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Selecting the Best Sub-Region Indexing the Images in the Case of Weak Segmentation Based On Local Color Histograms

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***Abstract*—**Color Histogram is considered as the oldest method used by CBIR systems for indexing images. In turn, the global histograms do not include the spatial information; this is why the other techniques coming later have attempted to encounter this limitation by involving the segmentation task as a preprocessing step. The weak segmentation is employed by the local histograms while other methods as CCV (Color Coherent Vector) are based on strong segmentation. The indexation based on local histograms consists of splitting the image into N overlapping blocks or sub-regions, and then the histogram of each block is computed. The dissimilarity between two images is reduced, as consequence, to compute the distance between the N local histograms of the both images resulting then in N*N values; generally, the lowest value is taken into account to rank images, that means that the lowest value is that which helps to designate which sub-region utilized to index images of the collection being asked. In this paper, we make under light the local histogram indexation method in the hope to compare the results obtained against those given by the global histogram. We address also another noteworthy issue when Relying on local histograms namely which value, among N*N values, to trust on when comparing images, in other words, which sub-region among the N*N sub-regions on which we base to index images. Based on the results achieved here, it seems that relying on the local histograms, which needs to pose an extra overhead on the system by involving another preprocessing step naming segmentation, does not necessary mean that it produces better results. In addition to that, we have proposed here some ideas to select the local histogram on which we rely on to encode the image rather than relying on the local histogram having lowest distance with the query histograms.

***Keywords*—**CBIR, Color Global Histogram, Color Local Histogram, Weak Segmentation, Euclidean Distance.

I. Introduction

OWING to the huge amount of information available, in the early years, information retrieval (IR) field has received a significant attention, from researcher's community, as an active research topic; indeed, a lot of efforts have been put into this direction in attempts to develop a suitable system able to satisfy the user intent expressed by the submitted query. To construct such system, researchers have concentrated their powers on the three components of the information retrieval system: indexation, interrogation and the matching process. In the matter of interrogation, the queries formulated by the user to ask an IR system has, usually, the same form of the elements composed the collection being asked. Queries in the case of documents retrieval system are composed from words or terms while picture or sketch is the form of queries within image retrieval systems. For the matching process which is responsible in the ranking of the results as visualized to the user, there are two alternatives: computing distances between query and the elements of the repository or calculating the closeness between them. The indexation, usually done on offline, constitutes the important process of an information retrieval; it consists of encoding the elements of the corpus to ask utilizing the same signature, this latter has commonly the characteristic to be more compact and more significant compared to the elements being indexed. We focus on this paper on the indexation stage in the case of content based image retrieval system (CBIR) where there is large number of signatures. Histogram coming from the statistic area constitutes the oldest signature using to index images. The lack of spatial information represents the main limit of this indexation method. This shortcoming has lead researchers to propose new techniques taking into account the spatial information which has given birth to a wide range of methods originated all from the global color histogram method. The local color histogram, addressed in this paper, constitutes the simple way to alleviate the limitation of the traditional color histogram.

We address in this paper, the local color histogram for designating the sub-region or the local histogram considered as the signature encoding the image.

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II. CBIR Features

For the aim of alleviating the problems faced with the annotation, another alternative has appeared which relies on the features taken out from the image its self; this approach is called CBIR (Content Based Image Retrieval). The CBIR approach attempts to assess the similarity between images arranged based on some low level visual features[1] like color [2], texture [3], [4] and shape [5].

A. Color

Due to the important place of the numerical images, the color is considered as the best feature being used to arrange images; indeed, it is the base feature from which the other features can be designated. The color is usually considered as the first feature utilized to build a content image retrieval system. As evidenced by many recent works, it is assumed as an effective feature [6].

B. Shape

This feature is used within many images retrieval systems. Taking out the shape attributes required a robust segmentation task as a preprocessing step [6], which is, generally, critical to get.

III. Global Color Histogram

In retrospect of what have been achieved in the CBIR field, we can find a large number of indexing methods, one of this is a color histogram coined in [7]. This technique has been used in many works and is admitted as one of the oldest basic method for CBIR. Many techniques have been originated from the color histogram which possesses the merit of the simplicity to compute, although, it holds the disadvantage of inability to spatially locate colors in images. In [8], the authors report the following well known pros and cons for histograms:

- Histograms are sensitive to noisy interferences such as illumination changes and quantization errors.
- Large dimension of histogram involves large computation on indexing.
- It does not take into consideration color similarity across different bins.
- Histograms cannot locate objects within an image.
- Two perceptually very different images with similar color distribution will be considered similar by a color histogram based retrieval system (Fig. 2).

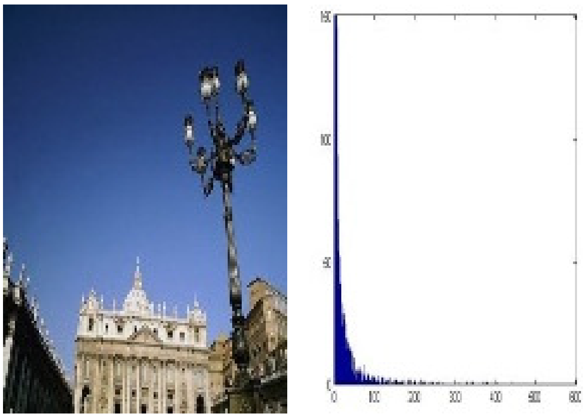

Fig. 1 An image and its global histogram distribution

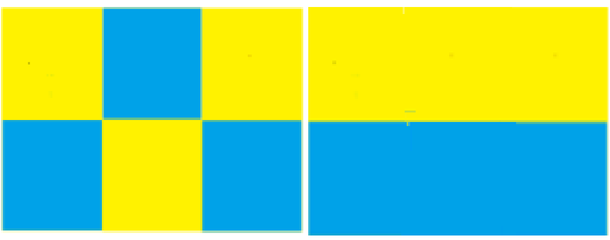

Fig. 2 Two Perceptually Different Images with Equal Color Global Distribution

IV. Local Color Histogram

The simplest and obvious way of introducing the spatial information lacked within global color histogram is the method used by Gong and others [9]. They divided the images into nine equal parts and calculated a histogram for each of these. This gives some spatial sensitivity, but increasing the computing power and storage needed. An approach to LCH not using equally sized regions of the image was proposed by Lu and other [10]. We split here the image into three regions as depicted in the Fig. 3.

Fig. 3 Images segmented into three regions

V. Experiments and Results

The experiments were carried out on a collection of 100 images selected from the Wang database [11]. We have used the Euclidian distance defined by (1) to check the dissimilarity between histograms.

$$l_2(H,\grave{H}) = \left(\sum_{m=1}^{M}\left(H_m - \grave{H}_m\right)^2\right)^{½} \qquad (1)$$

where H_m and $\grave{H}_m$ are the two histograms whose the dissimilarity is being assessed and M is their common bins number.

There are primarily two widely used measures for judging the CBIR performance: the precision and the recall [12]. The precision is defined as the ratio of relevant images retrieved to all images retrieved, while the recall is defined as the ratio of relevant images retrieved to all relevant images in a database, or the probability given that an image is relevant that it will be retrieved.

$$Precision = \frac{Numberofrelevantimagesretrieved}{Totalnumberofimagesretrieved} \quad (2)$$

$$Recall = \frac{Numberofrelevantimagesretrieved}{TotalnumberofrelevantimagesintheDatabase} \quad (3)$$

Notice that we make use of the Euclidean distance to assess the dissimilarity of the images queries and the images of the asked collection; in addition, as the colors reduction is mandatory when working with histograms, each image is represented using its 16 dominant colors. How many colors to keep in order getting good results moves beyond the scope of this paper, which does matter here is to compare between two things and so using the same configuration with the both cases.

The first goal of this paper is to compare between the employing of the global histogram and the local one from in terms of performance. Fig. 4 illustrates Precision vs. Recall in the both cases:

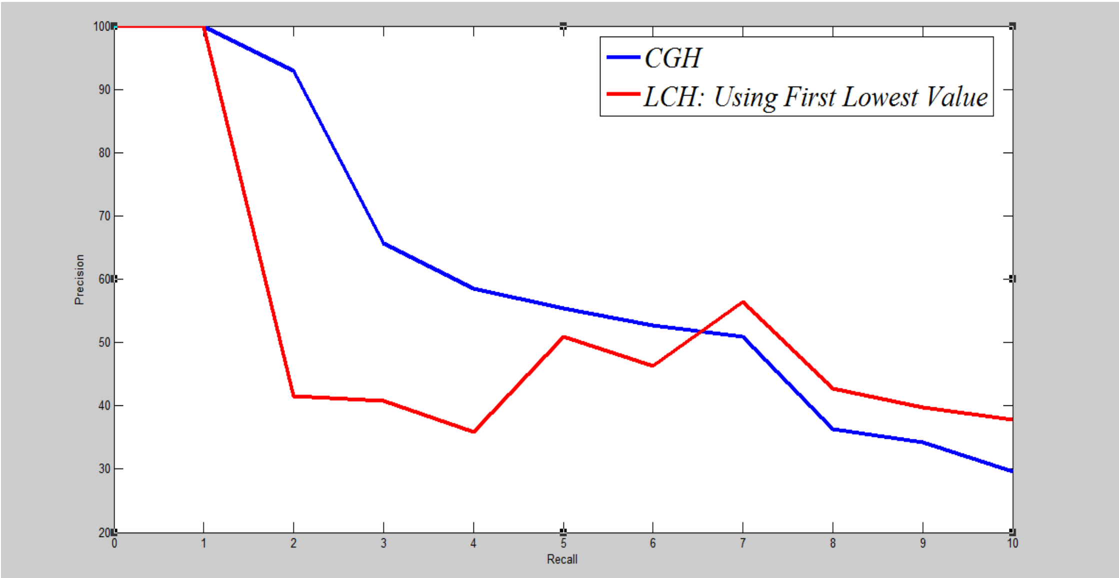

Fig. 4 The Average Precision/Recall curves in the case of Color Global Histogram (CGH) and Color Local Histogram (the first lowest value)

As depicted in the Fig. 4 above, the global histogram produces results better than local histogram when trusting on the first lowest value during the comparison of the LCHs. The Table I below shows the results obtained when relying on other values:

TABLE I
DIFFERENT SCENARIOS OF LHC

Recall	Precision								
	LCH (using first lowest value)	LCH (using second lowest value)	LCH (using third lowest value)	LCH (using fourth lowest value)	LCH (using fifth lowest value)	LCH (using sixth lowest value)	LCH (using seventh lowest value)	LCH (using eighth lowest value)	LCH (using ninth lowest value)
10%	100%	100%	100%	100%	100%	100%	100%	100%	100%
20%	41,56%	45,70%	45,57%	45,93%	43,04%	41,37%	45,19%	41,52%	39,98%
30%	40,81%	41,75%	41,84%	42,03%	35,91%	34,52	36,57%	35,91%	34,69%
40%	35,82%	35,82%	36,31	35,79%	31,31%	30,68%	33,13%	32,75%	31,41%
50%	50,86%	43,71%	43,55%	43,90%	44,51%	43,53%	45,41%	43,82%	44,20%
60%	46,26%	44,08%	47,96%	46,68%	46,90%	45,49%	48,78%	46,62%	45,82%
70%	56,47%	55,52%	54,21%	55,98%	56,82%	55,07%	56,65%	57,70%	58,91%
80%	42,73%	42,04%	41,96%	41,04%	44,03%	42,06%	44,51%	44,41%	43,95%
90%	39,76%	42,79%	42,83%	43,11	43,51%	42,71%	46,14%	44,98%	43,98%
100%	37,79%	38,56%	39,59%	40,30%	39,65%	39,65%	42,53%	40,75%	39,45%

In light of the results obtained above, it seems that relying on other values performs better than basing on the first lowest value.

The question stills open, which value we should to rely on when comparing two images based on their local histograms. There are several ideas to being with:

- Choosing the local histogram representing the target image which gives the lowest value with all the query local histograms. For achieving this, the average distance between each target image local histogram with all the query local histograms (LCHS) should be calculated.
- Computing the average distance of all image local histograms distances, in other words, the distance between a query image and a given image is the average of the nine distances resulting from comparing all the query image local histograms with all the considered image local histograms. This final distance represents the dissimilarity between the target and the query images (LCHM).
- Choosing the local histogram which very near to the other local histograms within the same target image (LCHR).

The results obtained when following these ideas are showed in the table below:

TABLE II
PROPOSED SCENARIOS OF LCH

Recall	Precision			
	LCH (using first lowest value)	LCHS	LCHM	LCHR
10%	100%	100%	100%	100%
20%	41,56%	56,79%	45,70%	57,61%
30%	40,81%	41,04%	42,64%	42,78%
40%	35,82%	35,93%	33,49%	37,45%
50%	50,86%	45,66	43,36%	45,60%
60%	46,26%	45,98%	47,34%	43,82%
70%	56,47%	56,04%	59,02%	54,85%
80%	42,73%	42,44%	44,01%	41,29%
90%	39,76%	40,03%	43,53%	39,69%
100%	37,79%	36,86%	39,86%	38,60%

As shown above Table II, the results given when applying the three scenarios seem to be better comparing to the first case which relies on the first lowest value but the results are far from those returned when using the global histograms. Moreover, the results are not better than the ideal case of choosing (one among nine). The ideal case of choosing is depicted in the Fig. 5 below comparing to the global histogram:

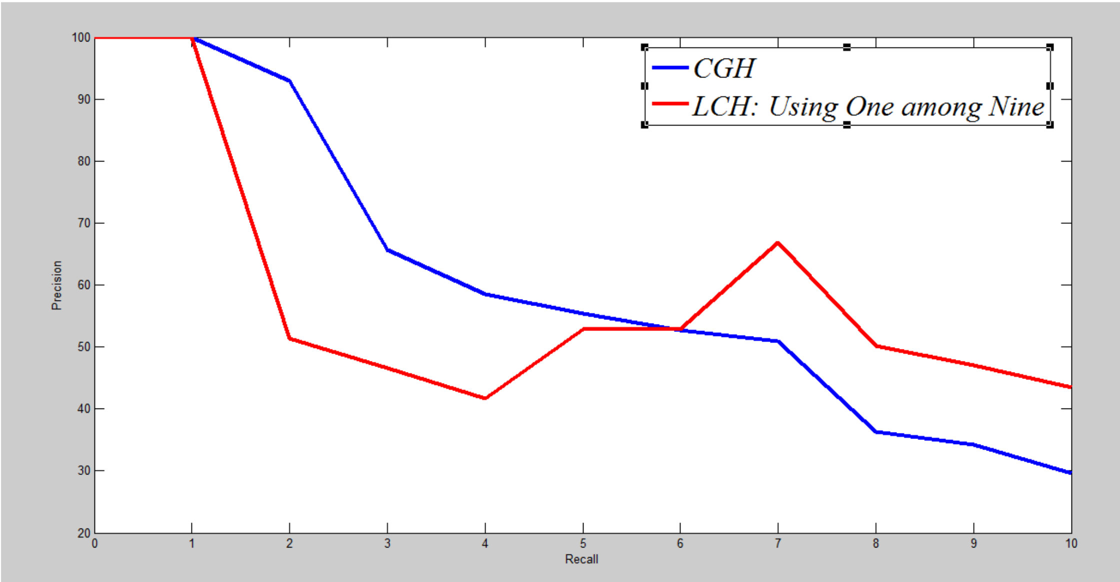

Fig. 5 The Average Precision/Recall curves in the case of Color Global Histogram (CGH) and Color Local Histogram (one among Nine)

As shown above, we can get better results trusting on local histograms but it is not clear which value to take into account. Because we cannot answer statistically the question which value to consider, it is mandatory to rely on other intelligent tools as machine learning.

VI. Conclusion

We agree that the local histogram is an alternative able to encounter the lack of spatial information but without ensuring that it ameliorates performance. According to the results achieved in this paper which considers the following configuration: the RGB as a representation space, the histogram as an indexation method and the Euclidian Distance as a method to check the dissimilarity, it comes out that global histogram performs better than local histogram. We have proposed here some ideas helping to choose the local histogram on what we rely on to represent images in order to produce good results better even than those given by the global histogram. Local histogram indexation method can produce much more but with employing some other intelligent tools able to select the ideal local histogram.

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