse conditions. Since the multifractal analysis considers not only the local information but also the global image, this method is more suitable in generating stable results against disturbances that occur on the captured image due to diffusive light reflection and unstable illumination through a multi-scale approach. Moreover, most false alarms from leaf vein are further decreased by comparing the size and shape with the whitefly.

The Watershed algorithm may also segment whitefly images in variable illumination conditions. However, a large number of false alarms are generated. Similarly, the EGBIS algorithm is advantageous in detecting pests on a scanned image under laboratory conditions. However, it is less feasible in dealing with leaf images under field conditions with varying amounts of illumination.

6. Conclusions

A multifractal analysis is proposed for detecting small-sized greenhouse pests (whitefly; Genus Bemisia) whose images are highly affected by diffusive reflection and variable illumination under field conditions. Multifractal analysis is a feasible methodology in identifying whiteflies (Genus Bemisia) from the leaf images.
compared to other methods, such as Watershed and EGBIS. The multifractal algorithm with MF_MIN, which is proposed by this investigation, is superior in precision and recall scores because it shows a higher F measure (0.886) that do other methods, Watershed (0.602) and EGBIS algorithm (0.428). The MF_MIN method is outstanding in lowering the FPR (8.2%) to a greater extent than are other methods (10.8 – 49.8%), and effectively controls diffusive lighting and variable illumination conditions in the greenhouse. According to our experimental results, multifractal analysis with MF_MIN is the best option for the detection of small objects under variable light conditions. Considering the highly variable light conditions in greenhouses due to varying weather and time, dynamic processes are required to deal with variable image features both locally and globally. Multifractal analyses can be further developed to classify different species under greenhouse conditions in the future under varying illumination conditions.

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