Pattern recognition based on soft boundaries: a proposal applied to tree species identification from texture in trunk images

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Abstract. Plant taxonomy can be complex, time consuming, and impractical in the absence of leaves, fertile branches, flowers and fruits. Thus, species identification from texture in trunk images can be an alternative. However, patterns recognition with hard boundaries has caused low performance when samples have features belonging to more than one species. Therefore, a fuzzy approach was developed, aiming evaluate its performance in the identification of 11 tree species. Co-occurrence descriptors were extracted from grayscale images, and a principal component analysis was performed to avoid redundant information. Then, texture patterns were defined using soft boundaries by gaussian curve membership function. Moreover, we proposed a procedure to progressive addition of fuzzy patterns during the training, in order to improve performance. As a result, accuracy of 0.86 during hold-out validation was achieved. From these findings, we concluded that the fuzzy approach can be a promising strategy to species identification aided by computational intelligence.

Keywords: Image processing; Fuzzy classifier; Principal component analysis; Trunk images; Brazilian forest.

1 Introduction

Computational intelligence has been widely applied in various fields, such as medical diagnostics, industrial process, precision agriculture and environmental management [1, 2, 3]. On the other hand, tree species identification using computer methods, such as pattern recognition in digital images, still is recent and with many issues to overcome [4, 5]. For instance, current methods focus on the digital image processing of tree leaves [6, 7, 8, 9, 10], but many species lose their leaves at some seasons of the year.

Using trunk images can be an alternative, but there is fewer studies reported in literature [11]. Moreover, classification based on patterns with hard boundaries (classical sets) has caused low performance when the samples have features belonging to more than one species, i.e., causing the pattern classes to overlap [12].

In similar situations, where this overlap leads to an ambiguity in object recognition, defining the patterns by means of soft boundaries (fuzzy sets) can be an alternative [13]. Thus, a fuzzy classifier could assign a sample into one or more classes (tree species), but with certain degree of membership, supporting its identification.

Therefore, the main purpose of present study was to evaluate the fuzzy pattern recognition applied to tree species identification from texture features in trunk images.

2 Experimental

2.1 Texture feature extraction from tree trunk images

Tree trunk images (2560 x 1920 pixels) of 11 species from the Brazilian deciduous native forest were used: *Anadenanthera falcata* (*Af*), *Gochnatia polymorpha* (*Gp*), *Cedrela fissilis* (*Cf*), *Chorisia speciosa* (*Cs*), *Schizolobiun parahyba* (*Sp*), *Caesalpinia ferrea* (*Ca*), *Hymenaea courbaril* (*Hc*), *Inga vera* (*Iv*), *Erythrina speciosa* (*Es*), *Tabebuia roseo-alba* (*Tr*), and *Centrolobium tomentosum* (*Ct*).

Images were obtained using a digital camera, taken at different heights of the trunk, all around the trees. Then, a central area was cut from each image, and using a moving mask (512 x 512 pixels) the samples were thus obtained. Instances of samples for each of the 11 tree species are shown in Figure 1.

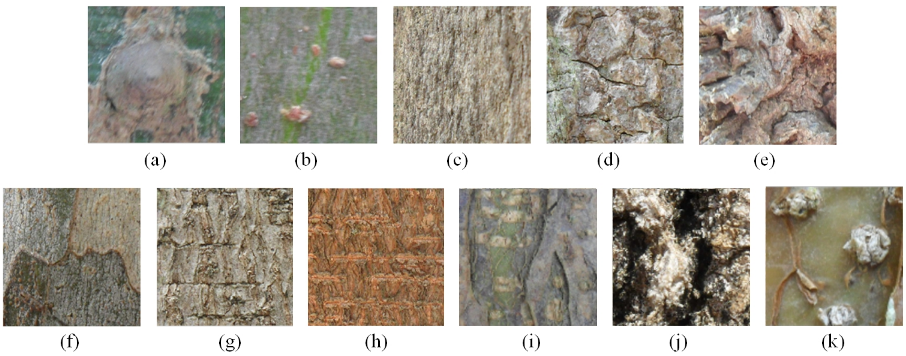

Fig. 1. Trunk images with 512 x 512 pixels from: (a) *Chorisia speciosa*, (b) *Schizolobiun parahyba*, (c) *Gochnatia polymorpha*, (d) *Cedrela fissilis*, (e) *Anadenanthera falcata*, (f) *Caesalpinia ferrea*, (g) *Hymenaea courbaril*, (h) *Inga vera,* (i) *Centrolobium tomentosum*, (j) *Tabebuia roseo-alba*, and (k) *Erythrina speciosa*.

Thereby, 1188 images were generated, being 108 per species, from which 76 samples (70%) were used for the pattern extraction and fuzzy classifier construction (training set) and 32 (30%) for performance assessment (testing set).

Pattern recognition was based on co-occurrence descriptors. For that, the images were transformed from RGB system to HSV space, and the V channel was used in the study.

Thus, co-occurrence matrix (G) was created from the grayscale image. A widely used texture analysis method, G is a tabulation about often of different combinations of intensity levels in an image, whose calculations are spatially related, sensitive to directions or orientations (rotational angles) [14].

In the present study, the descriptors extracted from G were contrast, correlation, energy and homogeneity, measured at a distance (*d*) between pixels equal to 1, 3, 5 and 7, in the directions (*o*) 0º, 45º, 90º, and 135º.

Contrast (c) measures the comparative intensity between a pixel and its neighbor over the entire image [15], as in:

$$c = \sum_{i=1}^{k} \sum_{j=1}^{k} (i-j)^2 p_{ij} , \quad \textbf{(1)}$$

where k is the row (or column) dimension of square co-occurrence matrix (G), ij is an element of the G, and p_{ij} is an estimate of probability that a pair of points satisfying O, operator that defines the relative position (distance and direction) of two pixels.

Considering a mean computed along rows (m_r) and columns (m_c), a correlation (r) infers how correlated a pixel is to its neighbor over the entire image [15, 16], calculated by:

$$r = \sum_{i=1}^{k} \sum_{j=1}^{k} \frac{(i-m_r)(j-m_C)}{\sigma_r - \sigma_c} p_{ij} , \quad \textbf{(2)}$$

where σ_r and σ_c are in the form of standard deviation computed along rows and columns, respectively, and

$$m_r = \sum_{i=1}^{K} iP(i) \quad \text{and} \quad m_c = \sum_{j=1}^{K} jP(j) , \quad \textbf{(3)}$$

$$\sigma_r^2 = \sum_{i=1}^{K} (i-m_r)^2 P(i) \quad \text{and} \quad \sigma_c^2 = \sum_{j=1}^{K} (j-m_c)^2 P(j) , \quad \textbf{(4)}$$

$$P(i) = \sum_{j=1}^{K} p_{ij} \quad \text{and} \quad P(j) = \sum_{i=1}^{K} p_{ij} . \quad \textbf{(5)}$$

The energy (ε) returns the sum of squared elements (p_{ij}) in G and homogeneity (H) measures the closeness of gray levels in the spatial distribution over image, which are respectively obtained as in:

$$\varepsilon = \sum_{i=1}^{k}\sum_{j=1}^{k} p_{ij}^{2} \quad , \tag{6}$$

$$H = \sum_{i=1}^{k}\sum_{j=1}^{k} \frac{p_{ij}}{1+|i-j|} \quad . \tag{7}$$

Whereas each texture descriptor was measured at various distances and directions, such features could be highly correlated. Therefore, a Principal Component Analysis (PCA) was performed to avoid the use of variables with redundant information.

PCA is a technique used to transform the original coordinates for a system of orthogonal axes, resulting in synthetic variables linearly uncorrelated, the called principal components [17].

Thus, the principal components (F_i) are linear combinations of the original variables (X_i), obtained in decreasing order of variance ($\lambda_1 > \lambda_2 > \lambda_3 \ldots \lambda_p$).

To do so, principal components were determined by solving the characteristic equation of the correlation matrix (R), as in:

$$\det[\mathrm{R} - \lambda \mathrm{I}] = 0 \quad , \tag{8}$$

where λ_i are the eigenvalues or characteristics root of R, for each of which there is an eigenvector $\boldsymbol{w}_i$, such that the principal component F_i is determined as in:

$$\mathrm{F}_i = w_{i1}\mathrm{X}_1 + w_{i2}\mathrm{X}_2 + \cdots + w_{ip}\mathrm{X}_p \quad , \tag{9}$$

where p is the number of original variables.

Thus, principal components with greater cumulative variability were used as input variables (antecedents) in the fuzzy classifier.

2.2 Fuzzy-based pattern recognition

Fuzzy texture patterns for each species i (sp_i) were defined by means of gaussian curve membership function (gaussmf), as given by:

$$\varphi_{spi}(x) = \exp\left(-\frac{(x-\mu_1)^2}{2\sigma^2}\right) , \tag{10}$$

where φ_{spi} defines the degree of membership of x in the species i, μ_1 and σ are average and standard deviation calculated for this sp_i, respectively.

Then, fuzzy inference process was developed according to the following procedures:

- one conditional statement (if-then rule) was formulated to support the identification of each tree species;

- in each if-then rule, the fuzzy patterns of species *i* (sp_i) were declared as antecedents, while the sp_i was defined as consequent;

- antecedents were interconnected via fuzzy intersections (AND=min), to formulate simultaneous occurrence of patterns that characterize the same tree species;

- in the output of each if-then statement is assigned to sample a degree of membership in the tree species supported by that statement;

- due to the use of the operator 'min', the membership value was always equal to the lowest degree among those assigned to the antecedents;

- membership values assigned to each species in the output of each statement are compared; and

- finally, species identified by the fuzzy classifier corresponds to one with the highest degree of membership.

The inclusion of all patterns in each conditional statement could result in a conservative classifier, i.e., with a low false positive rate (fp_{rate}). On the other hand, an excessive number of patterns can also decrease the rate of true positive (tp_{rate}). This may occur because the identification would be conditioned to membership in a large number of patterns.

Therefore, in order to improve the performance of fuzzy classifier, the following procedures were tested during the training:

- each conditional statement is initially composed only by fuzzy pattern that provides better distinction among sets that characterize each species;

- an assessment is performed to identify species for which there is confusion (misidentification);

- a new fuzzy pattern is added in conditional statements aiming to reduce confusion;

- alternately, the classifier performance is assessed and then a new fuzzy pattern is added, until there is no improvement in performance;

Thereby, we expect that the selective and progressive addition of patterns can avoid reduction of the true positive rate, i.e., samples attributed incorrectly to other species.

Moreover, since the patterns have been established, the manipulation of the weights of each conditional statement could reduce the false positive rate, i.e., reducing incorrectly assigned samples to its supported species. Therefore, complementarily the following procedures were tested:

- from the last assessment performed, statements with higher false positive rate are identified;

- the weight of the identified statements is reduced and, alternately, its performance is assessed again, until there is no reduction in false positive rate.

It is worth mentioning that, although adaptive techniques, as a neuro-fuzzy system, could have been used for automating some procedures, we prefer to perform as aforementioned, due to the exploratory nature of this study. Thus, the procedures performed required greater engagement and manual adjustments, consequently this allowed a deeper understanding of the process, its advantages and limitations.

2.3 Performance assessment

For assessing the performance, a hold-out validation was carried out. In this regard, two mutually exclusive subsets were used, one training subset and another for testing, compounds randomly by 70 and 30% of the samples, respectively.

Thus, classification results with the test samples were analyzed using metrics calculated from Confusion Matrix method, including precision, sensitivity, false positive rate, accuracy, and kappa [18].

Precision (P) for each species (sp_i) was estimated based on the ratio of correctly classified samples (TP_{spi}) by the total number of samples identified as belonging to sp_i (I_{spi}), as in:

$$P\ (sp_i) = \frac{TP_{sp_i}}{I_{sp_i}}\ . \tag{11}$$

Sensitivity, also called true positive rate (tp_{rate}) or hit rate, for each sp_i was estimated as the ratio of correctly classified samples (TP_{spi}) over the total number of samples actually belonging to sp_i (V_{spi}), as in:

$$tp_{rate}\ (sp_i) = \frac{TP_{sp_i}}{V_{sp_i}}\ . \tag{12}$$

False negative rate (tn_{rate}), measures the proportion of negatives samples (TN_{spi}), i.e., number of samples belonging to others species, incorrectly identified as belonging to sp_i, given by:

$$fp_{rate}\ (sp_i) = 1 - \frac{TN_{sp_i}}{TN_{sp_i} + FP_{sp_i}}\ , \tag{13}$$

where, FP_{spi} is the total number of false positive samples [18].

Accuracy (θ_I), or overall hit rate of the classifier, was estimated by the ratio of correctly classified samples in all evaluated species by the total number of samples (n_T), as in:

$$\theta_1 = \frac{1}{n_T}\sum_{i=1}^{n_{sp}} T_{sp_i}\ , \tag{14}$$

where, n_{sp} is the total number of species.

In addition, to further evaluate the fuzzy-based approach, the agreement between the predicted classes and true species was measured by the kappa index (K), defined by:

$$K = \frac{\theta_1 - \theta_2}{1 - \theta_2}\,, \qquad \textbf{(15)}$$

where,

$$\theta_2 = \frac{1}{{n_T}^2}\sum_{i=1}^{n_{sp}}(V_{sp_i} \cdot I_{sp_i})\,. \qquad \textbf{(16)}$$

3 Results and Discussion

As a result of the PCA, we find that the first 13 principal components accumulated 99.9% of the information contained in the 64 original variables, as shown in Figure 2, where the eigenvalues also can be seen.

This result confirms the possibility of high correlation among some texture patterns, based on co-occurrence descriptors measured at various distances and directions. In this case, PCA allowed a dimensionality reduction, i.e., using the smallest number of uncorrelated variables in the pattern recognition.

Then, the model to support the tree species identification based on a fuzzy approach was developed using only the first 13 principal components. For these components, the fuzzy patterns defined by membership functions given in (10) are shown Figure 3.

Analyzing Figure 3, it is observed that although the characteristic patterns of some tree species have a distinctive average, they also have dispersion with a certain overlapping of the fuzzy sets.

Thus, using soft boundaries by means of gaussian curve function allowed assigned different degrees of membership according to the frequency of samples by each species in the input space.

It is noted that cumulative variability decrease progressively from first to the thirteenth principal component. Consequently, increase the confusion among species due to the reduction tendency of useful information to distinguish their characteristic patterns.

However, we can note that the ninth (F9) provided better distinction than others from lower order, as the seventh and eighth principal components (F7 and F8). This is possibly due to the fact that both inter and intra class variations are included by PCA.

Besides that, even in the first principal component the capability of providing distinction among fuzzy sets is not the same for each species. In this sense, it can be seen that F1 provides the best distinction between *Cedrela fissilis* (*Cf*) and *Centrolobium tomentosum* (*Ct*). On the other hand, this is the same principal component (F1) that causes ambiguity in the recognition between *Cedrela fissilis* (*Cf*) and *Inga vera* (*Iv*) (greater overlap).

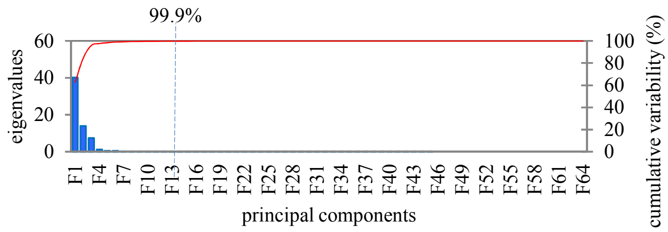

Fig. 2. Eigenvalues and accumulated variability of principal components.

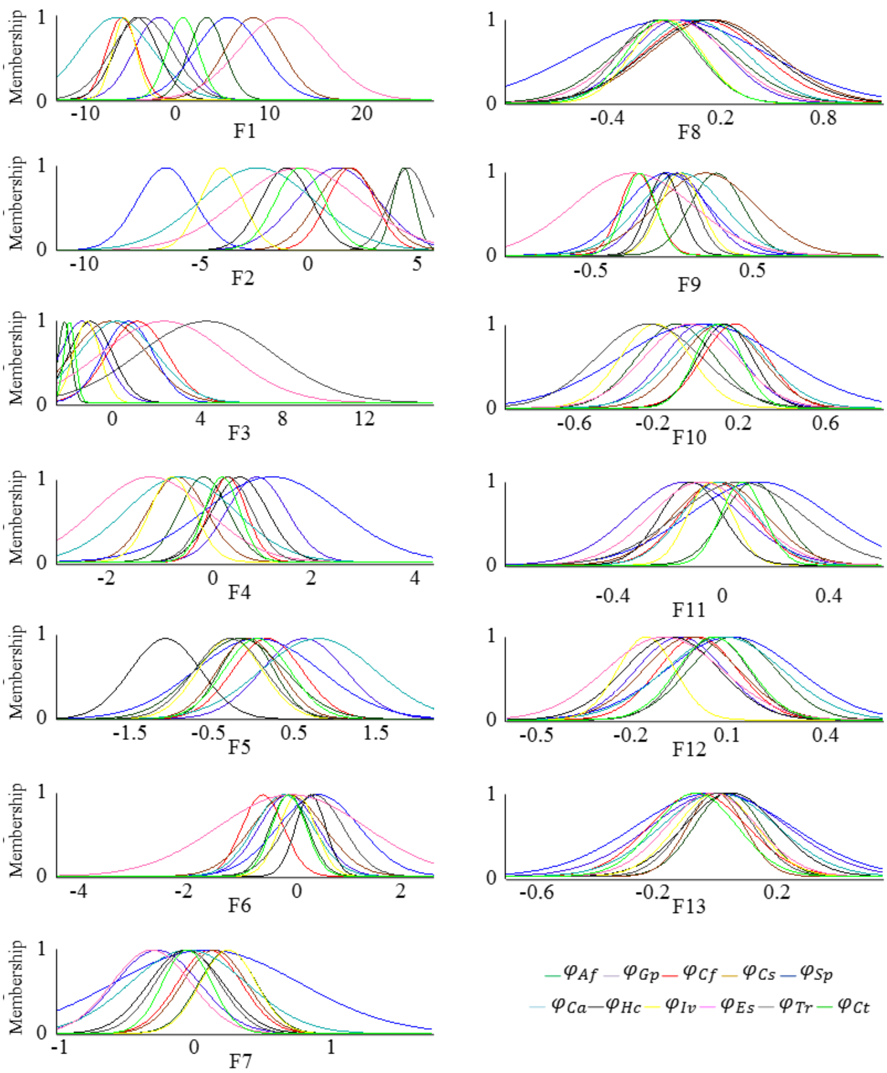

Fig. 3. Fuzzy patterns defined for the first 13 principal components.

Table 1. Antecedents used in the conditional statement to support tree species identification.

Tree species	Antecedents Functions	Weight (ρ)
Anadenanthera falcata	F_1, F_2, F_3	0.75
Gochnatia polymorpha	F_1, F_2, F_3, F_4, F_5, F_9	0.65
Cedrela fissilis	F_1, F_2, F_3, F_5	1
Schizolobiun parahyba	F_1, F_2	0.8
Chorisia speciosa	F_1, F_2, F_7, F_9	1
Caesalpinia ferrea	F_1, F_2, F_4, F_5, F_9, F_{10}, F_{12}	0.2
Hymenaea courbaril	F_1, F_2, F_5, F_{10}	0.8
Inga vera	F_1, F_2, F_5, F_{12}	1
Erythrina speciosa	F_1, F_2, F_4, F_7, F_9	0.8
Tabebuia roseo-alba	F_1, F_2, F_3, F_5, F_6	1
Centrolobium tomentosum	F_1, F_2, F_5, F_9	1

Therefore, this indicates the importance of the selective and progressive inclusion of principal components as antecedents in each conditional statement to avoid confusion as much as possible.

An example of conditional statement (if-then) formulated to support the identification of species *Anadenanthera falcata* (*Af*) is shown below, and the antecedents used to support the others tree species can be seen in Table 1:

$$\text{If } (F_1 \text{ is } \varphi_{Af}) \text{ and } (F_2 \text{ is } \varphi_{Af}) \text{ and } (F_3 \text{ is } \varphi_{Af}) \text{ then } \varphi_{Af}(x) \text{ is min } \{F_1, F_2, F_3\}\ (\rho). \qquad \mathbf{(15)}$$

where, ρ is weight of conditional statement.

By analyzing Table 1, we can see that for most of the tree species until four patterns were enough to better distinction from their samples. In contrast, for others species, especially *Caesalpinia ferrea* (*Ca*) and *Gochnatia polymorpha* (*Gp*) a greater number was needed for distinction their patterns with those of other species.

Consequently, the use of more patterns makes the classifier more conservative, causing minor rate of true positive (tp_{rate}). The same fact causes higher rate of false positive (fp_{rate}) and, to control this, a weight reduction of the conditional statements which support their identification also was needed. The performance improvement due to these procedures can be seen in the Table 2.

According to the accuracy in the hold-out validation, we can observe that the fuzzy classifier provided significant results during testing. Even in the conservative condition, using all the 13 principal components and weight equal to 1 in all if-then rules, the fuzzy classifier achieved 78% accuracy in the identification of 11 tree species.

Table 2. Accuracy measure of the tree species identification based on fuzzy classifier.

Antecedents	Training	Testing
All the 13 principal components and weight equal to 1 in all if-then rules	0.78	0.78
Progressive inclusion of principal components and weights adjustment	0.87	0.86

However, selective and progressive inclusion of principal components and weights adjustment provided a significant improvement in performance, reaching 86% accuracy in the tests. Therefore, the proposed procedures provided an increase of 10% over prior performance, in conservative condition.

As a confusion matrix, testing results are summarized in Table 3, whose performance metrics are shown in Table 4.

It is noted that fuzzy classifier obtained high precision (P_{rate}) for almost all species evaluated, especially *Schizolobiun parahyba* and *Inga vera* with 100% of achievement, as well as *Anadenanthera falcata*, *Hymenaea courbaril, Erythrina speciosa*, and *Tabebuia roseo-alba,* equal or above 88%. Thus, including *Cedrela fissilis* (86%) and *Chorisia speciosa* (85%), more than 85% of the samples identified as belonging to 8 of the 11 species were correct.

There were only two species with a more significant occurrence of false positive (fp_{rate}), *Gochnatia polymorpha* (3%) and *Caesalpinia ferrea* (3%), due to inclusion of samples belonging to others species (commission error).

Table 3. Confusion matrix for the testing results of the fuzzy classifier.

True species \ Identifying species	Anadenanthera falcata	Gochnatia polymorpha	Cedrela fissilis	Schizolobium parahyba	Chorisia speciosa	Caesalpinia ferrea	Hymenaea courbaril	Inga vera	Erythrina speciosa	Tabebuia roseo-alba	Centrolobium tomentosum
Anadenanthera falcata	29	0	0	0	2	0	0	0	0	1	0
Gochnatia polymorpha	2	23	2	0	0	3	0	0	0	1	1
Cedrela fissilis	0	3	24	0	0	2	1	0	0	2	0
Schizolobiun parahyba	0	0	0	32	0	0	0	0	0	0	0
Chorisia speciosa	0	0	0	0	29	0	0	0	3	0	0
Caesalpinia ferrea	0	4	2	0	0	22	1	0	1	0	2
Hymenaea courbaril	0	0	0	0	0	0	29	0	0	0	3
Inga vera	0	1	0	0	0	1	1	29	0	0	0
Erythrina speciosa	0	0	0	0	2	0	0	0	29	0	1
Tabebuia roseo-alba	2	0	0	0	1	0	0	0	0	29	0
Centrolobium tomentosum	0	1	0	0	0	2	1	0	0	0	28

Table 4. Performance metrics for the testing results of the fuzzy classifier.

Species	Performance Metrics				
	P	tp_{rate}	fp_{rate}	θ_1	K
Anadenanthera falcata	0.88	0.91	0.01		
Gochnatia polymorpha	0.72	0.72	0.03		
Cedrela fissilis	0.86	0.75	0.01		
Schizolobiun parahyba	1.00	1.00	0.00		
Chorisia speciosa	0.85	0.91	0.02		
Caesalpinia ferrea	0.73	0.69	0.03	0.86	0.85
Hymenaea courbaril	0.88	0.91	0.01		
Inga vera	1.00	0.91	0.00		
Erythrina speciosa	0.88	0.91	0.01		
Tabebuia roseo-alba	0.88	0.91	0.01		
Centrolobium tomentosum	0.80	0.88	0.02		

Nevertheless, even for those species fp_{rate} is considerably low due to the fact that the proportion of samples belonging to species sp_i (32 samples) and belonging to the other (320) is very unbalanced in the one-against-all strategy.

In addition, it was also observed that the fuzzy classifier achieved expressive hit rates (tp_{rate}), hitting all, or almost all (29 in 32), samples belonging to *Schizolobiun parahyba*, *Anadenanthera falcata*, *Chorisia speciosa*, *Hymenaea courbaril*, *Inga vera*, *Erythrina speciosa*, and *Tabebuia roseo-alba*.

However, there were species with low sensitivity, specially *Caesalpinia ferrea* (69%), *Gochnatia polymorpha* (72%) and *Cedrela fissilis* (75%), due to larger errors of omission, not computing samples belonging to this species.

Despite this, considering all analyzed tree species in the present study, the fuzzy classifier achieved an overall accuracy (θ_1) of 86.1% in the test during hold-out validation. Moreover, the kappa index equal to 84,6% indicates an almost perfect agreement between the predicted classes by fuzzy approach and the correct ones [19].

4 Conclusion

Due to limitations of current techniques, texture patterns recognition in tree trunk images has been considered as an alternative to support the species identification, but there are still issues to overcome. In this sense, considering that texture samples may have characteristics belonging to more than one species, this paper assessed the pattern recognition based on soft boundaries, as a methodological alternative.

In conclusion, from achieved results we can consider that the fuzzy approach represents a promising strategy to tree identification aided by computational intelligence. However, to further optimize this approach, in future works the use of other membership function, as the gaussian combination function, could be experienced in order to provide a best distribution fitting to the data, even as the use of fuzzy rule-based systems specialized to handle classification tasks.

References

1. Yemshanov, d., Mckenney, D. W., Pedlar, J. H.: Mapping forest composition from the canadian national forest inventory and land cover classification maps. Environ Monit Assess. 184, 55--69 (2012)
2. Vibhute, A., Bodhe, S. K.: Applications of Image Processing in Agriculture: A Survey. International Journal of Computer Applications. 52, 34--40 (2012)
3. Li, C., Jia, X., Li, H., Deng, L. Shi, X.: Digital image processing technology applied in level measurement and control system. Procedia Engineering. 24, 226--231 (2011)
4. Priya, A. C., Thanamani, A. S.: A survey on species recognition system for plant classification. International Journal Computer Technology & Applications. 3, 1132--1136 (2012)
5. Machado, B. B., Casanova, D., Gonçalves, W. N., Bruno, O. M.: Partial differential equations and fractal analysis to plant leaf identification. J. Phys.: Conf. Ser. 410 012066 (2013)
6. Silva, N. R., Florindo, J. B., Gómez, M. C., Kolb, R. M., Bruno, O. M.: Fractal descriptors for discrimination of microscopy images of plant leaves. J. Phys.: Conf. Ser. 490 012085 (2014)
7. Sá Júnior, J. J. M., Rossato, D. R., Kolb, R. M., Bruno, O. M.: A computer vision approach to quantify leaf anatomical plasticity: a case study on Gochnatia polymorpha (Less.) Cabrera. Ecological Informatics. 15, 34--43 (2013)
8. Kadir, A., Nugroho, L. E., Susanto, A., Santosa, P. I.: Leaf classification using shape, color, and texture. International Journal of Computer Trends and Technology. 2, 225--230 (2011)
9. Rossatto, D. R., Casanova, D., Kolb, R. M., Bruno, O. M.: Fractal analysis of leaf-texture properties as a tool for taxonomic and identification purposes: a case study with species from Neotropical Melastomataceae (Miconieae tribe). Plant Systematics and Evolution. 291, 103--116 (2011)
10. Casanova, D., Florindo, J. B. Bruno, O. M.: IFSC/USP at ImageCLEF 2011: Plant identification task. In: Conference and Labs of the Evaluation Forum, CLEF, Amsterdam (2011)
11. Boman, J.: Tree species classification using terrestrial photogrammetry. Dissertation, Umeå University, Umeå (2013)
12. Bressane, A., Roveda, J. A. F., Martins, A. C. G.: Statistical analysis of texture in trunk images for biometric identification of tree species. Environmental Monitoring and Assessment, 187(4), 1--9 (2015)
13. Konar, A. B.: Fuzzy Pattern Recognition, in Computational Intelligence, A. Konar (eds). pp. 125--138, Springer-Verlag Berlin Heidelberg (2005)
14. Rao, C. N., Sastry, S. S., Mallika, K., Tiong, H. S., Mahalakshmi, K. B.: Co-Occurrence Matrix and Its Statistical Features as an Approach for Identification of Phase Transitions of Mesogens. International Journal of Innovative Research in Science, Engineering and Technology. 2, 4531--4538 (2013)
15. Gonzales, R. C., Woods, R. E., Eddins, S. L.: Digital image processing using MATLAB. 2ed. Gatesmark Publishing (2009)
16. Harlick, R. M., Shanmugam, K., Dinstein, I.: Textural features for image classification. IEEE Transactions on Systems, Man and Cybernetics. 3, 610--621 (1973)
17. Rao, C. R.: The use and interpretation of principal component analysis in applied research, The Indian Journal of Statistics, 26(4), 329--358. (1964)
18. Fawcett, T.: An introduction to roc analysis. Pattern Recognition Letters. 1, 861--874. (2005)
19. Landis J. R., Koch, G. G. The measurement of observer agreement for categorical data. Biometrics, 33(1), 159—174 (1977).