iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 3 Issue: X Month of publication: October 2015

DOI:

www.ijraset.com
IC Value: 13.98

Volume 3 Issue X, October 2015
ISSN: 2321-9653

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Plant Image Retrieval System Using Color & Shape Feature

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Abstract— Image retrieval techniques have not been deployed significantly for plant in Agriculture sector. Agricultural sector of Indian Economy is one of the most significant parts of India. About 75% people are living in rural areas and are still dependent on Agriculture. About 43% of India's geographical area is used for agricultural activity. Image retrieval system is use full for the agricultural field to determine growth and insect attack of plant. Also it can be use for the Detecting weeds in the field, whether or not a plant is damage by a specified illness and distinguish weeds form soil regions. We are going to use color and shape features image retrival. Feature extraction like color and shape, is done by the different color techniques with SIFT for shape.

Index Terms— SIFT (Scale-invariant feature transform), nRGB, HVS, YCrCb color models, GMM.

I. INTRODUCTION

IMAGE Image retrieval system is effective technique in obtaining the exact image from the given database by inputting the features of image. This technique if deployed for plant in the agriculture application will be helpful in solving problems in agriculture field. Many retrieval systems have been developed, but the problem of retrieving images on the basis of their pixel content remains largely unsolved number of querying techniques like query by example, semantic retrieval, browsing for example images, navigating customized/hierarchical categories, querying by image region (rather than the entire image), querying by multiple example images, querying by visual sketch, querying by direct specification of image features, and multimodal queries (e.g. combining touch, voice, etc.) can be used to retrieve exact image. Content comparison can be done using image distance measurement, color, shape, texture manipulation.

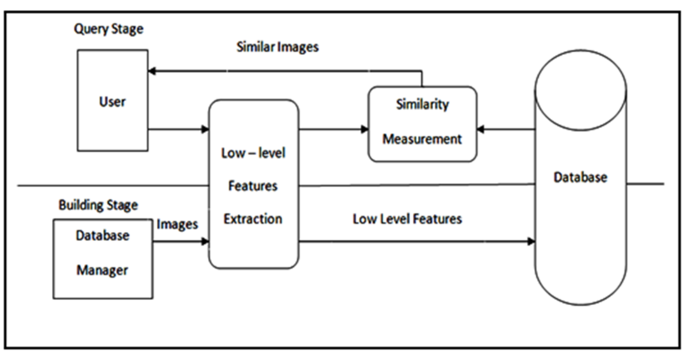

Fig 1.1: Block diagram of Image Retrieval System

II. SEGMANTED IMAGE

The image should be free from background. Now a days so many techniques are available to do image segmentation processes. For our system we are taking segmented image. The information given about the foreground and the background are given by the user as a rectangular selection around the object of interest. Pixels outside this selection are treated as known background and the pixels inside are marked as unknown. From this data we want to create a model that we can use to determine if the unknown pixels are either foreground or background. min-cut/max-flow algorithms from combinatorial optimization can be used to minimize certain important energy functions in vision[9,14]. In the Grab-Cut algorithm this is done by creating K components of multivariate Gaussian Mixture Models (GMM) for the two regions [5]. K components for the known background and K components for the

Volume 3 Issue X, October 2015
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

region that could be the foreground, giving a total 2K components.

Fig 2.1: Segmentation examples the input image, the seed points shown as white (background) and red (foreground) regions and the segmented images are shown in a row.

III. FEATURE EXTRACTION

In the developed system, images are analyzed using various color, and shape features. The use of color in plant retrieval is more complicated compared with most other Retrieval system applications, since most plants have green tones as their main color. Furthermore, the color of the flowers also poses a challenge: two flowering plants should be matched despite differences in flower colors. For instance, given a hyacinth of a certain color, ideally one should find its exact match from the database, as well as other hyacinth plants with different lower colors like the ones. We currently use some basic color features consisting of color histograms and color co- occurrence matrices obtained from the segmented image, to represent the color information. Probably the most important aspect of an object is its shape, and the same applies to plants as well. In the plant identification problem, both the leaf shape and the overall shape of the plant are important. We use the SIFT features to extract the local shape features of the plant and some newly proposed features extracted from the plant's outer contour, to describe the overall plant shape.

A. Color Feature

We used color histograms and color co-occurrence matrices to assess the similarity between two images [10–13]. If the overall color or color pair distributions of two images are close, they are matched as similar in terms of their colors. Three different color spaces are used to produce color histograms; namely RGB, normalized RGB (nRGB) and HIS color spaces [8,14]. In the RGB color space, each color is represented as a combination of the three primary color channels (Red, Green and Blue). In fact, different color spaces may be suitable in different applications. For instance, the nRGB and the HSI color spaces are often used in order to obtain robustness against illumination differences. The normalization process effectively normalizes for different illumination conditions. The colors are represented by three normalized color values (nR, nG, nB), which indicate the red, green and blue color ratio in a specific pixel. The normalization computation for red and green channels is formulated as follows:

$$nR = R/(R+G+B) \ \& \ nG = G/(R+G+B)$$

In the HSI color model, color is represented using its Hue, Saturation and Intensity values. The important feature of this color space is the separation of the intensity from the chromaticity. For the nRGB representation, one of the channels can be deduced from the normalized value of the other two (nR + nG + nB = 1); therefore, we compute the nRGB color histogram using only the values of two normalized channels, which affords more bins (for a total of 256 bins, using 4 bit for each of the nR and nG values). In the HSI space, the RGB Method 256 different hue values are quantized to 256 bins. The intensity value is intentionally discarded, while the saturation component is unused in the current work, for simplicity. Prior to histogram matching, we smooth the computed histograms by taking weighted averages of the consecutive bin values, so as to obtain some robustness against quantization problems. Although color co-occurrence is generally mentioned as a texture analysis method, it primarily indicates the distribution of color pairs. We use a 8×8 co-occurrence matrix computed from the HSI color space, where C[i][j] stores the number of neighboring image pixels having the hue values i and j . We generate the co-occurrence matrix using three different methods: (i) considering only four neighboring pixels (i.e. top, bottom, right and left neighbors); (ii) considering all eight neighboring pixels; and (iii) using 8-neighbors but ignoring the diagonal elements of the co-occurrence matrix [7]. Diagonal elements store the number of neighboring pixels that have the same quantized color and dominate the matching process since they correspond to large uniform color regions in the image.

Volume 3 Issue X, October 2015
ISSN: 2321-9653
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B. Shape Feature

The features the SIFT algorithm detects represent minima and maxima in scale space of these difference-of-Gaussian images. local features such as scale-invariant feature transform (SIFT) descriptors [1,2] are used for this problem, in locating objects within complex scenes At each of these minima and maxima, a detailed model is fit to determine location, scale and contrast, during which some features are discarded based on measures of their (in) stability [6]. Once a stable feature has been detected, its dominant gradient orientation is obtained, and a key-point descriptor vector is formed from a grid of gradient histograms constructed from the gradients in the neighborhood of the feature. Key-point matching between images is performed using a nearest-neighbor indexing method, followed by a Hough transform that finds key-points that agree on potential object poses, and finally a solution for affine parameters, which determines the specific location and orientation of each recognized object.

IV. MATCHING

The dissimilarity between a query image Q and a database image I is assessed according to the extracted feature(s). The metrics used in matching different features are explained in his section.

A. Color Matching

The RGB color dissimilarity score of two images Q and I is calculated using the Kullback–Leibler divergence (KL divergence) measure of the corresponding histograms h_Q and h_I :

$$\delta_{RGB}(Q,I) = -\sum_{i=1}^{512} h_Q(i) log h_I(i) + \sum_{i=1}^{512} h_Q(i) log h_Q(i)$$

Where $h_Q(i)$ and $h_I(i)$ are the values of i^{th} bin of Q's and I's
histograms, respectively. The KL-divergence of two histograms can be expressed using the concept of entropy; specifically how many bits are needed to represent the histogram of *I* by using the histogram of *Q* as the reference:

$$\delta_{RGB}(Q,I) = H(h_Q, h_I) - H(h_Q).$$

Here $H(h_Q, h_I)$ is called cross entropy of h_Q and h_I , while
$H(h_Q)$ is the entropy of Q's histogram.

B. Shape Matching

When using SIFT features, the similarity of two images is measured by the number of matching SIFT keypoints [2]. We use the following normalized SIFT dissimilarity score, for two images Q and I:

$$\delta_{SIFT}(Q,I) = 1 - \alpha(log_{10}(m+1))$$

Where *m* is the number of matching SIFT keypoints, α is a normalization constant with a current value of 0.25 and a logarithmic scale is used since the number of matching points range between 0 and possibly several hundreds. Note that sing the unnormalized number of matching SIFT points is sufficient for retrieval, if SIFT features are used alone. Normalization is necessary when combining the SIFT dissimilarity with the dissimilarity scores obtained from the other features.

V. DATABASE

Currently, we have 10 plant images from 5 different plant types in our database, collected mainly from the Web, but also by taking pictures of available Agricultural plants. The number of images for each plant type varies from type to type, ranging from 1 to 3 images, while the average number of images per plant is about 5. All the original images in the database are semi-automatically segmented to remove the background. The created house plant image database is publicly available. The data collection is ongoing, with the aim of extending the variety to a minimum of 100 different plants as part of future work.

VI. EXPERIMENTAL RESULTS

The performance of the system is evaluated by running tests over our plant image database. Each test is done as a one-versus-the-rest test, by querying each image in the database against the remainder. The main metric used in assessing performance is the top-N retrieval rates indicating whether the correct plant type is among the top N returned images. We used top-10 and top-15 retrieval rates, assuming that a user can easily and quickly identify the correct image among 10–15 returned images. In addition, we present the average minimum rank value which indicates the rank of the best matching correct plant, averaged over all queries. All three feature classes (color, shape and texture) are tested with all possible parameters and retrieval methods that we proposed. In addition to these individual tests, several combined methods are tested as well. In summary, test results show that the most useful individual feature class is color, followed by texture and global shape, and that the performance of the system is increased when combining several features. Since the performance of the proposed method is still relatively low, we also include the performance of a dummy engine, which randomly selects the retrieved images, in the overall result tables. The following sections present test results with comments on the performance of the retrieval methods

A. Results Using Color & Shape Combine

Shape	Color	Top-10%	Top-15%
SIFT	RGB	0.80	0.85
	HSI	0.70	0.76
	YCrCb	0.60	0.60
	Gray	0.80	0.53

Table 6.1 Accuracies of System for Shape + Color features

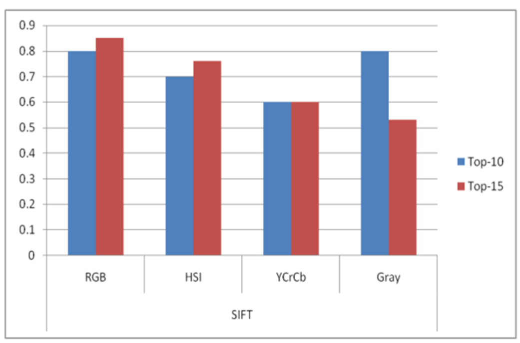

Figure 6.1 Result for the image retrieval system using combining Color & Shape feature

VII. CONCLUSION

We present a plant image retrieval system, with a segmentation preprocessing step. Extracting plant regions from images by the MFMC segmentation technique has given us an opportunity to focus solely on the plant, which increased consistency of the retrieved global features. Furthermore, combining different color and shape features extracted from the images enhance the accuracy of the system. Common techniques are used in color feature extraction steps: color histograms and color co-occurrence matrices on different color models. For shape-based retrieval, we used SIFT features that capture local characteristics of the plant, as well as newly proposed global shape descriptors that are based on the outer contour of the plant. The new global shape descriptors provided improvements over the existing methods. While there is clearly room for improvement, the proposed approach got promising results for the plant retrieval problem. Using color, and shape features in combination have improved the system performance.

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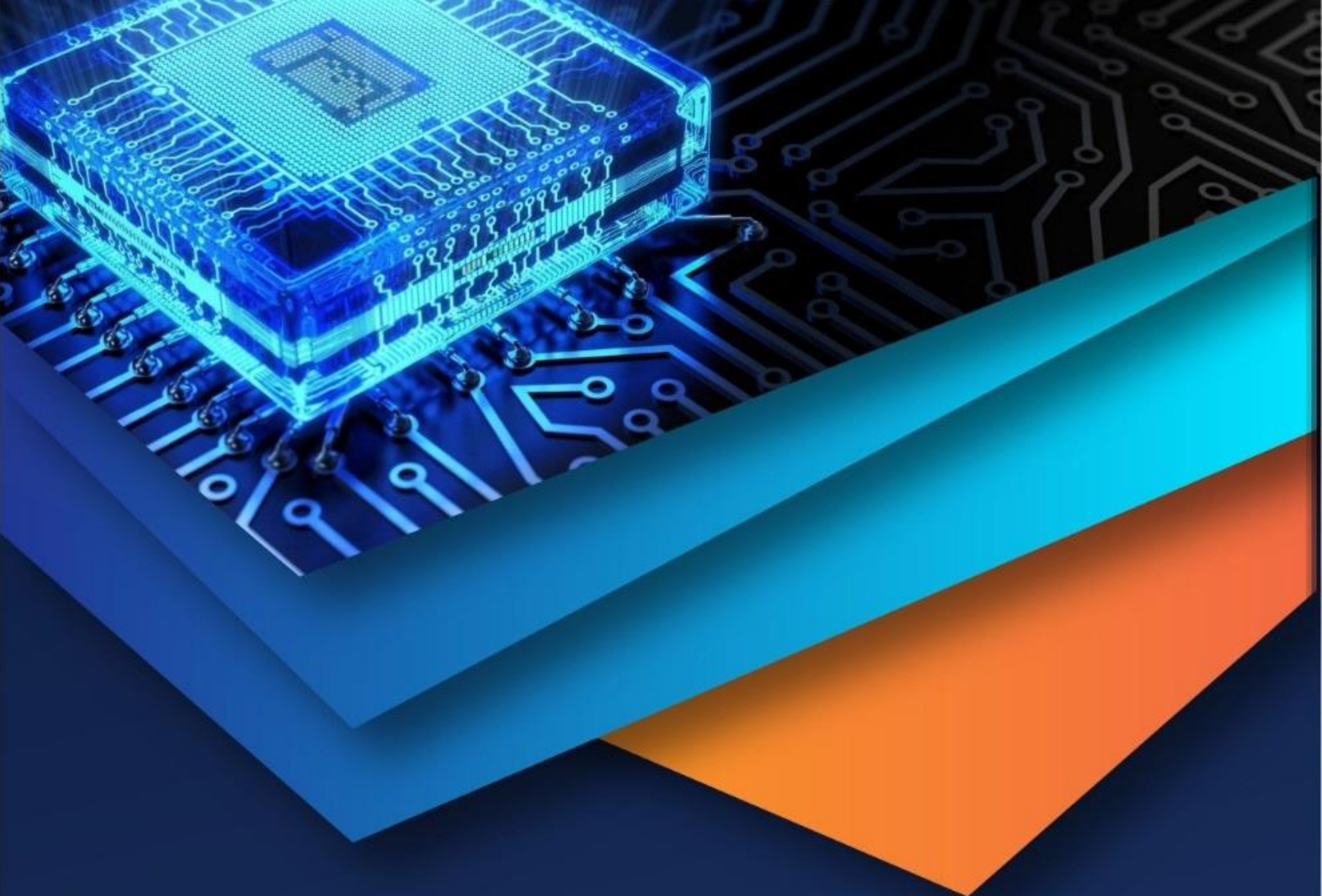

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