Classification of Flowers: A Symbolic Approach

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Abstract—In this work, we propose a skeleton based approach to classify flower images. Flowers are segmented using whorl based region merging segmentation. Skeleton of a flower is obtained from the segmented flower using a skeleton pruning method. The distance features are extracted from the skeleton endpoints and junction points. The features are normalized using discrete cosine transform. The reduced features are aggregated and represented in the form of an inter-valued type data and are stored in the knowledgebase. A symbolic classifier has been explored for the purpose of classification. To corroborate the efficacy of the proposed method, an experiment is 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 and it is shown that relatively a good performance can be achieved, using symbolic classifier.

Index Terms—Flower Segmentation, Discrete Curve Evolution, Discrete cosine transform, Symbolic representation, Classification.

I. INTRODUCTION

The objective of the work is to classify flowers using symbolic representation. 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 [1]. The 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., [2]). Since these activities are being done manually and they are mainly labor dependent, automation is necessary.

II. RELATED WORK

The classification of flowers has majorly three stages viz., segmentation, feature extraction and classification. 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. 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., [2]) 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 (Chan and Vese, [3], Saitoh et. al., [4]). Graph-based pixel labeling methods a global energy function is defined depending on both appearance and image gradients (Boykov and Jolly, [5]; Kumar et. al., [6]; Nilsback and Zisserman, [9]). Another classical category of segmentation algorithm is based on the similarity among the pixels within a region, namely region based segmentation. In region merging techniques, the goal is to merge regions that satisfy a certain homogeneity criterion. These includes (Calderero and Marques [10]; Ning et al., [11])

Different features are chosen to describe different properties of a flower. 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 Nilsback and Zisserman [7] used color vocabulary of HSV values. Yoshioka et al., [12] in their work performed quantitative evaluation of petal colors using principal component analysis. Texture of a flower has also been exploited for classification. Some flowers have characteristic patterns which are distinctive on their petals. Nilsback and Zisserman [7] describe the textures by convolving the images with MR8 filter bank. Guru et al., [13] 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. Guru et al., [14] designed a flower classification system using combinations of gray level co occurrence matrix, gabor responses. The features are fed into K nearest neighbor for classification. Guru et al., [15] proposed a method to classify flowers using only whorl region of flowers. 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. Nilsback and Zisserman [7] describe the shape features using scale invariant feature transform (SIFT) descriptors. Nilsback and Zisserman [8] 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 ([7] & [8]) used nearest neighbor classifier and support vector machine to classify the flowers. In other work Varma and Ray [16] used multiple kernel classifier to classify the flowers. However, as the number of classes increases classification becomes computationally expensive. To overcome this problem Das et al., [2] 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., [17] developed a flower image retrieval system by combining multiple classifiers using fuzzy c-means clustering algorithm. Saitoh et al., [6] 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 discriminant function. The recent developments in the area of symbolic data analysis have proven that the real life objects can be better described by the use of symbolic data, which are extensions of classical crisp data (Billard and Diday, [18]). Symbolic data appear in the form of continuous ratio, discrete absolute interval and multivalued interval with weightage, quantitative, categorical, etc. The concept of symbolic data analysis has been extensively studied in the field of classification and it has been proved both theoretically and experimentally that the classification approaches based on symbolic data outperform conventional classification techniques. In skeleton flowers representation, the distance between skeleton junction and end points of flowers of each class possess significant variations. Therefore, we felt that it would be more meaningful to capture these variations in the form of interval-valued features and to provide an effective representation for flower classification. To the best of our knowledge, no work has been reported in literature, which uses symbolic representation for flower classification. In this work while fixing inter valued feature we considered minimum and maximum of feature values.

The organization of the paper is as follows: section 3 presents the proposed methodology which includes flower segmentation, Skeleton Pruning and symbolic representation. In section 4 dataset and experimental results obtained using the proposed model are presented. The paper is concluded in section 5.
III. PROPOSED METHODOLOGY

The proposed method has five stages: Segmentation, Skeleton extraction, Feature reduction, Representation, and classification. The flowers are segmented using whorl based region merging segmentation and then flower skeleton is obtained using skeleton pruning method. The distance between skeleton junction points and end points is represented through symbolic approach. Finally the symbolic classifier is used to classify the flowers.

A. Segmentation

The flowers are segmented using proposed whorl based region merging segmentation. In flowers whorl region is identified using Gabor filter response and marked as foreground and boundary is marked as background. The flower is initially divided into regions using quick shift segmentation and later regions are merged into foreground & background using color histograms.

B. Whorl Detection

The Gabor response of a flower image is obtained at a specified orientation $\theta$ and a scale $\sigma$. The resulted Gabor responses will have different components constituting the boundary of the flower, whorl of the flower and other unwanted components. The boundary of the flower and whorl part of the flower will be the two largest connected components. The unwanted components which are small in size will be eliminated using morphological opening and closing operations. Once the smallest components are eliminated, we eliminate the largest connected component which is the boundary of the flower so that the remaining will be the whorl part of the flower. Whorl region of sample flowers are shown in Figure 1. Detailed discussion of whorl detection is presented in our early work [19].

C. Flower Segmentation

For flower segmentation, we enhance the work done by the Ning el al., [11] which deals with less number of images. In our method, an initial segmentation is required to partition the image into homogeneous regions for merging. For initial segmentation we used Quick shift segmentation (Vedaldi and Soatto,[20]). The major advantage of using Quick shift segmentation is greatly reduces the number of image primitives compared to the pixel representation and also it preserves boundary of different objects in the image. Therefore, quick shift has become a popular preprocessing for many computer vision applications. After initial segmentation, many small regions are available (see in figure 2). The color histograms are used as descriptors to represent the regions as the initially segmented small regions of the desired object often vary a lot in size and shape, while the colors of different regions from the same object will have high similarity. The RGB color space is used to compute the color histogram. Each color channel is quantized into 16 levels and then the histogram of each region is calculated in the feature space of $16 \times 16 = 4096$ bins. The key issue in region merging is how to determine the similarity between the unmarked regions with the marked regions so that the similar regions can be merged with some logic control. The Bhattacharyya coefficient is used to measure the similarity $\rho(R,Q)$ between two regions $R$ and $Q$.

$$\rho(R,Q) = \frac{\sum_{u=1}^{4096} \sqrt{Hist_R^u \cdot Hist_Q^u}}{\sqrt{Hist_R^u} \cdot \sum_{u=1}^{4096} \sqrt{Hist_Q^u}}$$

Where $Hist_R$ and $Hist_Q$ are the normalized histograms of $R$ and $Q$, respectively, and the superscript $u$ represents the $u$th element of them. Bhattacharyya coefficient $\rho$ is a divergence-type measure which has a straightforward geometric interpretation. It is the cosine of the angle between the unit vectors

$$(\sqrt{Hist_R^1}, \ldots, \sqrt{Hist_R^{4096}})^T \text{ and } (\sqrt{Hist_Q^1}, \ldots, \sqrt{Hist_Q^{4096}})^T$$

Higher the Bhattacharyya coefficient between $R$ and $Q$, larger is the similarity between them. In flower segmentation, the whorl detection region is called as object marker region and the boundary of the image is called as background marker region. We use green markers to mark the object while using blue markers to represent the background shown in figure 3. After object marking, each region will be labeled as one of three kinds of regions: the marker object region, the marker background region and the non-marker region. To extract the object contour, non-marker region must be assigned to either object region or background region. The region merging method starts from the initial marker regions and all the non-marker regions will be
gradually labeled as either object region or background region. Figure 4, shows the results of flower segmentation on flower images.

**D. Skeleton Pruning**

For flower skeleton generation we adopted the work proposed by Bai et.al, [21]. Initially, Discrete Curve Evolution (DCE) simplifies the polygon. Then the skeleton is pruned so that only branches ending at the convex DCE vertices remain. 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, may be relevant for a different shape, and therefore, it will remain. In order to obtain skeletons composed of only relevant branches, provided none are missing, an appropriate stopping criterion of the DCE simplification is needed. Usually we can use the same threshold as stopping criterion of DCE for the shapes in the same class, because they are very similar. A skeleton point having only one adjacent point is an endpoint (the skeleton endpoint); a skeleton point having three or more adjacent points is a junction point. If a skeleton point is not an endpoint or a junction point, it is called a connection point. The sequence of connection points between two directly connected skeleton points is called a skeleton branch. The obtained skeleton then envisaged as a graph. The figure 6 shows detected endpoints and junction points for given flower skeleton.

**E. Discrete Cosine Transforms**

We computed the Euclidean distance between pairs of detected skeleton endpoints and junction points. The obtained distance features vary between flower classes, in addition flower skeletons are more intra class variations. So it’s difficult to classify the flowers therefore we normalized the features using discrete cosine transform. The Discrete cosine transform (DCT) is a widely used method for image compression and as such it can also be used in dimensionality reduction of feature data. A discrete cosine transform (DCT) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. The DCT is conceptually similar to the discrete Fourier transform(DFT), but DCT does a better job than DFT by concentrating energy into lower order coefficients for feature data and also DCT is purely real (only magnitude). A DCT operation on a feature data produces coefficients that are similar to the frequency domain coefficients produced by a DFT operation. An N-point DCT has the same frequency resolution as and is closely related to a 2N-point DFT. The N frequencies of a 2N point DFT correspond to N points on the upper half of the unit circle in the complex frequency plane. For most feature data, after transformation the majority of signal energy is carried by just a few of the low order DCT coefficients. These coefficients can be more finely quantized than the higher order coefficients. Many higher order coefficients may be quantized to 0 (this allows for very efficient run-level coding). The efficiency purpose feature reduction varies from 5 to 100, and each feature is represented in symbolic.

**F. Symbolic Representation**

In this section, we use reduced discrete cosine transform distance features for symbolic representation of flower samples. As flower skeletons have considerable intra class variations in each subgroup, using conventional data representation, preserving these variations is difficult. Hence, the proposed work is intend to use unconventional data processing called symbolic data analysis which has the ability to preserve the variations among the data more effectively. In this work, symbolic representation (Guru and Prakash, [22]) has been adapted to capture these variations through feature assimilation by the use of an interval valued feature vector as follows.

Let \( \{T_1, T_2, T_3, \ldots, T_n\} \) be a set of \( n \) samples of a flower class say \( C_j; j = 1, 2, 3, \ldots, N \) (N denotes number of classes) and let \( F_i = \{d_{i1}, d_{i2}, d_{i3}, d_{i4}, \ldots, d_{im}\} \) be the set of \( m \) features (distances) of points of a skeleton characterizing the flower sample \( T_i \) of the class \( C_j \). Let \( \text{Min}_{jk} \) be the minimum of the \( k^{th} \) feature values obtained from all the \( n \) samples of the class \( C_j \) and let \( \text{Max}_{jk} \) be the maximum of the feature values obtained from all the \( n \) samples of the class \( C_j \).
Now, we recommend to capture the intra class variations in each $k^{th}$ feature value of the $j^{th}$ class in form of interval valued feature. That is, each class $C_j$ is represented by the use of interval valued features
\[
([d_{j1}^-,d_{j1}^+], [d_{j2}^-,d_{j2}^+], \ldots, [d_{jk}^-,d_{jk}^+])
\]
where $d_{jk}^- = \text{Min}_{jk}$ and $d_{jk}^+ = \text{Max}_j$.

Each interval representation depends on the minimum and maximum of respective individual features. The interval $[d_{jk}^-, d_{jk}^+]$ represents the upper and lower limits of the $k^{th}$ feature values of the class $j$. Now, a reference flower representing the entire class (all the samples of flower) is formed by using interval type and is given by
\[
RF_j = \left\{ [d_{j1}^-,d_{j1}^+], [d_{j2}^-,d_{j2}^+], \ldots, [d_{jm}^-,d_{jm}^+] \right\}
\]
(1.4)
where $c = 1, 2, \ldots, N$. It shall be noted that unlike conventional feature vector, this is a vector of interval-valued features and this symbolic feature vector is stored in the knowledgebase as a representative of the $j^{th}$ class. We recommend computing symbolic feature vectors for each individual sample of a class and storing them in the knowledgebase for future recognition requirements. Thus, the knowledgebase has $N$ number of symbolic vectors.

**G. Classification**

In this section we use the symbolic classifier (Guru and Prakash, [22]) for classifying the flowers. In classification model, a test sample of an unknown flower is described by a set of $m$ distances of type crisp and compared it with the corresponding interval type features (distances) of the respective symbolic reference samples $RF_j$ stored in the knowledgebase to ascertain the efficiency.

Let $F_i = [d_{i1}, d_{i2}, d_{i3}, \ldots, d_{im}]$ be an $m$ dimensional vector (of distances between points) describing a test flower. Let $RF_c; c = 1, 2, 3, \ldots, N$ be the representative symbolic feature vectors stored in knowledgebase. During flower classification process each $k^{th}$ distance (feature) value of the test flower is compared with the respective intervals of all the representatives to examine if the feature value of the test flower lies within them. The test flower sample is said to belong to the class with which it has a maximum acceptance count $A_c$.

Acceptance count $A_c$ is given by,
\[
A_c = \sum_{i=1}^{n} C(d_{ik}, [d_{ik}^-, d_{ik}^+])
\]
(1.5)
where,
\[
C(d_{ik}, [d_{ik}^-, d_{ik}^+]) = \begin{cases} 1 & \text{if } (d_{ik} \geq d_{ik}^- \text{ and } d_{ik} \leq d_{ik}^+) \\ 0 & \text{otherwise} \end{cases}
\]
When the database happens to be large, there is a possibility for a test flower sample to possess the same maximum acceptance count with two or more flower classes. Under such circumstances we recommend to resolve the conflict by the use of the following similarity measure (Guru and Prakash, [22]) which computes the similarity value between a test flower sample and each of the conflicting classes say $j^{th}$ class.

\[
\text{Total\_Sim}(F, RF_j) = \sum_{i=1}^{n} C(d_{ik}, [d_{ik}^-, d_{ik}^+])
\]
(1.6)

Here $[d_{jk}^-, d_{jk}^+]$ represents the $k^{th}$ feature interval of the $j^{th}$ conflicting class, and
\[
C(d_{ik}, [d_{ik}^-, d_{ik}^+]) = \max \left( \frac{1}{1+|d_{ik}^+ - d_{ik}^-|^\delta}, \frac{1}{1+|d_{ik}^+ - d_{ik}^-|^\delta} \right) + 1
\]
where $\delta$ is a normalizing factor.
IV. EXPERIMENTATION

A. Datasets

In this work we have created our own database of flower images 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. We introduce a dataset consisting of 3000 images divided into 30 flower classes. Figure 7 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.

B. Results

In this section, we intend to study the classification accuracy under varying features of DCT. We picked images randomly from the database and experimentation is conducted on database of 30 classes under varying training samples 40, 60 and 80 from each class. Figure 8 shows accuracy for different sets of training sample under varying reduction DCT features from 5 to 100. The feature reduction value 75 achieves the maximum accuracy of 49.5 for 40 training percent, feature reduction value 65 achieves the maximum accuracy of 63.71 for 60 training percent and feature reduction value 65 achieves the maximum accuracy of 91.2 for 80 training percent.

V. CONCLUSION

In this paper, we made a successful attempt to explore the applicability of the concepts of symbolic data to skeleton flower classification. The newly proposed model has an ability to capture the variations of the features in training samples of flower samples. The symbolic representation reduces the time taken to classify a given test sample of a unknown flower, as there is only one representative vector instead of n (training samples) number of representative vectors in the knowledge base. In order to investigate the effectiveness and robustness of the proposed method, we have conducted extensive experiments on our own dataset. In future we are planning considering only partial occluded flower for classification.
Fig 5: shows skeleton and detected endpoints and junction points for given input flower.

Fig 8: shows the accuracy for different training samples under varying features.

Fig 6. Sample flower images of 25 flower classes considered in this work.

Fig 8: shows the accuracy for different training samples under varying features.
REFERENCES