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

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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 (88.6%) 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.

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 famers' 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-Marin [8], an alternative solution for detection of crop

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insects. Singh et al. [9] reported on the use of near-infrared (NIR) hyperspectral 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 system has 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 of 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

$$I_{i,j,n} = \left[\frac{i}{\upsilon_n}, \quad \frac{i+1}{\upsilon_n}\right] \times \left[\frac{j}{\upsilon_n}, \quad \frac{j+1}{\upsilon_n}\right] \tag{1}$$

where, υ_n is an increasing sequence of positive integers, and let μ is a measure of probability of a domain defined as $[0, 1] \times [0, 1]$, considering that

$$\tau_n(q) = \frac{1}{\log\ \upsilon_n} \log\ \Sigma_i^* \Sigma_j^* \mu(I_{i,j,n})^q \tag{2}$$

where, Σ_i^* presents the summation of $\mu(I_{i,j,n})$, except $\mu(I_{i,j,n}) = 0$. When the limit of $\tau_n(q)$ exists, then

$$\lim_{n\to\infty} \tau_n(q) = \tau(q). \tag{3}$$

The Legendre transform of $\tau(q)$ is defined as

$$f_l(\alpha) = \inf_{q\in R}[\alpha q - \tau(q)]. \tag{4}$$

Considering the sets

$$E_\alpha = \left\{(x, y) \in [0, 1] \times [0, 1],\ \lim_{x\to\infty} \frac{\log\ \mu[I_n(x, y)]}{\log\ \upsilon_n} = \alpha\right\} \tag{5}$$

where, $I_n(x, y) = \left\{I_{i,j,n},\ \ (x, y) \in I_{i,j,n}\right\}$, α is the local Hölder exponents, and $f_h(\alpha)$ is defined as the Hausdorff dimension of E_α. Consider the following double limit,

$$f_g(\alpha) = \lim_{\varepsilon\to 0}\lim_{n\to\infty} \frac{\log\ N_n^\varepsilon(\alpha)}{\log\ \upsilon_n} \tag{6}$$

where, $N_n^\varepsilon(\alpha) = \text{card}\left\{I_{i,j,n},\ \alpha_n(I_{i,j,n}) \in [\alpha - \varepsilon, \alpha + \varepsilon]\right\}$. The symbol α_n is the coarse-grained Hölder exponent of μ at $I_{i,j,n}$, defined as

$$\alpha_n(I_{i,j,n}) = \frac{\log\ \mu(I_{i,j,n})}{\log\ \upsilon_n}. \tag{7}$$

In multifractal theory, the central issue is to select and compare the three descriptions of the singularities of the measure, namely, the “spectra” $(\alpha, f_l(\alpha))$, $(\alpha, f_g(\alpha))$, and $(\alpha, f_h(\alpha))$. The latter, $f_l(\alpha)$, is usually much easier to generate than the other spectra. $f_g(\alpha)$ and $f_h(\alpha)$, 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 $f_h(\alpha) \geq f_g(\alpha) \geq f_l(\alpha)$.