Automatic Recognition System Using Preferential Image Segmentation For Leaf And Flower Images

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ABSTRACT

Plant is one of the most important forms of life on earth. Plant recognition is very demanding in biology and agriculture as new plant discovery and the computerization of the management of plant species become more popular. The recognition is a process resulting in the assignment of each individual plant to a descending series of related plants in terms of their common characteristics. The process is very time-consuming as it has been mainly carried out by botanists. Computer-aided plant recognition is still very challenging task in computer vision as the lack of proper models or representation schemes, a large number of variations of the plant species, and imprecise image pre-processing techniques, such as edge detection and contour extraction. The focus of computerized living plant recognition is on stable feature's extraction of plants. The information of leaf veins, therefore, play an important role in identifying living plants. The ultimate goal of this project is to develop a system where a user in the field can take a picture of an unknown plant, feed it to the system carried on a portable computer, and have the system classify the species and display sample images of the closest matches within a couple of seconds.

Keywords

Preferential image segmentation, Tree of shapes, Curve matching, pre-processing, Filters, feature extraction

1. INTRODUCTION

Automatic plant classification systems are essential for a wide range of applications including environment protection, plant resource survey, as well as for education. With the aid of advanced information technology, image processing and machine learning techniques, automatic plant identification and classification will enhance such systems with more functionality, such as automatic labelling and flexible searching. Image segmentation and object recognition are two aspects of digital image processing which are being increasingly used in many applications including leaf recognition. In this paper, the Preferential Image Segmentation (PIS) [3] method is used to segment an object of interest from the original image. A probabilistic curve evolution method with particle filters is used to measure the similarity between shapes during matching process. The experimental results prove that the preferential image segmentation can be successfully applied in leaf recognition and segmentation from a plant image.

Plant is important for environment protection. However, the problem of plant destruction becomes worse in the few years. We should train people to know plant, which in turn, to treasure

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and protect plant. In addition to the limited number of expert botanists, automatic classification and recognition system for plant is necessary and useful since it can facilitate fast learning of plants.

Digital image processing is the use of the algorithms and procedures for operations such as image enhancement, image compression, image analysis, mapping, geo-referencing, etc. The influence and impact of digital images on modern society is tremendous and is considered as a critical component in variety of application areas including pattern recognition, computer vision, industrial automation and healthcare industries. Image processing can be roughly categorized as follows: imaging, image denoising, image restoration, image coding, image segmentation, image transformation, object representation and recognition, and content-based image retrieval. Typical tasks for computer vision are scene interpretation, object recognition, optical character recognition, registration, feature extraction and video tracking. Edge detection methods utilize intensity gradients to detect the boundaries of objects. However, edge detection methods usually generate edges that are not closed contours, and this causes difficulties for later processing such as object recognition. Curve evolution methods have been popular for image segmentation since the early 1990s. These methods evolve the initialized curve(s) to the boundaries of objects in an image. The evolution of the curves may be driven by image gradient information region information or their combination .These methods are theoretically solid and numerically stable. Moreover, these methods generate image segments enclosed by closed contours, which leads to straightforward post processing. When we wander around the fields, we can find lots of plant. However, we rarely know their names. We may consult their name with the book about plant but even such a book is on hand, it is not easy to find a proper section or an exact page showing the plant. It would be useful if we take a picture of the plant's leaf and feed the picture into a computer and the computer can aid recognition and classification of the plant. In addition, some knowledge about the plant can be obtained to facilitate learning. In this study, we try to analyze various leaf features so that some useful features can be extracted, which, in turn are used to achieve the goal of automatic classification of leaves. Plants are basically classified according to shapes, colors and structures of their leaves and flowers However, if we want to recognize the plant based on 2D images, it is difficult to analyze shapes and structures of flowers since they have complex 3D structures. On the other hand, the colors of leaves are always green; moreover, shades and the variety of changes in atmosphere and season cause the color feature having low reliability. Therefore, we decided to recognize various plants by the grey-level leaf image of plant. The leaf of plant carry useful information for classification of various plants, for example, aspect ratio, shape and texture. The system is user friendly. The user can scan the leaf and click the recognition button to get the solution.

There are many kinds of plants that exist on the earth. Plants play an important role in both human life and other lives that exist on the earth. Due to various serious issues like global warming, lack of awareness of plant knowledge, etc., the categories of plant is becoming smaller and smaller. Fortunately, botanists are realizing the importance of protecting plants and are discovering methods to protect them. In a similar fashion, there is also a need for recognizing a plant by its category, to help agriculturists / farmers during reproduction of extinct plants. The main challenge faced by them is the identification of the category to which a particular plant belongs to. To help them in this challenging venture, several researches (Man *et al.*, 2008; Lee and Chen, 2006) are conducted to automatically classify a plant into a category, when its leaf sample image is given as input.

Plant has plenty use in foodstuff, medicine and industry. And it is also vitally important for environmental protection. However, it is an important and difficult task to recognize plant species on earth. Designing a convenient and automatic recognition system of plants is necessary and useful since it can facilitate fast classifying plants, and understanding and managing them

(Tzionas *et al.*, 2005). The classification of plant leaves is a vital process in botany and in tea, cotton and other industries. Moreover, it can also be used for early diagnosis of certain plant diseases.

The paper is organized as follows. Section 2 describes the general architecture used by plant classifiers. Section 3 explains the preferential image segmentation, while section 4 summarizes the results and section 5 shows the conclusion and references.

2. GENERAL ARCHITECTURE

The general process for plant classification through leaf recognition is given in Figure 1.

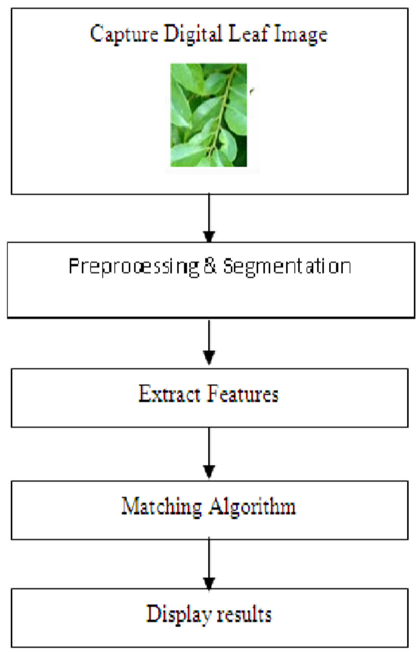


Figure 1 General architecture of Automatic Plant Classification system

The performance of object recognition depends on the performance of pre-processing and segmentation. Segmentation is defined as the process of partitioning a digital image into multiple segments, where the pixels inside each segment share certain visual characteristics such as color, intensity or texture. Adjacent regions are significantly different with respect to the same characteristics. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze (Shapiro and Stockman, 2001). Image segmentation locates objects and boundaries (lines, curves, etc.) in images. After segmentation, the image is represented by a set of segments, which collectively represents the entire image. The process of plant identification through leaf recognition is explained below.

2.1 Capturing Leaf Image

In this paper the leaves samples are collected in the forest and the leaves are full-grown. Leaf image could be captured using a scanner or CCD camera, (shown in Figure. The acquired images are RGB color images, so we need to convert the colors from RGB to Gray, by which we can avoid the color disturbed.

Figure 2 Sample Leaf

The above figure 2 shows the sample plant leaf. Since classification is a complex operation that needs high memory usage normally, lossy compression format like JPEG / BMP / GIF is used. For convenience take all the leaf images to be of the same size and resolution. Plants are basically classified according to shapes, colors and structures of their leaves and flowers. In addition, the colors of leaves are always green shades and the variety of changes in atmosphere cause the color feature having low reliability. Therefore, to recognize various plants using their leaves, the obtained leaf image in RGB format will be converted to gray scale before pre-processing. The formula used for converting the RGB pixel value to its greyscale counterpart is given in Equation 1.

$$Gray = 0.2989 * R + 0.5870 * G + 0.1140 * B \qquad (1)$$

where R, G, B correspond to the color of the pixel, respectively.

2.2 Pre-processing

The leaf image pre-processing refers to the initial processing of input leaf image to correct the geometric distortions, calibrate the data radiometrically and eliminate the noise and clouds that present in the data [15]. These operations are called pre-processing because they normally carried out before the real analysis and manipulations of the image data occur in order to extract any specific information. The aim is to correct the distorted or degraded image data to create a more faithful representation of the real leaf.

Various pre-processing techniques are then used to enhance the leaf image obtained. Several techniques like boundary enhancement, smoothening, filtering, noise removal, etc. can be applied to improve the quality of the leaf image. The following figure shows the pre-processing steps in leaf image.

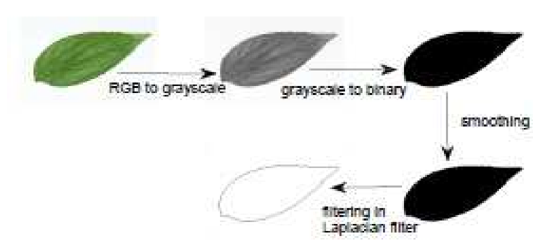
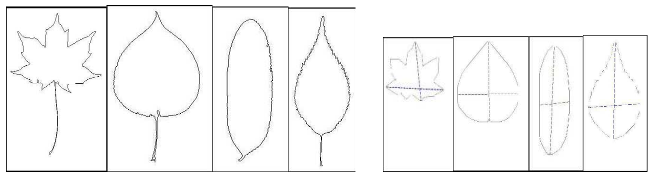


Figure 3 Pre-processing Example

2.3 Feature Extraction

Several feature extraction is performed to obtain the leaf contour. The image-threshold [3] operation is applied to the gray image to obtain the binary image of leaf shape. Then the binary image is traced to produce the contour of leaf by making use of the border tracing algorithm. The traced contour, length and width of leaf is shown in Figure 4.



(a) Leaf contour (b) Leaf length and width

Figure 4 Feature extraction

2.4 Image Segmentation

Image segmentation is a fundamental task in computer vision. Although many methods are proposed, it is still difficult to accurately segment an arbitrary image by any method alone. In recent years, more and more attention has been paid to combine segmentation algorithms and information from multiple feature spaces (e.g. color, texture, and pattern) in order to improve segmentation results. According to literature survey, segmentation algorithm is explained based on two properties such as, discontinuity and similarity. For leaf recognition, basic standard segmentation algorithms are taken and are discussed in this section.

Segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels) (also known as super pixels). More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

Several approaches to segmentation have been proposed which can be categorized into cluster based techniques (Pauwels and Frederix, 1999), histogram based techniques (Zwiggelaar, 2010) [9], compression based techniques (Ballester *et al.*, 2007) [15], edge detection, region growing methods (Chen and Georganas, 2008) [5], Graph partitioning methods (Sumengen and Manjunath, 2006), watershed transformation (Wenzhong and Xiaohui, 2010), etc. Another popular method used is the curve evolution methods (Farzinfar *et al.*, 2010). These methods evolve the initialized curve(s) to the boundaries of objects in an image. The evolution of the curves may be driven by image gradient information (Kichenassamy *et al.*, 1995; Caselles *et al.*, 1997), region information (Chan and Vese, 2001 [6]; Jehan-Besson *et* al., 2003) [2], or their combination (Tsai *et al.*, 2001)[4]. The image segments generated are enclosed by closed contours and are unsupervised which make it an ideal candidate for image post processing. These methods are more suitable for simple images and their performance degrades both in terms of segmentation and complexity, with complicated images (Paragios and Deriche, 2000). In such cases, the utilization of prior information is necessary for curve evolution methods in complicated image segmentation applications.

Several methods have been proposed that utilize prior information for supervised image segmentation. These methods usually propose new variational energy functions which integrate both the prior information and the gradient/region information in the image to be segmented. The minimizations of these functions can lead to segmentation results. Shape priors are utilized in (Cremers and Funka-Lea, 2005; Cremers *et al.*, 2002; Chen, 2002)[7,8] and (Leventon *et* al., 2000). Both intensity priors and shape priors are applied in Leventon *et al.*, (2000). Natural image statistics are employed for natural image segmentation in Heiler and Schnorr (2005). These methods usually work better than unsupervised methods. However, shape priors are primarily incorporated in supervised segmentation methods, and the information contained in the intensities is not always fully utilized. For example, the methods in Freedman *et al*. (2005) and Freedman and Zhang (2004) [10]make use of the intensity histograms only, and the spatial information is ignored. Furthermore, these methods usually have initialization problems because the energy functions have multiple local minimums. The methods are sensitive to the initial locations of the evolving curves.

In some cases, the user may be interested only in finding the location of an object within the image. In such cases the background and other non-interested objects need not be clustered. To perform such a task, the process of segmentation is combined with object recognition. This concept is the key idea behind “Preferential Image Segmentation” (PIS). PIS method is described as a method to preferentially segment objects of interests from an image and ignore the remaining portions of the image for this application. An example of leaf and flower set is shown in Figure 5 & 6.

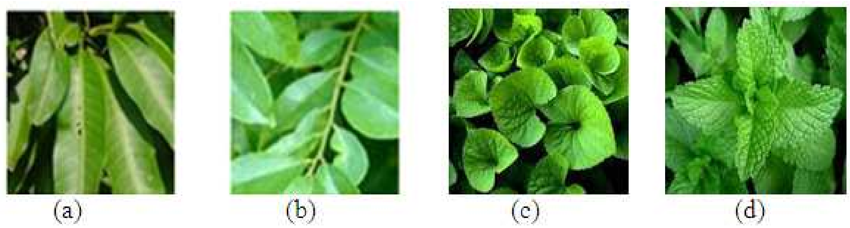


Figure 5 Sample Leaf images

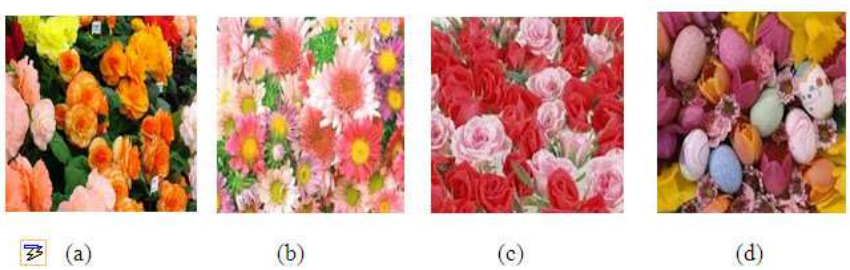


Figure 6 Sample Flower images

PIS can be considered as a method similar to object detection, where rough location of the object of interest is identified (Agarwal *et al*., 2004) [11]. The drawback behind this method is that it often neglects to provide the exact boundaries which are very important for segmentation. Similarly, classification methods (Aujol *et al*., 2003), image parsing methods (Tu *et al*., 2005)[14], wavelets (Aijol *et al*., 2003) and variational methods (Samson *et al*., 2000) can be considered similar to PIS. However, these methods classify the image as a whole instead of separating it into meaningful objects and additionally they are computationally intense.

This paper analysis the usage of PIS to segment leaves from a plant. Segmenting leaves from plant / tree is considered important in plant identification system. Automatic plant identification by computers is a very important task for agriculture, forestry, pharmacological science and etc. The general plant identification system is composed of four steps, namely, (i) pre-processing (ii) segmentation (iii) feature extraction and (iv) matching process. In this paper a method of PIS using tree of shapes for car recognition proposed by Pan *et al*. (2009) is analyzed and applied for our test bench.

3. PREFERENTIAL IMAGE SEGMENTATION (PIS)

A novel preferential image segmentation method is proposed in this paper using techniques from mathematical morphologies. This method is motivated by the utilization of prior information in curve evolution models. However, image topologies may provide better results for complicated cases. The proposed method utilizes a tree of shapes to represent the image content.

This representation provides a hierarchical tree for the objects contained in the level sets of the image. The hierarchical structure is utilized to select the candidate objects from the image. The boundaries of the selected objects are then compared with those of objects selected from prior images. By means of the tree of shapes and curve matching, the proposed method is able to preferentially segment objects with closed boundaries from complicated images. It is more straightforward to utilize prior information in this way than with the curve evolution methods, and there is no initialization problem. Furthermore, the method is invariant to contrast change and translation, rotation and scale. The method has been shown to work in the presence of noise.

Tree of shapes provides a natural way to represent the spatial relationships of the shapes in an image. It represents images based on the techniques of contrast-invariant mathematical morphologies. This method is based on the theory of image representation using connected components of set of finite perimeters in the space of functions with Weakly Bounded Variations (WBV). It shows that an image, if taken as a function of weakly bounded variation is guaranteed to be decomposed into connected components with closed boundary this is an extension to classical methods where an image is taken as a piecewise- smooth function. The representation of an image using a tree of shapes utilizes the inferior or the superior of a level line to represent an object, and considers the boundary of the inferior area as the shape of the object. Therefore, only closed shapes are generated. This representation also provides a tree structure to represent the spatial relationship for the objects in an image. Concept of "shape" is introduced to generate a unique inclusion tree for an image. A shape is defined as the connected components of a level set and the holes inside them. The whole image acts as the root of the tree located at the top level. The shapes in the same level are spatially disjoint in the image. The shapes in the lower level are spatially included in the shapes in the next higher level. The tree of shapes, therefore, provides a natural way to represent the spatial relationships between the shapes in the image.

The tree of shapes is used as a candidate to obtain the intensity information in the priori image which is used in preferential segmentation. A common method used to construct tree of shapes to both images (Figures 3a and 3b), whose features are then compared to identify the ratio of similarity between the images. However, the main disadvantage of this approach is the amount of shapes (features) generated, which is very huge. For examples, the example picture produces 3832 shapes (Figure 2b). The closed curves in Figure 4 correspond to the boundaries of the shape in the tree of shapes. These discovered boundaries provide valuable information which can be utilized during shape similarity measure.

3.1. IMAGE REPRESENTATION USING THE TREE OF SHAPES

The tree of shapes represents images based on the techniques of contrast-invariant mathematical morphologies .This method is based on the theory of image representation using connected components of set of finite perimeters in the space of functions with weakly bounded variations (WBV), as introduced in .It shows that an image, if taken as a function of weakly bounded variation is guaranteed to be decomposed into connected components with closed boundary .This is an extension to classical methods where an image is taken as a piecewise- smooth function.

The representation of an image using a tree of shapes utilizes the inferior or the superior of a level line to represent an object, and takes the boundary of the inferior area as the shape of the object. Therefore, only closed shapes are generated. This representation also provides a tree structure to represent the spatial relationship for the objects in an image. For a gray image with, the upper level set of value and the lower level set of value are obtained. The above definitions have several advantages. First, they represent regions instead of curves in an image, which provide a way to handle the contents inside the regions. Second, they are invariant to the contrast changes in an image, which may be caused by the change of lighting .Third, closed boundaries are acquired for each upper level set or lower level set, which can be utilized for shape matching of the regions. As the number of shapes increases, the computational complexity also increases, thus necessitating to reduce the number of shapes used during segmentation and shape comparison.

3.2. PLANAR CURVE MATCHING

The method in defines the shape of a curve as a conjunction of shape elements and further defines the shape elements as any local, contrast invariant and affine invariant part of the curve. These definitions are oriented to provide invariance to noise, affine distortion, contrast changes, occlusion, and background. The shape matching between two images are designed as the following steps.

1) Extraction of the level lines for each image. The level set representations are utilized here for the extraction. The level line is defined as the boundaries of the connected components as shown before.

2) Affine filtering of the extracted level lines at several scales. This step is applied to smooth the curves using affine curvature deformation to reduce the effects of noise.

3) Local encoding of pieces of level lines after affine normalization .Both local encoding and affine normalization are designed for local shape recognition methods. This step will help to deal with occlusions in real applications.

4) Comparison of the vectors of features of the images. Euclidean Distance is utilized to compare the feature vectors. The performance of curve matching between two curves is calculated after affine filtering, Curve normalization and local en-coding is calculated.

This is performed using the intensity information that is contained inside the shape. The intensity information by means of the tree of shapes includes the following features.

1. The number of objects (Nd) contained directly in the shape, which corresponds to the number of direct children of the shape in the tree, Nd=2 for the indicated shape in Figure 2a.

2. The total number of objects (Nt) contained in the shape, which corresponds to the total number of children below the shape in the tree Nt=3 for the indicated shape in Figure 2a.

3. The relative area change between the shape and its direct children. Suppose the area of the shape is S, and the areas of its direct children are S_i, where $1 \leq i \leq Nd$, the relative area change is then defined as

$$A = \prod_{i=1}^{Nd} \frac{S_i}{S}$$

4. The rough similarities of the boundaries of the shapes, which can be represented as the ratio of the circumferences (C) squared to the area (S) of the boundaries of the shapes (Gonzalez and Woods, 2002), i.e., $R=C^2/S$.

These features for the two shapes should be very close to match. Exact matching may not be achieved because of the differences between shapes, the effects of noise, lighting changes and cluttered background. Thresholds should be set for coarse matching to affect a rapid exclusion of most candidate shapes and can be adjusted according to the application.

The number of candidate shapes decreases substantially by means of the intensity features extracted from the tree of shapes. In the case of Figure 3b, the feature decreases the number of candidate shapes from 3832 to 977; the feature decreases the number from 977 to 83; the feature decreases the number from 83 to 1; the feature retains this candidate. The candidate shape left over matches the prior shape, as shown in Figure 2d. The process takes 1.70 s.

In most cases, however, the candidate shapes will decrease from thousands to tens. Curve matching is then performed on the boundaries of the resulting candidate shapes and the prior shapes. The candidate shape which best matches the prior's curve is taken as the preferential segmentation result.

The curve matching steps are outlined below:

1) Extraction of the level lines for each image. The level set representations (1), (2) are utilized here for the extraction. The level lines are defined as the boundaries of the connected components.

2) Affine filtering of the extracted level lines at several scales. This step is applied to smooth the curves using affine curvature deformation to reduce the effects of noise.

3) Local encoding of pieces of level lines after affine normalization. Both local encoding and affine normalization are designed for local shape recognition methods. This step will help to deal with occlusions in real applications.

4) Comparison of the vectors of features of the images. Euclidean distance is utilized to compare the feature vectors.

The performance of curve matching between two curves is calculated after affine filtering, curve normalization and local encoding. Suppose C_1 and C_2 and are two curves for matching, and S_1 and S_2 are pieces from and C_1 and C_2, respectively, then the performance to take S_1 and S_2 as the matching between C_1 and C_2 is calculated using the formula as shown below,

$$\text{Score} = \frac{l_1 \text{x} l_2}{L_1 \text{x} L_2}$$

where l_1=arclength(S_1), l_2=arclength(S_2), L_1= arclength(C_1) and L_2 = arclength(C_2). The maximum score over all possible matching pieces is taken as the matching between the curves C_1 and C_2. The implementation and description is provided in Lisani *et al*. (2003).

This paper introduced the usage of PIS segmentation for plant and flower recognition. The PIS method integrated image segmentation and object recognition using the tree of shapes, which is an approach to the mathematical description of morphology. The system was tested with several images and the results are discussed in the next section.

4. RESULTS

The system was evaluated using a series of benchmark images belonging to two categories. The first is the leaf images along with plant images. The second is flower images and their corresponding images. A total of 500 plant and flower images were collected (Set I). All these images were RGB color images of 256 x 256 pixels size. A total of 100 leaf and single flower images were stored separately (Set II). These pictures also belonged to RGB color space and care was taken to collect different sized images ranging from roughly 0.8 to 2 times the size of plants in the first set. Sample images of plants from Set I are shown in Figure 4. In a similar fashion, Figure 7&8 shows sample images of leaves in Set I and sample images of flower in Set II.

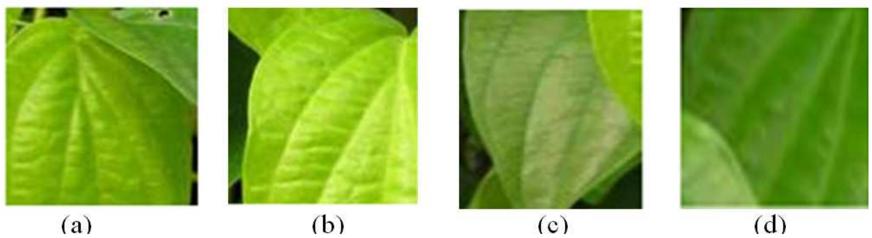


Figure 7 Sample images of leaves in Set I

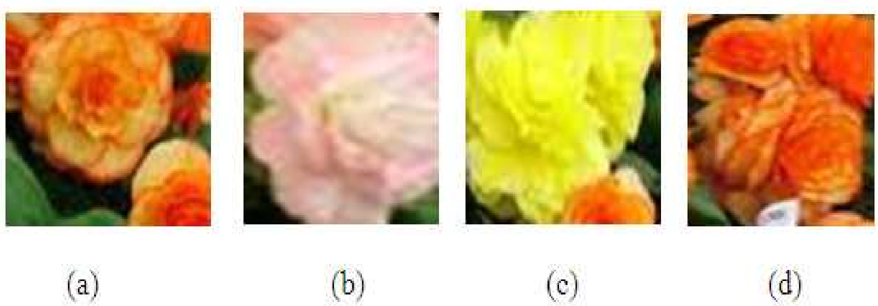


Figure 8 Sample images of flowers in Set II

The visual results obtained while using preference image segmentation with plants and flowers are given in this section. Figure 9 and 10 shows the image after PIS.

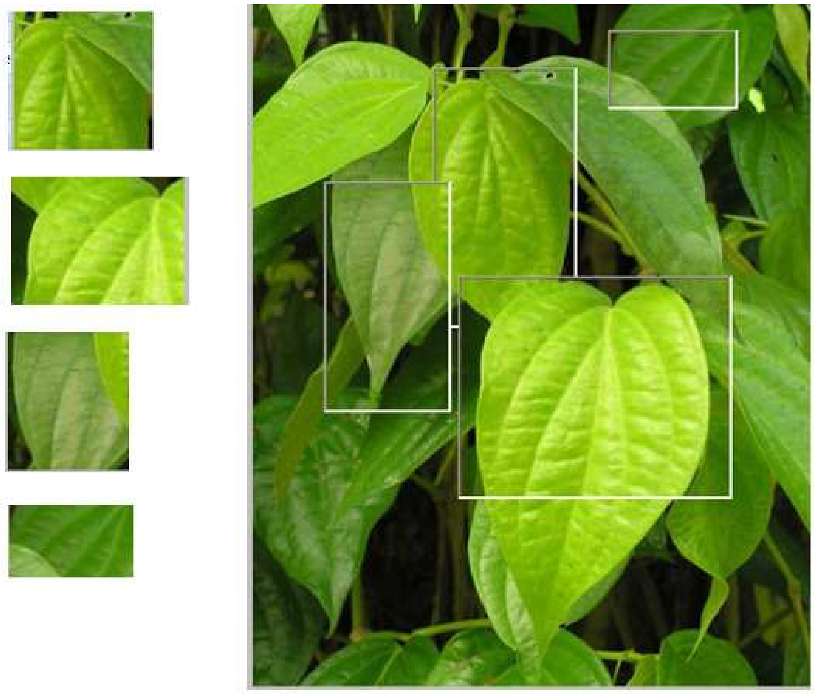


Figure 9 Leaf Recognition

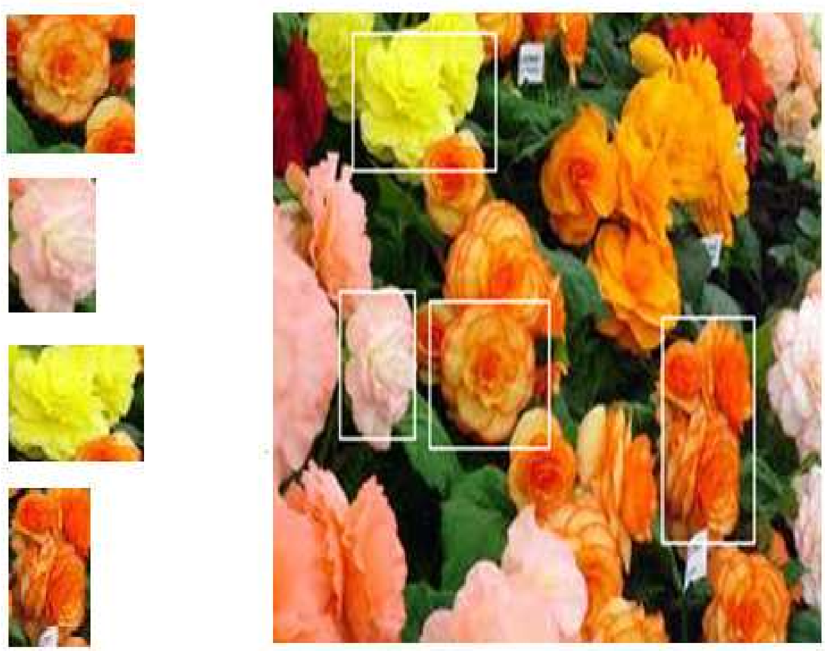
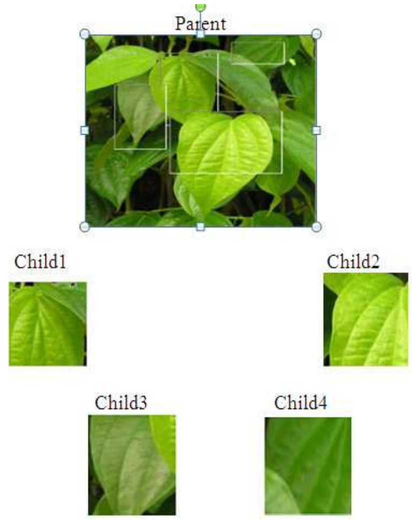


Figure 10 Flower Recognition



(a)

(b)

Figure 11 Tree of Shapes for leaf and flower

The tree of shapes obtained for Figure 9 and Figure 10 are shown in Figure 11. From the results, it is evident that the PIS algorithm is a good candidate for leaf and flower segmentation and object recognition from plants and set of flowers.

5.Conclusion

The computerization of the management of plant species become more popular. The recognition is a process resulting in the assignment of each individual plant to a descending series of related plants in terms of their common characteristics. The process is very time-consuming and it has been mainly carried out by botanists. Computer-aided plant recognition is still very challenging task in computer vision as the lack of proper models or representation schemes, a large number of variations of the plant species. The focus of computerized living plant recognition is on stable feature's extraction of plants. The information of leaf veins, therefore, play an important role in identifying living plants. The ultimate goal of this project is to develop a system where a user in the field can take a picture of an unknown plant, feed it to the system carried on a portable computer, and have the system classify the species and display sample images of the closest matches within a couple of seconds. In this project preferentilal image segmentation is proposed for automatic recoginition of leafs and flowers. This method encodes the prior information for preferential segmentation as a tree of shapes. The method is invariant to translation, rotation and scale transformations because both feature extraction and boundary matching are invariant to these transformations. All these features and the positive results obtained prove that the Preferential Image Segmentation method can be successfully exploited in leaf identification for plant recognition systems. Future research directions include testing the image with more flowers and leaf images and incorporating the PIS method into the leaf recognition system

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