Bark Recognition to Improve Leaf-based Classification in Didactic Tree Species Identification

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Abstract: In this paper, we propose a botanical approach for tree species classification through automatic bark analysis. The proposed method is based on specific descriptors inspired by the characterization keys used by botanists, from visual bark texture criteria. The descriptors and the recognition system are developed in order to run on a mobile device, without any network access. Our obtained results show a similar rate when compared to the state of the art in tree species identification from bark images with a small feature vector. Furthermore, we also demonstrate that the consideration of the bark identification significantly improves the performance of tree classification based on leaf only.

1 INTRODUCTION

Nowadays, the growth of urbanization and technology has reduced the knowledge and uses of plants by humans. However, the environment and its natural resources are raising a growing concern. The ability to identify the species of plants seems essential in the understanding of our green environment. Thereby, providing an inexperienced person, who had no knowledge in botany, with a tool to identify the plants that surround him would be a great advance.

The portion of the population using a smart-phone, incorporating a camera, a GPS, *etc.* grows increasingly. These phones allow furthermore to download additional applications with other functions than communication. These smart-phones are ideal materials for applications related to image analysis.

From these two facts, let us consider the case where a person, wandering through a forest or a city park, wishes to recognize a species of tree. He then takes a picture of the different organs of the plant (leaf, bark, flower) using his mobile phone. By means of interactions between the smart-phone (via the touch screen) and the user, and of course of treatments and image processing, the system would return a short list of species that may correspond to the plant the user seeks to identify, coupled with a confidence rate.

Applications for smart-phone have been developed to address this subject, such as Leaf Snap (Kumar et al., 2012), Pl@ntNet (Goëau et al., 2013a), or Folia (Cerutti et al., 2013). Furthermore, plant recognition has recently been the subject of research in the field of image processing. Challenges have been organized especially the ImageCLEF Challenge since 2011 (Goëau et al., 2011).

Even though the leaves are the most used organs for tree classification in the applications, as they are easily observed and described, the other parts of the tree can help the recognition of tree species. In this article, we focus on the recognition of tree species through the bark. We choose to process this part of the tree as it is always observable throughout the year (not like flowers or fruits), and can be easily photographed.

Since 2013, recognition of plants in the ImageCLEF Challenge spread to other plant parts and not only leaves as the 2011 and 2012 editions. In these challenges, the different teams program algorithms in order to recognize plant species through several images of the plant. In (Goëau et al., 2013b) and (Goëau et al., 2014) we can see the evolution of the extracted features used for the identification of the bark. Until 2014, the majority of the algorithms was based on the detection and characterization of points such as SIFT (Scale-invariant feature transform) (Lowe, 1999) or SURF (Speeded-Up Robust Features) (Bay et al., 2006), with color information as well as information from Fourier transforms or LBP (local binary pattern) (Ojala et al., 1996), with bag-of-word ap-

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proaches. Texture descriptors were not used for the bark recognition as they gave poorer results. Since the ImageCLEF 2015 edition (Goëau et al., 2015), there is a large use of deep learning approaches, not only for the classification, but also for the features extraction. The GoogLeNet convolutional neural network (Szegedy et al., 2015) has been employed by nearly half of the teams. Only one team used hand-crafted visual features.

These methods are efficient but first, they need lots of training images, which is often hard to obtain in the botanic domain. Secondly, they run as black boxes that is to say they only give a classification result without giving the user the possibility to understand the result. But, the work that is proposed in this article takes part of a pedagogic project the goal of which is to learn the user to recognize a tree or a shrub from its organ. For the leaves, a method based on botanic criteria has already been developed by (Cerutti et al., 2013), which allows showing the user the discriminant criteria during the recognition process. The presented work aims at pursuing in this way using features the botanists use to discriminate the bark. Notice also that as the goal is to do the image treatment on smart-phones, as very often the Internet is not reachable in the countryside, so we would like a feature vector with reasonable size and, computation time of it and classification time in real time that is to say in a few seconds.

In the following, we will present in part II the construction of the features vector describing a bark image. The next part III will display our different results on the bark database and the improvement of the processing of the bark on the tree species classification only based on the leaves.

2 BARK ANALYSIS

Our proposed method differs from the state of the art in the sense that it is based on the extraction of descriptors similar to those used by botanists from visual texture criteria. More specifically, the method simulates the bark recognition described by Michael Wojtech in his book (Wojtech, 2011). In this approach, the barks are first classified into different families as shown in Figure 1.

The first row contains photos of characteristic bark for each families. The second row highlights the distinctive bark structure of each photo of bark with a drawing. More drawings can be found in (Wojtech, 2011). After identifying the type of bark, botanists also take into account the color or other structural elements in order to recognize the tree species.

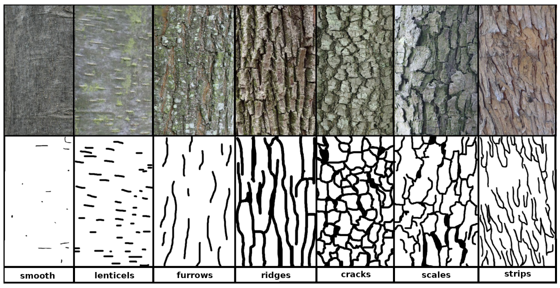

Figure 1: Different classes of bark structure based on visual criteria.

In the following parts, we present the extracted features to recognize the various types of barks and then the different tree species.

2.1 Shape of the Bark

In this section, we propose a method to describe precisely the structure of the bark, not only whether it has a vertical or horizontal structure. The goal is to identify the different types of bark (Figure 1), *i.e.*, bring out the forms (scales, straps, cracks, *etc*) of the bark. For this, at first, we need to extract the edges of the shapes. For this purpose, we use the Canny algorithm (Canny, 1986). Let us denote by M_H and M_V respectively the horizontal and the vertical maps obtained with a horizontal filter F_H and a vertical filter F_V.

$$F_H = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \text{ and } F_V = \begin{bmatrix} -1 & 0 & 1 \\ 2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{1}$$

The results of this Canny processing are visible on Figure 2 for M_H and on Figure 3 for M_V.

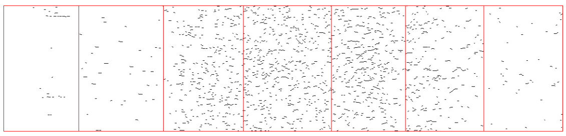
Figure 2: Map of horizontal edges M_H obtained from Figure 1.

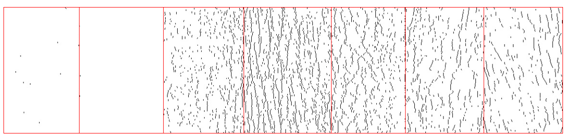
Figure 3: Map of vertical edges M_V obtained from Figure 1.

Using the maps of edges images, we can estimate the dissimilarity between the different families of bark. To characterize the distribution of contours, we propose to place a grid over the maps of edges images, and to count the number of intersections between the grid lines and the maps of contours. Specifically, from M_V (respectively M_H), we focus on the intersections between these contours and horizontal lines (vertical respectively) grid. Then, for each row (column respectively) grid, we calculate the number of intersections. This generates a "vertical word" (respectively "horizontal word") (see Figure 4).

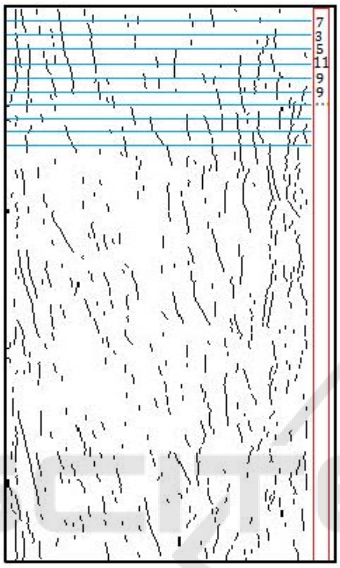

Figure 4: Formation of the vertical word.

More formally, let l be the number of rows of the image, c the number of columns, with λ_l the frequency of the vertical gridlines and λ_c the frequency of the horizontal grid. The higher the frequencies λ_l and λ_c , the higher the structure is precisely described. The "vertical word" W_V is the concatenation of the intersections v_l with l varying from 0 to l with the frequency of the grid λ_c.

$$v_l = \sum_{c=0}^{\left\lfloor \frac{c}{\lambda_c} \right\rfloor} \delta_{l,c} \qquad (2)$$

$$\text{with } \begin{cases} \delta_{l,c} = 1 & \text{if } M_V(\lambda_l, \lambda_c) = 1 \\ \delta_{l,c} = 0 & \text{else} \end{cases} \qquad (3)$$

$$\text{and } V = \{v_l\}_{0 \leq l \leq \left\lfloor \frac{l}{\lambda_l} \right\rfloor} \qquad (4)$$

M_H and M_V are finally characterized by two words, respectively W_H and W_V, that define the frequency and distribution of the edges. If a word contain mostly zeroes it means that the corresponding orientation is rather smooth. When the ridges of the bark are practically uninterrupted, the "vertical word" will be homogeneous. We will give in the Results section some elements to explain the choice the discretization steps in the two directions.

2.2 Bark Orientation

As we can see in Figure 1, barks may have structures with different orientations, *i.e.* horizontal, horizontal and/or vertical, or just be smooth. The orientation of the bark is a recognition criterion. The image filtering by Gabor wavelet can distinguish the direction and frequency of the structure of the bark. According to Huang (Huang et al., 2006), only 6 orientations and 4 scales for the sinusoid forming the Gabor wavelet are sufficient to analyse the bark. However, in the case of our application, the distance between the smart-phone and the tree trunk may vary. Our method must be scale independent as we can not control the camerawork. In addition, we want to determine, initially, whether the structure of the bark is horizontal or vertical, so only two orientations appears adequate (0°and 90°). Figure 5 shows an example of bark filtered by two identical Gabor wavelets except for the orientation.

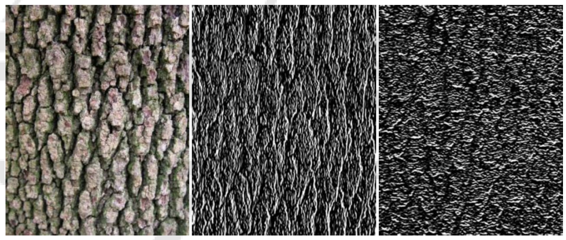

Figure 5: Results of 0°orientation Gabor filtering (center) and 90°(right) of the initial image (left).

In order to have a characteristic vector of each bark which is independent of the shooting distance, we average four filtered images by Gabor wavelets with four different sinusoidal scales. The scales are adjusted in order to highlight the horizontal and vertical ridges of the bark, similarly to Figure 1.

The feature vector G reflecting the orientation of the structure using Gabor filters consists of the mean and the standard deviation of the filtered image with an orientation of 0°, σ_0 and μ_0, and the standard deviation image filtered at 90°, σ_{90}. We considered including also the average of images at 90°, but this feature appeared as not discriminant, so we decided to leave it apart, ending up with a simple feature vector of dimension 3: $G : [\sigma_0 \; \mu_0 \; \sigma_{90}]$. For the moment, our features vector is composed of this Gabor vector and of W_H and W_V. We will show in the Results section the positive contribution of the Gabor vector concatenated with the two words W_H and W_V.

2.3 Bark Color

A second discriminant aspect for tree bark recognition used by botanists is the color. Colorimetric descriptors were used in the challenge Image CLEF 2013 by the teams showing the best results (Bakic et al., 2013) (Nakayama, 2013). Several color spaces were tested. We favored color spaces where color channels were independent of brightness as the descriptor should not be influenced by the presence of shadows or by the changing of illumination that can occur over the day and the year. The L* a* b* color space seemed appropriate because of the channel a* coding the red/green opposition and as we know the bark of trees have brown, red, green, or gray shades. However, the hue channel (H) of the HSV color space was chosen because it gives us better classification results. It is because the hue channel can also manage the case of yellowish bark. The hue channel allows to cover the whole range possible of bark color with a single channel with 256 bins, contrary to the concatenation of the a* and b* channels that would have given a doubled size color feature vector. As a reminder, we try to have a reasonable size feature vector. Figure 6 shows the hue histogram for some bark images.

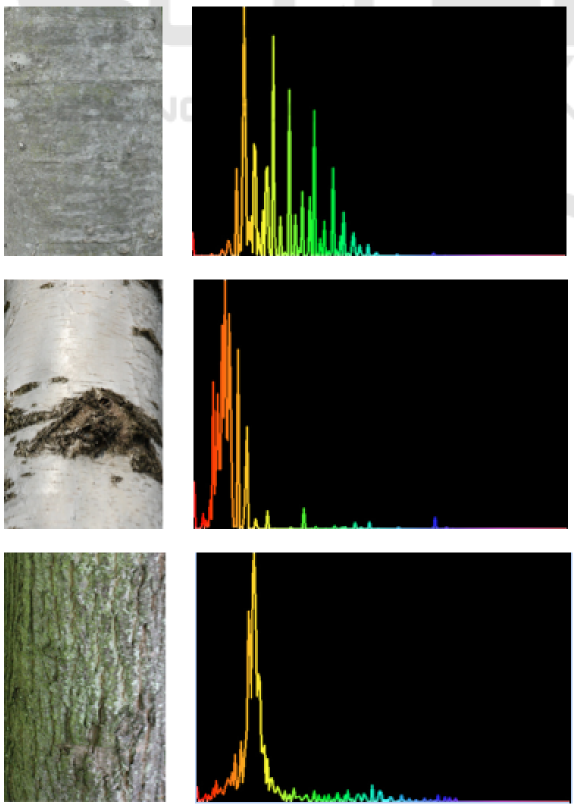

Figure 6: Hue histogram for different barks.

Finally, the feature vector used for bark classification $\mathbf{F}_b$ therefore consists in the concatenation of the vector of Gabor G, W_H and W_V and the hue histogram H.

3 RESULTS

3.1 Bark Classification

For the bark classification, we have a database of 2559 bark image belonging to 101 tree species from the data bank Pl@ntView[1]. Pictures of bark have the same orientation as the tree (portrait mode). In our practical application, we have re-sized these images in order that the picture contain only the texture of the bark, not the background, and no other elements such as branch, leaves, or lichen. As a matter of fact, we can make the assumption that the interface of the application can guide the user to take such a king of photos. However, we have kept the bark images which have a gradient of light or shadows (see Figure7). This allows us to have an algorithm which should work with images shot in non-optimal conditions by beginners. We may also note that the number of bark images is not the same for all the species (20 in average, but can go up to 100 for some species and 2 or 3 for others). The low number of samples for some species makes it difficult to train a performing classifier.

Figure 7: Bark of Acer Pseudoplatanus with homogeneous luminosity, gradient of light or shadows.

As expressed in the introduction, we use a SVM in order to classify the feature vector. The kernel of the SVM is a Radial Basis Function (RBF) kernel (Vapnik, 1999). We use a 1-vs-all algorithm, *i.e.* we have one binary SVM for each species, with the class species S versus the class non-S species. For each query bark, we compute the feature vector then we give this vector to all the 101 SVM classifiers. Afterwards the result is the species which the corresponding classifier gives the higher probability of affiliation

[1] http://publish.plantnet-project.org/project/plantclef

to the species S. On a Macbook Pro dating from 2011, with a processor 2.7 GHz IntelCore i7 and a memory 4 GB 1333 MHz, we get a classification result in less than a second. As the last smart-phones have on average a processor of 2 GHz and quad-core, that make us believe that our method could run on these devices.

Train is performed on half of the database, and tests are performed on the second half. We obtain a classification rate equals to 30,7%. If we observe the results of the plant task of the LifeCLEF challenges (Goëau et al., 2015), plant recognition via the stem gives the worst classification rate compared to the other other organs. The state of the art give around 30% of good identification. So, with our method, we achieve the same level with a quite short feature vector and without heavy classification process.

In the case of a smart-phone application, we can propose to the user a list of tree species which most likely match the tree he photographed. The Figure 8 shows the evolution of the classification rate according to the number of top answers returned. As said before, for a query bark image, we compute the probability of belonging to a species for each 1-vs-all binary SVM. We order them in decreasing order the probability and check if the true species is in the top one, top two, top three, and so on until top ten.

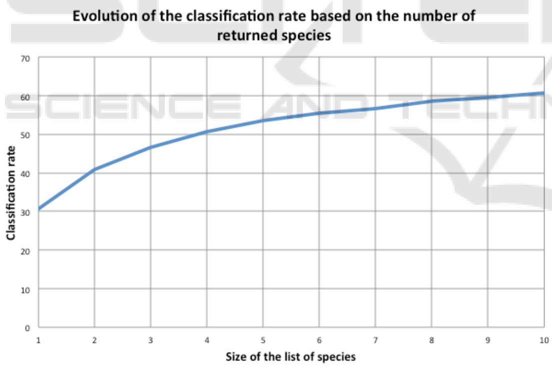

Figure 8: Evolution of the classification rate.

Obviously the classification rate increase with the number of proposed species. It gains 10% when we consider two species, and we have one chance out of two to have the true species with a list of 4 propositions. Then progression of the recognition rate slow down. Thus, at the end, the right species has a 60,8% chance of being among the first ten returned species.

3.2 Discussion Concerning the Influence of Our Bark Features

We would like to give details of the choices of our features vectors. First, to describe the structure of the bark, we developed W_H and W_V, and add information from bark image filtered with Gabor. We can think that the two "vertical and horizontal words" already capture the information given by Gabor. So we analyzed the classification results when the feature vector is composed of the two "words", the hue canal and Gabor vector, and when it is composed of only the two "words" and the hue canal. Results are visible on Figure 9, which represents the classification rate obtained if we return to the user a list of one, two or more possible species.

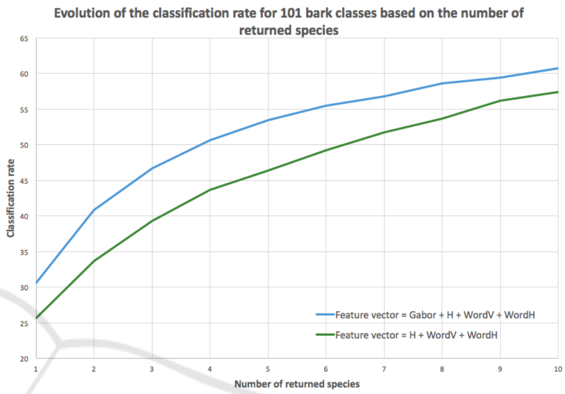

Figure 9: Evolution of the classification rate with and without the features extracted through Gabor.

As we can see, the classification rates when we do not take into account the Gabor vector are inferior compared to the ones obtained with the complete feature vector. Indeed, we lose on average 5% of right classification on the classification rates depending on the size of the list of returned species.

On the other hand, we studied the influence of the frequency of the grid used to compute the "vertical word" W_V and the "horizontal word" W_H. We computed the classification rate while varying the number of columns and lines of the grid respectively corresponding to W_H and W_V. We plan to give the user of the smart-phone application a list of five possible species. On Figure 10, we can see the evolution of the classification rate for the top 5 returned species.

Our results in section 3.1 are obtained with a grid composed of 70 columns and 50 rows. We are limited to 70 columns because the pixel widths of some of our train bark images are too small. On Figure 10, we can see that the best classification rate is obtained when the number of rows of the grid is 50 and the number of columns is 70. When the number of columns is reduced, we can see that the classification rate decreases. Finally, the finer the grid is, the higher the classification rate is because the grid gets precise information.

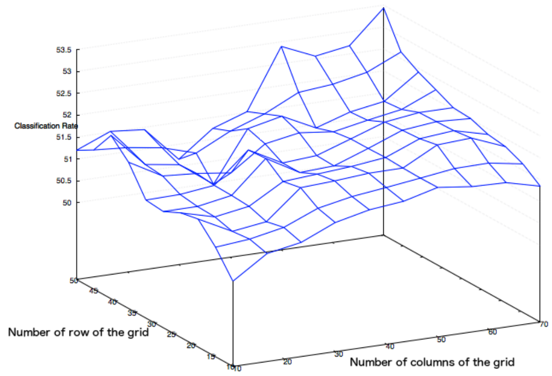

Figure 10: Influence of the frequency of the grid for the computation of W_H and W_V.

3.3 Influence of Bark Processing in Tree Leaves Classification

Most of the time, the leaves and the bark of a tree can be observable by a person who wants to know the species of a tree. In order to take advantage of this double source of information, we combine the recognition of the bark with the recognition of the leaf previously developed and integrated to Folia[2], the leaf identification mobile application based on the work of (Cerutti et al., 2013). We propose two combination methods. First we concatenate the features of the leaf and the features of the bark, and we use either the 1-vs-all SVM classifier or the classifier used in the Folia application (see (Cerutti et al., 2013)) for more information). Secondly, we make an *a posteriori* combination, *i.e.* we do classifications independently for the bark and for the leaf, then we combine the results of the two classifications.

The Folia application uses a Gaussian nearest neighbor classification in which the classifier builds a model of each species $\mathbf{S}$ as a multi-dimensional Gaussian distribution of its feature vectors, and estimates the distance of a new sample represented by its feature vector $\mathbf{F}_l$ to all the species models. To avoid that the species with a high variability absorb less variable classes, the distance $d_{GNN}(\mathbf{F}_l,\mathbf{S})$ is computed as the Euclidean distance to the surface of the hyper-ellipsoid defined by the centroid and covariance matrix of the species. The result of this classification is the species that achieves the minimal distance. The same classification approach can be used for the bark features $\mathbf{F}_b$ and the concatenated feature vector $\mathbf{F}_{b,l}$.

Our *a posteriori* combination method uses all the answers of the classifiers under the form of confidences (between 0 and 1) associated with each species. The SVM classifier already returns a confidences value $c_{SVM}(\mathbf{F},\mathbf{S})$ and a similar value can be computed from the Folia classifier: $c_{GNN}(\mathbf{F},\mathbf{S}) = e^{-\left(d_{GNN}(\mathbf{F},\mathbf{S})\right)^2}$. Then, the combination is performed as a multiplicative fusion of the confidence values for each species:

$$\overset{\otimes}{c}(\mathbf{F}_b,\mathbf{F}_l,\mathbf{S}) = \left(c(\mathbf{F}_b,\mathbf{S})\right)^{\frac{1}{\omega_b}} \left(c(\mathbf{F}_l,\mathbf{S})\right)^{\frac{1}{\omega_l}} \quad (5)$$

$$\text{with } \omega_l \text{ and } \omega_b \text{ the leaf and bark weighting} \quad (6)$$

The resulting confidence $\overset{\otimes}{c}$ is used to rank the species and the classification answer is the species corresponding to the highest combined confidence.

We tested these two combination approaches on a dataset of couples of bark and leaf images corresponding the same species, for which we extracted respectively the bark features presented in this article and the leaf shape features from the folia application. The leaf images are also from the Pl@ntView database. However, some tree species have leaf image but no bark image, and *vice versa*. Thereby, the number of species we consider is reduced to 72.

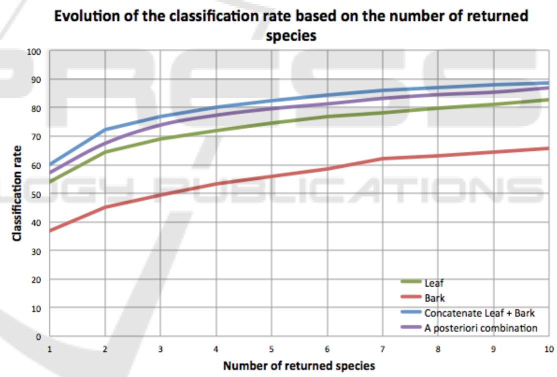

Figure 11: Classification with 1-vs-All SVM classifier.

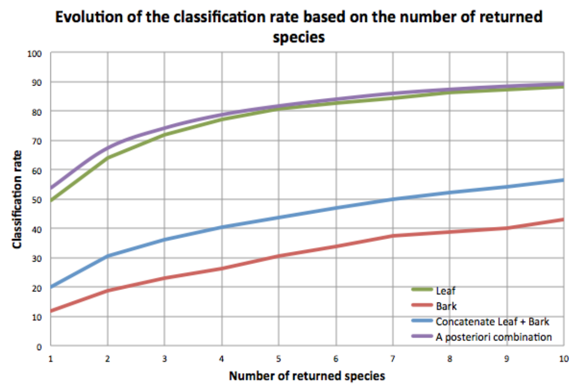

Figure 12: Classification with k-nn classifier from Folia.

On Figure 11 and Figure 12, we can see the evolution of the classification rate for the different me-

[2] http://liris.univ-lyon2.fr/reves/folia

thods. As we have reduced the number of classes, we observe as expected an improvement in the bark classification rate (red curve on Figure 11). But we can see that the classifier used in the Folia application is really not suitable for the bark feature vector (Figure 12). For the leaf classification (green curve), the 1-vs-all SVM classifier improves the classification rate for the top 1 predicted species, but from the top 3 species, the Folia classifier gives better results. We can note that when the two feature vectors (leaf+bark) are concatenated (blue curves), the SVM classifier (Figure 11) gives doubtlessly higher result than the Folia classifier (Figure 12). The classifier used in Folia is in fact not really suitable for longer vector.

Regarding the *a posteriori* combination (purple curves), taking into account the bark improves the classification rate when the leaf and the bark are recognized with the Folia classifier (Figure 12). But the performance are below the result with the concatenate vector with SVM (Figure 11). With the classifier used for the bark (one-vs-all SVM, Figure 11), the *a posteriori* combination show an improvement in the tree recognition when we take into account the bark and not only the leaf (purple curve). Yet it gives slightly worse results than when we supply the SVM with a concatenated feature vector of leaf and bark (blue curve).

In conclusion, we reach the best classification results when the features vectors of the bark and the leaf are concatenated and classified with the 1-vs-all SVM classifier.

4 CONCLUSION

In this article, we proposed an original method for the identification of plant species to recognize trees through the bark based on features used by botanists. Our results achieve the same level as the state of the art with a relatively short vector. We consider that our method can be run with a limited computational power and bearable by a smart-phone.

We also showed that taking into account the bark can improve the recognition rate of trees obtained only via the leaves. In a further work, we plan to improve the combination of the bark classification and the leaf classification by considering the results of the confusion matrix. As a matter of fact, if we take a look to the confusion matrix of our bark classification on Figure 13, we can notice that some barks are more predicted than they should. Indeed, we can clearly see some columns where there are a lot of boxes are green. It is the case for the classes where we have a lot of samples and a lot of variability in the bark. In a further work, we plan to take into account the results in this matrix to moderate the belief in bark results versus leaf results.

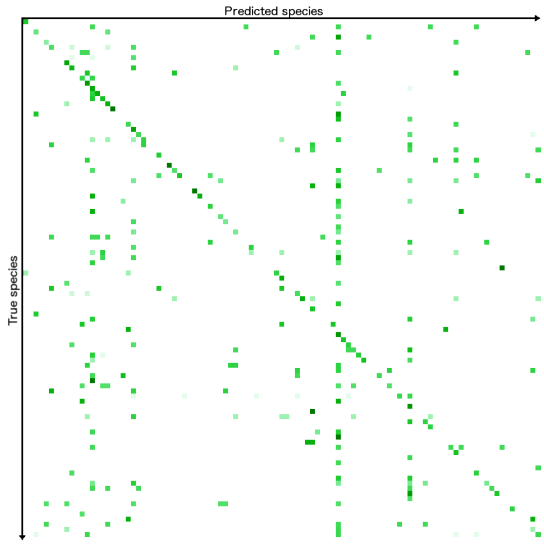

Figure 13: Confusion matrix: the greener the case, the greater the occurrences.

Moreover, as we plan to create an educational botanical smart-phone application, we would like to translate the data from our features vectors as tangible information for the user. For example, from the hue histogram H, we would like to tell the user that the bark of the tree is brown, gray, or yellowish, and with G, W_V and W_H tell about the structure of the bark (scales, strips, ridges, smooth, *etc*). Giving these information to the novice should help him to recognize tree species on his own.

Furthermore, we developed W_V and W_H for tree bark recognition, but we think that this concept could be applied to other contexts where texture characterization is important.

Finally, in order to further improve the tree recognition, we also want to extract features on the other organs of the tree, such as the flowers, which are the reproductive organs of the plant and therefore characteristic of the species, and also the fruits, which are characteristic of the genus.

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