An Efficient Hybrid Multichannel LBP Based Color Descriptor for CBIR

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Abstract Local Binary Patterns (LBP) was adopted for their accurate performance on various categories of scenes. Usually the LBP for three channels was gained by just combining the binary values from the three channels. But it usually increases the dimensionality of the pattern and also it performs slower than other methods. So as to solve this problem an effective hybrid multichannel LBP based color descriptor for CBIR which utilizes the information from all the channels including the cross channel information is introduced in this paper. Our new texture descriptor is based on the decoder concept which solves the dimensionality problem. Also to improve the retrieval rate the color descriptor which is designed using mean and std on HSV color space is combined with the texture descriptor. For the experiment we use four databases namely Corel-1k, KTH-TIPS, FTVL and USPTex databases which holds images of natural scenes, vegetables and textures. The results are computed using the average precision rate and average recall rate. The experiments proved that the better performance of the proposed decoder based color descriptor over the existing approaches.

***Keywords —Image retrieval, LBP, Multichannel, Color, Texture.* RGB**

I. INTRODUCTION

In the digital world image retrieval is demanding more and more attention in several applications like object recognition, agriculture, biomedical, texture classification, texture segmentation, face recognition, facial expression recognition etc.[1], [2], [3], [17], [20], [24], [25],[30], [31], [32], [33], [34], [40]. The development of digital image processing helps to search and browse images from large collection of images. The feature extraction is the basic step for any image retrieval system and its efficiency mostly depends upon the ways of extracting the features. The image retrieval processing techniques are developed based on two features: low level features and high level semantic concepts. The low level features include the color, texture, shape, spatial layout [8], [9], [23]. Semantic based image retrieval techniques are remaining limited and so that it is easy to use the low level features for the image retrieval processing.

Texture is one of the most important features of an image. The texture based image retrieval method LBP is very easy to implement. So that the texture based methods are widely used in the content based image retrieval systems. Various algorithms like gray level co-occurrence matrices [18], the Tamura texture feature [35], the Markov random field model [7], Gabor filtering [26] and local binary patterns [29] are designed for texture based image retrieval. Among that the LBP is very easy and efficient method for retrieving the images from the large database sets and become popular due to its reduced computational complexity.

The LBP descriptor was proposed based on the intensity values of an image [10,13, 14,15,16,17,19,21,27,28,36,39].Basically LBP is designed for only one channel that is for the gray scale images. The gray scale based LBP performs better in most cases but in some case it shows poor performance because the real world natural images are color images. A color image contains three channels (i.e. red, blue and green). So that for considering the three channels in the computation a novel decoder method was proposed. Many researchers adopted the multichannel concepts in their work. Some examples for multichannel based approaches are Local Color Occurrence Descriptor (LCOD)[11], Rotation and Scale Invariant Hybrid Descriptor(RSHD)[12], Color Difference Histogram(CDH)[22], Color Centrist[5] and mCENTRIST [37].

In order to avoid all these drawbacks and to decrease the dimensionality of the pattern we propose a novel multichannel decoder method where we can use any number of channels at a time. This uses an encoder mechanism for the transformation of local binary pattern relationship among the channels. The LBP plays a major role in the decoder method. This method also preserves the cross channel co-occurrence information. Normally this information increases the dimensionality of the pattern but the proposed method will not increasing the dimension because the information from each channel is captured by each of the decoder output channels. All these are done before the computation of the histogram.

Like texture feature color feature is also an important characteristic of an image. Color is a very important visual attribute. Color features give higher success rate than the gray scale features in image searching and retrieval process. It is very useful to identify the objects and natural scene categories. Some images have similar structure and are hard to recognize. So that for improving the retrieval performance and to improving the discrimination power texture features are combined with the color features. Many color spaces are designed namely L*a*b, HSV, RGB, YCbCr and OPPONENT color space. All of these color spaces RGB is mostly used color space and it is most popular in electronic

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systems for sensing, representing and displaying the images. It mixes the colors with the primary colors (red, green, blue) and reproduces a wide range of colors.

So that the RGB color space is used for computing color features using LBP based decoder descriptor. We also used the HSV color space in the color descriptor and combined the two descriptors to improve the retrieval process.

The rest of the paper is organized as section II explains the related works; section III introduces the proposed descriptor; the section IV shows the experimental results and finally the section V conclude the paper in the right way.

II. RELATED WORKS

For image representation and classification several methods are proposed based on LBP features. Extraction of LBP features is computationally efficient and the fusion of different features shows a good retrieval rate [6], [38]. Local image descriptor is best to perform the texture based image retrieval [4], [38]. Some of the works which are related to our research are mentioned here.

Basically in LCOD [11] the red, green, blue channels are quantized and then it was pooled to form a single image and finally the occurrence of the each quantized color is computed to form the feature descriptor. RSHD [12], these was similar to the LCOD and computed the occurrence of texture patterns. The color quantization is used in the CDH [22] approach. The Color CENTRIST [5] approach quantized all the three channels of the HSV color image and then it was represented as 1,2,5 binary bits respectively. Finally concatenated the binary bits and convert back to decimal to form a single image and then features are computed over it. In these approaches the drawbacks occur in the form of information loss during the quantization process.

mCENTRIST [37] was designed in such a way that, in two channels some of the bits in binary patterns are transformed and the transformed binary pattern are concatenated and the histogram computation is performed over it. The transformation was done for only two channels when more than two channels are used, the same mechanism is applied to other combination of channels and this increases the computational cost of the descriptor. This creates a major drawback for this mCENTRIST approach. To overcome from these drawbacks and to improve the performance over the approaches we proposed a multichannel decoder based LBP color descriptor. In these any number of channels can be used at a time. Here a transformation function is used to encode the relationship among the local binary patterns of the channels.

The transformation was done based on the decoder concept and also the complement information is preserved without increasing the dimension too high. Moreover before the histogram computation the joint information is captured by each decoder outputs. To show the better performance we conduct experiments over four database including natural scenes and color textures.

III. DESCRIPTORS

In our work the texture features and color features are combined for improving the retrieval performance. Two color spaces namely RGB color space which is used in LBP descriptor computation and HSV color space is used in color descriptor computation. Block diagram of the proposed work is shown below in Fig.1.

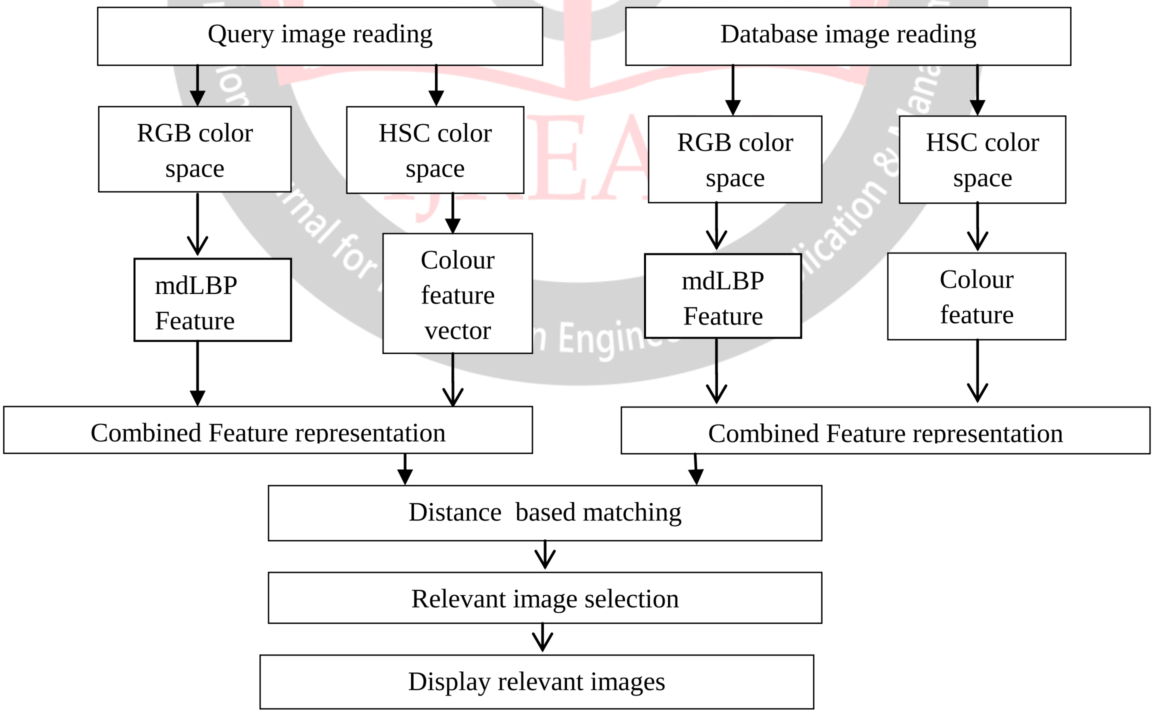

Fig.1.Flowchart of proposed work.

The color is one of the extensively used features to construct meaningful descriptor for the image. One of the significant image features that make the image recognition easily by human is color. . Usually colors are defined in three dimensional color spaces. Normally the color of each pixel is determined by the combination of the red, green, and blue

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intensities stored in each color plane at the pixel's location. Color can be represented in various color spaces. Color space is the mathematical representation of a set of colors. Among these color spaces, each component of the HSV color space contributes directly to the human conceptual understanding of colors. The three color components of HSV are Hue, Saturation (lightness) and Value (brightness). In HSV, Hue (H) distinguishes colors, Saturation (S) gives percentage of white added to pure color space and Value (V) represents the intensity of perceived light. The advantage of HSV color space is that it is closer to human conceptual understanding of colors and has the ability to separate chromatic and achromatic components. So HSV color space is used in this color descriptor and is shown in Fig.2.

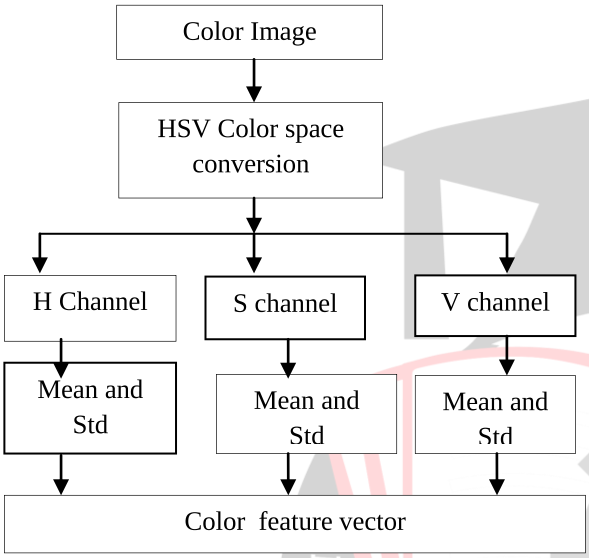

Fig.2. Flowchart of Color feature vector computation

The important color attributes, Mean (μ_t) and Standard Deviation ($\boldsymbol{\sigma}_t$) for a HSV color component of an image can be written as in using Equ.1 and Equ.2.

$$\mu_t=\frac{1}{NP}\sum_{i=1}^{NP} P^t{}_i \quad (1)$$

$$\boldsymbol{\sigma}_t=[\frac{1}{NP-1}\sum_{i=1}^{NP}(P^t{}_i-\mu)^2]^{1/2} \quad (2)$$

where $t\in\{H,S,V\}$. Here $P^t{}_i$ indicates the i^{th} pixel of t^{th} color component on HSV color space of an image, NP is the total number of pixels in the image and μ_t and $\boldsymbol{\sigma}_t$ represent the mean and standard deviation of t color component in HSV color space of an image.

The multi channel decoder based local binary pattern (mdLBP) utilizes the local binary pattern information of multiple channels. In this a transformation function is used, which encodes the local binary patterns. This transformation is based on the decoder concept. The original LBP operator is a unified approach for structural texture analysis. The LBP code is calculated by comparing the pixel with its eight neighboring pixels. For each neighboring pixels the result is set to one if the value is less than the center pixel value otherwise it was set to zero. The LBP code for the center pixel is calculated by multiplying the results with the weights given by the powers of two and summing them up together. The LBP code is calculated by using Equ.3 and Equ.4

$$LBP^t(x,y)=\sum_{n=1}^{N} LBP_n^t(x,y)\times 2^{(n-1)} \quad (3)$$

where,

$$LBP_n^t(x,y)=\begin{cases}1, & P^t{}_n(x,y)\geq P^t(x,y)\\ 0, & otherwise\end{cases}, \quad (4)$$

N is the no. of neighbors around P^t(x,y) (N=8)

$n\in[1,N]$

c is 3 for color images representing three channels

$t\in[1,c]$

$t=0$ for Red channel

$t=1$ for Green channel

$t=2$ for Blue channel

The flowchart of multichannel decoder based local binary pattern feature vector (i.e. *MDLBP*) of an image from its Red (R), Green (G) and Blue (B) channels is shown in the below Fig.3. The multichannel decoder generated 2^c number of output channels, where c is the number of input channels. The values of $LBP_t^n(x,y)$ are in the binary form (i.e. either 0 or 1), like that the values of $MDLBP_{t_1}^n(x,y)$ are also in the binary. These binary values are generated from the multichannel decoder map $MDM^n(x,y)$.

Mathematically, the truth map $MDM^n(x,y)$ is defined as using Equ.5,

$$MDM_n(x,y)=\sum_{t=1}^{c} 2^{(c-t)}\times LBP_n^t(x,y) \quad (5)$$

$n\in[1,N]$ and

$\in[1,c]$

From the multichannel decoder map $MDM_n(x,y)$ the multichannel decoder based local binary pattern $mdLBP_{t_2}^n(x,y)$ for pixel (x,y) is computed using Equ.6 as,

$$MDLBP_n^{t1}(x,y)=\begin{cases}1, & if\ MDM_n(x,y)=(t_1-1)\\ 0, & otherwise\end{cases} \quad (6)$$

$t_1\in[1,2^c]$ and $n\in[1,N]$.

In a RGB image, for $t_1=1$(n^{th} neighbor in red, green and blue channels is smaller than the center values in their respective channels) the value of $MDLBP_{t_1}^n$ is 1. For $t_1=4$ (n^{th} neighbor in red channel is smaller than the center value in that channel and the n^{th} neighbor in green and blue channels are greater than the center values in respective channels) then the value of $MDLBP_{t_1}^n$ is 1. Simply we say that $MDLBP_{t_1}^n$ represents a unique combination of red, green and blue channels i.e. encoding of the cross channel information

The multichannel decoder based local binary patterns $MDLBP^{t_1}(x,y)$ for the center pixel (x,y) is computed from $MDLBP_n^{t_1}(x,y)$ using the following equation Equ.7.

$$MDLBP^{t_1}(x,y)=\sum_{n=1}^{N} MDLBP_n^{t_1}(x,y)\times(2)^{(n-1)} \quad (7)$$

$t_1\in[1,2^c]$

The final feature vector (i.e. histogram) of multichannel decoder based LBP are computed by concatenating the histograms of MD*LBPs* over each output channel respectively which was given in Equ.8 as,

$$MDLBP=\frac{1}{C+1}\left[H^{MDLBP^1},H^{MDLBP^2},\dots,H^{MDLBP^{2^c}}\right] \quad (8)$$

LBP-histograms are calculated to compare the query image with the database images. To compare the histograms, distance measures are used and get something that will tell

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how much these histograms are equal (0 - 100%). The shortest similarity score is measured using the different distances between the query image and Database images. The basic aim of distance measures is to find out the similarity between the feature vectors of two images. Many types of distances are available to find out the similarity e.g. Euclidean distance, L1 or Manhattan distance, Canberra distance, Chi-square (Chisq) or $\chi 2$ distance, Cosine distance, and D1 distance. We use the Chi-square distance because it gives better performance than the other distance measures.

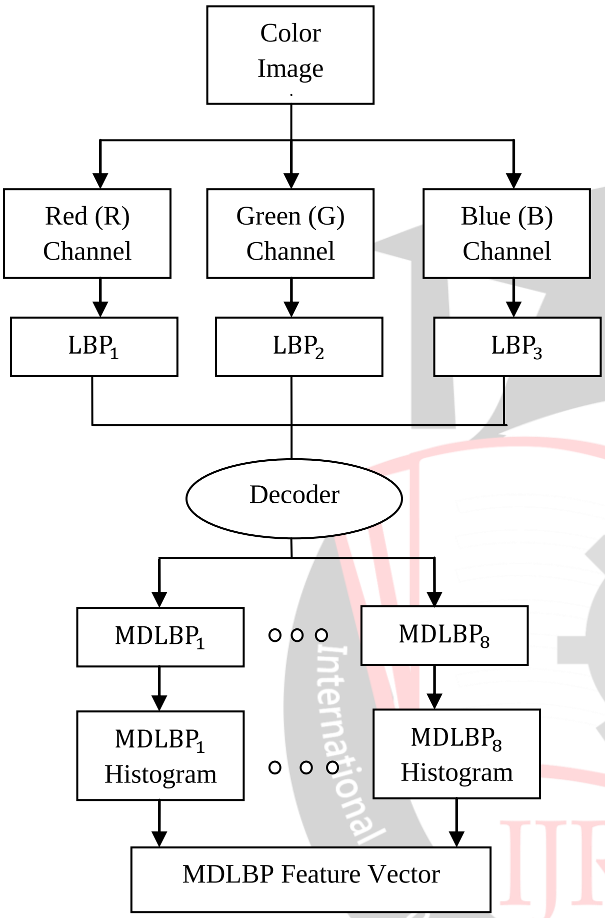

Fig.3. Flowchart of MDLBP

The effectiveness of the proposed descriptor is represented by using the precision and recall curves. *Pr* and *Re* are the precision and recall for the k^{th} query image and defined by the following equation Equ.9 as

$$Pr(k)=\frac{NS}{NR} \quad \& \quad Re(k)=\frac{NS}{ND} \tag{9}$$

where *NS* is the number of similar images retrieved, *NR* is the number of images retrieved, and *ND* is the number of similar images in the whole database.

The average retrieval precision (ARP) and average retrieval rate (ARR) are given using Equ.10 and Equ.11 as

$$ARP=\frac{\sum_{i=1}^{TC} AP(i)}{TC} \tag{10}$$

$$ARR=\frac{\sum_{i=1}^{TC} AR(i)}{TC} \tag{11}$$

where

TC is the total number of categories in that database

$$AP\ (i)=\frac{\sum_{j=1}^{TC_i} Pr(j)}{TC_i}$$

$$AR(i)=\frac{\sum_{j=1}^{TC_i} Re(j)}{TC_i}$$

where TC_i is the number of images in the i^{th}category of that database.

IV. EXPERIMENTS AND RESULTS

The main aim of content based image retrieval is to find out the most similar images of a query image in the whole database. We use Corel-1k, USPTex, KTH-TIPS, FTVL databases to evaluate the proposed descriptor. The Corel-1k database contains many categories of images like mountains, flowers, buses, horses, elephants, foods and the FTVL database contains vegetable images and the other databases contains texture images. The performance of the proposed descriptor is investigated by using the average precision and average recall rate.

A. Comparison with existing approaches

Experiments are performed over four 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 with color descriptor. The performance of proposed descriptor are investigated with the existing methods by using ARP and ARR over Corel-1k, KTH-TIPS, USPTex, FTVL databases is shown in Table 1 and in Table 2 also in Fig.4 and in Fig.5. The Table 1 shows that proposed method works well for all databases mentioned in the table than the existing method. Also it proves that the proposed method getting better result for USPTex database with 99.7% of ARP. The Table 2shows that proposed method works well in terms of ARR also. Also it proves that the proposed method getting better result for USPTex database with 49.9% of ARP

Fig.4 and Fig.5 shows the better performance of proposed method. The maLBP performs better than the existing method LBDP, mdLBP performs better than the LBDP and it also performs better than maLBP and the performance of the proposed method is better than the above existing methods. The results are reported using average retrieval precision (ARP) and average retrieval rate (ARR) as the function of number of retrieved images (NR). Fig.6. shows the ARP vs NR plots for LBDP, maLBP, mdLBP and the proposed descriptor over Corel-1k databases. Fig.7 shows the ARP vs NR plots for LBDP, maLBP, mdLBP and the proposed descriptor over FTVL databases. All the descriptors performed well over the FTVL database than the Corel database.

Table 1. ARP (%) analysis

Category	ARP(%); (Top matches = 5)			
	Corel-1k	KTH-TIPS	USPTex	FTVL
LBDP[13]	54.2	59	88.2	93.6
maLBP[14]	72.2	73.2	94.6	95.2
mdLBP[14]	74.2	76.2	99.6	95.3
Proposed	75.6	77.6	99.7	97.6

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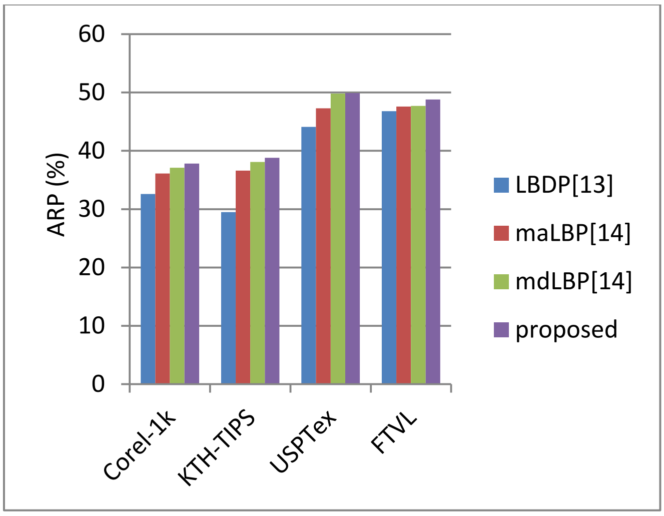

Fig.4. .ARP (%) analysis

Table 2. ARR (%) analysis

Category	ARR(%); (Top matches = 5)			
	Corel-1k	KTH-TIPS	USPTex	FTVL
LBDP[13]	32.6	29.5	44.1	46.8
maLBP[14]	36.1	36.6	47.3	47.6
mdLBP[14]	37.1	38.1	49.8	47.7
proposed	37.8	38.8	49.9	48.8

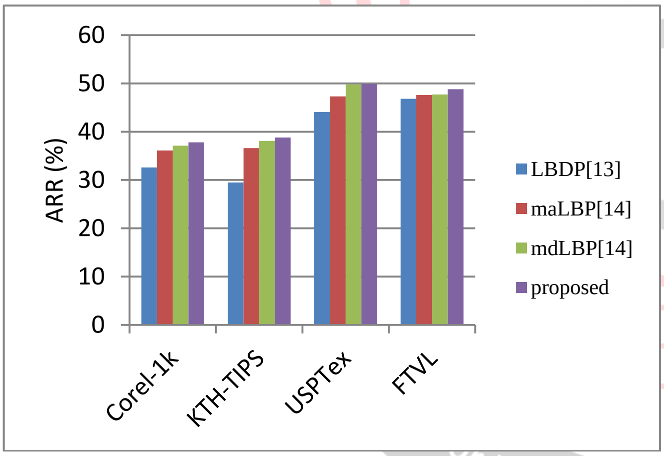

Fig.5. ARR (%) analysis

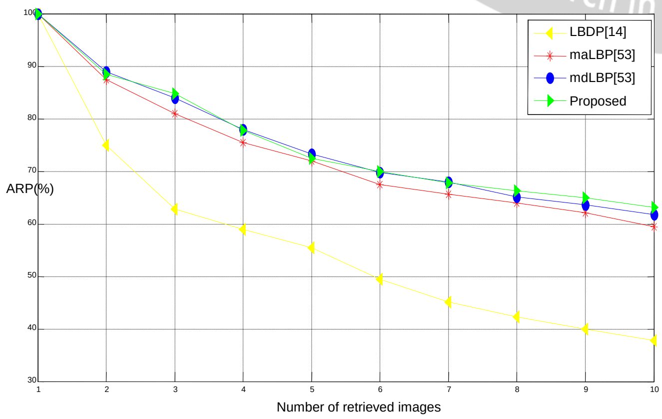

Fig.6. ARP vs NR plot over Corel-1k

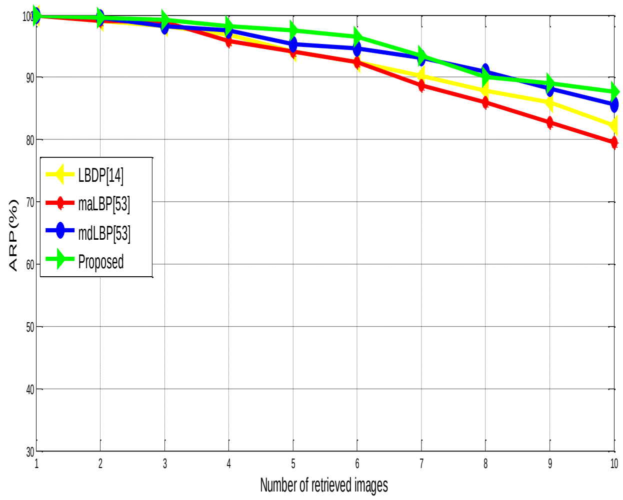

Fig.7. ARP vs NR plot over FTVL

The Fig.6 and Fig.6 shows that the ARP values for each NR ∈ [1,10] using decoder based proposed descriptor are higher than LBDP, maLBP and mdLBP over the Corel-1k, FTVL database. This shows the better performance of the proposed descriptor over the Corel-1k, FTVL database. The image retrieval experimental results over the Corel-1k databases are demonstrated in terms of the ARR vs NR plots using each descriptor is shown in figure.8. Fig.9. shows the ARR vs NR plots for LBDP, maLBP, mdLBP and the proposed descriptor over FTVL

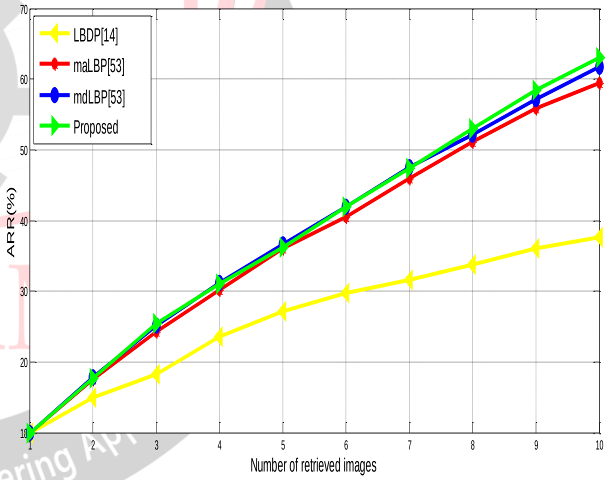

Fig.8. ARR vs NR plot over Corel-1k

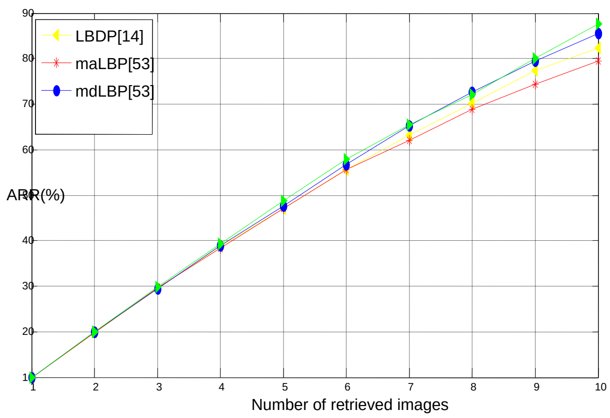

Fig.9. ARR vs NR plot over FTVL

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V. CONCLUSION

In this paper an efficient hybrid multichannel LBP based color descriptor for CBIR which utilizes the information from all the channels including the cross channel information is introduced in this paper. Usually these process increases the dimension of the pattern. Our new texture descriptor is based on the decoder concept which does not increase the dimension of the pattern. Also the color descriptor calculated using mean and std on HSV color space is combined with the texture descriptor to improve the performance much better. For the experiment we use four databases namely Corel-1k, KTH-TIPS, FTVL and USPTex databases which holds images of natural scenes, vegetables and textures. The results are computed using the average precision rate and average recall rate. The experiments proved that the better performance of the proposed LBP based color descriptor over the existing approaches. The proposed method getting better result for USPTex database with 99.7% of ARP and 49.9% of ARP.

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