# DISTANCE MEASURES FOR COLOR IMAGE RETRIEVAL


*D. Androutsos*[†], *K. N. Plataniotis*[‡] *and A. N. Venetsanopoulos*[†]

[†] Digital Signal & Image Processing Lab
Department of Electrical & Computer Engineering
University of Toronto
10 King's College Road, Toronto, Ontario, M5S 3G4, CANADA
http://www.dsp.toronto.edu
{zeus,anv}@dsp.toronto.edu

[‡]Ryerson Polytechnic University, Department of Math, Physics & Computer Science
350 Victoria Street, Toronto, Ontario, M5B 2K3, CANADA
kplatani@acs.ryerson.ca



## ABSTRACT

In this paper we address the issue of image database retrieval based on color using various vector distance metrics. Our system is based on color segmentation where only a few representative color vectors are extracted from each image and used as image indices. These vectors are then used with vector distance measures to determine similarity between a query color and a database image. We test numerous popular vector distance measures in our system and find that directional measures provide the most accurate and perceptually relevant retrievals.


## 1. INTRODUCTION

Efficient access to digital data has become an issue of utmost importance recently. In particular, the amount of digital image and video data available is staggering and the challenging issues of cataloging and retrieval has gained increasing importance. Without a doubt, efficient access to relevant data directly determines its value.

As digital acquisition and storage grow, a number of industrial fields, such as medical imagery, graphic arts, textile and paint, satellite imagery, criminology and film, require efficient access to their data. Content-Based Image Retrieval (CBIR) is a relatively new research area which is dedicated to the image retrieval problem [1] and a number of image database system have been developed [2, 3].

A key aspect of image databases is the creation of robust and efficient indices which are used for retrieval. Color remains the most important low-level feature which is used to index database images [4]. This is not surprising since visual recognition and human recall are highly dependant to color.

However, the majority of retrieval techniques implement color histograms for image retrieval using color. These histogram-based techniques provide good results, however, issues such as histogram dimensionality, and the lack of good perceptually-based similarity measures call for new methods. Furthermore, the granularity which histogram techniques provide is not essential for efficient retrieval since it is our *perception* of color that is of utmost importance and, as humans, we cannot discern the difference between very close color values.

In this paper we study various vector distance measures which we implement in our image database system for image retrieval by color. We use color segmentation to extract regions of prominent color and use representative vectors from these extracted regions in the image indices. Distance measures are then used in the query process to determine image similarity. Section 2 describes our database system and the indexing process. Section 3 discusses the distance measures implemented and Section 4 presents some results. Finally, Section 5 concludes the paper with a final discussion.

## 2. COLOR INDEXING

To build indices into our image database we take into consideration factors such as human color perception and recall. For example, as humans it is very difficult, if not impossible, for us to visually discern the difference between two very close $(R, G, B)$ values, e.g., $(255, 48, 32)$ and $(254, 48, 32)$. Furthermore, if we were




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to describe the color content of an image, we would use terms such as red, dark yellow or deep green, not RGB values. Essentially, we build a low level model of the image in question in our mind and compare candidate images to this model. The color *granularity* provided by histogram indexing is, in most cases, not necessary, especially when the final observer is a human.

### 2.1. HSV Segmentation

Our method of color indexing implements segmentation to extract regions within the image which contain perceptually similar color. We do this by thresholding the HSV histograms of the image. Specifically, it is the *hue* histogram which contains most of the color information. The *saturation* and *value* are examined and used to determine which regions of the image are achromatic. We have found, in the literature and experimentally [5, 6], that colors with *value*$<$ 25 can be classified as **black** and that colors with *saturation*$<$ 20 and *value*$>$ 60 can be classified as **white**.

The remaining pixels all fall in the chromatic region of the HSV cone, as shown in Figure 1. We build the *hue* histogram of these remaining pixels and threshold the resulting peaks to segment the image into $n$ regions. Finally, we calculate the average color of each of

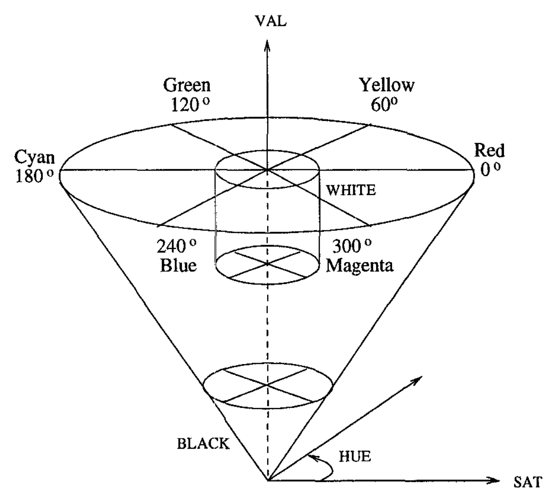


Figure 1: HSV cone depicting BLACK and WHITE regions.

the $n$ regions and use that RGB value as each regions representative vector. Figure 2 shows a typical image and its corresponding *hue* histogram. Figure 3 shows the segmented result after histogram thresholding. As can be seen, the result is an accurate low-level representation of the color content in the image using only $n$

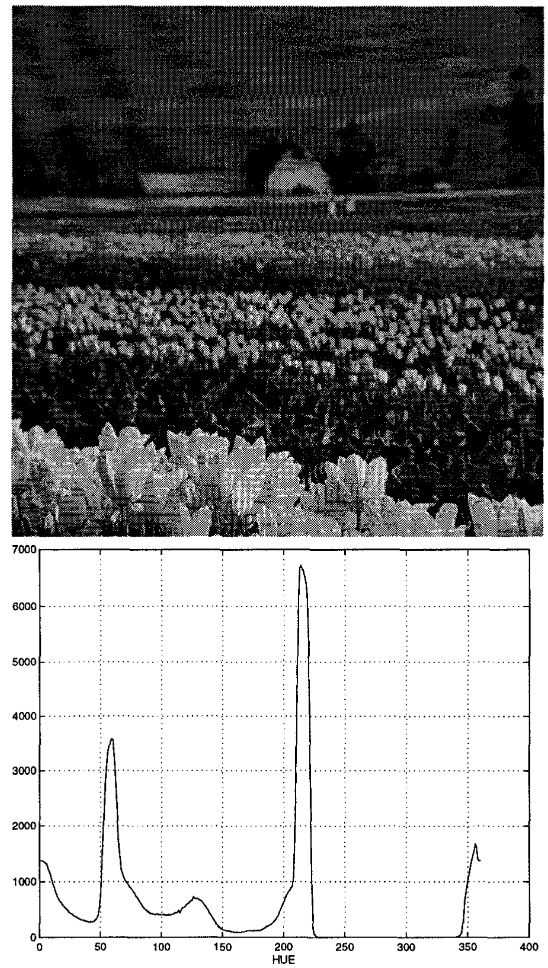


Figure 2: Typical image and its HUE histogram.

color vectors. In addition, we also have at our disposal spatial color information which can also be indexed.

The above segmentation technique was performed on 2000 24-bit natural images of 512 $\times$ 512 resolution and each $n$ representative vector for each image, were used to build each index.

## 3. DISTANCE MEASURES

To perform the actual image retrieval we investigated a number of vector distance measures to discover which gave the most accurate and perceptually correct result:

1. The generalized *Minkowski* metric ($L_M$ norm):

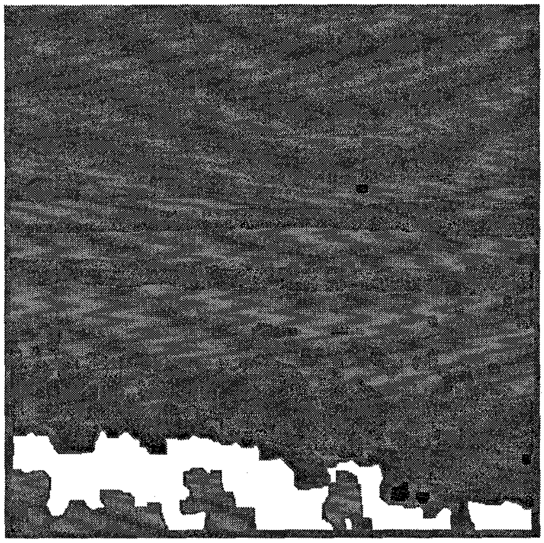

Figure 3: Segmented image.

$$d_M(i,j) = (\sum_{k=1}^{p} |(x_i^k - x_j^k)|^M)^{\frac{1}{M}}, \qquad (1)$$

where $p$ is the dimension of the vector $\vec{x}_i$ and $x_i^k$ is the $k^{th}$ element of $\vec{x}_i$. Three special cases of the $L_M$ metric are of particular interest, namely, $L = 1, 2, \infty$.

2. The *Canberra* distance defined as follows:

$$d_c(i,j) = \sum_{i=1}^{p} \frac{|x_i^k - x_j^k|}{|x_i^k + x_j^k|}, \qquad (2)$$

where $p$ is the dimension of the vector $\vec{x}_i$ and $x_i^k$ is the $k^{th}$ element of $\vec{x}_i$. The *Canberra* metric applies only to non-negative multivariate data, which is the case when color vectors described in the RGB reference system are considered.

3. Another distance measure applicable only to vectors with non-negative components, such as color signals is the *Czekanowski coefficient*, defined as follows:

$$d_z(i,j) = 1 - \frac{2\sum_{k=1}^{p} \min{(x_{ik}, x_{jk})}}{\sum_{k=1}^{p} (x_{ik} + x_{jk})} \qquad (3)$$

4. The *angular distance* between two vectors can be used to quantify similarity:

$$\theta = 1 - \frac{2}{\pi} cos^{-1}(\frac{\vec{x}_i \cdot \vec{x}_j}{|\vec{x}_i||\vec{x}_j|}), \qquad (4)$$

Since, similar colors have almost parallel orientations, significantly different colors point in different overall directions in the RGB color space. Thus, the angular distance which quantifies the orientation difference between two color signals is a meaningful measure of their similarity.

5. We have also developed a new distance measure which combines the angle between two vectors and their magnitude difference. When two vectors under consideration are collinear, only magnitude difference is used to quantify intensity differences:

$$d_N(i,j) = \qquad (5)$$
$$1 - \underbrace{\left[1 - \frac{2}{\pi} cos^{-1}(\frac{\vec{x}_i \cdot \vec{x}_j}{|\vec{x}_i||\vec{x}_j|})\right]}_{angle} \underbrace{\left[1 - \frac{|\vec{x}_i - \vec{x}_j|}{\sqrt{3 \cdot 255^2}}\right]}_{magnitude}.$$

Since we deal with RGB vectors, we are constrained to one quadrant of the Cartesian space. Thus, the normalization factor of $\frac{2}{\pi}$ in the *angle* portion is attributed to the fact that the maximum angle which can possibly be attained is $\frac{\pi}{2}$. Also, the $\sqrt{3 \cdot 255^2}$ normalization factor, in the *magnitude* part of (6), is due to the fact that the maximum difference vector which can exist is $(255, 255, 255)$ and its magnitude is $\sqrt{3 \cdot 255^2}$.

This measure has the added advantage that the magnitude and angle portions can be assigned weights to stress one over the other.

## 4. RESULTS

The query was performed by providing a *query color* from a color picker and the system applied the given distance measure to each $n$ representative vectors of each database image. In addition we chose to look for images which contain over 50% of the query color. The results were then numerically sorted and the best 23 images were displayed along with the query color. Quantitative performance was evaluated by calculating the retrieval rate, defined as [7]:

$$R_{i,j} = \frac{N_j}{N_i} \times 100, \qquad (6)$$

where $N_i$ is the total images in a given query set $Q$, (i.e., all images in the database which match the query), and $N_j$ are the number of images which appear in the top $N_i$ retrieval positions which are part of $Q$. The set $Q$ was obtained by asking a number of volunteers to manually search through our 2000 image database and list the images which were considered to contain at least 50% of a given query color with $RGB$ values of $130, 164, 53$. Table 1 lists the retrieval rates for the above mentioned distance measures. Clearly, it can be seen that the angular-based measures perform much better in terms of retrieval rate. For qualitative analysis, figures 4-10 depict the top 23 retrieval results for the 7 discussed measures. In addition, the query color is included in the top-left corner of each figure. As indicated from Table 1, the Czekanowski measure gives the poorest result, where the majority of retrieved images are visually erroneous.

Table 1: Retrieval rate for 7 different vector distance measures

| *measure* | $R_{i,j}$ |
|---|---|
| $L_1$ | 54.2 |
| $L_2$ | 54.2 |
| $L_\infty$ | 37.5 |
| *canberra* | 37.5 |
| *czekanowski* | 20.8 |
| *angle* | 75.0 |
| *combo* | 71.0 |

The $L-norms$ provide improved results (Figs. 4-6). The $L_1$ and $L_2$, in particular, provide similar retrieval results, especially in the first 6 rankings.

The Canberra measure (Fig. 7, provided good ranking for the first 6 positions but then included many erroneous images in the remaining results.

The angular distance-based measures (Figs. 9-10, perceptually provided the best retrieval results of the investigated measures. All the retrieved images, with the exception of 5, exhibited a high color content similar to the query color.

Figure 4: Retrieval result using $L_1$ norm. Top left image is the query color. Decreasing similarity from left to right, top to bottom.

Figure 5: Retrieval result using $L_2$ norm. Top left image is the query color. Decreasing similarity from left to right, top to bottom.

## 5. CONCLUSIONS

In this paper we have investigated various vector distance measures for use in color image retrieval. In our system, we color segment each database image and generate representative RGB vectors for each of the $n$ colors extracted from each image. These $n$ vectors are then used as database indices for each color image. We test a number of well-known distance measures using these indices and a query color and we have found that angle-based distance measures provide perceptually accurate results with a high retrieval rate.

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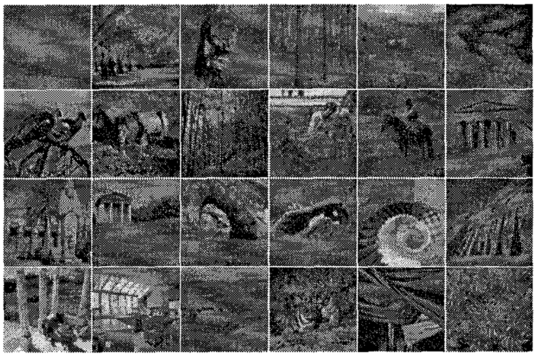

Figure 6: Retrieval result using $L_\infty$ norm. Top left image is the query color. Decreasing similarity from left to right, top to bottom.

Figure 7: Retrieval result using *Canberra distance.* Top left image is the query color. Decreasing similarity from left to right, top to bottom.


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Figure 8: Retrieval result using *Czekanowski distance.* Top left image is the query color. Decreasing similarity from left to right, top to bottom.

Figure 9: Retrieval result using *angular distance.* Top left image is the query color. Decreasing similarity from left to right, top to bottom.

Figure 10: Retrieval result using the new *combination distance.* Top left image is the query color. Decreasing similarity from left to right, top to bottom.