A Gravitational Model for Plant Classification Using Adaxial Epidermis Texture

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Abstract. The leaves are very informative plant organs. They are extensively used in plant anatomical studies focusing taxonomy. Their both inner and outer structures provide very discriminant features from vegetal species. In this study, we propose using images from adaxial epidermis for plant classification. The adaxial epidermis is a very variable region in a plant leaf cross-section. It differs in color, number of layers and presence/absence of hypodermis. To accomplish this task, we propose combining complexity analysis methods with a gravitational collapsing system to extract texture features from adaxial epidermis samples. Experimental results show that this combination of techniques surpasses traditional and state-of-the-art methods in both grayscale and color images of adaxial epidermis.

Keywords: Adaxial epidermis · Texture analysis · Color · Gravitational system

1 Introduction

Plant classification has been the focus of intensive research in computer vision. One of its most important goals is to explore information sources that are not used in traditional taxonomy, such as that present in leaves. This plant organ can provide features related to its venation and contour [1] and surface texture [2]. Furthermore, recent studies have proven that its tissues can provide discriminative features as well [3].

We can obtain plant features from different attributes, such as color, shape and texture, being the latter one of the most relevant. Even though there is no

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formal definition for the texture attribute, it is possible to understand it as an image composed by models that are repeated in its exact form or with small variations [4]. Such restricted definition is more suitable for artificial textures. Natural textures usually present a random and persistent pattern with a cloudlike appearance [5]. There are many methods that can extract feature vectors from grayscale and color textures, ranging from the classical methods (co-occurrence matrices [6], Gabor filters [7], wavelet descriptors [8]) to the recent or state-of-the-art methods (Bouligand-Minkowski fractal dimension [9], micro-structure descriptors [10]).

This paper aims the classification of grayscale and color images of adaxial epidermis, a very discriminative tissue, thus contributing to plant identification. This leaf tissue has already provided discriminative signatures, as seen in [11,12], proving to be very suitable for plant classification. We used eight species from the neotropical savanna of Brazil. They are: *Byrsonima intermedia* A. Juss., *Miconia albicans* (Sw.) Triana, *Tibouchina stenocarpa* (DC.) Cogn., *Vochysia tucanorum* Mart., *Xylopia aromatica* (Lam.) Mart., *Gochnatia polymorpha* (Less.) Cabrera, *Miconia chamissois* Naudin and *Jacaranda caroba* (Vell.) A. DC [12].

In this study we aim to extend the work previously published in [13–15], where we proposed and evaluated the technique in the classification of synthetic and natural texture. In this paper we focus on a biological problem in order to assess the discrimination ability of our approach. Moreover, the growing and disposal of cells in microscopic biological images are influenced by external factors. This leads to the absence of a well-defined pattern in their texture, increasing the challenge of their recognition.

2 A Gravitational System

We propose simulating a simplified gravitational system from an image I. Since different pixels present different masses, we consider each pixel (x, y) as a particle whose mass is its intensity, $m = I(x, y)$. We also set a central mass M at the center of the image. This mass works as a black hole and it attracts each particle towards it. There is no influence among the particles, only between each particle and the central mass.

Each particle has a singular movement according to its mass and distance from the image center. As a result, an image is able to produce different collapse stages for each time step t. In each collapse stage, a new texture pattern is produced based on the new positions of the particles. Each collapse stage represents a step in the evolution of the system. Complexity descriptors, such as fractal dimension and lacunarity, can be used to describe each stage, resulting in a signature for the image in collapsing process. More details about the gravitational system for grayscale and color images can be found in [13–15].

3 Complexity Analysis

Mandelbrot first developed the concept of fractal dimension to characterize the complexity of a new class of sets called fractals [16]. Nowadays, fractal dimension has been extended to describe other objects (shape and texture) in terms of their irregularity and space occupation [9,16].

Throughout the years, many methods were developed to estimate fractal dimension, here included the Bouligand-Minkowski fractal dimension. This method is known for its great sensitiveness to the structural changes of the object [4,17]. In order to apply this method to a texture pattern, we first create a surface $S \in R^3$ from the texture pattern I by using the function $\mathrm{f} : I(x,y) \rightarrow S(x,y,I(x,y))$. In the sequence, we compute the influence volume $V(r)$ of the surface S. We perform this task by dilating each point of S using a sphere of radius r:

$$V(r) = \left|\left\{s' \in R^3 | \exists s \in S : |s - s'| \leq r\right\}\right|. \tag{1}$$

The Bouligand-Minkowski fractal dimension D is estimated as

$$D = 3 - \lim_{r \to 0} \frac{\log V(r)}{\log r}. \tag{2}$$

Although its known ability to discriminate texture patterns, Mandelbrot realized that completely different texture patterns may present the same fractal dimension, rendering it useless to characterize such samples. To overcome this problem, Mandelbrot introduced the lacunarity. This method enables us to describe a texture pattern in terms of spatial dispersion using a specific gap size [16,18].

Different approaches exist to compute lacunarity. In this study, we consider the gliding-box algorithm [18,19]. This method glides a box of $l \times l$ pixels size to compute the distribution of gaps in the image and, thus, its lacunarity. For each box, the method computes the relative height of that portion of the image

$$h_l(i,j) = \lceil v/l \rceil - \lceil u/l \rceil, \tag{3}$$

where u and v are the minimum and maximum pixel values inside the box, respectively. From the probability density function $Q_l(H)$ of the relative height $h_l(i,j)$, the lacunarity for a box size l is defined as

$$\Lambda(l) = \sum H^2.Q_l(H) / \left(\sum H.Q_l(H)\right)^2. \tag{4}$$

4 Proposed Feature Vector

In [14,15], we proposed a feasible feature vector to characterize an image modeled as a gravitational system in process of collapse. We used two sets of fractal dimension and lacunarity values computed at each time step t of the gravitational collapse to compose a feature vector as follows

$$\boldsymbol{\psi}_{T,R,L} = \left[D_{t_1}(R), \ldots, D_{t_k}(R), \Lambda_{t_1}(L), \ldots, \Lambda_{t_k}(L)\right], \tag{5}$$

where $D_t(R)$ and $\Lambda_t(L)$ represent, respectively, the sets of fractal and lacunarity descriptors computed for a specific set of radii and box sizes, $R = \{r_1, r_2, \ldots, r_N\}$ and $L = \{l_1, l_2, \ldots, l_M\}$, at a specific time step in $T = \{t_1, t_2, \ldots, t_k\}$.

We used this approach to obtain a feature vector as each stage in the collapsing process represents a different relationship among pixels and, therefore, it is a new source of information to be explored. Moreover, fractal dimension is an excellent tool to measure structural changes in a system in collapse due to its great sensitiveness, while lacunarity is able to discriminate systems which present the same fractal dimension although the differences in their structures.

5 Experiments and Results

In our experiment we addressed the problem of plant leaf classification. More specifically, we aim plant classification from the analysis of its adaxial epidermis. We built a database containing 30 texture windows acquired from eight different plant species. Figure 1 shows examples of samples in the database. Additional details about the database can be found in [11]. Each texture window has 150 pixels height while its width is determined by the adaxial surface epidermis thickness, which can vary from species to species. To avoid an undesirable influence of thickness in the computed descriptor, we opted to use a mosaic of 150×150 pixels size. We produced this mosaic for each sample by using a scheme of copy and reflection of the texture pattern over y axis, as shown in Figure 2.

To compute the proposed feature vectors we must set up some parameters of the gravitational process: the mass of the black hole at the center of the image, M, and the gravitational constant G. According to previous studies [13–15], we set $G = 1$, so that, we do not limit, or accelerate, the movement of a particle. The mass M is a value which depends on the image size. As the width of the mosaic image is 150×150 pixels size, and according to the study performed in [13], we computed the mass as $M = 281.25$. For the feature vector parameters, we evaluated different configurations. Among all the combinations of parameters evaluated, we achieved the best results when using $R = \{3, 4\}$ and $L = \{2, 3, 4, 5, 6\}$, at a specific time step set $T = \{1, 3, 6, 9\}$

For the evaluation of our approach, we carried out two experiments. In the first experiment we used grayscale images of adaxial epidermis and we compared our approach to the following grayscale texture analysis methods: Fourier descriptors [20], co-occurrence matrices [6], Gabor filters [7] and wavelet descriptors [8]. In the second experiment, we used color images of adaxial epidermis and the following color texture analysis methods: Gabor EEE [21], HRF [22], multiLayer CCR [23], LBP + Haralick [24], and MSD [10]. The parameters of the compared methods were set up according to either their original papers or, when it was not possible, to the most common use in literature.

For the experimental evaluation, we used Linear Discriminant Analysis (LDA), a supervised statistical classification method, over the computed feature vectors, in a *leave-one-out cross-validation* scheme [25].

Table 1 shows the results obtained when we compare the gravitational approach to other important methods in the grayscale adaxial epidermis database.

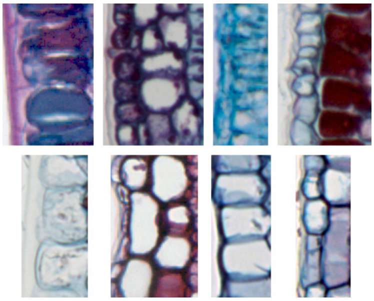

Fig. 1. Adaxial epidermis images of the eight species considered.

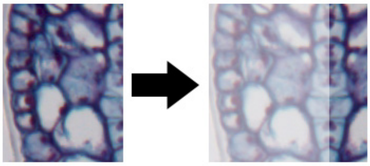

Fig. 2. Process of building a texture mosaic by copy and reflection.

We notice that the classification accuracy obtained by our approach surpasses all the other methods. As an example, our approach achieves a result 2.50% superior, while using around 42% less descriptors, when compared to the second best method (Gabor filters). This result indicates that the gravitational model associated with complexity descriptors is very suitable for discriminating grayscale images from adaxial epidermis tissue.

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

Methods	Descriptors	Success rate (%)
Gravitational model	28	89.58
Fourier descriptors	74	74.58
Co-occurrence	16	83.75
Gabor filters	48	87.08
Wavelet descriptors	18	76.67
LBP	10	77.92

Table 2 shows the comparison of the gravitational model with recent and state-of-the-art color analysis methods for the classification of the adaxial epidermis database. For this comparison, we applied the gravitational approach in each channel of the RGB image. This resulted in a total of three feature vectors per image. We concatenated these feature vectors into a single one, which was used to describe the image sample.

The result obtained by our approach confirms that the gravitational model is very suitable for the analysis of adaxial epidermis. Moreover, the results clearly indicate that the color attribute must be considered in adaxial epidermis classification. When comparing the results achieved in grayscale and color images (Tables 1 and 2, respectively), we noticed an increase of 7.5% in the classification accuracy. This difference is equivalent to 18 images correctly classified.

In relation to other color approaches, the gravitational approach yields a success rate 0.83% superior to the second best method (multiLayer CCR). However, our approach uses only 84 descriptors against 640 of the multiLayer CCR method. This is, clearly, a great advantage of our approach.

Table 2. Comparison results for different color texture analysis methods.

Methods	Descriptors	Success rate (%)
Gravitational model RGB	84	97.08
Gabor EEE	192	93.75
HRF	-	45.42
MultiLayer CCR	640	96.25
LBP + Haralick	10	84.58
MSD	72	85.83

Computer vision research applied to adaxial epidermis is very recent. For instance, we know only our three previous works [3,11,12] related to this subject. Among them, only paper [11] can be used for comparison as it adopts the same database (converted into grayscale) and the same performance measurement (accuracy). In such paper, we obtained a success rate of 93.33% while in this work our approach yielded a success rate of 89.58% (see Table 1). Although our current result is inferior, it is important to consider two important facts: first, the paper [11] also proposes a very powerful texture analysis method based on Bouligand-Minkowski fractal dimension; second, in the paper [11] we used 50 descriptors while in this paper we used only 28 descriptors. Moreover, if we consider the color adaxial epidermis database, the performance increases to 97.08% (see Table 2), that is, 3.75% superior to the best result of the paper [11]. This corroborates the assumption that the gravitational model RGB is very suitable for analyzing adaxial epidermis tissue.

6 Conclusion

In this paper, we presented a study addressing the problem of leaf texture classification. By using a simplified gravitational system combined with complexity analysis methods we were able to extract discriminative features from a leaf cell tissue, from both color and grayscale images. We compared these features to other grayscale and color texture analysis methods found in literature. Results showed that these features surpass all the compared approaches and achieve high accuracy, proving to be very suitable for plant classification.

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