An Approach to Explore the Role of Color Models and Color Descriptors in the Optimization of Semantic Gap in Content based Image Retrieval

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ABSTRACT
Content based image retrieval (CBIR) systems retrieve images based on their primitive features such as color, texture, shape etc. The semantic gap is defined as the inconsistency between the image retrieval based on these low level image features and high level human semantics. In this paper, the comparative analysis of various color model transformations is presented with the help of our proposed methods based on three color descriptors i.e. color histogram, color moments and color coherence vectors to determine the applicability of these models and descriptors for the reduction of semantic gap. Support vector machines are used to classify images into different semantic classes. The results are inferred with the help of performance parameters like precision, recall, and mean average precision. Experimental results suggest that the proposed approach gives a good evaluation of the applicability of color models as well as color descriptors for optimization of semantic gap in CBIR.

General Terms
Image Processing, Pattern Recognition, Classification

Keywords
Color models, Content based image retrieval (CBIR), Mean Average Precision, Semantic gap, Support vector machines.

1. INTRODUCTION
Content based image retrieval system(CBIR)[1-7] is stated as the retrieval of images based on low level or primitive image features such as shape, color, texture, etc. This retrieval is usually based on the similarity index rather than on the exact match [2]. The critical issue in CBIR system is the development of an effective and efficient feature extraction method for image representation that complies with the human perception subjectivity. This subjectivity occurs in all semantic levels while analyzing images because different users in same situation or the same user in different circumstances may analyze or classify the same image differently. This inconsistency between the image retrieval based on low level image features and high level human semantics is termed as the Semantic Gap [6-10]. Color is one of the most extensively used visual features in image retrieval. Color features are relatively strong to the viewing angle, translation and rotation of the regions of interest in an image. Although color is certainly not the most important primitive feature when it comes to semantic retrieval, but if spatial distribution of colors is considered while extracting color features for an image, it constitutes a good launching point for future work consisting of the development of more sophisticated image retrieval system which is directly supportive to optimize the semantic gap in content based image retrieval. In CBIR applications, color images can be treated in various ways by different color models [12-23]. A color model is a mathematical system to represent colors. No color model can be considered as universal because colors can be interpreted and represented in different ways. With a large variety of available color models, the foreseeable question that arises is how to select the color model and color descriptor that produce the best result for particular query image retrieval.

In this paper, the performance of a wide variety of color models and various color descriptors is evaluated. Overall 7 methods based on one or more color descriptors for color feature extraction are proposed. Every method is implemented for evaluating the performance of 10 color model transformations. Support vector machine classifiers [11,24] are used to classify the images into semantic classes like Manmade Indoor, Manmade Outdoor and Natural Outdoor. Initially the experiments are done on our own database comprising of 450 images from various categories like Store, bedroom, kitchen, snowy mountains, buses, coast, street, twilight, buildings and forest. Later the same experiments are done on a standard database of James Z. Wang et.al. [25] consisting of 1000 images of different categories like African people, buildings, beaches, buses, dinosaurs, elephants, roses, horses, snowy mountains and food plates. The results from this paper lead to novel methods to choose an appropriate color model with an appropriate combination of color descriptors for the optimization of semantic gap in CBIR.

The rest part of this paper is organized as follows. Section 2 focuses on the classification approach and related methodology for semantic gap reduction by reviewing various color models and color descriptors. Experimentation based on proposed methods is given in section 3. In section 4, the results are shown and the role of color models and color descriptors for the reduction of semantic gap in CBIR is discussed . Finally, the section 5 concludes the paper and throws light on the scope of the future work.

2. CLASSIFICATION APPROACH AND RELATED METHODOLOGY FOR THE OPTIMIZATION OF SEMANTIC GAP
Classification is one of the approaches to optimize the semantic gap in CBIR. Classification is the process of extracting low level image features (LLIFs) and mapping them to semantically meaningful concepts i.e. high level image features (HLIFs). LLIFs are not directly relevant to the user for image retrieval task whereas HLIFs have direct

meaning to the user. LLIFs are to be extracted first in order to classify images into semantically meaningful classes. The extracted information should be unique for the particular image and similar to the information extracted from similar images. The primitive features required for image classification are color features and holistic structure features. If the spatial distribution is considered while extracting color features of an image, then color features can also be considered as holistic structure features [24]. Thus in this paper, the approach used for optimization of semantic gap in CBIR is based on feature extraction by color descriptors.

Color histogram (CH), Color Moments (CM) and Color coherence vectors (CCV) are used for feature extraction for CBIR. Color Histogram is an effective representation of the distribution of color contents in an image if the color pattern is unique as compared to rest of the data set . Computation of CH is easy and fast and it is robust to translation and rotation about the view axis. However it changes slowly with the scale, occlusion and viewing angle [27]. Color moments are efficient and effective in representing color distributions in the images and extensively used in many commercial retrieval systems e.g. QBIC [28, 29] especially when image contains just an object. Mathematically, the first three moments i.e. first order (mean), second order (variance) and third order (skewness) are stated as shown in equations (1) to (3).

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} \qquad (1)$$

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij}-\mu_i\right)^2} \qquad (2)$$

$$S_i = \sqrt[3]{\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij}-\mu_i\right)^3} \qquad (3)$$

Where f_{ij} is the value of the i^{th} color component of image pixel j and N is the No. of pixels in the image. Color moments are a very compact representation compared to other color features. In some cases, an image may not be solely determined by its color histogram or the distribution of colors in it. One image may be consisting of a large No. of scattered pixels with a particular color while another image may includes the same amount of pixels with that color but its pixels are gathered into the same area. The two different images may have same color histogram but different spatial arrangement of colors. CCV includes the information about spatial location of colors in an image[30].

Here, the retrieval efficiency is evaluated by using these color descriptors individually and it is marked that the performance is improved further when these descriptors are combined with one another.

It is important to explore different color models that are used to transform the color information of an image into a new co-ordinate system so that the comparison of color information can be made easier and perceptually more correct. Different color models that are analyzed in this paper are RGB, CMYk, I1I2I3, HSV, YIQ, YUV, L*a*b*, XYZ, YCbCr and HMMD.

Primary color model RGB [21, 23] is a device dependent color model which is usually used for color display and is non-linear with visual perception. However this model does not exhibit perceptible benefits over gray scale models in terms of convergence accuracy [21]. The Euclidean distance between colors in RGB space does not corresponds to the way the humans perceive the distance between colors [26]. Thus this may lead to unsatisfactory image classification. CMYK is another device dependent color model which is used for passive devices that deposit colored pigments on paper, such as color inkjet printers and copiers. XYZ is derived from RGB and it consists of tristimulus values which give the chromaticity components. Intensity and chromaticity information are strongly mixed in each of the RGB channels. Non correlated color model I1I2I3 is introduced by Ohta [31] after a colorimetric analysis of 8 images and realizes an efficient minimization of the inter channel correlations for natural images.

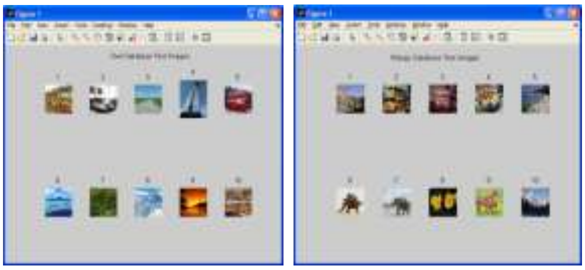
Color models based on luminance and chrominance components are YUV, YIQ, YCbCr, HSV, etc. YUV and YIQ models are used for analog television transmission whereas YCbCr is used for digital television transmission. Y is related to luminance and U, V, I, Q, Cb and Cr are related to chrominance. HMMD (Hue-Max-Min-Diff) is a perceptually uniform color model [7, 32] defined in three dimensions i.e. sum and difference axes and Hue angle. HSV color model is the non-linear but reversible transformation from RGB and it corresponds closely to the way humans describe and interpret colors.

One of the perceptual color models, $L^*a^*b^*$ also known as CIELAB, is a device independent color model which is also designed to correspond well with human perception of colors [26]. Here, a color is defined by the value of three channels, where the first represents the brightness, the second represents the color on a green to red scale and the third represents a color on a blue to yellow scale. $L^*a^*b^*$ color model gives the Munsell system of color classification [33].

3. EXPERIMENTATION

The retrieval tests are carried out in order to verify which color descriptor method gives good retrieval results based on highest recall and precision parameters. Performance of different color models is also evaluated. Further the best two methods have been evaluated using a single performance parameter i.e. Mean average precision(MAP) for all color models. To verify the applicability of color models and effective color feature extraction methods for semantically meaningful image retrieval, the results are noted for three semantic classes that are Manmade Indoor, Mandmade Outdoor and Natural Outdoor.

In these experiments, two databases are used. One is our own database created by collecting 450 images from 10 different categories i.e. store, bedroom, street, building, buses, coast, forests, snowy mountain, twilight and kitchen as shown in Figure 1(a). Another is the standard database of James Z. Wang et.al.[25] and it is a subset of 1000 images of the Corel database which were selected manually to form 10 classes of 100 images each. The images are subdivided into 10 sufficiently distinct classes (e.g. buildings, buses, African people, food plates, beaches, dinosaurs, elephants, roses, horses and snowy mountains as shown in Figure 1(b)) such that it can be assumed that a user wants to find the other images from the class if the query is from one of these classes. The database is created at Pennsylvania University and is publically available.



(a) (b)

Fig 1: Test Images from (a) Own Database (b) Wang's Database

The experimentation involves two stages, training and testing for image retrieval. Training procedure is shown in Figures 2(a) and Figure 2(b). In the first stage, database images are converted into desired color models and their features are computed using selcted color descriptor method. Structures for four semantic sub-classes like manmade,natural,indoor and outdoor are formed by providing features matrix of database images and the targets corresp onding to these classes to the SVM for training. Linear Kernel as well as non linear kernel i.e. Gaussian Radial Basis Function(RBF) [34] is used and it is observed that RBF outperformed the Linear Kernel in both accuracy and convergence time. Therefore in this paper, results using RBF kernel are shown. Linear kernel is used only for color moments method.

Second stage consists of image retrieval procedure which is shown in Figure 3. Given a query image, the color model conversion is carried out, its color feature vectors are computed. By using these color features and the structures obtained for four sub-classes, SVM classifiers classify the

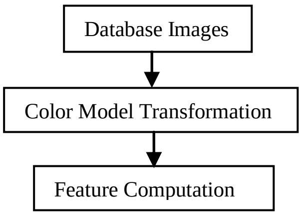


Fig 2(a)

query image into sub-classes. Further, the query image is identified as one of the three main classes that are Manmade indoor, Manmade Outdoor or Natural outdoor. In addition to this, the query image features are compared with those of the database images using Euclidean distance as it is the most commonly used distance metric for image retrieval. Experimentation is done using Quadratic distance but more semantically relevant images are retrieved using Euclidean distance.

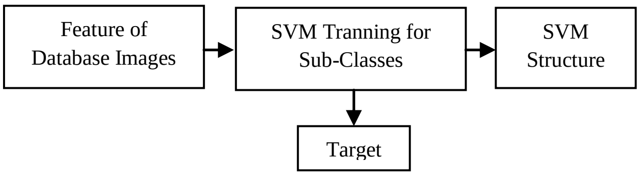


Fig 2(b)

Fig 2: Training Process: (a) Feature Computation of database images and (b) Formation of SVM Structures

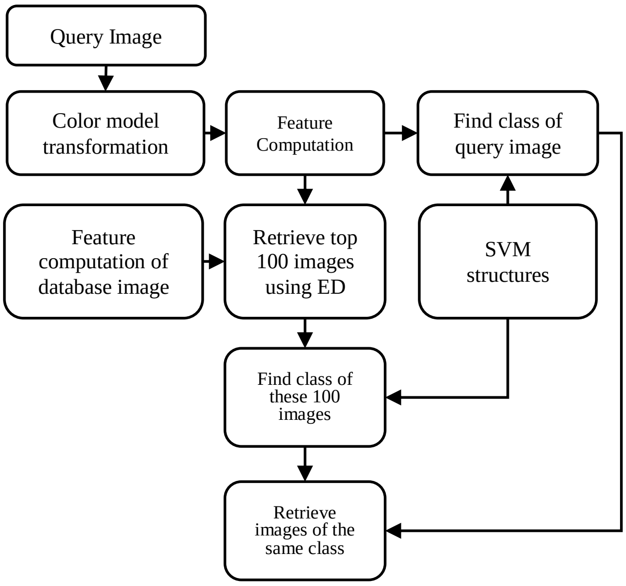


Fig 3: Image Retrieval Process

In this paper, results based on only Euclidean distance (ED) are presented. Top 100 images having minimum distance are retrieved. From these 100 images, only images having the same class as that of the query image are displayed.

The color descriptors given in the literature i.e. CH[27], CM[28] and CCV[30] are used here and their performance is compared with our proposed methods based on the combination of these descriptors i.e. CH-CM, CH-CCV, CCV-CM, CH-CM-CCV. Also every method is implemented using different color models. Performance parameters used for the assessment of color models and color descriptors are Precision, Recall and Mean Average Precision (MAP). MAP term not only gives the retrieval efficiency but also shows how quickly the image is retrieved. Hence rank wise image retrieval can be evaluated. Performance Parameters [35-38] used for comparing various color models as well as various color descriptors are given by the equations (4) to (6).

$$Precision = \frac{No.\ of\ relevant\ images\ retrieved}{Total\ No.\ of\ images\ retrieved} \quad (4)$$

$$Precision(r) = \frac{No.\ of\ relevant\ images\ retrieved\ at\ rank\ r}{r} \quad (5)$$

$$Recall = \frac{No.\ of\ relevant\ images\ retrieved}{Total\ No.\ of\ relevant\ images\ in\ the\ database} \quad (6)$$

The average precision is defined as the mean precision after every relevant image is retrieved. The parameter MAP as shown in equation (7) is the mean of the precision for each relevant image is retrieved. MAP measures the average performance of multiple retrieved images.

$$MAP = \frac{\sum_{r=1}^{N}\left(pre(r) \times rel(r)\right)}{No.\ of\ relevant\ images\ in\ the\ database} \quad (7)$$

Where N is the total No. of retrieved images, r is the rank of the retrieved image; rel(r) is a binary function (0 or 1) indicating whether the retrieved image at the given rank r is relevant to the query image, and pre(r) is the precision at the given rank r. This measure favors the features that can retrieve relevant images earlier.

4. RESULTS AND DISCUSSION

Initially the experiments are done on our own database. Sample query images are shown in Figure 1. Figure 4 shows the retrieval results for the query image 'Building' (similar to the image in topmost corner of Figure 4) when it is transformed into I1I2I3 color model. The feature extraction method used is CCV-CH-CM. Class of this query is identified as "Manmade Outdoor".

Precision-Recall graphs for all the color models are shown in Figure 5. It is observed that I1I2I3 model gives the best retrieval accuracy (Recall-0.84) when compared with other models.

The similar experiment is done on sample query images from each category with all color models and color feature extraction methods and results are obtained. Results for highest Recall and corresponding color models for all color feature extraction methods are shown in Table 1 and Table 2 respectively.

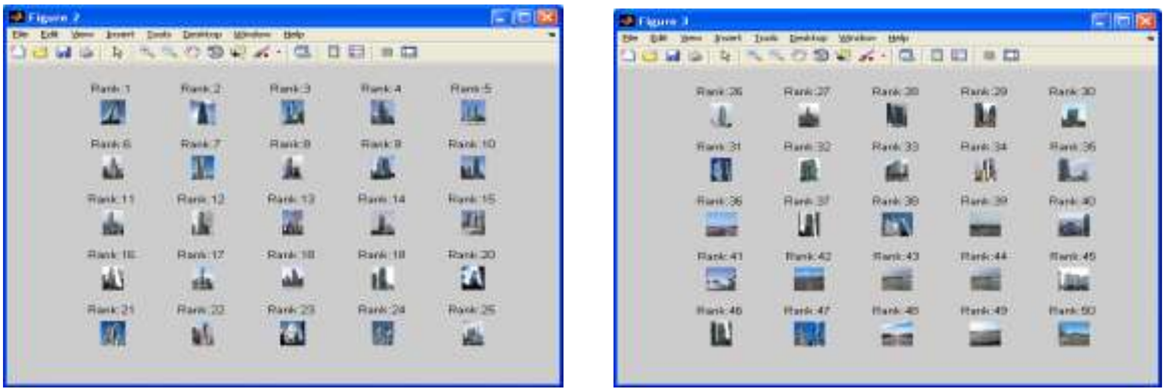


Fig 4: Retrieval Results for 'Building' Image (similar to the image at 'Rank 1') with I1I2I3 color model transformation using proposed method (CCV-CM-CH)

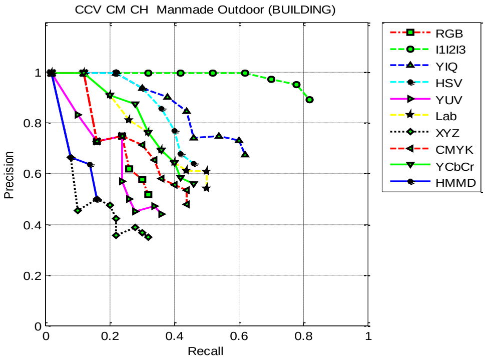


Fig 5: Precision-Recall Graphs for 'Building' image using different color models

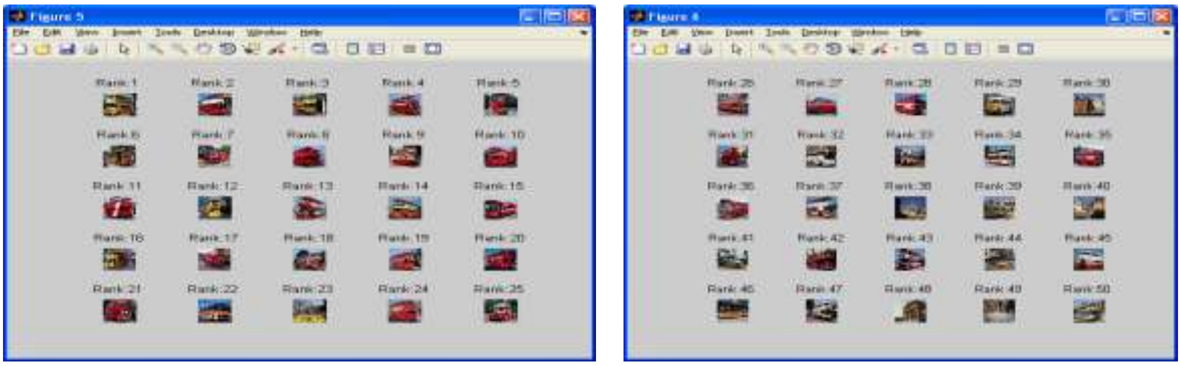
Table 1. Maximum Recall Values Obtained by All color feature extraction methods on Own Database

Image Category	CH	CM	CCV	CH-CM	CCV-CM	CCV-CH	CCV-CM-CH
Store	0.84	0.54	0.76	0.72	**0.94**	0.7	0.72
Bedroom	0.72	0.48	0.54	0.6	0.68	0.72	**0.8**
Street	0.56	0.4	0.58	0.54	0.64	**0.66**	0.58
Building	0.74	0.52	0.84	0.86	**0.96**	0.84	0.84
Bus	**1**	0.72	0.84	0.92	0.94	0.98	0.96
Coast	0.64	0.5	0.5	0.7	0.64	0.72	**0.76**
Forest	0.94	0.96	0.94	**0.98**	0.96	**0.98**	**0.98**
Snow Mountain	**1**	0.68	0.6	**1**	**1**	0.88	0.92
Twilight	**0.98**	0.92	0.8	**0.98**	0.94	**0.98**	**0.98**
Kitchen	0.52	0.48	0.76	0.44	0.8	0.64	**0.84**

Table 2. Optimum Color Models for All Methods (Own Database)

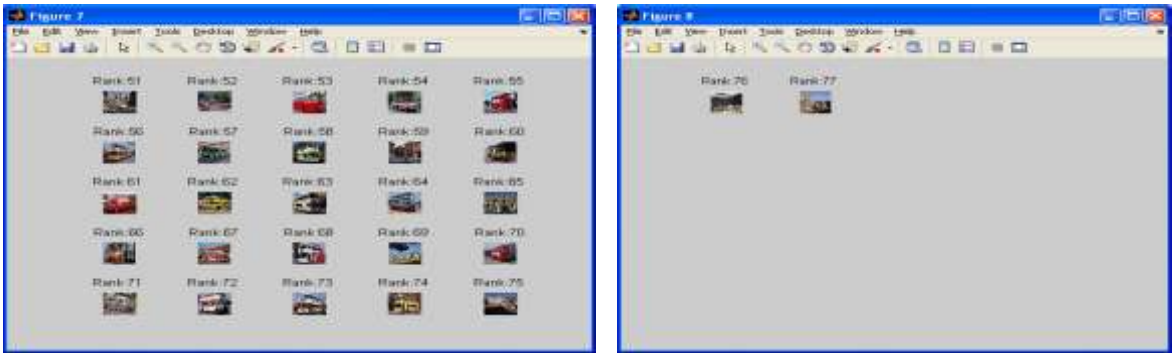
Image Category	CH	CM	CCV	CH-CM	CCV-CM	CCV-CH	CCV-CM-CH
Store	HMMD	L*a*b*	HMMD	RGB	HMMD	YUV,RGB	RGB
Bedroom	CMYK	YCbCr	HMMD	L*a*b*	YCbCr	YIQ	L*a*b*
Street	HMMD	L*a*b*	I1I2I3	I1I2I3	I1I2I3	L*a*b*	I1I2I3
Building	I1I2I3	I1I2I3	I1I2I3	I1I2I3	L*a*b*	I1I2I3	I1I2I3
Bus	HMMD	L*a*b*	YCbCr	HSV	YCbCr	HSV	HSV
Coast	YCbCr	YCbCr	HSV	L*a*b*	HMMD	CMYK	L*a*b*
Forest	YCbCr	CMYK	I1I2I3	L*a*b*	I1I2I3	HSI	L*a*b*
Snow Mountain	YCbCr	CMYK	HSV	YCbCr	CMYK	YIQ	HMMD
Twilight	YIQ	HMMD	YUV	I1I2I3	YUV	YIQ	YIQ
Kitchen	YIQ	RGB	YIQ	L*a*b*	CMYK	L*a*b*	L*a*b*

It is marked that the results are improved by our proposed methods based on the combination of two or all color descriptors. So, for further analysis of color models, the best performed two methods that are CCV-CM and CCV-CM-CH are considered. Here, the same experiments are done on Wang's standard database. The retrieval results for one of the 'Bus' images are shown in Figure 6. Precision-Recall plots by CCV-CM-CH method for all color models are shown in Figure 7. It is observed that I1I2I3 color spaces gives good retrieval accuracy.



(a) **(b)**

Fig 6 (a) and (b): Retrieval Results for 'Bus' Image with I1I2I3 color model transformation using proposed method (CCV-CM-CH)



(c) **(d)**

Fig 6 (c) and (d): Retrieval Results for 'Bus' Image with I1I2I3 color model transformation using proposed method (CCV-CM-CH)

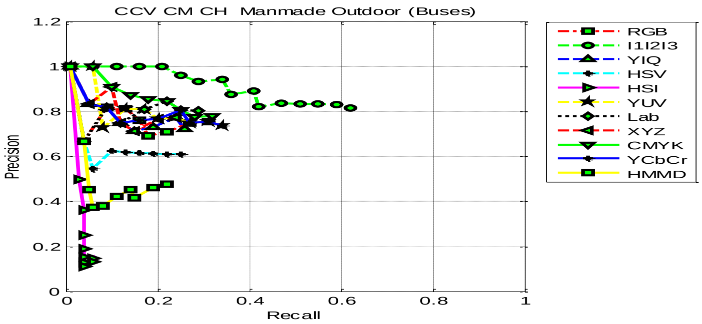


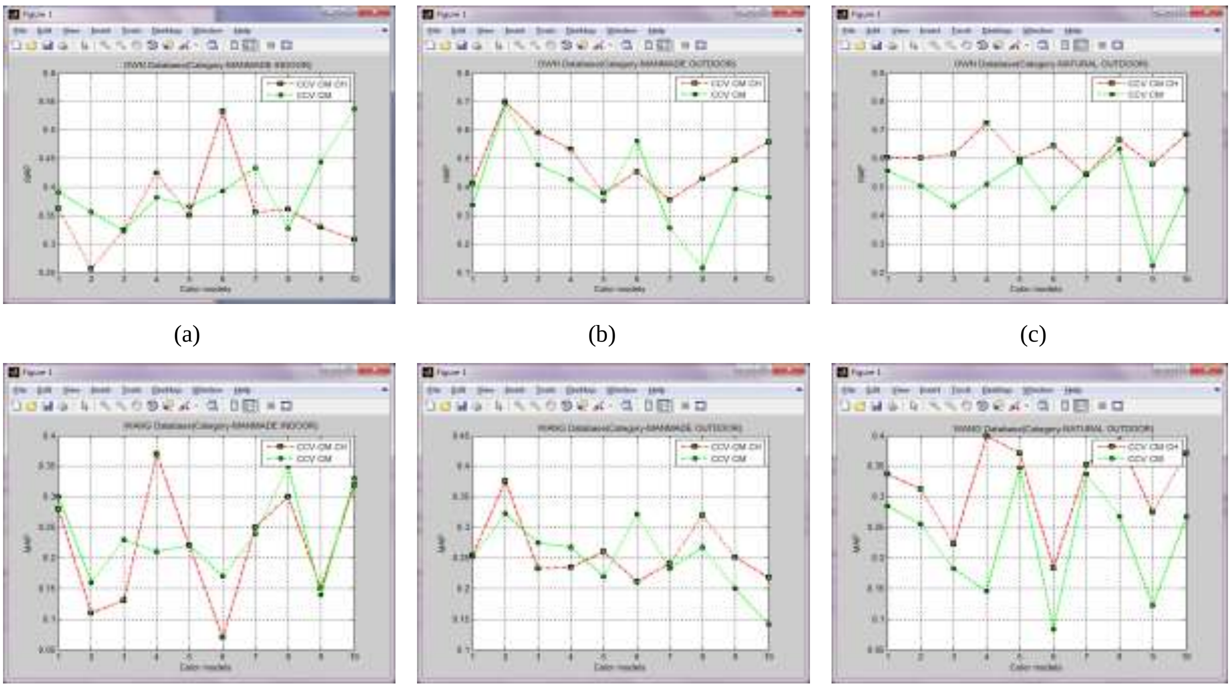
Fig 7: Precision-Recall Graph for 'Bus' image using different color models

In CBIR, rank-wise retrieval of semantically meaningful images is of prime importance. To find out how quickly the semantically meaningful images are retrieved, MAP parameter which is based on the retrieval rank of positive images is calculated. This is obvious from Table(3). Though precision is same for HSV and XYZ transformations, and recall is same for all the three transformations, the MAP values are different. In case of HSV(MAP(0.3)), more relevant images are retrieved at earlier rank than other two cases(MAP (0.27) and (0.28)).

Table 3. Retrieval Results for 'Building' Category from Wang's Database Using CCV-CM-CH Method

Parameters	RGB	HSV	XYZ
No. of relevant images retrieved	33	33	33
Total No. of images retrieved	47	44	44
No. of relevant images in the database	100	100	100
Precision	0.70	0.75	0.75
Recall	0.33	0.33	0.33
MAP	0.27	0.3	0.28

To optimize the semantic gap in CBIR, it is required to find the suitable color model for particular semantic class of images. Therefore an average MAP for different semantic classes like Manmade indoor, Manmade outdoor and Natural outdoor using all color models is computed as shown in Figure 8. Horizontal axes show the color models from 1 to 10 in the order of RGB,I1I2I3, YIQ, HSV,YUV, $L^*a^*b^*$, XYZ, CMYk, YCbCr and HMMD respectively.



(a) (b) (c)

(d) (e) (f)

Fig 8 : Graphs for Average-MAP Vs Color Models for our 'Own' synthesized Database ((a),(b),(c)) and Wang's Standard Database ((d),(e),(f)) for three semantic classes such as Manmade Indoor ,Manmade Outdoor and Natural Outdoor

From own database, images of store, bedroom and kitchen categories are considered as Manmade indoor; Street, buildings and bus images are considered as Manmade outdoor whereas coast, forest, snow mountains and twilight images are from Natural outdoor category. Similarly from Wang's database, food images are considered as Manmade indoor, buildings and bus categories as Manmade outdoor and Natural outdoor class consists of images of Africans, beach, dinosaurs, elephants, roses, horses and snowy mountains.

It is marked that the more improved retrieval results are obtained by using our proposed method i.e. CCV-CM-CH for feature extraction. The primary color model RGB shows comparatively better results only for natural images as compared to manmade images. The HSV color model proves to be the best for Natural outdoor images as it describes the perceptual color relationship more accurately than RGB and other color models. Another perceptually uniform color model HMMD and secondary color model CMYk are also found to give good rank-wise retrieval results for Natural outdoor images. However, HSV may be the best choice for Natural outdoor class as the computational time required for HMMD and CMYk is very high as compared to HSV. Though non correlated color model I1I2I3 is usually preferred for natural images [31], from our results it is marked that this model gives best semantically meaningful results for Manmade outdoor class of images. It can be inferred from the results on our own database that perceptual color models such as L*a*b* , HSV and HMMD performed well in Manmade indoor class of images but experiments on Wang's database do not confirm the efficiency for L*a*b* model.

5. CONCLUSION AND FUTURE SCOPE

In this work, the performance of a wide variety of color models in combination with different color descriptors for semantically meaningful content based image retrieval is presented and evaluated. The main question addressed in this paper is that which color model is suitable along with which color descriptors so that it will be helpful to optimize the semantic gap. In the current work, performance parameters i.e. Precision, Recall and MAP (mean Average Precision) are used. Our experimental results suggest that the proposed approach gives a good evaluation of the applicability of color models for the reduction of semantic gap. Different color models along with different color descriptors mentioned in the proposed methods can be applied for the image retrieval of more semantically meaningful images. It should be noted that the proposed methodology may be further improved by using more classes so as to get more semantically relevant results. By combining other features such as texture, shape, etc. along with color can improve retrieval results close to human interpretation. To reduce semantic gap further for large databases, one may use database reduction techniques like hue histogram reduction method [39].

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