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Directional Binary Code for Content Based Image Retrieval

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ABSTRACT

Image feature Extraction in Local Binary pattern compares the centre pixel value only with the current neighborhood pixel value. so in this paper we introduce a Directional Binary Code(DBC) Algorithm in which comparison made in all direction, provides an efficient pixel transformation for a given RGB Color image. Content Based Image Retrieval (CBIR) best compares the feature attributes with images in the database. Feature vector is extracted by comparing the pixel values of corresponding RGB channels of a given input image. The extracted values fed into the adder and decoder block addressing the four output channels of adder and eight output channel of decoder. Histogram for the output channel is computed. Feature vector is extracted from the same histogram, The distance measurement between the feature vector is to verify the image is in the database or not. Minimum distance provide the most similar images with the evaluation criteria.

Index Terms-Content Based Image Retrieval, DBC, Histogram, Feature Extraction, Local Binary Pattern.

I INTRODUCTION

Content Based Image Retrieval is, the term used to describe the process of retrieving similar images from a large collection, on the basis of image features such as texture, shape and color, scene categorization and color descriptors are used in evaluating feature extraction based on its histogram value analysis [9]. A color image is made up of pixels, each of which holds three numbers corresponding to the red, green and blue levels of the image at a particular location. Each color pixel can be stored in three bytes (24 bits) of memory.[2] The RGB color model is an additive color model in which red, green, and blue light is added together in various ways to reproduce a broad array of colors. Color images are often built of several stacked color channels, each of them representing value levels of the given channel .A various discriminative approaches for image retrieval used in large databases are binary coding and hashing [3].In existing approaches some of the efficient extracting techniques used is local binary pattern(LBP)[1],HOG[3], **Local tri-directional weber patterns (LTriWPs) , Weber local descriptor (WLD)[12]**. **Local binary pattern (LBP)** is a type of visual descriptor used for classification of visual image. In which comparison directly placed with current and centre pixel, with the binary values used for extracting common conversion of RGB grayscale value input to the adder and decoder function output gains

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Feature vector produces an histogram where counting the pixel values provide an entire feature for an image. Weber Local Descriptor is the mutual relationships of current pixel Neighborhood pixel with different direction is differential excitation. The histogram computation and concatenation takes place over the transformed binary patterns is fixed. The mCENTRIST [1] is an example of this category where else combination of two channels provides an complexity.

II RELATED WORK

1. A Color Descriptor for Scene Categorization: color CENTRIST descriptor to describe global shape information by not only gradient derived from intensity values but also color differences between pixels in local image patches. Color CENTRIST is suitable for the images with high color variation and provides performance increment in almost all datasets. Color models images are not invariant to the rotation and scale [12]. Detecting semantic category of an image is undeniable. Through extensive evaluations on various datasets, we demonstrate that the color CENTRIST descriptor is not only easily to be implemented, but also reliably achieves performance over that of CENTRIST

2. Shrink Boost for Selecting Multi-LBP Histogram Features in Object Detection: Boosting step uses weighted training samples to learn a full high dimensional classifier on all features. This avoids over fitting to few features and improves generalization. Next, a "shrinkage" step shrinks least discriminative classifier dimension to zero to remove the redundant features. In our object detection system, we use "shrink boost" to select sparse features from histograms of local binary pattern (LBP) of multiple quantization and image with its adjacent neighbor and the center pixel are encoded in binary form based on the differential direction relationship between the pixels which in turn increases the computational cost of the descriptor .To overcome an above problem we go for adder and decoder content, to preserve the cross channel information in the lower pixel values of adder and decoder with the histogram analysis is maintained.[9]
channels to learn classifiers with the centre value of pixel with the neighborhood boost up pixel values with

3. Content Based Image Retrieval Using Color Histogram: On querying an image, a condensed set of candidate images which have the similar Grid Code as that of the input image are obtained. The color histogram for an image is to construct by quantizing the colors within the image and counting the number of pixels of each color channel. The feature vector of an image can be derived from the histograms of its color components and finally can set the number of bins in the color histogram to obtain the feature vector of desired size. Thus the grid code of an image is obtained through the quantization of the feature vector derived from the histogram of the desired color component of the image. Segregation of unwanted contents in the images from useful part becomes complex. In grid technique only limited set of candidate images are possible [8].

4. Local Tri-directional Weber Patterns: A New Descriptor for Texture and Face Image Retrieval. The renowned pattern based algorithms like Local binary pattern (LBP) and Weber local descriptor (WLD) bring out the gray scale relationship of centre pixel with its neighborhood pixels. Mutual

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relationship of the current pixel with its adjacent neighborhood pixels in three directions is used. Further, the relationship among neighborhood pixels is encoded based on the magnitude of differential excitation. Differential excitation reveals that the current pixel belongs to an edge or a spot. Complexity occurs in magnitude of excitation [12][10].

5. Dominant Local Binary Patterns for Texture Classification: This DLBP retain the rotation invariant and histogram equalization. the spatial distribution of gray values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features [15]. The proposed approach has been evaluated by applying a large number of classification tests to histogram-equalized, randomly rotated and noise corrupted images in Outex , Brodatz, Meastex, texture image databases. *Classification accuracy in various texture databases and image conditions [11].*

III DIRECTIONAL BINARY PATTERNS WITH PROPOSED DESCRIPTOR:

In this section we use directional binary code algorithm to extract features, in which 5*5 matrix is used to extract the feature from neighborhood pixels with the directions 0, 45, 90, 135 degree, for more accurate pixel values we go for directional binary code in which pixel values are more confined within the boundary region, so retrieval rate will be more better than the proposed system. Consider a centre pixel p_c with eight neighborhood pixel (p_1,…….p_8). ,so the color image is converted into gray scale image, with directional binary code for feature extraction .Each pixel values are defined with the predefined color for proposed system, starts at the range of 0,255 as shown in fig 1.1, fig 1.2.

Fig 1.1 RGB image with gray scale conversion.

1. Directional Binary Pattern (DBP)

DBC is applied on image to encode the directional edge information. It captures the spatial relationship between any pair of neighborhood pixels in a local region along a given direction. It reflects the image local feature. It extracts more spatial information than LBP. Let Zi,j be a point in a cell, four directional derivatives at Zi,j are given

d=1,

I ‘0,d(zi,j)=I($z_{i,j}$)- I(zi,j-d);

I ‘45,d(zi,j)=I(zi,j)- I(zi-d,j+d);

I ‘90,d(zi,j)=I(zi,j)- I(zi-d,j);

I ‘135,d(zi,j)=I(zi,j)- I(zi-d,j-d);

The resized image of size 50*50 is partitioned into 100 cells of 5*5 matrixes. Fig 1.3 shows a 3*3 neighborhood centre on Zi,j taken out of 5*5 cell size, where each cell contributes one coefficient. We define the texture in a 3x3 pixels neighborhood of an image as a joint distribution of the gray levels in the 9 pixels. F($Z_{0,..}Z_7$).The center pixel, around which are Z_0…,Z_7 and Our operator is not only a gray scale texture operator, but also an encoding of directional differential patterns, which are given by the directional differential equations:

f $$\Delta I(Z_C)_\theta = I(Z_C) - I(Z_i) \quad \left(i = 0, \ldots, 7,\ \theta = \frac{i\pi}{4}\right),$$

The directional binary pattern output is fed into the adder and decoder function where

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the histogram values are computed. Multichannel adder and decoder with the 4 output of encoder and 8 outputs of decoder is estimated.the histogram for each pixel value with the weighted function is computed in adder and decoder block,whereas adder and decoder provides the avoidance of useless information with preservance of cross channel information.The derivation of prescribed descriptor is based on the directional pattern with the direction applied in angular scale , the directional code is a pattern based code.

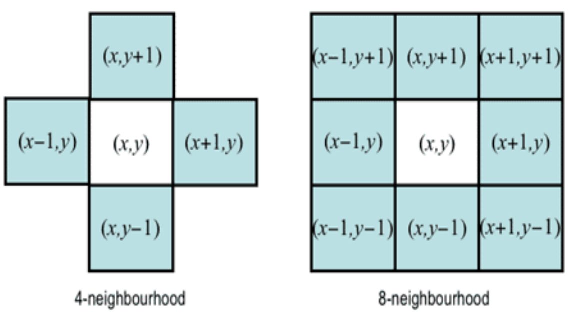

Fig 1.2 pixel extraction

2. ADDER AND DECODER FOR DIRECTIONAL BINARY CHANNELS:

The multichannel adder based Directional binary patterns maDBPnt1 (a, b) and multichannel decoder based Directional binary patterns mdDBPnt2 (a, b) are the outputs of the multichannel DBP adder and multichannel DBP decoder respectively, where s1 □ [1, d+ 1] and s2 □ [1, 2d]. The values of DBPnt (a, b) are in the binary form (i.e. either 0 or 1). Thus, the values of maDBPnt1 (a, b) and mdDBPnt2 (a, b) are also in the binary form generated from the multichannel adder map maMn(a, b) and multichannel decoder map mdMn(a, b) respectively corresponding to the each neighbor n of pixel (a, b)[6].Texture information for each three input channel is extracted from directional binary code pixel values are fed into the adder and decoder of maMn(a,b) and mdMn(a,b). The directional pattern input with adder and decoder function with weighted values used to compute the histogram [9][13].The adder block of four outputs and decoder block of 8 output represented within the truth table value function shown in Fig1.4. The defined function of adder and decoder are expressed using the formulae. [4]

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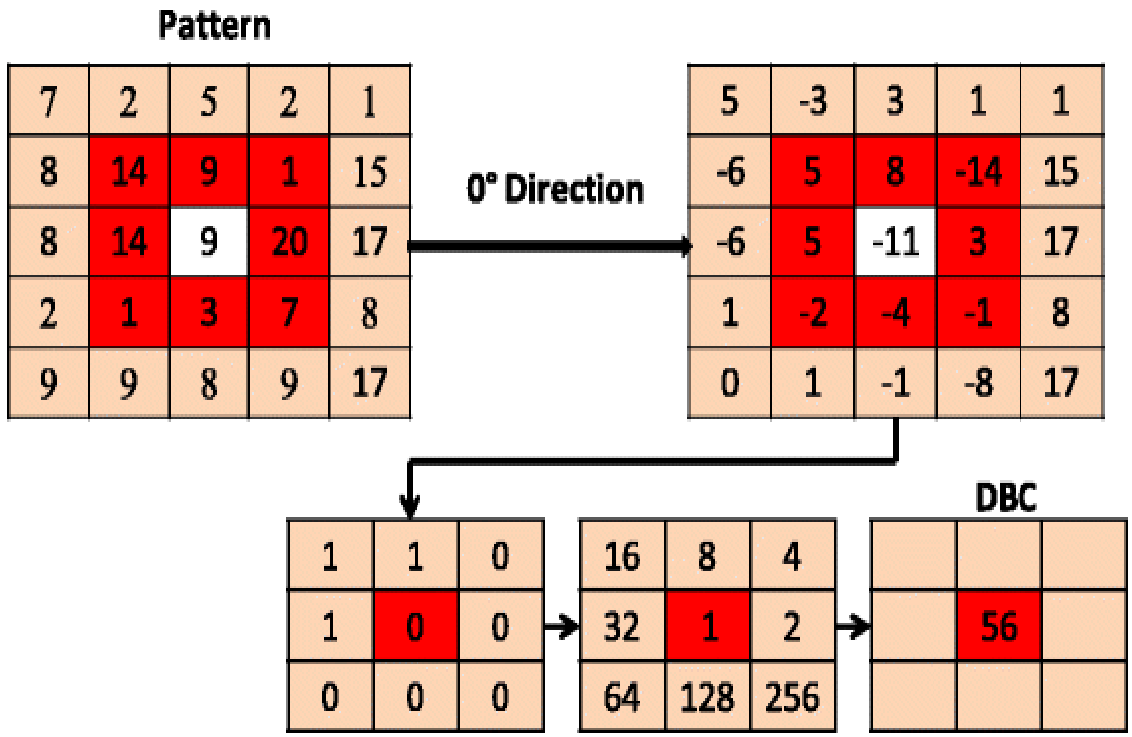

Fig 1.3 structure of Directional Binary Pattern

DBC p1(a,b)	DBC p2(a,b)	DBC p3(a,b)	maMn(a,b)	mdMn(a,b)
0	0	0	0	0
0	0	1	1	1
0	1	0	1	2
0	1	1	2	3
1	0	0	1	4
1	0	1	2	5
1	1	0	2	6
1	1	1	3	7

Fig 1.4 Adder and decoder map with directional code of RGB Input channel

The multichannel adder based directional pattern with maDBCpt1n(a,b) for pixel (a,b) from multichannel adder map is stated as, maMn(a,b) and x1 is defined as (x1-1) if it states 1 or else 0, similarly the multichannel decoder based directional pattern with mdDBCpt1n(a,b) for pixel (a,b) from multichannel decoder map is stated as, mdMn(a,b) and x2 is defined as(x2-1) if it states 1 or else 0

maDBCx1(a,b)={1,if maMn(a,b)=(x1-1) or 0},

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mdDBCx2(a,b)={1,if mdMn(a,b)=(x2-1)
or 0},

3. METRIX BASED ON DISTANCE MEASURE:

In the domain of image retrieval from large databases using attributes like color, texture histogram, each dimensional feature vector may be considered as a attribute in the „n□ dimensional vector space. Thus, a feature vector is mapped to a point in the n-dimensions [6]. This mapping helps us to perceive the images as high-dimensional points. The advantage of this representation is that one can now use different distance metrics for (i) finding comparison between two images and (ii) ordering a set of images based on their distances from a given image. This enables one to do a nearest neighbor search on a large database of images and retrieve a result set containing images that are closest matches to a user-specified query. It is evident that the images and their ordering depend both on the feature extraction method as well as on the distance metric used. In this work, Euclidean distance metrics has been used as a similarity rule. This is the final task of image retrieval in which minimum distance measures are use to calculate the distance between the image in database and input image based on its feature vector. The distance measure used here is Euclidean distance measures. According to the Euclidean distance formula, the distance between two points in the feature vector with coordinates input image (x, y) and database image (a, b) is given by,

E distance = sqrt (sum((Q-D).^2));

Q and D are the images based on the input query image and the database images, query image determines two coordinates (x,y) from which the q resultant value (i.e) Q=(x-y),and D=(a-b) which is the resultant vector of difference between the database images, The distance measurement for the Euclidean gives the best distance measure when compared with the other distance approaches, whereas the minimum retrieval time provides the best retrieval rate. The minimum distance vector is calculated and shown in Fig1.6 and Fig1.7 with the distance point measurement helps to measure accuracy rate with other approaches.

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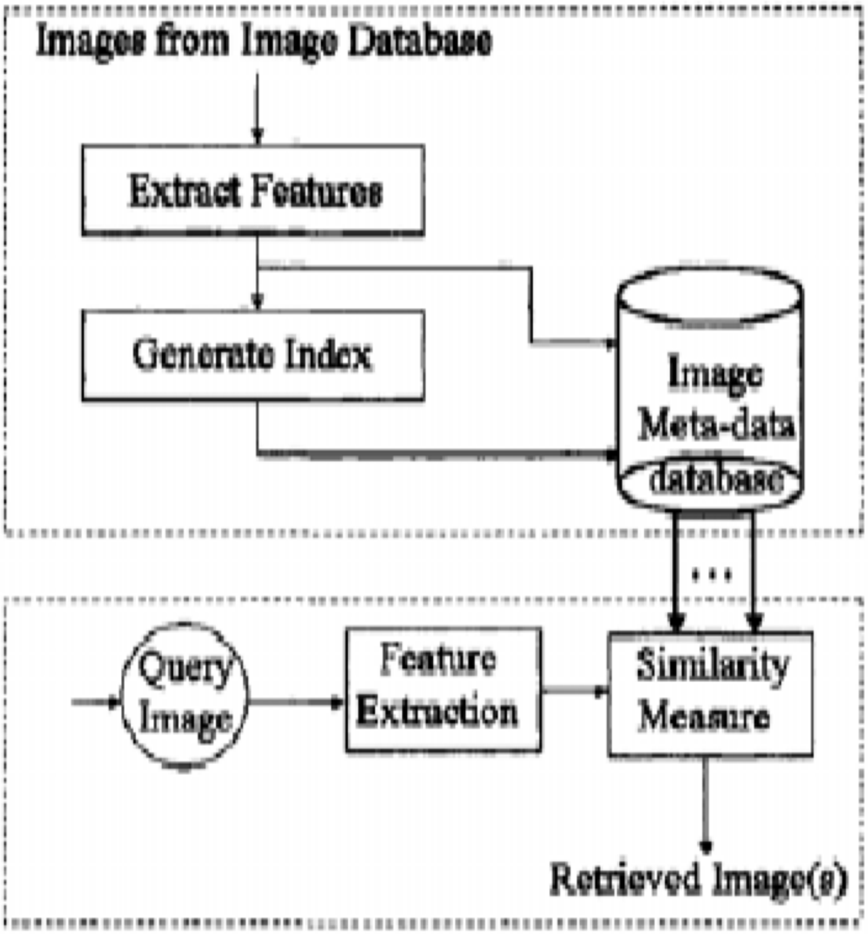

Fig 1. 5 The computational flow of image retrieval

IV EXPERIMENTAL RESULTS :

In this section, experimental results have been reported. The system was implemented in Matlab 8.3. with the Pentium machine Processor 2.20 GHz with 2 GBytes of RAM. The COREL database is used for experiment Purpose. It consists of 1000 images with 100 images in each category. The categories of the5 random images from each of the 10 category as the query image have been arbitrarily chosen. An ideal image retrieval system is predicted to retrieve all the similar images. The precision rate is defined as the ratio of the total number of similar images in the database T_S to the number of retrieved images ,retrieval rate is defined as the total number of retrieved images(T_r) to the number of images in the dataset.(T_d) Precision rate=T_S/T_R and retrieval rate T_s/T_d n

pattern recognition and information retrieval binary classification, **precision** (also called positive predictive value) is the fraction of retrieved instances that are relevant, while **recall** (also known as sensitivity) is the fraction of relevant instances that are retrieved. Both precision and Recall is based on the measure of relevance. These curve produces relevant output.

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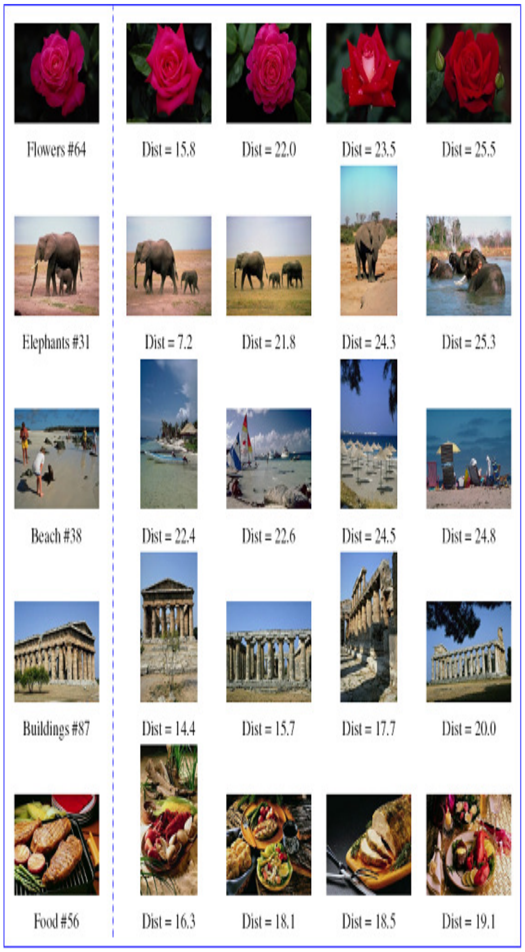

Fig 1.6 Distance criteria evaluation

Fig 1.7 Retrieval of images from dataset

V. EVALUATION CRITERIA OF PROPOSED SYSTEM ANALYSIS WITH THE EXISTING MEASURE:

In Euclidean distance measure the feature vector calculated from the histogram of query image and the database images are computed using the formula by negotiating the feature vector of both query and database images after adding square and square root on both vector.

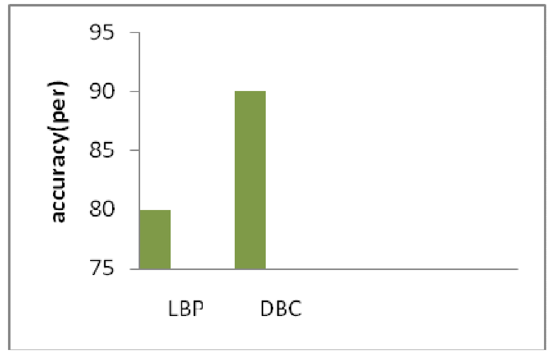

Fig 1.8 Comparison of LBP with DBC

The performance of the proposed descriptors is much improved for three input channels and also in the RGB color space. The descriptors noise robust is achieved through the noise robust pattern\, it becomes possible through the proposed directional binary code algorithm over each channel as the input to the adder/decoder.

Figure 1.8, 1.9 comparison of LBP with DBC based on precision and recall rate

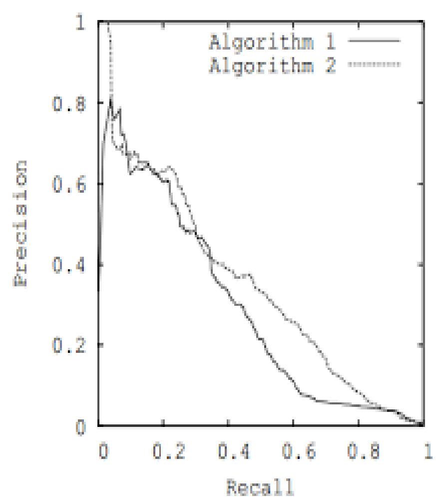

Fig 1.9 comparison based on precision and recall

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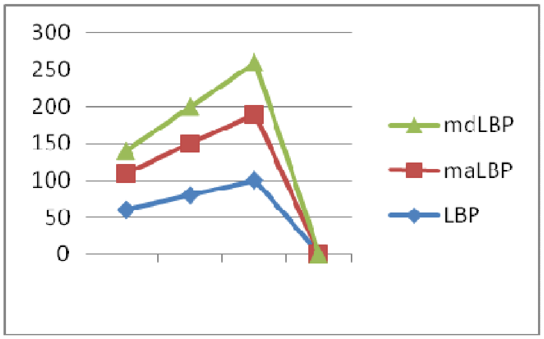

Fig 1.10 Existing approaches with multichannel adder and decoder based on retrieval rate

In case of normal binary pattern [7], the accuracy rate is lower when compared with the multichannel approaches in addition of adder and decoder scheme which in turn increases the retrieval rate by pixel value extraction with cross channel pixel value, so it addition of lower dimensions helps to save the result of pixel value with nearest pixel during comparison and in addition best feature extraction through this adder and decoder concept made to increase precision and recall rate value with these features the graph 1.10 shows the accuracy rate increase when compared with normal binary descriptor, binary classification, precision is analogous to positive predictive value. Precision takes all retrieved images s into consideration. It can also be evaluated at a given cut-off rank, considering only the topmost images returned by the system. The algorithm 1 provides the directional binary code curve of precision and algorithm 2 provides the local binary pattern curve. We have performed extensive image retrieval experiments over various databases of varying number of categories as well as varying number of images per category to report the improved performance of proposed multichannel decoded local binary patterns. Consideration of both the values of adder and decoder able to compute histogram functions with the accuracy. We have reported the results using average retrieval precision, average retrieval rate, average precision per category (AP) and average recall per category.

VI CONCLUSION

In this paper, a directional binary code algorithm is used through which the pixel value output for each RGB input channel is extracted in all directions, so obtain results will be more efficient and clear when compared with existing Local Binary Pattern algorithm, in which pixel values are compared with only nearest neighborhood pixel, whereas proposed algorithm with respect to current pixels in all direction, so average retrieval rate is also increased. It is also deduced that Euclidean distance measure is better suited with the proposed image descriptors. Finally the proposed methods are evaluated using image retrieval experiments over ten databases having images of natural scene and color textures. The results are computed in terms of the average precision rate and average retrieval rate and improved performance is observed when compared with the results of the existing multichannel based approaches over each database. The increased dimension of the decoder based descriptor slows down the retrieval time which is the future direction of this research. future work is to include the magnitude and produces a clear representation, the noise robust inclusion is done in weighted function of adder and decoder block, but it produces only the partial implementation of noise pattern distortion, so in further to reduce it completely enhancement has been carried out. The average retrieval rate and performance measurement is calculated from the distance measure, which in turn implies only the dissimilarities between the feature descriptor, so enhancement is applied for similarities in descriptor also.

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