A multiple strategy for plant species identification using images of leaf texture

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Abstract

In our planet there are thousands of plant species, being important to catalog these to help in the biodiversity preservation. However, identifying various plant species is not an easy task, even for specialists. Methods of computer vision for identifying plant species are interesting solutions for these difficulties. This work aims to analyze the efficiency of texture feature extraction methods applied in the identification of plant species by means of images of its leaves. For this, different texture descriptors were applied in three different databases. The obtained results indicate that local phase quantization (LPQ)-based methods achieve great efficiency and robustness. Additionally, the combination of LPQ-based methods with a segmentation based fractal texture analysis (SFTA) has increased the correct classification rate in all databases.

1. Introduction

It is estimated that there are approximately 298,000 plant species on our planet, being 215,644 species cataloged by taxonomists (Mora et al., 2011). These numbers suggest that the identification of plant species, although it is a classic biological problem, still requires the attention of researchers. Conventional methods using traditional morphological analysis by specialists continue to be used. However, even for specialists, plant species identification is a very difficult task and may require a lot of knowledge and analysis time (Bonnet et al., 2016; Wäldchen & Mäder, 2018).

Aiming to overcome these challenges, the search for alternative solutions to plant species identification has emerged. Methods that make use of computer vision for plant identification are a very interesting alternative because of their automaticity, the ease aggregation of new information and a more agile classification compared to that made by taxonomists.

The literature presents several methods for plant identification, which can be classified according to the visual aspects analyzed, models and forms of application (Wäldchen & Mäder, 2018). However, computational methods are not yet as accurate compared to human identification, which motivates further research aiming at further exploration of this area (Bonnet et al., 2016).

This research aims to identify plant species using texture features of leaf images. Texture descriptors were used to extract features from each image. For this, several texture descriptors were analyzed in three leaf databases aiming to evaluate their robustness.

Texture descriptors were individually tested in each database and their results were analyzed to identify the most reliable and robust texture characterization to identify plant species through leaf images. Later, the features provided by the descriptors were combined in a multiple strategy to get more accurated results. The results show that the descriptor based on Local Phase Quantization (LPQ) achieves the best results. Additionally, the combination of LPQ-based descriptors with a fractal dimension-based texture analysis descriptor increased the correct classification rate significantly in all experimental databases.

The remainder of this paper is organized as follows: Section 2 describes the main forms of computer vision-based plant identification methods present in the literature; Section 3 describes the steps followed for plant identification along with the image databases used. Section 4 presents the obtained results and, finally, Section 5 concludes and lists the main contributions of this research.

2. Plant species identification

Plants are commonly identified by their external attributes such as leaves, flowers and fruits (Wäldchen & Mäder, 2018). In general, only one of these parts is used in an automated analysis, mainly because it is difficult to acquire data from multiple parts of a plant (Wäldchen et al., 2018). Flowers and fruits have a lot of information that can be used for plant identification, but they are not available through-

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out the year (Ash et al., 1999), and flower image collection is much more complex to acquire because they cannot be scanned (Nilsback & Zisserman, 2006). Leaves are available most of the year (Cerutti et al., 2013) and their near-planar shape is useful for image acquisition (Wang et al., 2008).

Due leaves vary greatly in color according to weather or season, characterization methods that use color information are not widely used (Wang et al., 2014). Many studies focus on the use of leaf shape characteristics for plant species identification (Wäldchen et al., 2018), but shape-based methods may suffer from point of view or rotation interference. The use of texture has proved to be a satisfactory choice for leaf image identification, as it can be measured in various types of images, such as full-leaf images, window cuts of the original image, microscopic images, and others (Casanova et al., 2009a). There are several texture-based feature extraction methods in the literature based on several concepts such as fractals (Silva et al., 2014), Fourier transforms (Da Silva et al., 2016), local binary patterns (Elnemr, 2017) and convolutional neural networks (Wang et al., 2018).

3. Texture analysis for plant species identification

Several steps may be required for identifying plant species using images. In general, these steps can be divided into three large groups (Wäldchen & Mäder, 2018), namely: image acquisition, feature extraction and classification.

Image acquisition consists of defining a technology and standardization to acquire images that best suit the desired application. For this study three public image databases were selected: Flavia (Stephen Gang Wu & Shiang, 2007) which is composed of full-leaf images obtained from 32 plant species of Nanking in China, *1200Tex* (Casanova et al., 2009b) which consists of window images of leaf textures obtained from 20 plant species of the Brazilian Cerrado, and, *Midrib* (da Silva et al., 2015) is a microscopic image database of the cross section of the central leaf vein (Figure 1. With these different data sets it is possible to ascertain the potential of texture-based algorithms for plant identification based on leaf images. Feature extraction seeks to extract information from the images that best define them. For this, five texture descriptors were selected:

- *Grey Level Cooccurrence Matrix* (GLCM) (Haralick et al., 1973) is a classic descriptor that focuses on the distribution of gray levels in an image, where gray levels cooccurrence matrices are generated from pixel values and their neighbors;
- *Local Binary Patterns* (LBP) (Ojala et al., 2002) generates binary values comparing if the pixel is smaller than its immediate neighbors (1 if true, and 0 false).

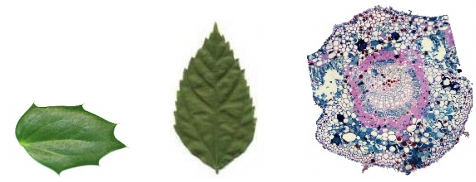

Figure 1. Samples of leaf images from *Flavia*, *1200Tex* and *Midrib* databases.

  Then a histogram is computed to provide the frequency at which a pixel in the neighborhood is greater than the central pixel.
- *Local Phase Quantization* (LPQ) (Ojansivu & Heikkilä, 2008) uses phase information from Fourier frequency domain according to the pixel neighborhood. Finally, binary patterns are generated and a histogram is created similar manner to LBP;
- *Rotation Invariant Local Phase Quantization* (RI-LPQ) (Ojansivu et al., 2008). It is similar to LPQ, but initially the orientation of the characteristics is calculated to then perform the LPQ steps;
- *Segmentation-based Fractal Texture Analysis* (SFTA) calculates the fractal dimension of the boundaries of the binary image regions obtained from the original image using the *Two-Threshold Binary Decomposition* method. The method implemented by the authors in (Costa et al., 2012) also use the gray level and average region size as features.

4. Experiments

For this study the classifier *k-nearest neighboors* (*k-NN*) was used, as it proves to be very effective (Amancio et al., 2014). All images have been converted to gray levelsand the 10-fold cross validation scheme was used. The value of k for *k-NN* was varied from 1 to 9 using only the odd values of this range. The best results for the *Flavia* and *Midrib* databases were obtained by the RI-LPQ method and $k = 1$ in k-NN, which was able to surpass the result of the original study that made these databases available. For the *1200Tex* database, the best result was obtained by the LBP method and $k = 7$.

The best results obtained by each descriptor were separated and presented in Tables 1, 2 and 3, showing the number of features ($\#feat$), the rate of correct classifications (CCR) of each method, the Kappa index and the Mean Absolute Error (MAE). In the following we concatenate the feature vectors of each descriptor with each other, thus generating ten pairs of combined feature vectors. The ten pairs were applied to the three databases. The best result obtained for the *Flavia* database was LPQ + SFTA, for the *1200Tex* database was the LBP + LPQ combination and for the *Midrib* was RI-LPQ+SFTA. In all cases, the results of this investigation perform better than the results of the original databases investigations.

Table 1. Results for the *Flavia* database.

METHOD	# FEAT	CCR(%)	KAPPA	MAE
GLCM	16	68,54	0,6750	0,0204
LBP	59	86,16	0,8570	0,0096
LPQ	256	94,44	0,9426	0,0045
RI-LPQ	256	94,55	0,9437	0,0045
SFTA	57	84,90	0,8440	0,0104
GLCM+LBP	75	87,36	0,8695	0,0089
GLCM+LPQ	272	95,39	0,9523	0,0039
GLCM+RI-LPQ	272	95,18	0,9502	0,0041
GLCM+SFTA	73	87,15	0,8673	0,009
LBP+LPQ	315	96,12	0,9599	0,0035
LBP+RI-LPQ	315	95,76	0,9561	0,0037
LBP+SFTA	117	91,66	0,9139	0,0062
LPQ+RI-LPQ	512	96,80	0,967	0,0031
LPQ+SFTA	313	97,12	0,9702	0,0029
RI-LPQ+SFTA	313	96,38	0,9626	0,0033

Table 2. Results for the *1200Tex* database.

METHOD	# FEAT	CCR(%)	KAPPA	MAE
GLCM	16	46,33	0,4351	0,0595
LBP	59	76,58	0,7535	0,0356
LPQ	256	72,67	0,7123	0,0478
RI-LPQ	256	71,33	0,6982	0,0458
SFTA	52	57,33	0,5509	0,0532
GLCM+LBP	75	79,00	0,7789	0,0347
GLCM+LPQ	272	78,58	0,7746	0,0438
GLCM+RI-LBP	272	74,50	0,7316	0,039
GLCM+SFTA	67	66,17	0,6439	0,0441
LBP+LPQ	315	84,58	0,8377	0,0285
LBP+RI-LPQ	315	80,83	0,7982	0,0299
LBP+SFTA	110	84,25	0,8342	0,027
LPQ+RI-LPQ	512	82,92	0,8202	0,0347
LPQ+SFTA	307	82,92	0,8202	0,0284
RI-LPQ+SFTA	307	79,92	0,7886	0,0376

5. Conclusions

The difficulty in identifying plant species, usually done manually by taxonomists, coupled with the need for environmental preservation, has made the search for alternative methods in plant identification a very important field to be studied, both by biology and computing. Computational methods are a great alternative, given their autonomy and speed compared to manual classification.

Given the importance and the great difficulty of performing the identification of plant species, the search for alternative solutions to the classification made by taxonomists shown a very important area to be studied, both for biology and for computing. The results presented in this investigation reveal the high robustness and quality of texture description methods for plant classification, which can be used for both macroscopic and microscopic plant species identification.

Table 3. Results for the *Midrib* database.

METHOD	# FEAT	CCR(%)	KAPPA	MAE
GLCM	16	43,23	0,4202	0,0241
LBP	59	61,06	0,6023	0,0176
LPQ	256	81,18	0,8079	0,0102
RI-LPQ	256	89,77	0,8955	0,0070
SFTA	39	81,35	0,8095	0,0101
GLCM+LBP	75	68,48	0,6781	0,0148
GLCM+LPQ	272	83,00	0,8264	0,0095
GLCM+RI-LPQ	272	90,43	0,9023	0,0068
GLCM+SFTA	55	83,00	0,8264	0,0095
LBP+LPQ	315	81,02	0,8062	0,0102
LBP+RI-LPQ	315	88,94	0,8871	0,0073
LBP+SFTA	98	82,84	0,8247	0,0096
LPQ+RI-LPQ	512	90,43	0,9023	0,0068
LPQ+SFTA	295	87,29	0,8702	0,0079
RI-LPQ+SFTA	295	93,40	0,9326	0,0057

There are several computational vision methods capable of identifying plant images, but texture-based methods are very comprehensive, as they work very efficiently at different image scales, from macro to micro, and suffer less interference from brightness and angle variation. The results presented in this investigation reveal the high robustness and quality of texture description methods for plant species identification. The results pointed to a large capacity of the texture classification method *RI-LPQ*, where it was able to achieve more than 94% of accuracy for the *Flavia* database.

The multiple strategy of the feature vectors of the different methods provided a high improvement in the classification. The SFTA method, which individually did not achieve the best results, managed to achieve the best result for the *Flavia* database combined with the LPQ method, with more than 97% accuracy. The SFTA method also achieved the highest percentage of correctness together with the RI-LPQ method for the *Midrib* database with a result higher than 93%. Finally, a desired percentage of correctness was reached for the *1200Tex* database, with the combination of the LBP and LPQ methods, exceeding 84% of accuracy.

References

Amancio, D. R., Comin, C. H., Casanova, D., Travieso, G., Bruno, O. M., Rodrigues, F. A., and da Fontoura Costa, L. A systematic comparison of supervised classifiers. *PLOS*

ONE, 9(4):1–14, 04 2014.

Ash, A., Ellis, B., Hickey, L. J., Johnson, K., and Wilf, P. Manual of leaf architecture - morphological description and categorization of dicotyledonous and net-veined monocotyledonous angiosperms by leaf architecture. *Washington D. C.: Smithsonian Institution*, 1999.

Bonnet, P., Joly, A., Goëau, H., Champ, J., Vignau, C., Molino, J.-F., Barthélémy, D., and Boujemaa, N. Plant identification: man vs. machine. *Multimedia Tools and Applications*, 75(3):1647–1665, Feb 2016.

Casanova, D., de Mesquita Sá Junior, J. J., and Bruno, O. M. Plant leaf identification using gabor wavelets. *International Journal of Imaging Systems and Technology*, 19(3): 236–243, 2009a.

Casanova, D., de Mesquita Sá Junior, J. J., and Bruno, O. M. Plant leaf identification using gabor wavelets. *International Journal of Imaging Systems and Technology*, 19(3): 236–243, 2009b.

Cerutti, G., Tougne, L., Mille, J., Vacavant, A., and Coquin, D. A model-based approach for compound leaves understanding and identification. In *2013 IEEE International Conference on Image Processing*, pp. 1471–1475, 2013. Melbourne, VIC, Australia.

Costa, A. F., Humpire-Mamani, G., and Traina, A. J. M. An efficient algorithm for fractal analysis of textures. In *2012 25th SIBGRAPI Conference on Graphics, Patterns and Images*, pp. 39–46, Aug 2012. Ouro Preto, Brazil.

da Silva, N. R., ao Batista Florindo, J., Gómez, M. C., Rossatto, D. R., Kolb, R. M., and Bruno, O. M. Plant identification based on leaf midrib cross-section images using fractal descriptors. *Plos One*, 2015.

Da Silva, N. R., da Silva Oliveira, M. W., de Almeida Filho, H. A., Pinheiro, L. F. S., Rossatto, D. R., Kolb, R. M., and Bruno, O. M. Leaf epidermis images for robust identification of plants. *Scientific reports*, 6:25994, 2016.

Elnemr, H. A. Feature selection for texture-based plant leaves classification. In *2017 Intl Conf on Advanced Control Circuits Systems (ACCS) Systems 2017 Intl Conf on New Paradigms in Electronics Information Technology (PEIT)*, pp. 91–97, Nov 2017.

Haralick, R. M., Shanmugam, K., et al. Textural features for image classification. *IEEE Transactions on systems, man, and cybernetics*, (6):610–621, 1973.

Mora, C., Tittensor, D. P., Adl, S., Simpson, A. G. B., and Worm, B. How many species are there on earth and in ocean? *PLoS Biology*, 9(8), 2011.

Nilsback, M. E. and Zisserman, A. A visual vocabulary for flower classification. In *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06)*, volume 2, pp. 1447–1454, 2006. New York, USA.

Ojala, T., Pietikainen, M., and Maenpaa, T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(7):971–987, 2002.

Ojansivu, V. and Heikkilä, J. Blur insensitive texture classification using local phase quantization. In Elmoataz, A., Lezoray, O., Nouboud, F., and Mammass, D. (eds.), *Image and Signal Processing*, pp. 236–243, Berlin, Heidelberg, 2008. Springer Berlin Heidelberg.

Ojansivu, V., Rahtu, E., and Heikkila, J. Rotation invariant local phase quantization for blur insensitive texture analysis. In *2008 19th International Conference on Pattern Recognition*, pp. 1–4, Dec 2008. Tampa, FL, USA.

Silva, N., Florindo, J., Gómez, M., Kolb, R. M., and Bruno, O. M. Fractal descriptors for discrimination of microscopy images of plant leaves. In *Journal of Physics: Conference Series*, volume 490, pp. 012085. IOP Publishing, 2014.

Stephen Gang Wu, Sheng Bao Forrest, E. Y. X. Y.-X. W. Y.-F. C. and Shiang, C.-L. A leaf recognition algorithm for plant classification using probabilistic neural network. *IEEE 7th International Symposium on Signal Processing and Information Technology*, dec 2007. Cario, Egypt.

Wäldchen, J. and Mäder, P. Plant species identification using computer vision techniques: A systematic literature review. *Archives of Computational Methods in Engineering*, 25(2):507–543, Apr 2018.

Wang, X.-F., Huang, D.-S., Du, J.-X., Xu, H., and Heutte, L. Classification of plant leaf images with complicated background. *Applied Mathematics and Computation*, 205 (2):916 – 926, 2008.

Wang, Z., Sun, X., Ma, Y., Zhang, H., Ma, Y., Xie, W., Wang, Z., and Zhang, Y. Plant recognition based on intersecting cortical model. In *2014 International Joint Conference on Neural Networks (IJCNN)*, pp. 975–980, 2014. Beijing, China.

Wang, Z., Sun, X., Yang, Z., Zhang, Y., Zhu, Y., and Ma, Y. Leaf recognition based on dpcnn and bow. *Neural Processing Letters*, 47(1):99–115, Feb 2018.

Wäldchen, J., Rzanny, M., Seeland, M., and Mäder, P. Automated plant species identification—trends and future directions. *PLOS Computational Biology*, 14(4):1–19, 04 2018.