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DESIGN AND IMPLEMENTATION OF AN ALGORITHM FOR PLANTS IDENTIFICATION AND CLASSIFICATION BASED ON PHYSICAL CHARACTERISTICS OF THEIR LEAVES USING COMPUTER VISION

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ABSTRACT

In this paper, it's described an algorithm for plants identification based on leaves physical features using image processing techniques and the feed forward neural network specialized on patterns recognition. As fundamental step, the sobel operator is used to highlight the leaves boundaries and veins. After obtaining those features, the new image is transfer to the frequency space through the wavelet transform as basis for the main vector of every sample. Finally, the results are evaluated according to percentage of samples correctly identified. The algorithm is adapted to a visual interface that allows the user to observe the steps of the image processing and get the leaf information.

Keywords: leaves, computer vision, neural networks, feed forward net, image processing, wavelet transform.

INTRODUCTION

Plants are among the most important sources of life. While they are fundamental in the stages of oxygen circulation in the planet, their importance is drastically significant as food producers for the human being. Because humans are omnivores need plants to survive, but it is much more than that: They need different types of plants in order to meet their physiological needs, since a single plant cannot provide everything that humans need (Chevalier, *et al*., 2014).

Due to the dynamics of the relationship between plants and humans, the interest of the latter has been aroused in the study of the relevance of the different kinds of plants that inhabit the ecosystems that surround it and the conservation of species. However, classification and identification of plants is a complicated task from the point of view of the procedure.

Currently, the initial stages of classification used for the identification of morphological characteristics or inspection of plant patterns are based on the visual supervision by the people. Although it is a significant aid, sometimes it is not so fast or accurate and requires consideration of other variables, such as plant flora, which has led the human being to seek new methods and technologies to improve this type of processes (Satti, *et al*., 2013).

According to the theory of plant taxonomy, it can be inferred that the leaves of plants are more useful and direct basis to differentiate one plant from others. On the other hand, leaves can be easily found and harvested everywhere (Wang, *et al.*, 2014).

So far, most of the work of developing techniques for identifying plants through physical information of their leaves has been done around the study of shapes and color patterns, being limited by aspects like similarity between different species. Munisami *et al.* (2015) developed an identification system, based on physical dimensions of the leaves and color histogram, using KNN classification with a percentage accuracy of 87.3% of 640 samples belonging to 32 different plant species.

Chaki *et al.* (2015) proposed a new method of classification and identification using a combination of leaf shape and texture. The efficacy of the system was verified using two neuronal systems: neuro-fuzzy controller and a feedforward back-propagation multilayer perceptron. The best result was 87.1% of 930 samples belonging to 31 species.

Arun *et al.* (2012) developed a system of identification of medicinal plants leaves. They used gray-tone space-dependent matrices (GTSDM), grayscale texture, and local binary pattern operators. This method has an accuracy percentage of 94.7% of a database of 250 samples of 5 plant types.

Kadir *et al*. (2012) suggested a method that employs veins, shape, color and texture as a source of leaf information. They calculated 54 different characteristics and used a probabilistic neural network. The accuracy rate of the system was 95% of the database used.

This article contains a proposal for the classification and identification of plants of the university Surcolombiana headquarters, based on physical characteristics of the leaves using the wavelet transform and the feedforward neuronal network specialized in pattern identification with the help of Matlab software.

MATERIALS AND METHODS

Process description

The process of identifying leaves belonging to a database is shown in Figure-1. This work proposes a simple statistical analysis calculating different constants that will conform the characteristic vector of each sample, based on the image obtained when applying the wavelet transform to the result of the treatment of the original image.

Species selection

According to the "Catalog of floristic species of the University Surcolombiana, Neiva headquarters" (Ospina *et al.*, 2014), in the central headquarters of the University are 3,166 individuals distributed in 128 species and 58 families: 766 individuals of trees of 54 species, 1128 shrub individuals of 32 species, 836 herb individuals of 33 species, 564 palm individuals of 8 species, 28 individuals of vines of 3 species.

The most important discriminant in the sample collection process is the distance between the base and the apex of the leaf, which should be less than 50 cm by the ability of the environment to acquire images. In addition, there were other limitations such as the low number of individuals of middle age and difficulty of access.

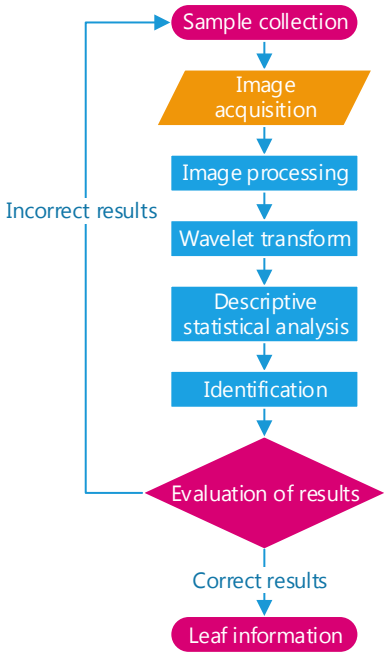

Figure-1. Flow chart of the leaf identification process.

A total of 620 samples were collected from 31 species, 20 samples per species. Of the total samples, 70% (14 samples) were used for system training and 30% (6 samples) for network evaluation.

Conditions of the sample

It is very probable to find leaves with damage caused by factors such as fungi, insects, environmental characteristics or the life time of the leaf, which can affect the quality of the sample and, by extension, the probability of a correct identification by the system. To guarantee a correct work in the process of image treatment and identification of each sample, the following conditions must be guaranteed:

- Dust-free samples, free of diseases, protective layers or fabrics, insect damage and any physical distortion of the leaf (breaks, holes, etc.).
- Distance between base and apex less than 50 cm.
- Approximate average size with respect to all leaves of the plant.
- Sample in middle age.

Controlled environment

In order to make the image acquisition phase practical, inexpensive and easy to use, the environment was completely made of aluminum. A spherical dome was used, which balances the lighting around the leaf, providing contrast. It has a diameter of 50cm and has a flat plate, also of polystyrene, located in an equidistant way in which are placed 12 LEDs of 3W. This type of illumination allows smoothing unnecessary features of the leaf such as fissures, fine veins, defects or superficial affections of the epidermis, texture, reliefs and wrinkles. Additionally, it eliminates shadows and dust. The acquisition environment is shown in Figure-2.

Figure-2. Dome for the acquisition of the images.

IMAGE PROCESSING

In Figure-3, the steps of the image processing process of the sheet to be identified are observed. Initially, the inclination of the leaf is approached in such a way that the line from the base to its apex is located parallel to the x axis. This is necessary because the wavelet transform, as will be explained below, delivers a matrix with information of local changes that are altered if the orientation of the image varies.

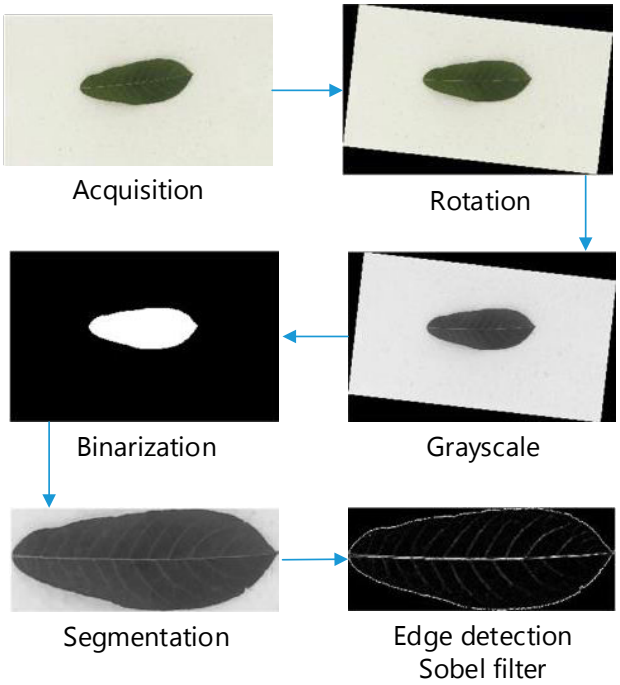

Figure-3. Stages of the treatment of the leaf image.

The final objective of the image treatment is to highlight the edge and the most prominent or notable ribs of the leaf with the help of the Sobel operator. This is why the information that does not correspond to the object of interest (leaf) should be deleted by segmenting the image based on the binarization of the same. The rectangle in the sheet is trimmed and textures are detected.

The Sobel operator calculates the magnitude of the largest possible change and the direction of the same in each pixel of the image (Patnaik and Yang, 2012). In other words, it shows how likely it is to see anintensity change in a pixel and, therefore, to represent a border and its direction. The results of the convolution between the image and the Sobel operator, based on next equations, are shown in Figure-4, where a) object of interest, b) horizontal gradient, c) vertical gradient, and d) convolution of vertical and horizontal gradients.

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * I G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} * I$$

$$G = \sqrt{{G_x}^2 + {G_y}^2}$$

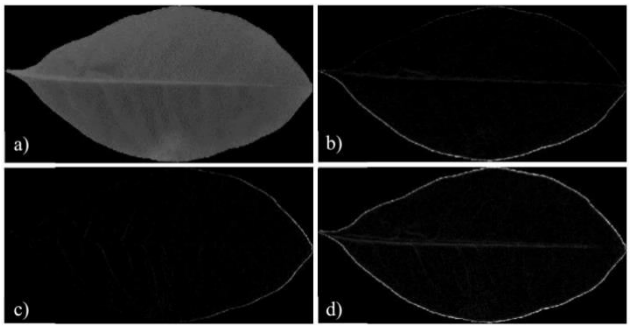

Figure-4. Sobel filter application.

WAVELET TRANSFORM

The image resulting from the application of the sobel filter, which will be called the fundamental image during the course of the article, is transferred to the space of the frequency through the discrete wavelet transform.

The wavelet transform allows the analysis of signals whose frequency varies over time, multiplying the signal by a specific wave, depending on the application, through the windowing technique (Pathak, 2009). When taking an image, the wavelet transform applies band-pass filters in order to separate the information contained at low and high frequencies. Then, the process is repeated with the obtained images. These iterations are known as levels.

When applying this transform to the fundamental image, several versions of it are obtained in which the resolution varies. However, as the level is increased, more information is lost and the probability of retaining the important information of the original signal decreases. In other words, the greater the level, the less information one has and, by extension, the more important the fundamental characteristics of the fundamental image are ambiguous.

In the present application, it is convenient to be at a level as close as possible to the original signal, because as the level is increased it is more likely to encounter two fundamental images of two different species of leaves that have very similar information. Therefore, level 1 is the most appropriate.

Figure-5 shows the Wavelet transform - Level 1. a) The approximation coefficients (CE), b) coefficients of details horizontal (CDh), c) coefficients of details vertical details (CDv), and d) coefficients of details diagonal (CDd)

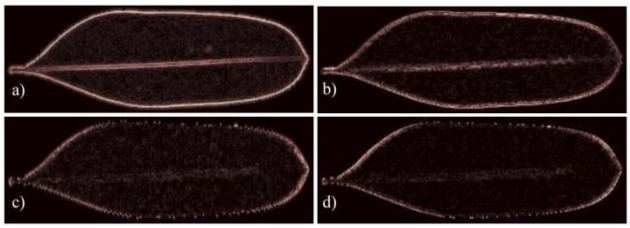

Figure-5. Wavelet transform - Level 1.

STATISTIC ANALYSIS

The information that represents each sample must be concise, relevant and that it contributes differentiation between samples of different species. This information is

given in a vector, because it is the way in which the neural network interprets it: one vector per sample.

It is not reasonable to construct a vector with the coefficients of the transform, since its extension would be very large even for the smallest leaf. That is why it is necessary to interpret each matrix of coefficients in such a way that there are still clear differences between samples of different species.

Therefore, a basic analysis of descriptive statistics is performed in which are calculated: approximation coefficients matrix size, coefficients value average, variance, standard deviation and mean absolute deviation. These variables are calculated for the approximation matrix, since it is the one that contains the most important information of the leaf, and is strengthened by the calculation of the standard deviation in the detail matrices, since the other variables do not make a relevant contribution in the differentiation of the samples of different species of leaves.

The characteristic vector is described in the following equation.

$$Vector = [a \quad b \quad c \quad d \quad e \quad f \quad g \quad h \quad i]$$

a : number of row of *CA*
b : number of columns of *CA*
c : standard deviation of *CA*
d : standard deviation of *CDh*
e : standard deviation of *CDv*
f : standard deviation of *CDd*
g : mean of *CA*
h : variance of *CA*
i : mean absolute deviation of *CA*

NEURAL NETWORK

The feedforward backpropagation network, specialized in pattern identification, belongs to Matlab Neural Network toolbox. The network consists of two hidden layers, with 50 neurons each, and the output layer with 31 neurons. The activation function for the hidden layers is sigmoidal tangensial, and a linear function is used for the output layer. The training method used is the graded conjugate gradient (Trainscg). The network architecture is shown in Figure-6.

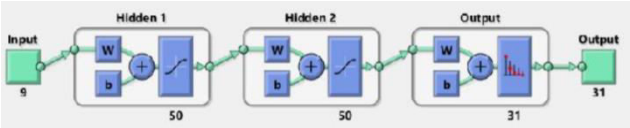

Figure-6. Neural network architecture.

RESULTS AND DISCUSSIONS

Of the total training samples (14 samples per species for a total of 434 samples), the network identifies 100% of them.

The system has an effectiveness of 95.6989%, identifying 178 samples of 186. Table-1 shows the results of the identification for each species. Of the 31 leaf samples shown in Table-1, seven samples obtained a successful result below 100%, and just one sample obtained a successful result below 70%.

Table-1. Results of the database samples identification.

Sample	Samples identified correctly	Samples not identified	Percentage of success
Leaf 1	6	0	100%
Leaf 2	6	0	100%
Leaf 3	6	0	100%
Leaf 4	6	0	100%
Leaf 5	6	0	100%
Leaf 6	6	0	100%
Leaf 7	5	1	83.33%
Leaf 8	6	0	100%
Leaf 9	6	0	100%
Leaf 10	6	0	100%
Leaf 11	6	0	100%
Leaf 12	6	0	100%
Leaf 13	6	0	100%
Leaf 14	6	0	100%
Leaf 15	5	1	83.33%
Leaf 16	6	0	100%
Leaf 17	6	0	100%
Leaf 18	4	2	66.66%
Leaf 19	5	1	83.33%
Leaf 20	6	0	100%
Leaf 21	6	0	100%
Leaf 22	6	0	100%
Leaf 23	6	0	100%
Leaf 24	5	1	83.33%
Leaf 25	6	0	100%
Leaf 26	6	0	100%
Leaf 27	5	1	83.33%
Leaf 28	6	0	100%
Leaf 29	5	1	83.33%
Leaf 30	6	0	100%
Leaf 31	6	0	100%

Samples that were not correctly identified have a characteristic vector that approaches that of samples from other species or leaves the range on which the vectors of the same species are found.

Within the group of samples from leaf 7 (*Muntingiacalabura* L., Chicható) for evaluation of the network, it was found that sample 6 was not correctly identified. The system has found that its pattern is more similar to some sample of leaf 21 (*Guareaguidonia* (L.) Sleumer, Bilibil). The above is shown in Figure-7 and Figure-8.

For leaf 15 (Codiaeum Variegatum, Crotoamarillo), the system has found that the pattern of sample 3 is very similar to some sample of leaf 9 (Erythroxylum coca Lam, coca). This is shown in Figure-9 and Figure-10.

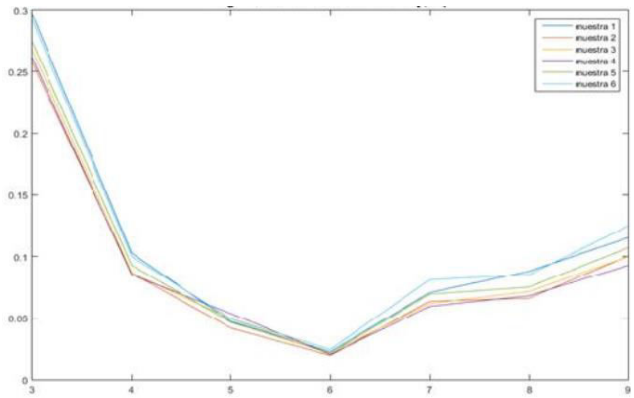

Figure-7. Evaluation of leaf 7 samples - Segment of characteristic vector VC [:, 3: 9].

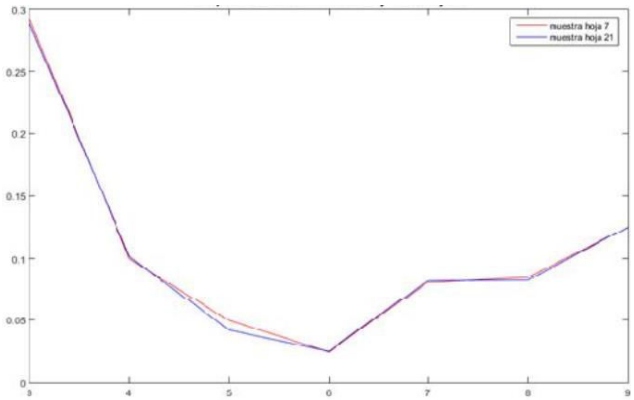

Figure-8. Comparison between leaf 7 and leaf 21 samples.

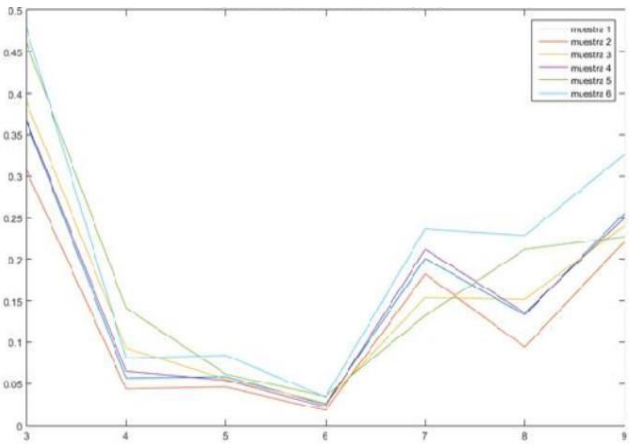

Figure-9. Evaluation of leaf 15 samples - Segment of characteristic vector VC [:, 3: 9].

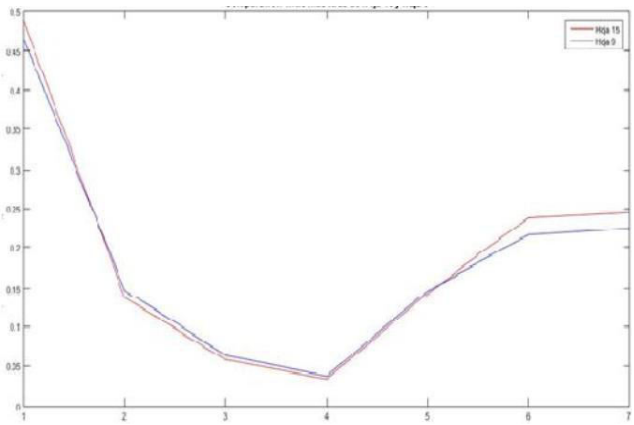

Figure-10. Comparison between leaf 15 and leaf 9 samples.

CONCLUSIONS

The present application has an effectiveness of 95.6989% in the identification of 186 samples (6 samples per species). This shows that the space of the wavelet transform provides enough information to make each sample unique and different from the others, guaranteeing excellent identification. However, it is necessary to emphasize that the wavelet transform was made based on information of nerves and edges, in addition to the texture, that between leaves of the same family and with similar physical characteristics can cause the system to deliver erroneous results. Samples of the same species must have a constant pattern or with little variability in aspects such as size, color and shape. Large variations in these variables, among samples of the same species, is proportional to the probability of not correctly identifying the leaf.

The identification will be correct as long as the physical quality parameters of the sample are respected. Stains, dust, imperfections caused by insects or by the environment, will reduce the probability of obtaining the expected result.

Illumination plays a fundamental role in the image acquisition stage, as it allows the elimination of stages in pre-processing, such as image smoothing and the elimination of imperfections such as dust. Additionally, it eliminates shadows, which can be considered as noise, and highlights useful information such as sample ribs.

Matlab, as a tool for digital image processing, is software that has a large set of functions and algorithms that allow successful applications. Although it is not specialized software and its libraries for image processing is limited, compared to libraries like Opencv, its performance is acceptable.

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