A Fusion System for Tree Species Recognition Through Leaves and Barks

Rihab Ben Ameur, Lionel Valet and Didier Coquin
LISTIC, University Savoie Mont Blanc
74944 Annecy le Vieux, France

***Abstract*—In the last decades, data fusion techniques proved their performances especially in the case of complex recognition system. The idea is to use those techniques in the context of tree species recognition. In this paper, we propose to fuse information extracted from barks with those extracted from leaves. The goal is to increase the power of discrimination of the proposed fusion system and to achieve better detection results than those obtained when using only the leaves. Two fusion system architectures, corresponding to two fusion strategies are compared in this paper.**

I. Introduction

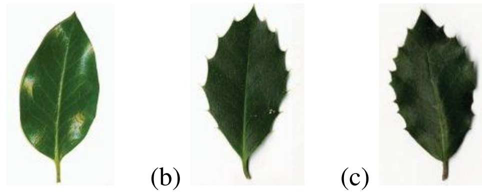
Tree species recognition is a very challenging task and is one of the major concerns at present. Many researches have been carried out in order to deal with this problem and to find the better tree species recognition system.a very challenging task. Some of those systems use attributes extracted from leaves. In [1], a thresholding method is combined with an H-maxima transformation based method to extract the leaf veins. In [2], a new multi-resolution and multidirectional curvelet transform is applied on subdivided leaf images to extract leaf information. In other works, tree sepcies are recognised through barks. The main used bark texture features are Gabor filters [3] and Gray-level Co-occurrence matrices (GLCM) [4] and [5]. Some other works use different tree organs in order to recognise tree species. In [6], the tree recognition system is based on the combination of component retrievals, leaf, flower and bark. In [7], we presented two strategies for tree species recognition through leaves allowing the obtainment of a set of the five most corresponding species. As the use of different trees organs proved its ability to improve performances of the tree species recognition system [6], the idea is to combine information about leaves with information about barks, flowers, GPS information,... Actually, we have only features extracted from leaves and barks database. Thus, as a first step, we have decided to combine those two sources of information and to evaluate the ability of trees barks to improve performances achieved by only leaves.

The data fusion techniques [8], consisting in combining data from multiple sensors, proved their performances in different domains. In the context of this work[1], available information are often uncertain, incomplete and imprecise for many reasons that could be illustrated studying the specificities of the barks and leaves database. First in this paper we consider 5067 photographs of leaves and 2587 photographs of barks from PlantCLEF 2014 [2]. Those photographs represent 72 tree species found in the France territory. So, the supervised classification problem we consider is a multi-class problem with a very large number of classes (72 classes). It's important to note that the number of photographs per class is different: some classes contain more than 200 samples while others are represented by only five samples. This may affect model training and generate biased results. Second, there is a significant intra-class variability: a same species can be represented by two or multiple leaves or barks which are widely different. Also, we have a high inter-class similarity: leaves or barks belonging to different species can be very similar. Intra-class variability and inter-class similarity between leaves are illustrated on figure 1. Figure 2 represents inter-class similarity and intra-class variability between barks.

Specificities of used databases affect largely the quality of attributes. Because of the intra-class variability and the inter-class similarity, extracted attributes are not enough informative, not linearly separable and even noisy. Different theories to manage those data imperfections are proposed in the literature: fuzzy set theory [9], possibility theory [10], rough set theory [11] or imprecise probability theory [12]. The Dempster-Shafer theory (DST) [13] also known as Belief functions has been shown to be a powerful framework for reasoning with imprecise and uncertain sources of information which is our case. For that reason, we choose to use it in the context of tree species recognition. Yet, one of the major problems of this theory is its high computational complexity that increases exponentially with the number of classes to be treated. To deal with this problem, the general framework proposed by Martin [14] is used as well as an approximation of belief functions. Section 2 exposes the proposed fusion system. Tests on leaves and barks databases are presented in section 3.

[1]This work has been supported by the French National Agency for Research with the reference ANR-15-CE38-0004 (ReVeRIES project)

[2]http://www.imageclef.org/2014/lifeclef/plant



(a) (b) (c)

Fig. 1: (a) and (b) present the intra-classes variability (the Holly), (b) and (c) present the inter-classes similarity (the Holly and the Oak)

(a)

(b)

Fig. 2: (a) and (b) present respectively the similarity between barks belonging to different species and the variability between barks belonging to the same species

II. Fusion system

The recognition of tree species through leaves and barks, illustrated in figure 3, consists first in extracting attributes characterising those two modalities. A supervised sub-classification step consists then on using those attributes as inputs of random forest classifiers (trained using 200 trees and the information gain classification method) and providing a distribution of probabilities in the space of species as outputs. Finally, a fusion system allows the combination of data provided by different sub-classifiers and provide a list of the most corresponding species.

In this work, two fusion system strategies are proposed. The first strategy consists first in fusing information provided by different leaves sub-classifiers and then refine obtained results with information about barks. Contrary to the first strategy, the second strategy doesn't separate leaves sub-classifiers from barks sub-classifiers, it fuse all of them in cascade according to an order driven by the sub-classifiers performances.

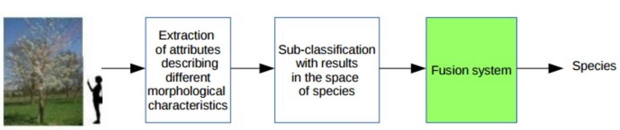


Fig. 3: Principal steps of tree species recognition

TABLE I: sizes of vectors $\overrightarrow{A_i}$ for each morphological characteristic C_i

Modality	C_i	$\overrightarrow{A_i}$	$[a_{i,1}, ..., a_{i,j}]$
the leaf	C_1: the base and the apex	$\overrightarrow{A_1}$	$[a_{1,1}, ..., a_{1,10}]$
	C_2: the margin	$\overrightarrow{A_2}$	$[a_{2,1}, ..., a_{2,9}]$
	C_3: the global shape	$\overrightarrow{A_3}$	$[a_{3,1}, ..., a_{3,5}]$
the bark	C_4: the color of the bark texture	$\overrightarrow{A_4}$	$[a_{4,1}, ..., a_{4,255}]$
	C_5: the orientation of the bark texture	$\overrightarrow{A_5}$	$[a_{5,1}, ..., a_{5,3}]$

A feature selection step, presented in [15], allows the building of 3 vectors of attributes extracted from leaves: The vector of attributes noted $\overrightarrow{A_1}$ characterising the margin and extracted using LMS descriptor [16], the vector of attributes $\overrightarrow{A_2}$ characterising the apex and the base of the leaf and extracted using a polygonal model parameters, leaves base parameters and tip models as well as a curvature scale histogram [15] and finally the vector $\overrightarrow{A_3}$ characterising the shape of the leaf [17]. 2 other vectors of attributes are extracted from barks: The vector $\overrightarrow{A_4}$ characterising the color hue H of the HSV color space (this color shade is used since it is robust with regard to the stem luminosity variations) [18] and the vector $\overrightarrow{A_5}$ characterising the orientation and the frequency of the structure composing the bark [19]. Table I shows the sizes of each vector.

Globally, we remark that vectors sizes are not very important expect $\overrightarrow{A_4}$ which wasn't reduced since the reduction causes less of this vector performances. Each vector of attributes is used to train a random forest [20] sub-classifier. As output of each sub-classifier, we have a distribution of probabilities P_i in the space of species E with $E = \{e_1, ..., e_k, ..., e_{72}\}$.

The fusion system is based on the theory of Dempster-Shafer [13] called also theory of Belief functions that provides an efficient frame to deal with imprecise information.
Let $\Theta = \{\Theta_1, ..., \Theta_N\}$ be a frame of discernment composed of N exclusive and exhaustive hypothesis and $2^\Theta = \{\emptyset, \Theta_1, \Theta_2, ..., \Theta_N, \{\Theta_1, \Theta_2\}, \{\Theta_1, \Theta_3\}, ..., \Theta\}$ the power set of all possible combinations of the elements of Θ. A mass function defined on the power set of Θ is a function $m : 2^\Theta \rightarrow [0, 1]$ verifying:

$$\sum_{A \subseteq \Theta} m(A) = 1 \quad (1)$$

In our application, the frame of discernment corresponds to E, the set of sought-after species.

To transit from the theory of probabilities (output of the sub-classifiers) to the theory of belief functions, we implement the method named "an Ω BBAs Subset" presented in details in [21]. It consists first in ordering the probabilities P_i of a sub-classifier S_i

$P_i(e_{(1)}) \geq P_i(e_{(2)}) \geq P_i(e_{(3)}) \geq ...P_i(e_{(N-1)}) \geq P_i(e_{(N)})$ and then computing the masses as follows:

$$\begin{aligned}
m\{e_{(1)}, e_{(2)}, ..., e_{(N-1)}, e_{(N)}\} \equiv& N * P_i(e_{(N)}) \\
m\{e_{(1)}, e_{(2)}, ..., e_{(N-2)}, e_{(N-1)}\} \equiv& (N-1) * (P_i(e_{(N-1)}) - \\
& P_i(e_{(N)})) \\
m\{e_{(1)}, e_{(2)}, ..., e_{(N-3)}, e_{(N-2)}\} \equiv& (N-2) * (P_i(e_{(N-2)}) - \\
& P_i(e_{(N-1)})) \\
& ... \\
m\{e_{(1)}, e_{(2)}, e_{(3)}\} \equiv& (3) * (P_i(e_{(3)}) - P_i(e_{(4)})) \\
m\{e_{(1)}, e_{(2)}\} \equiv& (2) * (P_i(e_{(2)}) - P_i(e_{(3)})) \\
m\{e_{(1)}\} \equiv& (1) * (P_i(e_{(1)}) - P_i(e_{(2)}))
\end{aligned}$$

The global idea of the fusion system is to fuse the sub-classifiers two by two. Thus, at each fusion level n we can analysis the contribution of each sub-classifier. Each time we fuse two sub-classifiers together, the appropriate combination rule should be chosen. The combination rule allows to fuse 2 masses $m_1(B)$ and $m_2(C)$ originate from 2 different sources in order to obtain a mass function $m(A)$ with A, B and C are elements of the power set 2^Θ . This combination consists in according a mass to all elements of the power set 2^Θ. As we work with potentially conflicting data, this choice depends on the degree of conflict which is expressed in the interval [0 , 1] and refers to the calculation of the mass of the empty set as follows:

$$m(\emptyset) = \sum_{B \cap C = \emptyset} m_1(B) m_2(C) \tag{2}$$

If the conflict is important (≥ 0.8), we use the disjunctive combination rule

$$m(A) = \sum_{B \cup C} m_1(B) m_2(C), \forall A \in 2^\Theta \tag{3}$$

Else we use the combination rule of Dempster

$$m(A) = \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1 - \sum_{B \cap C = \emptyset} m_1(B) m_2(C)} \tag{4}$$

The problem we treat is a complex real world problem with a lot of confusion, uncertainty and imprecision. If, as a result of the fusion process, we present to the user just the first most likely species, this response may contain an important degree of uncertainty. On the other hand, if the response of the system is in the form of a sub-set of the most likely species, the degree of uncertainty will be reduced. We think that providing an information which is less precise but more certain may be more useful for the user. Thus, the decision making step we propose allows the selection of the most corresponding sub-sets of species by using two of the most used criteria for making decision in the theory of belief functions: The plausibility Pl and the credibility Cr [13]. We use those decision making criterion in order to find the more suitable to the problem we treat. Indeed, the classification problem presented in this paper is a multiclass problem with a relatively huge number of classes (72 classes). It is preferable that the system provides the user with the most precise information while having always a good performance and a minimum of errors. Thus, the goal is to obtain a sub-set of classes with a small size while having always a relatively important classification ratio. Thus, we consider that the best decision making criterion is the one which provides the best compromise between the classification ratio and the size of the selected sub-set. As presented in equations 5 and 6 the maximum of credibility and plausibility criterion appears to be respectively an optimistic and a pessimistic criterion.

$$Cr(A) = \sum_{B \subseteq A, B \neq \emptyset} m(B) \tag{5}$$

$$Pl(A) = \sum_{A \cap B \neq \emptyset} m(B) \tag{6}$$

With those criteria, we obtain for each individual an element A of the power set of E having the maximum of plausibility or the maximum of credibility and containing several species.

TABLE II: Performances R_i of sub-classifiers S_i

S_i	S_1	S_2	S_3	S_4	S_5
R_i	41%	28%	43%	30%	12%

III. Experiments and results

A. evaluation of sub-classifiers quality

At learning step, sub-classifiers S_i were trained using attributes extracted from 2535 photos of leaves and 1292 photos of barks. The performances of the sub-classifiers are presented in Table II and are calculated as the percentage of well classified individuals at test step relised on 2532 photos of leaves and 1295 photos of barks. We remark that sub-classifiers performances are limited. That's due to multiple factors: specificities related to the database, quality of extracted attributes... To evaluate the quality of sub-classifiers, we plot the confusion matrix corresponding to leaves and barks sub-classifiers and we take as an example in this paper the confusion matrix corresponding to the apex and the base of the leaves S_1 and the HSV space S_4 (color of barks). Presented in figure 4, the confusion matrix (the rows present known classes and the columns present the predicted ones) corresponding to S_1 shows the relatively important ability of the base and apex sub-classifier to discriminate species. The majority of species are well identified. However, we note that some species are hard to identify: species 21 to 26 and species 59 to 63. Presented in figure 5, we remark that the confusion matrix relative to the classification of the attributes characterising the barks color S_4 is largely less good than the confusion matrix relative to S_1. There is an important confusion between species that appear into the matrix by

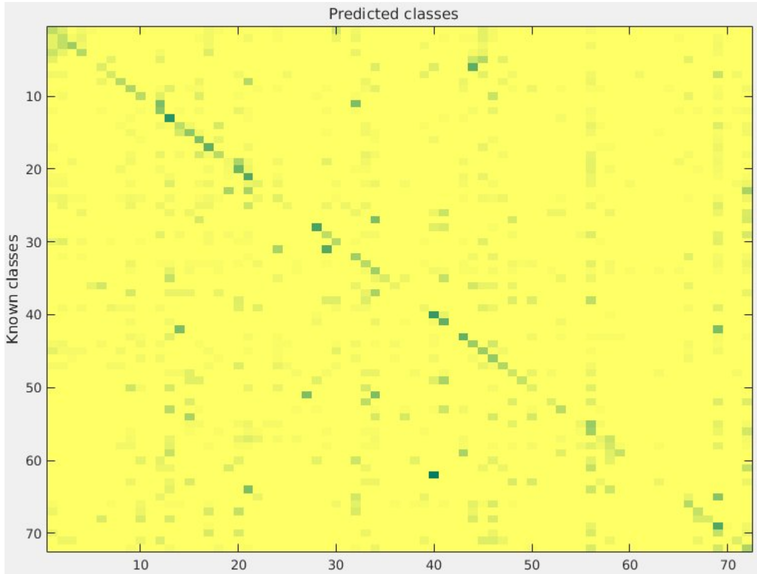


Fig. 4: Confusion matrix of the base and apex sub-classifier S_1

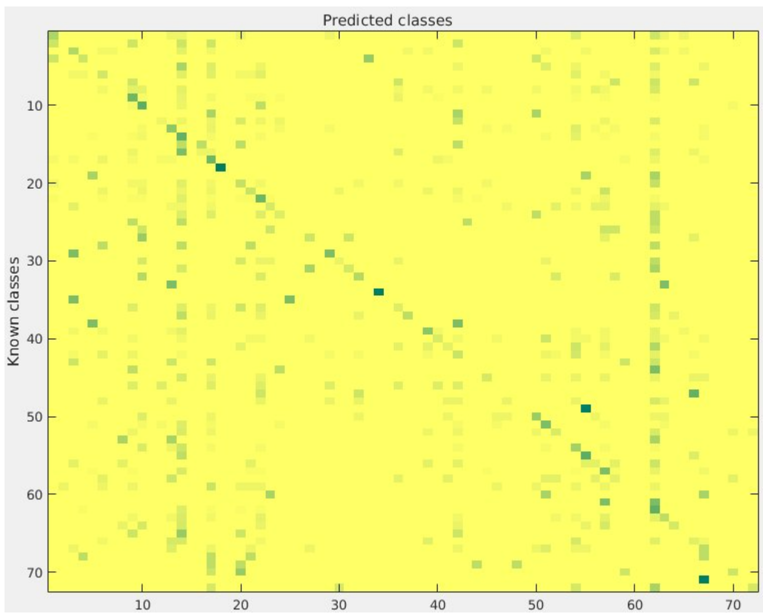


Fig. 5: Confusion matrix of the HSV space sub-classifier S_4

value outside the diagonal, sign of miss classification.

We can conclude that discrimination of species using leaves is much more efficient than with barks. Moreover, it is possible that barks provide information that could be useful to improve classification ratio obtained with only leaves as we remark that species which are hard to discriminate using leaves, may be easily discriminated using barks. These observations led to the implementation of 2 fusion strategies.

B. Evaluation of the final decision

The making decision step selects, for each individual and by the use of a decision criterion, a sub-set of species which is the most susceptible to contain the true species. The set of species resulting from this selection is noted R and is an element of the power set of E. It have a variable size which depends on all the fusion process. When an individual corresponds to conflicting data, the fusion system will use the disjunctive combination rule which leads to the building of big size sub-sets. Thus, the making decision step normally ends with a selection of a big size sub-set of species. The evaluation of the fusion system results is done at each fusion level n and based on 4 criterion:

- T: classification ratio computed by assessing the presence of the true species in R
- NB_{moy}: the mean cardinality of R
- NB_{max} and NB_{min}: the maximum and the minimum size of R

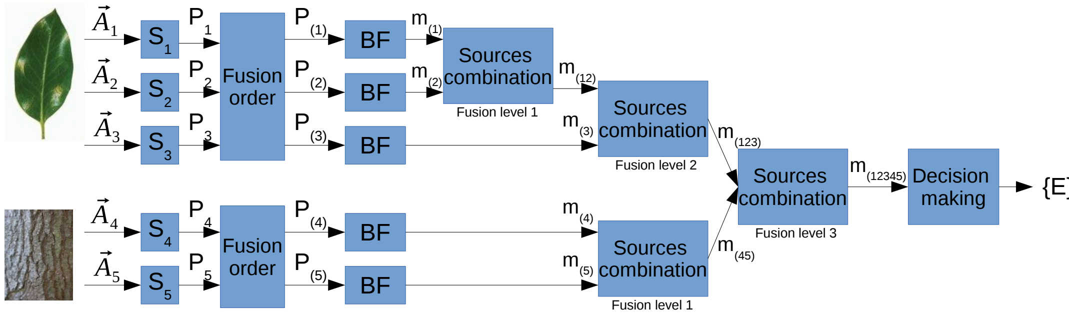


Fig. 6: First fusion strategy

C. First fusion strategy

The first fusion strategy, presented in figure 6, consists in fusing data provided by leaves sub-classifiers, fusing data provided by barks sub-classifiers and then fusing obtained results together.
As presented in Table III, we have a classification ratio of 84.20% when fusing leaves sub-classifiers with $NB_{mean} = 6$ and $NB_{max} = 37$. The application of the first fusion strategy increases the classification ratio with 0.67% with $NB_{mean} = 7$ and $NB_{max} = 39$. It's true that the addition of barks doesn't bring an important improvement to the classification results. But, it is important to note that, although the weak classification ratio relative to barks modality (Table IV) which brings confusion to the system, the architecture of the proposed fusion system does not allow to confusing sources of information to decrease its performances. To gather more evidence about the system behavior, we tried to analyse the behavior of each species.

Figure 7 represents the classification ratio per species. We remark that the classification ratio is highly variable from one species to another. For some species, we have a null classification ratio while for others all belonging individuals are well classified. When using only barks, we obtain 13 species which have a null classification ratio and 2 species with a null classification ratio when using only leaves. When fusing those 2 modalities, we remark that we have no more species with a null classification ratio. Moreover, only 6 species have a classification ratio less than 40%.

As we have the decision corresponding to each pattern, it is possible to recognise the species which corresponding individuals present very conflicting data. For those species, the mean size of R is important since, when combining different sources of information, the disjunctive combination rule is used each time the degree of conflict is superior to 0.8. The use of this rule leads to big size focal elements. For that, the idea is to gather patterns belonging to the same species and to calculate the mean size of R subsets for each species. Figure 8 shows that the mean size of R per species is, for the most of the species, more important for barks compared to the leaves. In the case of barks, we note important imprecision for species 20, 51, 55, 58, 64 and 67. When fusing leaves with barks, we remark that the mean size of R decreases for some species and increases for others like species 10, 25 and 42. Thus, we can say that the fusion of leaves with barks leads to an improvement of the system precision for some species and a degradation for others.

TABLE III: Results of leaves sub-classifiers fusion at each fusion level n (first fusion strategy)

		max Pl	max Cr
n=1	T	73.93%	86.22%
	NB_{moy}	3	8
	NB_{max}	24	42
	NB_{min}	1	1
n=2	T	71.52%	84.20%
	NB_{moy}	2	6
	NB_{max}	33	37
	NB_{min}	1	1

TABLE IV: Results of barks sub-classifiers fusion (first fusion strategy)

		max Pl	max Cr
n=1	T	45.10%	56.37%
	NB_{moy}	7	12
	NB_{max}	52	58
	NB_{min}	1	2

Figure 9 shows, for each species, the percentage of individuals which have a mean number of species NB_{mean} superior to 7 after the fusion process (The threshold is fixed to 7 as we consider that species which have an important percentage of individuals with NB_{mean} superior to 7 are imprecise). The barks are very confusing. The leaves also but are a little better. The fusion of the barks and the leaves increases the imprecision of the system.

The analysis of the first strategy allows us to say that, although their relatively poor quality, barks sub-classifiers permit an increase of the classification ratio per species. But, they decrease the precision of some species at the same time. It is worth to note that a better management of barks data may provide more useful information to the fusion system and thus improve the performances of the fusion system while keeping a good compromise between classification ratio and precision.

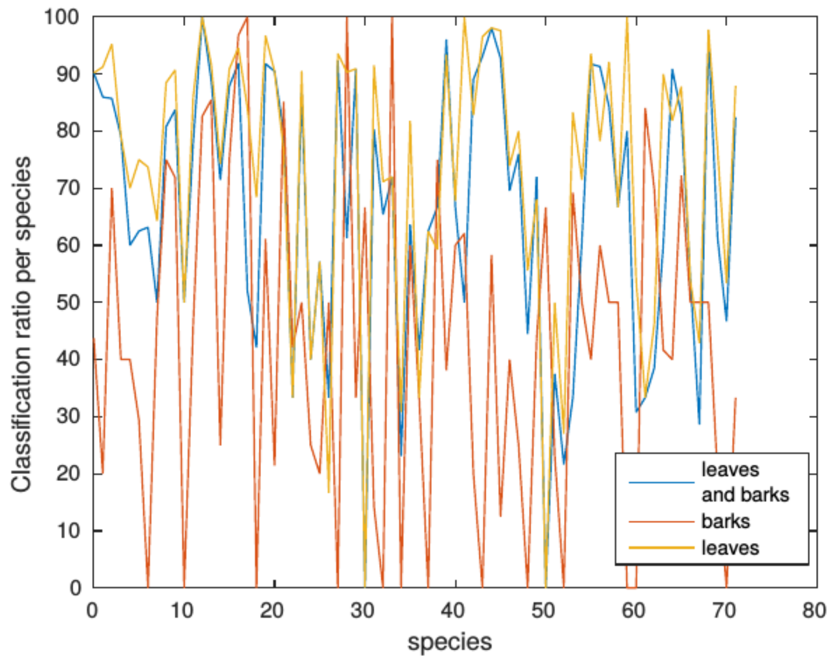


Fig. 7: Classification ratio per species (first fusion strategy)

TABLE V: Results of barks and leaves fusion (first fusion strategy)

		max Pl	max Cr
n=1	T	72.47%	84.87%
	NB_{moy}	3	7
	NB_{max}	31	39
	NB_{min}	1	1

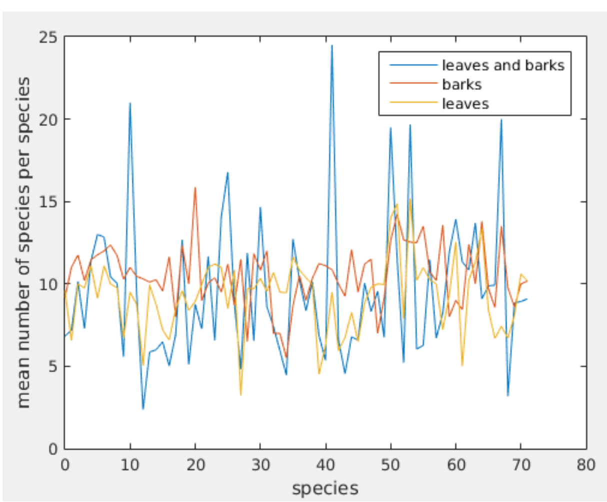


Fig. 8: Mean size of R per species (first fusion strategy)

D. Second fusion strategy

The second fusion strategy, presented in figure 10, consists in ordering all sub-classifiers according to their performances and fusing them in cascade while respecting the established order. Table VI shows results obtained with this strategy. We obtain a classification ratio of 78.79% with $NB_{mean} = 7$ and $NB_{max} = 58$. Using this strategy and compared to the results obtained when fusing only leaves sub-classifiers, we note that the addition of the barks decreases the performances of the system.

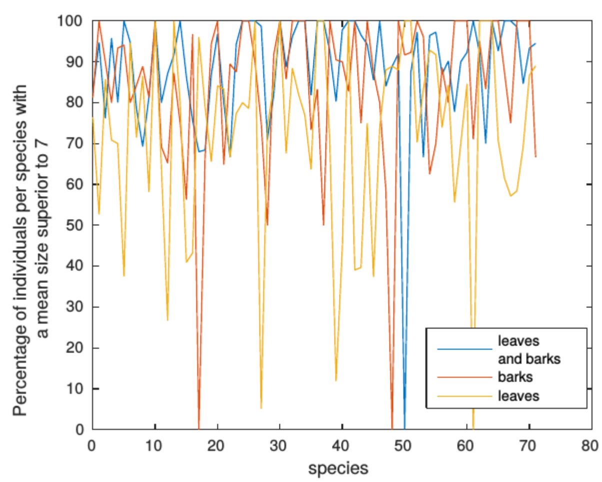


Fig. 9: Percentage of individuals with $NB_{mean} > 7$ per species (first fusion strategy)

As in the case of the first strategy, the fusion of the barks and the leaves presented in 11 shows an improvement in terms of the number of species which still having a null classification ratio after the fusion process. But, in terms

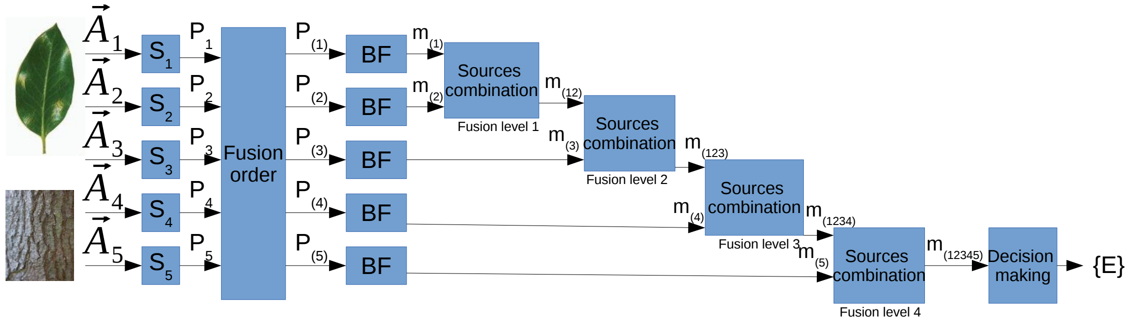


Fig. 10: Second fusion strategy

of the mean size of subsets per species NB_{mean} presented in figure 12, we note that NB_{mean} per species increases and reached peaks more important than those reached with the first strategy. That may be explained as follow: in the first strategy, we fuse barks sub-classifiers which have a relative poor quality. This fusion allows an improvement of the quality of those sub-classifiers. Thus, when fusing them with results of leaves sub-classifiers, the degree of conflict is lightened. In contrast, when fusing in cascade all sub-classifiers, there is more important chances to fuse very conflicting information and thus to use the disjunctive combination rule which influences directly the size of the constructed subsets. Also, the use of a totally cascade fusion topology leads to the accumulation of errors. Indeed, the major drawback of this topology is the incapacity of the following sub-classifiers to compensate errors made by the fusion of the previous sub-classifiers [22] [23]. Finally, we remark that the percentage of individuals with NB_{mean} superior to 7 per species, presented in 13, is less important than in the case of the first strategy. The reduction of the size of the subsets may explain the decrease of the classification ratio. Indeed, the cascade topology fusion accumulate errors made by previous sub-classifiers while reducing the subsets size as we use the Dempster combination rule for non conflicting data. All those factors may lead to the decrease of the percentage of individuals with NB_{mean} superior to 7 while accumulating errors which leads to the decrease of the classification ratio per species.

Comparison of results obtained when using the 2 fusion strategies shows that the first strategy is more interesting and more performing than the second strategy. We tried in this paper to improve performances obtained when using only leaves by adding information about barks. Through experiments and interpretation, we can see that combining all information we have about barks with information we have about leaves isn't the most appropriate strategy. It seems that for some species, the addition of barks isn't very useful and causes the injection of confusion in the fusion system. Thus, it will be more interesting to bring information about barks only when the information about leaves is insufficient and information about barks is enough reliable.

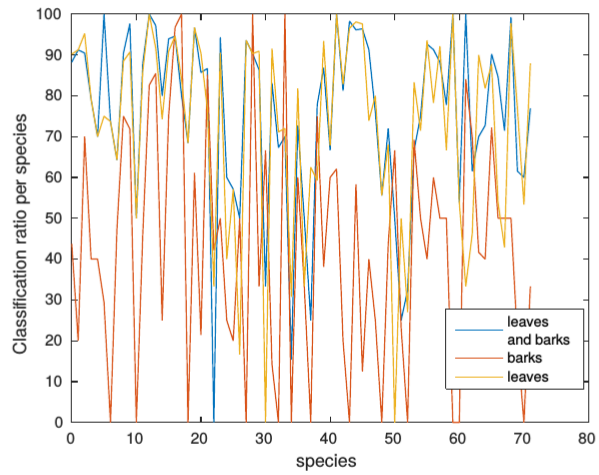


Fig. 11: Classification ratio per species (second fusion strategy)

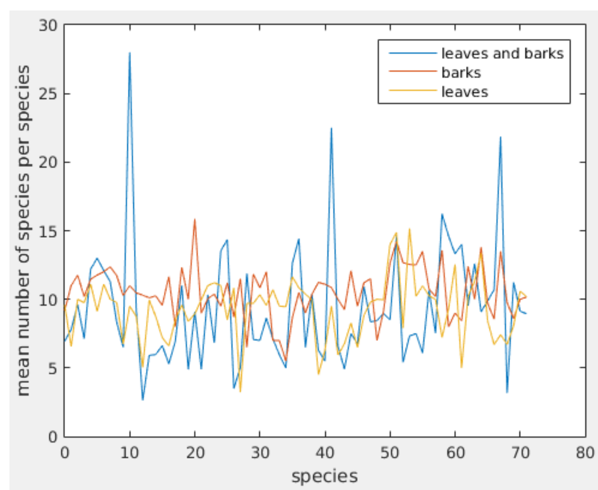


Fig. 12: Mean size of R per species (second fusion strategy)

IV. Conclusion and Prospects

In this paper, we propose two fusion strategies aiming to recognise tree species through leaves and barks. It is worth noting that leaves sub-classifiers are more performing and bring much useful information than barks sub-classifiers. Thus, the system should be able to manage confusion introduced by barks. Compared to the second strategy, the first strategy

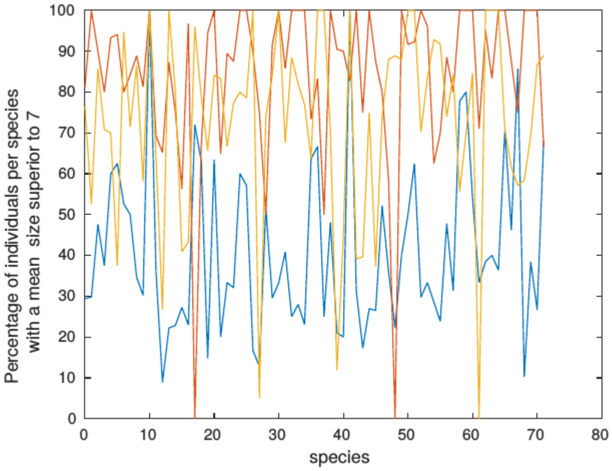


Fig. 13: Percentage of individuals with $NB_{mean} > 7$ per species (second fusion strategy)

TABLE VI: Results of second fusion strategy

		max Pl	max Cr
n=1	T	68.76%	80.85%
	NB_{moy}	3	10
	NB_{max}	43	55
	NB_{min}	1	1
n=2	T	71.60%	79.90%
	NB_{moy}	3	7
	NB_{max}	51	56
	NB_{min}	1	1
n=3	T	72.35%	79.50%
	NB_{moy}	3	7
	NB_{max}	51	56
	NB_{min}	1	1
n=4	T	72.47%	78.79%
	NB_{moy}	4	7
	NB_{max}	58	58
	NB_{min}	1	1

proved its performances and its ability to manage such a kind of problem. But, it still needs many improvements in order to further increase the classification ratio when fusing leaves with barks. As perspectives, it will be important to adapt the system to the quality of recognition of each species. Thus, species which are well identified using only leaves will not use information about barks in order to reduce confusion. If barks are enough to identify species, information about leaves will not be used. Despite Random forest classifiers, which algorithms has built-in bagging, are used as classifiers in this work, it will be interesting to further explore ensemble learning methods (boosting [24], bagging [25],...) in order to inject diversity in data level and achieve the optimal performances of the classifiers.

References

[1] N. Valliammal and S. Geethalakshmi, "Hybrid image segmentation algorithm for leaf recognition and characterization," in *Process Automation, Control and Computing (PACC), 2011 International Conference on*. IEEE, 2011, pp. 1–6.

[2] S. Prasad, P. Kumar, and R. Tripathi, "Plant leaf species identification using curvelet transform," in *Computer and Communication Technology (ICCCT), 2011 2nd International Conference on*. IEEE, 2011, pp. 646–652.

[3] Z. Chi, L. Houqiang, and W. Chao, "Plant species recognition based on bark patterns using novel gabor filter banks," in *Neural Networks and Signal Processing, 2003. Proceedings of the 2003 International Conference on*, vol. 2. IEEE, 2003, pp. 1035–1038.

[4] J. Y. Tou, Y. H. Tay, and P. Y. Lau, "Rotational invariant wood species recognition through wood species verification," in *Intelligent Information and Database Systems, 2009. ACIIDS 2009. First Asian Conference on*. IEEE, 2009, pp. 115–120.

[5] R. Bremananth, B. Nithya, and R. Saipriya, "Wood species recognition using glcm and correlation," in *Advances in Recent Technologies in Communication and Computing, 2009. ARTCom'09. International Conference on*. IEEE, 2009, pp. 615–619.

[6] S.-J. Kim, B.-W. Kim, and D.-P. Kim, "Tree recognition for landscape using by combination of features of its leaf, flower and bark," in *SICE Annual Conference (SICE), 2011 Proceedings of*. IEEE, 2011, pp. 1147–1151.

[7] R. Ben Ameur, L. Valet, and D. Coquin, "Sub-classification strategies for tree species recognition," Cancum, Mexico, Dec 2016.

[8] F. Castanedo, "A review of data fusion techniques," *The Scientific World Journal*, 2013.

[9] L. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, no. 3, pp. 338 – 353, 1965.

[10] D. Dubois and H. Prade, "Ranking fuzzy numbers in the setting of possibility theory," *Information Sciences*, vol. 30, no. 3, pp. 183 – 224, 1983.

[11] Z. Pawlak, *Rough Sets: Theoretical Aspects of Reasoning about Data*, 1991, ch. Imprecise Categories, Approximations and Rough Sets, pp. 9–32.

[12] P. Walley, "Towards a unified theory of imprecise probability," *International Journal of Approximate Reasoning*, vol. 24, pp. 125 – 148, 2000.

[13] G. Shafer, *A Mathematical Theory of Evidence*, Princeton, 1976.

[14] A. Martin, "Implementing general belief function framework with a practical codification for low complexity," *Advances and applications of DSmT for Information Fusion-Collected works*, vol. 3, pp. 217–273, 2009.

[15] G. Cerutti, L. Tougne, J. Mille, A. Vacavant, and D. Coquin, "Understanding Leaves in Natural Images - A Model-Based Approach for Tree Species Identification," *Computer Vision and Image Understanding*, vol. 117, no. 10, pp. 1482–1501, Oct. 2013.

[16] G. Cerutti, L. Tougne, D. Coquin, and A. Vacavant, "Leaf margins as sequences: A structural approach to leaf identification," *Pattern Recognition Letters*, vol. 49, pp. 177 – 184, 2014.

[17] H. Liu, D. Coquin, L. Valet, and G. Cerutti, "Leaf Species Classification Based on a Botanical Shape Sub-Classifier Strategy," in *22nd International Conference on Pattern Recognition*, Stockholm, Sweden, Aug. 2014, pp. 1496–1501.

[18] A. Wendel, S. Sternig, and M. Godec, "Automated identification of tree species from images of the bark, leaves and needles," in *16th Computer Vision Winter Workshop*. Citeseer, 2011, p. 67.

[19] Z.-K. Huang, D.-S. Huang, J.-X. Du, Z.-H. Quan, and S.-B. Guo, *Bark Classification Based on Gabor Filter Features Using RBPNN Neural Network*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 80–87.

[20] L. Breiman, "Random forests," *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.

[21] J. Sudano, "Inverse pignistic probability transforms," in *Information Fusion, 2002. Proceedings of the Fifth International Conference*, vol. 2, 2002, pp. 763–768.

[22] L. Lam, "Classifier combinations: implementations and theoretical issues," in *International Workshop on Multiple Classifier Systems*. Springer, 2000, pp. 77–86.

[23] Y. Lu, "Knowledge integration in a multiple classifier system," *Applied Intelligence*, vol. 6, no. 2, pp. 75–86, 1996.

[24] Y. Freund and R. E. Schapire, "A desicion-theoretic generalization of on-line learning and an application to boosting," in *European conference on computational learning theory*. Springer, 1995, pp. 23–37.

[25] L. Breiman, "Bagging predictors," *Machine learning*, vol. 24, no. 2, pp. 123–140, 1996.