AN EFFICIENT INDEXING APPROACH FOR CONTENT-BASED IMAGE RETRIEVAL

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Abstract

In this paper an efficient indexing and retrieval technique is proposed for identification of plant images. The plant images have been retrieved as herbs, shrubs and trees based on color and texture features. We have collected 20 images of five plant species, amounting to total of 100 images, herbs, shrubs, and trees. Hence, totally there are 300 images of leafy mass and bark of 15 plant species. All the images are captured in natural environment using a digital camera.The proposed workconsists of four phases such as pre-processing, segmentation, feature extraction and image retrieval. In the pre-processing stage, the images of leafy mass and bark with complex background information and noise is filtered out by using Unsharp filtering method. In the segmentation method 2D-OTSU threshold based segmentation technique is used to separate the object from the background. For feature extraction the Modified Color Co-occurrence Matrix (MCCM) and Gabor Filter is used to retrieve the color and texture of the images from the database. Finally for retrieval of the images from the database Fast Indexing scheme for CBIR method is used. Then multi-dimensional indexing technique is employed using tree structures, R* tree. A graph is plotted to compare the retrieval result of both technique. Indexing Technique gives better retrieval rate.

Keywords:

Content Based Image Retrieval(CBIR), Color Features,Texture Features, Image Segmentation and Image Retrieval.

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1. Introduction

A typical CBIR system for retrieving images from database based on their similarity to a query image consists of four main steps. First, extract the image features to convert the image from space based on pixel to that based on feature. The feature extraction is the basic process of a CBIR system. The system will select appropriate feature spaces and explore various visual features to characterize an image. Next, construct feature vectors based on selected features, by which images in the database are represented. Later on, compare the image feature vectors of a query image (or regions in query image, or many query images) with the target images in database by computing a similarity measure to search the "most similar" images in the database. Finally, output queried image results similar to query image based on the specific ranking method. Some different similarity measure algorithms are designed to search the similar image in the database.

Many approaches have been proposed such as the text-based retrieval and the content based image retrieval (CBIR). Text-based approach consists to attach keywords or labels to each item and then to perform searches based on these labels. CBIR approach extracts low-level features to index image such as color, texture and shape[9].

In this paper two approaches have been characterizing leafy mass and tree bark images of color and texture will be retrieved[3]. The effective indexing and fast searching of images on based on visual features pose a significant issue in CBIR, Commonly a tree structure is utilized to store image information since it has high-dimensional metric space. The majority of these multi-dimensions, Indexing methods perform significantly well for dimensions. We have used R*-Tree structure to achieve better performance and efficiency.

2. Related Works

Seong-o shim,Tae-sun choi., [1] proposedModified Color Co-occurrence Matrix (MCCM) for image feature. First, CCM was simplified to account the number of certain colored pairs between all possible adjacent pixels in the image. For adjacency, four-connectedness was chosen. In this case, the diagonal matrix of CCM explains the color histogram of pixels that belong to the homogeneous regions. Suresh Pabboju, A. Venugopal Reddy., [2] presented an elegant and effective system for content-based image indexing and retrieval. The system exploits the global and regional features of the images for indexing and fractional distance measure as similarity measure for retrieval. Jiatao Sonl, Zheru Chi., [3]presenteda texture based bark classification method. The method uses two types of texture features, one is the gray-level co-occurrence matrix metries and the other is the binary texture feature, named Long Connection Length Emphasis (LCLE).M.V.Sudhamani, Dr.C.R.Venugopal., [4]the new algorithm cluster-based R*-tree indexing is proposed and compared the efficiency with R* -tree and sequential search. The accuracy of the retrieval system is measured and compared the results.

Suihua Wang, Ailing Zhao., [5]presents a reasoning-based image indexing and retrieval framework which uses content-based image index and retrieval techniques to extract low-level characteristics of images and identify their semantic contents, in which the low-level image features and the complex objects could be linked together.

3. The System Architecture

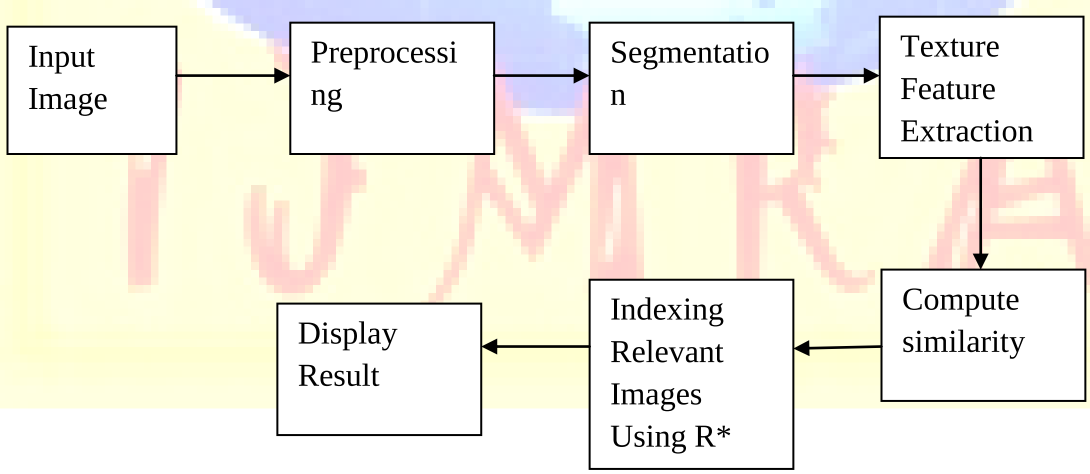


Fig.1 Block diagram for content-based image retrieval using indexing

The main methodology used in this paper is Retrieve and Indexing the leafy mass and Bark images based on color and texture feature extraction. The fig.1 gives the proposed model with different modules used in this paper. At the starting input image is filtered using Unsharp filtering method, and then apply segmentation using OTSU method, the texture feature extraction module using Gabor filter and MCCM Method.Similarity between images is computed. Finally image indexing method apply on clustered image database using R* Tree.

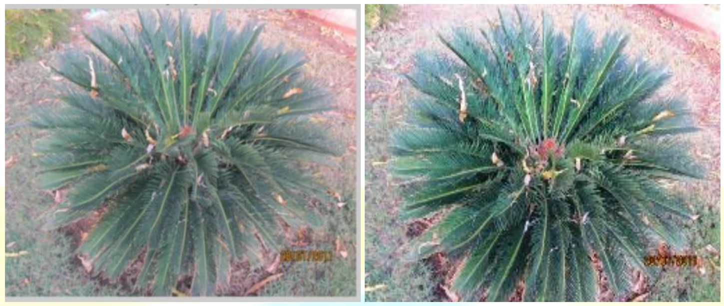
4. Content Based Image Retrieval Method

The problem of searching identical images from large image repositories on basis of their visual contents is called Content-Based image retrieval [9]. The term 'content' in CBIR refers to colors, shapes, textures, or any other information that can be possibly obtained from the image itself and 'Content Based' denotes that the search will consider the concrete contents of the image.Indexing remarkably affects the speed of data access besides supporting the accuracy for retrieval process and thus is a significant factor in image database systems.

4.1 Pre-processing Method

In the image processing and pattern recognitionsystem, the input original image must be pre-conducted.Because the plant in the image which is collected in natureby digital equipment chronically exposure to the naturalworld, there are all kinds of noise leaving in the crown,trunk, and the background. Before the image segmentation,we must remove the noise in the plant image. First of all isto deal with plant image de-noising. In the image denoising,how to retain the important feature of the image(edge, texture, and line, etc.) has been a focus problem in image processing work. The selection of filter is veryimportant, because it is determine whether as much aspossible to keep the plants edge and the texture feature ofthe canopy, and at the same time it can de-noising fast.

In the first pre-processing stage, the images ofleafy mass and bark from the camera having a lot of background information and noise that will be first filtered out by using Unsharp filtering method.The "Unsharp" of the name derives from the fact that the technique uses a blurred, or "Unsharp," positive to create a "mask" of the original image. The Unsharped mask is then combined with the negative, creating the illusion that the resulting image is sharper than the original.An Unsharp filter is an operator used to sharpen images.



(a) Input Image **(b)Sharpened Image**

Fig.2 Preprocessing results for leafy mass images

4.2 Segmentation Method

Segmentation refers to the process of dividing a digital image into multiple segments or a setof pixel it is also sometimes known as super pixels. The need of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries, lines and edges in images. 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. The ultimategoal of the segmentation is to identify the semantically meaningful components in the image.

OTSU method has long beenconsidered the best practice of threshold auto-selectionmethods. This method is simple in calculation. And it iswidely applied in real-time image processing system. When we segment a-channelwith threshold method, this study chooses two-dimensionOTSU algorithm which automatically selects the optimalthreshold for segmentation. Because two-dimension OTSUalgorithm not only takes into account the grayscaleinformation of pixels, but also considers the space-relatedinformation of pixels and their neighborhoods.Typically, an object pixel is given a value of “1” while a background pixel is given a value of “0.” Finally, a binary image is created by coloring each pixel white or black, depending on a pixel's labels.

(a) Input Image **(b) Output Image**

(Before segmentation) **(After segmentation)**

Fig. 3 Segmentation result for bark images

4.3 Texture Feature Extraction using Gabor Filter and MCCM method

Feature extraction is transforming the input data into the set of features still describing the data with sufficient accuracy. In pattern recognition and image processing, feature extraction is a special form of dimensionality reduction.Feature extraction is used when the input data to an algorithm is too large to be processed and it is suspected to be redundant (much data, but not much information). To extract relevant features from the images resulting in quantitative information for each object. The approach employed in this study was to use statistical texture analysis to determine a set of measures to provide object-background as well as object-object discrimination.

4.3.1 Gabor Filter

Gabor filter is one of the most popular signal processing based approach for texture extraction. Basically, Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and specific direction. It acts as a local band pass filter with certain optimal joint localization properties in both the spatial domain and the frequency domain. An image is filtered with a set of Gabor filters with different preferred orientations and spatial frequencies and the features, which are obtained from a feature vector [2].

Texture features are found by calculating the mean and variation of the Gabor filtered image. For a given image I(x, y) with size P×Q, its discrete Gabor wavelet transform is given by a convolution:

$$G_{mn}(x,y) = \sum_s \sum_t I(x-s, y-t)\Psi^*_{mn}(s,t) \quad \text{Eqn (1)}$$

Where s and t are filter mask size variables and Ψ^*_{mn} is the complex conjugate of Ψ_{mn} which is a class of self-similar functions generated from dilation and rotation of the following mother wavelet:

$$\Psi(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp\left[\frac{1}{2}\left(\frac{x^2}{\sigma^2}+\frac{y^2}{\sigma^2}\right)\right].\exp(j2\pi W_x) \quad \text{Eqn (2)}$$

Where W is the modulation frequency.

4.3.2 Modified Color Co-occurrence Matrix (MCCM)

Another approach is to extract texture features from the image is MCCM was proposed as an image feature. First CCM was simplified to account the number of certain colored pairs between all possible adjacent pixels in the image. For adjacency, four–connectedness was chosen. In this case, the diagonal matrix of CCM explains the color histogram of pixels that belong to the homogeneous regions[12].We calculated the following texture feature for image extraction using MCCM technique**s** like Mean, Standard Deviation, Entropy, Energy and Contrast.

4.3.3Color Space

Each color space has its own appear background and application region. When segmenting a color image, the selection of color space plays a decisive role on the segmentation results[1]. The commonly color spaces used in color image processing include RGB color space, HIS color space, Lab color space, and so on. At present, the general color digital images are RGB format. RGB color space is based on the theory of three-basic color to build. RGB format is the most basic color space. Other color space models can be obtained through the RGB formatconversion. But the RGB color space is not ahomogeneous visual perception space, it is not conduciveto image segmentation based on color feature. HSI colorspace uses color characteristics of a direct sense of thethree quantities: the brightness or lightness (I), hue

(H),saturation (S) to describe the color. This method is more inline with the human eye habits to the description of thecolor, but the expressed colors are incomplete visualperceived color. The Lab color space is a homogeneousspace for visual perception, the difference between twopoints in the Lab color space is same with the humanvisual system. It applies to represent and calculate of alllight color or object color, so the Lab color space is veryeffective in color image analysis[5].

Color: One of the most important features that make possible the recognition of images by humans is color. Color is a property that depends on the reflection of light to the eye and the processing of that information in the brain.

Color Descriptors

There are many different ways of extracting the color information from an image, some of the basic ones are color histograms and color moments.

Color Spaces:

1. **RGB:** this color space comes from an additive model in which the three primitive colors red/green/blue are added together to reproduce the all range of colors. Similar in a way to the HVS it is widely used and present in all CRT monitors.
2. **HSV:** stands for Hue, Saturation, Value, it is a cylindrical-coordinate representation and is known for its intuitivity i.e. close to how a person would describe a color.HSV color space it is a popular choice for manipulating color. The HSV color space, representing hue, saturation and color value (brightness) has the shape of a hexagonal cone. The angle is given by the hue, the distance from the Centre of the cone by the saturation and the vertical position by the value

4.3.4 Realization of the Color Channel Separation

The principle of color sub-channel method is todecompose color space components of color image intomultiple single-channel images in color space. The colorspace can choose color space RGB, HSI, Lab or othercolor space. The single-channel image information afterdecomposition can be described as the gray-scale image.

5. Similarity/ Distance Measure

Similarity measure is one of the key items in the process of image retrieval that decides the effectiveness and the efficiency of the retrieval technique [7].Content-based image retrieval calculates visual similarities between a query image and images in a database. Accordingly, theRetrieval result is not a single image but a list of images ranked by their similarities. Different similarity/distance measures will affect retrieval performances of an image retrieval system significantly.The visual similarities between a query image and images in an image database are determined as an alternative to exact image matching in case of content based image retrieval. Consequently a list of images ranked in order of their resemblance with the query image is enlisted as a result of retrieval. Lately, numerous similarity measures have been developed for image retrieval that works on basis of approximations of the distribution of features. The retrieval performance of an image retrieval system is greatly influenced by different similarities or distancemeasures.

Similarity measure for texture: Euclidean DistanceAlgorithm:

1. Decompose query image.
2. Get the energies of the first dominant k low frequency components.
3. For image i in the database obtain the k energies.
4. Calculate the Euclidean distance between the two sets of energies, using

$$D_i = \sum_{k=1}^{k} \left(x_k - y_{i,k} \right)^2 \qquad \text{Eqn (3)}$$

Increment i. Repeat from step 3**:** Using the abovealgorithm, the query image is searched for in the imagedatabase. The Euclidean distance is calculated betweenthe query image and every image in the database.

6. Indexing and Retrieval using R* Tree Structures

R*-treesare a variant of R-trees used for indexing spatial information. R*-trees support point and spatial data at the same time with a slightly higher cost than other R-trees [8].

An R*-Tree satisfies the following properties

- The R*-tree is a balanced disk-based tree structure.
- Root has at least two children unless it is a leaf.

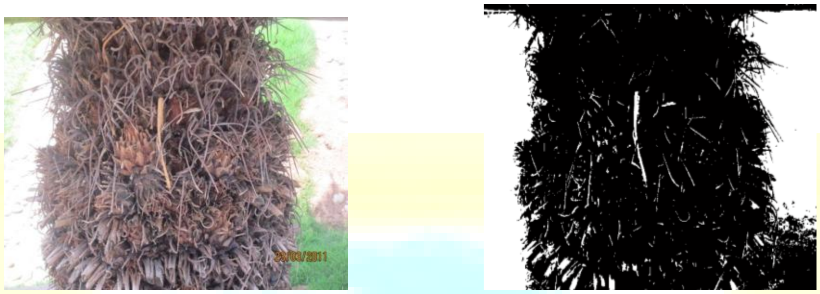
- ➢ Spatial objects are clustered based on the proximity of their locations.
- ➢ Each sub-tree is bounded by the Minimum Bounding Rectangle (MBR) of all objects in it.
- ➢ Each node is a disk page and has >= m (min # of entries) entries.
- ➢ Efficiency metric = number of disk-pages accessed

The following remarks emphasize thesuperiority of the **R*-tree in comparison to the R-trees**

- The R*-tree is the most robust method which is underlined by the fact that for every query file and every data file less disk accesses are required than by any other variants To say It m other words, there is no experiment where the R*-tree is not the winner.
- The gain in efficiency of the R*-tree for smaller query rectangles is higher than for larger query rectangles, because storage utilization gets more important for larger query rectangles This emphasizes the goodness of the order preservation of the R*-tree (i e rectangles close to each other are more likely stored together in one page).
- Surprisingly in spite of using the concept of Forced Reinsert, the average insertion cost is not increased, but essentially decreased regarding the R-tree variants.
- Minimization of area, margin, and overlap is crucial to the performance of R-tree / R*-tree.
- The R*-tree attempts to reduce the tree, using a combination of a revised node split algorithm and the concept of forced reinsertion at node overflow. This is based on the observation that R-tree structures are highly susceptible to the order in which their entries are inserted, so an insertion-built (rather than bulk-loaded) structure is likely to be sub-optimal. Deletion and reinsertion of entries allows them to "find" a place in the tree that may be more appropriate than their original location. → Improve retrieval performance.

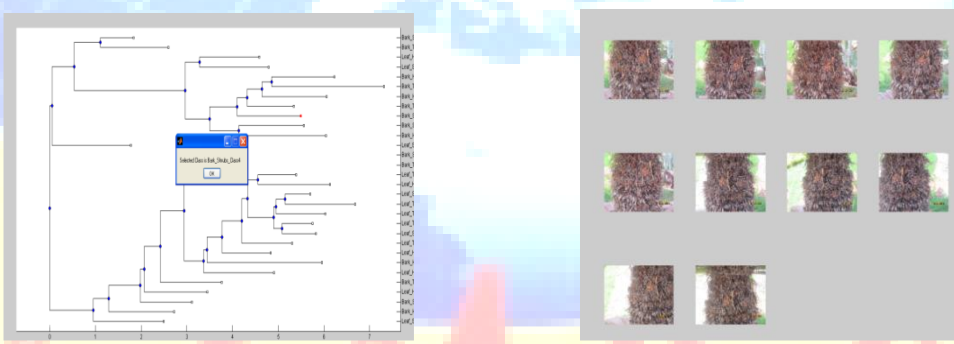
7. Experimental Results

Experimental results show segmentation of plant images, then classify images into bark and leafy mass plants,generate R*-tree Structure for given query image and finally result shows retrieval results of query image.



(a) Original Image(b) Segmented Image

Fig.4 Clustering and indexing of the Cycas sps bark Original and Segmented plant image



(a) R* Tree Generation (b) Retrieval Results

Fig.5 Retrieval results of R* tree generation andretrieval results

Evaluation of performance

Given a collection of documents, a set of queries and human expert's responses to the above queries, the ideal system will retrieve exactly what the human dictated. Performance in terms of precision and recall is calculated. The most popular way to evaluate the performance of a retrieval system is to calculate the percentage of relevant documents retrieved and also their relative order. Ideally, a system should retrieve all the relevant documents first, keeping the number of non-relevant documents that are retrieved before the relevant ones as minimum as possible.

Precision and Recall are the most widely used retrieval performance measurement in literature. It is based on categorical matching. The precision P and recall R are then defined asRecall is the percentage of the total relevant documents retrieved and is defined as:

$$Recall = \frac{Number of relevant images retrieved |R_a|}{Total number of images in database |R|}$$

Precision refers to the capability of the system to retrieve only the relevant documents. Precision can beexpressed as:

$$Precision = \frac{Number\ of\ relevant\ images\ retrieved |R_a|}{Total\ number\ of\ images\ retrieved |A|}$$

For each query, the precision of the retrieval at each level of the recall is obtained. The experimental results show that the proposed system can improve the retrieval accuracy as well as reduce the time for retrieval.

A set of recall and precision curves are joined together and this curve is called the precision-recall curve. Recall is inversely proportional to precision. For the sake of comparison, we prefer a non-increasing precision-recall curve and hence we use an interpolated precision-recall curve as our retrieval measure.

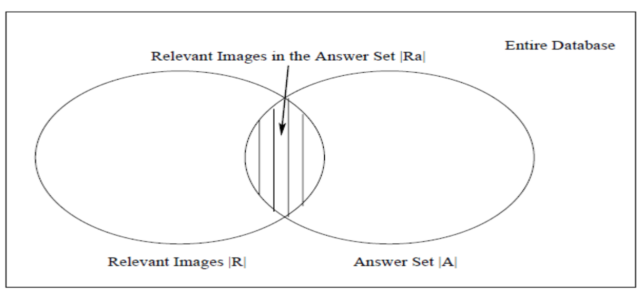


Fig.6The diagrammatic representation of precision and recall

Table 1: Retrieval efficiency of Herbs

SL. NO	PLANT NAME	NO.OF RETRIEVED IMAGES		RETRIEVAL ACCURACY	
		Leafy mass	Bark	Leafy mass	Bark
1	Catharanthes	16	18	80%	90%
2	Colacasia esculenta	14	18	70%	90%
3	Costus Speciosa	16	18	80%	90%

4	Seasamum indicum	14	16	70%	80%
5	Ocimum sanctum	16	14	80%	70%

Table 2:Retrieval rate of feature extraction for herbs leafy mass

(Precision Vs recall)

Precision	Recall			
	Combined feature	MCCM	Gabor feature	Color feature
0.1	0.98	0.95	0.93	0.91
0.2	0.95	0.92	0.91	0.9
0.3	0.9	0.89	0.85	0.83
0.4	0.89	0.85	0.83	0.8
0.5	0.85	0.82	0.8	0.79
0.6	0.83	0.81	0.8	0.78
0.7	0.79	0.75	0.73	0.7
0.8	0.75	0.73	0.7	0.69
0.9	0.73	0.7	0.69	0.67
1	0.7	0.69	0.67	0.65

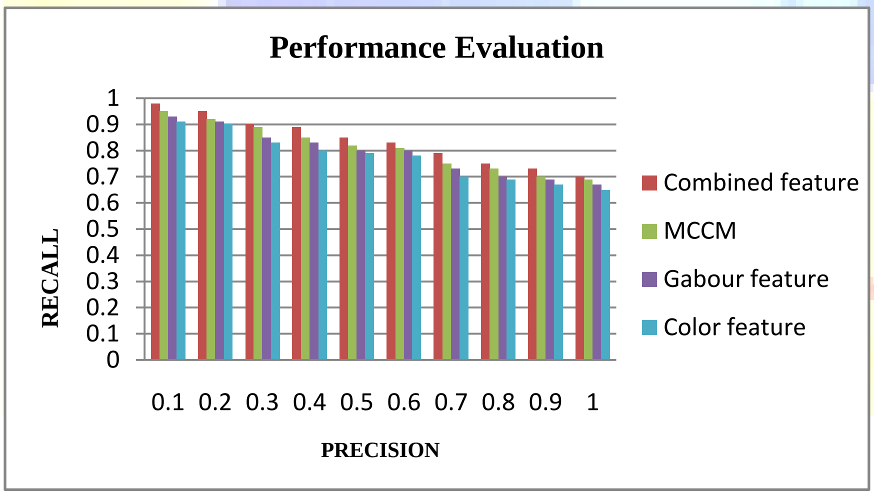


Fig. 7 Performance Evaluation graph for Herbs leafy mass

8. Conclusion

The goal of Content-Based Image Retrieval (CBIR) systems is to operate on collections of images and, in response to visual queries, extract relevant image A clustering and indexing techniques has been proposed which is suitable for plant image database. Content Based Image Retrieval by Indexing method to improve retrieval performance with good accuracy, more result can be produced. Results shows that OTSU segmentation is highly effective for extracting plant image from background. Combination of gabor filter and MCCM are very effective for feature extraction from plant image.We have also presented a novel approach forimage segmentation to extract the region features effectively. R*-Tree data structure is used in indexing the region features. Theexperimental results show that the proposed system can improvethe retrieval accuracy as well as reduce the time for retrieval.

However, we need to perform further experiments with a larger dataset and with different datasets to get more confidence in experimental results with better feature extraction.The future of CBIR depends a lot on the collective focus and overall progress in each aspect of image retrieval, and how much the average individual stands to benefit from it.

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