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Automated identification of tree species from images of the bark, leaves and needles

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Abstract. *In this paper a method for the automated identification of tree species from images of leaves, bark and needles is presented. The automated identification of leaves uses local features to avoid segmentation. For the automated identification of images of the bark this method is compared to a combination of GLCM and wavelet features. For classification a Support Vector machine is used. The needle images are analyzed for features which can be used for classification.*

The proposed method is evaluated on a dataset provided by the "Österreichische Bundesforste AG" ("Austrian federal forests"). The dataset contains 1183 images of the most common Austrian trees. The classification rate of the bark dataset was 69.7%.

1. Introduction

Identification of tree species from images of bark, leaves, and needles is a task which requires expertise. This expert knowledge can be expected from foresters and botanists. For people without this knowledge the identification of tree species is a difficult assignment since the difference between some tree species is small or information for the identification, like the shape of the leaf, or the color and haptics of the bark have been forgotten.

Within a project with the "Österreichische Bundesforste AG" ("Austrian federal forests") people should be able to identify tree species using their mobile devices by photographing leaves, bark, or needles of a tree and the identification is done automatically by the mobile device and additional information for this tree species is then displayed on the screen.

An approach for an automated classification of the tree species from images of the leaves has been presented in Fiel and Sablatnig [4] which avoids the binarization of the leaves. In contrast, this work proposes a method for the automated classification from bark images using local descriptors based on the method for the identification of leaf images. The advantage of the proposed approach is that the same methodology can be used for leaf and bark images. Thus, a preprocessing step can be introduced to distinguish between leaf and bark images without calculating new features. Furthermore the proposed method is compared to a combination of Gray Level Co-occurence Matrices (GLCM) and wavelet features.

The needle images are analyzed for features which can be used for classification and a method is described to distinguish between fir and spruce needles.

This paper is organized as follows: Section 2 reviews the state of the art for automatic identification of plant species from images of the bark. In Section 3 the methodology for the identification of bark images is presented and features which can be used for the identification of needle images are searched. The results are presented in Section 4. Finally a conclusion is given in Section 5.

2. Related work

This section describes the current methods for the automated identification of the tree species. First an overview of the identification using books is given, then the automated classification of images bark is given. To the best knowledge of the author no work has been published about the identification of tree species using images of needles.

The traditional identification of tree species is done manually by using a book like Godet [5]. For the classification of leaves and needles, these books contain a diagnostic key where the user has to make various decisions which describes the leaf or the needle better in each step. The users have to follow a tree step by step to identify the leaf. Since the bark can not be described as easily as leaves or needles, the user has to scroll through the book and has to look for the corresponding bark. The process of the identification can take several minutes since it includes scrolling through the book because most of the decisions lead to another page. Also the users have to be familiar with the vocabulary or have to compare the leaf with the illustrations in the book.

The automated identification of plant species from photos of the bark is done with a texture analyzing methods. Wan et al. [12] made a comparative study based on statistical features. The gray level run length method, GLCM, histogram method, and the auto-correlation methods are compared. For each GLCM the entropy, angular second moment, contrast, inverse different moment, cluster tendency, cluster shade, correlation, maximum probability, and two correlation information measures are calculated. The best results are achieved with the GLCM with an average recognition rate of 77%, followed by the auto-correlation method with 72% and the run-length method with 69%. The histogram method has the lowest results with 65%. To improve the classification rate each of the three color channels are handled separately. This improves the recognition rate for the GLCM method to 89%, for the run-length method to 84% and for the histogram method to 80%. The dataset used contained 160 preselected images of 9 classes.

Song et al. [11] proposed to use a combination of gray scale and binary texture features. As gray scale texture features the GLCM and as binary texture features the long connection length emphasis are used. The classification rate with a nearest neighbor classifier is 87.5% on a dataset containing 180 images of 8 classes.

Huang et al. [8] uses fractal dimension features additional to the GLCM features. The fractal dimension describes the complexity and self-similarity of texture at different scales. For the classification a three layer artificial neural network is used and a recognition rate of 91.67% is achieved. The dataset consisted of 360 preselected images of 24 classes.

Huang [7] combined color and textural information for bark image recognition. Both information were extracted using the multiresolution wavelets. For the textural features the energy of the wavelet transformed images have been used. The color features were gained by transforming the color from RGB values to the YCbCr color space and calculating the energy at depth 3 of the wavelet pyramid for each channel. A radial basis probabilistic neural network is used for classification and an average recognition rate of 84.68% is achieved. The dataset consisted of 300 preselected bark images.

Chi et al. [2] proposed to use Gabor filter banks for the recognition due to its efficiency and accuracy. They introduced multiple narrowband signals model to overcome problems with textures with a lot of maximas. The recognition performance for this approach is 96%. The dataset containted 8 classes of plants and each class containing 25 samples.

3. Methodology

In this section the methodology for the automated identification of tree species from images of the bark is presented, followed by an evaluation of needles images for classification. The automated identification of tree species from images of the leaves is described in Fiel and Sablatnig [4].

3.1. Identification of bark

Classification of the bark is done by using texture analysis methods. In Chen et al. [1] texture is defined as repetitive patterns that occur in a region. The bark of trees does not have exact periodical and identical patterns due to natural growth. Natural cover of the bark, like moss and lichens, distort these patterns or the repetitive occurrence. Due to different lighting conditions the gray values of the patterns are changing and influence the recognition of the patterns. The color of the bark can not be taken into account since with changing lighting conditions and cameras the variance is high.

One of the defining qualities of texture is the spatial distribution of gray values. This distribution can be described using statistical texture analysis methods like the GLCM which was introduced by Haralick et al. [6]. It describes the spatial distribution of the gray values in an image in given orientation and distance. The features used for the classification are contrast, correlation, homogeneity and energy.

Other techniques rely on signal processing like wavelets which was introduced to multi-resolution signal decomposition by Mallat [10]. It allows the decomposition of a signal using a series of elemental functions which are created by scalings and translations of a base function. Thus, wavelets provide spa-

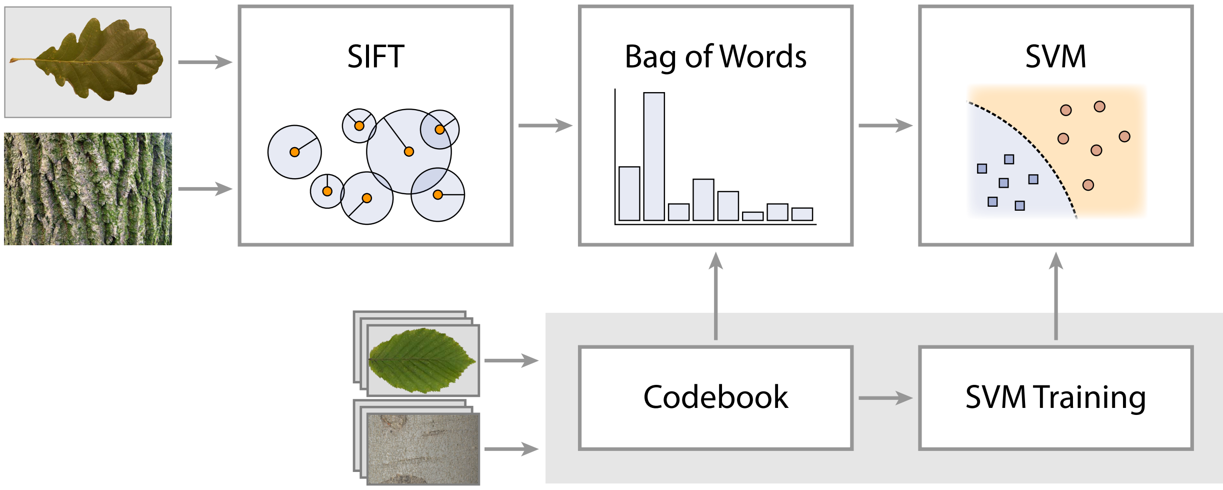


Figure 1: Workflow of the proposed methodology: The input image is normalized to a gray scale image on which the SIFT features are calculated. A histogram of occurrences is generated by searching the nearest cluster center in the codebook which is used for the classification. The gray area represents the machine learning part where codebooks are generated from the trainingsset. For each image in the trainingsset a histogram of occurrences is calculated which are then used to train the SVMs.

tial and frequency information at different scales. As feature for the classification the average energy of the wavelets coefficients are used.

Zhang et al. [13] showed that SIFT features, introduced by Lowe in [9], can keep up with common texture classification methods. The SIFT features are used to describe the texture of the region. Since this method is used for the automated identification of the leaf images it has also been tested on bark images. The advantage of this method is that it does not rely on periodical patterns but on patterns which occur frequently in the image. With the bag of words approach, which was introduced by Csurka et al. [3], these patterns do not have to be identical since the nearest cluster center is searched which represents similar regions. So the method from Fiel and Sablatnig [4] which is used for the identification of leave images is also applied for the automated identification of tree species from images of the bark.

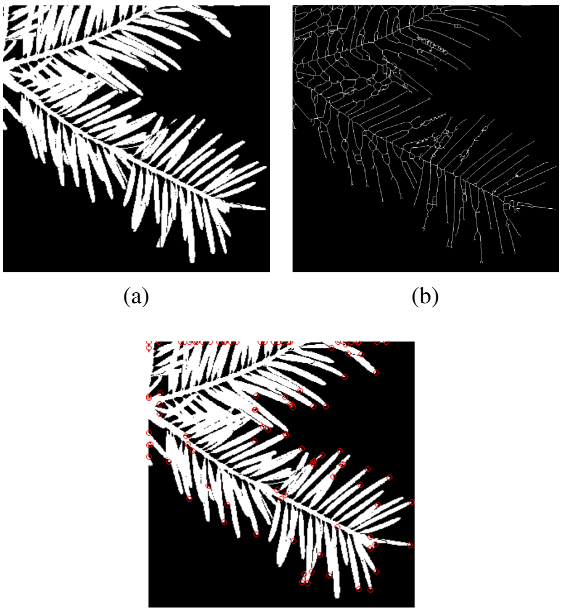
Figure 1 illustrates the workflow which is used for the classification. The method consists of three steps. First the images are transformed into a normalized gray scale image. There the SIFT features are calculated by searching keypoints in the images using DoG at different scales. The neighborhood of these keypoints are then described using orientation histograms which are then used for a bag of worlds model. Features of the trainings set were clustered to form a codebook. New images can then be described by generating a histogram of occurrences of the nearest cluster center. This histogram can then be classified using a one-vs-all Support Vector Machine (SVM).

A SVM is used since it rather minimizes the overall risk than the overall error of a training set, which results in a good generalization performance even for high-dimensional features. To handle multiple classes the one-vs-all approach is used. It generates a SVM for each class which classifies the data points of the class against all other data points. The classification is done by a winner-takes-all strategy, meaning that the classifier with the highest output function assigns the class. For each class the value of the output function can be used as percentage of belonging to this class. Thus, a threshold can be introduced to eliminate images which have only a small percentage of belonging to a class.

3.2. Identification of needles

The dataset of needle images contains the 6 most common Austrian conifer trees which can be divided into two classes. The first class are trees on which one needle grows separately on the branch and the second class are the trees on which the needles grow on clusters at the branch.

Fir and Spruce are the two trees on which the needles grow separately on the branch. The easiest way to distinguish their needles is that the spruce needle has two white stripes on the backside. Since it can not be assumed that every image shows the backside of the needle this characteristic can not be used. The next differences between the needles is that spruce needles are blunt and they grow in one plane on the branch and fir needles are pointed and they can grow in every direction. Due to overlapping needles of the spruce the grow direction can not be determined. The endings of the needles are found by segmenting the image (see Figure 2 a)) followed by calculating the skeleton of the needles (see Figure 2 b)). The endpoint of the skeleton are the endpoints of the needles (see Figure 2 c)). The endings of the needles are now analyzed by calculating features like the eccentricity, solidity, curvature features, and the moment invariants.



(a) (b) (c)

Figure 2: Finding the endings of the needles of an image of a spruce. The segmentation of the branch and the needles from the background is shown in (a). In the middle is the skeleton of the first image and with this skeleton the endpoints of the needles can be found (c).

The trees on which the needles grow in cluster are distinguished by the number of needles in the cluster. The endings of the needles can be found with the method described above. Since the needles in the cluster are overlapping and the clusters are lying close to each other the number of needles in the cluster can not be determined.

4. Experiments and results

In this section the experiments and results are presented. The experiments were done on datasets which were provided by the “Österreichische Bundesforste AG”. In Section 4.1 the experiments on the leaf dataset are presented. Afterwards, in Section 4.2, the experiments on the bark dataset are evaluated.

Since no method has been found to identify the tree species from images of the needles no experiments have been carried out for the trees on which the needles grow in clusters. Fir and spruce can be identified by analyzing the endings of the needles. 5 of 5 images of the fir and 7 of 9 images of the spruce were identified correctly. The spruce needles are misclassified since the needles are rotated on the branch and so the blunt ending of the spruce needles become pointed in the image.

4.1. Experiments on the leaf dataset

The leaf dataset consists of 134 images of the five most common Austrian broad leaf trees. This images are scaled to either 800 pixel height or 600 pixel width. Each class has between 25 and 34 images. Experiments have shown that 30 cluster centers for each class lead to the best results on our dataset.

The description of the results has already been shown in Fiel and Sablatnig [4]. For reasons of completeness the results are shown again in Table 1.

	Ash	Beech	Hornbeam	Mountain oak	Sycamore maple
Ash	**14**	1		1	1
Beech		**20**		2	
Hornbeam	1		**25**		
Mountain oak				**14**	
Sycamore maple					**15**

Table 1: Confusion matrix of the first experiment on the leaf dataset. The tree names on the top are the estimated classes, the names on the left side the true classes.

4.2. Experiments on the bark dataset

The bark dataset consists of 1183 images of the eleven most common Austrian trees. The images, which are showing a section of the bark of the size of approximately an A4 paper, are scaled to either 800 pixel height or 600 pixel width. Each class contains between 16 and 213 images.

The first experiment is done on the whole bark dataset. The amount of the centers has been set to 30 per class and the size of the trainings set is set to 30, which was evaluated empirically. Classes which have less then 30 images are also trained but no images are left for testing. These classes are skipped in the rows of the table. The results are shown in Table 2. The classification rate is 69.7%. The highest recognition rate has the Spruce with 82% (101 out of 123 images), followed by the fir with 76% (51 out of 67). 55 images (which are 72%) of the black pine images are assigned to the correct class. The larch and the swiss stone pine have a classification rate of 70 respectively 67% (77 out of 110 respectively 12 out of 18 images). 62% of the mountain oak image are assigned correctly which are 29 out of 47. The scots pine has a recognition rate of 53% (53 out of 100). The ash has the poorest result with 33% but since there are only three images remaining in the test set this result is not representative.

The same dataset was tested with a combination of GLCM features (contrast, correlation, energy, and homogeneity) and the average energy of the wavelets coefficients. The GLCM features are calculated for 0, 45, 90, and 135 degrees with a distance of 1 and 5 pixels and the depth of the wavelet packet was 5. The results of this experiment are presented in Table 3. The classification rate is 61.2%. All three remaining images of the ash dataset are identified correctly. The fir and the spruce are the classes with the second best recognition rate of 67% respectively 65%. 53% of the black pine are assigned to the correct class, whereas the method has the worst performance on the mountain oak and the swiss stone pine with 43 respectively 39%.

The next experiment was done on a subset of the bark images containing 9 images of each class. The trainings sets are maximal 30 images, for those classes which have less then 39 images the rest of the dataset was used as trainings set. The number of centers per class for the bag of word method remained at 30.

This subset was presented with an online survey to two employees of the “Österreichische Bundesforste AG”. The first is a biologist, who studied at the University of Natural Resources and Life Sciences in Vienna and is now working in the natural resource management department and the second is a forest ranger with practical experience of more than 15 years. The classification rate of the first experts was 56.6% and the classification reate of the second expert was 77.8%. Both experts said at the end of the experiment that they had the biggest problem by distinguishing the three pine species and the larch. Sample images which are showing that the difference between the classes is often lower then the intraclass variance can be seen in Figure 3. Both experts noted that they use other chracteristics for the identification, like the location where the tree grows, the habit of the bark, or the buds on the branches.

Figure 3: Sample images to show the intraclass difference. The first row shows 3 images of black pines, the second row shows two images of a scots pine and one image of a larch.

The proposed method is also applied on the same subset of images. The results of this experiment can be seen in Table 4. The classification rate is 65.5%, which is approximately between the rate of the two experts. The ash, beech, black pine, fir, and spruce have a recognition rate of 88.8%. The hornbeam and the swiss stone pine have a recognition rate of 77.7%. 6 of the 9 images of the scots pine are classified correctly and 5 of the mountain oak images are assigned correctly. None of the larch or sycamore maple are identified. The reason why none of the sycamore maple is classified correctly is that in these images shadows occur and the trees are covered with moss and lichens. 6 of the larch images are assigned to the black pine class, also three images of the scots pine,

	Ash	Beech	Black pine	Fir	Hornbeam	Larch	Mountain oak	Scots pine	Spruce	Swiss stone pine	Sycamore maple
Ash	**1**							1	1		
Black pine	1		**55**			10		10			
Fir			1	**51**		2	3	1	9		
Larch			13	1		**77**	1	11	2	3	2
Mountain oak	2		2		1	3	**29**			6	4
Scots pine	1		10	4	2	19		**53**	4	6	1
Spruce	2	1		4	2		7	1	**101**	1	4
Swiss stone pine					1	2	1	2		**12**	

Table 2: Confusion matrix of the experiment on the bark dataset with a trainings set size of 30 images. The tree names on the top are the estimated classes, the names on the left side the true classes. Classes where no images are left for testing are skipped in the first column.

	Ash	Beech	Black pine	Fir	Hornbeam	Larch	Mountain oak	Scots pine	Spruce	Swiss stone pine	Sycamore maple
Ash	**3**										
Black pine			**40**			16		15	1	3	1
Fir				**45**		3		9	7	2	1
Larch			12	1		**71**		21		5	
Mountain oak	4		1			2	**20**	8	4	7	1
Scots pine			11	2		17		**64**	2	3	1
Spruce	4	3		6	12	4	2	3	**83**	2	4
Swiss stone pine			1	2		1		5	1	**7**	1

Table 3: Confusion matrix of the experiment with combined features of the GLCM and wavelets. The trainings set contained maximal 30 images per class. Classes where no images are left for testing are skipped in the first column.

which confirms that the three pines and the larch are hard to identify. This was already shown in Figure 3.

5. Conclusion

This paper presented a method for an automated identification of tree species from images of the bark based on the method for the identification of leaves. The method described uses local features to describe the texture since local features can keep up with texture classification methods [13]. No method has been found for the classification of the needle images. A method has been presented to distinguish between fir and spruce needles but the images has to be in good quality because segmentation is needed and the endings are analyzed.

The proposed method consisted of three steps. First the images were transformed into a normalized gray scale image. There the SIFT features were calculated and the neighborhood of these keypoints are then described using orientation histograms. Features of the trainings set are clustered. For each feature in an image the nearest cluster center is searched and the histogram of the occurrences can then be used to train a one-vs-all SVM. When classifying a

	Ash	Beech	Black pine	Fir	Hornbeam	Larch	Mountain oak	Scots pine	Spruce	Swiss stone pine	Sycamore maple
Ash	**8**		1								
Beech		**8**							1		
Black pine			**8**							1	
Fir				**8**					1		
Hornbeam					**7**		2				
Larch			6			**-**		2	1		
Mountain oak	3						**5**	1			
Scots pine			3					**6**			
Spruce								1	**8**		
Swiss stone pine			1					1		**7**	
Sycamore maple	1		4	1					1	2	**-**

Table 4: Confusion matrix of the experiment on the bark dataset used for the experiments with the experts. The tree names on the top are the estimated classes, the names on the left side the true classes.

new image the SIFT features are calculated and the histogram of the nearest cluster centers is used as input for the SVM.

Experiments and results have been presented datasets of leaf and bark images. The classification rate for the leaf dataset was 93.6%. When applying the proposed method on the bark dataset the classification rate was 69.7%. A subset of the bark images were generated and experiments with two experts were made. The classification rates of the two experts were 56.6 respectively 77.8%. When applying the proposed method to this subset the classification rate was 65.6% which is approximately in between.

The disadvantage of the proposed method is that the calculation of the SIFT features is computational intensive and due to the clustering for the bag of word model online learning is not possible. The advantage is that the proposed method can be applied to leaf and bark images. Thus, a preprocessing step can be introduced to distinguish between bark and leaf images without calculating new features.

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