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Shape, Color and Texture Based CBIR System Using Fuzzy Logic Classifier

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Abstract: The perfect image retrieval and retrieval time are the two major challenges in CBIR systems. To improve the retrieval accuracy, the whole database is searched based on many image characteristics such as color, shape, texture and edge information which leads to more time consumption. This paper presents a new fuzzy based CBIR method, which utilizes colour, shape and texture attributes of the image. Fuzzy rule based system is developed by combining color, shape, and texture feature for enhanced image recovery. In this approach, DWT is used to pull out the texture characteristics and the region based moment invariant is utilized to pull out the shape features of an image. Color similarity and texture attributes are extorted using customized Color Difference Histogram (CDH). The performance evaluation based on precision and BEP measures reveals the superiority of the proposed method over renowned obtainable approaches.

Keywords: Image retrieval, color histogram, texture, edge orientation, retrieval accuracy.

1 Introduction

The advancement in multimedia technology and multimedia communication leads to increase in volume of images and there is a requirement to develop a Image Data Base Management System. These systems require the functionalities such as efficient image searching, scanning and easy image retrieval. The users of database may from different domains including crime prevention, remote sensing, medicine application, architecture design etc. Though lot of image retrieval schemes is available, a better solution for efficient retrieval of information from digital image databases is required in many fields. For example, the hospital database may comprise of huge volumes of computed tomography (CT) images, magnetic resonance (MR) images and electrocardiography (ECG) signals, electroencephalography (EEG) signals. Content based Image Retrieval (CBIR) technique is one of the simple methods which are based on low down level visual attributes such as color, texture and shape [Wang, Qiu, Liu et al. (2013)]. Color feature is one of the essential features of images that is broadly used in image retrieval techniques and object detection schemes. The two important color descriptors are Color Difference Histogram (CDH) and

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color correlogram. CDH can be used to identify the color difference in different background using perceptual uniform color difference. Several CBIR techniques based on color feature utilize CDH for retrieval process [Liu and Yang (2013)].

Texture is an important image characteristic which acquires the surface attributes of an image and their association with neighboring atmosphere. It is comparatively higher visual feature than color feature that has the ability to depict the structural array of a section in the image. Edge histogram descriptor is one of the popular tools for analyzing texture feature of image [Subrahmanyam, Maheshwari and Balasubramanian (2012)]. Shape features are useful in CBIR applications other than color and texture features, since human perception mainly based on shape of the objects and images. Shape feature provides better retrieval results due to its dependability on geometric measurement [Liu, Zhang, Hou et al. (2010)]. Retrieval techniques based on one specific feature like colour, texture, shape may provide better performance only on specific set of images. The performance of these techniques may degrade while using different type of images [Huang, Kumar, Mitra et al. (1997)]. For example, color based schemes focus the visual stuffing relating to colors and simply ignore shape and texture feature. Similarly, shape based schemes do not consider colour histogram and texture of an image.

Based on the above discussions, it is revealed that single image feature can carry out well when applied to an exact type of images, but the performance is poor for different dataset of images. To overcome these issues, all the image features can be integrated so that the performance is not degraded for any type of images. Hence, our proposed considers all probable image characteristics such as colour, shape and texture for image retrieval. Iqbal et al. [Iqbal and Aggarwal (2002)] developed a CBIR technique based on textural, structural and colour characteristics [Iqbal and Aggarwal (2002)]. The colour histogram technique is helped for colour feature extraction and Gabor filter is used for texture attribute mining. The Line junction and line crossing of the image structure are used to correspond to the structural image. The image retrieval procedure is done using the weighted linear combination of colour histogram, texture and structural standards. Lin et al. [Lin and Chen (2009)] proposed a smart CBIR application with colour and texture features [Lin, Chen and Chan (2009)]. It is based on colour co-occurrence matrix (CCM) and colour sharing for the K-mean (CHKM) system. The CCM calculates the probability of rate of the same pixel colour between each pixel and its neighboring one. CHKM is used to categorize every one the pixels into a k-cluster based on the color distribution.

The soft computing approaches have been successfully applied for digital image retrieval techniques because of their capability to represent vague and imprecise information [Pun and Wong (2011)]. From the review of CBIR schemes, various approaches are classified in Fig. 1. Soft computing based clustering algorithms have been developed for CBIR based shape feature [Yankov and Keogh (2006)]. [Yankov and Keogh (2006)] developed a method for shape clustering that is represented by descriptive prototypes [Kontschieder, Donoser and Bischof (2009)]. First, a set of early labels is formed with respect to prospective cluster prototypes. After that, an agglomerative method is used to purify initial labels iteratively. Unsupervised clustering based on diffusion maps and non-linear dimensionality reduction of object shapes is proposed [Rajpoot and Arif (2008)]. Here, each cluster group is assigned to a prototype representative that is computed based on shapes belong to the equivalent cluster. A fuzzy clustering process based on Fuzzy C-Means Algorithm has been used to find semantic groups and the equivalent shape prototypes [Castellano, Fanelli and Torsello (2011)].

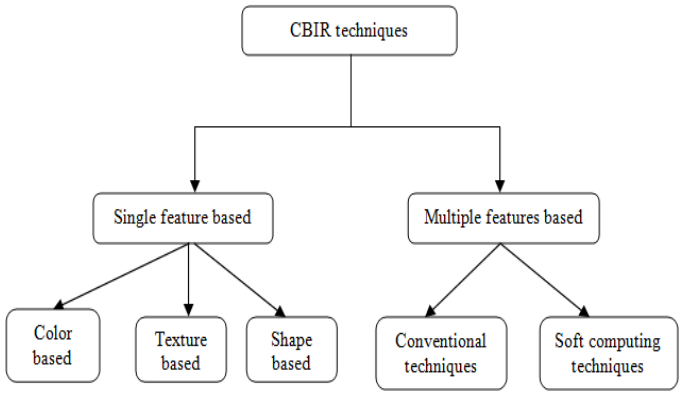

Figure 1: Classification of CBIR Techniques

In general object features can be better handled by fuzzy techniques while comparing with crisp sets and rules [Krishnapuram, Medasani, Jung et al. (2004)]. Hence it is possible to retrieve images accurately in fuzzy techniques while traditional approaches may miss some important information of images. In the proposed method, all probable image characteristics such as color, shape and texture are applied in addition to fuzzy logic classifier based on fuzzy sets and rules. A new fuzzy based CBIR approach is developed by combining all image features in fuzzy logic classifier for better image retrieval. Here, DWT is applied to pull out the texture characteristics. The region based moment invariant is applied to mine the shape characteristics of an image and color similarity features are extracted by modified Color Difference Histogram.

2 Methodologies used for color, texture and shape Features extraction

In this work, CBIR is support on image features like shape, color and texture with fuzzy logic classifier. These image features are extracted using DWT for texture, modified CDH for color and region based moment invariant for shape.

2.1 Discrete wavelet transform

Texture feature of images are identified using DWT statistical features in this work. DWT can be applied to find the energy and standard deviation using wavelet sub-band coefficients [Kokare, Biswas and Chatterji (2005)]. The energy and standard deviation of an image using pyramid structured DWT can be determined by the Eqs. (1) and (2).

$$E_k = \frac{1}{M^2}\sum_{i=1}^{M}\sum_{j=1}^{M}\left|x_k(i,j)\right| \tag{1}$$

$$\sigma_k = \sqrt{\frac{1}{M^2}\sum_{i=1}^{M}\sum_{j=1}^{M}(x_k(i,j)-m_k)^2} \tag{2}$$

Where (i, j) indicates the elements of sub-band coefficient matrix, kth sub-band of DWT with dimension M x M and coefficients $x_k(i, j)$ and standard mean value is m_k [Kokare, Biswas and Chatterji (2005)]. Mean and standard deviation are the two important wavelet statistical features that are useful for texture feature extraction.

2.2 Modified color difference histogram

Colour feature is considered as one of the most vital visual feature for image retrieval. Color images are represented by various image models like HSI, HSV, and YCrCb. It also plays an important role in human perception. One of the accepted color model is RGB, where each element represents colour, red, green and blue. Though there are lot of methodologies available for color feature extraction, colour histogram is the most preferred and effective one [Liu and Yang (2013)]. CDH merge the make use of of orientation, color and color difference. CDH features are calculated in Lab color space which is extracted with respect to the color perception of human beings [Liu and Yang (2013)].

The Colour Difference Histogram is stated as for color feature and texture feature as follows:

$$H(I_C(i,j)) = \sum\sum\sqrt{(\Delta L)^2+(\Delta a)^2+(\Delta b)^2} \tag{3}$$

$$H(I_T(i,j)) = \sum\sum\sqrt{(\Delta L)^2+(\Delta a)^2+(\Delta b)^2} \tag{4}$$

Where H( ) indicates the histogram of the image whereas the I_C(i,j) and I_T(i,j) are used to extort color and texture attributes.

From the Eq. (3), we take note of that the flag to proportion of each shading part is not comparable in the whole locale. Chromatic mechanism in ‘a’ and ‘b’ are moderately more uproarious than the shading space ‘L’ part.

Hence, Gaussian filtering can be applied on these components to enhance the recovery precision. In most images, 3*3 Gaussian filter with a variance of 0.25 is applied for effective noise removal in chromatic components. Some typical images may use 5*5 Gaussian filters. The prosecution of CDH descriptor is significantly improved when noise is productively disengaged from the chromatic segments 'an' and 'b' of Lab shading space.

2.3 Region based moment invariant

Shape also plays a crucial role for matching objects in the retrieval process [ElAlami (2011)]. Shape features are extracted using segmentation approaches. Two popular approaches are contour based and region based. Contour based methods extracts the boundary features of an image well, however they may ignore some important features available inside the boundaries of an image. Region-based methods are based on the object shape and are useful in identifying both boundary and section. Region-based methods are based on moment theory, for example Hu moments, Legendre moments and

Zernike moments [Wong, Shih and Liu (2007)]. The moment theory provides valuable information for feature extraction. While comparing with moment theory, moment invariants method are superior for identification of objects and expression of objects [Mohamed, Haniza, Puteh et al. (2006)]. Hence we preferred region based moment invariant method in this work for shape feature extraction.

3 Fuzzy logic classifier

A fuzzy logic framework is a nonlinear mapping of an information highlight vector into a scalar yield [Kosko (1997)]. Fuzzy set theory and fuzzy logic present the system for the nonlinear mapping. Fuzzy logic is preferred for certain applications where conventional mathematical methods and models are ineffective. In the spectrum sensing applications, fuzzy logic is mainly used in the decision making while the neural learning algorithm is trained in order to identify the available spectrum hole. Fuzzy based decision making has more degree of freedom in the dynamic spectrum sensing environment. Fuzzy logic can be utilized in the applications using fuzzy logic controllers or fuzzy logic classifiers. Fig. 2 shows the fuzzy inference system which performs Fuzzy based decision making. It comprises of fuzzifier, Inference engine, rule base, and defuzzifier. Fuzzifier crisp input is converted into the fuzzy quantity using the fuzzification process. The inference engine processes the information and makes the decision using the rule base or knowledge base.

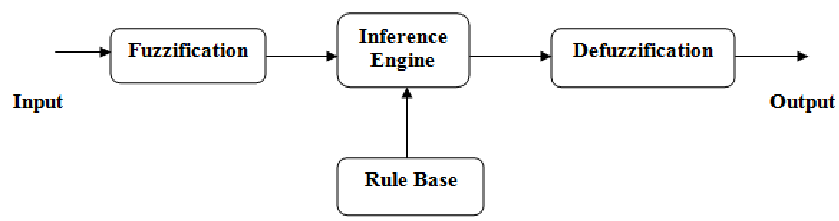

Figure 2: Fuzzy inference systems

In this work, CBIR is performed using the fuzzy inference system based on the extracted image features. The fuzzifier converts the available information which is used to identify the relevant images in the inference system. The fuzzy membership functions are utilized to model and evaluate the inputs. After obtaining the fuzzy sets, they are evaluated by rule base, which comprises of 'if-then' statements to decide the image retrieval with certain fuzzy-sets. These fuzzy rule set are given to a fuzzy inference system to decide about the accurate retrieval. Fuzzy inference system (FIS) incorporates human knowledge to perform inferencing and decision making. FIS or fuzzy inference engine is based on expertise knowledge base which can be expressed in terms of 'IF-THEN' rules. These rule bases have been deployed in many systems to predict the uncertain behavior. The major advantage of inference engine is that it does not need to know the actual physical process and its application.

4 Proposed fuzzy based CBIR technique

Conventional CBIR schemes proposed in the literature are based on single feature and general mathematical descriptors. To overcome the drawbacks in the existing CBIR schemes, all promising image characteristics such as shape, colour and texture are utilized in the proposed approach. In addition to these feature extraction, fuzzy logic classifier is incorporated to improve the retrieval accuracy which is based on fuzzy sets and rules.

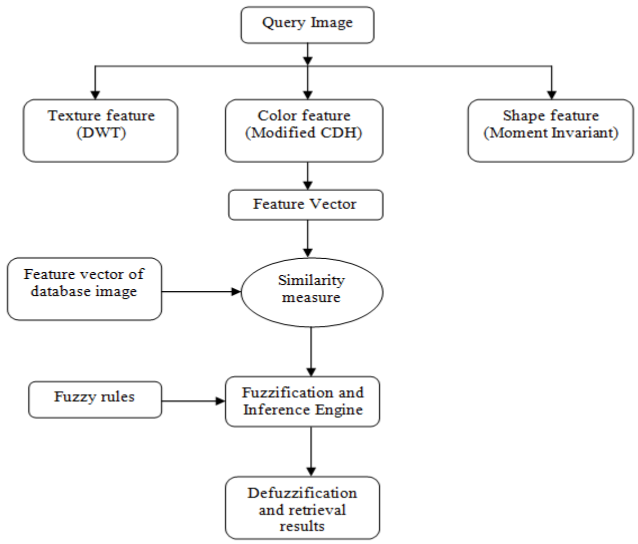

Figure 3: Proposed CBIR approach

A new fuzzy based CBIR approach is developed by combining all image features in fuzzy logic classifier for better image retrieval. Here, DWT is utilized to extract the texture characteristics. The region based moment invariant is helped to extract the shape features of an image. Shading similitude highlights are extracted utilizing modified Color Difference Histogram (CDH). Fig. 3 shows the steps involved in the proposed CBIR system. Similarity measure is performed after deriving the feature vector by combining texture, color and shape features. The feature vector of reference image is analyzed with the feature vectors obtained from the data base pictures. If the similarity measure is successful, the result is passed to the fuzzification process. In this stage, the retrieval process is improved using fuzzy rules and inference engine. Once the fuzzy rules are properly matched, the defuzzification is performed for the accurate retrieval of database images. The comparison between two images is calculated numerically that display the strength of associations between them.

Similarity measure can be performed by calculating the Euclidean distance between two feature vectors as Long et al. [Long, Zhang and Feng (2003)].

$$F(X^a, X^b) = \sqrt{\sum_{i=1}^{n} (X_i^a - X_i^b)} \tag{5}$$

where X^a and X^b are reference image and database image respectively, and i indicates the feature range. The higher resemblance between images is indicated by closer distance.

5 Results and discussion

Simulations are carried out to assess the retrieval performance of the projected fuzzy based CBIR system. All the experiments were simulated using MATLAB® v. 7.10. Two standard databases Wang's and OT-scene have been used for assessing the performance of the proposed system.

Fuzzy logic toolbox of Matlab has been utilized for fuzzy based processing. The two well known fuzzy controllers are Sugeno type and Mamdani type. In this work, Mamdani type fuzzy logic controller is used as a classifier. Three input membership functions are used for texture, color and shape and output membership function gives the similarity output. The membership functions are based on bell shaped and triangular functions. The Mamdani fuzzy logic controller with input and output membership functions are shown in Fig. 4. The rule editor based on three input members with 27 fuzzy rules is provided in Fig. 5.

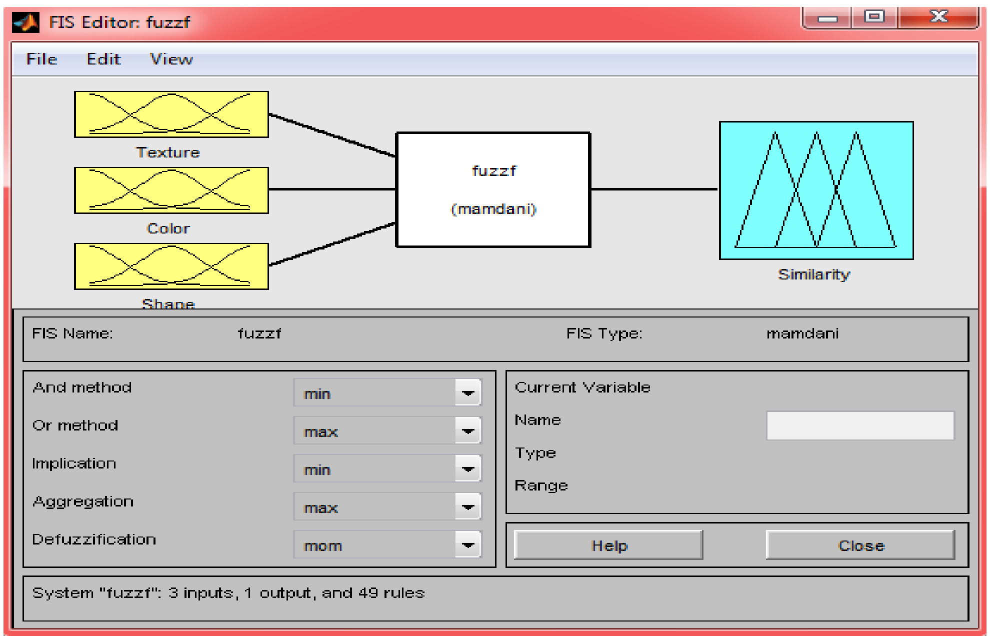

Figure 4: Fuzzy logic controller used for determining similarity

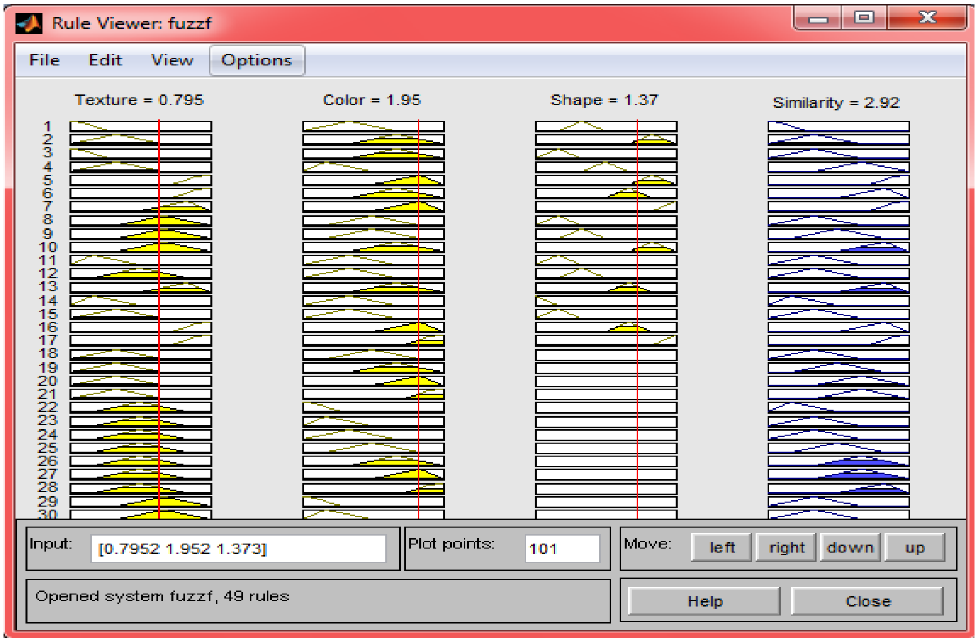

Figure 5: Rule Editor editor based on three inputs

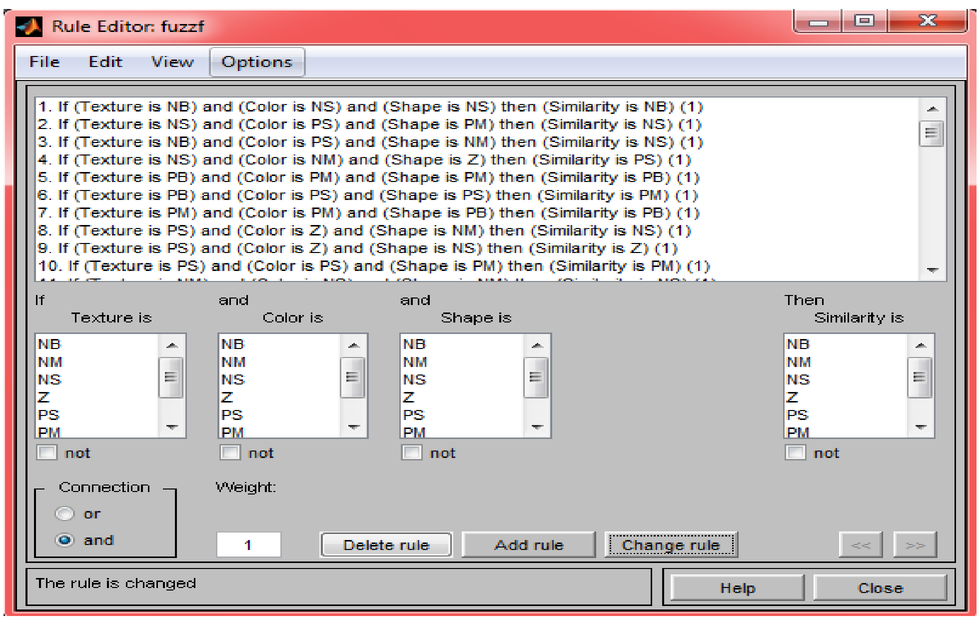

Figure 6: Rule viewer widow of fuzzy logic controller

Fig. 6 shows the rule viewer window of fuzzy logic controller. The similarity outputs can be noted for various input combinations of texture, color and shape. The retrieved database images for query images 'bus', 'beach' and 'building' are shown in Fig. 7.

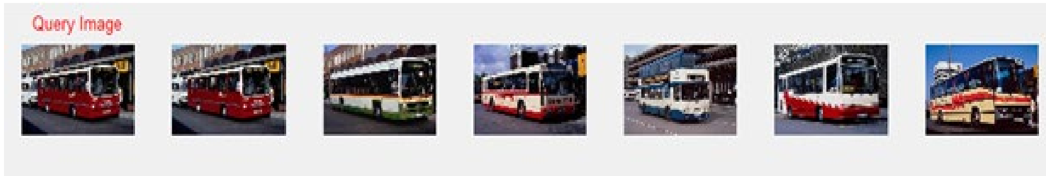

Figure 7: Retrieved database images for the query image bus

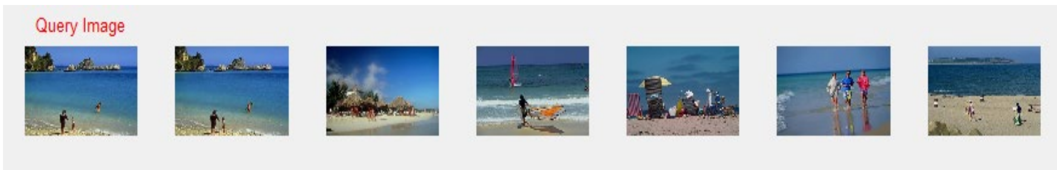

Figure 8: Retrieved database images for the query image beach

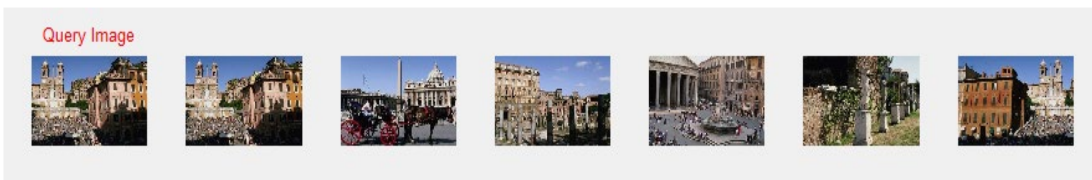

Figure 9: Retrieved database images for the query image building

In order to estimate the performance the proposed fuzzy based CBIR, the standard measures used in CBIR such as Precision and Recall are utilized. The Precision (P) and Recall (R) are defined below [Viitaniemi and Laaksonen (2007)].

P = IN/R

R = IN/T

Where IN is the number of database images extracted with respect to the reference pictures. T is the aggregate number of database pictures. R indicates total number of images extracted. Tab. 1 shows the precision values obtained for the proposed scheme and compared with existing CDH+Z-score, ART + Min-max and CDH + edge orientation techniques.

Table 1: Comparison based on precision

Query Image	CDH+Z-score	ART +Min-max	CDH + edge orientation	Fuzzy based CBIR
Dinosaur	47	36	64	73
Beach	59	61	78	87
Building	64	72	84	89

Other than precision and recall measures, Bull's Eye Performance (BEP) is a popular measure among the image retrieval researchers. Tab. 2 provides BEP values obtained using proposed and existing methodologies. Suppose, there are N, total count of images to a query image Q and retrieved images may be 2N images. In these images, if it is possible to retrieve z images, then BEP is calculated by

$$BEP = \frac{z}{N}$$

Table 2: BEP Comparison

Query Image	CDH+Z-score	ART+Min-max	CDH+edge orientation	Fuzzy based CBIR
Bus	43.48	43.96	45.78	51.23
Beach	46.75	47.26	49.24	55.32
Building	49.61	49.93	51.21	65.43

6 Conclusions

A new fuzzy based CBIR approach is presented in this paper. DWT is helped to separate the texture features, whereas region based moment invariant is utilized to pull out the shape features of an image. Colour similarity and texture characteristics are extracted using customized Color Difference Histogram (CDH). Fuzzy logic classifier is used to improve the retrieval accuracy using combined feature vector. The performance evaluation based on precision and BEP reveals the superiority of the proposed method over well-known existing approaches.

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