Partial differential equations and fractal analysis to plant leaf identification

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Abstract. Texture is an important visual attribute used to plant leaf identification. Although there are many methods of texture analysis, some of them specifically for interpreting leaf images is still a challenging task because of the huge pattern variation found in nature. In this paper, we investigate the leaf texture modeling based on the partial differential equations and fractal dimension theory. Here, we are first interested in decomposing the original texture image into two components $f = u + v$, such that u represents a cartoon component, while v represents the oscillatory component. We demonstrate how this procedure enhance the texture component on images. Our modeling uses the non-linear partial differential equation (PDE) of Perona-Malik. Based on the enhanced texture component, we estimated the fractal dimension by the Bouligand-Minkowski method due to its precision in quantifying structural properties of images. The feature vectors are then used as inputs to our classification system, based on linear discriminant analysis. We validate our approach on a benchmark with 8000 leaf samples. Experimental results indicate that the proposed approach improves average classification rates in comparison with traditional methods. The results suggest that the proposed approach can be a feasible step for plant leaf identification, as well as different real-world applications.

1. Introduction

The plant cataloging activity is essential to taxonomical studies, especially in Ecology and Botany. Traditionally, it is first necessary: i) to collect and dry some branch of the plant, ii) to process the voucher, iii) to compare it with other vouchers in the herbaria using diagnostic keys, and then iv) to send the material to specialists for confirmation [1]. The main advantage of using leaves in such activity is related to three main facts: (1) in contrast to flowers and fruits, they are found during all seasons, (2) the morphological analysis is considered easy-handling and can provide important features for taxonomy purposes, (3) they are posed to present greater differentiation scope by exploring geometric aspects.

In this paper, we investigate the use of partial differential equations and fractal dimension theory to describe the texture present in leaves. As a first step, the leaf image f is decomposed using the non-linear partial differential equation of Perona-Malik [2] into two components $f = u+v$, where u, v represent the cartoon component and the oscillatory or textural component, respectively. This decomposition enhances the texture component and successfully filter noise while preserving relevant edge details in the image. Then, we estimated the fractal dimension of the enhanced texture component by using the Bouligand-Minkowski method [3, 4]. We have chosen this fractal method rather than other ones due to its precision in quantifying structural properties of images. Finally, the feature vector, which describe the texture image, is used as input to our classification system.

In order to validate the proposed approach, we have used a database containing 20 leaf samples of 40 species of plants. According to the experimental results, the proposed approach improves the average classification rate compared to traditional texture methods. Thus, we conclude that our approach can be used as a feasible step for plant leaf identification, as well as different real-world applications.

2. Partial Differential Equations to Image Texture Enhancement

The two-dimensional Perona and Malik equation is the most conventional PDE in the literature [2]. The discrete formulation can be implemented by:

$$I_{t+1}(x,y) = I_t(x,y) + \frac{1}{4}\sum_{i=1}^{4}\left[g(\nabla I_t^i(x,y)).\nabla I_t(x,y)\right] \quad (1)$$

where (x, y) denotes the spatial position of each pixel, and $\nabla I_t(x, y), i = 1, 2, 3$ and 4 correspond to the brightness gradients of neighbors north, south, east and west. A possible coefficient function, updated at each iteration by the gradient function, is given by the inverse quadratic:

$$g\left(\nabla I\right) = \frac{1}{1 + \left(\frac{|\nabla I|}{K}\right)^2} \quad (2)$$

where the parameter K is a constant that acts as an edge strength threshold. The computational scheme described in this section generates a scale-space representation, that is, it creates from the input image a family of derived images. After creating the multiscale representation, we obtain two components of every new image: cartoon and texture component. The texture component is determined by the subtraction of the original image and cartoon approximation.

Next section, the fractal method of Bouligand-Minkowski is briefly reviewed. Then, we present our strategy and we point what is different to the conventional approach.

3. Bouligand-Minkowski Fractal on Image Analysis

Let us consider a gray level image $f(x, y)$ represented as a surface $S(x, y, z)$, where (x, y) are the spatial position of the image and z corresponds to the intensity of the pixel [3]. Given the surface S, we can measure the influence of volume $V(r)$ by the dilatation of each point $p \in S$ by using a sphere of radius r. We show an example of this process in Figure 1. The surface of the image is created (Figure 1 (a)), and then it is dilated by sphere of different radius r, as can be seen in Figure 1 (b) and (c).

Here, the arrangement of points of the surface changes the process of expansion. While the value of r grows, the spheres produced by different points on the surface begin to interact up. It causes effects on the final amount of $V(r)$. Thus, for each r value we calculate the volume V to compose a feature vector [5].

4. A Hybrid Approach for Texture Analysis

A traditional strategy is to compute feature vectors by means of a fractal analysis method. However, it does not explore the richness of the feature description task. Instead of obtaining a single value captured from the image, we create a multiscale representation by using the partial differential equations. Such strategy enable us to enhance structures perceived in certain levels of observation. The diagram of Figure 2 summarizes the approach proposed here.

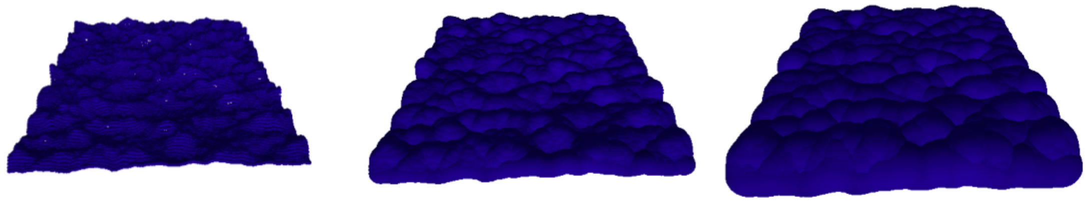

Figure 1. Example of the dilation process for two diferent radiuses.

To clarify, we divide our approach in three main steps: (1) color samples from a plant leaf species are obtained and converted to gray-level, (2) we represent an input image by using Perona and Malik equation before straight adopt fractal analysis. After decomposing an image, we obtain two components: cartoon (u) and texture (v) component. The enhanced texture component is determined by the subtraction of the original image and cartoon approximation, and finally in (3), we employ the fractal analysis of Bouligand-Minkowski.

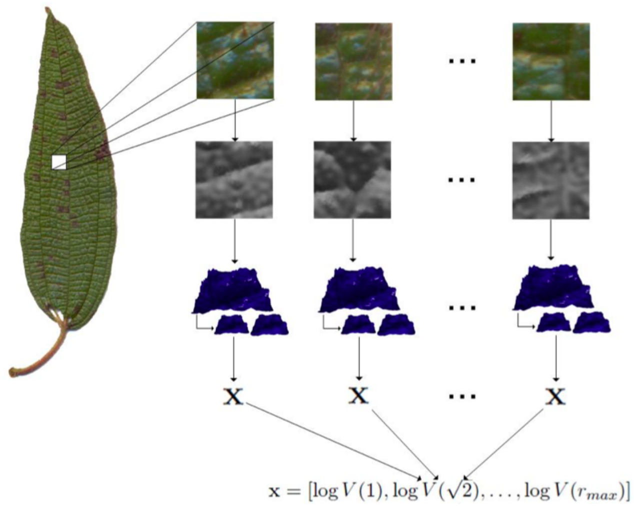

Figure 2. The process used to classify a leaf.

5. Experimental results

In this section, we describe the leaf database used in the experiments and the results of the proposed approach. Given the leaf image, it is possible to identify different plant species using the extracted features of the image. However, the direct classification was not used in this work. First, we randomly extract 10 texture samples from each leaf and, therefore, 10 feature vectors are available for each leaf. To minimize problems with noise and texture variation we have calculated the mean of these 10 feature vectors. With a single feature vector for each leaf, we have chosen to use the Naive Bayes classifier in the 10-fold cross validation.

5.1. Leaf database

Each leaf was digitalized with a traditional scanner (HP-Scanjet 3800) with resolution of 1200dpi (dots per inch). The high resolution was used to access the details in image texture. To avoid rotation problems, all leaves were oriented in the same direction while assembled on the scanner. Both surfaces of the leaf epidermis were digitalized (abaxial and adaxial ones). The adaxial surface of some species can be seen in Figure 3. In the final database, we have used 40 species of plants with 20 leaves for each specie.

Figure 3. Two species of leaf textures used in the experiments.

5.2. Results

The experimental results are shown in Table 1. The Boulingand-Minkowski fractal dimension (FD), which extract features from the original texture image, achieved a correct classification rate of 85.20. Using the texture component, the correct classification rate improves from 85.20 to 87.00, which demonstrates the importance of the PDE on the process. As expected, the cartoon component did not provided satisfactory results since homogeneous regions does not present useful information of textures.

Table 1. Classification results for the leaf database.

Method	N. of Features	Correct Classification Rate
Boulingand-Minkowski FD	85	85.20 (±1.05)
Cartoon Component + FD	85	74.37 (±1.82)
Our approach (Texture Component + FD)	85	**87.00** (±1.11)

6. Conclusion

The results suggest that the computer-aided plant classification is an area that can provide new useful tools for experimental taxonomists and plant morphologists, improving their work, bringing also new forms to asses informative characters that can be useful in systematic and phylogenetic studies. The method proposed here may represent a new, important tool for non-taxonomic botanists or ecologists, working with plant species with very similar morphology, since it requires easily available equipment, such as a regular computer and an optical scanner.

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