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Plant images classification based on the angles between the leaf shape-contour points

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***Abstract*—In this paper we compare two shape-based descriptors for plant leaf image classification. The leaves in the dataset are already segmented from the background only the contour detection algorithm is applied to extract the contour points and generate the shape-based descriptors. We propose a reduced size descriptor based on the angles between three points of the leaf contour and compare this descriptor with other similar descriptors based on their classification quality. The classification quality is measured both with 1-nearest neighbor comparison and with RBF-SVM model trained on the generated descriptors.**

Keywords*— *image processing; leaf image classification; machine learning

I. INTRODUCTION

Plant identification based on plant images receives an increased attention from the image processing and machine learning community in recent years. Especially interesting is the plant identification based on images of their leaves. One of the problems that need to be asessed towards creating an efficient system for plant identification is the plant classification. There are several datasets available that allow the benchmark of algorithms for plant identification based on their leaves. Also several approaches can be identified that are mainly used for leaf classification. These approaches can be based on the leaves textures; the leaves shape exterior contours or a combination of both of them. The main drawback of the approaches for plant leaf classification based on the leaf shape is that they depend on the successful prior segmentation of the leaf from the image. Texture based descriptor don't have this drawback. Texture based descriptors, however, requre higher resolution images of the leaves for a successful extraction of the texture. Higher resolution images are not always available and their processing requires more computational resources. This is why in this paper we focus our attention towards the classification of plant leaf images based on the contour of their leaves. One of the first approaches for contour based matching is described in [1] and is also widely used in combination with other shape features. In [2] the shape context descriptor [3] is used in combination with the SIFT descriptor [4] to classify leaf images. The approach in [6] uses the shape of the leaves to extract points and generate descriptor based on the triangles that the points on the leaves contour make. Time series analysis can also be used if the points of the margins of the leaf are considered as data series [7]. In [5] the authors suggest a probabilistic combination of both texture based and shape based approaches. Many other approaches exist in the literatures that are used to classify leaf images. The available contour based descriptors are mainly used with k nearest neighbors (k-NN) classifiers and with SVM classifiers.

In this paper we present a simplified version of the descriptor described in [6] that gives comparable results with the compared descriptors. First we describe the descriptors that are extracted from the images. Then we describe the algorithms used to build the classification model and the parameters that are used for those algorithms, then we give the obtained results and the conclusion and finally we refer to future improvements and additions to the work described in this paper.

II. ANGLE BASED DESCRIPTOR

Our descriptor is based on the descriptors described in [6]. The authors prpopose several descriptors based on the triangular area that are created by the geometric properties of triplets of chosen points on the exterior contour of the leaf image. They use four types of descriptors based on the relationship between the three points. They use Triangle Area Representation or TOA descriptor that uses only the area that the triangle between three points of the contour take. The next descriptor is the Triangle Size Length representation or TSL descriptor that uses normalized side lenghts between the central and the two neighboring points. Then they use the Triangle represented by two side lengths and an angle or TSLA descriptor that uses the size of the sides and the angle between the points and finally the Triangle represented by two oriented angles or TSA descriptor represented by two consecutive angles between the points. All of the proposed descriptors are scale invariant since the neighboring points are taken with different distances. First the leaf shape contour is represented by N consecutive points that are evenly distributed on the contour. Next, for each point of the leaf contour we select two neighbor points that are on each side of the selected point. To achieve scale invariance multiple neighboring points are selected for each point. Each neighbor point is distanced equaly from on both sides of the chosen point by D points. We select *Ns* such neighbors on each side that represent the angle between the neighbor points on *Ns* scales. The distance between the points on each scale increases by *D* so that on the normal scale we have distance of 1 between the points and on each next scale we increase the distance by *D*. We are using the linear increment for the distance between points on each scale. The other option is to use logaritmic increment where the distance between points on each scale increases logaritmicly but this option was not taken into consideration in our work.

In the proposed descriptor in this paper we neglect the information for the distance between the points of the TSLA or the consecutive angle of the TSA descriptor. We only calculate the angle that each selected point make with its 2 neighbors. The obtained angle between each point is illustrated on Fig 1.

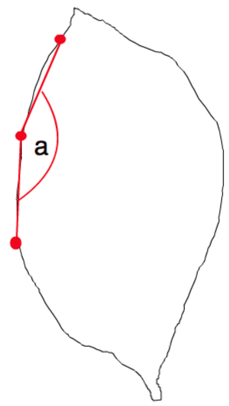

Fig. 1. Angle 'a' between the selected point and its connection with its neighbors

The main motivation for ignoring the distance is to check the significance of the distance between the points of the contour for the quality of the leaf classification.

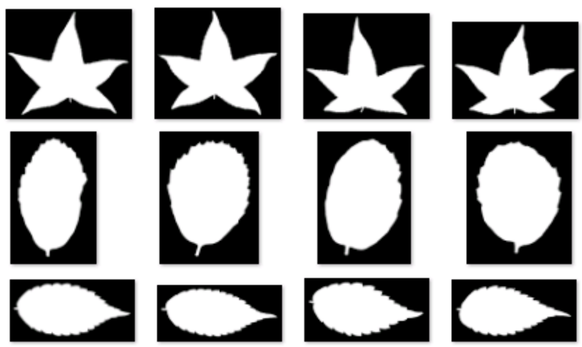

Fig. 2. Example shape images from the 100 plant dataset used in [5] from three different classes of leaves

What we are trying to verify is the significance of the angle relationship between the points of the shape contour in the shape classification process. Based on the observation of the dataset used for the comparison of the descriptors, which can be seen in Fig. 2, the leaf images have the same or close enough orientation. Which means that the descriptors and the obtained results do not account for the rotation of the leaves.

III. Experimental Setup

To test the classification accuracy of our descriptor we are using the 100 leaves dataset [5]. The dataset is divided on 11 train and 5 test images from each of the 100 classes. For each of the 16 images for each plant we first generate the TSLA descriptor and our descriptor. In this work are only investigating the significance of the angle between the points on each scale and wether we can ignore the distances in the TSLA descriptor to obtain comparable results with the original descriptor. The authors in [5] use leave-one-out approach or 16-fold cross validation to evaluate the classification performance while in this paper we use 2/3 of the dataset for training and 1/3 for testing.

We are using our own implementation of the TSLA descriptor. The method used to train the classification model also defers from the reported method in [6] where the authors use Locality Sensitive Hashing (LSH) [11] to compare each of the *N* generated descriptors for each image with each descriptor of every other image and use an evaluation function to calculate the similarity between the leaf shapes. Locality sensitive hashing is used to speed up the comparison between the descriptors, because comparing the *N* descriptors from a single image with each of the *N* descriptor of every other image is a time consuming task due to the large number of floating-point operations needed to calculate each distance.

In our approach we generate a bag of visual words (BOW) descriptor for each of the images. The BOW uses a visual word dictionary that is generated by k-means clustering of all descriptors in the train set. Each of the centroids of the k-means clustering represents a single word in the dictionary. Based on this, we can calculate which descriptor represents which word by calculating the distance between the descriptors and each of the k centroids. In this experiment we use Eucledian distance to measure the distance between the centroids and the descriptors. The Eucledian distance is used also for the k-means clustering of the training data when the centroids are generated. Other distances can also be used for this purpose but their evaluation is out of the scope of this paper. In our experiment k is set to 6000, so the visual dictionary will contain 6000 words. This number was chosen empirically based on manual evaluation of the training set. We chose 500, 1000, 3000, 6000 and 10.000 length dictionary. The best initial results on the validation on the train set by using three-fold cross-validation with 1-NN classification were obtained for 6000 and this number was used for the generation of the full model for the testing phase. The performance of the BOW based classification, as expected, increased with the increase in the number of visual words in the dictionary with a very slight degradation of performance for k=10.000 when compared to k=6000.

After this step, for each image, a term frequency – inverse document frequency (tf-idf) approach similar to [8], is used to generate the descriptor. The term frequency represents the number of times a single visual word is found inside the image and the inverse document frequency represents the number of images the same term is found in. If the visual word is found in large number of images, that visual word brings less information about the general characteristics of the images and has small contribution in uniqueily classifying the image. So for each visual word we calculate the number of appearences in each image and we normalize this number with the number of images in which the word appears, giving more significance to visual words that appear less frequently in images. These visual words give the biggest contribution in uniquely describing the characteristic of the images and the class they represent.

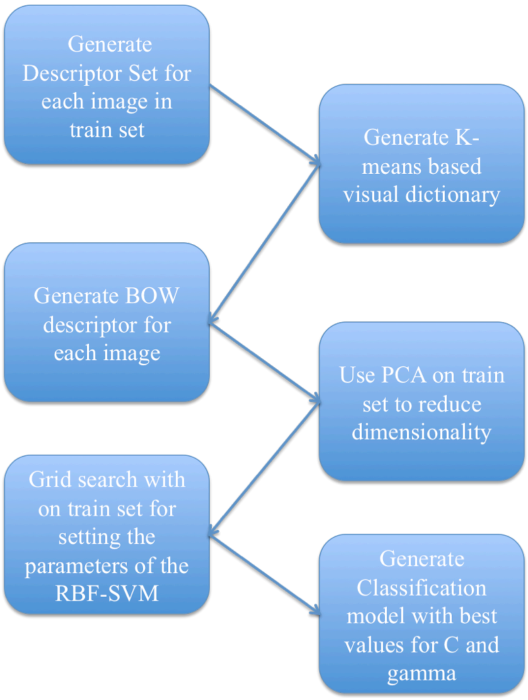

Fig. 3. Data flow for the RBF-SVM based classification model generation process

To reduce the dimensionality of the descriptor Principal Components Analysis (PCA) [9] is used. The PCA is a statistical method that reduces the dimensionality of the descriptors by analyzing and grouping corelated attributes of the feature vector.

The generated descritors are then used in two ways. First, we use the descriptors of each image in the training set as a model for 1-NN classification of the test images. Second, the model for each plant is generated with the set of the descriptors with training an Radial Based Function kernel Support Vector Machine (RBF-SVM). For the TSLA descriptor a grid search is performed for the RBF-SVM and the best results were obtained for C=1.000.000 and gamma=0.00001. For our descriptor the best results are obtained for C=100.000 and gamma=0.0001. The grid search is done for $C=10^{-2}$ to 10^{6} and $gamma=10^{-5}$ to 10^{2}. Both searches are done with exponential increasing steps for the parameters as recommended in [13]. WEKA [10] is used for the PCA and the RBF-SVM grid search and for the k-means clustering we are using the OpenCV [12] implementation of the algorithm. After the descriptors are generated we use the build RBF-SVM model to classify the images from the test set. We use WEKA as a data mining tool that contains many different preprocessing and analsys tools which are suitable for fast model generation and evaluation of the obtained results.

IV. RESULTS AND CONCLUSION

We evaluated the classification performance based on the two classification models. The obtained results are shown in Fig. 4 and Fig. 5. We used 1-NN approach, for the first evaluation, by comparing each image from the test set with each image of the training set and assign the class of the leaf image of the test set based on the class of its nearest neighbor in the training set. The average precisions obtained are 40.4% for TSLA descriptor and 40.2% for our descriptor. The weighted average Area under Curve of Receiver operating characteristic (AUC of ROC) [15][16] for the TSLA descriptor is 0.699 and for our descriptor 0.698. For the second evaluation we used the approach ilustrated in Fig. 3 for generating the model with an RBF-SVM. The average precision obtained is 54.2% for TSLA with SVM and 50.4% for our descriptor and the weighted average AUC of ROC is 0.769 for the TSLA descriptor and 0.751 for our descriptor. Altough the AUC of ROC is used for binary classification, the WEKA implementation uses an approach suggested by [16] which uses the Mann-Whitney statistic for calculating weighted average AUC of ROC for evaluation of multiclass classification problems according to the WEKA online documentation.

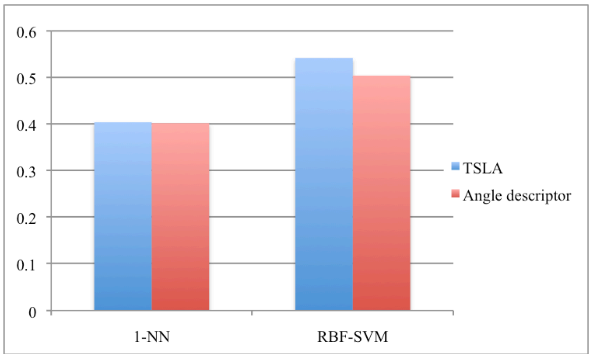

Fig. 4. Classification precision for TSLA and Angle descriptor for both 1-NN and RBF-SVM

As it can be seen from these results we sacrifice little performance of the descriptor but obtain three times smaller shape based descriptor that can be used for leaf image classification and used for the task of plant identification. Also from the results we can conclude that there is a significant improvement when using the RBF-SVM model based classification in comparison to the 1-NN classification when using the obtained descriptors on the given dataset which was expected.

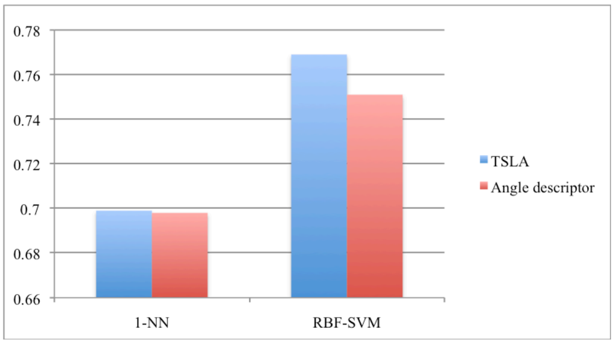

Fig. 5. Region under ROC for TSLA and Angle descriptor for both 1-NN and RBF-SVM

V. FUTURE WORK

We plan to verify the classification quality of the proposed descriptor by using other available leaf image datasets and compare the results between the two approaches. One of the challenges would be to see if the reduction of dimensionality of the initial descriptor, by ignoring the distance, would repeat the results even on datasets where the rotation of the leaf images is present. Further, additional improvements might be expected by modifying the way we obtain the BOW descriptor for the images with using other techniqes for generating the visual word centroids. We also plan to further verify the results by comparing the performance with other comparison techniques that would exclude the dictionary approach but will compare the descriptors as described using LSH. We expect that including other shape information that can be combined with our descriptor would increase the classification performance.

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