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CBIR using multilevel wavelet decomposition and adaptive thresholding tecniques

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ABSTRACT

The need for efficient Content Based Image Retrieval (CBIR) system has increased hugely. Efficient and effective retrieval techniques of images are desired because of the explosive growth of digital images. Content Based Image Retrieval is a promising approach because of its automatic indexing retrieval based on their semantic features and visual appearance. In CBIR, image is described by several low level image features, such as colour, texture, shape or the combination of these features. With appealing time-frequency localization and multi-scale properties, wavelet transform proved to be effective in feature extraction and representation. This paper presents multilevel wavelet decomposition and adaptive thresholding technique to extract shape and texture feature of the query image and to retrieve the similar images from the database. Edge detection is done using Daubechies (db2) wavelet. Zernike moments (ZM) are used to represent the shape. Efficiency of retrieval method is tested using precision and recall on Wang's dataset.

Introduction

Digital image libraries and other multimedia databases have been dramatically expanded in recent years. Storage and retrieval of images in such libraries become a real demand in industrial, medical, and other applications. Content Based Image Retrieval (CBIR) is considered as a solution. In such systems image database is stored in terms of features like shape, colour, texture and spatial locations etc. In this paper, we are focusing on the Shape Based Image Retrieval (SBIR). Shape defines contour as well as whole area of an image. As human perception is generally focused on shape, so images can be represented on the basis of shape features [8]. Shape description techniques are divided into two groups: Contour based and Region based. Contour based descriptions concentrate only on boundary lines hence they are not suitable for complex shapes that consists of several disjoint regions such as clipart, emblem, trademark or various shapes in natural scenes. Region based methods consider the whole area of the object and are most suitable for complex images. Commonly region based methods use moment description to describe a shape. But regular moments store redundant information; low order moments are sensitive to noise [4]. There are different region based descriptors like Generic Fourier Descriptor (GFD), Legendre Moments (LMs), Zernike Moments (ZMs) etc. ZMs have certain desirable properties i.e. rotation invariance, robustness to noise, fast computations of each moment order. ZMs are orthogonal moments i.e. the individual contribution of each moment order is separated.

Many methods have been proposed to represent object shape such as polygonal approximation [7], finite element models [8], rectilinear shapes [9] and Fourier-based shape descriptors [10]. However, the prerequisite of the success of these algorithms is that images have been accurately segmented into regions or objects. Some approaches require complicated segmentation, either automatically or manually. The drawback of these approaches is that, if the query image segmentation result is not accurate enough, the retrieval performance will be affected. In the cases of segmentation failure, it will be even difficult to perform the retrieval. Furthermore, the image segmentation is still one of the most challenging issues in the research field of image processing. Since robust and accurate image segmentation is difficult to achieve, the use of shape features for image retrieval has been limited to special applications.

Different image retrieval techniques based on various visual contents have been proposed [3]-[8], address issues on feature extraction and shape estimation. P Liu, K Jia [9] proposes a method to increase the efficiency of a system by making use of combined features. Ryszard S. Choras, Tomasz Andrysiak, and Michal Choras[13], discuss on integrated colour, texture and shape information for content-based image retrieval. Paper address different techniques for shape extraction and similarity measure between query image and image database. These techniques use traditional edge detection methods or the combined methods to extract the features. With appealing time-frequency localization and multi-scale properties, wavelet transform proved to be effective in feature extraction and representation, and thus has been successfully applied especially in image coding and denoising. Many edge detection methods using wavelets have been proposed. D.N. Verma, Vrinda Mar

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and Bharti[19] explained an efficient approach for colour image retrieval using Haar wavelet. J. Pan [20] has proposed an edge detection combining wavelet transform and canny operator based on fusion rules.

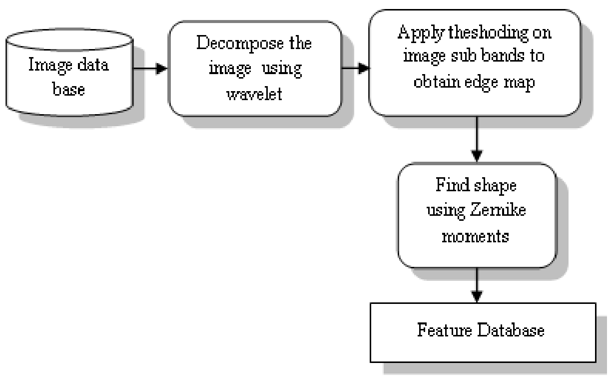
An important step before shape extraction is edge detection. Edge detection refers to the process of cclassical methods of edge detection involve convolving the image with an operator (a 2-D filter), which is constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions. There are extremely large number of edge detection operators available, each designed to be sensitive to certain type of edges. Variables involved in the selection of an edge detection operator include edge orientation, noise environment and edge structure. Wavelet transforms are multi-resolution image decomposition tool[22] that provide a variety of channels representing the image feature by different frequency sub bands at multi-scale.

We propose an effective method to detect edges using adaptive thresholding in multilevel decomposition of image and shape representation using ZM. Also texture is extracted. Feature vector contain shape and texture features. Similarity is calculated based on Canberra distance with the more weightage given to shape feature.

The rest of the paper is organized as follows: Section II discusses the proposed method. Section III explains the extraction of two features shape and texture. Section IV provides the techniques to compute similar images. Section V experimental details. Section VI analyses the results obtained. Section VII conclusion and summary of the work.

Proposed Method

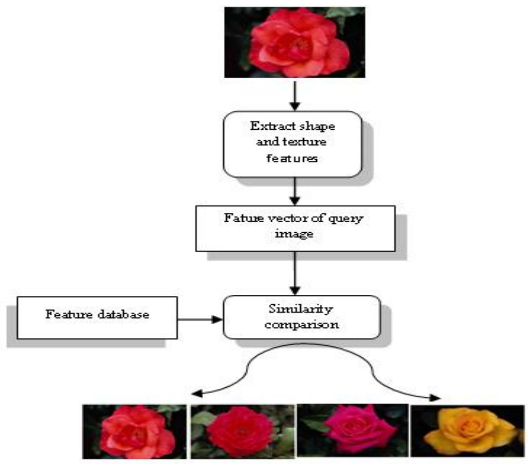
There are mainly two steps involved in the implementation of CBIR. 1) Feature extraction. 2) Similarity computation. RGB colour image is converted to Lab space as luminous component is more prominent here. Low level features such as shape and textures are extracted from the image by applying multilevel wavelet decomposition and thresholding on the image. Pixel level edge information obtained from edge image is converted to shape feature by applying Zernike moments. Features are calculated for whole image dataset and stored in feature database. This pre-processing step is shown in Fig. 1. When query image is given as input to the CBIR system it extracts the features of query images and compares with the features of image database. Similarity comparison is done using Canberra distance. Framework of proposed system is shown in Fig. 2.



Feature extraction (Preprocessing)

Feature Extraction

Feature is anything that is localized, meaningful and detectable. In an image noticeable features include corners, lines, objects, colour, shape, spatial location, motion and texture.



Frame work for proposed CBIR

Shape Feature

Shape of an object is the characteristic surface configuration as represented by the outline or contour. Shape recognition is one of the modes through which human perception of the environment is executed. It is important in CBIR because it corresponds to region of interests in images. Edge detection is important step before shape representation.

Edge Detection using Wavelet Decomposition

Edges define the boundaries between regions in an image, which helps with segmentation and object recognition. They can show where shadows fall in an image or any other distinct change in the intensity of an image. Edge detection is a fundamental of low-level image processing and good edges are necessary for higher level processing [1]. Traditional edge-detection algorithms such as gradient-based edge detectors, Laplacian of Gaussian (LOG), zero crossing, and Canny edge detectors suffer from some practical limitations. So the proposed method uses multi resolution wavelets such as Daubechies as wavelets are real and continuous in nature and have least root-mean-square (RMS) error. Also they are more suitable for detecting discontinuities and break down points in images which helps in finding edge of an image.

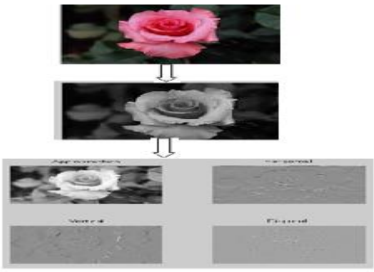
Wavelets are irregular and asymmetric. They have varying frequency. Wavelet analysis can be applied to one dimensional data (signals) and two dimensional data (images). The main reason and advantage for applying the wavelet transform to the detection of edges in an image is the possibility of choosing the size of the details that will be detected.

Given f(x) is a one-dimensional input signal, A 1-D discrete wavelet transform is defined as in (1).

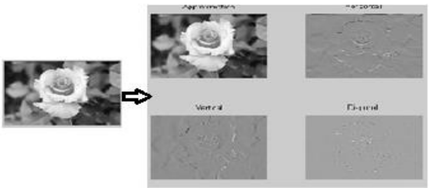
$$\phi_{jk}(x) = 2^{-j/2}\phi(2^{-j}x - k)$$

$$\psi_{jk}(x) = 2^{-j/2}\psi(2^{-j}x - k) \qquad (1)$$

Where $\varphi(x)$ and $\psi(x)$ are the scaling function and wavelet function[19] respectively, $\varphi_{jk}(x)$ and $\psi_{jk}(x)$ are the two orthogonal function basis sets. The computation of wavelet transform of a 2-D image involves recursive filtering and sub-sampling. At each level, there are three detail images. We denote these detail images as LH (containing horizontal information in high frequency), HL (containing vertical information in high frequency), and HH (containing diagonal information in high frequency). The decomposition also produces one approximation image, denoted by LL, which contains the low frequency information. The wavelet transform can recursively decompose the LL band[22]. First level decomposition of image is shown in Fig. 3. Second level decomposition is applied on image sub band LL approximation and another set of LH1, HL1 and HH1 are produced as shown in Fig 4.

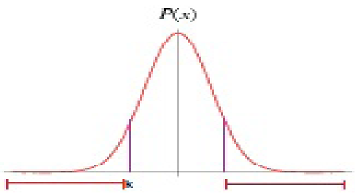


First level wavelet decomposition of an image



Second level wavelet decomposition of an image

Proposed work adopts two level decomposition of image using Daubechies(db2) wavelet. All components of 1st level an 2nd level are used for shape feature extraction. To get all strong and weak edge information, all four components are used. The proposed work determines four edge maps by multiplying four masks with the approximation component at each level based on the theory of concept of pixel distribution as shown in Fig.5 These four masks are obtained by setting two different thresholds on horizontal, vertical, and diagonal components. Threshold value k is set as shown in Fig. 5.



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Distribution of pixel information

P(x) in the Fig. 5 is similar to the distribution of pixel information in all of the decomposed components of the image. By setting a threshold k, the whole area between the two lines of k will be removed off and only the pixels lying on the either side of the k line (shown by red straight lines in above figure) are considered. If the threshold line (k) moves away from the central line, prominent edges are obtained(less information). So, two different thresholds are set in this work to get more edge information.

Algorithm for edge detection using wavelet decomposition

Input query image.

Convert it to gray scale.

Decompose the image using wavelets.

Obtain approximation a, horizontal h, vertical v and diagonal d components.

Filter out the strong edges of horizontal, vertical and diagonal components by using k1σ and k2σ where σ is the standard deviation of respected image. (k1 and k2 values depend on the standard deviation of images and may differ for each image).

Get first edge map by applying k1σ on h, v and d components and combining them and then multiplying the resulting mask with the approximation component.

Obtain second edge map similarly as that of first one by using k2σ.

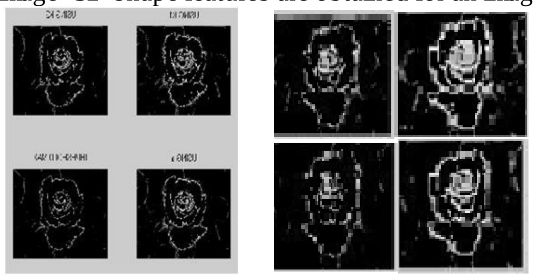
Get third edge map by applying both k1σ and k2σ on approximation component.

Obtain fourth edge map by finding the highest intensity pixels (both positive and negative values) among h, v and d components and by multiplying with approximation component.

Four edge maps are obtained for each input image at each level.

Above steps are repeated for second level decomposition.

Eight edge maps obtained after decomposition is shown in Fig.6. Applying the Zernike moments on eight edge maps of Query image 32 shape features are obtained for an image.



Edge maps

Zernike moments

Shape feature extractors describe the general topological and statistical gray level distribution. Zernike moments are one of the most popular shape descriptors. Zernike moments[12] have many desirable properties, such as rotation invariance, robustness to noise, expression efficiency. The complex ZM are derived from Zernike polynomials. Which are a set of complex, orthogonal polynomials [26] defined over the interior of a unit circle $x^2 + y^2 = 1$.

$$V_{nm}(x,y) = V_{nm}(\rho,\theta) = R_{nm}(\rho)\exp(jm\theta)$$

$$R_{nm}(\rho) = \sum_{s=0}^{\frac{n-|m|}{2}} (-1)^s \frac{(n-s)!}{s!(\frac{n-|m|}{2}-s)!(\frac{n-|m|}{2}-s)!}\rho^{n-2s} \qquad (2)$$

where n is a non-negative integer, m is an integer such that n-|m| is even and |m|≤ n,

$$\rho = \sqrt{x^2 + y^2}\text{, and } \theta = \tan^{-1}\frac{y}{x} \qquad (3)$$

Projecting the image function onto the basis set, the Zernike moments of order n with repetition m is given by:

$$A_{nm} = \frac{n+1}{\pi}\sum_x \sum_y f(x,y)V_{nm}(x,y)\text{ , } x^2 + y^2 \le 1 \qquad (4)$$

It has been shown that the ZM on a rotated image have the same magnitudes. Therefore $|A_{nm}|$ can be used as a rotation invariant feature of the image function. $|A_{nm}|$ is a special case of Radial Zernike moments.

Texture feature

The Query image is decomposed into approximation, horizontal, vertical and diagonal components. For horizontal, vertical and diagonal components μ (mean) and σ standard deviation are calculated[26]. 6 features are obtained for the image .

$$\mu = \left(\frac{1}{n}\right)\sum_{i=1}^{n}(x_i\, y_i\ ) \qquad (5)$$

$$\sigma = \left(\left(\frac{1}{n-1}\right)\sum_{i=1}^{n}(x_i y_i - \mu)^2\right)^{1/2} \qquad (6)$$

Feature vector for image data set is calculated as follows:

Query Image	Total retrieved	Relevant & Retrieved	Irrelevant & Retrieved	Error Rate	Precision	Recall
Flower	20	20	0	0.00	1.00	0.20
Bus	40	38	2	0.05	0.95	0.40
Horse	60	55	05	0.08	0.92	0.60
Beach	80	70	10	0.13	0.87	0.87
Food	100	84	16	0.16	0.84	0.90

$$f_{\text{texture-Zernike}} = \{ f_{\text{texture}} \} \cup \{ f_{\text{Zernike}} \}$$

Similarity Computation

Similarity between two images is obtained by evaluating the Canberra distance formula between the feature vectors of Query image and each image from database. Similar images in the database are retrieved by calculating the distance between query image feature and feature database vectors. Canberra distance formula is used for calculating the distance and is given by (7).

$$CD_k = \sum_{i=1}^{n} \frac{|x_i - y_{ik}|}{|x_i| + |y_{ik}|} \qquad (7)$$

Where CD is the Canberra distance, x and y are the feature vectors of query and database images respectively, n is the length of the feature vector. And k = 1 to m, where m is the number of images in image database. Images are indexed based on the distance between the query image and images in the database. Similar Images are displayed in the ranking order.

Implementaion

For the purpose of experimentation, an image database having established ground truth is used. A set of 1000 images assorted into 10 categories with 100 images in each category, forms the dataset. The images are of size either 384 x 256 or 256 x 384. The 10 image categories available are: Africa, Beaches, Buildings, Buses, Dinosaurs, Elephants, Flowers, Horses, Mountains and Food. The images in each category are numbered (Category 1: 0 to 99, Category 2: 100 to 199 etc…). Ten query images from each category are used to check the performance efficiency. Matlab Ver. 9.0 is used to implement the system.

Result

The performance of the retrieval system can be measured in terms of its recall (or sensitivity) and precision (or specificity). Recall measures the ability of the system to retrieve all models that are relevant. Precision measures the ability of the system to retrieve only models that are relevant [12]. They are defined as:

$$\text{Precision} = \frac{\text{No. of relevant images retrieved}}{\text{Total number of images retrieved}} \qquad (8)$$

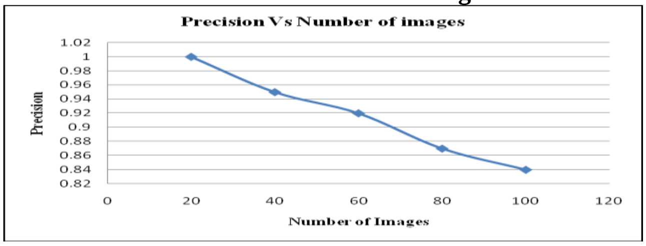
$$\text{Recall} = \frac{\text{No. of relevant images retrieved}}{\text{Total no. of relevant images in database}} \qquad (9)$$

These are the standard measures in IR (Information Retrieval), which give a good indication of the system performance. Also, we can measure the error rate by using the following method [15].

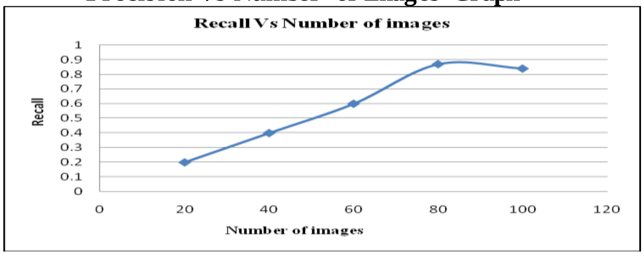
$$\text{Error} = \frac{\text{Number of non}-\text{relevant images retrieved}}{\text{Total number of images retrieved}} \qquad (10)$$

We have performed all the experiments on heterogeneous database [16] (A test database has been used in SIMPLIcity paper[17]) containing 1000 images. Test has been carried out for 10 different queries. Results of five quires have been shown in Table I. Each database image was manually marked as relevant or irrelevant on the basis of our query image. Results show that higher precision can be obtained by retrieving lesser number of images. For higher retrieval of images the recall is less than one. Different graphs shown in Fig 7, Fig. 8 and Fig 9. tell the performance of proposed method. Fig. 10 and Fig 11 shows the top 10 images retrieved for flower and food query images.

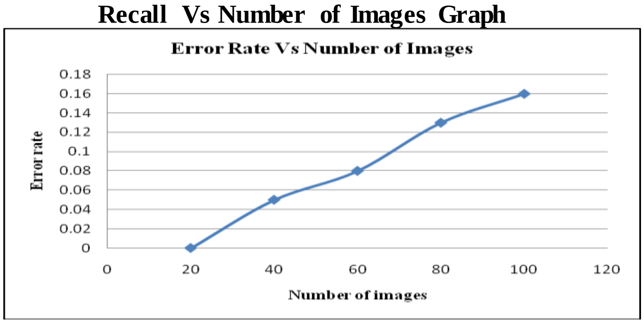
Precision-Recall for different categories



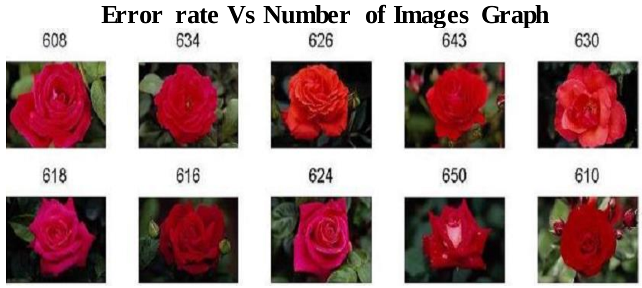
Precision Vs Number of Images Graph



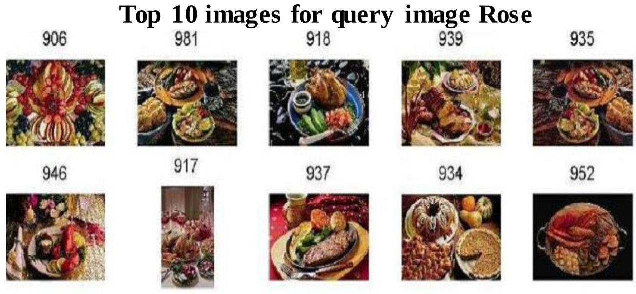
Recall Vs Number of Images Graph



Error rate Vs Number of Images Graph



Top 10 images for query image Rose



Top 10 images for query image Food

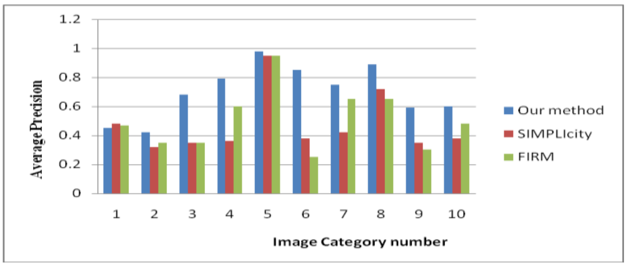
We bench mark our results with the well known standard image retrieval algorithms such as SIMPLIcity [17] and FIRM [18]. Weighted precision is calculated for different categories. The weighted average of precision values within k_i retrieved images are computed as shown in (11).

$$\bar{p}(i) = 1/(100) \sum_{k_1=1}^{100} n_k/100 \qquad (11)$$

k_i = 1,…., 100. n_k is the number of matches within the first k_1 retrieved images. The weighted precision as obtained from each category is shown in Table II. In most of the cases the average precision for each category is better than SIMPLIcity [17] and FIRM [18] due to the robust feature set used in our proposed method. Comparison of our method with SIMPLIcity [17] and FIRM [18] is shown in bar graph Fig. 12. Our method proved to be better than other two methods.

Comparative evaluation of weighted average precision

Category	Our method	SIMPLIcity [17]	FIRM [18]
1. Africa	0.45	0.48	0.47
2. Beach	0.42	0.32	0.35
3.Building	0.68	0.35	0.35
4. Bus	0.79	0.36	0.6
5.Dinosaur	0.98	0.95	0.95
6.Elephant	0.85	0.38	0.25
7.Flower	0.75	0.42	0.65
8.Horses	0.89	0.72	0.65
9.Mountains	0.59	0.35	0.3
10.Food	0.6	0.38	0.48



Weighted average precision for different methods

Conclusion

In this paper we presented multilevel wavelet decomposition method to extract shape and texture feature of the query image and to retrieve the similar images from the image data set. The key contribution of proposed work is detection of edges using wavelet based techniques to overcome the problem of traditional edge detectors such as poor anti-attack, noise-sensitivity and not complete information of extracted edge. Two level wavelet decomposition helps to retain the different pixel information to obtain the different edge images in turn get robust shape features. The experimental results demonstrate the efficiency and robustness of proposed system. It is found that average retrieval accuracy of the proposed method is 70 % and 91.65% for top 10 images for different categories of the images.

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