Relevant feedback dependent semantic annotation for Content based image retrieval using region labeling and texture patterns.

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Abstract

Recently, Content-based image retrieval (CBIR) has become an important part of image information retrieval system. Image contents play an important role in image retrieval. In content-based image retrieval system there are three basic steps, i.e. visual feature extraction, multidimensional indexing, and retrieval system design. In this paper, we have presented an effective image retrieval system using features like texture patterns and region. Here, we have chosen three different features such as region and texture orientation & location (spatial). Initially, we use the texture pattern technique for pixel based orientation and spatial features of image in CBIR system. And then, we use region based feature selection using existing technique. These features are extracted from the query image and matched with the feature library using the existing distance matching methods. After that, all feature vectors will be stored in the database using clustering procedure. Finally, the relevant images that have less matched distance than the predefined threshold value are retrieved from the image database after accommodating the feedback technique and annotation. Experimental results, including performance metrics, with the efficient retrieval systems, demonstrate the effectiveness of my approach.

Keywords: Texture, region, Fuzzy local information C-means (FLICM), Multi Texton Histogram (MTH), relevant feedback dependent semantic annotation.

1. Introduction

Growth in large collection of images has been drastically increasing owing to the availability of cheaper storage devices, fast computers & communication technologies, internet access of databases, and much more. Retrieving of images most efficiently from such large collection, based on their content, has become an important research issue for database, image processing and computer vision communities [1]. A technique named Content-based image retrieval (CBIR) [2, 3, 4, 5] is used for extracting similar images from an image database. In CBIR, “Content-based" means that, the search that analyzes the actual contents of the image, and the term 'content' refers to colors, shapes, textures, or any other information that can be derived from the image itself. The most challenging feature of CBIR technique is to viaduct the gap between low-level feature layout and high-level semantic concepts [6]. The CBIR consists of the following two steps for searching the images from the database: 1.) a feature vector is computed and stored in a feature database for each image in the database, 2.) in a given query image, the feature vector is compared to the feature vectors of the image database and images which are most similar to the query image are returned to the user. The features and measures used for comparing two feature vectors must be highly efficient to match similar images [9].

CBIR has been extensively applied in advertising, medicine, crime detection, entertainment, and digital libraries. [7]. In CBIR applications, the user typically provides an image (or a set of images) with no indication of which portion of the image is of interest. Thus a search in classical CBIR often relies upon a global view of the image [6]. However, designing of CBIR system with these objectives becomes difficult as the size of image database increases. CBIR based on color, texture, shape, and edge information are available in the literature [8]. Indeed, content-based image retrieval exploits primitive visual features that humans use to analyze and understand the content of the image, thus reducing the cognitive effort of the user in accessing the database and retrieving results that better match user's expectation [10].

To capture the local characteristics of an image, many CBIR systems either subdivide the image into fixed blocks, or more commonly partition the image into different meaningful regions by applying a segmentation algorithm. In both the cases, each region of the image is represented as a feature vector of feature values extracted from the region. Other CBIR systems extract salient points (also known as interest points), which are locations in an image where there is a significant variation with respect to a chosen image feature [6]. In CBIR systems, the retrieval of the appropriate images for the provided uncertain image is carried out by comparing the characteristics of the uncertain image and the images in the database. So, the characteristics of the image must have a strong correlation with semantic meaning of the image. Relevant images are retrieved according to minimum distance or maximum similarity [11] measure calculated between feature of query image and every image in the image data base [8].

To narrow down the gap and improve the retrieval performance, many promising mechanisms are introduced, among which relevance feedback [12], [13] and region-based image retrieval (RBIR) [14], [15] have been widely used and have shown their effectiveness in many existing systems. As an online learning process, relevance feedback involves the user in the retrieval session and asks the user to judge the relevance of some selected images. With the help of the labeled images, the system can capture the query concept more quickly. In RBIR, each image is segmented into several regions, from which features are extracted. Since region-based features can represent images in object level and accord with human perception better, RBIR often achieves more satisfactory retrieval performance.

Our work: Here, we have considered three different features such as texture orientation, spatial information and region. Initially, we use the texture pattern technique for pixel based orientation and spatial features of image in CBIR system. And then, we use region based feature selection using existing technique. These features are extracted from the query image and matched with the feature library using the existing distance matching methods. After that, all feature vectors will be stored in the database using clustering procedure. Finally, the relevant images that have less matched distance than the predefined threshold value are retrieved from the image database after accommodating the feedback technique and annotation.

Our Contribution: We summarize our contribution as follows.

1) We evaluate the feature extraction of the image based on region labeling and texture pattern in the images.

2) The Fuzzy local information C-means (FLICM) and Multi Texton Histogram (MTH) approach is used to describe image features. For region feature extraction the FLICM clustering Algorithm is used. The FLICM is completely free of any parameter de-termination, while the balance between the noise and image de-tails is automatically achieved by the fuzzy local constraints, enhancing concurrently the clustering performance. And for texture orientation detection and spatial

information MTH algorithm is used. It mixes the advantages of co-occurrence matrix and histogram by mapping the dimension of co-occurrence matrix using histogram.

3) The Euclidean distance method is used for region based image similarity measurement and retrieval of similar images from the database. And the low sensitivity of image histograms makes it a feasible technique for indexing applications of texture based image matching and retrieval.

3) Also we present the relevance feedback based semantic annotation for retrieval of most relevant image with the help of Graphical User Interface (GUI) tool in Matlab.

The rest of this paper is organized as follows; in Section.2 the related work is presented. We briefly introduce our proposed approach in Section.3. In Section.4, our proposed method is presented. Experimental results and discussion in Section.5 and it is followed by Performance analysis and conclusion in Section.6 and section.7 respectively.

2. Review of related works

Copious number of researches has been carried out on image retrieval resulting in various approaches and technique used to retrieve images. Chueh-Yu Li and Chiou-Ting Hsu [16] has presented a graph-theoretic approach for interactive region-based image retrieval. When dealing with image matching problems, they used graphs to represent images, transform the region correspondence estimation problem into an inexact graph matching problem, and present an optimization technique to derive the solution. They defined the image distance in terms of the estimated region correspondence. In the relevance feedback steps, with the estimated region correspondence, they presented to use a maximum likelihood method to re-estimate the ideal query and the image distance measurement. Furthermore, their maximum likelihood method combined with the estimated region correspondence improves the retrieval performance in feedback steps.

Fei Li *et al.*[17] developed a content-based image retrieval (CBIR) that has been an active research topic in the last decade. As one of the promising approaches, graph-based semi-supervised learning has attracted many researchers. However, while the related work mainly focused on global visual features, little attention has been paid to region-based image retrieval (RBIR). In their paper, a framework based on multilabel neighborhood propagation was presented for RBIR, which can be characterized by three key properties: (1) For graph construction, in order to determine the edge weights robustly and automatically, mixture distribution is introduced into the Earth mover's distance (EMD) and a linear programming framework is involved. (2) Multiple low-level labels for each image can be obtained based on a generative model, and the correlations among different labels are explored when the labels are propagated simultaneously on the weighted graph. (3) By introducing multilayer semantic representation (MSR) and support vector machine (SVM) into the long-term learning, more exact weighted graph for label propagation and more meaningful high-level labels to describe the images can be calculated.

Md. Monirul Islam *et al.*[18] presented a region based image retrieval that has received significant attention from number of researches because it can provide local description of images, object based query, and semantic learning. In their paper, they apply curvelet transform to region based retrieval of color images. The curvelet transform has shown promising result in image denoising, character recognition, and texture image retrieval. However, curvelet feature extraction for segmented regions is challenging because it requires regular (e.g., rectangular) shape images or regions, while segmented regions are usually irregular. An efficient method was presented to convert irregular regions to regular regions. Discrete curvelet transform can then be applied on these regular shape regions. Their experimental results and analyses show the effectiveness of their shape transform method. They also showed the curvelet feature extracted from the transformed regions outperformed the widely used Gabor features in retrieving natural color images.

Xugang *et al.* [19] presented a Region-Based characteristic image retrieval method foundation, presented a new kind of the color image retrieval method based on wavelet transformation G-Regions Of Interest (GROI). they first use HVS (Human Visual System) characteristic to choose the color space which fit for the visual characteristics, then use K-means clustering to extract the areas of interest in the wavelet transform domain, and using the local energy of the wavelet coefficients in the areas of interest as the texture feature, color’s mean and variance as the color feature, the barycentric coordinates as the position feature. They calculated the similarity between the image content and retrieval.

Shaofeng Jiang *et al.*[20] presented a region based image retrieval and relevant feedback (RF) system for Medical cerebral MRI images. In the system, firstly, the brains were extracted from cerebral images by a modified BET algorithm, and then were segmented into regions by EM algorithm based on Gauss Mixture Model. Each region was represented by fuzzy features. When performing retrieval, both regional and global features were used. To optimize the retrieval result, there paper used reweighting relevance feedback method (RW) to optimize regional features and presented reweighting Bias Map based relevance feedback method (RW-Bias Map) to optimize global features. The computation of RW is very fast, but only uses the relevant images. RW-Bias Map is based on RW and Bias Map feedback method, it can use both the relevant images and the irrelevant images, but the computation of RW-BiasMap is slowly, so in there paper only uses it to optimize the global features.

Xiaohua Peng *et al.* [21] presented an image retrieval method based on interest image region by asymmetrical blocking. An image is segmented into the interest region and background region on a certain rule. For the interest image regions, the color histogram of the uneven blocks is extracted as the color characteristic. They also collect the mean and variance value of the Gabor filtering results of background blocks as texture features of the background image. Then, the images can be retrieved by synthesizing the image color and texture features. They tested their approaches by analyzing the results of recall and precision indicators for the Corel image database.

Wei Huang *et al.* [22] developed a searching interested images based on visual properties or contents of images is a challenging problem and it has received much attention from researchers. The gap between low-level visual features and high-level semantic understanding of images, which is also known as the semantic gap problem, is the bottleneck to further improvement of the performance of a content-based image retrieval system. In order to solve this semantic gap problem, one of the most popular approaches in recent years is to change the focus from the global content description of images into the local content description by regions (region-based image retrieval) or even the objects in images (object-based image retrieval). Although much research in region-based image retrieval has already been done, there are still three main problems need to be tackled properly: (a) local region-based features, (b) similarity measures, and (c) relevance feedback based on regions.

Songhe Feng *et al*. [23] presented localized content-based image retrieval (LCBIR) that has emerged as a hot topic more recently due to the fact that in the scenario of CBIR, the user was interested in a portion of the image and the rest of the image is irrelevant. In their paper, they propose a novel region-level relevance feedback method to solve the LCBIR problem. Firstly, the visual attention model is employed to measure the regional saliency of each image in the feedback image set provided by the user. Secondly, the regions in the image set are constructed to form an affinity matrix and a novel propagation energy function is defined which takes both low-level visual features and regional significance into consideration. After the iteration, regions in the positive images with high confident scores were selected as the candidate query set to conduct the next-round retrieval task until the retrieval results were satisfactory.

3. Problem definition and solution

The primary intention of my research is to design and develop a technique for content based image retrieval using region labeling as well as texture patterns. Literature presents a lot of work for content-based image retrieval using different set of feature. Among the different techniques, region-based techniques have received a significant interest in recent years. Accordingly, the works presented in [16, 17], describe the content-based image retrieval based on regions label and relevance feedback. When analyzing these two works, the relevant images can be missed out if the same type of images presented in different angle. Also, the semantic richness is needed further to obtain most relevant images. In order to handle these challenges, the texture pattern will be incorporated along with the region labeling to identify the relevant images. Here, the image matching distance will be used to match the region-labeled image and the texture pattern will be matched with histogram-based distance. Also, user feedback-based weights will be used to combine these two different set of image representation. Additionally, the semantic annotation can be easily included based on the users' output obtained from the relevant feedback. This will be stored as semantic annotation that will surely improve the results in future. The implementation will be carried out using the MATLAB software.

4. Proposed Method

Proposed method for content based image indexing and retrieval using region labeling and texture features with relevance feedback and semantic annotation. The number of low-level characteristics of image can be extracted from the images as feature vectors and stored as image indexes. The user query is an image that is indexed by its features, and the recovered images are placed with respect to their resemblance to the query image. Humans incline to use high-level features to interpret images and measure their similarity and image low-level features such as color, texture, shape, etc. frequently break down to distinguish the high level semantic concepts. Statistical models have been proposed to exploit the similarities between image regions or patches, which are represented in a uniform vector. We focus on region labeling and texture-based image interpretation for image retrieval using FLICM and MTH algorithms.

1] Database system

Proposed architecture of a Relevant feedback dependent semantic annotation for Content based image retrieval system using region labeling and texture patterns is shown in fig () below. The functionalities supported by our architecture are: Data insertion = feature extraction & image indexing, Query processing = feature extraction, image matching & retrieval**.** In data insertion scheme the process of feature extraction from images and storing them into the image database is done**.** The database images are indexed according to their feature vectors to speed up retrieval and similarity computation. The query processing, block is coordinated as: the interface lets the users to specify a query image and to visualize the retrieved similar images. The query processing unit extracts the feature vector from a query image and evaluates the similarity between the query image and the database images using the Euclidean distance and the difference of histogram (DOH) method. Next, it clusters the database images according to the similarity to the query image and forwards the most similar images to the interface module. Based on the relevant feedback from the user the image in the database is annotated. Observe that both the data insertion and the query processing units use the feature vector extraction process.

Block diagram and explanation:

2] Feature extraction

Feature extraction is used to reduce the dimensionality. When the input image to an algorithm is too large to be processed and it is distrusted to be unfavorably redundant then this image will be transcoded into a meaningful set of features called features vector. This transforming process is called feature extraction. If the features distilled are carefully selected, then the features set will pull out the relevant information from the input image in order to perform the desired task using this repressed representation instead of the original input. One of the major issue stems from the number of variables involved in analyzing the complex data. A large amount of memory is required for the analysis of large number of variables and calculated power or a categorization al

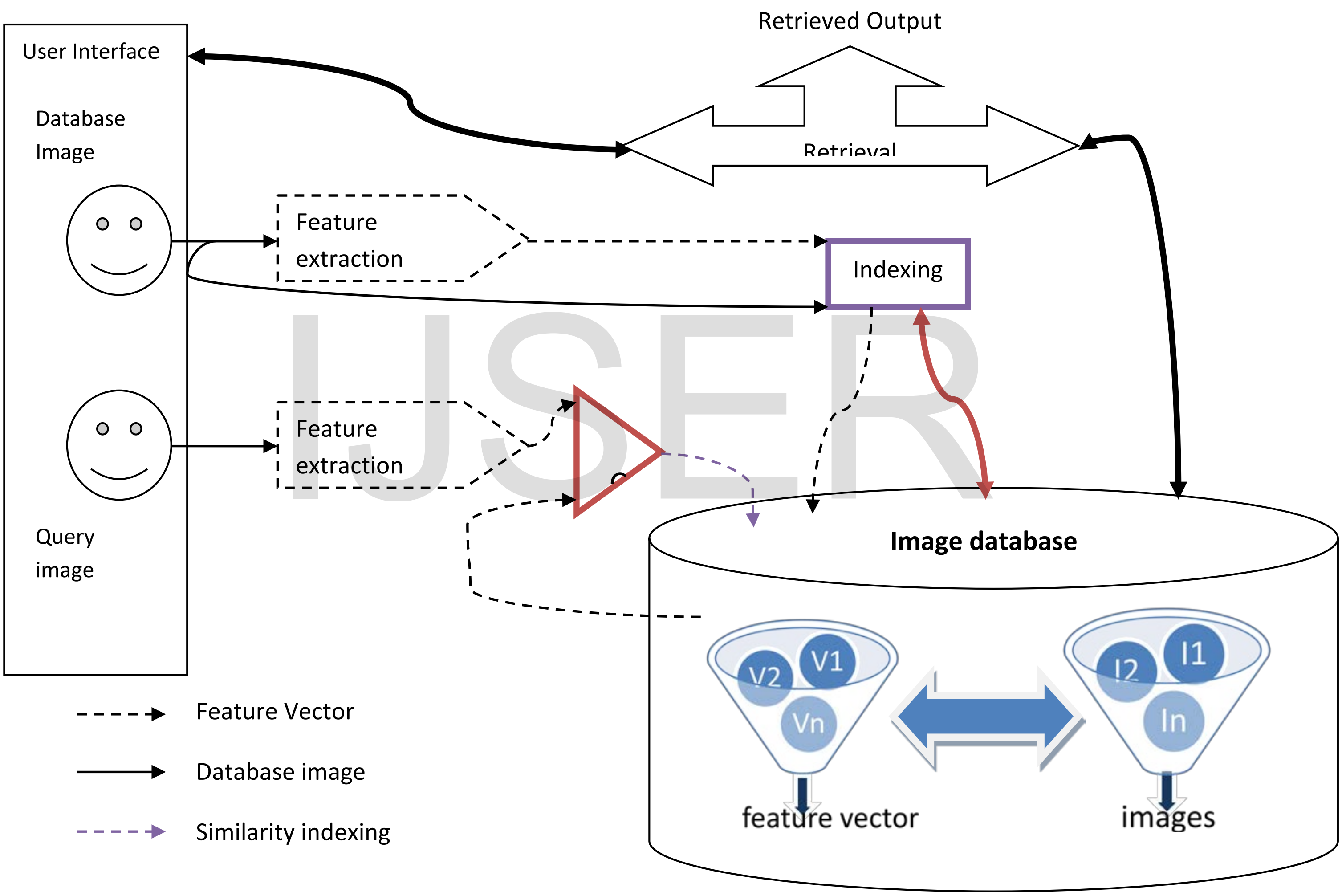


Fig (1): shows the block schematic of the proposed content based image retrieval method.

-gorithm which oversiuts the trailing sample and infers unsatisfactorily to new samples. Therefore, we extract the features of the image by applying two different algorithms. For region labeling the Fuzzy local information C-means (FLICM) clustering Algorithm is used. It can determine the spatial and gray level relationship. A computationally efficient algorithm called Multi Texton Histogram for texture orientation detection and spatial information is used. It can represent the spatial correlation of color and texture orientation. It mixes the advantages of co-occurrence matrix and histogram by mapping the dimension of co-occurrence matrix using histogram.

A) FUZZY LOCAL INFORMATION C-MEANS (FLICM) CLUSTERING ALGORITHM

The fuzzy local neighborhood factor in FLICM can determine [26] the spatial and gray level relationship and is fully free of any parameter extraction. FLICM has the following features:

1) It is relatively independent of the types of noise, and as a result, it is a better choice for clustering in the absence of prior knowledge of the noise;

2) At the same time the fuzzy local constraints integrates both the local spatial and the local gray level relationship in a fuzzy way;

3) It is free from parameter extraction, as the fuzzy local constraints can automatically be determined,

4) The balance among image details and noise is automatically achieved by the fuzzy local constraints, enhancing concurrently the clustering performance.

All these features make FLICM suitable for image clustering algorithm. So, the fuzzy factor [26] defined as

$$G_{gp} = \sum_{q \in N_p} \frac{1}{(d_{pq}+1)} \left(1 - u_{gq}\right)^{a} \left\|x_q - v_g\right\|^2 \qquad (1)$$

Where the p^{th} pixel is the center of the local window (for example, 3x3),

k is the reference cluster and the q^{th} pixel belongs in the set of the neighbors falling into a window around the p^{th} pixel (N_p). $d_{p,q}$ is the spatial Euclidean distance between pixels (p) and, q, u_{kq} is the degree of membership of the q^{th} pixel in the g^{th} cluster, 'a' is the weighting exponent on each fuzzy membership, and v_g is the prototype of the center of cluster 'g'.

FLICM algorithm

Fuzzy Local In-formation C-Means (FLICM) clustering algorithm incorporates local spatial and gray level information into its objective function, [26] defined in terms of

$$J_a = \sum_{p=1}^{N} \sum_{g=1}^{c} \left[u_{gp}^{a} \left\| x_p - v_g \right\|^2 + G_{gp} \right] \qquad (2)$$

The two necessary conditions for J_a to be at its local minimal extreme, with respect to u_{gp} and v_g is obtained as follows:

$$u_{gp} = \frac{1}{\sum_{q=1}^{c} \left(\frac{\left\| x_p - v_g \right\|^2 + G_{gp}}{\left\| x_p - v_q \right\|^2 + G_{gp}} \right)^{1/a-1}} \qquad (3)$$

$$v_g = \frac{\sum_{p=1}^{N} u_{gp}^{a} x_p}{\sum_{p=1}^{N} u_{gp}^{a}} \qquad (4)$$

Thus, the FLICM algorithm is given as follows.

Step1. Set the number c of the cluster prototypes, fuzzification parameter 'a' and the stopping condition∈.
Step2. Initialize randomly the fuzzy partition matrix.
Step3. Set the loop counter B = 0.
Step4. Calculate the cluster prototypes using (4).
Step5. Compute membership values using (3).
Step6. max$\{U^{B} - U^{B+1}\}$ < ∈ then stop, otherwise, set B = B+1 and go to step 4.

When the algorithm has converged, a defuzzification process takes place in order to convert the fuzzy partition matrix U to a crisp partition. The maximum membership procedure is the most important method that has been developed to defuzzify the partition matrix U. This procedure assigns the pixel p to the class C with the highest membership.

$$C_p = arg_g \left\{ max\{u_{gp}\} \right\}, \qquad g = 1, 2, \ldots\ldots, c. \qquad (5)$$

It is used to convert the fuzzy image achieved by the proposed algorithm to the crisp segmented image. The measure used in the FLICM objective function (2) is still the Euclidean metric as in FCM, which is computationally simple. Moreover, differently from FCM, FLICM is robust because of the introduction of the factorG_{gp} , which can be analyzed as follows.

The noise tolerance and outliers resistance property completely relies on the definition of, as it is seen in (2). G_{gp} is automatically determined rather than artificially set, even in the absence of any prior noise knowledge.

The major characteristics of the FLICM are:

• It provides noise-immunity;

• It preserves image details;

• It is free of any parameter selection;

• It is applied on the original image.

Therefore, FLICM adopting seems able to preserve more image details (spatial) than the other methods.

B) MTH

Texture orientation analysis plays an important role in computer vision and pattern recognition. As orientation of texture images has a strong influence on human's perception of a texture image, it can also be used to figure out the shape of textured images. In an image, the orientation map lays out the object boundaries and texture structures, and it puts up most of the semantic content in the image.

Texton orientation detection

Applying some gradient operator, such as the Sobel operator, to a gray level image along horizontal and vertical directions, the two gradient images are obtained, denoted by g_a and g_b . A gradient map $g(a, b)$ can be obtained, with the gradient magnitude and orientation [27] defined as

$$|g(a,b)| = \sqrt{g_a^2 + g_b^2} \text{ and } \theta(a,b) = arctan\left({}^{g_a}/_{g_b}\right) \qquad (6)$$

For full color images, there are red, green and blue channels. So the full color image is first converted into a gray image, and then the gradient magnitude and orientation from the gray image is detected. In order to detect the edges caused by chromatic changes, the following method is used. [27] Cartesian space,

let $m = (a_1, b_1, c_1)$ and $n = (a_2, b_2, c_2)$ their dot product is defined as

$$m.n = a_1a_2 + b_1b_2 + c_1c_2 \qquad (7)$$

So that,

$$\cos(\widehat{m,n}) = \frac{m.n}{|m||n|} = \frac{(a_1a_2+b_1b_2+c_1c_2)}{\sqrt{a_1^2+b_1^2+c_1^2} \; . \; \sqrt{a_2^2+b_2^2+c_2^2}} \qquad (8)$$

Then, the Sobel operator is applied to each of the red, green and blue channels of a color image $f(a, b)$. The gradients along a and b directions can be denoted by two vectors $m(R_a, G_a, B_a)$ and $n(R_b, G_b, B_b)$ where R_a denotes the gradient in R channel along horizontal direction, and so on. Their dot product can be defined [27] as

$$|m| = \sqrt{R_a^2 + G_a^2 + B_a^2} \qquad (9)$$

$$|n| = \sqrt{R_b^2 + G_b^2 + B_b^2} \qquad (10)$$

$$m.n = R_a.R_b + G_a.G_b + B_a.B_b \qquad (11)$$

The angle between m and n is then defined [27] as

$$\cos(\widehat{m,n}) = \frac{m.n}{|m|.|n|} \qquad (12)$$

$$\theta = arccos[\cos(\widehat{m,n})] = arccos\left[\frac{m.n}{|m|.|n|}\right] \qquad (13)$$

After the texture orientation b of each pixel is computed, we quantize it uniformly into 18 orientations with 101 as the step-length.

Texton detection

Texton types are defined on a 2x2 grid, as shown in Fig.2. The four pixels are denoted asV1, V2, V3andV4. If the two pixels in gray have the same value, then the grid will form a texton. Therefore the 4 texton types are denoted as T1, T2, T3andT4, respectively. Fig.3 illustrates the working mechanism of texton detection. In the color index image C(a, b), we move the 2x2 block from left-to-right and top-to-bottom throughout the image to detect textons with 2 pixels as the step-length. If a texton is detected, then the original pixel values in the 2x2 grids are kept unchanged. Otherwise it will have zero value. Finally, we will obtain a texton image, denoted by T(a, b). The four texton types used in MTH contain richer information.

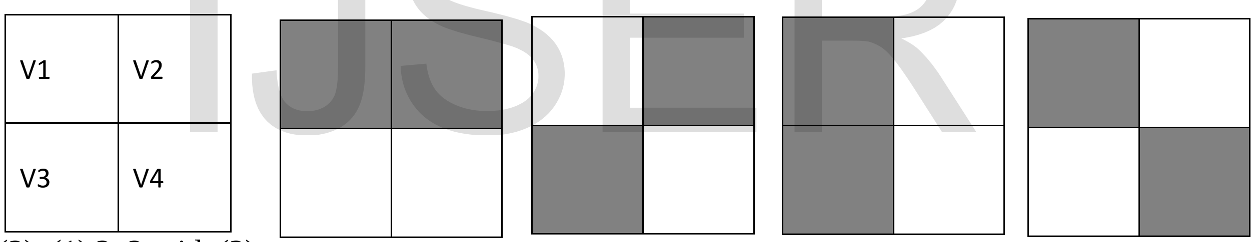


Fig (2): (1) 2x2 grid; (2)
T1; (3) T2; (4) T3; (5) T4; shows Texton types defined in MTH.

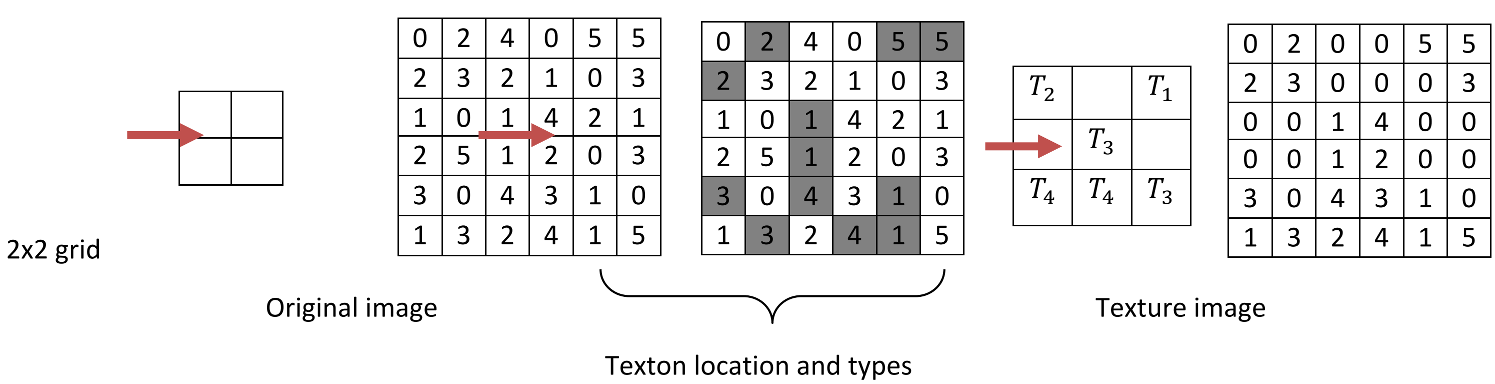


Fig (3): Illustration of the Texton detection process.

In order to combine the advantages of co-occurrence matrix and histogram, the MTH descriptor is used.

The values of a texton image T are denoted [27] as U ϵ {0, 1,…, U-1}. Denote by p_1= (a_1, b_1) and p_2= (a_2, b_2) two neighboring pixels, and their values are T (p_1) =U_1 and T (p_2) =U_2. In the texture orientation image $\theta(a, b)$, the angles at p_1 and p_2 are denoted by $\theta(p_1)$=v_1 and $\theta(p_2)$=v_2. In texton image T, two different texture orientations may have the same color, while in texture orientation image$\theta(a, b)$; two different colors may have the same texture orientation. Denote by N^{th} co-occurring number of two values $v_1$andv_2, and by $\bar{N}^{th}$ co-occurring number of two values W_1andW_2. With two neighboring pixels whose distance is D, we define the MTH as follows:

$$\text{H}\,(\text{T}(p_1)) = \begin{cases} N\{\theta(p_1) = v_{1\,\wedge}\,\theta(p_2) = v_2 \| p_1 - p_2| = D\} \\ \quad where\ \theta(p_1) = \theta(p_2) = v_1 = v_2 \end{cases} \tag{14}$$

$$\text{H}\,(\theta(p_1)) = \begin{cases} \bar{N}\{T(p_1) = W_{1\,\wedge}\,T(p_2) = U_2 \| p_1 - p_2| = D\} \\ \quad where\ T(p_1) = T(p_2) = U_1 = U_2 \end{cases} \tag{15}$$

The MTH algorithm analyzes the spatial correlation between neighboring color and edge orientation based on four texton types, and then forms the textons co-occurrence matrix and describes the attribute of texton co-occurrence matrix using histogram. This is why we call it multi-texton histogram (MTH). Fig.3 shows two examples of the MTH approach. H(T(p_1)) can represent the spatial correlation between neighboring texture orientation by using color information, leading to a 64 dimensional vector. H($\theta(P_1)$) can represent the spatial correlation between neighboring colors by using the texture orientation information, leading to an 18 dimensional vector. Thus in total MTH uses a 64+18=82 dimensional vector as the final image features in image retrieval.

3] Indexing

The act of categorization and plying an index in order to make details of the object easier to recover is said to be as Indexing. The indices are derived from the image content and can be defined as a numerical scale used to compare variables with one another or with some reference number. In content based image retrieval system effective indexing and fast searching of images based on visual features is an important issue.

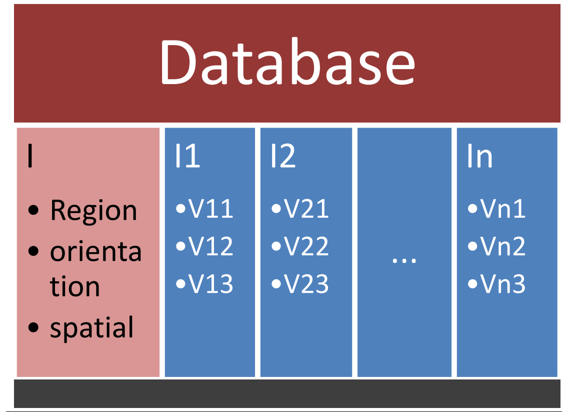


Fig (4): shows the representation of indexing scheme.

The feature extraction of the images ‘I’ in the database of the region and texture representation gives individual feature vector ‘Vj’ for viz; region ‘V1’, texture orientation ‘V2’, spatial information ‘V3’. This feature vector of an image is indexed with respect to the image in the database. The images in the image database;

I =I_i; for {0 <= i <= n,

Where; i = no. of images in the database (0 to n) are indexed based upon the image information i.e., I_i =V_{ij}; for {0<= i <= n and

0 <= j <= m,

Where; m = no. of features to be extracted for the $i^{\ th}$ image.

Here, as we extract three features from an image, the feature vectors for the same are denoted as; V_{i1}= Region labeling, V_{i2} = Texture orientation, and V_{i3} = Spatial information.

As shown in the figure (4) above the images ‘Ii’ are placed column-wise and the corresponding feature vectorsV_{i1}, V_{i2} to V_{i3} are placed row-wise. So that, it will be convenient while the image matching process to extract the similarity features between the query image and the image in the database.

4] Image matching and Retrieval

Image matching and retrieval techniques are generally based on image feature vectors, such as color, texture, and shape. An important criterion for designing a retrieval technique is that the output must include all similar (with respect to color, shape, texture, etc.) images in the database.

As the database contains large number of images, it will consume a lot of time to retrieve the similar image to the query image. So we propose a clustering based technique to retrieve the similar image from the large database by clustering the finite amount of image feature vectors. The 'g' number of clusters with 'n' number of images and feature vectors are matched using the distance measurement method and an image with the most similar image feature vectors in the g^{th} cluster is selected.

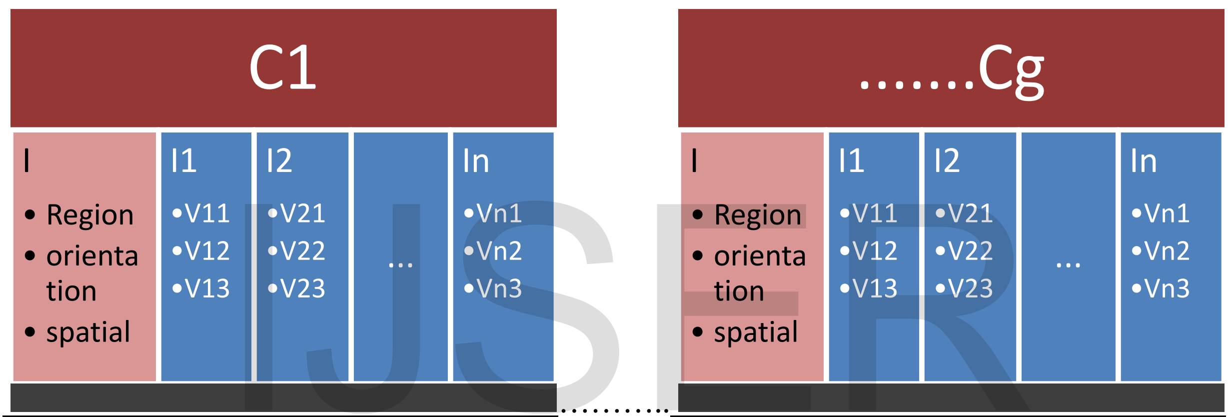


Fig (5): Clustering based Image indexing.

Euclidean distance method for matching and retrieval of region in an image

The proposed cluster based indexing method aiming to speed-up the evaluation of range of queries, allowing the database to be dynamic. The database entries are straight forward and there is no need to reconstruct the entire index list of the database. This is accomplished by reducing the number of prospect images, i.e. images on which the desired region-matching problem has to be solved.

There are various image retrieval techniques used in various applications. We use the Euclidean distance method for region based image similarity measurement [25, 24] and retrieval of similar images from the database. When query image (q) is given, the region feature of that image is identified. By comparing feature vector of query image with feature vector of the images in database, the distance between images will be measured and shortest distance will be considered as best matching image in that matching process. In the same way, the most similar images will be identified by measuring the Euclidean distance in order to retrieve the similar images from the database. The distance d between two image feature vectors is calculated by using the following equation.

$$d_{jl} = \sqrt{\sum_{k=0}^{t} (V_{jk}} - V_{lk})^2 \qquad (16)$$

Where,

t is the dimension of the feature vector

V_{lk} is the l^{th} feature vector of the query image (q),

V_{jk} is the j^{th} feature vector of the database image (I_i).

If the feature vectors are identical the score becomes zero and it increases as the match becomes less perfect.

Histogram based technique of distance measurement for matching texture feature in an image

Image histograms have often been used for color images indexing. They provide an idea at a glance of the image content. Histogram-based techniques have recently become popular in image indexing applications owing to their low complexity [24, 4]. In this technique, the histogram of a query image is compared with the histograms of all the images in a database. Swain et al, [24, 4] proposed a technique to use histogram intersection for matching color objects where the basic possibility is that similar images will have similar color distributions. This concept can be stretched forth to grey level images. The grey level distribution is unmoved to image rotation and change gradually with transformation. Thus, the low sensitivity of image histograms makes it a feasible technique for indexing applications. The histogram of the query image and the images in the database are compared and the images with least difference of histograms (DOH) are chosen for next level of search. The distance between two histograms can be expressed as

$$h_{jl} = \sum_{k=0}^{t} \left[\frac{(V_{jk} - V_{lk})^2}{(V_{jk} + V_{lk})} \right] \tag{17}$$

Where,

t is the dimension of the feature vector

V_{lk} is the l^{th} feature vector of the query image (q),

V_{jk} is the j^{th} feature vector of the database image (I_i).

Relevance feedback based Semantic Annotation

Human sensing of image similarity is taking place within the mind and modified by individual bias. In spite of the fact that content-based methods put up promising ways for image retrieval, normally, the retrieval results based on the resembles of visual features are not semantically meaningful. Also, each type of visual feature inclines to capture only one facet of image attribute and in general it is difficult for a user to define clearly how different facets are united. To overcome these drawbacks we implement the relevance feedback technique based semantic annotation, with which it is possible to meaningfully correlate and label between high-level and low-level features.

Relevance feedback is used to improve the effectiveness of information systems. Our intention is to use the feedback from the user to improve system performance. Here, we use the GUI tool in matlab. For a given query image, the system first retrieves a cluster with the nearest possible indexed list of images according to a predefined image matching techniques (Euclidean and Histogram distance matching techniques). Then, the user selects the retrieved cluster of images as relevant (positive) images to the query or irrelevant (negative) images. Along with it, the user will also annotate the relevant images by a labeling the images. The system will rectify the retrieval results based on the relevant feedback and present a new list of images to the user. Thus, the scheme is called relevant feedback dependent semantic annotation.

5. Results and Discussion

The experimental results of our proposed design are simulated using Matlab 7.12.0. and the performance of the proposed system is analyzed using the evaluation metrics such as precision, recall and F-measure. All the experiments were performed on 3.00GHz Intel(R) Pentium(R) D, 1.00GB RAM, and 32-bit operating system with windows7 professional.

GUI tool for relevant feedback and image Annotation.

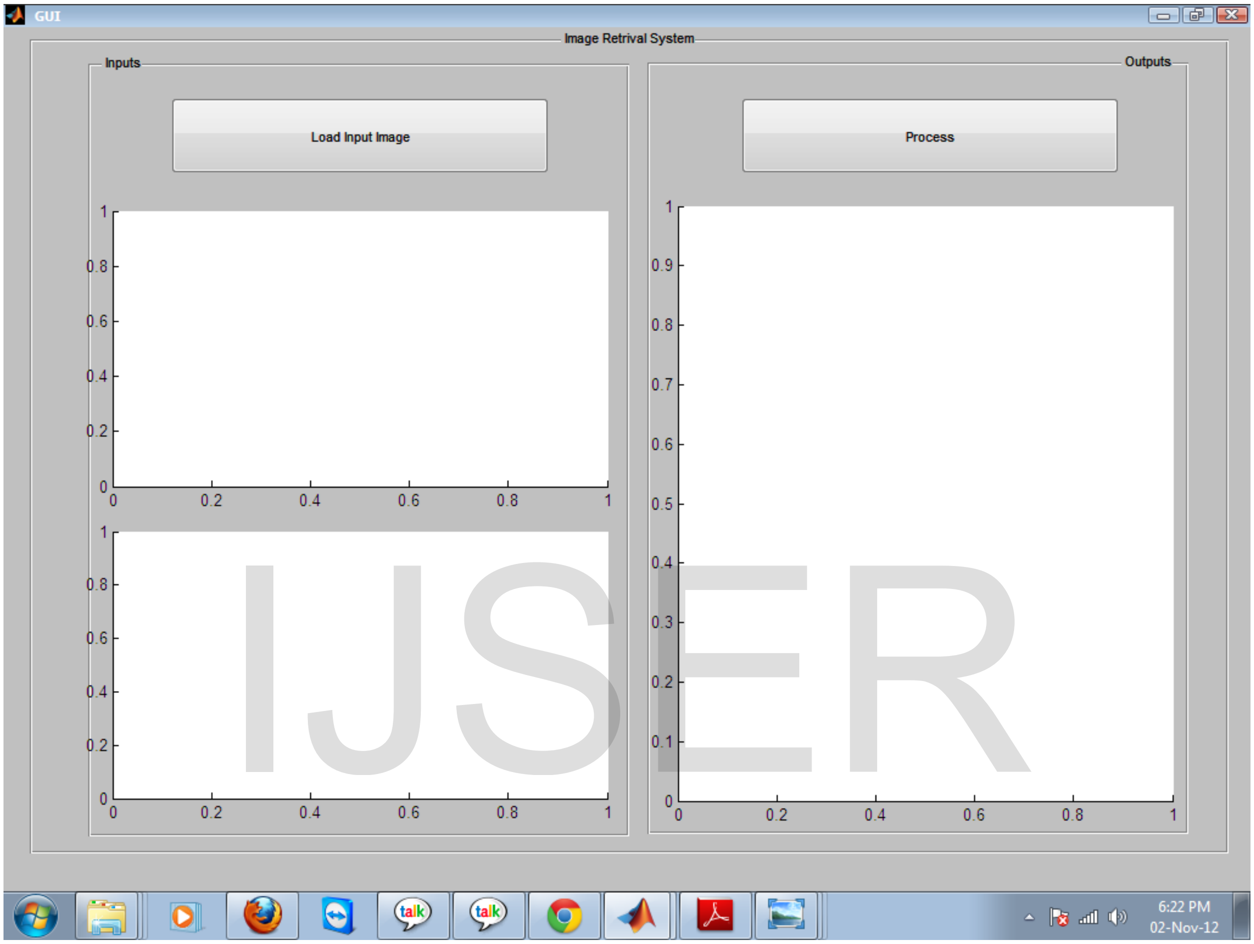


Fig (6): shows the GUI in Matlab7.12.0 for relevant feedback and semantic Annotation implementation in our proposed system.

Now, we shall discuss the procedure for the relevant feedback and semantic Annotation implementation. The GUI window in fig (6) is the first step, where we have to load an input query image to our proposed system. For example, we choose a butterfly image as a query image, this image when loaded our approach extracts the features of the image and after matching with the database image features, and the system retrieves a single image and asks the user to select a relevant image. This process can be clearly understood from the fig (7), fig (8) and fig (9) below.

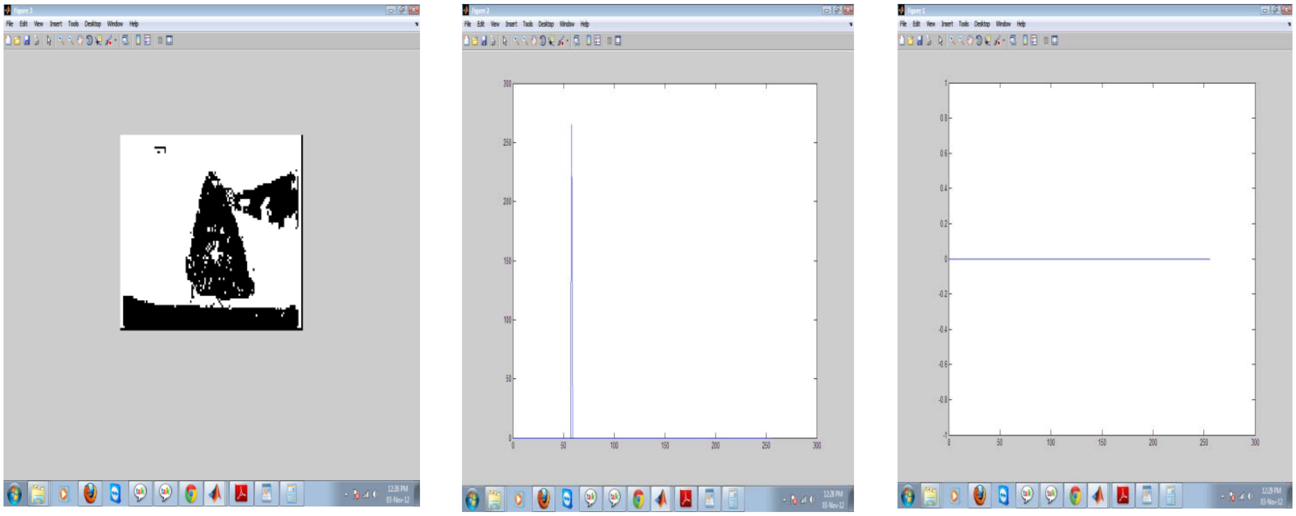
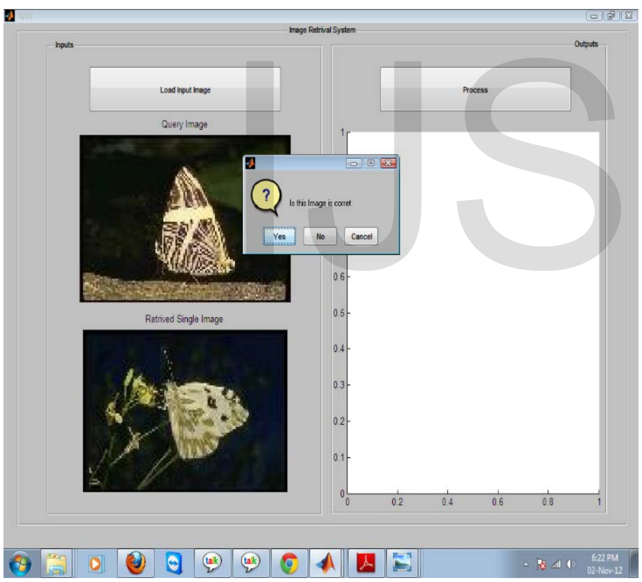
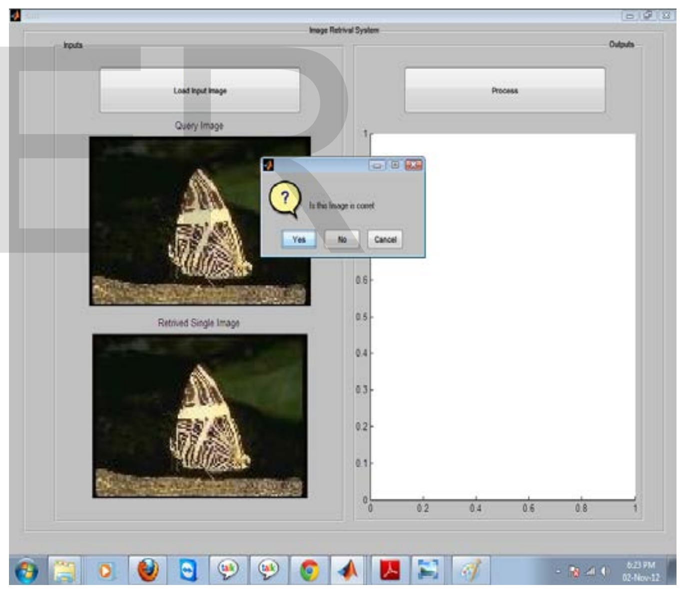


Fig (7): shows the Euclidean distance matching for region based feature extraction(FLICM) and The Histogram distance matching for texture orientation and spatial feature extraction (MTH).





In figure.8 a butterfly image is retrieved but is irrelevant In figure.9 a butterfly image is retrieved but is relevant

i.e., the retrieved image is not the similar image. Thus the user will select the no option on the pop window. But, in figure.9 we can see that as soon as the user reply 'no' to the system, another similar butterfly image is retrieved for the asked query image and hence the user marks it as a correct image if it is so.

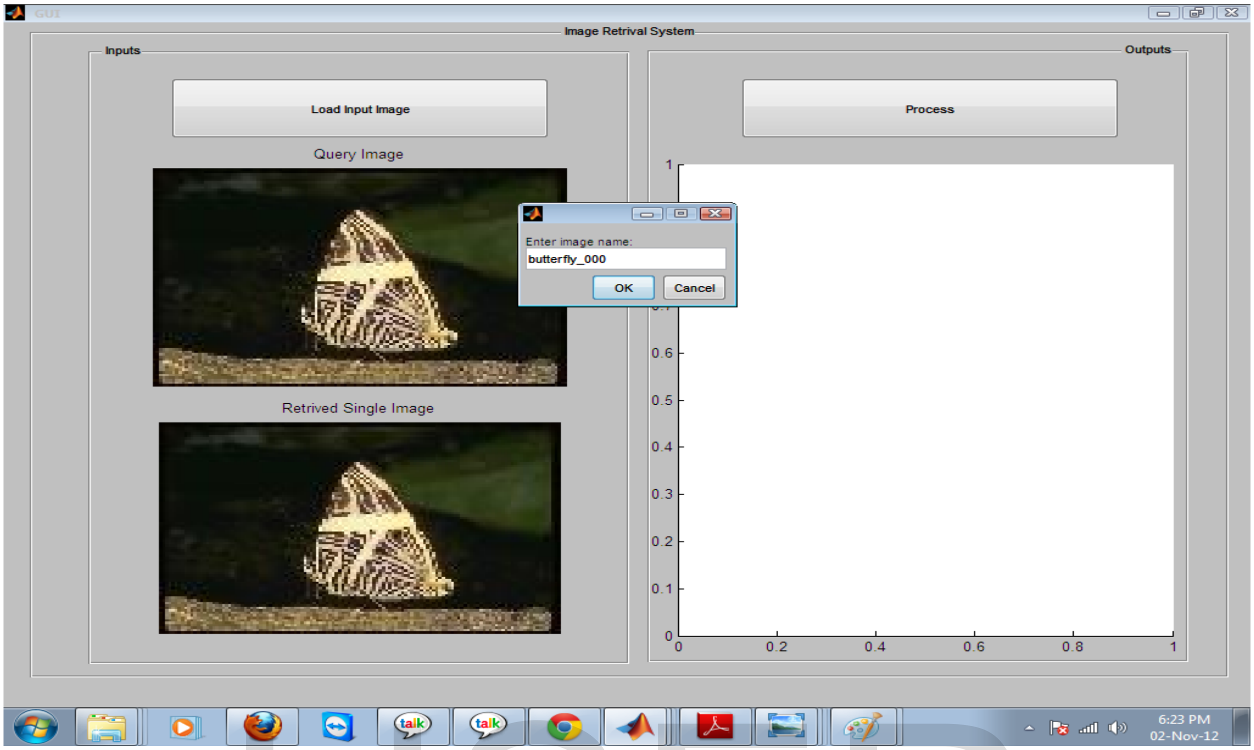


Fig (10): explains the image annotation of relevant image.

The after the feedback from the user that the retrieved image is a relevant image the image annotation is done by labeling the image (ex. butterfly_00) as shown in fig (10). The annotated image is stored in the indexed database by the name butterfly_000. After updating this information the new cluster of image is retrieved in fig (11).

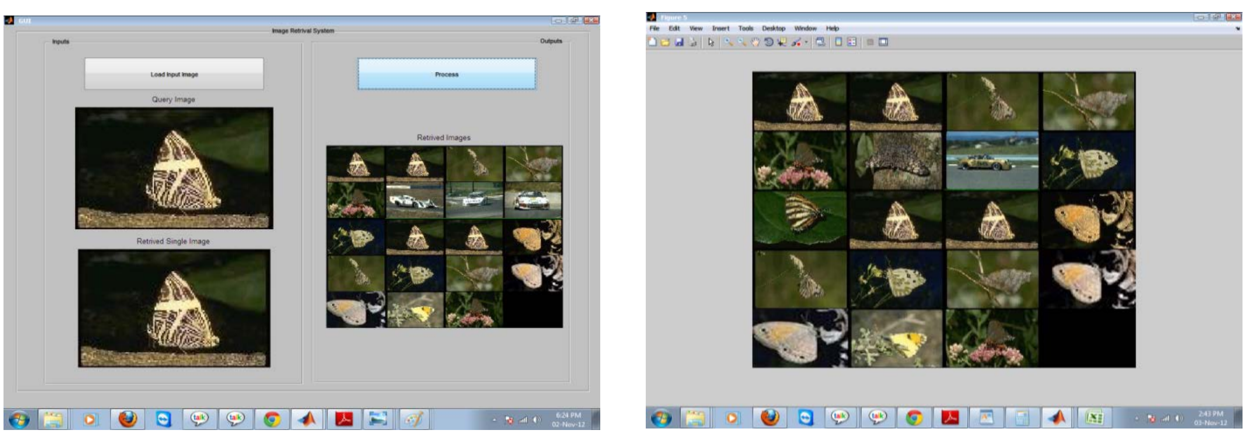


Fig (11): feedback and annotation the updated resulting image cluster for the given query.

6. Performance analysis

The performance of our proposed content based image retrieval (CBIR) approach is analyzed on the input dataset using the precision, recall and F-measure. For performance analysis of the proposed system, images from each X-category are queried to the proposed system and results are evaluated with the following evaluation metrics:

$$Precision = \frac{[no. of\ correct\ images\ retreived]}{[total\ no. of\ retreived\ images]}$$

$$Recall = \frac{[total\ no. of\ correct\ images\ ]}{[total\ no. of\ images\ in\ dataset\ of\ X\ type]}$$

$$F - measure = \left[\frac{2 * (Precision * Recall)}{(Precision + Recall)}\right]$$

Table.1: Color query images of Butterflies and their corresponding metrics precision, recall and F-measure.

I C	Image s	Name of the images	No. of images	retrieved images	correct images	Precision	Recall	F-measure
1	0.jpg	Butterfly	25	19	16	0.8421052	0.64	0.727272727
2	1.jpg	Butterfly	25	19	16	0.84210	0.64	0.727272727
3	2.jpg	Butterfly	25	19	16	0.84210	0.64	0.727272727
4	3.jpg	Butterfly	25	19	16	0.84210	0.64	0.727272727
5	4.jpg	Butterfly	25	19	8	0.42105	0.32	0.363636364
6	6.jpg	Butterfly	25	19	13	0.68421	0.52	0.590909091
7	7.jpg	Butterfly	25	19	13	0.68421	0.52	0.590909091
8	8.jpg	Butterfly	25	19	11	0.57894	0.44	0.5
9	9.jpg	Butterfly	25	19	16	0.84210	0.64	0.727272727
10	10.jpg	Butterfly	25	19	14	0.73684	0.56	0.636363636
11	11.jpg	Butterfly	25	18	17	0.94444	0.68	0.790697674
12	12.jpg	Butterfly	25	17	17	1	0.68	0.80952381
13	13.jpg	Butterfly	25	17	16	0.94117	0.64	0.761904762
14	14.jpg	Butterfly	25	19	17	0.89473	0.68	0.772727273
15	15.jpg	Butterfly	25	20	18	0.9	0.72	0.8
16	16.jpg	Butterfly	25	20	18	0.9	0.72	0.8

17	17.jpg	Butterfly	25	20	14	0.7	0.56	0.622222222
18	18.jpg	Butterfly	25	20	19	0.95	0.76	0.844444444
19	19.jpg	Butterfly	25	19	14	0.73684	0.56	0.636363636
20	20.jpg	Butterfly	25	20	19	0.95	0.76	0.844444444
21	21.jpg	Butterfly	25	19	16	0.84210	0.64	0.727272727
22	22.jpg	Butterfly	25	19	14	0.73684	0.56	0.636363636
23	23.jpg	Butterfly	25	20	17	0.85	0.68	0.755555556
24	24.jpg	Butterfly	25	20	17	0.85	0.68	0.755555556
25	25.jpg	Butterfly	25	19	14	0.73684	0.56	0.636363636
						0.80995	0.617	0.7004648

For our proposed CBIR system, we have taken two types of datasets such as color images and medical images. Table.1 and Table.2 shows the color query images and corresponding precision, recall and F-measure metrics. Table.3 shows the medical query images and corresponding precision, recall and F-measure metrics. The Graph.1 below shows the performance of our proposed system in retrieving the relevant images and it clearly differentiate the results obtained for different images.

Table.2: Color query images of Cars and their corresponding metrics precision, recall and F-measure.

IC	Images	Name of the images	No. of images	retrieved images	correct images	Precision	Recall	F-measure
1	1609.jpg	car	23	20	4	0.2	0.17391304	0.186046512
2	1610.jpg	car	23	20	3	0.15	0.13043478	0.139534884
3	1612.jpg	car	23	20	6	0.3	0.26086956	0.279069767
4	1615.jpg	car	23	20	5	0.25	0.21739130	0.23255814
5	1616.jpg	car	23	20	6	0.3	0.26086956	0.279069767
6	1619.jpg	car	23	20	9	0.45	0.39130434	0.418604651
7	1620.jpg	car	23	19	13	0.6842105	0.56521739	0.619047619
8	1621.jpg	car	23	20	11	0.55	0.47826087	0.511627907
9	1623.jpg	car	23	20	12	0.6	0.52173913	0.558139535
10	1625.jpg	car	23	20	14	0.7	0.60869565	0.651162791
11	1626.jpg	car	23	20	15	0.75	0.65217391	0.697674419
12	1627.jpg	car	23	19	16	0.8421052	0.69565217	0.761904762
13	1628.jpg	car	23	19	16	0.8421052	0.69565217	0.761904762
14	1630.jpg	car	23	19	15	0.7894736	0.65217391	0.714285714
15	1631.jpg	car	23	20	16	0.8	0.69565217	0.744186047

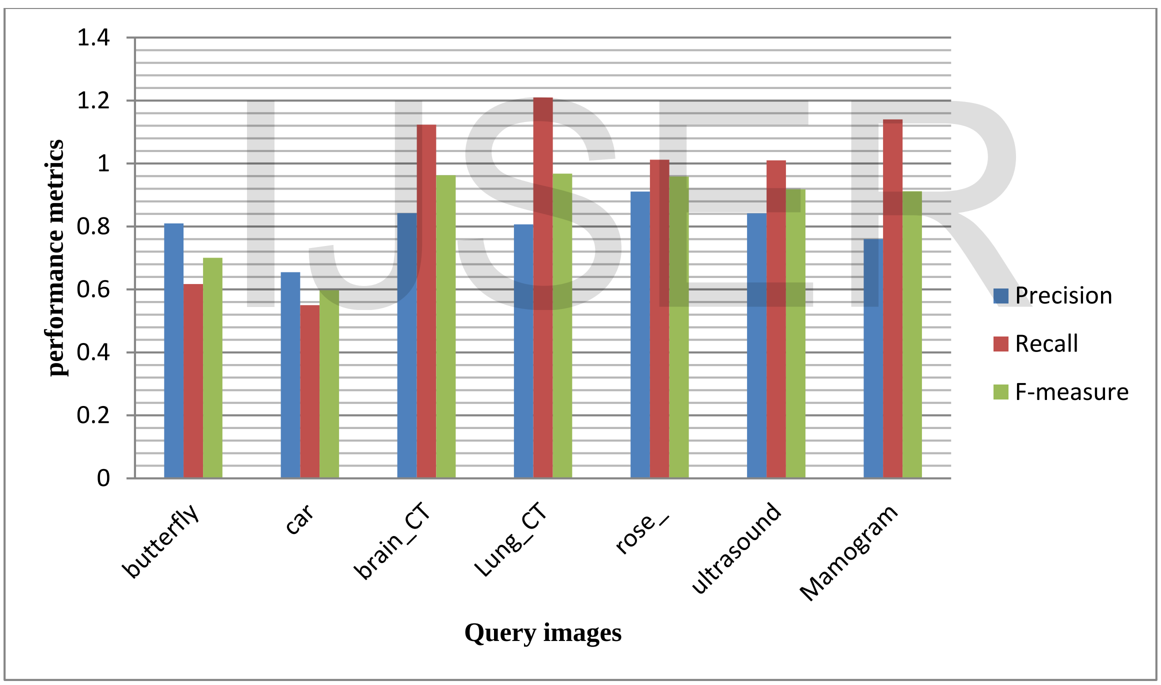
16	1632.jpg	car	23	20	17	0.85	0.73913043	0.790697674
17	1634.jpg	car	23	19	16	0.8421052	0.69565217	0.761904762
18	1635.jpg	car	23	20	16	0.8	0.69565217	0.744186047
19	1636.jpg	car	23	19	16	0.8421052	0.69565217	0.761904762
20	1637.jpg	car	23	18	16	0.8888888	0.69565217	0.780487805
21	1638.jpg	car	23	19	16	0.8421052	0.69565217	0.761904762
22	1639.jpg	car	23	18	16	0.8888888	0.69565217	0.780487805
23	1640.jpg	car	23	19	17	0.8947368	0.73913043	0.80952381
						0.6546402	0.55009451	0.597648465

Table.3: Medical query images of Brain, lung, etc. and their corresponding metrics precision, recall and F-measure.

Images	Name of the images	No. of images	retrieved images	correct images	Precision	Recall	F-measure
Brain_CT_1	Brain_CT_1	9	20	10	0.5	1.111111111	0.689655172
Brain_CT_2	Brain_CT_2	9	20	10	0.5	1.111111111	0.689655172
Brain_CT_3	Brain_CT_3	9	20	10	0.5	1.111111111	0.689655172
Brain_CT_4	Brain_CT_4	9	20	10	0.5	1.111111111	0.689655172
Brain_CT_6	Brain_CT_5	9	20	10	0.5	1.111111111	0.689655172
Brain_CT_7	Brain_CT_7	9	20	10	0.5	1.111111111	0.689655172
Brain_CT_8	Brain_CT_8	9	20	11	0.55	1.222222222	0.75862069
Brain_CT_9	Brain_CT_9	9	20	10	0.5	1.111111111	0.689655172
Brain_CT_10	Brain_CT_10	9	20	10	0.5	1.111111111	0.689655172
					0.505555	1.12345679	0.697318008
Images	Name of the images	No. of images	retrieved images	correct images	Precision	Recall	F-measure
Lung_CT_1	Lung_CT_1	10	20	13	0.65	1.3	0.866666667
Lung_CT_2	Lung_CT_2	10	20	13	0.65	1.3	0.866666667
Lung_CT_3	Lung_CT_3	10	20	11	0.55	1.1	0.733333333
Lung_CT_4	Lung_CT_4	10	20	11	0.55	1.1	0.733333333
Lung_CT_5	Lung_CT_5	10	20	11	0.55	1.1	0.733333333
Lung_CT_6	Lung_CT_6	10	20	11	0.55	1.1	0.733333333
Lung_CT_7	Lung_CT_7	10	19	14	0.736842105	1.4	0.965517241
Lung_CT_8	Lung_CT_8	10	20	12	0.6	1.2	0.8
Lung_CT_9	Lung_CT_9	10	19	12	0.631578947	1.2	0.827586207
Lung_CT_10	Lung_CT_10	10	20	13	0.65	1.3	0.866666667

					0.611842	1.21	0.812643678
Images	Name of the images	No. of images	retrieved images	correct images	Precision	Recall	F-measure
Mamogram_1	Mamogram_1	10	20	10	0.5	1	0.666666667
Mamogram_2	Mamogram_2	10	20	13	0.65	1.3	0.866666667
Mamogram_3	Mamogram_3	10	20	12	0.6	1.2	0.8
Mamogram_4	Mamogram_4	10	20	10	0.5	1	0.666666667
Mamogram_5	Mamogram_5	10	20	10	0.5	1	0.666666667
Mamogram_6	Mamogram_6	10	20	11	0.55	1.1	0.733333333
Mamogram_7	Mamogram_7	10	20	12	0.6	1.2	0.8
Mamogram_8	Mamogram_8	10	19	12	0.631578947	1.2	0.827586207
Mamogram_9	Mamogram_9	10	20	12	0.6	1.2	0.8
Mamogram_10	Mamogram_10	10	20	12	0.6	1.2	0.8
					0.573157	1.14	0.762758621
Images	Name of the images	No.of images	retrieved images	correct images	Precision	Recall	F-measure
rose_2	rose_2	9	20	9	0.45	1	0.620689655
rose_3	rose_3	9	20	9	0.45	1	0.620689655
rose_4	rose_4	9	20	9	0.45	1	0.620689655
rose_5	rose_5	9	20	9	0.45	1	0.620689655
rose_6	rose_6	9	20	9	0.45	1	0.620689655
rose_7	rose_7	9	20	9	0.45	1	0.620689655
rose_8	rose_8	9	20	9	0.45	1	0.620689655
rose_9	rose_9	9	20	9	0.45	1	0.620689655
rose_10	rose_10	9	20	10	0.5	1.111111111	0.689655172
					0.455555	1.012345679	0.62835249
Images	Name of the images	No. of images	retrieved images	correct images	Precision	Recall	F-measure
ultrasound_1	ultrasound_1	10	20	10	0.5	1	0.666666667
ultrasound_2	ultrasound_2	10	20	10	0.5	1	0.666666667
ultrasound_3	ultrasound_3	10	20	10	0.5	1	0.666666667

ultrasound _4	ultrasound _4	10	20	10	0.5	1	0.666666667
ultrasound _5	ultrasound _5	10	20	10	0.5	1	0.666666667
ultrasound _6	ultrasound _6	10	20	10	0.5	1	0.666666667
ultrasound _7	ultrasound _7	10	20	10	0.5	1	0.666666667
ultrasound _8	ultrasound _8	10	20	10	0.5	1	0.666666667
ultrasound _9	ultrasound _9	10	20	11	0.55	1.1	0.733333333
ultrasound _10	ultrasound _10	10	20	10	0.5	1	0.666666667
					0.505	1.01	0.673333333



Graph.1: The evaluation metrics viz; Precision, Recall and F-measure in column clusters clear represents performance of our proposed approach.

From the performance analysis tables above and the graph it is clear that precision of our system for top 10 to 15 best retrieved images give best results, since some set of images in database (for example; the total set of Lung_CT images are only 10 in the database but the no. of retrieved cluster of images are 20. Hence, in table.3 we can see the average precision value for Lung_CT image is 0.611842 but if we take avg. precision for top 15 results then it is 0.806666667 which is

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ideal.) are less than the no. of images in the cluster (i.e., 20 images in a cluster). Therefore, we consider the top 10 to 15 images for precision metric which can be observed in graph.1. However, in the evaluation result table.1, 2 & 3 the results are retained for no. of retrieved images (=20) is shown and not for top 10 to15.

7. Conclusion

The purpose of this research is to develop an effective "relevant feedback dependent semantic annotation for Content based image retrieval system" using region labeling and texture patterns. We extract region feature of an image using FLICM algorithm and also extract texture patterns of an image using MTH algorithm. Then the clustered indexing and matching is executed based on Euclidean distance for Region features and Histogram Distance matching for Texture patterns for image retrieval. Our experiments on a color and medical image dataset have shown effective retrieval using a GUI based feedback and annotation concepts.

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