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Classification of Leaves based on Fusion Features

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***Abstract*— There are number of image classification systems however, most of them are applied only for general image databases and a few are intended for specified databases out of which a fewer for leaf databases. In spite of the number of expert botanists, a convenient classification system for the leaf is still necessary. In this paper, we propose a classification method using feature level fusion for the leaf databases of Flavia leaves dataset, Swedish leaf dataset and ICL dataset. The reasons are that fusion based features give better accuracy than single feature. The effectiveness of the proposed method has been demonstrated by various experiments using SVM and KNN classifiers to classify leaves.**

***Keywords*— GIST, SIFT, Classification, IDSC.**

1. INTRODUCTION

Developing a framework for a leaf classification system is a difficult task because of lot of appearance variations caused due to in imaging conditions, deformations and variations between different instances of same category. Leaf classification poses an extra challenge over categories such as bikes cars, airplanes etc., because of large similarity between classes, and also due to being non-rigid objects that can deform in many ways. Leaf classification is a process resulting in the assignment of each individual leaf of related leaves. So far, this time-consuming process has mainly been carried out by botanists. There is a huge number of leaves species worldwide. To handle such volumes of information, development of a quick and efficient classification method has become an area of active research. In addition to the conservation aspect, classification of leaves is also necessary to utilize their medicinal properties and using them as sources of alternative energy sources like bio-fuel. In recent times computer vision methodologies and pattern recognition techniques have been applied towards automated procedures of leaf recognition. Currently, leaves classification is one of the most difficult tasks in computer vision due to 1) lack of proper models or representations. 2) A great number of biological variations that a species of leaf can take. 3) Imprecise image preprocessing techniques such as edge detection and contour extraction, thus resulting in possible missing features. Since the shape, texture, scale invariant, descriptors are important features for leaves to categorize various leaves classes, the study of leaf image classification will be an important step for plant identification. In this paper, we propose a scheme for leaf image classification based on fusion of features. In particular, we discuss three features, GIST feature descriptor, SIFT feature and IDSC (Inner Distance Shape Context). The organization of the paper is as follows: section 2 provides an overview of previous work, section 3 outlines the proposed method and feature computation, section 4 provides the detail of adopted database, section 5 describes about classification, In section 6 &7 gives experimental results obtained and the overall conclusion.

2. Previous Work

Many methodologies have been proposed to examine plant leaves in an automated mode. A large percentage of such works utilizes shape recognition techniques to model and represent the contour shapes of leaves, however additionally, color and texture of leaves have also been taken into consideration to improve recognition accuracies. One of the earliest works [1] employs geometrical parameters like area, perimeter, maximum length, maximum width, elongation to differentiate between four types of rice grains. In [2], the authors propose a hierarchical technique of

representing leaf shapes first by their polygonal approximations and then by introducing more and more local details in subsequent steps. In [3], the authors use the Curvature Scale Space (CSS) technique and k-NN classifiers to classify chrysanthemum leaves. Both color and geometrical features have been reported in [4] to detect weeds in crop fields employing k-NN classifiers. Statistical discriminate analysis along with color based clustering and neural networks have been used in [5] the classification of a flowered plant and a cactus plant. Fuzzy logic decision making has been utilized in [6] to detect weeds in an agricultural field. In [7], the authors propose a two-step approach of using a shape characterization function called centroid-contour distance curve and the object eccentricity for leaf image retrieval. The centroid-contour distance (CCD) curve and eccentricity along with an angle code histogram (ACH) have been used in [8] for plant recognition. The effectiveness of using fractal dimensions in describing leaf shapes have been explored in [9]. In contrast to contour-based methods, region-based shape recognition techniques have been used in [10] for leaf image classification. Elliptic Fourier harmonic functions have been used to recognize leaf shapes in [11] along with principal component analysis for selecting the best Fourier coefficients. In [12] the authors propose a leaf image retrieval scheme based on leaf venation for leaf categorization. Leaf venations are represented using points selected by the curvature scale scope corner detection method on the venation image and categorized by calculating the density of feature points using non parametric estimation density.

Neural Networks have been used in [13] to classify plant based on parameters like size, radius, perimeter, solidity and eccentricity. In [14] to model the uneven shapes of leaves Wavelet and Fractal based features have been used. In [15] to improve the accuracy texture features along with shape features have been used. In [16] to model the leaf structure Zernike moment and Polar Fourier transform have been proposed. In [17] the classification of leaf images, have been done using Gabor filter and Jeffrey divergence measure. In [18] authors propose Guiding Active Contours for plant leaf segmentation and classification.

3. Proposed Methodology

The proposed method consists of two stages learning and classification. In the learning stage we extract GIST, SIFT and IDSC features of the leaf. These features are requires to different classifiers Support vector machine, K-nearest neighbor to know the class label of the leaf. The block diagram showing the proposed classification process of flowers is given in Fig. 1.

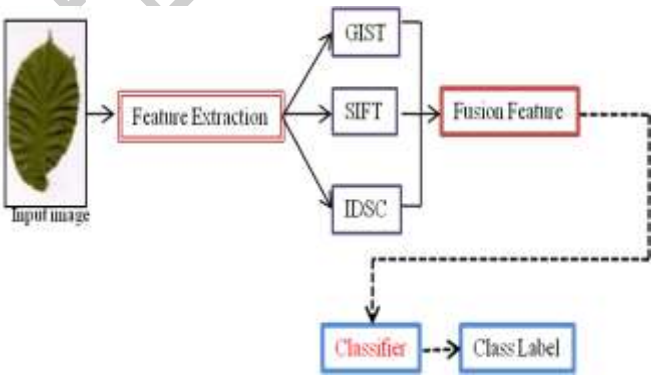

Fig. 1 Block diagram of the proposed method.

Fig. 2 Flavia leaf database.

Fig. 3 ICL leaf database.

Fig. 4 Swedish leaf database.

Table I. Classifiers accuracy for datasets.

SVM & KNN Classifiers accuracy for each dataset							
Datasets	Trail ratio	SVM			KNN		
Swedish leaf Dataset	40:60	98.03%	97.62%	96.29%	87.33%	88.25	89.59
	60:40	98%	97.77%	97.33%	89.63%	91.67	92.77
	80:20	99.11%	98.66%	96.88%	90.53%	91.32	92.01
Flavia Dataset	40:60	90.66%	90.43%	89.97%	85.47%	86.55	87.52
	60:40	92.79%	91.16%	90.86%	86.35%	87.76%	87.89%
	80:20	92.97%	92.89%	91.01%	87.74%	88.21%	88.89%
ICL Dataset	40:60	83.69%	83.62%	82.92%	80.96%	80.57%	82.15%
	60:40	86.04%	85.79%	84.93%	82.17%	82.93%	83.09%
	80:20	89.23%	88.93%	87.73%	84.86%	84.92%	85.28%

3.1. Feature Extraction

3.1.1 GIST

We used GIST descriptor [24] to extract individual class of leaf image descriptive feature. The GIST descriptor computes wavelet image decomposition. Each image location is represented by the output of filters tuned to different orientations and scales. We use a Gabor-like filters steerable pyramid with 8 orientations and 4 scales applied to the intensity (monochrome) image. To capture global image properties while keeping some spatial information, we take the mean value of the magnitude of the local features averaged over large spatial regions. The square output of each filter is averaged on a 4×4 grid.

3.1.2 Dense SIFT (Scale-Invariant Feature Transform)

SIFT descriptors are densely extracted [22] using a flat rather than Gaussian window at two scales (4 and 8 pixel radii) on a regular grid at steps of 1 pixels. First, a set of orientation histograms are created on 4×4 pixel neighborhoods with 8 bins each. These histograms are computed from magnitude and orientation values of samples in a 16×16 neighboring region such that each histogram contains samples from a 4×4 sub region of the original neighborhood region. The magnitudes are further weighted by a Gaussian function with equal to one half the width of the descriptor window. The descriptor then becomes a vector of all the values of these histograms. Since there are 4×4 histograms each with 8 bins the vector has 128 elements. This vector is then normalized to unit length in order to enhance invariance to affine changes in illumination. Next, kernels are computed from spatial pyramid histograms at three levels [23].

3.1.2 IDSC (Inner Distance Shape Context)

The inner-distance shape context, defined as the length of the shortest path within the shape boundary, to build shape descriptors. It is easy to see that the inner-distance is insensitive to shape of leaves. The shape context uses the Euclidean distance to measure the spatial relation between landmark points. Belongie et al. showed that the SC+TPS (Thin-Plate-Splines)[21]. is very effective for shape matching tasks. A shape is represented as a sequence of boundary points: $P = \{p_1, \cdots, p_n\}$, $p_i \in R_2$, Shape Context is a descriptor of interest point, i.e. a histogram: $h_i(k) = \{p_j: j 6= i, x_j - x_i \in bin(k)\}$, in which bins are uniformly divided log-polar space. The cost of matching point p_i on the first shape to point q_j on the second shape is computed using chi-square distance. Minimize total matching cost, This could be solved by Hungarian method, $\pi(i)$ is a permutation.

For two points $x, y \in O$, their inner distance, denoted as $d(x, y; O)$, is the length of the shortest path connecting x and y within O. Given two boundary point p, q and their shortest path $\Gamma(p, q; O)$, the angle between the contour tangent at p and the direction of $\Gamma(p, q; O)$ at p is the inner angle,

θ(p, q; O). Since the contours provide ordering information, and use dynamic programming to solve the matching problem, instead of using bipartite graph matching. By default the two contours are aligned at start and end points. If not, we have to try different alignments but if we firstly rotate them according to the moments, then we need only try a small fixed number k = 4 or 8 alignments.

4. Database

We adopted two approaches to classify for the leaf databases of The Flavia dataset is composed of 1907 scans of leaves belonging to 32 species (Fig 2), several methods were tested in [19] on Flavia. Swedish leaf image dataset [18] of 1125 images with 15 different species haws sample leaves (Fig 4). The Swedish leaf dataset is very challenging because of its high inter-species similarity and ICL-Plant Leaf plant leaf database[20]. The ICL-Plant Leaf database was constructed at the Intelligent Computing Laboratory (ICL) of Institute of Intelligent Machines, Chinese Academy of Sciences. It contains more than 20,000 leaf images of 221 plant species(Fig 3). The images were captured at different periods, and have different locations and natural illuminations.

5. Classification

We have used classifiers viz., support vector machine (SVM) and K-nearest neighbor (KNN). The motivation behind using SVM is due to its simple structure and training manner. The most important advantages of SVM are (i) the training is easy and instantaneous, (ii) additionally, it is robust to noisy examples and (iii) the speed of SVM is high. KNN is part of supervised learning that has been used in many applications in the field of data mining, statistical pattern recognition, image processing and many others.

5.1. Support Vector Machine

Classification of the leaf was carried out using the SVM (Support Vector Machine) technique. In the first phase, the study attempted to classify the leaf into their respective classes. In the following phase, the potential of SVM to classify different leaf image types was examined. A SVM optimally separates the different classes of data by a hyperplane (Karatzoglou and Meyer, 2006; Kavzoglu and Colkesen, 2009; Vapnik, 1998). The points lying on the boundaries are called support vectors and the middle of the margin is the optimal separating hyperplane (Meyer, 2001; Mountrakis et al., 2011). An optimum hyperplane is determined using a training dataset, and its generalization ability is verified using a validation dataset. Training vectors xi are projected into a higher dimensional space by the function φ. SVM finds a linear separating hyper plane with the maximal margin in this higher dimensional space. The methodology for SVM implementation are well described by Karatzoglou and Meyer (2006) and Kavzoglu and Colkesen (Kavzoglu and Colkesen, 2009). The study used a polynomial kernel and employed 'one-against-one' technique to allow multi-class classification.

5.2. KNN Classifier

The KNN classifier based on the distance is direct and simple. Special interest was given to KNN due to its Simplicity and Efficiency. It is one of the simplest classifiers with features fitting our requirements. Its testing time, however, grows linearly with the size of the training set, limiting the scalability of the classifier. It is based on distance measures in feature space but instead of comparing f_s to a class representative value, it compares it to all samples of the training set $f_t i$ selecting the first k closest ones. We call the subset of k-closest training samples K.

6. Experimental Results

This section describes the proposed approach's testing results. The classification was performed using SVM and KNN classifier. The results obtained with these schemes were used to compare the classification technique and to conclude this study. Below table shows the classification rate for SVM & KNN classifiers. The time taken and the accuracy attained with the classification scheme are the important viewpoints of any user. It is determined that SVM classification scheme is better than KNN for a dataset with large number of images whereas, KNN surpasses the SVM approach for a smaller dataset. The efficiency is calculated in terms of accuracy.

7. Conclusion

In this work we proposed a plant classification system based on fusion features. We have used GIST, SIFT, IDSC features for the purpose

classification. It is observed that the proposed classification of leaves based on fusion features achieves relatively a good classification accuracy when compared to entire leaves based classification.

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