Parametric approach to the retrieval of lossy compressed color images

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ABSTRACT

The rapid development of the Internet in the early 1990s caused an explosive growth of publicly accessible multimedia resources. It created a new viewpoint on storage, distribution, and processing of enormous collections of images. Along with the development of the World Wide Web there is much effort dedicated to create a content-based image retrieval systems which are able to efficiently index, retrieve and manage large scale databases. In this paper we propose a color indexing method based on the Gaussian Mixture Model of color histograms. The model parameters serve as signatures enabling fast and efficient color image retrieval. In this paper we show that the proposed approach is robust to color image distortions introduced by lossy compression artifacts and therefore it is well suited for indexing and retrieval of Internet based collections of color images stored in lossy compression formats.

Keywords: Color image, Gaussian Mixture Model, color histogram, lossy compression, image retrieval

1. INTRODUCTION

The rapid developments in communication and information technologies lead to an exponentially growing number of images being captured, stored, and made available on the Internet. However, managing this vast amount of visual information remains a difficult task.\textsuperscript{1–3} A number of general-purpose image search systems have been proposed such as IBM QBIC,\textsuperscript{4} SIMPLicity,\textsuperscript{5} MIT Photobook,\textsuperscript{6} ALIPR\textsuperscript{7} and Blobworld\textsuperscript{8} to address this task.

The problem presented in this paper is as follows: given a query image, a system should retrieve all images whose color structure is similar to that of the query image independently on the applied lossy coding. Although color-based retrieval methods are generally effective, many techniques are storage-memory consuming. Therefore, we specify a model describing efficiently the color image content which can be stored as a set of parameters and used as an image signature.

In the proposed method we apply the Gaussian Mixture Model (GMM) as a descriptor of the image color distribution. Its main advantage is that it overcomes the problems connected with the high dimensionality of standard color histograms. Additionally, the proposed method based on the weighted two-dimensional Gaussians is robust to distortions introduced by compression techniques and therefore it can be used for the retrieval of images contained in the web-based databases, which very often store images in lossy formats, like GIF and JPEG.

2. COLOR IMAGE HISTOGRAM MODEL

In this work we operate in the normalized rgb space, which is independent on the color intensity $I$: $I_{ij} = R_{ij} + G_{ij} + B_{ij}$, $r_{ij} = R_{ij} / I_{ij}$, $g_{ij} = G_{ij} / I_{ij}$, $b_{ij} = B_{ij} / I_{ij}$, where $i, j$ denote image pixels coordinates.

Histogram $\Phi(x, y)$ in the $r - g$ chromaticity space is defined as $\Phi(x, y) = N^{-1} \{ r_{i,j} = x, g_{i,j} = y \}$, where $\Phi(x, y)$ denotes a specified bin of a two-dimensional histogram with $r$ - component equal to $x$ and $g$ - component equal to $y$, the symbol $\sharp$ denotes the number of elements in a bin and $N$ is the number of image pixels.

Image compression can significantly influence the properties of the $r - g$ histogram because of the distortions of color information introduced by lossy compression techniques.\textsuperscript{9} Figure 1 (left column) illustrates the urgent need for histogram correction, in order to diminish the negative influence of the compression process leading in consequence to a failure.

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Figure 1. The comparison of r-g histograms and their GMM models for a 24 bit original (a) and its lossy versions: GIF (b), JPEG25 (c) and JPEG10 (d). Each pair depicts 2D visualization of the r-g histogram of the image (left) and the corresponding surface plot of GMM, (right).

of the retrieval system (which will be presented in Fig. 4). To alleviate the problems connected with the distortions of the color histograms introduced by lossy compression, we propose to approximate the color histogram built in the r−g chromaticity space by the Gaussian Mixture Model, whose parameters are estimated via Expectation-Maximization (EM) algorithm.\textsuperscript{10–12}

For any iterated algorithm, such as EM, there arises the problem of deciding when the estimation process should be
terminated. The EM algorithm is known to converge to local maximum. In order to estimate the model complexity we have chosen a set of natural color images having various $r-g$ histogram structures and applied GIF and JPEG compression with varying quality levels (QL). The applied compression ratios for JPEG were 1:11 (QL=80), 1:21 (QL=50), 1:25 (QL=25) and 1:30 (QL=10). For the purpose of our technique, we posed a hypothesis, that there exists a minimal model structure which is sufficient to accurately reflect the distribution of the $r-g$ histogram.

Having built the Gaussian Mixture Model of the original and compressed image histograms, we compared it with the histogram of the original image. For that purpose we used several widely known distance measures, like $L_1$ distance ($L_1D$), $L_2$ distance ($L_2D$), Bhattacharyya Distance (BD), Peak Signal to Noise Ratio (PSNR) and computed the difference between the histogram of the evaluated image and the surface generated by the model of its histogram. The results of the experiments lead to the conclusion that about 75 iterations, (in some cases even 50) is fairly enough to reflect the histogram structure independently on the used compression scheme, (see Fig. 2a).

Choosing the proper number of model components is also crucial for the accuracy of the evaluated model and final efficiency of the image retrieval. Figure 2b) shows the dependence of the $L_1$ distance between the test image histogram and its approximation obtained using the GMM on the number of its components. Similar results were obtained for various images and histogram similarity measures. The performed experiments lead to the conclusion that it is reasonable to build models consisting of only 7 components.

![Figure 2 - Dependence of the $L_1$ distance between the histogram of the test image used in Fig. 1 and its GMM approximation on the number of iterations of the EM algorithm (a) and number of GMM components (b) for the original and compressed images.](image)

Figures 1 and 3 show the $r-g$ histogram and the visualizations of the obtained GMMs for original images and their compressed versions using 7 GMM components after 75 iterations of the EM algorithm. The comparison of the histograms of true color originals, compressed images and histograms approximated by the GMM, reveals a very good fitting to the original histogram due to the GMM ability to smooth histogram distortions caused by lossy compression.

As it was mentioned before, lossy compression introduces artifacts or strongly degrades the $r-g$ histogram and therefore the color palette of an image is significantly influenced (JPEG compression method) or decreased (GIF compression method). The aim of the approach proposed in this paper is to compensate the loss of color information contained in an image. Figure 4 illustrates the importance of the compensation of the $r-g$ histogram discontinuities caused by lossy compression, when GIF method was applied, in order to counteract failure of retrieval process, resulting in large number of false positives. When no refining method is applied to the $r-g$ histogram, standard methods, used for choosing most similar images in a database, operate on corrupted information and therefore their results might be inaccurate, as can be observed in the example shown in Figure 4. Although the number of colors present in an image is significantly decreased during GIF compression process, lost chromaticity information can be restored by the application of the proposed approach and in consequence satisfactory retrieval results can be obtained.

Figure 5 illustrates the robustness of GMM approximation of the $r-g$ histogram. We applied the proposed approach to a database consisting of 1303 color images of the collection of WebMuseum. As a query served four paintings of Paul
Figure 3. Illustration of the GMM based histogram approximation: a) test image from the database of Wang, b) its r−g histogram and the visualizations of the histogram estimation utilizing the GMM, (c-d).

Cézanne and Vincent van Gogh. The comparison of the results, evaluated for the the GMM based approximation of originals and their compressed versions, reveals good performance when standard histogram distances (such as $L_1$) or parametric ($EMD$ described in the next Section) measures are applied. The color range of the query is preserved by candidate images in contrary to those retrieved on the basis of the r-g histogram without any applied correction. Similar results, shown in Figure 6, were obtained for the database of Wang.

3. RETRIEVAL EFFICIENCY

The retrieval technique based on Gaussian Mixture Model described it this paper was tested on the database of Wang, consisting of 1000 color images, divided into 10 distinct classes (i.e. ‘Buses’, ‘Beach’, ‘Horses’, ‘Flowers’) of 100 images.

In order to test the methodology of the retrieval presented in this paper, extensive experiments were conducted. At the beginning, the model of a mixture of normal densities was built using the EM algorithm. Having model’s parameters computed, a comparison between the histogram of the query image and of those belonging to the image database was performed and the images were ordered according to the values of $L_1$, $L_2$, BD and PSNR distance measures. Additionally we used Mean Magnitude Error (MME), Histogram Intersection (HI) and the Earth Mover’s Distance (EMD).

The Earth Mover Distance is based on the assumption that one of the histograms reflects "hills" and the second represents "holes" in the ground of a histogram. The measured distance is defined as a minimum amount of work needed to transform one histogram into the other using a “soil” of the first histogram. As this method operates on signatures and their weights, using the approach based on the Gaussian Mixture Models we assigned as signature values the mean of each component and for the signature weight the weighting coefficient of each Gaussian in the model.

In order to evaluate the efficiency of the proposed indexing method we validated its accuracy through Recall and Precision. Recall is the fraction of relevant images in the database that have been retrieved in response to a query, whereas Precision is defined as the fraction of the retrieved images that are relevant to the query image.
As can be seen in the Precision vs. Recall plots, (Figs. 7a and 7b) the $L_1$, HI and MME (as they are linearly dependent), BD and EMD measure of histogram dissimilarity perform quite well. For the evaluation of the retrieval results obtained using the GMM we have chosen the $L_1$ distance. As can be observed the efficiency of retrieval is not affected by the compression artifacts introduced to the images from the database and the usefulness of the GMM approximation for the histogram based image retrieval is the main contribution of the paper.

The overall behavior of our retrieval method can be specified by average recall($\hat{\varrho}$) and average precision($\hat{\rho}$). Average recall is defined as a sum of the ranks of correct answers $O_i$ over each query divided by the number of queries $q$: $\hat{\varrho} = \frac{1}{q} \sum_{i=1}^{q} \frac{\text{rank}(O_i)}{\xi}$. And average precision is defined as a sum of $\frac{1}{\text{rank}(A_i)}$ divided by number of queries $q$: $\hat{\rho} = \frac{1}{q} \sum_{i=1}^{q} \frac{1}{\text{rank}(A_i)}$. Highly ranked images contribute more to the $\hat{\varrho}$ measure. As a consequence, the smaller $\hat{\varrho}$ measure the better. There is also an opposite relation for $\hat{\rho}$, if a method has a better performance then $\hat{\rho}$ measure is higher.

In order to describe the retrieval efficiency we also applied the Recall vs. Scope analysis. Assuming that for each query image $O_i$ (which is called multiple query) there are multiple answers $A^1_i, \ldots, A^\xi_i$, the recall measure is defined for a scope $s$ as: $\Upsilon_i(s) = \frac{\xi}{\xi} \sum_{j=1}^{\xi} \frac{\text{rank}(A_j^i)}{\xi}$. The average recall measure $\hat{\Upsilon}$ is evaluated taking the average over all query images in the database.

The results of the experiments performed on a collection of 50 images from the Wang database consisting of pictures with unique and multiple answers are shown in Tab. 1. The results obtained for that set show that the $L_1$ and BD distances yield good retrieval results. The results obtained using the EMD are quite impressive as the EMD between the histograms obtained using the GMM can be calculated without the generation of the histogram surfaces and its application increases significantly the computational speed of the retrieval process.

<table>
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<th>distance measure</th>
<th>$L_1D$</th>
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<th>BD</th>
<th>EMD</th>
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<td>0.85</td>
<td>0.48</td>
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</tbody>
</table>

Table 1. Performance of various histogram distance measures for a collection of 50 images with 6 multiple query answers.
Figure 5. Retrieval results for the original test images of Cézanne and van Gogh chosen from the collection of 1303 color paintings of WebMuseum (http://www.ibiblio.org/wm/) and their lossy compressed versions. The retrieval was evaluated using the $L_1$, and $EMD$ distances for: GMM of originals, GMM of lossy compressed versions (using GIF method) of originals and on the basis of r-g histogram of lossy compressed originals (using GIF method) and $L_1$ distance. For each query (left) four highest ranked images are shown. Retrieval based on the proposed approach successfully compensate the r-g histogram discontinuities caused by lossy compression. Note the poor results delivered by comparing directly the histograms of the images in the GIF format.

(Figs. 7a and 7b) reveal that the performance rate for standard bin by bin similarity measures (such as $L_1$ metric) and $EMD$ measure can be considered as similar. It is an important conclusion because $EMD$ provides more efficient scheme of evaluating image similarities as this method does not require the bin by bin comparison of the whole histogram and because image indexing is done by assigning only its GMM parameters. We tested also retrieval effectiveness for lossy compressed versions of originals, for GIF and JPEG$_{25}$ compression (Figs. 8a and 8b) using $L_1$ distance measure and the $EMD$ method. It can be noticed that there is no significant difference in the retrieval power for the various applied compression operations and the results are not dependent on the type of applied similarity measures.

With reference to retrieval results obtained on the basis of the r-g histograms evaluated on lossy compressed versions of originals (GIF method) shown in Figures 4, 5 and 6 we tested the retrieval effectiveness based on the r-g histogram and its GMM approximation (illustrated by Figs. 8c and 8d). As similarity measure we used $L_1$, $L_2$ and BD distances for histogram based retrieval and $EMD$ measure for histogram approximation. The Precision vs. Recall plots confirm previously presented results. The retrieval process based on GMM approximation of the r-g histogram significantly outperforms those performed for histogram with no refining methods applied.

Due to the inherent features of the normalized rgb space it is obvious that in the of $EMD$ similarity measure the distance between colors is not always equal to the perceptual sensation perceived by a human observer. In order to alleviate this problem other color spaces can be applied.
Figure 6. Retrieval results obtained with the new method for the original test images chosen from the database of Wang and their lossy compressed versions. The retrieval, based on the r-g histogram of lossy compressed version of originals (GIF) and the GMM based approximations of its compressed versions (GIF and JPEG25) was evaluated using the $L_1$, $L_2$, BD and EMD distances as denoted. For each query (left) four highest ranked images are shown. If no histogram refining method is used the retrieval process fails producing large number of false positives due to corrupted information provided by the r-g histogram.
Figure 7. Efficiency of the retrieval scheme expressed by Precision vs. Recall plots evaluated on the original dataset - 'Africans'(a) and 'Horses'(b). The plots present the retrieval efficiency obtained using the GMM of the r-g histograms of original images, using various distance measures.

Figure 8. Efficiency of the retrieval scheme expressed by Precision vs. Recall plots evaluated on the original dataset - 'Africans' (a, b), 'Horses' (c) and 'Food' (d) and on its lossy compressed versions. The plots obtained using the $L_1$ distance (a) and $EMD$ (b) show that retrieval power is similar independently of applied compression method. The plots c) and d) illustrate significant loss of retrieval capability of method when the r-g histogram (lossy compressed version of originals obtained using GIF method) serves as a basis of retrieval (for $L_1$, $L_2$, $BD$ similarity measures) in comparison to the GMM approximation for $EMD$ similarity measure, (black line).
4. CONCLUSIONS AND FUTURE WORK

In this paper we presented a novel image indexing method that enhances the capabilities of a retrieval systems utilizing the color histograms. Our technique extracts the image color structure in the form of parameters of a Gaussian Mixture Model. The experiments revealed that 7 components of the GMM and about 75 iterations of the EM algorithm assure satisfactory retrieval results. The main advantage of the proposed method is its robustness to artifacts introduced by lossy compression. The performed tests show that the proposed framework is a useful and robust tool that can be used for the retrieval of images in web based databases.

In the future we want to apply other color spaces and test the proposed technique on other databases. The important part of further research efforts will be focused on the comparison of our technique with other histogram based solutions. Additionally we intend to incorporate some nonparametric estimation techniques for the restoration of color image histograms distorted by compression artifacts.

On the basis of presented results we conclude that the proposed approach provides an efficient compensation of the distortions of color information caused by lossy compression.

REFERENCES