SKELETON BASED APPROACH FOR FLOWER CLASSIFICATION

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Abstract- In this paper, we present an effective system for recognizing flower images taken by digital cameras. A flower image is segmented by eliminating the background using an iterated Graph Cut method. We obtained the skeleton from the segmented flower images using skeleton pruning method. The shape context feature are extracted from skeleton of flower images. In this work, nearest neighbor is used as a classifier. To corroborate the efficacy of the proposed method, an experiment was conducted on our own data set of 30 classes of flowers, containing 3000 samples. The data set has different flower species with similar appearance (small inter-class variations) across different classes and varying appearance (large intra-class variations) within a class. In addition, the images of flowers are of different poses, with cluttered background under different lighting and climatic conditions. An experiment has been conducted by picking images randomly from the database, it is shown that relatively a good performance can be achieved, using shape context features with the nearest neighbor classifier algorithm.

Key words – Segmentation, Skeleton Pruning, Shape Context, Nearest Neighbor.

Introduction
The objective of the work is to classify flowers from images. Flowers and the ability to identify them has been fascinating humans for hundreds of years. The taxonomy originally contained approximately 8000 plants, but has since been extended to encompass more than 250000 flower species around the world [30]. However, even when an image is sufficient, classifying a flower may still need a guidebook because with advances in digital and mobile technology it is easy to capture pictures of flowers, but it is still difficult to find out what they are. Once we know the name of a flower we can find more information about a flower on the web, but the link between obtaining an image of a flower and acquiring its name is missing. Therefore, our aim is to create an automatic guide that classifies an image of a flower. As flowers of different classes are more similar, developing a system to classify flower images is a very challenging task. Additionally, flower images captured in a real time, poses a number of challenges like variations in viewpoint, scale, illumination, partial occlusions, multiple instances etc. All these challenges need a very sophisticated algorithm to classify flowers. Also, the cluttered background makes the problem more difficult, as we need to classify the flower image from the background. Moreover, the greatest challenge lies in preserving the intra-class and inter-class variabilities. The floriculture has become one of the important commercial trades in agriculture owing to steady increase in demand of flowers. Floriculture industry comprises of flower trade, nursery and potted plants, seed and bulb production, micro propagation and extraction of essential oil from flowers. In such cases automation of flower classification is very essential. Further, flower recognition is used for searching patent flower images to know if the flower image applied for patent is already present in the patent image database (Das et. al., [5]). Since these activities are being done manually and they are mainly labor dependent, automation is necessary.

Related Work
Classification of flowers has majorly three stages viz., segmentation, feature extraction and classification. Before extraction of features from a flower image, the flower has to be segmented. The goal is to segment out the flower given only that the image is known to contain a flower, but no other information on the class or pose. In second step, different features are chosen to describe different properties of the flower. Some flowers are with very distinctive shapes, some have very distinctive color, some have very characteristic texture patterns, and some are characterized by a combination of these properties. Finally extracted features are used to classify the flower. Segmentation subdivides an image into its constituent parts or objects. The level to which this subdivision is carried depends on the problem being solved. That is segmentation should stop when the objects of interest in an application have been isolated. In general, autonomous segmentation is one of the most difficult tasks in image processing. Flowers in images are often surrounded by greenery in the background. Hence, the background regions in images of two different flowers can be very similar. In order to avoid matching the green background region, rather than the desired foreground...
region, the image is segmented. Pixel labeling method (Das et. al. [5]) uses only pixel appearance to assign a label to a pixel. The Contour-based methods which try to find the boundary of an object by locally minimizing energy function so that the segmentation boundaries align with strong gradients in the image. These include (Kass et. al., [13]), (Chan and Vese, [14]), (Mortensen et. al., [15]) and (Saitoh et. al., [8]). Graph-based pixel labeling methods, where a global energy function is defined depending on both appearance and image gradients (Boykov and Jolly, [2]; Rother et. al., [16]; Kumar et. al., [17]; Nilsback and Zisserman, [1]; Nilsback and Zisserman, [3]).

Different features are chosen to describe different properties of a flower. Some flowers are with very distinctive shapes, some have very distinctive colors, some have very characteristic texture patterns, and some are characterized by a combination of these properties. Some flowers exist in a wide variety of colors, but many have a distinctive color. The color of a flower can help narrow down the possible species, but it doesn’t enable us to determine the exact species of the flower. To handle this problem the color feature is described by taking the HSV values of the pixels (Nilsback and Zisserman [3]). The HSV values for each pixel in an image are clustered using k-means to have the color vocabulary. Yoshioka et. al., [6] in their work performed quantitative evaluation of petal colors using principal component analysis. They set a region of interest in each petal as a region representing the petal color pattern and defined the maximum square on each petal as the region of interest. Texture of a flower has also been exploited for classification. Some flowers have characteristic patterns which are distinctive on their petals. Nilsback and Zisserman, [3] describe the textures by convolving the images with MR8 filter bank. The filter bank contains filters at multiple orientations. Rotation invariance is achieved by choosing the maximum response over orientations. Guru et. al., [7] developed a neural network based flower classification system using different combinations of texture models such as color texture models, gray level co-occurrence matrix, gabor responses. David and Huang [18] explore a design-based method for feature fusion using Gabor filter and co-occurrence matrix. Leung and Malik [9] compute textons using a filter bank. The response to 48 different filters are computed for each pixel and concatenated into a 48 dimensional vector. Varma and Zisserman [10] use a smaller filter bank called Maximum Response (MR) filter. The shapes of individual petals, their configuration, and the overall shape of the flower can all be used to distinguish flowers. The difficulty of describing a shape is increased due to natural deformations of a flower. The petals are often very soft and flexible and hence can bend, curl, twist etc., which make the shape of a flower appear very different. The shape of a flower also changes with the age of the flower and petals might even fall off. Nilsback and Zisserman [1] describe the shape features using rotation invariant descriptors. The scale invariant feature transform (SIFT) descriptors are computed on a regular grid and optimize over three parameters: grid spacing M, radius R and number of clusters. Nilsback and Zisserman [3] describes the shape features using SIFT descriptors on the foreground region and on the foreground boundary. After feature extraction, the challenge lies in determining a suitable classifier. Nilsback and Zisserman (1) & (3) used nearest neighbor classifier and support vector machine to classify the flowers. In other work Varma and Ray [11] used multiple kernel classifier to classify the flowers. However, the number of classes increases configuration becomes computationally expensive. To overcome this problem Das et. al. [5] proposed an indexing method to index the patent images using the domain knowledge. The color of the flower is defined by the color names present in the flower region and their relative proportions. The database can be queried by example and by color names. Fukuda et. al. [22] developed a flower image retrieval system by combining multiple classifiers using fuzzy c-means clustering algorithm. In their system, flowers were classified into three categories of different structures: gamopetalous flowers, many-petaled flowers, and single-petaled flowers. For each structure, a classifier with specific feature set was constructed. Fuzzy c-means clustering algorithm was then used to determine the degree of membership of each image to each structure. The overall similarity is a linear combination of each individual similarity computed for each classifier with the weight being the degree of membership. The test database consists of 448 images from 112 species with 4 images per species. Experimental results have shown that the multiple-classifier approach outperforms any single-classifier approach. However, it is too rough a classification mechanism to classify flowers into three different categories according to the number of petals. Cho and Chi [23] proposed a structure-based flower image recognition method. The genetic evolution algorithm with adaptive crossover and mutation operations was employed to tune the learning parameters of the Back propagation Through Structures algorithm [24]. A region-based binary tree representation whose nodes correspond to the regions of the flower image and links represent the relationships among regions was constructed to represent the flower image content. Experimental results showed that the structural representation of flower images can produce a promising performance for flower image recognition in terms of generalization and noise robustness. In fact, the classification accuracy of the system depends on the selection of the feature values. Saitoh et. al., [8] describe an automatic recognition system for wild flowers. The objective is to extract both flower and leaf from each image using a clustering method and then to recognize using a piecewise linear discriminate function. In (Anxiang et. al., [12]) color features of flower are characterized using a histogram of a flower region and shape features are characterized by centroid-contour
Distance and Angle Code Histogram for the purpose of flower retrieval. From the literature survey it is understood that, there are quite a few attempts towards development of flower classification systems. Nilsback and Zisserman [1] noted that color and shape are the major features in flower classification. This is true only when the considered flower classes have less intra class variation. However, if there is a large variation within the class where the species of same types have different colors then color may not be the best suitable feature. For the purpose of classification a simple classifier such as nearest neighbor classifier, support vector machine have been used. Hence in this work we modified Iterated Graph Cut segmentation with initial segmentation of Chan-Vese method. We obtained skeleton of flowers using skeleton pruning method for segmented flower images and the shape context features are extracted. The extracted features are applied to nearest neighbor for classification of flowers. The organization of the paper is as follows. In section 2 the proposed method is explained with a neat block diagram along with a brief introduction to segmentation and flower skeleton extraction. Section 3 discusses about shape context features. The experimental results are discussed in section 4 and the paper is concluded in section 5.

Proposed Method
The proposed method has training and testing phases. In training phase, the flower images are segmented using graph cut segmentation method and then skeleton is obtained using skeleton pruning method from segmented flower images. From the skeleton of the flower the shape context features has been extracted and used to train the system using the nearest neighbor classifier. In testing phase a given test flower image is segmented and then its skeleton is obtained followed by extraction of the shape context features for recognition. These features are queried to nearest neighbor classifier to label an unknown flower. The block diagram of the proposed method is given in Fig. (1).

Segmentation
Flowers in images are often surrounded by greenery in the background. Hence, the background regions in images of two different flowers can be very similar. In order to avoid matching the green background region, rather than the desired foreground region, the image is segmented uses the Iterated Graph Cuts Algorithm proposed by Bo et al., [25]. In the original graph cuts algorithm, the segmentation is directly performed on the image pixels. There are two problems for such a processing. First, each pixel will be a node in the graph so that the computational cost will be very high; second, the segmentation result may not be smooth, especially along the edges. These problems can be solved by introducing image segmentation techniques, such as Chan-Vese Segmentation [14], watershed [26] to graph cuts. In [27], Li et al. used watershed for initial segmentation to speed up the graph cuts optimization process in video segmentation. In [25], Bo et al., used mean shift for initial segmentation because it produces less over-segmentation. In this paper, we choose to use Chan-Vese for initial segmentation because it produces less over-segmentation and has better edge preservation than watershed. The initial labeling \( f_0 \) of graph cuts is given by a group of foreground/background seeds from the user. Regions which have pixels marked as foreground are called foreground seed regions, while the regions with background seeds are thus called background seed regions. The initial sub-graph contains only seed regions. Start from the initial sub-graph, in the iteration only the adjacent regions to the previously labeled regions are added into the updated sub-graph. Running graph cuts algorithm on the updated sub-graph, an updated optimal segmentation is obtained. The iteration stops when all the region nodes are labeled as either foreground (i.e. object) or background. Fig. (3) shows examples of segmented images. The iterated graph cuts algorithm is summarized in Algorithm 1. We assume that the foreground regions are connected unless separated parts of the foreground are initially marked by the user. Therefore, the regions which cannot be involved in the iterations will be labeled as the background regions. Overall schematic diagram segmentation method is shown in fig. (2).

Flower Skeleton
After the segmentation of flower we extract skeleton of the flower from segmented flowers. The Skeleton integrates geometrical and topological features of the object, and it is an important shape descriptor for object recognition. Shape similarity based on skeleton matching usually performs better than contour or other shape descriptors in the presence of partial occlusion and articulation of parts.

Skeleton Pruning
We used the skeleton pruning method proposed by Bai et.al, [28]. First, Discrete Curve Evolution (DCE) simplifies the polygon. Then the skeleton is pruned so that only branches ending at the convex DCE vertices remain. For example, in Fig. 4(a), the original flower, in Fig. 4(b), the skeleton contains a lot of noise. In Fig. 4(c), all the endpoints of the Flower skeleton are vertices of the DCE simplified polygon. The pruned skeleton is guaranteed to preserve the topology of the shape and it is robust to noise and boundary deformation. The main benefit of using DCE is the fact that DCE is context sensitive. It recursively removes least relevant polygon vertices, where the relevance measure is computed with respect to the actual partially simplified versions of the polygon. Therefore, the remaining skeleton branches are determined in the context of the whole shape, e.g. the same branch that may be irrelevant for one shape, and is removed, maybe relevant for a different shape, and therefore, it will remain. In order to obtain skeletons composed of only relevant branches, provided none are missed, an appropriate stop criterion of the DCE simplification is needed. Usually we can use the same threshold as stop criterion of DCE for the shapes in the same class, because they are very similar.
Feature Extraction
We will extract inner distance shape context features from skeleton of flower. As our interest is to study the statistics of shape features useful for flower classification, an introduction to shape context features are given in the following subsection.

Inner distance Shape Context
A natural way to compute the inner-distance is using shortest path algorithms. The inner distance [29] is defined as the length of the shortest path within the shape boundary. This makes more sense for articulation invariance because, the object may undergo some deformation due to articulation, and the normal Euclidean distance measure finds the shortest path between the contour points that may cross the boundary of the object. But, we need to stay local to the object and measure the distance between pair of points because, we know that the object is still the same, but under some deformation. This concept is used in constructing the inner distance shape context (IDSC). Inner distance between each pair of points along the objects’ contour is computed. The inner angle is computed as the tangential direction at the starting point of the shortest path connecting two points. So, we have two bins, one for the distance measure, and the other for the orientation measure. So, each point along the contour will have a histogram binning for both distance and orientation, and this descriptor will be used to describe the shapes. Hence we adopted the tool provided by Ling [29].

Experimentation Results
In this work we have created our own database despite of existence of other databases as these are less intra class variations or no change in view point. We collected flower images from World Wide Web in addition to taking up some photographs of flowers that can be found in and around our place. The images are taken to study the effect of the proposed method with large intra class variations. We introduce a database consisting of 3000 images divided into 30 flower classes. Each class containing 100 images per class. The images are rescaled to the size 250×250. Fig. 5(a) shows a sample image of each 30 classes; Fig. 5(b) presents few samples of randomly selected flower classes. It is clearly understandable that there is a large intra class variation. The large intra-class variability and the small inter-class variability make this dataset very challenging.

Nearest Neighbor (KNN)
One of the simplest classifiers which we used is the Nearest Neighbor classifier [20][21]. The term of nearest can be taken to mean the smallest Euclidean distances in n-dimensional feature space. This takes a test sample feature in vector form, and finds the Euclidean distance between this and the vector representation of each training example. The training sample closest to the test sample is termed its Nearest Neighbor. Since the trained sample in some sense is the one most similar to our test sample, it makes sense to allocate its class label to the test sample. This exploits the ‘smoothness’ assumption that samples near each other are likely to have the same class.

Results
In this experimentation we intend to study the accuracy of Shape context feature. We picked images randomly from the database and experimentation is conducted five times for each class. We selected maximum, minimum and average of accuracy from randomly picked images. The experimentation has been conducted on database of 30 classes under varying number of training samples 30, 50 and 70 from each class. On 30 number of training samples the shape context features achieve maximum accuracy 77.44, minimum accuracy 74.5, average accuracy 75.71 with nearest neighbor classifier. On 50 number of training samples the shape context features achieve maximum accuracy 82.16, minimum accuracy 80.5, average accuracy 81.71 with nearest neighbor classifier. On 70 number of training samples the shape context features achieve maximum accuracy 87.1, minimum accuracy 85, average accuracy 85.88 with nearest neighbor classifier. Fig. (6) shows the accuracy with varying number of training samples.

Conclusion
In this paper we proposed a skeleton based flower classification system and also we combine the different segmentation techniques for flower segmentation. In this work we have considered inner distance shape context features and nearest neighbor as classifier for classification. Also we have created our own database of flowers of 30 classes each containing 100 flower images. The experimental results have shown that the inner distance shape feature achieves the good accuracy. We also intend to study the effect of color, shape features along with the combination with texture features assigning weights to different features at querying time.

References


Fig 1. Block diagram of the proposed work

Fig 2. Overall Segmentation Method

Fig 3. Segmentation results on a few sample images
Fig 4. (a) Original flower image (b) Skeleton with noise (c) Skeleton with DCE

Fig 5. (a) Sample flower images of 25 flower classes considered in this work. (b) Sample images of five different classes with large intra class variations.
Fig 6: Classification accuracy by varying training samples using Nearest Neighbor Classifier