IMAGE RETRIEVAL USING KRAWTCHOUK CHROMATICITY DISTRIBUTION MOMENTS

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Keywords: Image retrieval, chromaticity diagram, Krawtchouk moments, L*a*b* color space.

Abstract: In this paper a set of Krawtchouk Chromaticity Distribution Moments (KCDMs) for the effective representation of image color content is introduced. The proposed method describes chromaticity through a set of KCDMs applied on the associated chromaticity distribution function in the L*a*b* color space. The computational requirements of this approach are relatively small, compared to other methods addressing the issue of image retrieval using color features. This has a direct impact on the time required to index an image database. Furthermore, due to the short-length of KCDMs feature vector, there is a straight reduction on the time needed to retrieve the whole database. Comparing to previous relative works, KCDMs provide a more accurate representation of the L*a*b* chromaticity distribution functions, since no numerical approximation is involved in deriving the moments. Furthermore, unlike other orthogonal moments, Krawtchouk moments can be employed to extract local features of a chromaticity diagram. This property makes them more analytical near the centre of mass of the chromaticity distribution. The theoretical framework is validated by experiments which prove the superior performance of KCDMs above other methods.

1 INTRODUCTION

The color content of an image is perhaps the most dominant and distinctive visual feature. Several methods and techniques have been presented on using the color information for image retrieval, including the original work by Swain and Ballard (Swain and Ballard, 1991), Photobook (Pentland et al., 1996), IBM's QBIC Project (Niblack et al., 1993), and Han *et al.*'s work on fuzzy color histograms (Han and Ma, 2002). A color histogram captures the global color distribution in an image. Due to the fact that histograms are invariant to translation and rotation of the image, they comprise a valuable method for image color characterization.

Moment functions, due to their ability to represent global features, have found extensive applications in the field of image analysis. The chromaticity moments descriptors proposed in (Paschos et al., 2003) present a compact representation of the image color content. In Paschos *et al.*'s work on chromaticity moments (Paschos et al., 2003), a set of regular moments of both the trace and distribution of the chromaticity space are used as features for image indexing. The proposed method was tested on a dataset, mainly consisting of textured images. While

the method achieved very high retrieval rates for the specific dataset, when it was tested in the COREL photograph database, which contains images of general interest, the performance was significantly degraded. Yap *et al.* (Yap and Paramesran, 2006) proposed an effective scheme for content-based image retrieval based on chromaticity distribution moments (LCDMs), considering only the chromaticity distribution.

This research is motivated by the two works on chromaticity moments mentioned above, together with Yap *et al.*'s work on Krawtchouk moments (Yap et al., 2003), where a new set of orthogonal moments based on the discrete classical Krawtchouk polynomials is introduced. In this work, the notion of chromaticity moments is extended by proposing the use of Krawtchouk moments, instead of regular or Legendre moments. The orthogonality of Krawtchouk moments ensures minimal information redundancy and since the computation of chromaticity moments demands quantization of the chromaticity space, the use of discrete orthogonal moments remedies the discretization error problem associated with regular or Legendre moments. Instead of using the CIE XYZ and opponent color spaces as in (Paschos et al., 2003) and (Yap and Paramesran, 2006) respectively, the use of

the CIE L*a*b* color space is recommended, since it models more accurately human visual perception. Additionally, Krawtchouk moments can be employed to extract local features from any region of interest in the chromaticity space. It is shown that this property is crucial in the feature extraction of the distribution functions in the L*a*b* color space, since most of the information is concentrated in a certain area of the chromaticity diagram.

All of the above are thoroughly discussed and analysed in Section 2, where the method is presented. In Section 3 experimental results validate the fact that the method is both efficient and fast due to the small-feature vector length needed to characterize the chromaticity distribution function.

2 PROPOSED METHOD

In this section a brief theory on Krawtchouk moments (Yap et al., 2003) and their associated Krawtchouk chromaticity distribution moments is provided.

2.1 Krawtchouk Moments

The n-th order Krawtchouk polynomial is defined as:

$$K_n(x; p, N) = \sum_{k=0}^{N} a_{k,n,p} x^k = {}_2F_1\left(-n, -x; -N; \frac{1}{p}\right)$$

(1)

where $x, n = 0, 1, 2, \ldots, N$, $N > 0$, $p \in (0, 1)$ and ${}_2F_1$ is the hypergeometric function.

The set of $N+1$ Krawtchouk polynomials $\{K_n(x; p, N)\}$ forms a complete set of discrete basis functions with weight function

$$w(x; p, N) = \binom{N}{x} p^x (1 - p)^{(N-x)}$$

(2)

and satisfies the orthogonality condition

$$\sum_{x=0}^{N} w(x; p, N) K_n(x; p, N) K_m(x; p, N) = \rho(n; p, N) \delta_{nm}$$

(3)

where $n, m = 0, 1, 2, \ldots, N$ and

$$\rho(n; p, N) = (-1)^n \left(\frac{1-p}{p}\right)^n \frac{n!}{(-N)_n}$$

(4)

The set of weighted Krawtchouk polynomials $\{\overline{K}_n(x; p, N)\}$ is defined by

$$\overline{K}_n(x; p, N) = K_n(x; p, N) \sqrt{\frac{w(x; p, N)}{\rho(n; p, N)}}$$

(5)

The Krawtchouk moment of order $(n+m)$ for a given intensity function $f(x,y)$ is defined as

$$Q_{nm} = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \overline{K}_n(x; p_1, N-1) \overline{K}_m(y; p_2, M-1) f(x,y)$$

(6)

In the specific application $f(x,y)$ describes the chromaticity distribution function. The parameters N and M are defined by the chromaticity diagram's co-ordinate space. Observe from (6) that the appropriate selection of p_1 and p_2 enables local features at different positions of the chromaticity diagram to be extracted by the lower order Krawtchouk moments.

2.2 Krawtchouk Chromaticity Distribution Moments In the L*a*b* Color Space

The CIE L*a*b* (CIELAB) is the most complete color model typically used to describe all the colors visible to the human eye. The three basic coordinates represent the lightness of the color (L*), its position between red and green (a*) and its position between yellow and blue (b*).

Since the two-dimensional chromaticities (a,b) are sufficient to describe the color content of an image, the distribution of the color space can be defined as

$$D(a,b) = k$$

(7)

where k=number of pixels with chromaticity value (a,b). This function can be characterized without any numerical approximation by a set of Krawtchouk moments up to order $(n+m)$, defined respectively as:

$$Q_{nm} = \sum_{a=0}^{N-1} \sum_{b=0}^{M-1} \overline{K}_n(a; p_1, N-1) \overline{K}_m(b; p_2, M-1) D(a,b)$$

(8)

where $n, m = 0, 1, 2, \ldots$, and N, M are the dimensions of L*a*b* color space.

2.3 Computational Aspects

The computation of the n-th order weighted Krawtchouk polynomial directly from (5) is unpractical in terms of computational complexity. In addition, since not only x and y but also p_1 and p_2 are varying parametres in the specific application, the computation and storage of the polynomial's values is prohibitive in terms of the memory space needed. This becomes a significant disadvantage towards Legendre polynomials, since the number of computations for obtaining the polynomial value of degree n can be reduced to n additions and n multiplications.

The relationship associating Krawtchouk moments with geometric ones can be used in order to

face the aforementioned problem. The Krawtchouk moments of $f(x,y)$ can be written in terms of geometric moments as:

$$Q_{nm} = [\rho(n)\rho(m)]^{-\frac{1}{2}} \sum_{i=0}^{n} \sum_{j=0}^{m} a_{i,n,p_1} a_{j,m,p_2} M_{ij} \quad (9)$$

where $\{a_{k,n,p}\}$ are coefficients determined by (1). Therefore Q_{nm} is a linear combination of geometric moments M_{ij} up to order $i = n$ and $j = m$.

3 EXPERIMENTAL STUDY

In this section, experimental results are provided in order to confirm the allegation that Krawtchouk moments are more effective for the characterization of chromaticity diagramms in the L*a*b* color space.

3.1 Image Database and Accuracy Measures

The image database used for the experimental study is actually a portion of the COREL database and consists of 1000 color images, stored in JPEG format with size 384 x 256 or 256 x 384 pixels. The images are divided into ten categories, each consisting of 100 photographs. The set of LCDMs, CMs and KCDMs is calculated for each image, resulting in a feature vector $\mathbf{V} \in \Re$, with a specified length L. When a query image is presented, the feature vector is compared to that of all the images in the database. For each query image I_{query}, G images $I_{retrieved}^{k}$, $k = 1, 2, \ldots, G$ with the smallest distances are retrieved. A minimum distance classification is performed by using the Euclidean distance metric. If R is the number of correctly matched images, N_c is the number of images in the category and N_t is the total number of images in the database, then the recall rate can be defined as:

$$r(I_{query}) = \frac{R}{N_c} \quad (10)$$

and the precision as

$$p(I_{query}) = \frac{R}{G} \quad (11)$$

It is obvious that an accurate retrieval result implies high values in recall and precision.

The safest way to evaluate the accuracy of retrieval algorithms is the precision versus recall curve. The precision versus recall curve is usually based on 11 standard recall levels which are 0%, 10%, 20%,..., 100%. Retrieval algorithms are evaluated by simulation for a satisfying number of queries. In this case, for each query a distinct precision versus recall curve

is generated. To evaluate the retrieval performance of an algorithm over all test queries, the precision figures at each recall level are averaged as follows

$$\overline{P}(r) = \sum_{i=1}^{N} \frac{P_i(r)}{N_q} \quad (12)$$

where $\overline{P}(r)$ is the average precision at recall rate r, N_q is the number of queries used, and $P_i(r)$ is the precision at recall level r for the i-*th* query.

3.2 KDCMS Performance

In this subsection comparisons are made between the proposed method, CMs and LCDMs. Both CMs and LCDMs were modified to work in the L*a*b* color space.

An example of the retrieval results at a fixed recall level of 10% for different values of D is presented in figure (1), which shows a graph of the results with respect to the maximum order D of moments used. The case of $r = 10\%$ was chosen, since it is the most appropriate and commonly used level for web search. It can be seen that the average precision rate of KCDMs is higher than that of LCDMs or CMs for all the possible values of D. The majority of mistaken retrievals is due to the close similarity of color content between different categories.
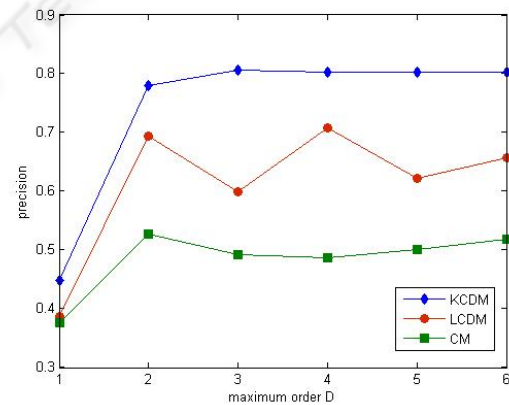

Figure 1: Comparison of retrieval precision of KCDMs, LCDMs and CMs with respect to maximum order D. (at a fixed recall rate= 10%).

In the previous section it was mentioned that the most secure way of evaluating retrieval algorithms is the precision versus recall diagrams. Figures (2) and (3) present the average precision versus recall curves for the cases of KCDMs, LCDMs and CMs. The maximum order of moments used in order to characterize the color content of the images is $D = 2$ and $D = 3$ in

figures (2) and (3) respectively. It can be observed that in both cases KCDMs outperforms the other methods. KCDMs provide higher precision levels than the other two methods at all possible recall levels, particularly for the case of $D = 3$.
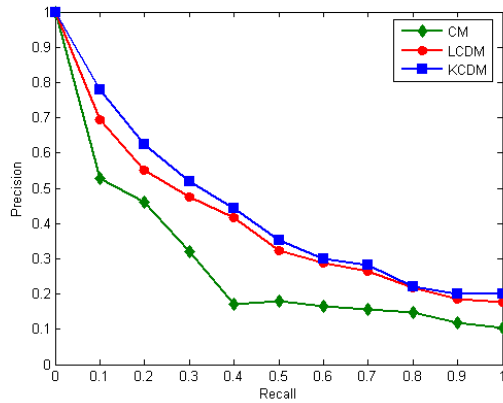

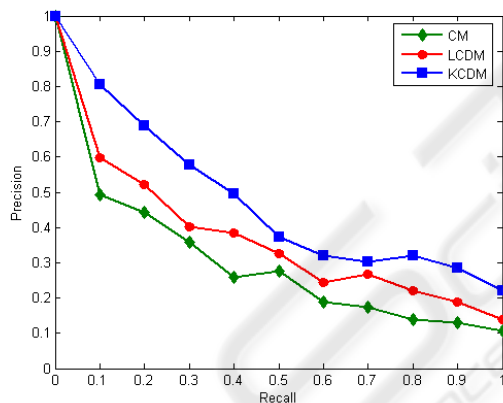Figure 2: Precision versus Recall for D=2.

Figure 3: Precision versus Recall for D=3.

4 CONCLUSIONS

In this paper Krawtchouk Chromaticity Distribution Moments are introduced for the effective representation of color content for use in image retrieval. KCDMs provide a powerful set of color descriptors with low computational complexity. They have proved to be more efficient for the description of chromaticity diagrams in the L*a*b* color space, since Krawtchouk polynomials are polynomials of a discrete variable and hence no numerical approximation is involved in deriving the moments. It is also

shown that Krawtchouk moments can be more analytical near the centre of mass of the chromaticity distribution, unlike regular or Legendre moments which capture global features. This can be achieved by varying the probability of the associated binomial distribution. Moreover, since the KCDMs feature is compact, they can easily be incorporated into more complex CBIR systems to work together with other features, such as shape and texture descriptors.

Experimental results proved the effectiveness of KCDMs as chromaticity distribution descriptors. For as little as ten KCDMs terms a retrieval precision of 0,8064 at a fixed recall level of 10% can be obtained. The comparative study verified via the precision versus recall diagrams, proved that KCDMs perform significantly better than other proposed methods. Finally, due to the short-length of the KCDMs feature vector, a small number of computational operations are needed for the retrieval process. This property is crucial, considering the large size image databases which exist nowadays.

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