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A New Analysis of Image Retrieval and Extraction of Perceptually Important Colors for Image Matching

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Abstract

We present a color matching algorithm that models behavior of the human visual system in capturing color appearance of an image. The method is well suited for creating small color codebooks used in image analysis and retrieval. We then introduce a statistical technique to extract perceptually relevant colors. The aim of this study was to analyze users' behavior during image retrieval exercises. Results revealed that users tend to follow a set search strategy: firstly they input one or two keyword search terms one after another and view the images generated by their initial search and after they navigate their way around the web by using the 'back to home' or 'previous page' buttons. These results are consistent with existing Web research. Many of the actions recorded revealed that subjects' behavior differed depending on if the task set was presented as a closed or open task.

Keywords: Image Retrieval, color codebooks, color histogram, optimal color composition distance metric (OCCD), dominant color components (DCC)

Introduction

However, although histogram features are simple to compute, they lack discriminatory power in retrieval of large image databases. Hence, instead of basic histogram search, many sophisticated representations have been proposed [11-[4].Further improvement of color features can be achieved only by adding the elements of human perception into the model. Color features have been extensively used in image database retrieval, especially in cases The simplest color representation is ***color histogram.*** It is usually employed in combination with the Euclideau distance as a ***color metric,*** providing undemanding yet efficient retrieval method. Further improvement of color features can be achieved only by adding the elements of human perception into the model According to the reported results, even though visual features do not capture semantic meaning of an image, there is a significant correlation with semantically relevant information.. Therefore, in this work we model behavior of the human visual system in capturing color appearance of an image. We propose a technique for extraction of perceptually relevant colors and a new color metric that facilitates this representation such as digital cameras and scanners. In order to effectively manage these digital images, an image album or an image filing system has become the subject of study. As the Internet grows so the task of image retrieval becomes more complicated. From an educational perspective the role of images as important educational aids is unquestionable. Images not only serve to support curriculum and extracurricular subjects but can, if used properly, enhance students understanding of concepts and issues and in some cases provide the teacher with an alternative and inexpensive source of study materials.

2. Color Feature Extraction

When viewing the global color content, human visual system eliminates fine details and averages colors within small areas. Consequently, on the global level, we perceive image only as a combination of few most prominent colors, even though it's color histogram might be very "busy" [4]. Hence, the goal of the proposed method is to determine dominant colors by taking into account both global color information (captured through the image histogram) and local information (extracted from the spatial relationships between the most frequently occurring colors following steps: **1)** color quantization through the specially designed compact codebook, **2)** spatial correlation processing to extract dominant colors and **3)** estimation of color distribution. Extracted dominant colors and their area percentages are then used as a feature vector in-conjunction with a new distance function to measure color similarity between two images. Each of these steps will be described in the succeeding sections.

3. Extraction of visually important color

Hence, here we propose a statistical method to identify "speckle" colors and remap them to the surrounding dominant color. As the first step we partition an image into non-overlapping NxN windows. For each window, we compute a ***neighborhood color histogram matrix, Hmm,*** where ***m*** is the number of colors found in the region. Entry ***H[i,*** *j* *]*

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represents the number of times that pixel with color j appears in the *DxD* neighborhood of a pixel with color ***i,*** divided by the total number of pixels in the *DxD* neighborhoods of pixels having color ***i.*** Consequently, each row ***i*** in ***H,,*** represents the color histogram in the collection of neighborhoods of pixels having color ***i.*** Based on ***H,,*** matrix, speckle colors are detected and remapped in the following manner. For each color ***i,*** we examine row ***i*** and find the entry ***H[i,k]*** that has the maximum value. If ***k*** equals ***i,*** then ***i*** is determined to be a dominant color, and no remapping is done. Otherwise, ***i*** is determined to be a speckle color occurring in the neighborhood of the dominant color ***k.*** Hence, all pixels with the color ***i*** are remapped to the color ***k.*** The occasional blocking effect due to windowing does not cause serious problem in this case, since we compare images by color composition and ignore texture and edge features. Fig. **1** illustrates the feature extraction: 2(a) is the original image, 2(b) is the image after color quantization, and 2(c) shows the result after extraction of dominant colors and remapping.

4. Optimal Color Composition Distance

We first define a color component of an image as a pair ***CCi (Ii*** ,Pi) , where ***I;*** is the codebook index and ***Pi*** is the area percentage occupied by that color. A color component CC; is considered to be dominant if ***Ii;*** represents perceptually relevant color. Hence, the color composition of an image is represented by the set of ***dominant color components*** (DCC) found in the image. Based on human perception, for two images to be considered similar in terms of color composition, two conditions need to be satisfied. First, the colors of dominant color components of the two images need to be similar. Second, the color components with similar colors need to have similar area percentage. To overcome these problems we define a optimal color composition distance metric (OCCD). It measures the difference between two images in terms of color components based on the optimal mapping between the two corresponding sets of color components. First, the set of color components of each image is quantized into a set of *n* color units, each with the same area percentage p, where ***n*p=*** 100. We call this set the quantized color component set. Different color units in this quantized set may have the same color, and the number of color units labeled with a particular color ***1;*** is proportional to the corresponding area percentage ***Pi.*** Since every unit now has the same area percentage, it suffices to label each by the color index along. Thus the color composition of an image is now represented as a set of *n* labeled units. Let us consider images A and B, with the quantized color component sets $\{CA / U_A^1\ U_A^2,\ldots\ U_A^n\}$ and $\{CB / U_B^1\ U_B^2,\ldots\ U_B^n\}$ Let $I(U_x^K)$, $x = \{A, B\}$, $k = 1,\ldots, n$ denotes the color index of the unit U_x^K and let $\{M_{AB}, /m : C_A \text{-----} C_B\}$ be the set of one-to-one mapping functions from set C_A to set C_B. Each mapping function defines a mapping distance between the two sets:

$$MD(C_A,C_B)=\sum_{i=1}^{N} W(I(U_A^i),I(m_{AB}(U_A^i))),$$

where ***W(i,*** j) is the distance between color i and color j in a given color codebook. Our goal is to find the optimal mapping function, denoted m_{AB}, which minimizes $MD(C_A, C_B)$. The distance between the images **A** and ***B*** is then de-fixed to be the minimal mapping distance, denoted by $MD(C_A, C_B)$ The above optimization problem can be formulated as the minimum cost graph matching problem. Given an undirected graph defined by a set of nodes and edges associated with costs, the minimum cost graph matching problem is the problem of finding the set of disjoint edges with the minimum total cost. The complexity of the solution for a general bipartite graph is ***0(n3),*** where *n* is the number of nodes in the graph Given two images ***A*** and ***B*** with quantized color component sets C_A and C_B we create a graph G_{AB}. The graph contains ***2n*** nodes, one for each color unit in C_A or C_B, and ***n2*** edges, one between each node in C_A and each node in C_B. The cost for an edge is defined to be the distance between the corresponding colors. The resulting m h is undirected, bipartite graph. Clearly, $MD(C_A,C_B)$ is obtained by solving the minimum cost graph matching problem for ***GAB***

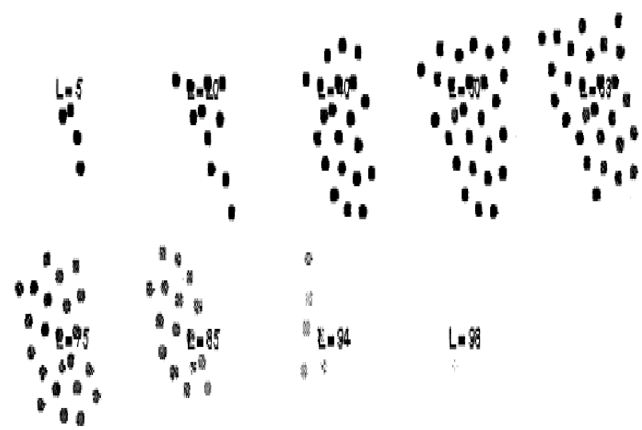

Fig. 1: Example of the color codebook with 139 colors.

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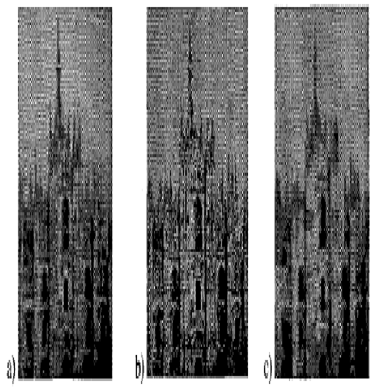

Fig. 2: Color quantization and spatial processing: a) original image, b) color quantized image and c) image after color remapping

In the current implementation of the method, the parameters *n* and ***p*** are chosen to match the human perception. Experiments on the images from our databases have shown that, with the current codebook, colors that occupy less than ***5%*** of image are usually not perceived. Also, previously reported subjective studies had demonstrated that humans are not able to perceive large number of colors within an image [4]. Hence, we found it sufficient to assign n = **20** and ***p*** = ***5,*** allowing maximum of **20** dominant color components.

5. Experimental Results

The new algorithm (OCCD) and compare it to some previously proposed methods. The comparison includes: 1) the simplest retrieval scheme based on the Euclidean distance

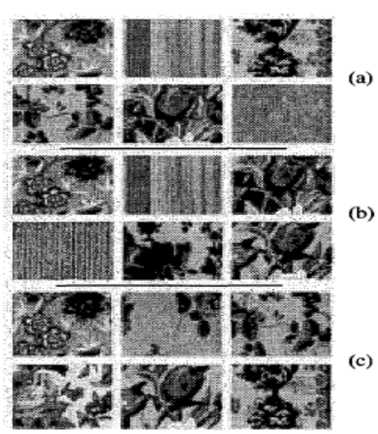

Fig. 3: Retrieval results using: a) traditional histogram, b) histogram intersection, and c) OCCD methods.

between the target and query histograms, **2)** Swain's HI method [l], **3)** MDM metric [2] and **4)** modified MDM metric [4]. For the comparison we used a database with 335 color patterns. This database was chosen because there is very little meaning attached to it **-** in that way we were able to test our scheme and compare it to other methods without too much bias of the semantic information Fig. 3 illustrates the performances of the simplest histogram method and HI compared to that of the OCCD. All results are displayed with the query image at the upper-left corner, and the five retrieved images arranged from left to right and top to bottom in order of decreasing similarity. In this example, both histogram based methods fail to retrieve some of the very similar images, since they ignore close colors that happen to fall into different quantization bins. OCCD succeeds to retrieve these images by allowing flexibility. To definitively compare these methods we carried out a subjective experiment. Fifteen representative patterns were chosen from the database as query images. For each query image, four different retrieval results were generated using the HI, MDM, modified MDM and OCCD method, respectively. Each query result contained the top five matching images retrieved from our database, displayed in the same manner as the examples in Figs. 3 and 4. For most images the evaluation results were consistent among different subjects. Ten of the fifteen images yielded majority votes (e.g., >***6)*** for a single scheme as the best, indicating that the corresponding rankings were reasonably consistent. The remaining five images have been discarded since the rankings were too scattered to be interpreted reliably. Of the ten query images with consistent rankings, the results produced by OCCD method had majority votes a**s** the best method for eight images, and the results produced by histogram intersection were voted best for two images. The average ranks for each scheme computed from these ten query images were: 2.3, 2.8, 3.3 and 1.6 for HI, MDM modified MDM and OCCD, respectively. These results demonstrate that the proposed method indeed best matches human perception.

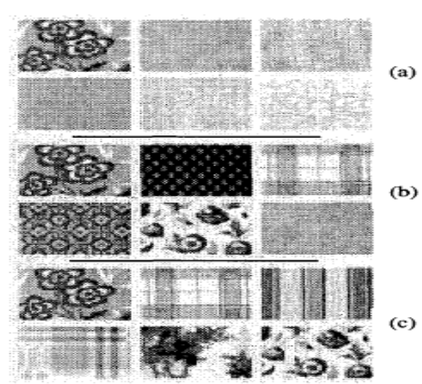

Fig. 4: Retrieval results using: a) MDM, b) modified MDM, and c) OCCD method.

6. Conclusion

For the comparison we used a database with 335 color patterns. This database was chosen because there is very little meaning attached to it For most images the evaluation results were consistent among different subjects. Ten of the fifteen images yielded majority votes (e.g., *>6)* for a single scheme as the best, indicating that the corresponding rankings were reasonably consistent

7. References

[l] J. Huang et al**.,** "Combining supervised learning with color correlograms for content-based image retrieval," in *Proc. ACM Conference on Multimedia***,** p. 325, ACM, 1997.
[2] Y. Rui *et al.,* "A relevance feedback architecture for content based multimedia information retrieval systems," in *IEEE*
[3] Y. Ishikawa ***et*** al., "Mindreader: Querying databases through multiple examples," in *Proc. 24th VLDB Con$,* 1998.
[4] B. Bhanu ***et al.,*** "Learning feature relevance and similarity metrics in image databases," in ***IEEE CBAIVL,*** 1998.
[5] **N.** Cristianini and J. Shawe-Taylor, ***An Introduction to Support Vector Machines.*** Cambridge, UK: Cambridge University Press, 2000.
[**6**] B. C. Jones, ***Local Feature Saliency Maps for Persistent Relevance Feedback-Driven Content-Based Image Retrieval.*** Ph.D. dissertation, Vanderbilt Univ., 2001[l] M. Swain and D. Ballard, "Color indexing", ***Int. Journal*** of ***Computer Vision,*** vol. 7, no. 1, pp. 11-32, 1991.
[7] W. Y. Ma, **Y.** Deng and B. **S.** Manjunath, 'Tools for texturdcolor base search of images", **In *Proc.*** of ***SPIE,*** vol. 3016.1997.
[8] S. Pei and C. Cheng, "Color image processing by using binary quaternion moment-preserving thresholding technique", ***IEEE Trans. Image Proc.,*** vol. 8, no. 5, pp. 614-628, May 1999.
[9] A. Mojsilovic, J. Kovacevic, J. Hu, R. J. Safranek and K Ganapathy, "Matching and retrieval based on the vocabulary and grammar of color patterns", ***IEEE Trans. Image Proc.,*** vol. 9, no. 1, pp38-54, January 2000.
[10] B. Rogowitz, T. Frese, J. Smith, C. Bouman, and E. Kalin,"Perceptual image similarity experiments", ***Proc.*** of ***SPIE,*** 1997.
[11] A. Mojsilovic, and E. Soljanin, "Quantization of Color Spaces and Processing of Color Quantized Images by Fibonacci Lattices", ***IEEE Trans. on Image Processing,*** (submitted).