CHAPTER 4

Performance Analysis of Different Color Spaces and Evaluation of Similarity Matrix in Content Based Image Retrieval

In the present chapter an attempt has been made to explain different color spaces and their use in image retrieval. One way of extracting a signature from an image is to generate a color histogram and these signatures are being used for different purposes like Image data base indexing etc. In addition to these signatures, the image features/attributes like color space, the number of histogram bins (quantized space) and distance metrics are also used for histogram matching etc. and they also play an important role in Image retrieval. A color histogram based Image retrieval algorithm has also been explained. The key issue of this algorithm is the selection of an appropriate color space and evaluation of the quantized space and distance metrics on the performance of retrieval by color similarity. The goal of this chapter is to measure the model performance in predicting human judgment in similarity measurement for various images, to explore the capability of the model with a wide set of color spaces, and to find out the optimal quantization of the selected color spaces.

4.1 Introduction

The extraction of color features from digital images depends on an understanding of the theory of color and the representation of color in digital images, through color spaces. The transformations between different color spaces and the quantization of color information are primary determinants of a given feature extraction method. Color is usually represented by color histogram, color correlogram, color coherence vector and color moment, under a certain color space (Swain and Ballard, 1991; Wan and Kuo, 1996a; Stricker and Orengo, 1995; Pass et al., 1996; Huang et al., 1997a). Mehtre et al., (1995) defined the problem of color-image indexing and retrieval in the following statement: “Assume that there are a large number of color images in the database. Given a query image, we would like to obtain a list of images from the database, which are ‘most’ similar in color to the query image.” It characterizes both the global and
spatial distribution of the color. In image retrieval, the color histogram is the most commonly used color feature representation. A color histogram is a vector, where each element represents the number of pixels falling in a bin, in an image (Lu and Phillips, 1998). The color histogram serves as an effective representation of the color content of an image, if the color pattern is unique, compared to the rest of the data set. The color histogram is easy to compute and effective in characterizing both the global and local distribution of colors in an image. The advantage of the color histograms is their robustness with respect to geometric changes of projected objects. Histograms are invariant to translation and rotation around the viewing axis and vary slowly with changes of view angle, occlusion and scale. More effective retrieval results can be obtained if quantization techniques are performed on a more perceptually uniform color space, since the perceptually similar colors have the higher possibility to be in the same quantized color bin, hence more meaningful for similarity measure (Wang et al., 1997). In the performance evaluation experiments of Ma and Zhang (1999), it is shown that the color histogram runs much faster than the color coherence vector and color auto-correlogram, performs almost as good as the color coherence vector and does not perform much worse than the best color auto-correlogram. Therefore the color histogram has been used in our system and the HSV color space is chosen for two reasons. First, it is perceptual, which makes HSV a proven color space particularly amenable to color image analysis (Androtsos, 1999; Cheng and Sun, 2000). Second, the benchmark result (Ma and Zhang, 1999) has shown that the color histogram in the HSV color space performs the best. The color histogram has been discussed in section 3.2.1.a.

4.2 Color Space

Color is a sensation created in response to excitation of our visual system by electromagnetic radiation known as light (Gonzalez and Woods, 1992; MacDonald, 1999). Color feature is one of the most significant features of image retrieval. A color space is a model for representing color in terms of intensity values. It specifies how color information is represented. There are many color models to express the color in an image, such as the RGB, CMY(K), YUV, YCrCb, MTM, HSV, HSB, HLS, CIE L*a*b*, CIE L*u*v color models (Foley et al., 1996; Ma and Zhang, 1998; Mojsilovic et al., 2002; Wyszecki and Stiles, 1982; Bergman, 2002). Color is a best feature for
initial level of filtering. Before selecting an appropriate color description, color space must be determined first (Long et al., 2003).

The branch of color science concerned with the appropriate description and specification of a color is called colorimetry (Wyszecki and Stiles, 1982). Since there are exactly three types of color photo-receptor cone cells, three numerical components are necessary and sufficient to describe a color, provided the appropriate spectral weighted functions are used. Therefore, a color can be specified by a tri-component vector. The set of all colors form a vector space called color space or color model. The three components of a color can be defined in many different ways leading to various color spaces (Wyszecki and Stiles, 1982; Boynton, 1979). Color spaces provide a rational method to specify order, manipulate and effectively display the object colors taken into consideration. A well chosen representation preserves essential information and provides insight to the visual operation needed. Thus, the selected color model should be well suited to address the problem's statement and solution. The process of selecting the best color representation involves knowing how color signals are generated and what information is needed from these signals. Although color spaces impose constraints on color perception and representation they also help humans in performing important tasks. In particular, the color models may be used to define colors, discrimination between colors, judge similarity between colors and identify color categories for a number of applications (Sharma and Trussell 1997; Sharma et al., 1998). A color space is a model for representing color in terms of intensity values. It specifies how color information is representing color in terms of intensity values. It specifies how color information is represented. We have used color space such as the YUV, YIQ, HSV, CIE LAB and YCbCr.

The selected color systems under the study are described below. The assumption that there are three types of cone receptors in the retina is widely accepted; so three components are necessary and sufficient to describe a color. Accordingly, the set of all perceivable colors can be represented within a three-dimensional space. The axes of a color space, called primary colors, can be chosen arbitrarily. A convenient set, universally used for color measurement, is the CIE 1931 (X, Y, Z) - system adopted by the Commission International de l’Eclairage (CIE) (Wyszecki and Stiles, 1982). Each distinct point in the CIE XYZ space corresponds to a unique color perception. In this
space, the pure color component in the absence of brightness, such as hue and chroma, can be represented with x and y chromaticity coordinates defined by:

\[
x = \frac{X}{X + Y + Z}, \quad y = \frac{Y}{X + Y + Z}, \quad z = \frac{Z}{X + Y + Z}
\] (4.1)

4.2.1 RGB Color Space

The standard RGB established by CIE in 1931 with three monochromatic primaries at wavelengths 700 nm Red, 546.1 nm Green, and 435.8 nm Blue is the RGB spectral Primary Color Coordinate system. To represent the RGB color space, a cube can be defined on the R, G and B axes, as shown in Figure 4.1. White is produced when all the three primary colors are at M, where M is the maximum light intensity, say M=255. The axis connecting the black and white corners defines the intensity:

\[
I(R, G, B) = R + G + B
\] (4.2)

All points in a plane perpendicular to the grey axis of the color cube have the same intensity. The plane through the color cube at points R = G = B = M is one such plane. The projection of RGB points on the rgb chromaticity triangle is defined by Gevers, (1999):

\[
r(R, G, B) = \frac{R}{R+G+B}
\] (4.3)

\[
g(R, G, B) = \frac{G}{R+G+B}
\] (4.4)

\[
b(R, G, B) = \frac{B}{R+G+B}
\] (4.5)
4.2.2 CIELAB Color Space

The CIE $L^*a^*b^*$ (CIELAB) system gives a quantitative expression for the Munsell system of color classification. It is intended to yield a perceptually uniform spacing of colors. It is easy to use from the perspective of human perception. In 1976, the CIE recommended a new system $L^*a^*b^*$, computed from the XYZ color system, having the property that the closer a point is to another point, the visual similar the colors are. However in the RGB space, for changing color from one to another, one has to adjust the three primary components R, G, and B. $L^*a^*b^*$ is the most complete space color specified by the international commission on illumination. It describes all the colors visible to the human eye and was created to serve as a device independent model to be used as a reference. The $L^*a^*b^*$ system based on the three dimensional coordinate system based on the opponent theory using black-white $L^*$, red-green $a^*$, and yellow-blue $b^*$ components. The $L^*$ axis corresponds to the lightness where $L^*=100$ is white and $L^*=0$ is black. Further, $a^*$ ranges from red $+a^*$ to green $-a^*$ while $b^*$ ranges from $+b^*$ to blue $-b^*$. The $L^*$, $a^*$ and $b^*$ coordinates are computed from the X, Y and Z tristimulus values as follows:

CIE XYZ to CIE $L^*a^*b^*$ (CIELAB) (Poynton, 1996; Gevers, 1999):

\begin{align}
L' &= 116 \left( \frac{Y}{Y_n} - 16 \right) + 16, \\
a^* &= 500 \left( f \left( \frac{X}{X_n} \right) - f \left( \frac{Y}{Y_n} \right) \right). 
\end{align}

Figure 4.1 (a) RGB Color Space (b) Definition of hue saturation in the chromaticity plane.
\[ b^* = 200 \left( f \left( \frac{X}{X_n} \right) - f \left( \frac{Z}{Z_n} \right) \right) \]  

(4.8)

Where

\[ f(t) = \begin{cases} 
\frac{1}{t^3} & \text{if } t > \left( \frac{6}{29} \right)^3 \\
\left( \frac{29}{3} \right) t + \frac{4}{29} & \text{otherwise}
\end{cases} \]  

(4.9)

Here \( X_n, Y_n \) and \( Z_n \) are the CIE XYZ tristimulus values of the reference white point (the subscript n suggests "normalized"). The asterisk (*) after \( L, a \) and \( b \) are part of the full name, since they represent \( L^*, a^* \) and \( b^* \) are shown in Figure 4.2.

\[ \text{White} \]
\[ L^* \]
\[ \text{Yellow} -b^* \]
\[ \text{Green} -a^* \]
\[ \text{Blue} -b^* \]
\[ \text{Red} +a^* \]
\[ \text{Black} \]

Figure 4.2 LAB Color Space.

### 4.2.3 HSV Color Space

When viewing a color object, human visual system characterizes it by its brightness and chromaticity. The latter is defined by hue and saturation. Brightness is a subjective measure of luminous intensity. It embodies the achromatic notion of intensity. Hue is a color attribute and represents a dominant color. Saturation is an expression of the relative purity or the degree to which a pure color is diluted by white light. The HSV model is motivated by the human visual system. In the HSV model, the luminous component (brightness) is decoupled from color-carrying information (hue and saturation) are shown in Figure 4.3.
The HSV color model is defined as follows (Smith, 1978):

\[
H = \begin{cases} 
60 \left( \frac{G - B}{\delta} \right) & \text{if } MAX=R \\
60 \left( \frac{B - R}{\delta} + 2 \right) & \text{if } MAX=G \\
60 \left( \frac{R - G}{\delta} + 4 \right) & \text{if } MAX=R \\
\text{not defined} & \text{if } MAX=0
\end{cases}
\]  
(4.10)

\[
HS = \begin{cases} 
\frac{\delta}{MAX} & \text{if } MAX \neq 0 \\
0 & \text{if } MAX = 0
\end{cases}
\]  
(4.11)

\[
V = MAX
\]  
(4.12)

Where \( \delta = (MAX - MIN) \), \( MAX = \max(R, G, B) \), and \( MIN = \min(R, G, B) \). Note that the R, G, B values in Equation (3.10) are scaled to \([0, 1]\). In order to confine H within the range of \([0, 360]\), \( H = H + 360 \), if \( H < 0 \).

### 4.2.4 YUV Color Space

Originally used for PAL (European "standard") analog video, YUV is based on the CIE Y primary, and also chrominance. This is a linear transformation of Yxy, in an attempt to produce a chromaticity diagrams in which a vector of unit magnitude (difference between two points representing two colors) is equally visible at all colors. Y is
unchanged from XYZ or Yxy. Difference non-uniformity is reduced considerably, but not enough. A third co-ordinate, \( w \), can also be defined but is redundant (Ford and Roberts, 1998).

\[
\begin{align*}
    u &= \frac{2x}{(6y - x + 1.5)} \\
    v &= \frac{3y}{(6y - x + 1.5)}
\end{align*}
\]

(4.13) (4.14)

The YUV model is based on the opponent color theory of human vision and intends to approximate color differences as perceived by humans as shown in Figure 4.4.

![Figure 4.4 YUV Color Space.](image)

4.2.5 YIQ Color Space

The nonlinear RGB to YIQ conversion is defined by the following matrix transformation (Gonzalez and Woods, 1992; Poynton, 1996):

\[
\begin{bmatrix}
    Y \\
    I \\
    Q
\end{bmatrix} =
\begin{bmatrix}
    0.299 & 0.587 & 0.114 \\
    0.596 & -0.275 & -0.321 \\
    0.212 & -0.523 & 0.311
\end{bmatrix}
\begin{bmatrix}
    R \\
    G \\
    B
\end{bmatrix}
\]

(4.15)
YIQ is perceptually non-uniform color space and thus not appropriate for perceptual color difference quantification shown in Figure 4.5. For example the Euclidean distance is not capable of accurate measuring the perceptual color distance in the perceptual non-uniform YIQ color space. Therefore, YIQ is not the best color space for quantitative computations involving human color perception.

![Figure 4.5 YIQ Color Space.](image)

### 4.2.6 YCbCr Color Space

YCbCr also written as YC\(_B\)C\(_R\), is a family of color spaces used as a part of the color image pipeline in video and digital photography systems. \(Y'\) is the luma component and \(C\_B\) and \(C\_R\) are the blue-difference and red-difference chroma components. \(Y'\) (with prime) is distinguished from \(Y\) which is luminance, meaning that light intensity is non-linearly encoded using gamma correction. \(Y'\)C\(_b\)C\(_r\) is not an absolute color space; rather, it is a way of encoding RGB information. The actual color displayed depends on the actual RGB primaries used to display the signal. Therefore a value expressed as \(Y'\)C\(_b\)C\(_r\) is predictable only if standard RGB primary chromaticities are used. Figure 4.6 shows \(Y'\)C\(_b\)C\(_r\) color space.

To compute \(Y'\)C\(_b\)C\(_r\) from nonlinear R‘G‘B‘ in the range of [0, 1] the following set should be used (Poynton, 1996; de Dios and Garcia, 2003):
4.3 Color Space Quantization

True-color images typically contain thousands of colors, which make their display, storage, transmission, and processing problematic for this reason, color quantization (reduction) is commonly used as a preprocessing step for various graphics and image processing tasks. In the past, color quantization was a necessity due to the limitations of the display hardware, which could not handle over 16 million possible colors in 24-bit images. Although 24-bit display hardware has become more common, color quantization still maintains its practical value (Celebi, 2009). Modern applications of color quantization in graphics and image processing include: image compression (Yang and Tsai, 1998), image segmentation (Deng and Manjunath, 2001), watermarking (Kuo and Cheng, 2007), and content based image retrieval (Wan and Kuo, 1996 a, b; Deng et al., 2001; Singha and Hemachandran, 2011 a, b; Liu and Yang, 2012).

In order to produce color histograms, color quantization has to be applied. Color quantization is a process that optimizes the use of distinct colors in an image without affecting the visual properties of an image. In order to reduce the computation, the color quantization can be used to represent the image, without a significant reduction in image quality, thereby reducing the storage space and
enhancing the process speed (Hafner et al., 1995). The effect of color quantization on the performance of image retrieval has been reported by many authors (Wan and Kuo, 1996 a, b; 1998; Zhang, 2004; Singha and Hemachandran, 2011 a, b). The complexity of the matching process can be reduced by using quantized color space (Swain and Ballard, 1991). Because there are many colors, to reduce the complexity in histogram computation, the color space needs to be quantized (Rui et al., 1999).

### 4.4 Proposed Algorithms

In this section, the proposed image retrieval algorithms, based on color histogram, have been described: In the first method an attempt has been made to study the effect of different color spaces such as HSV, YCbCr, LAB, YIQ, and YUV on the Image retrieval. The description of the color space is given in section 4.2. In the second method, the effect of different quantization schemes, such as (8X4X4), (8X8X4), (8X8X8), (16X4X4) and (18X3X3), on the image retrieval has been studied and the third method tries to study the effect of different distance functions such as Euclidean Distance (ED), Manhattan Distance (MD), Intersection Distance (ID), and Quadratic Distance (QD) on the image retrieval. An explanation regarding the different distance functions is given in section 3.3. The block diagram of proposed generic content based image retrieval using color histogram technique is shown in Figure 4.7.

![Block diagram for proposed image retrieval using Color Histogram (CH)](image-url)
4.4.1 Image retrieval algorithm based on color histogram using different color space:

Step 1: Convert RGB image into HSV color space or (YUV, or YIQ, or LAB, or YCbCr).

Step 2: Color quantization is carried out using color histogram by assigning 8 levels to hue, 8 to saturation and 8 to value to give a quantized HSV space with $8 \times 8 \times 8 = 512$ histogram bins.

Step 3: The normalized histogram is obtained by dividing with the total number of pixels.

Step 4: Repeat step 1 to step 3 on an image in the database.

Step 5: Calculate the similarity matrix through Intersection Distance (ID) between the query image and the image present in the database.

Step 6: Repeat the steps from 4 to 5 for all the images in the database.

Step 7: Retrieve the matching images from the image database, based on the indices in the similarity matrix. Where the indices value gives the degree of matching and the zero value indicates that the query and database images are matching more and the increase in the indices value indicates the less similarity.

4.4.2 Image retrieval algorithm based on color histogram using different quantization scheme:

Step 1: Convert RGB image into HSV color space

Step 2: Color quantization is carried out using color histogram by assigning 8 levels to hue, 8 to saturation and 8 to value to give a quantized HSV space with $8 \times 8 \times 8 = 512$ histogram bins or $((8 \times 4 \times 4) \text{ or } (8 \times 8 \times 4) \text{ or } (16 \times 4 \times 4) \text{ or } (18 \times 3 \times 3))$.

Step 3: The normalized histogram is obtained by dividing with the total number of pixels.

Step 4: Repeat step 1 to step 3 on an image in the database.

Step 5: Calculate the similarity matrix through Intersection Distance (ID) between the query image and the image present in the database.

Step 6: Repeat the steps from 4 to 5 for all the images in the database.
Step 7: Retrieve the matching images from the image database, based on the indices in the similarity matrix. Where the indices value gives the degree of matching and the zero value indicates that the query and database images are matching more and the increase in the indices value indicates the less similarity.

4.4.3 Image retrieval algorithm based on color histogram using different similarity matrix:

Step 1: Convert RGB image into HSV color space
Step 2: Color quantization is carried out using color histogram by assigning 8 levels to hue, 8 to saturation and 8 to value to give a quantized HSV space with $8 \times 8 \times 8 = 512$ histogram bins.
Step 3: The normalized histogram is obtained by dividing with the total number of pixels.
Step 4: Repeat step 1 to step 3 on an image in the database.
Step 5: Calculate the similarity matrix through Intersection Distance (ID) between the query image and the image present in the database or {Euclidean Distance (ED), or Manhattan Distance (MD) or Histogram Quadratic Distance (QD)}.
Step 6: Repeat the steps from 4 to 5 for all the images in the database.
Step 7: Retrieve the matching images from the image database, based on the indices in the similarity matrix. Where the indices value gives the degree of matching and the zero value indicates that the query and database images are matching more and the increase in the indices value indicates the less similarity.

4.5 Experimental Results and Discussion

The proposed methods have been implemented on a MATLAB environment and tested on a general-purpose set of WANG database, which was downloaded from http://wang.ist.psu.edu/docs/related/. It contains 1,000 images grouped into 10 different categories with each containing 100 images. The images in the same category are considered as similar images. The sample of WANG database is shown in Figure 4.8.
The objective of the paper is to design a CBIR system that is simple to use, easy to handle large Image data bases, and fastest to retrieve images using low level features such as color. In the proposed method, the search is usually based on similarity rather than the exact match. For experimental purpose 100 random query images, 10 for each category were selected from the database. The similarity between the histograms is expressed through a floating point number between 0 and 1. Equivalence is designated with similarity value 0 and the similarity between two histograms decreases when the similarity value approaches to 1. For each random query, the top 10 results were selected to compute average precision and recall values.

Image retrieval using color histogram for different color space such as HSV, YCbCr, LAB, YIQ and YUV is described in section 4.4.1. To calculate the efficiency of different color spaces, for precision and recall, the equations 3.23, 3.24 and 3.25 of section 3.5 have been used. The performance evaluation of different color spaces using the average precision, the average recall and average time taken (in seconds) are shown in Table 4.1. From the table it can be observed that the HSV color space gives highest average precision and recall values. Image retrieval using Color Histogram for different combination of quantization schemes such as (8X4X4), (8X8X4), (8X8X8), (16X4X4) and (18X3X3) is mentioned in section 4.4.2 and the performance of the image retrieval using color histogram for different quantization scheme in terms of average precision and recall and average time taken by different quantization scheme are shown in Table 4.2. From the results it can be observed that the average precision and recall value of the quantization (8X8X8) scheme gives best result as compare to other quantization schemes and the average time taken is also reasonably good. Image retrieval using Color Histogram for different distance functions such as Euclidean Distance (ED),
Manhattan Distance (MD), Intersection Distance (ID), and Quadratic Distance (QD) is mentioned in section 4.4.3. The average precision and recall value, average time taken by different distance functions are shown in Table 4.3, and it can be observed that the average precision and average recall value of the Intersection Distance (ID) gives good results as compare to other methods. It can be concluded that the image retrieval using color histogram, the combination of (8X8X8) quantization scheme, HSV color space and Intersection Distance (ID) will give the best result. Image retrieval using color histogram {8X8X8, HSV, ID} for 10 different categories such as (1) African People, (2) Beach, (3) Building, (4) Buses, (5) Dinosaurs, (6) Elephants, (7) Flowers, (8) Horses, (9) Mountains and (10) Food, are shown in Figure 4.9 (a-j).

Table 4.1 Average Precision/Recall using different color space.

<table>
<thead>
<tr>
<th>Category</th>
<th>RGB</th>
<th>HSV</th>
<th>YCbCr</th>
<th>LAB</th>
<th>YIQ</th>
<th>YUV</th>
</tr>
</thead>
<tbody>
<tr>
<td>African People</td>
<td>0.76</td>
<td>0.86</td>
<td>0.76</td>
<td>0.8</td>
<td>0.78</td>
<td>0.78</td>
</tr>
<tr>
<td>Beach</td>
<td>0.54</td>
<td>0.56</td>
<td>0.68</td>
<td>0.56</td>
<td>0.58</td>
<td>0.5</td>
</tr>
<tr>
<td>Building</td>
<td>0.72</td>
<td>0.66</td>
<td>0.66</td>
<td>0.66</td>
<td>0.76</td>
<td>0.42</td>
</tr>
<tr>
<td>Buses</td>
<td>0.82</td>
<td>0.92</td>
<td>0.86</td>
<td>0.82</td>
<td>0.74</td>
<td>0.78</td>
</tr>
<tr>
<td>Dinosaurs</td>
<td>0.1</td>
<td>0.98</td>
<td>0.9</td>
<td>0.98</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td>Elephants</td>
<td>0.94</td>
<td>0.9</td>
<td>0.92</td>
<td>0.98</td>
<td>0.88</td>
<td>0.9</td>
</tr>
<tr>
<td>Flowers</td>
<td>0.56</td>
<td>0.6</td>
<td>0.56</td>
<td>0.52</td>
<td>0.5</td>
<td>0.52</td>
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<tr>
<td>Horses</td>
<td>0.84</td>
<td>0.82</td>
<td>0.9</td>
<td>0.84</td>
<td>0.72</td>
<td>0.88</td>
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<tr>
<td>Mountains</td>
<td>0.64</td>
<td>0.52</td>
<td>0.42</td>
<td>0.52</td>
<td>0.58</td>
<td>0.54</td>
</tr>
<tr>
<td>Food</td>
<td>0.7</td>
<td>0.76</td>
<td>0.66</td>
<td>0.68</td>
<td>0.8</td>
<td>0.64</td>
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<td>Average Precision/Recall</td>
<td>0.662</td>
<td>0.758</td>
<td>0.732</td>
<td>0.736</td>
<td>0.732</td>
<td>0.694</td>
</tr>
<tr>
<td>Average Time Taken</td>
<td>4.2s</td>
<td>7.1s</td>
<td>5.4s</td>
<td>19.4s</td>
<td>5.3s</td>
<td>6.5s</td>
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Table 4.2 Average Precision/Recall using combination of different quantization scheme

<table>
<thead>
<tr>
<th>Category</th>
<th>(8X4X4)</th>
<th>(8X8X4)</th>
<th>(8X8X8)</th>
<th>(16X4X4)</th>
<th>(18X3X3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>African People</td>
<td>0.86</td>
<td>0.86</td>
<td>0.86</td>
<td>0.86</td>
<td>0.9</td>
</tr>
<tr>
<td>Beach</td>
<td>0.48</td>
<td>0.54</td>
<td>0.56</td>
<td>0.46</td>
<td>0.48</td>
</tr>
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<td>Building</td>
<td>0.64</td>
<td>0.66</td>
<td>0.66</td>
<td>0.78</td>
<td>0.76</td>
</tr>
<tr>
<td>Buses</td>
<td>0.92</td>
<td>0.94</td>
<td>0.92</td>
<td>0.92</td>
<td>0.9</td>
</tr>
<tr>
<td>Dinosaurs</td>
<td>0.82</td>
<td>0.86</td>
<td>0.98</td>
<td>0.86</td>
<td>0.82</td>
</tr>
<tr>
<td>Elephants</td>
<td>0.8</td>
<td>0.84</td>
<td>0.9</td>
<td>0.86</td>
<td>0.84</td>
</tr>
<tr>
<td>Flowers</td>
<td>0.62</td>
<td>0.62</td>
<td>0.6</td>
<td>0.6</td>
<td>0.54</td>
</tr>
<tr>
<td>Horses</td>
<td>0.84</td>
<td>0.8</td>
<td>0.82</td>
<td>0.84</td>
<td>0.92</td>
</tr>
<tr>
<td>Mountains</td>
<td>0.52</td>
<td>0.5</td>
<td>0.52</td>
<td>0.46</td>
<td>0.42</td>
</tr>
<tr>
<td>Food</td>
<td>0.72</td>
<td>0.74</td>
<td>0.76</td>
<td>0.74</td>
<td>0.68</td>
</tr>
<tr>
<td>Average Precision/Recall</td>
<td><strong>0.722</strong></td>
<td><strong>0.736</strong></td>
<td><strong>0.758</strong></td>
<td><strong>0.738</strong></td>
<td><strong>0.726</strong></td>
</tr>
<tr>
<td>Average Time Taken</td>
<td><strong>7.8s</strong></td>
<td><strong>7.3s</strong></td>
<td><strong>7.16s</strong></td>
<td><strong>7.11s</strong></td>
<td><strong>7.2s</strong></td>
</tr>
</tbody>
</table>

Table 4.3 Average Precision/Recall using different histogram distance function

<table>
<thead>
<tr>
<th>Category</th>
<th>Euclidean Distance (ED)</th>
<th>Manhattan Distance (MD)</th>
<th>Intersection Distance (ID)</th>
<th>Quadratic Distance (QD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>African people</td>
<td>0.84</td>
<td>0.84</td>
<td>0.86</td>
<td>0.84</td>
</tr>
<tr>
<td>Beach</td>
<td>0.28</td>
<td>0.56</td>
<td>0.56</td>
<td>0.54</td>
</tr>
<tr>
<td>Building</td>
<td>0.2</td>
<td>0.64</td>
<td>0.66</td>
<td>0.64</td>
</tr>
<tr>
<td>Buses</td>
<td>0.52</td>
<td>0.92</td>
<td>0.92</td>
<td>0.92</td>
</tr>
<tr>
<td>Dinosaurs</td>
<td>0.74</td>
<td>0.98</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td>Elephants</td>
<td>0.78</td>
<td>0.9</td>
<td>0.9</td>
<td>0.88</td>
</tr>
<tr>
<td>Flowers</td>
<td>0.42</td>
<td>0.6</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>Horses</td>
<td>0.64</td>
<td>0.82</td>
<td>0.82</td>
<td>0.82</td>
</tr>
<tr>
<td>Mountains</td>
<td>0.28</td>
<td>0.52</td>
<td>0.52</td>
<td>0.54</td>
</tr>
<tr>
<td>Food</td>
<td>0.66</td>
<td>0.74</td>
<td>0.76</td>
<td>0.76</td>
</tr>
<tr>
<td>Average Precision/Recall</td>
<td><strong>0.536</strong></td>
<td><strong>0.752</strong></td>
<td><strong>0.758</strong></td>
<td><strong>0.752</strong></td>
</tr>
<tr>
<td>Average Time Taken</td>
<td><strong>6.4s</strong></td>
<td><strong>7.6s</strong></td>
<td><strong>7.6s</strong></td>
<td><strong>20.2s</strong></td>
</tr>
</tbody>
</table>
Figure 4.9 (a-j) Retrieved results, with the top left image as the query image.
4.6 Chapter Summary

In this chapter, an image retrieval technique using color feature has been presented. In this study the suitability of five different color spaces such as HSV, YCbCr, LAB, YIQ and YUV; different quantization schemes and four different histogram distance metrics such as Euclidean Distance (ED), Manhattan Distance (MD), Intersection Distance (ID) and Quadratic Distance (QD) where investigated. For the given data set, experimental result shows that the average precision and recall of HSV color space, combination of (8X8X8) quantization bin and intersection distance (ID), gives better results as compared to other color spaces, other combination of quantization bin and other distance measure schemes.