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An Efficient Texture Based Feature Extraction Method for Content Based Image Retrieval

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Abstract— **Image retrieval is an application of computer vision technique, searches digital images in large databases. In earlier phase this need was satisfied by retrieving the relevant images from different database simply. Where there is a restriction that the retrieved images was not relevant to the user query because the images were not retrieved based on content where another drawback is that the manual searching time is increased. To address this problem CBIR is developed which is a technique for retrieving images on the basis of automatically-derived features such as colour, texture and shape of images. In existing work, high level filtering such as Anisotropic Morphological Filters, particle filter and hierarchical Kaman filter were used along with feature extraction method based on color and gray level features. To get high performance measure, the existing work can be extended by extracting various features such as color texture feature and gray texture features. The methods of Gray level co-occurrence matrix and Color-Level co-occurrence matrix are used for extracting color and gray texture feature respectively. In order to extract texture information Texture Units (TU) are used such as Basic Texture Unit (BTU), Reduced Texture Unit (RTU) and Fuzzy based Texture Unit (FTU) is estimated for each texture which is being extracted. These texture units extract textural information of an image with complete characteristics of textures. Finally the extracted feature has been selected and combined by using Particle Swarm Optimization (PSO). Experimental results shows better performance when compare with the existing work.**

Keywords— ***Content-Based Image Retrieval (CBIR), Color Texture feature extraction, Gray-level Texture feature extraction, Texture Units, Particle Swarm Optimization (PSO)***

I. Introduction

Content based image retrieval or CBIR is a technique for the retrieval of images based on visual features such as color, shape and texture. In CBIR, each image stored in the database has features that can be extracted and compared to the features of the query image. This process involves two steps: They are Feature extraction and matching. The first process involves extracting features to a distinguishable extent. In second process these features can be match to yield visually similar results.

A. Color

Color is an important feature in which it makes humans to recognize the image efficiently. It is a property which depends on the reflection of light to the eye and the process that information by the brain. The method used for representing color information in CBIR is color Histogram. Color histogram is a type of Bar chart, in which each bar represents particular color of the color space that is being used. Quantization process can be done for reducing the number of bins by obtaining colors which are very similar to each other and putting them in the same bin. Clearly quantization reduces the information about the content of images and it is a tradeoff between processing time and quality.

B. Texture

Texture is a property of the surface which describes the visual pattern and each patterns maintains homogeneity. It is an important spatial feature which is useful for identifying regions or objects of interest in an image. In past various textures based methods are developed for extracting features of images. Those methods yield high level interpretation by giving quantitative information on images. Texture is one of the essential primitives in human vision and texture features which have been used for identifying the content of images.

II. Related Works

In [1] Yong Rui describes Color as one of the most widely used visual features which are invariant to image size and orientation.

In [2] Serge Belongie used a method which uses Expectation- Maximization on color and texture features together to retrieve an image, as well as a new image

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representation explicitly. EM algorithm iteratively models the combined distribution of color and texture with a mixture of Gaussians parameter then the resulting pixel cluster memberships provides a resultant image. After that the image is decomposed into regions in which a description of each region's of color, texture, and spatial characteristics. In a querying task, the user can directly access the regions in order to see the retrieval image based on of the query image and specify which features of the image are important to the query.

In [3] L.Zheng describes CBIR in microscopic pathology image database by based on similarity content to the user for the supplied query images. In this similarity is based on image feature types such as image texture, wavelet coefficients, color histogram and Fourier coefficient by using dot product of vector as a distance metric. Distance measure have been validated by agglomerative cluster analysis.

In [4] Young Deok Chun described a CBIR based method for a combination of texture and color features. For color feature, color auto correlograms of the hue and saturation of component images in HSV color space are used. Texture features include BVLC and BDIP moments of the component image. These extracted features are combined in the multi resolution wavelet domain.

In [5] Hatice Cinar Akakin described the design and development of a multi-tiered content-based image retrieval (CBIR) system for microscopic images using a reference database that contains images of more than one disease. In this CBIR system uses a multi-tiered approach for classification and retrieval of microscopic images by involving specific subtypes. This system allows both multi-image and slide-level query image retrieval to protect the semantic consistency among the retrieved images.

In [6] Kavitha describes the statistical texture feature using gray-level co occurrence matrix (GLCM). In this image retrieval technique uses local color and texture features in which an image is partitioned into different sub-blocks of equal size. Color of each sub-block is extracted by quantifying the HSV color space and the color feature is represented by cumulative histogram. Similarly, texture of each sub-block is taken by using gray level co occurrence matrix. Query and target image can be matched by one to one matching and Euclidean distance is used for retrieving the similar images.

In [7] Maheshwari described a method in which Color moment and Gabor filter are used for the feature extraction of image dataset. Hierarchical clustering algorithm and K-means has also utilized to combine the image dataset into several clusters.

In [8] Choras et al. described an combined form of color, texture and shape feature extraction method in which Gabor filtration method is used for determining the number of regions of interest. They estimated texture and color features from the ROIs by based on threshold Gabor features and histograms. Then estimate color moments and shape moments in YUV color space and Zernike moments. The features have been proved efficient in determining similarity between images.

In [9] S. Liapis describes one or two dimensional histograms of the CIELab chromaticity coordinates are chosen as color features, and thus variances of these features are extracted by discrete wavelet frames analyses which are chosen as texture features.

In [10] A. Vadivel used a SDHSV color histogram as a color feature and Haar or Daubechies' wavelet moment as a texture feature. Energies of DCT coefficients and the mean and covariance of RGB values are used as color and texture features in [11] respectively which was described by H. Permuter.

In existing work the concept of CBIR using the high level filtering methods and feature extraction process has been presented. The filtering is done by using two filtering techniques called hierarchical Kaman filter and particle filter and Anisotropic Morphological Filters. In Anisotropic Morphological Filters are used on binary to filter the noise effectively. The hierarchical Kaman filter in which it eliminates the global linear figure and the particle filter handle the local nonlinear figure. After this the feature extraction is based on color feature and gray level feature. By quantifying the HSV color space into non-equal intervals the color of each sub-block is extracted. The color feature s represented by cumulative color histogram. Texture of each one sub-block is attained by using gray level co-occurrence matrix. After these two processes the normalization process is executed to make the components of feature vector equal importance. The similarity measurement from these observations is finished based on mahalanobis distance which is to measure distance for every observation.

Current research extends and explores existing work by considering texture feature. Proposed Content based image retrieval has been done by extracting Texture features such as color texture feature and gray texture feature. Texture unit can be estimated for these two extracted feature. Each extracted texture includes Texture units (TU) such as Basic Texture Unit (BTU), Reduced Texture Unit (RTU) and Fuzzy based Texture Unit (FTU).These extracted features can be combined by means of Particle swarm optimization(PSO). Here the features are selected and combined then gives out best possible combined features. Then query image can b matched with the database image in a one to many progress. With this resultant images will be retrieved from the database images based on the query image in an efficient manner.

The main contribution of this works as follows:

Collecting the images and maintain in a database and train that images by applying the filtering and feature extraction methods which can be briefly explain below.

Get the user query image and test the image with the same filtering and feature extraction techniques.

Combine the extracted feature by using PSO.

Produce the content based image collections with respect to the user query image.

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III. PREVIOUS WORK

The challenge of semantic gap between the low-level visual features and the high-level semantic concepts is occurrence by Content-based image retrieval (CBIR) system. It would be valuable to make CBIR arrangements which maintain high-level semantic query. The CBIR fundamentally performs two main tasks; at the outset feature extraction, which is extracting feature position from the query image which is in general known as feature vectors or else signatures of the image which perfectly characterizes the substance of each image in the database.

Content based Image retrieval is an efficient method to look from beginning to end of an image database through image features such as color, texture, shape, pattern or any combinations of them. Previous research extracted two important features such color and gray level features.

For each image in the image database, these two features are extracted and the obtained feature space (or vector) is stored in the feature database. When a query image arrives the feature space of image will be compared with the images those in the feature database one by one and the similar images with the smallest feature distance will be retrieved.

The steps for extracting color feature is as follows:

Step1: Separate three color planes such as Red, Green and Blue from the image.

Step2: For every image surface row mean and column mean of colors are calculated.

Step3: The average of all row means and all columns means is calculated for each image.

Step4: The features of all 3 planes are combined to form a feature vector. These vectors are stored in the feature database once the feature vectors are generated for all images in the database.

Step5: The Mahalanobis distances between the feature vector of query image and the feature database are calculated using Equation given below.

$$d_{ij} = \left(\left((\overline{X}_i - \overline{X}_j)^T \right) S^{-1} (\overline{X}_i - \overline{X}_j) \right)^{1/2} \rightarrow (1)$$

The value of d is calculated by summation of the squares of difference of the features of database image and query image as mentioned in Eq. (1). Lower the value of E ie in above Eq. point to higher relevance to the query image.

Next, a gray level feature of an image can be extracted by using grey-level co-occurrence matrix is described as follows: Given an image assent to be location operator, and p is a matrix whose element is the number of times that points with grey level (intensity) occur, in the position specified by the relationship operator, relative to points with grey level. $g\ (j)$. Let P be the matrix that is produced by dividing with the total number of point pairs that satisfy p. is a measure of the joint probability that a pair of points satisfying p will have values is called a co-occurrence matrix defined by p. The relationship hand is defined by an angle θ and distance d.

IV. PROPOSED TEXTURES BASED FEATURE EXTRACTION FOR EFFICIENT IMAGE RETRIEVAL

Texture is a significant spatial feature which is useful for identifying regions of interest in an image. Various texture based methods are developed for extracting features of images. For effective image retrieval system, especially images poor illumination, resolution levels and noises, the crucial factor is used for the selection of appropriate and efficient similarity feature. Current work deals with extracting color texture features and gray level texture features and texture unit of these two extracted feature can be extracted. These extracted texture units of color and gray level texture features are Basic Texture Unit (BTU), Reduced Texture Unit (RTU) and Fuzzy based Texture Unit (FTU). These units give out textual information with complete texture characteristics in all directions instead of working in only one displacement vector. To address these issues the present paper proposed new similarity texture feature derived from the novel idea of Basic Texture Unit (BTU), Reduced Texture Unit (RTU) and Fuzzy based Texture Unit (FTU).

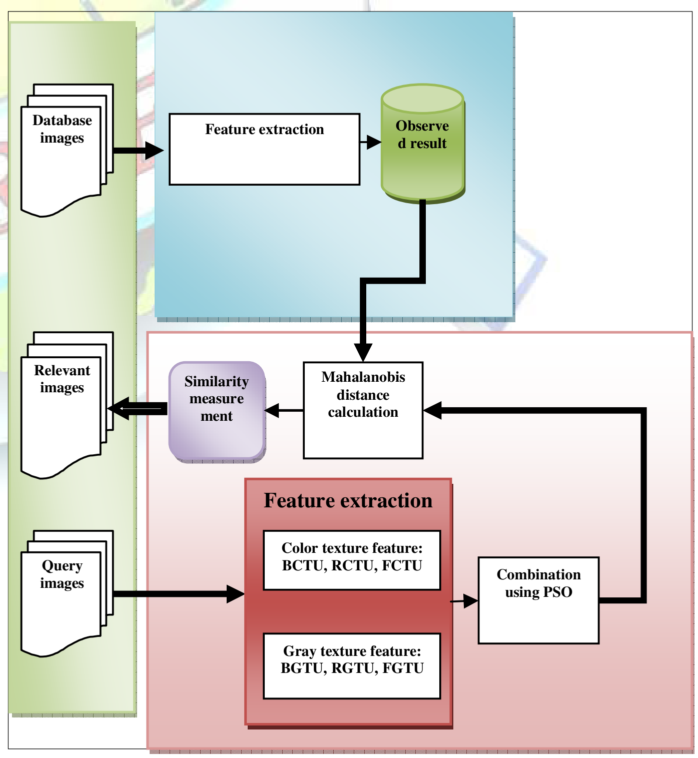

Figure 1:Overall System Architecture

The three units can be described briefly in the following section:

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A. Basic Texture Unit (BTU)

A brief review of the Texture Unit (TU) methods of calculating texture unit can be described from which texture spectrum can be constructed. Consider the digital image, each pixel is surrounded by its eight neighbouring pixel. Local texture information can be extracted from its 3X3 pixels. This represents the smallest complete unit by means of having eight directions surrounding the pixel. Neighbourhood of these pixel can be denoted by nine elements such as I={ I0,…….I8},where I0 represents the intensity value of the centre pixel and Ii={1.2,…8} represents the intensity value of the neighbouring pixel i. Texture unit can be defined by the set of these eight elements. TU = { E1,E2…E8} where Ei={i=1,2….8} which is determined by the following equation

$$\text{Ei}=\begin{cases} 0 \; if \; I_i < I_0 \\ 1 \; if \; I_i = I_0 \;\; for : i = 1,2,\ldots 8 \\ 2 \; if \; I_i > I_0 \end{cases}$$

The basic texture units (BTU) can be calculated by the following equation

$$N_{BTU} = \sum_{i=1}^{8} E_i \times 3^{i-1}, N_{BTU} \in \{0,1 \ldots .(3^8-1)\}$$

B. Reduced Texture Unit (RTU)

The texture unit of RTU is defined by following equation:

$$E_i = \begin{cases} 0 \; if \; I_i < I_0 \\ 1 \; if \; I_i \geq I_0 \end{cases} \text{ for i=1, 2….8}$$

The element Ei takes same positions as pixel i. In this each element of Texture Unit has one the two possible values, hence the combination of all eight elements results 28 =256 possible TU in total. These 256 texture units are labelled by following equation:

$$N_{RTU} = \sum_{i=1}^{8} E_i \times 2^{i-1}, N_{RTU} \in \{0,1 \ldots (2^8-1)\}$$

Where NRTU represents the Reduced texture unit and E_i is the i^{th} element of TU={ E1,E2…E8}.

C. FuzzybBased Texture Unit (FTU)

The previous texture units were unable to categorize the differences from less or greater and far greater than from the grey level value of central pixel. In order to incorporate this feature on 3X 3 masks, concept of RTU can be extended to Fuzzy texture unit FTU.

The texture Unit of fuzzy FTU is defined by following equation:

$$\begin{cases} 0 \; if \;\; I_i < I_0 \; and \;\; I_i < X \\ 1 \; if \;\; I_i < I_0 \; and \;\; I_i > Y \\ \quad 2 \qquad\quad I_i = I_0 \qquad for \; i = 1,2,3 \ldots 8 \\ 3 \; if \;\; I_i > I_0 \; and \;\; I_i > X \\ 4 \; if \;\; I_i > I_0 \; and \;\; I_i > Y \end{cases}$$

Where x, y are user specified values

The corresponding fuzzy texture unit FTU of elements TU={E1,E2…E8} can be computed by following equation

$$N_{FTU} = \sum_{i=1}^{8} E_i \times 5^{\left(\frac{i-1}{2}\right)}$$

The range of FTU lies between BTU and RTU.

D. Gray Texture feature extraction

Gray texture feature can be extracted by using Gray level co-occurrence matrix estimating grey-level relationships between pixels of image.

In statistical image analysis, GLCM (Gray-level co-occurrence matrix) is a common technique used to estimate image properties that is related to second-order statistics. In one offset the relation between two neighbouring pixels is considered as the second order texture, in which the first pixel is called as reference and the second one as the neighbour pixel. GLCM is said to be joint probability of two dimensional matrix $P_{d,\theta}(i,j)$ between pair of pixels separated by d distance in a particular direction θ.Using GLCM gray texture feature can be extracted by using Homogeneity for feature vector estimation. Homogeneity can be defined as follows:

$$\text{Homogeneity}_{d,\theta} = \sum_{i,j} \frac{P_{d,\theta}(i,j)}{1+|i-j|}$$

E. Gray texture Unit (GTU)

Texture unit can be described by taking the relative grey-level relationships between the central pixel and its neighbour pixels .Gray level texture can be decomposed into set of Gray texture units (GTU).These texture unit represents statistical texture unit, local texture aspect in an image for revealing gray level texture information.

The three different texture units for gray level image can be represented as Basic Gray Texture Unit (BGTU), Reduced Gray Texture Unit (RGTU) and Fuzzy Gray based Texture Unit (FGTU).

The three texture units for gray level texture feature can be represented as follows:

$$N_{BGTU} = \sum_{i=1}^{8} E_i \times 3^{i-1}, N_{BGTU} \in \{0,1 \ldots .(3^8-1)\}$$

Where NBGTU denotes number of basic Gray level texture Units.

$$N_{RGTU} = \sum_{i=1}^{8} E_i \times 2^{i-1}, N_{RGTU} \in \{0,1 \ldots (2^8-1)\}$$

Where NRGTU denotes number of Reduced Gray level texture Units .and

$$N_{FGTU} = \sum_{i=1}^{8} E_i \times 5^{\left(\frac{i-1}{2}\right)}$$

Where NFGTU denotes number of Fuzzy Gray level texture Units respectively.

F. Color Texture feature extraction

Color images can be represented by HSV and RGB color space. Color texture feature extraction is done by two types of RGB representation: The first one computes feature vector (FV) from extracted feature of RGB channels

Feature vector_1= { FE(R) , FE (G),FE(B) }

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Second types estimates Feature vector from the relation between all six combination of RGB

$Featurevector_2$= {FE(RGB),FE(RBG),FE(GBR), FE(GRB),FE(BGR),FE(BRG)}

Where these combinations of colors are computed from

RGB=round(c1R+ c2G+ c3B)
RBG= round(c1R+ c2B+ c3G)
GBR= round(c1G+ c2B+ c3 R)
GRB= round(c1G+ c2R+ c3B)
BGR= round(c1B+ c2G+ c3R)
BRG= round(c1B+ c2R+ c3G)

Where c1: c2 : c3 represents the ratio

Color texture can be extracted by using the method called Color level co-occurrence method (CLCM). In this scenario, Feature vector is estimated directly from 3D RGB color space. For distance d=1 the cube of 3X3X3 size is created. Three CLCM matrices are estimated for every channel. For example CLCM estimation of channel green is as follows:

$$CLCM_{i,j}(G)=\sum_{m=-1}^{1}\sum_{n=-1}^{1} relation(img(i,j,2)|img(i+m,j+n,2))$$

Where $m \wedge n \neq 0$,

$$CLCM_{i,j}(GR)=\sum_{m=-1}^{1}\sum_{n=-1}^{1} relation(img(i,j,2)|img(i+m,j+n,1))$$

$$CLCM_{i,j}(GB)=\sum_{m=-1}^{1}\sum_{n=-1}^{1} relation(img(i,j,2)|img(i+m,j+n,3))$$

Where img. is an image represented by RGB(Red, Green, Blue) color space.

Final CLCM feature vector is expressed as follows:

Feature Vector={FE(R),FE(RG),FE(RB),FE(G), FE(GB),FE(GR),FE(B),FE(BG), FE(BR)}

G. Color Texture Unit

The three different texture units for color image can be represented as Basic color Texture Unit (BCTU), Reduced color Texture Unit (RCTU) and Fuzzy color based Texture Unit (FCTU).

The three texture units for color texture feature can be represented as follows:

$$N_{BCTU}=\sum_{i=1}^{8} E_i \times 3^{i-1}, N_{BCTU} \in \{0,1 \ldots (3^8-1)\}$$

Where NBCTU denotes number of basic Color texture Units.

$$N_{RCTU}=\sum_{i=1}^{8} E_i \times 2^{i-1}, N_{RCTU} \in \{0,1 \ldots (2^8-1)\}$$

Where NRCTU denotes number of Reduced Color level texture Units and

$$N_{FCTU}=\sum_{i=1}^{8} E_i \times 5^{(\frac{i-1}{2})}$$

Where NFGTU denotes number of Fuzzy Color level texture Units respectively.

H. Feature Selection and optimization using PSO

Feature selection and combination of these selected features can be done by well known optimization technique called Particle swarm optimization. Particle swarm optimization (PSO) was developed by Kennedy and Eberhart in which it is an expansion of a social behaviour of simulated system that integrates concept such as nearest-neighbour velocity matching and acceleration by distance. Current work extends PSO for the combination of different extracted features. These extracted features includes color texture feature, gray texture feature , Basic color Texture Unit (BCTU), Reduced Color Texture Unit (RCTU), Fuzzy color based Texture Unit (FCTU). Basic Gray Texture Unit (BGTU), Reduced Gray Texture Unit (RGTU) and Fuzzy Gray based Texture Unit (FGTU).

Algorithm for combination of these features can be done by following step wise process:

Step1: Initialize all extracted feature as particles

Step2: Initialize respective weight for all particles

Step3: Combine information from both particles and weights

Step 4: Select best particle and combine these particles based on fitness value.

The fitness value of a particle is calculated by using distance measure χ^2 of following equation

$$\chi^2(a,b)=\sum_{i=1}^{n} w_i \frac{(a_i-b_i)^2}{a_i+b_i}$$

Where a and b are the features of database and query image, w_i denotes weight of the ith particle.

The retrieval of image in the database for the query image can be done by (1: N) process. This process can be repeated for all database and query image until retrieving top matched image.

V. Results and Discussion

In our experiment first the query image is got from the user. Then the process of feature extraction such as color texture feature with its texture units and Gray texture features with its units will be extracted. Then these features can be combined by using PSO. At the end the resultant images will be retrieved from the collection of database based on the input query image. These steps will be shown as figures as follows:

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A. Precision vs Number of images

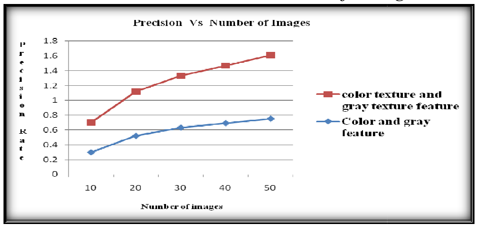

Figure 2: Precision vs. Number of images

This graph shows the precision rate of existing and proposed system based on two parameters of precision and the number of images. From the graph we can see that, when the number of number of images is advanced the precision also developed in proposed system but when the number of images is improved the precision is reduced somewhat in existing system than the proposed system. From this graph we can say that the precision of proposed system is increased which will be the best one. The values are given in below Table 1:

TABLE 1: PRECISION VS. NUMBER OF IMAGES

S.NO	Number of images	Existing system	Proposed system
1	10	0.30	0.40
2	20	0.52	0.60
3	30	0.63	0.70
4	40	0.69	0.78
5	50	0.75	0.86

In this graph we have chosen two parameters called number of images and precision which is help to analyze the existing system and proposed systems. The precision parameter will be the Y axis and the number of images parameter will be the X axis. The blue line represents the existing system and the red line represents the proposed system. From this graph we see the precision of the proposed system is higher than the existing system. Through this we can conclude that the proposed system has the effective precision rate.

B. Recall vs. Number of images

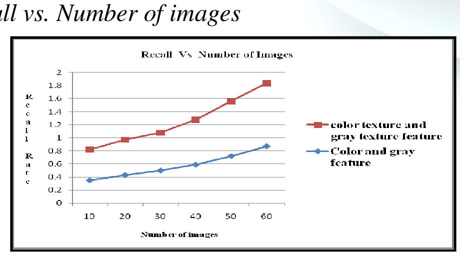

Figure 3: Recall vs. Number of images

This graph shows the recall rate of existing and proposed system based on two parameters of recall and number of images. From the graph we can see that, when the number of number of images is improved the recall rate also improved in proposed system but when the number of number of images is improved the recall rate is reduced in existing system than the proposed system. From this graph we can say that the recall rate of proposed system is increased which will be the best one. The values of the recall rate are given in a below table 2:

TABLE 2: RECALL VS. NUMBER OF IMAGES

SNO	Number of images	Existing system	Proposed system
1	10	0.35	0.47
2	20	0.43	0.54
3	30	0.50	0.58
4	40	0.59	0.69
5	50	0.72	0.84
6	60	0.87	0.97

In this graph we have chosen two parameters called number of images and recall which is helping to analyze the existing system and proposed for the recall rate estimation. In X axis the iteration parameter has been taken and in Y axis recall parameter has been taken. . From this graph we see the recall rate of the proposed system is in peak than the existing system. Through this we can conclude that the proposed system has the effective recall.

C. F-measure vs. Number of images

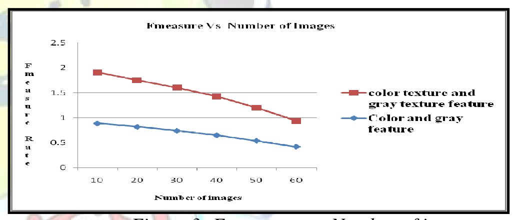

Figure 3: F-measure vs. Number of images

This graph shows the F-measure rate of existing and proposed system based on two parameters of F-measure and number of images. From the graph we can see that, when the number of number of images is improved the F-measure rate also improved in proposed system but when the number of number of images is improved the F-measure rate is reduced in existing system than the proposed system. From this graph we can say that the F-measure rate of proposed system is increased which will be the best one. The values of the F-measure rate are given in a below table 3.

TABLE 3: F-MEASURE VS. NUMBER OF IMAGES

SNO	Number of images	Existing system	Proposed system
1	10	0.89	1.02
2	20	0.82	0.93
3	30	0.74	0.86
4	40	0.65	0.78
5	50	0.54	0.66
6	60	0.42	0.52

In this graph we have chosen two parameters called number of images and F-measure which is help to analyze the existing system and proposed systems on the basis of F-measure. In X axis the iteration parameter has been taken and in Y axis F-measure parameter has been taken. From this graph we see the F-measure rate of the proposed system is in peak than the existing system. By this we can conclude that the proposed system has the effective F-measure.

VI. CONCLUSION

In this paper we proposed new methods for CBIR system for efficient retrieval of images. Different Texture features such as color and Gray texture feature can be extracted. Based on these extracted textures Corresponding Texture Units such as Basic Texture Unit (BTU), Reduced Texture Unit (RTU) and Fuzzy based Texture Unit (FTU) has been estimated for each Extracted feature. These units results complete texture characteristics of an image. Finally extracted texture can be selected and combined using Particle Swarm Optimization. The experimental results shows that this proposed technique is much better than the existing system for content based image retrieval process.

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