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An Optimized Image Retrieval approach based on Color, Shape and Texture

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1. ABSTRACT

In the last few years, more and more information has been published in computer readable formats. A huge amount of the information in older books, journals and newspapers has been digitized and made computer readable. A big record of films, music, images, satellite pictures, books, newspapers, and magazines have been made accessible for computer users. Internet communication or facilities makes it possible for the human to access this vast amount of information. The big challenge of the World Wide Web or search engines is that the more information available about a given topic, the more difficult it is to locate accurate and relevant information. All the users know what type of information they want, but they are not sure where to find it. Search engines can facilitate the ability of users to locate such relevant information. [3]

2. INTRODUCTION

An image retrieval system returns a set of images from a collection of images in the database[1][2][3][4] to meet up the user's demand with similarity evaluations such as image content similarity, edge pattern similarity, color similarity, etc. An image retrieval system offers a proficient way to access, surf, and retrieve a set of similar images in the real-time applications. Some approaches have been developed to capture the information of image contents by directly computing the image features from an image as reported in [5][6][7][8][9][10].

The image retrieval system works as a classifier to break up the images in the image database into two modules, either relevant or irrelevant. When results are irrelevant, the feedback loop is repeated until the user is satisfied. Relevance feedback involves the user to label the similar and dissimilar image. An efficient image retrieval technique is used to retrieve similar images in various stages. The images firstly retrieved on color basis and the resultant retrieved images further match with their shape and texture feature respectively.

2.1 Text-Based Image Retrieval and Content-Based Image Retrieval

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In text-based image retrieval system, images are indexed on the basis of keywords, topic headings, or classification codes, which is play a role as retrieval keys during search and retrieval [23]. The manual keyword explanation and methods of text retrieval was the initial model used for image retrieval. This system was feasible when the collection of images were small. However, this approach was not practically implemented when the collections of images were large and a huge amount of manual effort was required, which was also time-consuming and inconsistent in naming keywords among different users. To defeat this problem a new approach called Content Based Image Retrieval (CBIR) was proposed (Zhu et al. 2000).

2.2 Content-based image retrieval (CBIR)

Content-based image retrieval (CBIR) is the use of computer vision to the image retrieval difficulty that is the crisis of searching for digital images in huge databases. "Content-based" means that the search will evaluate the actual contents of the image. 'Content' word refers colors, shapes, textures, or some other information that can be taking from the image itself.[29]

CBIR consists the two phases first is the indexing phase where image information like the color, shape, and texture is enumerated into features that are stored in an index data structure. Second is the retrieval phase where is searching for an image in the CBIR index. Color similarity is obtained by computing a color histogram for every image with the purpose of identifies the ratio of pixels within an image holding specific values. Tentative images based on the colors they contain are one of the most commonly used techniques because it does not depend on image size or direction. The color searches will usually keep comparing color histograms. [22]

LITERATURE SURVEY

Guo et al. (2014) proposed a method on CBIR using features extracted from half toning-based block truncation coding. In this study, an image retrieval system is offered by exploiting the ODBTC encoded data stream to construct the image features, namely color co-occurrence and bit pattern features. The proposed scheme provides the best average precision rate compared to other scheme. This scheme can also be applied to video retrieval. [25]

Mehtre et al. (1995) proposed a method on shape measure for CBIR. In this proposed method, discuss effectiveness of several shape measures for content based correspondence retrieval of images. The different shape measures implemented include outline based features like as chain code based string features, Fourier descriptors, UNL Fourier features, region based features like as invariant moments, Zemike moments, pseudo-Zemike moments, and combined them. [31]

Dubey et al. (2014) proposed a method on rotation and scale invariant hybrid image descriptor and

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retrieval. In this proposed method, an efficient approach is presented to encode the color and texture features of images from the local neighborhood of each pixel. RSHD is promising under rotation and scaling. Also it can be effectively used under transformations of more complex image. [22]

Mona Mahrous Mohammeda et al. (2015) introduces a technique for content-based image classification and retrieval using PCNN. This technique uses an optimized Pulse-Coupled Neural Network to extract the visual features of the image in a form of a numeric vector called image signature. They evaluated our prototype against one of the widely used techniques and that the proposed technique can enhance the search results. [35]

Mohsen Sardari Zarchi et al. (2015) introduce a concept-based model for image retrieval systems model retrieves images based on two conceptual layers. First layer is the object layer; the objects are detected with the discriminative part-based approach. Second layer is designed to recognize visual composite, a higher level concept to specify the related co-occurring objects. The experiments are carried out on the well-known Pascal VOC dataset and results show that the model significantly outperforms the existing content-based approaches. [36]

Ming Zhang et al. (2014) proposed a novel image retrieval method like hybrid information descriptors (HIDs) that consisting of mutual information descriptors (MIDs) and self information descriptors (SIDs). It comparing with further vacant methods applied to content-based image retrieval (CBIR) on four datasets and show the usefulness and effectiveness of the HIDs. The broad experimental results can also demonstrate this. [37]

Subrahmanyam Murala et al. (2014) introduce expert content-based image retrieval system using robust local patterns. The local region of the image is represented by making the use of local difference operator and separating it into two components such that sign and magnitude. The achievement of the technique presented when compared to SLBP and other existing transform domain techniques in terms of their evaluation measures. [38]

Yu-Chai WAN et al. (2014) introduce Online Learning a Binary Classifier for Improving Google Image Search Results It is promising to get better web image search results during exploiting the results and visual contents for learning a binary classifier which is used to refine the results. This paper proposes an algorithm framework as a solution to this problem. The training data selection process is divided into two stages such as initial selection for triggering the classifier learning and dynamic selection in the iterations of classifier learning. They investigate two main ways of initial training data selection clustering based and ranking based, and compare automatic training data selection schemes through manual approach. This algorithm is effective to improve Google search results, especially at top ranks, thus is helpful to reduce the user effort in finding the desired images by browsing the position in depth. Even so, it is still worth meditative to make automatic training data selection scheme better towards perfect human annotation. [39]

Yeong-Yuh Xu et al. (2015) introduce Multiple-instance of learning based assessment neural networks for image retrieval. This paper proposes a multiple-instance learning based decision neural network (MI-BDNN) that attempts to link the semantic gap in CBIR. The proposed approach considers the image retrieval problem as a MIL problem wherever a user's preferred image theory is learned by training multiple-instance learning based decision neural network with a set of exemplar images, each of which is labeled as conceptual related (positive) or conceptual unrelated (negative) image. The MI-BDNN based CBIR system is developed, and the results of the experiments showed that multiple-instance learning based decision neural network can successfully be used for real image retrieval and classification problems. [16]

Menglin Liu et al. (2015) introduce a chroma texture-based method in color image retrieval. The large numbers of experiments performed and proved that the chroma texture feature was a very important complement to the traditional fluorescence texture. The effectiveness of the image retrieval is enhanced a lot by combination of fluorescence texture and chroma texture with a lower-dimensional vector. [17]

Bugatti et al. (2014) proposed Perceptual similarity queries in medical CBIR systems through user. In this paper, they present a novel approach to perform similarity queries over medical images, maintaining the semantics of a given query posted by the user. And also present a highly effective strategy to survey user profiles, taking advantage of such labeling to implicitly gather the user perceptual similarity. The profiles maintain the settings desired for each user, allowing tuning of the similarity assessment, which encompasses the dynamic change of the distance function employed through an interactive process. Experiments on medical images show that the method is effective and can improve the decision making process during analysis. [40]

Verma et al. (2015) proposed a Local extrema co-occurrence pattern for color and texture image retrieval. In this paper they present a new image retrieval technique; local extrema co-occurrence patterns (LECoP) using the HSV color space. HSV color space is used in this method to utilize the color, intensity and brightness of images. Local extrema patterns are applied to define the local information of image, and gray level co-occurrence matrix is used to obtain the co-occurrence of LEP map pixels. The local extrema co-occurrence pattern extracts the local directional information from local extrema pattern, and converts it into a well-mannered feature vector with use of gray level co-occurrence matrix. The presented method is tested on five standard databases called Corel, MIT

VisTex and STex, in which Corel database includes Corel-1k, Corer-5k and Corel-10k databases. Also, this algorithm is compared with previous proposed methods, and results in terms of precision and recall are shown in this work. [41]

Meng jian et al. (2015) proposed an Interactive image retrieval using constraints. In this paper, they present a novel interactive image retrieval framework using constraints. First, extract the user region of interest (ROI) from queries by simple user interaction using adaptive constraints-based seed propagation (ACSP), and obtain initial retrieval results based on the ROI. Then, improve the retrieval results by active learning from the user relevance feedback using ACSP. Since ACSP is very effective in propagating the user interactive information of constraints by employing a kernel learning strategy, it successfully learns the correlation between low-level image features and high-level semantics from the ROI and relevance feedbacks. Experimental results demonstrate that the proposed framework remarkably improves the image retrieval performance by ACSP-based constraint propagation in terms of both effectiveness and efficiency. [42]

Khemchandani et al. (2015) proposed a Color image classification and retrieval through ternary decision structure based multi-category TWSVM. In this paper, they present Ternary Decision Structure based multi-category twin support vector machines (TDS-TWSVM) classifier. Twin support vector machines (TWSVM) formulation deals with finding non-parallel plane classifier which is obtained by solving two related Quadratic Programming Problems (QPPs). The proposed TDS-TWSVM classifier is an extension of TWSVM so as to handle multi-class data and is more efficient in terms of training and testing time of classifiers. The experimental results depict that TDS-TWSVM outperforms One-Against-All TWSVM (OAA-TWSVM) and binary tree-based TWSVM (TB-TWSVM) in terms of classification accuracy. [43]

Bhaskar reddy et al. (2014) proposed a Content based image indexing and retrieval using directional local extrema and magnitude patterns. In this paper, they integrate the concept of directional local extremas and their magnitude based patterns for content based image indexing and retrieval. The standard directional local extrama pattern (DLEP) extracts the directional edge information based on local extrema in 0°, 45°, 90°, and 135° directions in an image. However, they are not considering the magnitudes of local extremas. The proposed method integrates these two concepts for better retrieval performance. The performance of the proposed method is compared with DLEP, local binary patterns (LBPs), block-based LBP (BLK_LBP), center-symmetric local binary pattern (CS-LBP), local edge patterns for segmentation (LEPSEG) and local edge patterns for image retrieval (LEPINV) methods by conducting two experiments on benchmark databases, viz. Corel-5K and Corel-10K databases. The results after being investigated show a significant improvement in terms of their evaluation measures as compared to other existing methods on respective databases. [44]

Yasmin et al. (2014) proposed An Efficient Content Based Image Retrieval using EI Classification and Color Features. In this paper, images are decomposed in equal squares of minimum 24 × 16 size and then edge detection is applied to those decomposed parts. Pixels classification is done on the basis of edge pixels and inner pixels. Features are selected from edge pixels for populating the database. Moreover, color differences are used to cluster same color retrieved results. Precision and recall rates have been used as quantification measures. It can be seen from the results that proposed method shows a very good balance of precision and recall in minimum retrieval time, achieved results are comprised of 66%-100% rate for precision and 68%-80% for recall. [45]

Wiselin Jiji et al. (2015) proposed Content-based image retrieval techniques for the analysis of dermatological lesions using particle swarm optimization technique. This method presents extraction of effective color and shape features for the analysis of dermatology images. The proposed algorithm used color and shape feature vectors and the features are normalized using Min–Max normalization. Particle swarm optimization (PSO) technique for multi-class classification is used to converge the search space more efficiently. The results using receiver operating characteristic (ROC) curve proved that the proposed architecture is highly contributed to computer-aided diagnosis of skin lesions. Experiments on a set of 1450 images yielded a specificity of 98.22% and a sensitivity of 94%. [46]

Zarchi et al. (2014) proposed A semantic model for general purpose content-based image retrieval systems. This model is used to overcome semantic gap in CBIR. In this model an interactive image segmentation algorithm is carried out on the query image to extract the user-interested regions. To recognize the image objects from regions, a neural network classifier is used in this model. In order to have a general-purpose system, no priori assumptions should be made regarding the nature of images in extracting features. So a large number of features should be extracted from all aspect of the image. The high dimensional feature space, not only increases the complexity and required memory, but also may reduce the efficiency and accuracy. Hence, the ant colony optimization algorithm is employed to eliminate irrelevant and redundant features. To find the most similar images to the query image, the similarity between images is measured based on their semantic objects which are defined according to a predefined ontology. [47]

Raghuwanshi et al. (2016) proposed Texture image retrieval using adaptive tetrolet transforms. Tetrolets provide fine texture information due to its different way of analysis. Tetrominoes are applied at each decomposition level of an image and best combination of tetrominoes is selected, which better shows the geometry of an image at each level. All three high pass components of the decomposed image at each level are used as input values for feature extraction. A feature vector is created by taking standard deviation in combination with energy at each subband. Retrieval performance in terms of accuracy is tested on group of texture images taken from benchmark databases: Brodatz and VisTex. Experimental results indicate that the proposed method achieves 78.80% retrieval accuracy on group of texture images D1 (taken from Brodatz), 84.41% on group D2 (taken from VisTex) and 77.41% on rotated texture image group D3 (rotated images from Brodatz).[48]

Vipparthi et al. (2015) proposed Dual directional multi-motif XOR patterns: A new feature descriptor for image indexing and retrieval. This method is entirely different from the existing motif representation. Here introduced a new methodology of extracting one standard 2×2 grid at distance two and four 1×3 smart grids along dual directions which are not present in existing motif representation. This entire operation is implemented on '*V*' color space of HSV color plane. Further, the XOR operation is performed on the transformed new motif images which are not present in the literature (local binary patterns (LBP) and motif co-occurrence matrix (MCM)). The performance of the proposed method is tested by conducting two experiments on Corel-5000 and Corel-10,000 databases. Experimental results demonstrate that it is much more efficient in terms of average retrieval precision (ARP) and average retrieval rate (ARR). [49]

Yang et al. (2015) proposed a Color image representation using invariant exponent moments. In this paper, they analyze the rotation, scaling, and translation (RST) invariant property of EMs, and propose a content-based image retrieval approach using invariant EMs. Experimental results show that the EMs can be used as an effective descriptor of global image content, and the proposed retrieval approach yields higher retrieval accuracy than some current state-of-the-art retrieval methods. [50]

3. PROPOSED WORK

The actual color data of an image is stored as arrays of values, known as channels. Typically an image will have at least 3 channels, representing red, green, and blue color values. But the values stored in array could represent other color spaces. Normally each image has 3 (or 4) channels of image data. The current 'color space' of an image determines what the data of each channel represents. The channels are named 'Red', 'Green', 'Blue', as that is the type of image data that is stored in those channels. However that is not always the case. Don't think of the 'R' or 'Red' channel as being red, think of it as 'channel 1' which could contain data for 'red', 'hue', 'cyan', or other things depending on the color space of the image. Red is just a label for the channel used for red or the first channel.

The second most common color space used is 'CMYK', which defines the amount of color 'ink' that should be applied to a darken a 'white' piece of paper (a subtractive colors pace). Note that K is

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short for "blacK", which a negated intensity values of the image.

As this is very common the 'RGB' channels also have an alternative naming of 'Cyan', 'Magenta', and 'Yellow', or just the letters 'C', 'M' and 'Y', though in reality they refer to the same set of channels that is used for 'RGB' images. A special fourth color channel is also added for the 'Black' or 'K' color channel. This basically means that the color channel for "Green" actually refers to the exact same color channel as would be used for "Magenta". Whether the data itself is 'green' or 'magenta' depends NOT on the name of the channel, but the 'color space' of the image in memory.

The same thing happens for other color spaces. For example using a 'LAB' color space means the 'Red' channel contains the 'Lightness' value, while 'Green' channel holds the 'A' (or red-green) value, and 'Blue' channel holds the 'B' (or blue-yellow) value.[64]

Figure 3.1 show the channel extraction of the original image into red, green and blue channels.

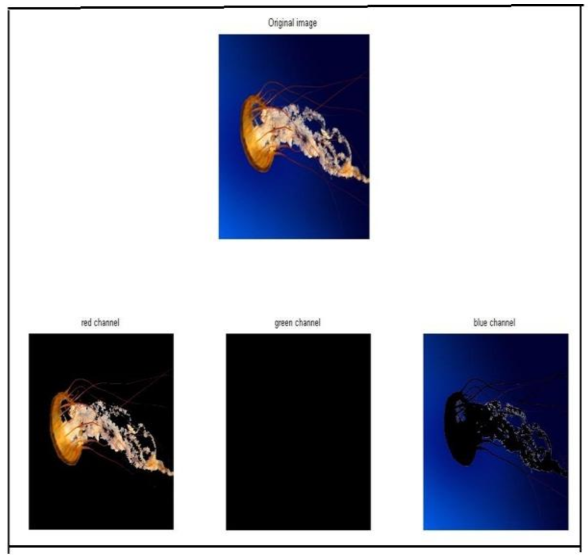

Fig. 3.1: Channel extraction from original image.

3.1 Algorithm of proposed color filter

In this work, we design a color filter with the help of extract the red channel, green channel and blue channel from the original image. The algorithm of color filter is as follow:

Step 1: Read the RGB image by using 'imread' command.

Step 2: Analysis the pixels and find the maximum and minimum value of the pixel for each channel like red channel, green channel and blue channel.

Step 3: On the basis of maximum and minimum value of the pixel we extract the value of pixels for each channel.

Step 4: After extraction of pixels store the pixels of particular channel in a matrix form.

Step 5: Now three matrices are generated for red channel, green channel and blue channel pixels.

Step 6: Display these matrices with help of 'imshow' command.

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Step 7: The resultant images show the red channel, green channel and blue channel objects.

The figure 3.6 and figure 3.7 show the output of the proposed color filter. This figure contains the red channel, green channel and blue channel of the original image.

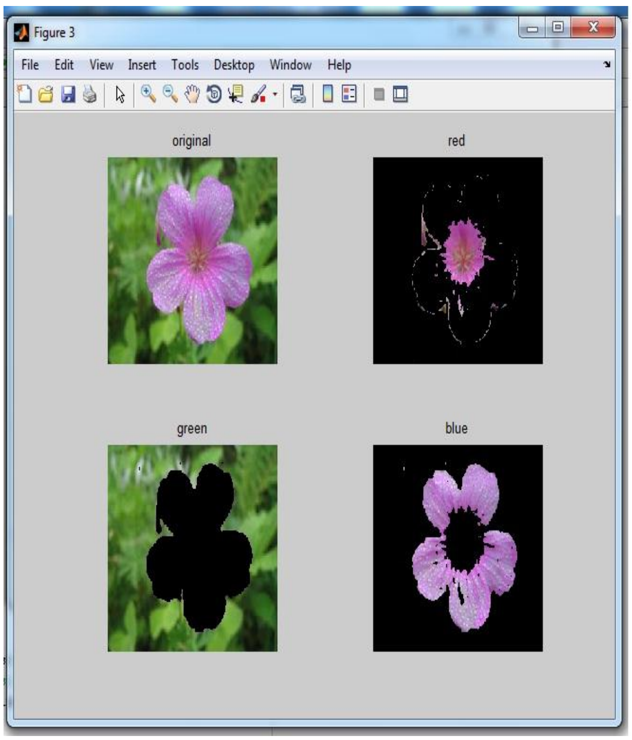

Fig. 3.6: Output of the proposed color filter.

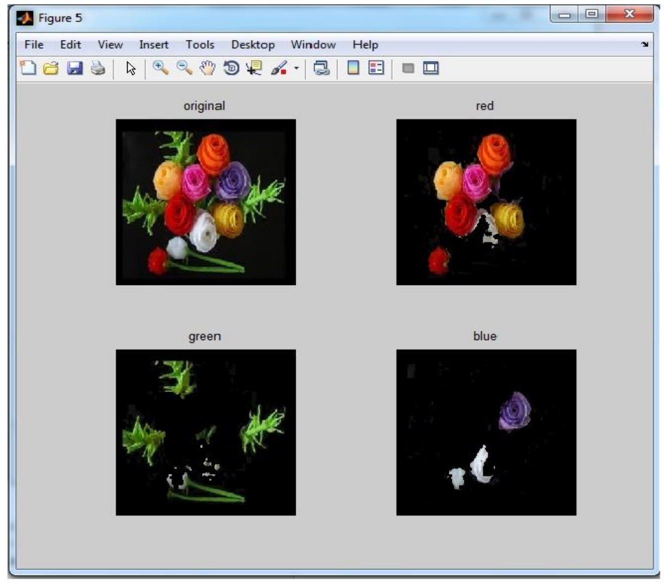

Fig. 3.7: Output of the proposed color filter.

3.6 Retrieval system

It searches the earlier maintained information to find the matched images from database. The output will be the similar images having same or very nearby features [14] as that of the query image. The processing of the retrieval system is shown in figure 3.9.

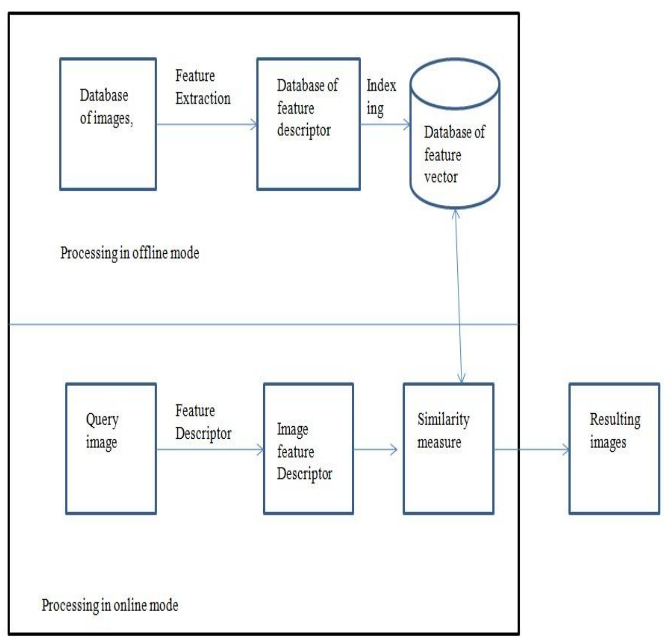

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Fig. 3.9: Block diagram of retrieval system.

The retrieval system is used to retrieve images that are relevant to a given query from a database. Relevancy is judged based on the content of images. Several steps are needed for this. First, the features from the images are extracted and their values and indices are saved in the database. Then the index structure is used to ideally filter out all irrelevant items by checking attributes with the user's query. Finally, attributes of the relevant items are compared according to some similarity measure to the attributes of the query and retrieved items are ranked in order of similarity.

3.7 Proposed Method of CBIR

Algorithm: *Input*: Query Image, *Output*: Retrieve similar images.

Step 1: Load query image.

Step 2: Perform the preprocessing on the query image.

Step 3: Apply the proposed color filter on query image to extract the red channel, green channel and blue channel.

Step 4: After extracting the channel we convert these channels into gray level images and perform the texture analysis on each channel with the help of statistical approach.

Step 5: Now we combining the texture properties of all channel and obtain a feature vector.

Step 6: We apply distance measure to compare the query image with the database images. The feature vector of all the images are also computed in the same manner and stored in the feature database.

Step 7: Retrieve the database images having best matches with the query image.

Step 8: Perform the majority voting to find the category of which maximum number of images are retrieved.

Step 9: Assign the type of category to the query image.

The figure 3.10 shows the flow chart of the working of proposed method where we get the query image and display it. After then we check the size of image is 256 * 256 or not, otherwise resize it. Now we extract the feature of query image by applying color and texture analysis and create a feature vector. This feature vector is used to perform the similarity measure on the database of images. After threshold matches we get the relative images that are similar to query image.

Flow chart:

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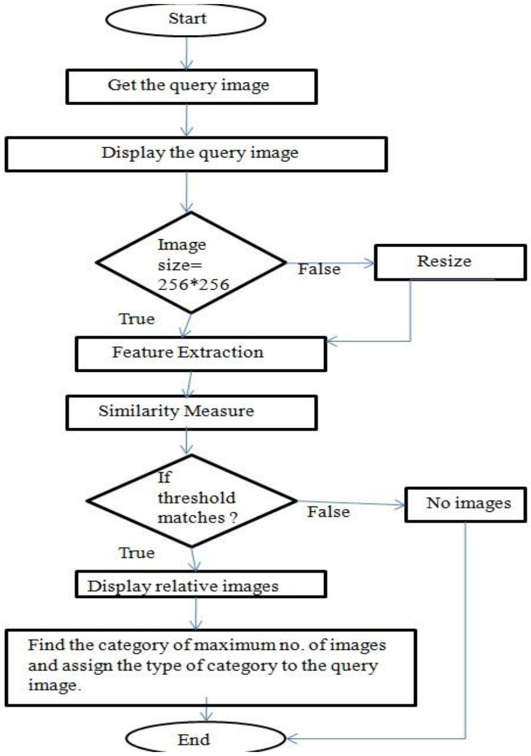

Fig. 3.10: Flow chart of proposed method.

The figure 3.11 shows the processing of proposed method CBIR using color and texture features. In this process we create a feature vector for database images and query image that is used to similarity measure. The feature vector is created in two phases. First phase is design of color filter where we read the image and preprocess it. We are analysis the value of pixels. After then find the maximum and minimum value of the pixel for each channel. On the basis of maximum and minimum value of the pixel we extract the red channel, green channel and blue channel with the region of interest. Second phase of feature vector is texture analysis phase where we perform the statistical measures such as average gray level, average contrast, smoothness, third moment, uniformity and entropy on each channel. After that we get the feature vector of the image. This process is performs on image dataset and obtain the feature vector of dataset. Similarly, find the feature vector for query image. That is used to perform similarity measure on feature vector of dataset. And we retrieve the similar images that provided final results.

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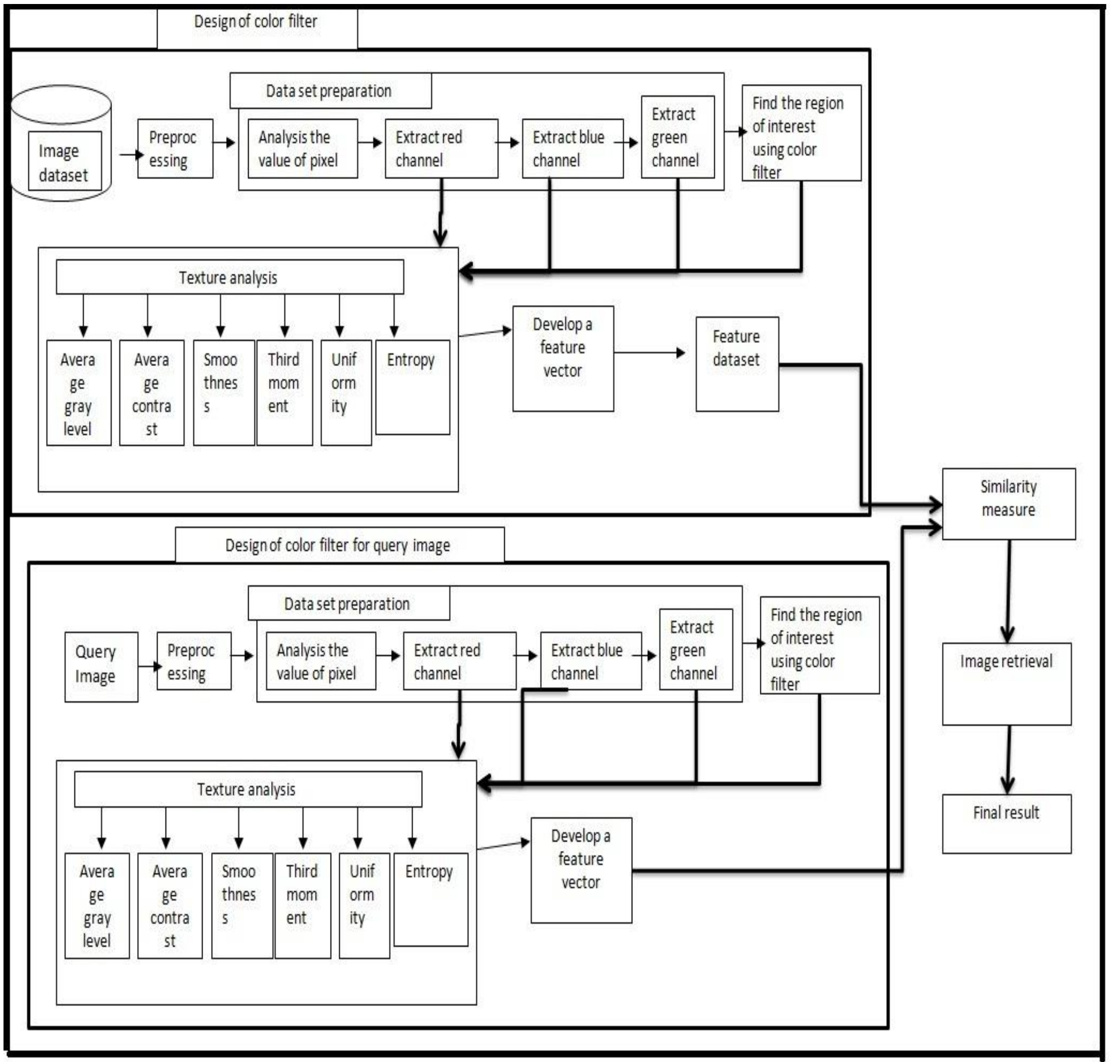

Fig. 3.11: Proposed method CBIR using color and texture features.

RESULTS

4.4 Experimental results

This section provides the experimental evaluation of present method. A computer system having Pentium IV, 2.8 GHz processor and 2 GB RAM is used for conducting experiments. This system has been implemented in MATLAB.

The performance of the proposed image retrieval system is tested using Corel database downloaded from http://wang.ist.psu.edu/docs/related/. The Corel image dataset contains 1000 images having 100 images of 10 categories, which include African people, Beaches, Building, Buses, Dinosaurs, Elephant, Flower, Horses, Mountains, Foods, respectively.

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Sample images from each of the categories are shown in figure 4.1.

Our experiments are performing on the dataset of 500 images that are taken from the corel-1000 images dataset. Experimental results show the average recall rate, average precision rate and average accuracy. All the results are shown in fig 4.2 to fig. 4.4.

Fig. 4.1: Sample images from each category of the dataset.

The figure 4.2 (a) and figure 4.2 (b) show the average accuracy for each class of the dataset and compare the proposed method with the WDH and CCV similarity measures. That provides the better results at each categories of the dataset.

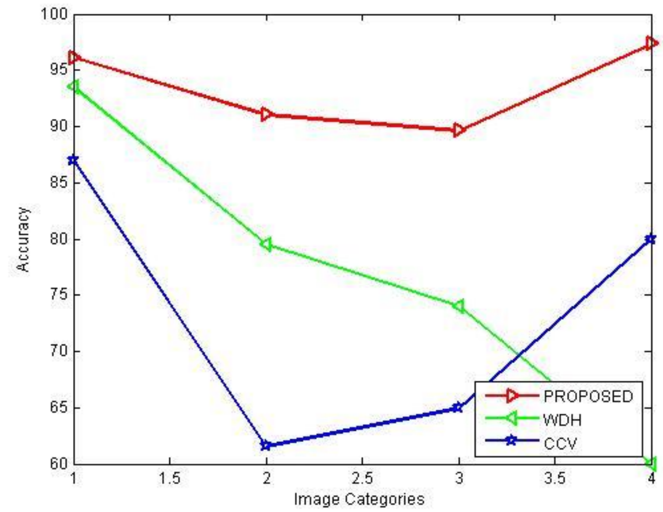

Fig. 4.2 (a): Average accuracy of each class of images.

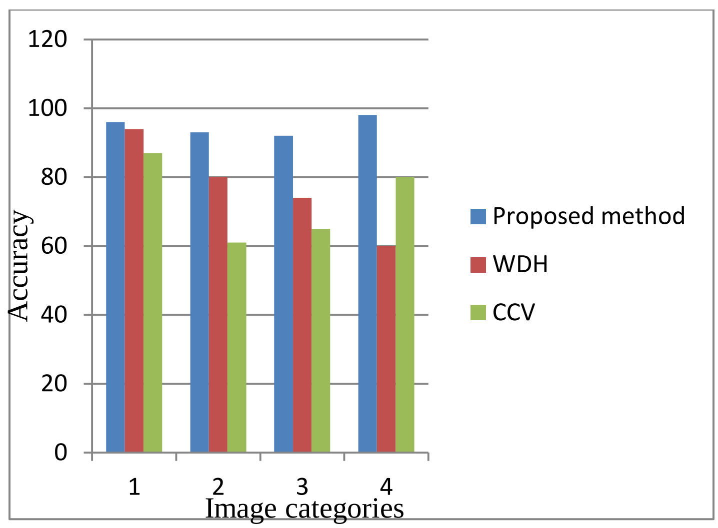

Fig. 4.2 (b): Average accuracy of each class of images.

The figure 4.3 (a) and figure 4.3 (b) show the average recall rate for each class of the dataset and compare the proposed method with the WDH and CCV similarity measures. That provides the better results at each categories of the dataset.

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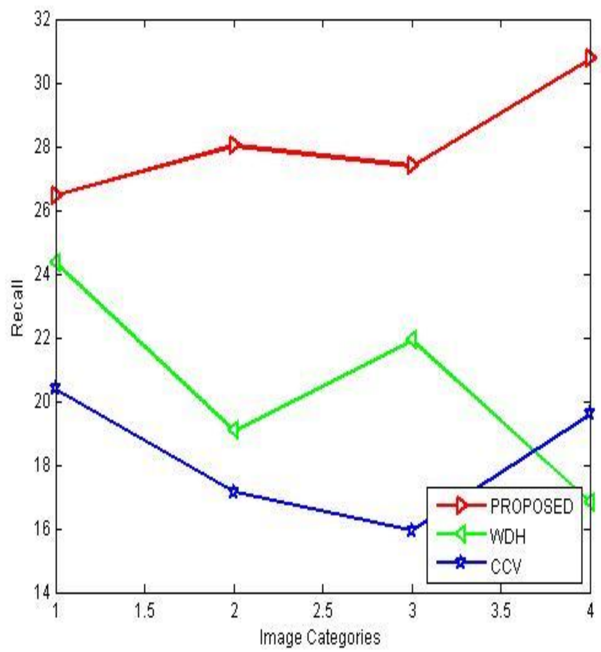

Fig. 4.3 (a): Average recall rate of each class of images.

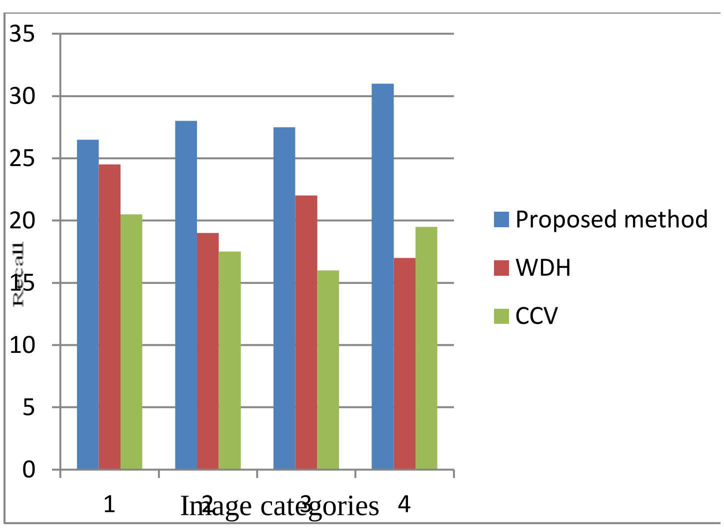

Fig. 4.3 (b): Average recall rate of each class of images.

The figure 4.4 (a) and figure 4.4 (b) show the average precision rate for each class of the dataset and compare the proposed method with the WDH and CCV similarity measures. That provides the better results at each categories of the dataset.

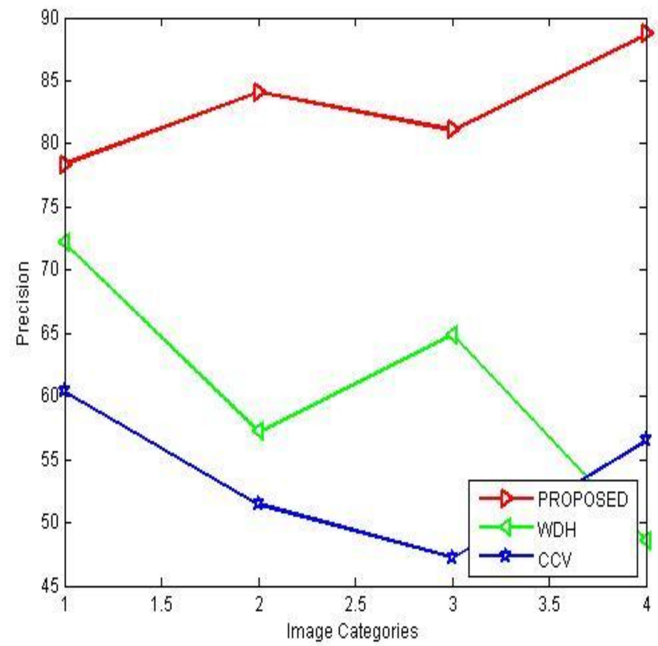

Fig. 4.4 (a): Average precision rate of each class of images.

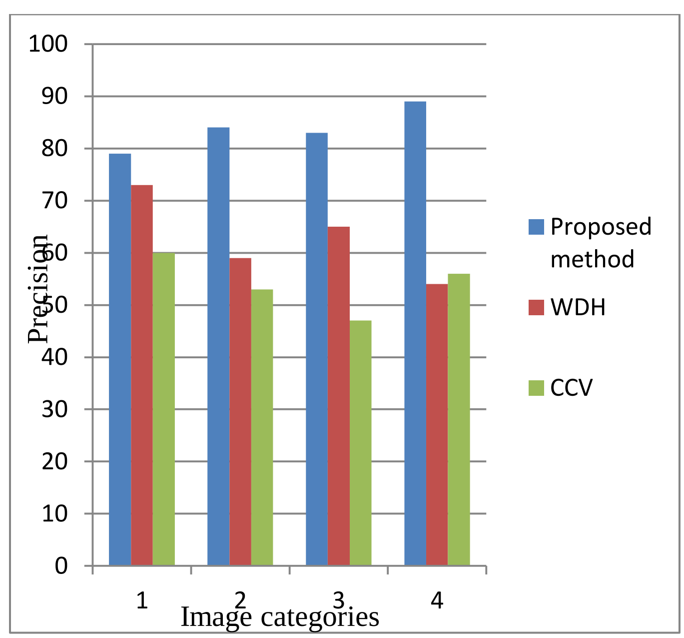

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Fig. 4.4 (b): Average precision rate of each class of images.

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

We analysis the all color based method which is used in the proposed method by authors. But color classification methods are not discussed in the above methods. So in the CBIR system we design a color filter with the help of it we extract the red channel, green channel and blue channel from the original image. After that we find a texture of all channels with the help of statistical texture analysis by using average energy/intensity, average contrast, relative smoothness, third moment, uniformity and entropy. The combination of texture of red channel, green channel and blue channel we create a feature vector for all images of the database. In previous methods various authors are used the local binary pattern because they use the binary object or black and white image for local binary pattern. But we analysis LBP method are used by various author and this method is superior that's why we analysis and studied the color channel based filter method to identify the object. This object based classifier is the unique and newly developed method which was not used by the any other. It helps to provides better results in the CBIR techniques. This proposed method is performed on the Corel dataset. Experimental results are shows the average accuracy, average precision rate and average recall rate. That is better than other existing methods like WDH (wavelet decomposed color histogram) and CCV (color coherence vector).

5.2 Future scope

In our proposed method we extract the color and texture features of the original image but if we extract the shape feature of the image after extraction of the color channel like red channel, green channel and blue channel. After then perform the texture analysis and obtain the feature vector of color, shape and texture then we may get the better results from the current results. And we can perform this method on the different and large datasets.

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