LOGO AND TRADEMARK DETECTION IN IMAGES USING COLOR WAVELET CO-OCCURRENCE HISTOGRAMS

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ABSTRACT

The use of histograms to characterize edge information in an image is a common technique for image indexing and retrieval. Two techniques that have recently shown promising success are the edge gradient histogram (EGH) and the Co-occurrence Edge Color Histogram (CECH). In this paper, we present a system for logo and trademark retrieval from a database of color logo images. Through the use of a 5-dimensional co-occurrence histogram, the system proposed captures the co-occurrence of colors and wavelet decomposition coefficients of pairs of pixels. The result is a more precise characterization of the spatial distribution of edge information in an image than the ones produced by the EGH and the CECH. We call this 5-dimensional co-occurrence histogram the Color Wavelet Co-occurrence Histogram (CWCH). Results demonstrate that our retrieval system performs better than both the EGH and the CECH.

***Index Terms*—** Wavelet transforms, Object recognition, Pattern recognition, Image databases, Image color analysis

1. INTRODUCTION

Content-based Image Retrieval (CBIR) defines the set of techniques used to retrieve relevant images from a database of images based on image content. The basis of CBIR is an object detection algorithm that possesses the ability to, given an image, detect objects that are closely associated with the requested content. Previous research in object detection in images has focused on the detection of specific objects of known geometric and shape characteristics, including but not limited to billboard advertisements [1] and trademark logos [2]. The applications for general object detection are numerous, ranging from commerce [2], to sports and entertainment [1] [3]. In this study, we focus on the detection of logos and trademarks in images. Different approaches have been previously examined, such as the use of color histograms [4], or shape information [5], or a combination of both [6]. Other approaches proposed the use of neural networks[7][8]. More recently, the use of co-occurrence histograms has been proposed, due to the ability of co-occurrence histograms to capture both color and spatial content of an image [9]. Unlike the method proposed by Swain *et. al.* [4], a geometric dimension is introduced in [9] where the frequency of occurrence of color pixel pairs that are separated by a certain distance is captured. More specifically, the Color Co-occurrence Histogram (CCH) proposed by Chang *et. al.* [9] records the number of pixel pairs of colors c_1 and c_2 that are separated by *d* pixels. However, the CCH proposed in [9] suffers from a fundamental flaw, in that all pixel pairs are considered, hence allowing regions of uniform color to potentially dominate the CCH bins. Luo et. al. [10] attempts to correct this by considering only edge pixels, hence the name Color Edge Co-occurrence Histogram (CECH) is given. Compared with the CCH, the CECH yields better retrieval results.

We improve the CECH by introducing a more accurate classification of edge information through the use of wavelet decomposition coefficients. Histograms of wavelet coefficients have been previously used in image indexing and retrieval. Androutsos *et. al.* [11] uses a histogram of vectors of wavelet coefficients for image indexing and retrieval. Moghadam *et. al.* [12] uses a histogram of the coefficients of a 3-level Daubechies wavelet decomposition as an image index for retrieval.

In this paper, we show that a co-occurrence histogram of both wavelet directional detail information and color is a more powerful technique than the CECH for image indexing. We propose using the sub-bands of the wavelet decomposition as well as the color value to build a five-dimensional Color Wavelet Co-occurrence Histogram (CWCH). In our experiments, we use the Haar transform as the wavelet function. We also introduce a more accurate representation of edge pixels than the one used in the CECH by only considering pixels whose wavelet magnitude, defined as the magnitude of the LH, HL, and HH coefficients[13], is non-zero. For a given pixel pair, the five dimensions of the co-occurrence histogram correspond to the wavelet magnitude and the color of each of the two pixels, as well as the distance that separates the two pixels. We also introduce the use of search windows of multiple sizes instead of a fixed-size search window when populating the CWCH.

The rest of the paper discusses our method and the experimental results in more detail. Section 2 discusses our proposed method, including the concept of using search windows of different sizes. Section 3 presents our experimental results, comparing our proposed method with three other methods using the retrieval rate and precision-recall graphs. Finally, we conclude this paper by stating our conclusions.

2. METHOD

Given a query logo image, our goal is to retrieve all logos similar to the query logo in a database of images. The images in the database and the query image are subsampled to 256 x 256 pixels. The database images are chosen such that they are of approximately equal height and width. Hence, subsampling the images to 256 x 256 does not geometrically distort the logo. The query image and all database images are strictly images of logos that contain no other objects. Given an image of size N x N pixels, the algorithm can be summarized in two main steps:

Color Quantization: The image pixels are quantized as per Luo et. al.'s [10]. Two stages of quantization are performed. The first stage quantizes all pixels to a set of 267 colors as defined by the ISCC-NBS, and the second stage quantizes the colors down to a set of 11 basic colors *S*; where *S* = {*black, white, gray, brown, yellow,* *orange, pink, red, purple, blue, green*}. Hence, the color of each pixel in the N x N image is now represented by one of the 11 color values in *S*.

Applying the Wavelet Decomposition and Building the CWCH: The Haar transform consists of two filters; a low pass filter and a high pass filter. The low pass filter is a simple averaging operation of two neighboring pixels, while the high pass filter is the average of the difference between two neighboring pixels [13].

Before the Haar transform is applied to the image, the image is reduced to a single channel by converting the image from RGB to grayscale. Given an image of N x N pixels, a single application of the Haar transform in both the horizontal and vertical directions yields four sub-bands, namely the LL, LH, HL and HH sub-bands. The sub-bands are produced via applying the low pass and the high-pass filters in different orders [13]. The LL sub-band is essentially a smaller summary image, while the LH sub-band corresponds to the vertical differences of the horizontal averages, which can be interpreted as the horizontal edges in the image. The HL sub-band represents the vertical averages of the horizontal differences; thus it emphasizes the vertical edges in the image. Finally, the HH sub-band represents the differences from both the horizontal and vertical averaging operations; thus emphasizing the diagonal edges in the image.

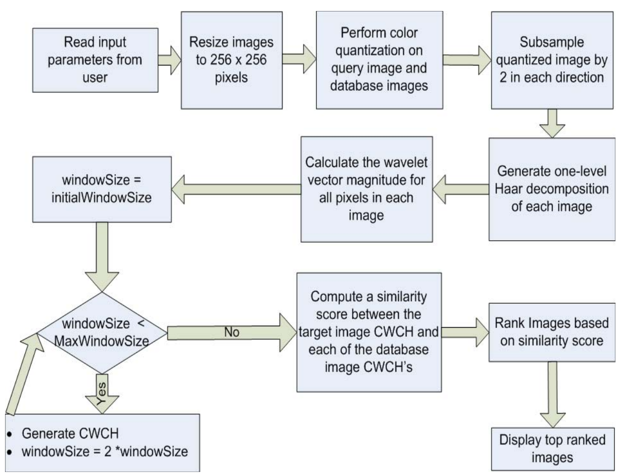

Fig. 1. A block diagram of our proposed retrieval system

Note that one level of wavelet decomposition subsamples the image by a factor of 2 in the horizontal and vertical directions. This in turn requires subsampling the set of color-quantized pixels from stage 1 by a factor of 2 in both directions. Each pixel p_1 can now be represented by a two-dimensional vector: the first dimension corresponds to the quantized pixel color, and the second dimension corresponds to the wavelet vector magnitude, which is the magnitude of the three dimensional wavelet decomposition vector. In other words, if we denote the wavelet vector magnitude of a pixel p_1 by wvm_1, then:

$$wvm_1 = \sqrt{p_1.h^2 + p_1.v^2 + p_1.d^2}, \qquad (1)$$

where $p_1.h$, $p_1.d$ and $p_1.v$ represent the HL, LH and HH sub-band coefficients respectively for p_1. If p_1 has been color quantized to the color c_1, it can be represented by the two dimensional vector v_1 = (c_1, wvm_1). For any two pixels p_1 and p_2, represented by the two vectors v_1 = (c_1, wvm_1) and v_2 = (c_2, wvm_2), and separated by a distance of *d* pixels, the CWCH records the number of occurrences *k* of such a pair. In other words:

$$CWCH(c_1, wvm_1, c_2, wvm_2, d) = k. \qquad (2)$$

2.1. Populating the CWCH using sliding search windows:

The CWCH is populated by having a search window of an arbitrary size (our choice was 20 x 20 pixels) slide across the image horizontally and vertically. The pixel located at the center of the window is next checked to see if its *wvm* is non-zero. If it is, then all pixels within the window with a non-zero *wvm* are considered, and the corresponding CWCH bin is incremented accordingly. Each of the distances within this window is mapped to a different distance bin. In other words, all pixel pairs of color c_1 and c_2 that are separated by 2 pixels within the window are mapped to the same CWCH bin, and all pixel pairs of color c_1 and c_2 that are separated by 3 pixels are mapped to a different CWCH bin. Ignoring pixels with a zero *wvm* ensures that only important features of the image are considered and that solid regions of color have no overpowering contribution to the CWCH.

2.2. Varying the search window size:

We also introduce the use of search windows of multiple sizes in order to capture more spatial and color information. Again, the concept of multiple window sizes is a new concept that was not present in the CECH, where the search window size was fixed. After one iteration through the image pixels, the process is repeated but now with the window size doubled. In this iteration, all pixel pairs consisting of the pixel at the center of the window and every boundary pixel of the window are considered, and the corresponding CWCH bin is incremented accordingly.

2.3. Similarity measure:

The similarity measure used is the histogram intersection. Histogram bins are traversed in order and the minimum value of the two bin counts is taken at each iteration, as shown below:

$$S_{CWCH}(H_1, H_2) = \sum_{bin=i}^{n} \frac{min(H_Q(bin), H_T(bin))}{\sum_{bin=i}^{n}(H_Q(bin))}, \qquad (3)$$

where *n* is the total number of bins, H_Q and H_T are the CWCH of the query image and the CWCH of the target image respectively.

3. EXPERIMENTAL RESULTS

To test our retrieval system, two query images were used : an image of the Ferrari logo and an image of the Kodak logo, both shown in Figure 2. For each image, retrieval tests were executed on a database of 3000 images. The database images are logo images gathered from various online resources. The image database for the Ferrari logo included 40 other images of the Ferrari logo, while the image database used for the Kodak logo included 20 other images of the Kodak logo. Figure 3 shows the top 100 retrieval results for the Ferrari logo, ranked with respect to the similarity score from left to right, and top to bottom. Figure 4 shows the top 100 retrieval results for the Kodak logo. We evaluate the retrieval performance using two measures: the retrieval rate, and the precision-recall graph.

(a) (b)

Fig. 2. Original (a) Ferrari and (b) Kodak logos

Fig. 3. The top 100 retrieval results for the Ferrari logo

3.1. Retrieval rate:

To quantify the retrieval performance the CWCH as well as that of the CECH and establish a basis of comparison, we use the retrieval rate. Given an image database that contains *n* query images, the retrieval rate is defined as the number of query images retrieved within the top *n* retrieval results. There are 40 Ferrrai logos in the database. Using the CECH, 2 of the top 40 retrieval results were Ferrari logos. Thus the retrieval rate is 2/40 = 5%. On the other hand, the number of Ferrari logos retrieved within the top 40 retrieval results using the CWCH is 20, as illustrated in Figure 3. This yields a retrieval rate of 20/40 = 50%. Therefore, the CWCH performs 10 times better than the CECH in terms of the retrieval rate. The CWCH also shows robustness against rotations and different scales, as evident in the top 11 retrieved results, all images of the Ferrari logo in different orientations, sizes and lighting conditions. Since there are 20 Kodak logo images in the database, we examine the top 20 retrieval results, in which 2 Kodak logos appear. Hence, the retrieval rate for the Kodak logo using the CWCH is 2/20 = 10%. On the other hand, none of the top 20 images were Kodak logos when the CECH was used, hence the retrieval rate for the CECH is 0%. This further demonstrates that the CWCH performs better than the CECH.

Fig. 4. The top 100 retrieval results for the Kodak logo

3.2. Precision-recall graphs:

Figures 5 and 6 show how the retrieval results for our proposed method compare with three other methods in terms of precision-recall graphs. The three other method are the CECH, the EGH, and the MPEG-7 EHD. The precision-recall graphs for the Ferrari logo in Figure 5 and the Kodak logo in Figure 6 demonstrate that the CWCH performs better than all three methods. More significantly, the CWHC significantly outperforms the CECH. This does not come as a surprise, since the CWCH produces a better classification of edge information in the image. More significantly, the CWCH assigns different edge strengths to edges, based on the magnitudes of the wavelet coefficients. Hence, the CWCH is a more accurate characterization of image features.

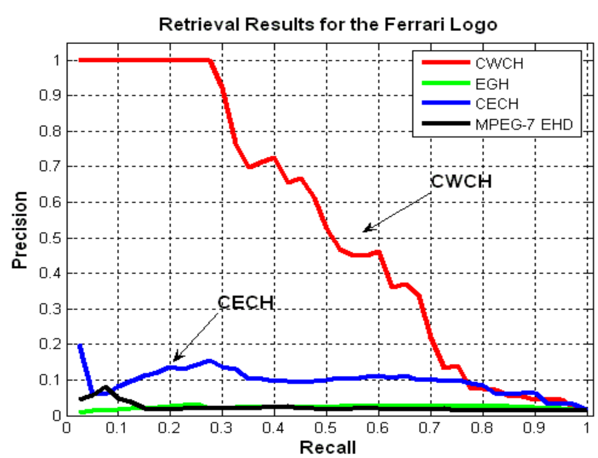

Fig. 5. Precision-recall graph for the Ferrari logo

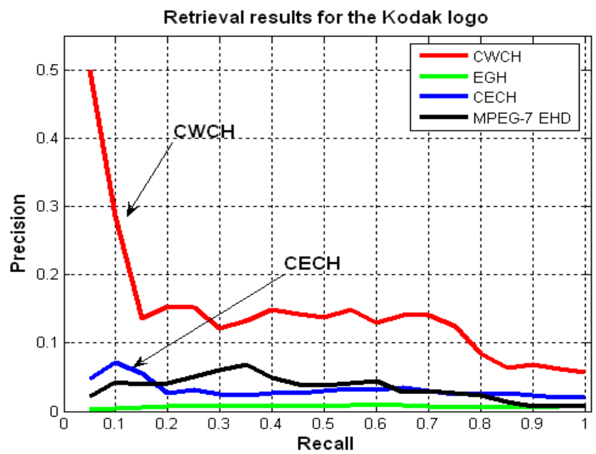

Fig. 6. Precision-recall graph for the Kodak logo

4. CONCLUSIONS

We presented a new method for color logo detection in images. We showed that our proposed Color Wavelet Co-occurrence Histograms (CWCH) produces better retrieval results than the EGH, the CECH and the MPEG-7 EHD. We achieve this through incorporating two more dimensions that capture the general shape information of the image, represented by the wavelet decomposition coefficients of a grayscale version of the image. The algorithm is still in its infancy stage, and with the ability to exploit multi-resolution analysis with wavelets, there is a great potential for further improvements. We are also investigating the use of different wavelet functions and the multiple levels of wavelet decompositions to achieve scale invariance. Also, the retrieval results are certain to further improve with the use of a better color quantization method than the one used by the CECH, which our system currently uses. We are currently investigating the use of a different color quantization method that uses the HSV color space and initial results are looking very promising.

5. REFERENCES

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