Color Fractal Descriptors for Adaxial Epidermis Texture Classification

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Abstract. The leaves are an important plant organ and source of information for the traditional plant taxonomy. This study proposes a plant classification approach using the adaxial epidermis tissue, a specific cell layer that covers the leaf. To accomplish this task, we apply a high discriminative color texture analysis method based on the Bouligand-Minkowski fractal dimension. In an experimental comparison, the success rate obtained by our proposed approach (96.66%) was the highest among all the methods used, demonstrating that the Bouligand-Minkowski method is very suitable to extract discriminant features from the adaxial epidermis. Thus, this research can significantly contribute with other studies on plant classification by using computer vision.

Keywords: Adaxial epidermis tissue · Texture analysis · Color · Fractal dimension · Bouligand-Minkowski method

1 Introduction

Traditional plant taxonomy cannot neither explore all possible information sources from plants (for instance, a leaf) nor extract all their discriminative attributes, such as contour, color and texture. This explains why, in the last years, there has been an increasing interest in solving problems from this knowledge field by using computer vision approaches. As examples of promising researches, we have works that aim to extract attributes from leaf contour and venation [1], the computation of texture signatures from a leaf surface [2], and the extraction of thickness measures and texture descriptors from various cell tissues presented in a leaf cross-section [3].

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Among all the features that can be computed from an image, texture is surely one of the most discriminative and widely studied. Even though texture does not possess a definite concept, it is easily recognized by humans. A suitable definition, yet restricted, is that texture is a model repeated in an exact way or with small changes over a surface [4]. Being texture a great source of information, many methods have been developed to extract signatures from it, such as co-occurrence matrices [5], Gabor filters [6], wavelet descriptors [7], tourist walk [8], local binary patterns (LBP) [9], gravitational models [10], shortest paths in graphs [11] etc.

All these mentioned methods were designed for grayscale textures. However, in recent years, many methods have been developed for color textures to increase the capacity of extracting discriminant signatures. Generally, such methods can be classified into three groups: parallel, sequential and integrative [12]. Parallel approaches consider color and texture as independent phenomena [13]. Sequential approaches divide the process of extracting signatures into two steps: first, the color texture is indexed; then, the indexed image is processed as a grayscale texture [14]. Integrative approaches consider the informative dependency between color and texture [15].

This work aims to contribute to plant taxonomy by applying an integrative state-of-the-art color texture analysis method to a very discriminative leaf tissue called adaxial epidermis. We extend the work proposed in [15], which presented the technique and aimed the classification of synthetic and natural texture. Here we focus on the application of the technique to a biological problem. Textures extracted from biological images do not necessarily present a well-defined pattern, specially in the microscopic scale, where the growing and disposal of cells are influenced by external factors. Thus, this work helps to establish the applicability of this method in biological problems.

Our presentation is organized as follows: Section 2 presents the Bouligand-Minkowski complexity descriptor. Section 3 describes the process of extracting signatures based on fractal errors. Section 4 presents the evaluated image database and the performed experiments. Section 5 shows the obtained results as well as a discussion on them. Finally, Section 6 presents some remarks about this work.

2 Complexity Analysis of Color Textures

A simple and efficient way to estimate the complexity of a shape or texture is through fractal dimension. It is a measurement based on the concept of self-similarity and it describes objects in images in terms of its irregularity and space occupation [15,16].

Among the methods developed throughout the years, the Bouligand-Minkowski method is considered one of the most accurate. This method is able to describe small structural changes in objects due to its great sensitiveness [4,17]. Firstly proposed for shape analysis, this method was extended to texture analysis by mapping the pixels of the image I onto a surface $S \in R^3$ by using the function $f : I(x, y) \to S(x, y, I(x, y))$. Then, each point of the surface is dilated by a sphere of radius r. This results in its influence volume and the Bouligand-Minkowski fractal dimension D is estimated as

$$D = 3 - \lim_{r \to 0} \frac{\log V(r)}{\log r}, \tag{1}$$

where

$$V(r) = \left| \left\{ s' \in R^3 | \exists s \in S : |s - s'| \leq r \right\} \right|, \tag{2}$$

is the influence volume of the surface S dilated using a sphere of radius r.

Usually, we build the surface S from a grayscale image. However, it is possible to map all color channels of a RGB image as different surfaces sharing the same space [15]. Let $I(x, y) = \{R(x, y), G(x, y), B(x, y)\}$ be a RGB color texture. For each color channel $C = \{R, G, B\}$, we are able to compute its respective surface S_C, which can easily be combined to form a single volume $S_{RGB} \in R^3$, as shown in Figure 1. Then, we apply the dilation process over this new volume. The influence volume computed from S_{RGB} enables us to explore how the channels are related to each other, thus taking into consideration the correlations among them and not only the characteristics of a single one.

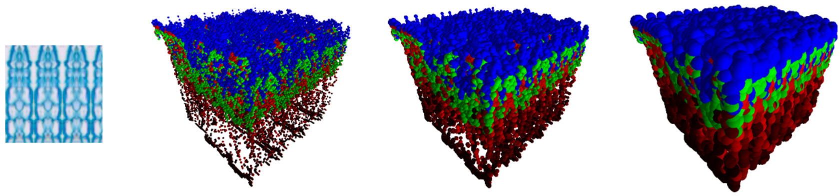

Fig. 1. From left to right: Original image; Computed surface S_{RGB} (each pixel is converted to a point in R^3; Surface dilated using $r = 2$ (each point is replaced by a sphere of radius $r = 2$); Surface dilated using $r = 5$ (each point is replaced by a sphere of radius $r = 5$).

3 Error-Based Fractal Signature

When we compute the fractal dimension D from its log-log curve, the information about fine structural changes are lost. The log-log curve presents a great richness of details and a single value computed through line regression is not able to fully represent it. To overcome this problem, we propose a feature vector which describes the error between the computed line regression and the original log-log curve to represent these curve details.

To compute these descriptors, consider a line with slope a and b its y-intercept estimated from log-log curve. Notice that $D = 3 - a$ is the estimated fractal dimension of the image. This line is just an approximation of the real behavior of the curve. To fully represent its characteristics, we propose a feature vector that represents the error e_i between the estimated line and the original curve at a given point i

$$e_i = a \times \log r_i + b - \log V(r_i), \tag{3}$$

From this definition, we create a feature vector which consists of n equidistant radius values selected from the log-log curve, as shown as follows:

$$\psi(n) = [e_1, e_2, \ldots, e_n]\,. \tag{4}$$

Additional details about the proposed feature vector can be found in the paper [15].

4 Experiments

To accomplish the adaxial epidermis classification, we used a database composed of 30 texture windows acquired from eight different plant species. Figure 2 shows one example for each species in the database. Each texture is 150 pixels height. The width varies from sample to sample as it is determined by the adaxial surface epidermis thickness. As this variation in the width could influence the performance of the method, we adopted a mosaic of 150×150 pixels size produced by copy and reflection of the texture pattern over y axis, as shown in Figure 3. Additional details about the plant species considered can be found in [18].

To compute the proposed feature vector, we used $r = 8$ for the dilation process of the Bouligand-Minkowski method. By using this radius value, we were able to compute a total of $n = 77$ equidistant points of the log-log curve. However, not all these points hold relevant discriminative information. In fact, as we increase the dilation radius, different texture patterns may look similar in terms of influence volume. The same principle applies to the descriptors computed at this range of radius values. Thus, we evaluate the behavior of the success rate as we increase the number of descriptors used (Figure 4). In general, the success rate increases as the number of descriptors n increases, achieving its maximum at $n = 46$. For $n > 46$, we notice the occurrence of a subtle, but constant, degradation of the discrimination ability of the proposed feature vector. This is due to the similarities in the influence volume. We evaluated the computed feature vectors using Linear Discriminant Analysis (LDA), a supervised statistical classification method, in a *leave-one-out cross-validation* scheme [19].

5 Results and Discussion

Table 1 presents the comparison between our proposed approach and other important color texture analysis methods. The obtained results clearly demonstrate the superior performance of the error-based fractal signature, as it provides the highest success rate (96.66%), with a difference of 0.41% when compared to the second best method. Although it seems a small advantage, it is necessary to take into account that both methods are very close to 100% of success rate, and,

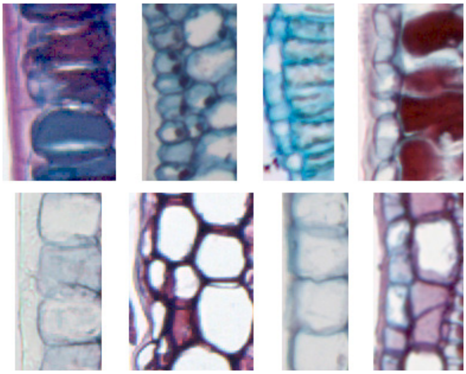

Fig. 2. Adaxial epidermis images of the eight species considered.

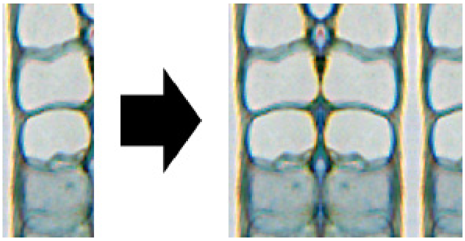

Fig. 3. Process of building a texture mosaic by copy and reflection.

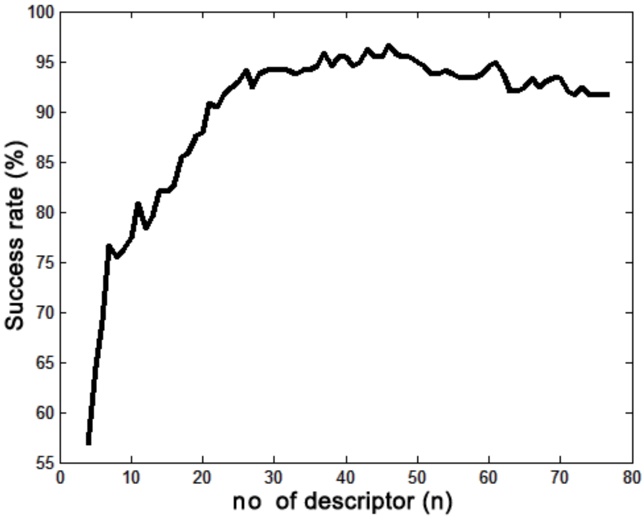

Fig. 4. Classification accuracy observed for different numbers of descriptors (n).

in such condition, whatever superior performance is very relevant. This is corroborated by the fact that three methods obtained less than 90.00% of success rate and Gabor EEE presented a performance 2.91% inferior when compared to our method. Moreover, we must stress that our approach has a small number of attributes (46), which is $7,2\%$ of the total of features used by the second best method. In this comparison, only LBP + Haralick method has a smaller number of features. However, this method provides the second worst success rate.

Table 1. Comparison results for different color texture analysis methods.

Methods	Descriptors	Success rate (%)
Gabor EEE [20]	192	93.75
HRF [21]	-	45.42
MultiLayer CCR [22]	640	96.25
LBP + Haralick [14]	10	84.58
MSD [23]	72	85.83
Proposed approach	46	96.66

We expected to compare our results on adaxial epidermis tissue to other works in literature. However, we were able to find only our three previous papers related to computer vision applied to this problem. This lack of related works confirms that this is a very recent and unexplored research topic. In [24], we used the same eight plant species, but only ten samples per class and Jeffries-Matusita distance [25] to select attributes provided by different texture analysis methods. For these reasons, it is not possible to perform a fair comparison between such paper and our present work. In [3], we adopted the same procedure of the paper [24] for adaxial epidermis images, but in a different image database, and, therefore, we could not use it for comparison as well. We performed a classification experiment in the same image database (converted into grayscale) used in this work in [18]. In such paper, the highest success rate is 93.33%, a result $3,33\%$ inferior to the success rate obtained by our proposed method. This increased performance reinforces that the based-error fractal signature is very suitable to discriminate the adaxial epidermis tissue.

6 Conclusion

In this paper, we addressed the problem of plant classification. To accomplish this, we computed a feature vector from color texture samples from adaxial epidermis of the plant species evaluated. This feature vector explores the details in the influence volume curve produced by the dilation of the three RGB color channels in a single step. Such dilation enables us to incorporate the information about the relationship between channels to the feature vector, thus improving its discrimination power. The comparison of these features with other color texture analysis methods shows that our approach achieves the highest classification results. Moreover, it uses fewer descriptors than methods with similar classification results, corroborating its great ability to discriminate different color patterns.

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