The New Integrated Color and Texture Based Image Retrieval Using Neuro-Fuzzy Approach

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***Abstract*— In this paper we introduce the new integrated color and texture based image retrieval technique using neuro-fuzzy approach for content based image retrieval. Most of the image retrieval systems are still incapable of providing retrieval result with high retrieval accuracy and less computational complexity. To address this problem, we developed color and texture based neural network -fuzzy logic approach for content based image retrieval using 2D-wavelet transform. The system performance improved by the learning and searching capability of the neural network combined with the fuzzy interpretation. This overcomes the vagueness and inconsistency due to human subjectivity. Multiresolution analysis using 2D-DWT can decompose the image into components at different scales, so that the coarest scale components carry the global approximation information while the finer scale components contain the detailed information. The empirical results show that the precision improved from 67% to 98% and average recall rate of 67% to 98% for the general purpose database size of 10000 images compared with existing approaches.**

***Keywords*-Content Based Image Retrieval,Wavelet transform,Fuzzy logic and neual network.**

I. INTRODUCTION

With the explosive growth in image records and the rapid increase of computer technologies, retrieving images from large-scale image databases becomes one of the most active research areas. To give all images text annotations manually is tedious and impractical and to automatically annotate an image is beyond current technology. Content-Based Image Retrieval (CBIR) is a technique to retrieve images semantically relevant to the user's query from an image database. It is based on the automatically extracted visual features from an image, such as color, texture and shape. In order to make use this vast amount data, efficient techniques to retrieve multimedia information based on its content need to be developed. This paper deals with the retrieval of images by the combinations of color, texture , neural network and fuzzy based approaches[1]-[2]

Content- based image retrieval (CBIR) approach has emerged as a promising alternative. CBIR has been a particular challenge as the image content covers a vast range of subjects and requirements from end users are often very loosely defined. In CBIR, images are indexed by its own visual contents, such as color, texture and shape. The challenge in CBIR is to develop the methods that will increase the retrieval accuracy and reduce the retrieval time. Hence, the need of an efficient retrieval of images supporting popular access mechanisms like CBIR arises.

In content based approach, users provide the system with image examples to retrieve the images. Despite tremendous improvement in content based retrieval, the content based retrieval approaches still have many limitations. First, it is difficult for the users to specify the visual queries with the low level features. Second, low level image features cannot precisely describe user information needs. There is gap between low level visual descriptions and the user's semantic expectation.[1][2]. Most early CBIR systems perform retrieval based primarily on global features ,including IBM'S QBIC[6] and MIT'S Photobook[7].It is not unusual that users accessing a CBIR system look for objects.Thus,the aforementioned systems are likely to fail, since a single feature computed for entire image content cannot sufficiently capture the important properties of the individual images. In this paper, we present neuro-fuzzy technique to retrieve the images with human visual perception using color and texture features.

The rest of the paper is organized as follows: Section II presents the previous related works in the area of fuzzy and neural network based image retrieval. Section III presents architecture developed to facilitate the proposed approach and Section IV experimental results and we presented conclusions.

II. PRIVIOUS RELATED WORKS

Fagin[24] and Ortega et al [25] are pioneers who integrated fuzzy logic models into CBIR systems .They proposed algorithms to evaluate the fuzzy query, and showed the effectiveness through proven theorems and experimental results. Medasani and krishnapuram [14] proposed a fuzzy-based linguistic query in their CBIR system. Their membership query is formulated by a Gaussian mixture membership function and fuzzy connectives. It provides natural and friendly interface to their system. Dubois et al [13] illustrated a fuzzy a fuzzy logic framework for a query by

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example scheme, where the users can give relevant or irrelevant examples together with their significance. Their framework shows the feasibility of using fuzzy-based relevance feedback in CBIR systems. Lin et al [26] designed a fuzzy logic CBIR system for finding textures. Their system provides users with linguistic and visual queries which are formulated by fuzzy triangular membership functions. The Lin's system also incorporates relevance feedback to improve the retrieval accuracy through iteratively modifying membership functions. Their fuzzy-based framework is simple, intuitive and effective in texture retrieval. It is worth mentioning that Lin's system as well as other fuzzy logic CBIR systems, does not retain each user's preference during retrieval, thus retrieval accuracy is impaired. Chih-Yi Chiu et al[12]framework is proposed to alleviate two problems in traditional CBIR systems, including the semantic gap and the perception subjectivity. Kulkarni et al [6],[17] is proposed a neuro –fuzzy technique for CBIR.It is based on fuzzy interpretation of natural language,neural network learning and searching algorithms. Our proposed system based on neuro-fuzzy with multiresolution analysis using wavelet transform capable of achieving better precision, average recognition rate and classification rate.

III. Proposed Architecture

An image retrieval system based on combined low level features using neuro-fuzzy is designed in this paper and shown in Fig.1.The query processing and image matching is the main contribution of the architecture. Features of images such as color, texture and shape are extracted from image and stored in the database. Three image features are extracted by this system, which are HSV color histogram feature, texture and shape features based on 2D wavelet filter. The query image is processed to compute color features as section IV. The same query image is given as input image for texture based retrieval, the 2D-DWT is applied to query image, texture features of the query image and database image is stored in the database. Our work proposes therefore to take advantage of the membership degree to each feature, fuzzifying the neural net works output by means of membership function. The query to retrieve the images from database is prepared in terms of natural language such as mostly content, many content and few content of the some specific color.Fuzzy logic is used to define the query. We define nine colors that fall within the range human perception. The feature representation set of colors are {red, green, blue, white, black, yellow, orange, pink, purple}.These nine colors used as input to the neural network and content type as output.*Mosly,many*,and *few* indicate the output. Accordingly the related similarity measure should proximity between two vectors, independently described by their respective features.

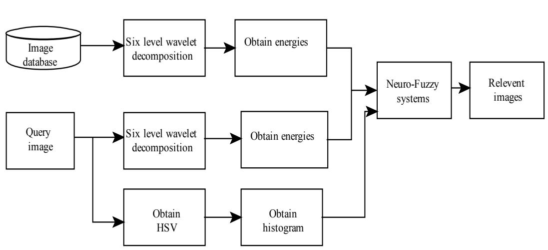


Fig.1 Proposed architecture

A. *Color Feature Based Image Retrieval*

Color is the most popularly used features in image retrieval and indexing. On the other hand, due to its inherent nature of inaccuracy in description of the same semantic content by different the color quantization and /or by the uncertainty of human perception, it is important to capture this inaccuracy when define the features. We apply fuzzy logic to the traditional color histogram to help capture this uncertainty in color indexing [1][2]

The ability of the color features to characterize perceptual similarity colors is greatly influenced by the selection of the color space and color space quantization scheme. The RGB color space is used in CBIR, even though it is perceptually not uniform. Other perceptually more uniform color spaces are HSV is obtained from RGB by using a non linear transform. Color quantization is essential in the extraction of any color feature due to the large number of colors that can be present in a single image. The color space is quantized to reduce the number of distinct colors in an image, and simply its feature vector.

(1).RGB to HSV Conversion

In Fig.2 Obtainable HSV colors lie within a triangle whose vertices are defined by the three primary colors in RGB space

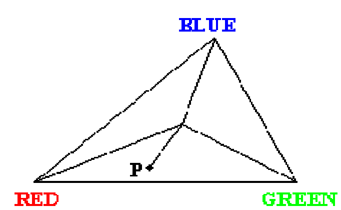


Fig.2.RGB to HSV Conversion

The hue of the point P is the measured angle between the line connecting P to the triangle centre and line connecting RED point to the triangle centre.

The saturation of the point P is the distance between P and triangle centre. The value (intensity) of the point P is represented as height on a line perpendicular to the triangle and passing through its centre. The greyscale points are situated into the same line and the conversion formula is as follows

$$H = Cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-}}\right. \quad (1)$$

$$S = 1 - \frac{3}{R+G+B}[\min(R, G, B)] \quad (2)$$

$$V = \frac{1}{3}(R+G+B) \quad (3)$$

(2).HSV to RGB Conversion

Conversion from HSV space to RGB space is more complex and given to the nature of the hue information, we will have a different formula for each sector of the color triangle.

Red-Green sector for $0^o<H\leq 120^o$

$$r = \frac{1}{3}\left[1 + \frac{ScosH}{cos(60^{0}-H)}\right] \quad (4)$$

$$b = \frac{1}{3}(1 - \quad (5)$$

$$g = 1 - (r + b) \quad (6)$$

Green-Blue sector for $120^0 < H \leq 240^0$

$$r = \frac{1}{3}(1 - s) \quad (7)$$

$$g = \frac{1}{3}\left[1 + \frac{ScosH}{cos\ (60-H)}\right] \quad (8)$$

$$b = 1 - (r + b) \quad (9)$$

Blue-Red sector for $240^o<H\leq 360^o$

(10)

(11)

b (12)

B. Color histogram based image search

In image retrieval, the color histogram is the most commonly used color feature representation. Statistically, it denotes the joint probability of the intensities of the three color channels. The most widely used color feature is the color histogram, which gives an idea about the colors present in an image and their percentages

The color histogram of an image is constructed by counting the number of pixels of each color. Retrieval from image databases using color histograms has been investigated fully. In these studies the developments of the extraction algorithms follow a similar progression as (1) selection of a color space,(2)quantization of the color space, (3)computation of histograms,(4) derivation of the histogram distance function,(5)identification of indexing shortcuts.[1]-[2],[21]-[22]

An image histogram refers to the probability mass function of the image intensities. This is extended for color images to capture the joint probabilities of the intensities of the three color channels. More formally, the color histogram is defined by,

$h_{A,B,C}(a,b,c)=N.Prob(A=a,B=b,C=c)$ (13)

Where A, *B* and *C* represent the three colors channels (R, G, B or H, S, V) and N is the number of pixels in the image.

(1). Similarity Measures

Instead of exact matching, content –based image retrieval calculates visual similarities between a query image and images and the database .Accordingly, the retrieval result is not a single image but a list of images ranked by their similarities with the query image. Many similarity measures have been developed for image retrieval based on the empirical estimates of the distribution of features in recent years. Different similarity and distance measures will affect retrieval performance of an image retrieval system significantly. we denote D(I,J) as the distance measure between the query image I and image J in the database; and fi(I) as the number of pixels in bin i of I.[1]-[2],[15]-[16],[21]-[22]

1.Quadratic Form Distance

The Minkowski distance treats all bins of the feature histogram entirely independently and does not account for the fact that certain pairs of bins correspond to features which are more perceptually more than other pairs. To solve this problem quadratic distance is introduced.[1]-[2],[15],[21]-[22].

$$D(I,J) = \sqrt{\left((F_I - F_J)^T A(F_I - F_J)\right)} \quad (14)$$

Where A=[aij] is a similarity matrix, and aij denotes the similarity between bin i and j.F_I and F_J are vectors that list all entries in fi(I) and fi(J).Quadratic form distance has been used in many retrieval systems for color histogram based image retrieval. It has been shown that quadratic form distance can lead to perceptually more desirable results than Euclidean distance and histogram intersection method as it considers the cross similarity between colors

The cross distance formula considers the cross-correlation between histogram bins based on the perceptual similarity of the colors represented by the bins. And the set of all cross-correlation values are represented by a matrix A**,** which is called a similarity matrix. And a(i, *j*) th element in the similarity matrix **A** is given by, for RGB space

$$a_{ij} = 1 - \frac{d_{ij}}{max\ (d} \quad (15)$$

$$a_{ij} = 1 - \frac{1}{\sqrt{5}}\left[(v_i - v_j)^2 + (s_i sinh_i - s_j sinh_j)^2 + (s_i cosh_i - s_j cosh_j)^2\right] \quad (16)$$

Where d_{ij} the distance between the color i and j in the RGB space. In this case the quantization of the color space is not perceptually uniform. The cross term contributes to the perceptual distance between color bins.

C .Texture Feature Based Image Retrieval

Texture analysis plays an important role in many image processing tasks, ranging from remote sensing to medical imaging, robot vision and query by content in large image databases. Various methods for texture feature extraction have been proposed during last decades (e.g.,[29]),but the texture analysis problem remains difficult and subject to intensive research.[31]

A major class of texture extractors relies on the assumption that texture can be defined by the local properties of pixel gray levels.From the image histogram, first order statistics can be derived and be used as texture features. It was soon argued that they did not suffice for adequate texture description and that second –order statistics were required, as efficiently reflected in features computed from co-occurrence matrix [30]. The conjuncture that second –order statistics suffice for texture analysis was later rejected[32] and various other texture analysis schemes were introduced(e.g.)based on Markov random field [33] fractal model[34] or more recently ,on wold decomposition[35]

A weakness shared by all these texture analysis schemes is that the image is analyzed at one single scale, a limitation that can be lifted by employing multiscale representations. Studies in the human visual system support this approach since researchers have found that the visual cortex can be modeled as a set of independent channels, each with a particular orientation and spatial frequency tuning.[36].

Several multichannel texture analysis systems have been developed [38][39].In particular ,Gabor filters were used perform texture segmentation[27],[40]-[41].In the last decade ,wavelet theory has emerged and became a mathematical framework which provides a more formal ,solid and unified framework for multiscale image analysis[42],[43].Typically ,the wavelet transform maps an image on a low resolution image and a series of detailed images. The low resolution image is obtained by iteratively blurring the image; the detail images contain the information lost during this operation. The energy or mean deviation of the detailed images are the most commonly used features for texture classification and segmentation problems.[3],[44],[45].

Since image is typically a two dimensional signal, a 2D equivalent of the DWT is performed. The original image is shown in Fig.3.This is achieved by first applying the L and H filters to the lines of samples, row by row, then refiltering the output to the columns by the same filters. As the result, the image is divided into 4 sub bands, LL, LH, HL and HH as depicted in Fig.4. The LL sub band contains the low pass information of horizontal, vertical and diagonal orientation. The LL sub band provides a half sized version of input image which can be transformed again to have more levels of resolution.Generally, an image is partitioned into L resolution levels by applying the 2D DWT (L-1) times.[3].

By wavelet transform, we mean the decomposition of an image with family of real orthogonal bases $\psi_{m,n}(x)$btained through translation and dilation of a kernel function $\psi($ known as mother wavelet

$$\psi_{m,n}(x) = 2^{\frac{-m}{2}}\psi(2^{-m}x - \qquad (17)$$

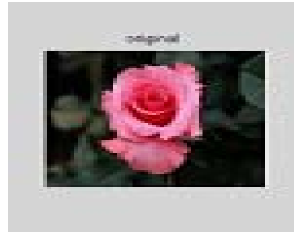
Where and are integers. Due to the orthonormal property, the wavelet coefficients of a signal $f($ can be easily computed via

$$c_{m,n} = \int_{-\infty}^{+\infty} f(x)\psi_{m,n}(x) \qquad (18)$$

and the synthesis formula

$$f(x) = \sum_{m,n} c_{m,n}\psi_{m,n}(\qquad (19)$$

can be used to recover $f($ from its wavelet coefficients



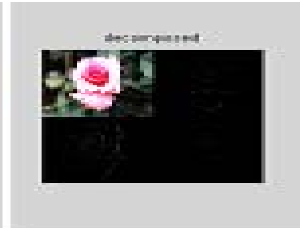


Fig.3.Orginal image Fig.4.One level decomposition

To construct the mother wavelet $\psi($, we may first determine a scaling function $\phi($which satisfies the two-scale difference equation

$$\phi(x) = \sqrt{2}\sum_k h(k)\phi(2x - k \qquad (20)$$

Then the wavelet kernel $\psi($ is related to the scaling function via

$$\psi(x) - \sqrt{2}\sum_k g(k)\psi(2x - \qquad (21)$$

where

$$g(k) \qquad (22)$$

The coefficients in (20) have to several conditions for the set of basis wavelet functions in (18) to be unique, orthonormal, and have a certain degree of regularity.

The coefficients and play a very crucial role in a given discrete wavelet transform.To perform the wavelet transform does not require the explicit forms of and but only depends on and .Consider a J-level wavelet decomposition which can be written as

$$f_0(x)$$

$$= \sum_k (C_{J+1,}k\phi_{J+1,}\kappa(x) + \sum_{j=0}^{J} d_{j+1,}k\psi_{j+1,}k(x \qquad (23)$$

Where coefficients are given and coefficients and at scale are related to the coefficients at scale via

$$c_{j+1,n} = \sum_k c_{j,k}\, h(k - 2 \qquad (24)$$

$$d_{j+1,n} = \sum_k c_{j,k}\, g(k - 2n \qquad (25)$$

Where $0 \le j$:.Thus,(24) and (25) provides a recursive algorithm for wavelet decomposition through $h($ and $g($,and the coefficients c for a low resolution component $\phi_{J,k}($.By using a similar approach,we can derive a recursive algorithm for function synthesis based on its wavelet coefficients d $0 \le j$: and c

$$c_{j,k} = \sum_n c_{j+1,n}\, h(k - 2n) + \sum_n d_{j+1,n}\, g(k - 2 \qquad (26)$$

It is convenient to view the decomposition (8) as passing a signal c through a pair of filters and with impulse responses $\tilde{h}($ and $\tilde{g}($ and down sampling the filtered signals by two (dropping every other sample), where $\tilde{h}($ and $\tilde{g}($ are defined as

$$\tilde{h}(n) = h(-n),$$

The pair of filters ***H*** and ***G.*** correspond to the half band low pass and high pass filters respectively, and are called the quadrature mirror filters in the signal processing literature [5]

The reconstruction procedure is implemented by up sampling the sub signals and and filtering with and ,respectively, and adding these two filtered signals together.Usually the signal decomposition scheme is performed recursively to the output of lowpass filter .

The wavelet packet basis functions can be generated from a given function as follows

$$W_{2n}(x) = \sqrt{2}\sum_k h(k \quad (27)$$

$$W_{2n+1}(x) = \sqrt{2}\sum_k g(k) \quad (28)$$

Where the function can be identified with the scaling function and with the mother wavelet .Then,the wavelet packet bases can be defined to be the collection of orthonormal bases composed of functions of the form ,where *l, k* ,*n* Each element is determined by a subset of the indices: a scaling parameter *l*, a localization parameter *k*, and an oscillation parameter *n*.

The 2D wavelet (or wavelet packet) basis functions can be expressed by tensor product of two 1-D wavelet (or wavelet packet) basis functions along the horizontal and vertical directions. The corresponding 2-D filter coefficients can be expressed as

(29)

$$h_{HL}(k,l) = g(k)h(l), h_{HH}(k,l) = g(k)g(l) \quad (30)$$

Where the first and second subscripts in (29) and (30) denotes the low pass and highpass filtering characteristics in the -and -directions respectively.[11]We have applied orthogonal wavelet transformation with dyadic subsampling. Wavelet decomposition of images is performed using db4 wavelet basis function. On application of the the above procedure, for an image of size 256 × 256, db4 wavelet yields suband matrices of 128×128 at the first level,64×64 at the second level, 32×32 at the third level, 16×16 at the fourth level of wavelet decomposition.[25][26][27]

We assume that any color is a fuzzy set. That means we will associate any color to a fuzzy functions, $\mu_c : \mu \rightarrow [$ and for any color of the universe, μ_c is the resemblance degree of the color to the color .The fuzzy model we define should follow the property that the resemblance degree decreases as inter-color distance increases. So we assume the particular color content for each image to *mostly, many* and *few* .In our model,the interpretation ranges of the values used are [0.9,1] for *mostly*,[0.4,0.5] for *many* and [0.15,0.25] for *few*.[5][6]-[7]

B. Semantic rule M

M is the semantic rule mapping from low-level feature U to the high level fuzzy semantics of T, that is to say, for u , $t \in T$.It assumes a value in [0,1] called degree of membership to according to the linguistic value .We can formally describe the task as sample set $\{(V_1, y_1) \ldots (V_n,$,in which $V_i \in U(i = 1, \ldots$ represents color histogram and $y_i(i = 1 \ldots$ is the degree of membership.[5]

Neural network is used as an adaptive retrieval system which incorporates learning capability into the network module where the network weights represent adaptability. This learning approach has several advantages over traditional retrieval approaches. It allows the retrieval system to solve the problem of fuzzy understanding of users' goals that are not realized by traditional approaches [7]

We have adopted a Self-Organizing Tree Map (SOTM) and a Learning Vector Quantization (LVQ) used to form integration.[4],[10]. The SOTM provides construction of unsupervised suitable classcificaion. It is more effective than the K-mean and the self organizing feature map(SOM)algorithm particularly when the input space is high dimensionality. Thus, SOTM is chosen in our work to locate centers in the high dimensional space of image features. To carry out SOTM/LVQ algorithms, we are given a set of training samples corresponding to retrieved images from a previous search operation.[4]

We denote this training data with two sets of vectors. Positive sample set(relevant images) X^+,and negative sample set(non-relevant images) $X^- =$.We assign each input vector in into an SOTM algorithm to create the weight vectors, where as the vectors in are used in the LQV algorithm for further adjustment of the weight vectors. SOTM algorithm is given as follows.[15]

Step 1. *Initialization*. Choose the root nodes from the available set of input vectors in a random manner.

Step 2. *Similarity matching*. Randomly select a new data point and find the best matching neuron at time step by using the minimum-distance Eudlidean criterion:

$$w \quad (1)$$

Step 3. *Updating*. If $\|$where is the hierarchy function used to control the levels of tree, then assign to the jth cluster,and adjust the synaptic weight vector according to the reinforced learning rule:

$$w_j(t+1) = w_j(t) + \alpha(t)[x(t) \quad (2)$$

Where is the learning rate, which decreases monotonically with time, Else form a new subnode starting with .

Step 4. *Continuation*. Continue with step 2 until no changes in the feature map.

The SOTM algorithm obtains a new set of cluster centres V_i where the number of centres is controlled by the the function .In the experiment, was initialized by the norm of the training vectors in ,and was reduced linearly.

Step 5. *Cluster Modification* .At this stage, the negative samples in are used to tune the decision boundaries of the initial set .We employ the antireinforced learning rule in the LVQ algorithm to perform this operation. The algorithm starts with randomly choosing input vector from the training set . Then, classify to the node if

$$\|x'_m(t) - v_i\| < \|x'_m(t) - v_k\| \quad (3)$$

apply the antireinforced learning rule to the corresponding cluster centers as

$$v_i(t+1) = v_i(t)- \tag{4}$$

Where η is the learning constant which decreases monotonically with the number of iterations , $0 \leq \eta(t)$:After several training data, the node vectors converge and the cluster modification process is complete.

We assign each input vector as centre of the corresponding Gaussian kernel in the network. For the arbitrary input vector x,the output of the *m*th RBF unit is given by

$$G_m(X, V_m, \sigma_m) = \exp\left(-\frac{(X-V_m)^T(X}{2\sigma^2_m}\right) \tag{5}$$

Where is a smoothing parameter defined as

$$\sigma_m \ \min \ \|V_m - , i=1,2\ldots M \tag{6}$$

with =0.5 being an overlapping factor.The estimated function output *f*(x)for x is then given as

$$f(x) = \sum_{m=1}^{M} G_m(X, V_m \tag{7}$$

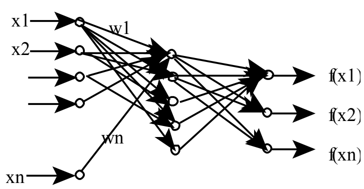


Fig.5.RBF Network

TABLE I

NEURAL NETWORK PARAMETERS FOR EXPERIMENTS

Inputs	Outputs	Hidden Units	Training Pairs	η	α	Iterations
10	3	5	307	0.7	0.2	50

IV. RESULTS AND DISCUSSION

The proposed framework tested with a general-purpose image database of about 10000 images approximately 1000 categories from COREL. In current experiments, two query images are chosen one from Corel database. The experiments performed with 1000 images from total 100 categories of images. The selected categories are roses, buses, elephant, lion, and sunflowers. Note that the categories how a common property that all the images of them distinct objects. The simulation results from the Corel database shown in Fig.6 and Fig.9. The wide range of queries which could be submitted as a result of different query images also possible**.** To check the retrieval time, average recall rate (AVRR), precision and fallout we have used the database with 10000 real world images [1],[7].

$$\text{Precision} = \frac{A}{} \tag{31}$$

(32)

A=Number of retrieved images
B=Number of relevant images

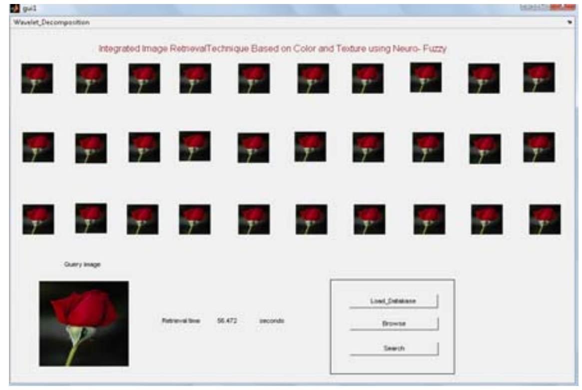


Fig.6.Retrieval of images from first experiment

TABLE II

Precision for various approaches

Approach	Precision(%)				
	Number of query images				
	1	2	3	4	5
Color	68	67	67	68	68
Texture	73	74	74	74	74
Proposed	98	99	99	99	99

Table II provides a detailed comparison of precision obtained for the top five different queries considered using color, texture features and proposed approach. Our proposed approach outperforms other existing methods. Precision performance improved from 68 % to 98% compared to color feature based retrieval and 74% to 98% compared to texture based retrieval for query image no .1.and almost same precision for all query images .For the top five queries computed and tabulated in Table II. The precision for ten different query images shown in Fig.7for the first experiment.

TABLE III

Average recognition rates for various approaches

Approach	Average recognition rate (%)				
	Number of query images				
	1	2	3	4	5
Color	69	70	69	69	69
Texture	75	75	76	75	75
Proposed	98	99	99	99	99

Table III provides a detailed comparison of average recall rate obtained for the top five queries considered using color, texture and proposed approach. Our proposed approach outperforms other existing methods. Average recognition rate performance improved 69% to 98 % compared to color and 75% to 98 % compared to texture on query image no.1.and almost high average recall rate for all other query images. For the top five queries computed and tabulated in Table.III. The Average recognition rates for ten different query images shown in Fig.8 for the first experiment.

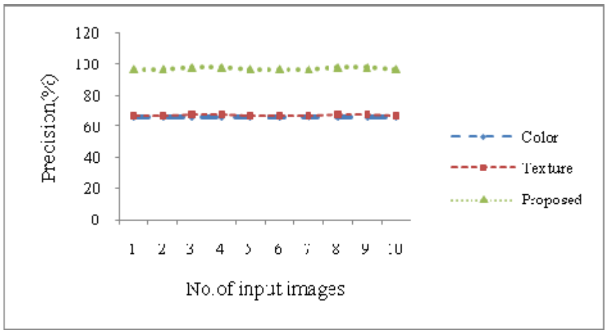


Fig.7. Query images versus precision

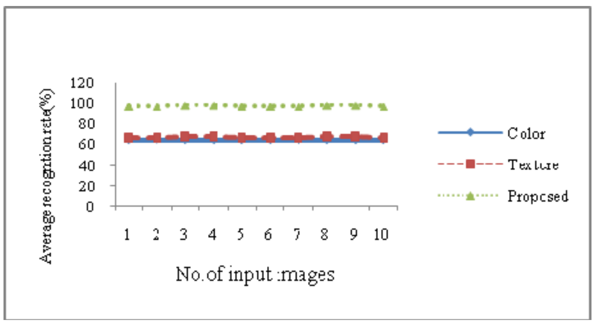


Fig.8. Query images versus average recognition rate.

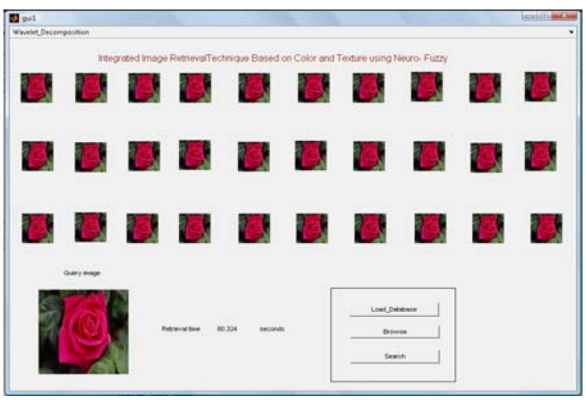


Fig.9.Retrieval of images from second experiment

TABLE III
Precision for various approaches

Approach	Precision(%)				
	Number of query images				
	1	2	3	4	5
Color	67	67	67	67	67
Texture	72	72	72	72	72
Proposed	98	98	98	98	98

Table III provides a detailed comparison of precision obtained for the top five different queries considered using color, texture features and proposed approach. Our proposed approach outperforms other existing methods. Precision performance improved from 67 % to 98% compared to color feature based retrieval and 72% to 98% compared to texture based retrieval for query image no .1.and almost same precision for all query images .For the top five queries computed and tabulated in Table III. The precision for ten different query images shown in Fig.10.for the second experiment.

TABLE IV
Average recognition rates for various approaches

Approach	Average recognition rate (%)				
	Number of query images				
	1	2	3	4	5
Color	68	68	68	68	68
Texture	73	73	73	73	73
Proposed	98	98	98	98	98

Table IV provides a detailed comparison of average recall rate obtained for the top five queries considered using color, texture and proposed approach. Our proposed approach outperforms other existing methods. Average recognition rate performance improved 68% to 98% compared to color and 73% to 98% compared to texture on query image no.1.and almost high average recall rate for all other query images. For the top five queries computed and tabulated in Table. IV. The Average recognition rates for ten different query images shown in Fig.11 for the second experiment.

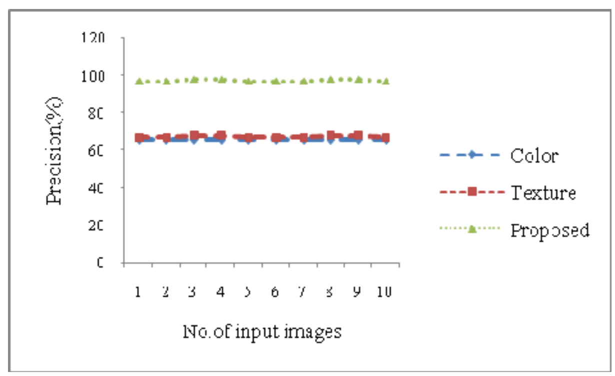


Fig.10. Query images versus precision

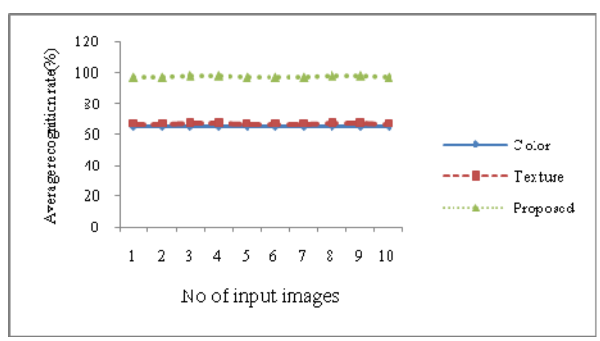


Fig.11. Query images versus average recognition rate.

CONCULSION

In this paper, we proposed new integrated color and texture based integrated image retrieval technique using neuro-fuzzy approach. It is proved that the proposed approach achieves better user interaction and also achieves high average recognition rate upto 98% and precision upto 99%. The experiment is conducted with 20 different queries and significantly the performance of the system is improved. This proposed approach also prove that access methods support CBIR mechanism unable to achieve better performance by only one method. The possibility of different distance measures also gives attractive performances could be explored in future

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