An New Improvement Method of Histogram Based Image Retrieval

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Abstract

In real time for the success of many methods similarity measure is considered as a very important role. Similarity measures are mainly analyzed in the context of ordered histogram type data, such as gray-level histograms of digital images or color spectra. The performance of the studied similarity measures can be improved using a smoothing projection called neighbor-bank projection distance functions utilizing statistical properties of data, e.g., the Mahalanobis distance. For the smoothing projection we use a technique called IHBM(Integrated Histogram Bin Matching).Although we use IHBM, in order to improve the similarity measures of ordered histograms ,we initially convert the image from RGB into HSV format, and then calculate the Ordered Histogram values, which is in turn used for calculating the similarity measurements. These measurements are then compared with different image values that are already stored in our backend database and finally we display the retrieved matched top ten images as output result. The proposed projection method seems also to be applicable for dimensional reduction of histograms and to represent sparse data in a more tight form in the projection subspace.

Keywords

Ordinal histograms, Distance functions, Image Retrieval, Similarity Measures, Histogram based Image Retrieval.

1. Introduction

For measuring the similarity measures we use a lot of distance functions. Of them the two most common ones that we are using is the Euclidean and Mahalanobis distances. In this paper our main motivation is to study different distance functions which are required for measuring similarity of ordered histograms. An ordered histogram is also defined as a histogram where the adjacent bins always contain related information. For constructing a robust similarity measure, we use a priori information of ordered bins by combining information collected from neighboring bins. For this there is no generic method for selecting a similarity measure or a distance function. However, a priori information and statistics measures can be used in selection or to establish a new measure as defined by (Aksoy and Haralick, 2001[10] and also by Hafner et al., 1995 [12]; Jin and Kurniawati, 2001; Mitra et al., 2002; Sebe et al., 2000). In our real words, a similarity measure is always an underlying property of an algorithm, and thus, the use of a measure is implicit. Still, the role and meaning of selecting a proper similarity measure in any algorithm should not be neglected. An ordered histogram (also called ordinal, defined by Cha and Srihari (2002))[11] is one type of histogram where adjacent bins always contain related information, for example a gray-level histogram or a color spectrum.

However, the current research work clearly shows that the land mover can be significantly outperformed. For this problem the authors have introduced a new subspace projection of the data, called as the neighbor-bank projection (defined by Kamarainen et al., 2001), where in this projection, the data is projected to a ordinal subspace which mainly reduces the dimension of the data by combining adjacent bins, and also represents sparse data in a more tight, smoothed, subspace. In this study, the most common similarity measures are evaluated in the context of ordered histograms and the interesting properties of the neighbor-bank projection are inspected. Our experimental results clearly show that the similarity measures can be significantly improved by the neighbor-bank projection, and also by smoothing projection technique that is done with help of IHBM, and furthermore, statistical properties of sparse data are more evident in the neighbor-bank subspace.

2. Related Work

In this section we mainly discuss some of the popular existing histogram similarity measures [1, 2, 3], namely, Histogram Intersection (HIM) Method, Histogram Euclidean Distance Method (HEDM) and Histogram Quadratic Distance Measures Method (HQDM).These following existing methods are studied in detail.

2.1 Histogram Intersection Method (HIM)

Histogram Intersection Method [2, 3] is mainly used for color image retrieval and also to find out the very known objects within images using the color histograms, this can be expressed as follows

$$D_{HI}(q,t) = \sum_{i=0}^{M-1} | h_q(i) - h_t(i) |$$

Where $D_{HI}(q,t)$ is the distance measuring between query input image q and the expected target image t, and h_q and h_t are the color histograms of input query and the target images respectively and m clearly denotes the number of bins of histogram.

2.2 Histogram Euclidean Distance Method (HEDM)

The HEDM is the Euclidean distance [2, 3] which is denoted as follows:

Where h_q and h_t are assumed to be the color histograms

$$D_{HED}(q,t) = (h_q - h_t)^T (h_q - h_t) = \sum_{i=0}^{M-1} (h_q(i) - h_t(i))^2$$

$D_{HED}(q, t)$ is the function which clearly represents distance between query image q and target image t, and also h_q and h_t is used to represent the color histograms of query and the target images respectively. The Figure.1 shown below represents the Minkowski distance Model stated above.

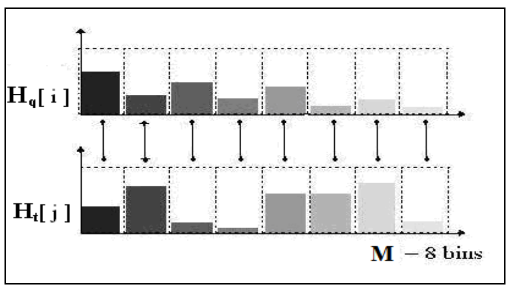

Figure 1. The Minkowski distance Model

2.3 Histogram Quadratic Distance Measures Method (HQDMM)

A Histogram Quadratic Distance Measure method is used in one of the IBM system called as IBM QBIC system, which is used for color histogram based image retrieval [1 , 2 , 3]. In [3], it is clearly reported that quadratic distance metric between color histograms provides more desirable results than "like-bins" that are only comparisons between color histograms. The quadratic form distance between histograms h_q and h_t given by

$$D_{HQDM}(q,t) = (h_q - h_t)^T A (h_q - h_t)$$

Where $D_{HQDM}(q,t)$ is the distance function which tells the distance between query image q and target image t, and also we represent h_q and h_t as the the color histograms of query and the target images respectively and $A = [a_{ij}]$ and a_{ij} denotes the adjacent similarity measure between image histograms with bins i and j. The Quadratic form metric is a true distance metric when $a_{ij} = a_{ji}$ and $a_{ii} = 1$.

We finally came to an clear conclusion that the HQDMM is computationally more expensive when compared with the Minkowski distance metric since it computes the cross similarity between all histogram bins as shown in Figure.2.

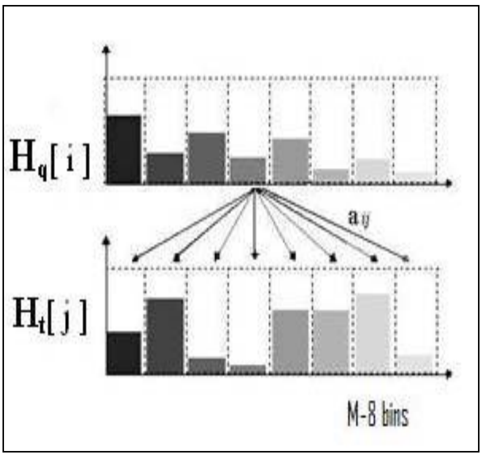

Figure 2. The quadratic distance measure

3. IHBM Projection Metric

The three main steps of the IHBM method is given below

1) Conversion of RGB space into HSV space for Quantization.

2) Compute the inter-bin distances matrix HISTd (Q, T) between all pairs of images. Where HISTd (Q, T) satisfies the monge property as given in equation 1, Q is query image and T is target image.

3) Computation of similarity measure using the proposed approach IHBM.

3.1 Hue Saturation and Value Color Space Metric

The determination of the optimum color space is an open problem, certain color spaces have been found to be well suited for the content-based query-by-color. The proposed method used HSV (Hue, Saturation and Value) Color space, because it is natural and is approximately perceptually uniform.

3.2 Hue Saturation and Value Quantization

HSV Quantization gives 18 hues, 3 saturations, 3 values, and 4 gray levels, which results 166 bins [3, 4] for each image. Then color histogram is computed for 166 bins, and then it is normalized.

3.3 Distance Metric between Histogram Bins

To compute the distance between a bin pair, HISTd (Qi, Tj) is determined by the color characteristics of the histogram bins[4]. HISTd (Qi, Tj) can be computed a priori, independent of the Query image and target images. A Monge distance matrix $D_{Q,T}$ is computed from the HISTd (Qi, Tj) which is constant[5]. This distance matrix satisfied

Monge condition i.e. $m \times m$ matrices $D_{Q,T} = [d_{i,j}]$ which fulfill the so-called Monge property[6] given in equation 12.

$$d_{i,j} + d_{i+1,j+1} \le d_{i,j+1} + d_{i+1,j} \quad \text{………..} \ \textbf{(12)}$$

Where 1 < I < m, 1 < j < m

Distance matrix DQ,T satisfies the discrete Monge condition. Then Hoffmann [5] pointed out that greedy approach gives an optimal solution.

3.3.1 Integrated Histogram Bin Matching (IHBM) Metric

IHBM (Integrated Histogram Bin Matching), is a novel metric Similarity measure to compare the color feature of quantized images. The main idea of this, consists of modeling the comparison of color-quantized images as a Transportation problem [5,6,7,8].This model deals with the determination of a minimum-cost plan for transporting a commodity from a number of supply nodes to a number of demand nodes.

At the time of the Partition the nodes are divided into two sets m and n, where nodes in m are supply nodes and nodes in n are demand nodes, and for each arc (i, j), i is in m and j is in n. Let Z denote total transportation cost, let x_{ij} denote the no. of units shipped from supply node i to demand node j, and cij denote the cost of shipping a unit shipped from supply node i to demand node j.The general form of the Transportation problem is then

$$\begin{aligned} &\textbf{Minimize} \quad Z = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij} \\ &\sum_{j=1}^{n} x_{ij} = s_i \quad \textbf{for all } i = 1,2,\ldots, m \\ &\sum_{i=1}^{m} x_{ij} = d_j \quad \textbf{for all } j = 1,2,\ldots, n \\ &x_{ij} \ge 0 \quad \textbf{for all } i \textbf{ and } j \end{aligned}$$

Where s_i denotes Supply Constraints and d_j denotes demand Constraints. For matching histogram bins of two images, the closest histogram bin pair is considered first. If the bins are of the same size then the two most similar bins are matched otherwise a partial match occurs. This process is repeated until all the histogram bins are matched completely. After matching histogram bins, the similarity measure is computed as a weighted sum of the similarity between histogram bin pairs, with weights determined by the matching scheme. This is known as **Integrated Histogram Bin Matching (IHBM),** which emphasizes the integration of histogram bins in the retrieval process. The Figure.5 represents the similarity measure mechanism of the proposed IHBM approach with 8 bins.

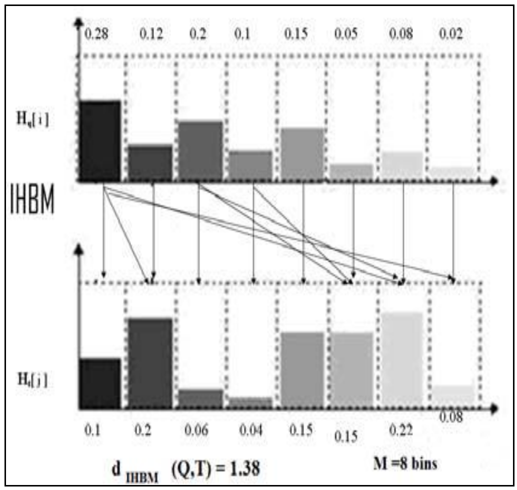

Figure.3. IHBM Approach

3.3.2 IHBM Algorithm

BEGIN

1 $D_{Q,T}$ = HISTd (Q, T)
2 Detect and compute the Monge sequence
$d_{i,j} + d_{i+1,j+1} \le d_{i+1,j} + d_{i,j+1}$
3 for each pair of histogram Bins Qi Є Q and T_j Є T
4 Qi .status = 0
5 Tj .status = 0
6 sort out the computed distances DQ,T in non-decreasing order
7 DIHBM = 0
8 for each distance DQ,T in non- decreasing order
9 if Qi . status = Tj . status = 0


```
if Qi . size < Tj . size
w = Qi . size
Tj . size = Tj . size – w
Qi . status = 1
else
w = Tj. size
Qi . size = Qi . size - w
Tj . status = 1
if Qi . size = 0 then Qi . status = 1
DIHBM = DIHBM + w × DQ,T
END
```

3.3.3 Metric Property for Similarity Measures

To prove the proposed similarity measure, DIHBM(Q,T) satisfies the conditions : nonnegativity, commutative and triangle inequality, the following proofs are given.

1. DIHBM(Q,T) has non-negativity property: DIHBM(Q,T) ≥ 0.

Proof:

DIHBM(Q,T) is nothing but the sum of DQ,T and each DQ,T has non-negativity property. Therefore, DIHBM(Q,T) also has the non-negativity by definition.

2. DIHBM(Q,T) has commutative property: DIHBM(Q,T)= DIHBM(T,Q).

3. DIHBM satisfies the triangle inequality property: DIHBM(P,Q) $\leq$ DIHBM(Q,R) + DIHBM(R,P) .

Proof:

Let the assignments Pi→ Qi be the assignments of DIHBM(P,Q) . Let Qi→ Ri be the assignments of DIHBM(Q,R) . Then Pi is assigned to Qj by Pi →Qi →Ri. Now by considering $D_{P,R} \leq D_{P,Q} + D_{Q,R}$ because D has Monge property. And DIHBM(P,Q) is an optimal greedy solution satisfies Monge Sequence. Since DIHBM = DIHBM + w × D ,then DIHBM(P, R) $\leq$ DIHBM(Q, R) + DIHBM(R, P). Therefore DIHBM(P, Q) $\leq$ DIHBM(Q, R) + DIHBM(R, P) .

4. Proposed System Architecture

The system architecture for improvement of Histogram based image retrieval is shown in figure 4.

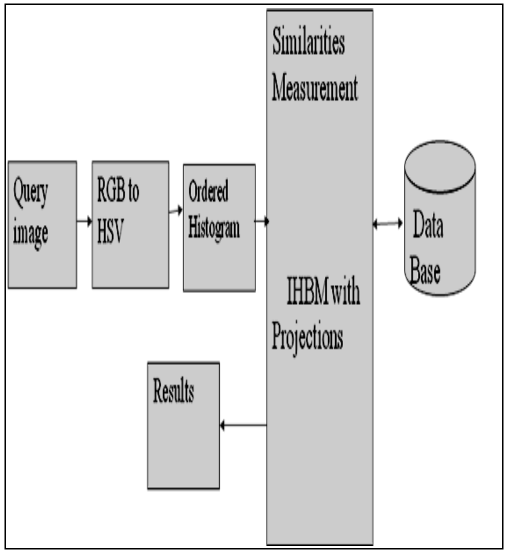

Figure. 4. Improvement of Histogram based Image Retrieval

5. Conclusion

In this paper, the properties of various distance metrics were examined primarily in the context of ordered histogram type data. A new smoothing projection, the neighbor-bank projection, IHBM Smoothing were also introduced. The smoothing projection seems to improve the accuracy of some of the studied distance functions and to have advantages when combined with methods utilizing the statistical properties of the data, such as the Mahalanob distance. Our new smoothing technique like IHBM is experimented on 50 color images and the experimental results with the help of tables and graphs clearly indicate the proposed method IHBM is more accurate and efficient than the three existing methods i.e. HIM, HEDM and

HQDMM. The proposed method is proved as metric, which satisfies non-negativity, commutative and triangle inequality properties.

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