# An efficient similarity measure (PMM) for color-based image retrieval

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**Summary**

Color histogram is an important Technical for color image database indexing and retrieving. However, the main problem with color histogram indexing is that it does not take the color spatial distribution into consideration. Previous researches have proved that the effectiveness of image retrieval increases when spatial feature of colors is included in image retrieval. In this paper, we introduce the local histogram to describe the spatial information of colors, to measure similarity between two images using the local histogram, the traditional approaches use the distance $L_1$. To improve performance of the CBIR system, the permuto-metric measure (PMM) is used to measure similarity of images instead of classic distance $L_1$. Experiment results prove that the CBIR using our new measure has better performance and perceptually relevant result.

***Key words:***

*Indexing, local histogram, distance* $L_1$, *permuto-metric measure.*

## 1. Introduction

Content-based image and video retrieval has become an important research topic academic and industrial in recent years [1, 2, 3, 4]. Research interest in this field has escalated because of the proliferation of video and image data in digital form. Right now, research on content-based image indexing and retrieval is mainly focused on the visual features of color, texture and shape.

Image indexing grew in the last decade and rapidly became color-oriented, since most of the images of interest are in colors. The indexes that described their content, however, were simple extensions of the features used to characterize shapes or images in a scalar domain (such as RGB images). The color histogram method was proposed very early [5] as an important mean of retrieve similarities. However, the main disadvantage of the color histogram method is that it is not robust to significant appearance changes because it does not include any spatial information. Recently, several schemes including spatial information have been proposed. Color correlogram [6] and color coherence vector [7] can combine the spatial correlation of color regions as well as the global distribution of local spatial correlation of colors. These techniques perform better than traditional color histograms. However, they require very expensive compotation.

Histograms of local appearance descriptors are a popular representation for visual recognition. They are highly discriminate and they have good resistance to local occlusions and to geometric and photometric variations. Such content-based retrieval techniques usually develop along with the use of a similarity measure, i.e., a scoring function that rates the similarity of two images. Thus, the similarity measure becomes an important research issue because it makes a significant effect on retrieval performance. Boujemaa [8] used a classic distance $L_1$ for measuring similarity between two images using the local histogram. However, the distance $L_1$ has a serious drawback as follows. It is reasonable that if two images have the same content visual can be considered similar. But in large bases images that measure $L_1$ becomes low to catch any deviation of visual content by the transformations: rotation and translation. Therefore due to the drawback, some results of the image retrieval are not so effective.

In this paper we interest to color local histogram, we present a new color measure that is a distance permuto-metric, which remains more stable performance by transformations geometry and provides a superior retrieval performance compared to the usual distance $L_1$.

This paper is organized as follows. The local histogram is reviewed in section 2. Section 3 explains the problem of using the classic distance $L_1$. The definition of measure permuto-metric is described in section 4. the implementation and experiments of the CBIR system is shown in section 5. finally, section 6 is devoted to concluding remarks.

## 2. The cumulated histograms

The problem of the color histogram is that only the color distribution in an image is captured. The cumulated histogram [8] is an effort to merge the spatial content. Intuitively, the local histogram expresses how the spatial

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geometry of color in the windows, if we divide the images into N windows, we notice that the information of local histograms $(h_i)_{1\le i\le N}$ computed on each window is richer than the global color histogram. If we combine informations on colors from the local histograms it will be possible to characterize better the geometric repartition of colors. The idea of accumulative histograms $\bar{h}$ is to embed geometric information on colors by emphasizing their local agglomeration in windows.
We introduce an additive accumulation of local histograms by:

$$\bar{h}(c) = \sum_{i=1}^{N} f(h_i(c)),\ \forall c \in \quad C$$

*Where f* is a function that emphasizes the local presence of colors.

The $L_1$ distance between two histograms can be written:

$$d_{L_1}(\bar{h}^1, \bar{h}^2) = \sum_{i=1}^{N}\sum_{c=1}^{M} \left| f(h_i^1(c)) - f(h_i^2(c)) \right|$$

We have a simplification expression for $d_{L_1}$ as:

$$d_{L_1}(\bar{h}^1, \bar{h}^2) = \sum_{i=1}^{N} d(h^1{}_i, h^2{}_i) \qquad \textbf{(1)}$$

where $d(h^1{}_i, h^2{}_i) = \sum_{c=1}^{M} \left| f(h_i^1(c)) - f(h_i^2(c)) \right|$

To have good results of this distance, after [8] one takes $f(x) = x^m$ with 0 <m <1 (for our experimental we choose the value m=1/3) .

## 3. The problem areas to use the measure histograms $L_1$

In big bases of images, the $L_1$ distance becomes weak to capture all deviation of visual content image by rotation or translation, the figure 1 present two images in black and white (every images are dived into 4 windows) that have the same general content but they are different by the measure classic $L_1$ .
Indeed

$$d_{L_1}(\bar{h}^1, \bar{h}^2) = \sum_{i=1}^{4} d(h^1{}_i, h^2{}_i) \quad \ge d(h_1^1,\ h_1^2)$$

The distance $d(h_1^1, h_1^2)$ is very big because the window 1 in the two images 1 and 2 are different in color.

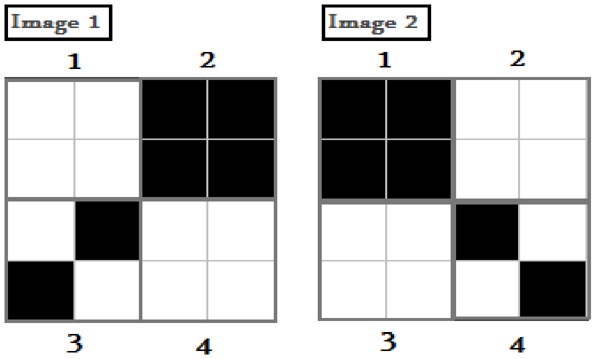

Fig. 1: two images with the same visual content, but with different similarity by measure $L_1$.

Because of the problems described in this section, to improve performance of the CBIR systems, the powerful idea in this paper proposes the PPM metric to measure similarity between two images.

## 4. The permuto-metric measure:

Let x= (x1, x2… xn) a vector, the set of vectors where its components are the permutations of component of x is noted $\sigma(x)$ and of cardinal n!.

### 4.1 Definition

A permuto-metric on the set $\Omega^n$ is application
$\psi$: $\Omega^n x \Omega^n \rightarrow IR^+$
Who satisfies the axioms according to:

$$1- \quad \Psi(x,y) = 0 \quad \Leftrightarrow \quad x \in \sigma(y)$$
$$2- \quad \psi(x,y) = \Psi(y,x)$$
$$3- \quad \Psi(x,y) \le \Psi(x,z) + \Psi(z,y)$$

One can call $\Psi$ the permuto-metric measure.
The couple $(\Omega^n, \Psi)$ is called a permuto-metric space.

Let's notice that the only difference between the definition and the one of a metric space is the permuted separation replaces the usual separation:
1' $\Psi(x,y) = 0 \quad \Leftrightarrow \quad x = y$
Therefore, two distinct points can be a null distance in a permuto-metric space.
However, the relation $\Psi$ *, definite in by the formula:
$x\, \Psi^*\, y \Leftrightarrow \quad \Psi(x,y) = 0$
is a relation of equivalence, one can consider the class of equivalence of one x point formed by all points that a null distance from x therefore: $\overline{x(\psi)} = \{ y \in \Omega^n \ / \ \Psi(x,y) = 0 \}$

Thus, $\overline{x(\Psi)}$ is the closing of x for the permuto-metric topology. The space quotient of $\Omega^n$ under $\Psi$ * is noted by:
$\overline{\Omega(\Psi)} = \{ \overline{x(\Psi)} \ / \ x \in \Omega^n \}$
The application $\overline{\Psi} : \overline{\Omega(\Psi)} \times \overline{\Omega(\Psi)} \Rightarrow IR$ defined by
$\overline{\Psi}(\bar{x}, \bar{y}) = \Psi(x, y)$
Is therefore a metrics for the space quotient. Let's notice that $\Psi$ , in the case or is already a metrics, the space quotient $\overline{\Omega(\Psi)}$ is homeomorphism to $\Omega^n$.
Otherwise, a permuto-metric can be treated as the function of a variable that measures the distance to a fixed point**.**

## 4.2 Theorem

E a set.
Let $d : E \times E \to IR^+$ a distance, then
The application:

$$Z : E^n \times E^n \to IR^+$$
$$(x, y) \to \quad Z(x, y)$$

Defined in the following way:

$$Z(x, y) = \inf_{s \in \sigma(y)} \sum_{j=1}^{n} d(x_j , s_j)$$

is a pemuto-metric measure.

Proof

1) Let $(x , y) \in (E^n)^2$
   $Z(x, y) = 0 \Leftrightarrow \quad x \in \sigma(y)$ is obvious

2) Let us show that
   Z(x, y)= Z(y, x) $\forall (x, y) \in (E^n)^2$

Indeed
let ( x,y) $\in$ $(E^n)^2$ with :
$y = (y_i)_{1 \le i \le n}$ , , $x = (x_i)_{1 \le i \le n}$

$$Z(x, y) = \inf_{s \in \sigma(y)} \sum_{j=1}^{n} d(x_j , s_j)$$

$\sigma(y)$ is a finite set, so

$$\exists \bar{y} = (\bar{y}_i)_{1 \le i \le n} \in E^n , \bar{y} \in \sigma(y) ,$$
$$Z(x, y) = \sum_{j=1}^{n} d(x_j , \bar{y}_j)$$

So $\exists \bar{x} \in \sigma(x)$ for that

$$Z(x, y) = \sum_{j=1}^{n} d(\bar{x}_j , y_j)$$

$$Z(x, y) = \sum_{j=1}^{n} d(y_j , \bar{x}_j)$$ Because $d$ is symmetric

$$Z(x, y) \ge Z(y, x)$$

Similarly we prove $Z(y, x) \ge Z(x, y)$
So $Z(x, y) = Z(y, x)$

3) Let us show that

$Z(Q, P) \le Z(Q, K) + Z(K, P)$
$\forall (P, Q, K) \in (E^n)^3$
With $P = (p_i)_{1 \le i \le n}$ , $Q = (q_i)_{1 \le i \le n}$ , $K = (k_i)_{1 \le i \le n}$
One has:

$$Z(Q, P) = \inf_{y \in \sigma(P)} \sum_{j=1}^{n} d(q_j , y_j)$$
$$\le \sum_{j=1}^{n} d(q_j , \varphi_j) + \inf_{y \in \sigma(P)} \sum_{j=1}^{n} d(\varphi_j , y_j) \quad \forall \varphi \in \sigma(K)$$
$$\le \sum_{j=1}^{n} d(q_j , \varphi_j) + \inf_{x \in \sigma(\varphi)} \sum_{j=1}^{n} d(x_j , p_j)$$
$$\le \sum_{j=1}^{n} d(q_j , \varphi_j) + \inf_{x \in \sigma(K)} \sum_{j=1}^{n} d(x_j , p_j)$$

Because $\sigma(K) = \sigma(\varphi)$

$$Z(Q, P) \le \sum_{j=1}^{n} d(q_j , \varphi_j) + Z(K, P) \quad \forall \varphi \in \sigma(K)$$
$$Z(Q, P) \le \inf_{\varphi \in \sigma(K)} \sum_{j=1}^{n} d(q_j , \varphi_j) + Z(K, P)$$
$$Z(Q, P) \le Z(Q, K) + Z(K, P)$$

End

To get a measure of similarity stable by rotation or translation, we can be considered the permuto-metric measure Z. It is easy to verify that the two images presented in Figure 1 are similar by Z
Indeed

$$z(\bar{h^1},\bar{h^2}) = \inf_{y \in Per(\bar{h^1})} \sum_{j=1}^{n} d(h^1{}_j, y_j)$$
$$= d(h^1{}_1, h^2{}_2) + d(h^1{}_2, h^2{}_1) + d(h^1{}_3, h^2{}_4) + d(h^1{}_4, h^2{}_3)$$
$$= 0$$

## 5. Experimental Results

In order to testify the validity of the method presented in the paper, a great number of experiments on an image database are performed. The database holds 1700 color pictures, which is composed of flowers, vehicles, landscape, animal, food, sea beach, construction and etc. So that the variety of images in the test set prevented any bias toward particular type of images. We indexed the image database by using RGB color. The color space is uniformly quantized into 8 bins / component quantization. The subdivision of the image used in our experience is four windows. To evaluate the test results we use the values precision (1) and recall (2) [9]. The used parameters are described as:

**RCR**= relevant cases retrieved; **RCI**= irrelevant cases retrieved; **RC**= retrieved cases; **RCB**= relevant cases in case base.

**P = RCR / RC,** where **RC =RCR +RCI.** **(1)**

**R= RCR/ RCB,** where **RCB** $\subset$ **RCR** **(2)**

Fig.2 presents the average precision curves of different representations and similarity measure without any indexing scheme. The performances of the proposed method using local histograms with permuto-metric similarity measure are evaluated and compared with the local histograms and the global color histogram on the classic similarity $L_1$. From Fig.2, it is clear that the proposed approaches using local histograms performed better then the global histogram specific image representation based on the average precision. Whereas, the performances of permuto-metric measure are slightly better among all approaches.

Fig.3, Fig.4 and Fig.5 shows retrieval results using the same images color. We compared our method with traditional approaches combined with the metric distance L1. Our method can return more correctly retrieved images than traditional methods.

## 6. Conclusion

This paper has shown that the local histogram using the classic distance $L_1$ in similarity measurement phase do not provide good performance. The reason is that a transformation of visual content of the image by rotation or translation does not change the degree of similarity.

The pemuto-metric measure is proposed to solve this problem. Also, the experiments demonstrate that the pemuto-metric measure provides better performance than the classic distance $L_1$.

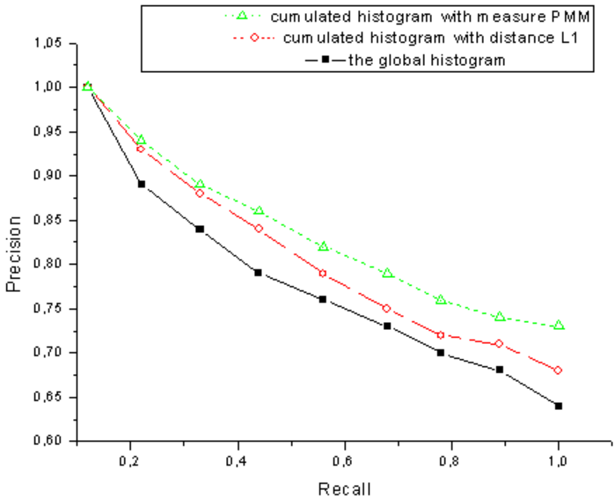


Fig. 2: precision-recall curves for the retrieval within the key-frames image database, using RGB color representation, uniform 8 bins/component quantisation and various color distribution: cumulated histogram with measure permute-metric, cumulated histogram with distance $L_1$ and the global histogram.

Fig. 3: Image retrieval for the same query image ( top left) using the RGB uniformly quantized color. The images are presented in the order of decreasing similarity, from left to right and top to bottom. Thus, for the given query, the retrieval by usual RGB histogram space and $L_1$ metric provides a 56 % accuracy.

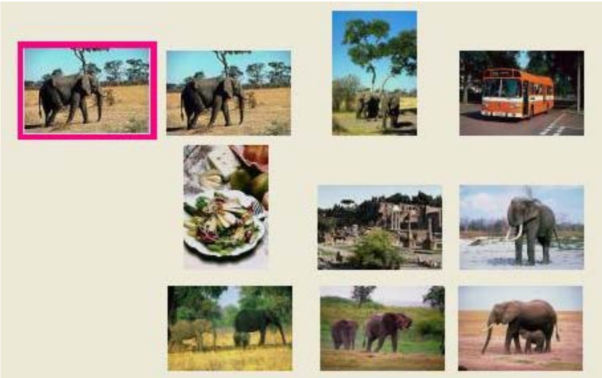

Fig. 4: Image retrieval for the same query image ( top left) using the RGB uniformly quantized color. The images are presented in the order of decreasing similarity, from left to right and top to bottom. Thus, for the given query, the retrieval by usual RGB the accumulated histogram with $L_1$ metric provides a 66 % accuracy.

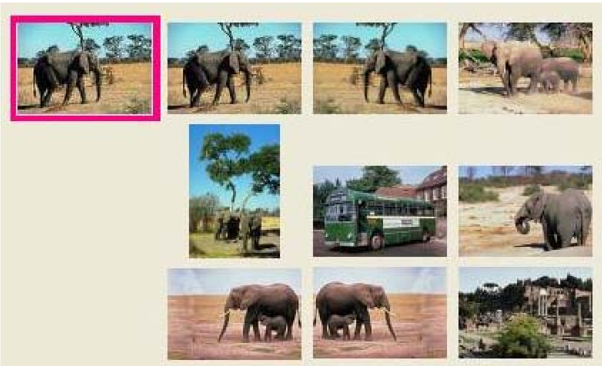

Fig. 5: Image retrieval for the same query image ( top left) using the RGB uniformly quantized color. The images are presented in the order of decreasing similarity, from left to right and top to bottom. Thus, for the given query, the retrieval by usual RGB the accumulated histogram with permuto-metric measure (PMM) provides a 78 % accuracy.

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