Uncertainty Based Sampling Approach for Relevence Feedback in Content Based Image Retrieval

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Abstract- Interest in the digital images has increased enormously over the last few years, but the process of locating a desired image in such a large and varied image collection becomes very difficult. Traditionally text in different languages is used for efficient retrieval of images; it has several drawbacks such as language constraint and subjectivity of human perception. Content-based image retrieval is a technique which uses visual contents such as color, texture and shape to search images from large image databases according to user's interest. Color is the most commonly used feature for content based image retrieval. The major drawback of usual color histogram based method (binning method) is that, it does not take image color distribution into consideration and inflexibly partition the underlying color spaces into a fixed number of bins. In this paper we propose a moment-preserving technique based on binary quaternion space for feature extraction. It aims to extract color features according to the image color distribution that significantly reduces the distortion incurred in the feature extraction process. It is observed that minimizing the distortion incurred in the feature extraction process of proposed color distribution based approach can improve the accuracy of retrieval. Our experimental results show that the proposed extraction methods can enhance the average retrieval precision rate by a factor of 25% over that of a traditional color histogram based feature extraction method. It is also observed that, this technique effectively reduces the average retrieval time. Further, in this paper we propose a novel probabilistic approach for relevance feedback based on the theory of uncertainty based sampling. It significantly enhances the retrieval precision and simplified the task of query refinement and improves usability of a system.

Keywords – CBIR, Relevance feedback, feature extraction, QMP

I. INTRODUCTION

Content-based image retrieval (CBIR) is a technique which uses visual contents of an image to search the desired images from large scale image databases according to user's interests. The visual content of an image is extracted and described by multidimensional feature vectors. Users provide example image to the retrieval system, the system then changes these examples into its internal representation of feature vectors. The similarity between the feature vectors of the query example and those of the images in the database are then calculated and retrieval is performed. The years 1994-2000 is considered as the initial phase of research and development on image retrieval by content Many techniques and approaches were proposed for fast and efficient retrieval of images. Color is the most commonly used feature for content based image retrieval. QBIC [20], Pictoseek [20] are some of the most popular systems which uses color histograms as one of the feature for feature extraction and image retrieval. In usual color histogram based method, color features are extracted to represent image color content and represented as color histograms. The histogram based methods inflexibly partition the underlying color spaces into a fixed number of bins, each of which corresponds to a bin in the histogram. The extraction process place pixels into their closest color bin. The weight of a bin in turn denotes the percentage of pixels in an image belonging to that bin. Therefore, a color histogram can be thought of as a quantized color distribution of an image. The major drawback of this method is that it does not take the image color distribution into consideration. While deciding the number of bins in a color histogram, it uses the same set of representative colors for every image. Therefore, color histogram based method provides little adaptability to the color content of an image, and color features may get heavily distorted if a small number of bins are used. To overcome this problem, we proposed a new feature extraction technique, Quaternion moment preserving [QMP], which is based on fundamental quaternion space. It takes image color distribution into consideration during feature extraction process and reduces the distortion which may occur during this process, by preserving a moments up to third moment.

Human computer interaction plays a very important role to improve usability of a CBIR system. Now day's human interactive systems have attracted a lot of research interest in recent years, especially for content based image retrieval systems. Contrary to the early systems, which focused on fully automatic strategies, recent approaches have introduced human-computer interaction [20].In content-based image retrieval (CBIR), the search may be initiated using a query as an example. The top rank similar images are then presented to the user. Then, the interactive process allows the user to refine his request as much as necessary in a relevance feedback loop. Many kinds of interaction between the user and the system have been proposed [22].

In this paper, we focus on statistical learning techniques using uncertainty based sampling for interactive image retrieval. In this approach, the retrieval task is considered as a classification problem. It aims to find the uncertain classes of images which can be selected to refine the query .To enhance the retrieval precision in successive iteration of retrieval; we propose a scheme for boundary correction, which corrects the noisy classification boundary in every iteration of classification.

The rest of this paper is organized as follows. The new color extraction method is proposed in Section II. The proposed relevance feedback approach is proposed in Section III. Section IV contains the experimental results. We conclude this paper in Section V.

II. COLOR FEATURE EXTRATION USING QMP

In this section, we will formulate the problem of color feature extraction and describes the QMP thresholding technique. Let *I* denote an image and ***a*** be a pixel in it. The color feature extraction can be defined as a function $F: I \rightarrow Q$ where Q is a set of representative colors. F maps a pixel a to representative color. Color histogram represents the percentage of pixels in *I* which are mapped into *Q*. If we treat the value of pixel in *I* as a random vector, H represents the quantized probability distribution of *I.* such an extraction methods fix *Q* for all images without considering their color distribution.

If we consider the value of a pixel in an image as a random vector, the color distribution of this image will be equivalent to the probability distribution of this random vector [17].With this view, we applied the quaternion-moment-preserving technique [QMP] which is proposed in [18] to the problem of feature extraction. The main theme of this paper is to find a proper function *F* for each image according to their color distribution which is derived with a moment preserving scheme in quaternion space.

A. Quaternion space

Each quaternion number can be denoted as

$$q=q_0+q_1.i+q_2.j+q_3.k \qquad (1)$$

Where i, *j* and k are the operation units of quaternion number. In our problem, color values *R, G, B* can be treated as a quaternion with $q_1 = R$, $q_2=G$, $q_3=B$ and $q_0=0$. Based on the definition of the quaternion, the first three orders of quaternion moments are defined as follows:

$$m_1=E(q_0)+E(q_1).i+E(q_2).j+E(q_3).k \qquad (2)$$

$$m_2=E(q_0^2+q_1^2+q_2^2+q_3^2) \qquad (3)$$

$$\begin{aligned} m_3=&E(q_0^3+q_0q_1^2+q_0q_2^2+q_0q_3^2) \\ &+E(q_1q_0^2+q_1^3+q_1q_2^2+q_1q_3^2)*i \\ &+E(q_2q_0^2+q_2q_1^2+q_2^3+q_2q_3^2)*j \\ &+E(q_3q_0^2+q_3q_1^2+q_3q_2^2+q_3^3)*k \end{aligned} \qquad (4)$$

Where *E* represents the sample mean.

The problem of QMP thresholding in a quaternion valued data set is to select a hyperplane *A* as a threshold, such that if those below-threshold data points and those above threshold data points are replaced by the representative Z_0 and Z_1 respectively, and the first three quaternion moments are preserved in the resultant two-level data set.

$$Zo=Z_{00}+Z_{01}*i+Z_{02}*j+Z_{03}*k \qquad (5)$$

$$Z1=Z_{10}+Z_{11}*i+Z_{12}*j+Z_{13}*k \qquad (6)$$

The authors in [18] derived the closed form solution of Z_0 and Z_1 and assumed that the first moment is 0.

B. QMP feature extraction technique

```
J ← {s};//J denotes the set of pixels clusters.
H ← Ø;//Ø denotes an empty set
do{
    V ←{si|si∈ J and si is not unsplitable};
        if(V = Ø) then break;
      sv←arg max_{si ∈ V} Var(si)
      (sa,sb)←BQMP(sv);
        If(sa=Ø or sb=Ø)then mark sv as unsplitable;
            else J ← J-sv∪ {sa,sd};
    }while (not terminate(MT,τ,|J|,Var(sv)));
    For each si∈ J {
        r̂i← Rep(si); wi← |si|/|s|;
    H← H ∪ hr1;
    }
    Return H;
```

The QMP thresholding technique extracts color features in two ways. In fixed cluster technique (FC), we will extract fixed number of pixel clusters from an image. In Variable cluster technique (VC), we will extract a variable number of pixel clusters from an image, and the number of pixel clusters extracted depends on the intra-cluster variances. The procedure of fixed cluster (FC) and variable cluster (VC) can be summarized in the following three steps:

1) Input a data set.
2) Find a sub cluster which can be split and whose variance is maximum and then use the QMP thresholding technique to split the sub cluster into two new sub clusters. If further splitting is not possible, mark it.
3) If there exist a cluster, which can be split:
(a) In the case of FC, repeat Step 2 until exactly N clusters are found;
(b) In the case of VC, repeat Step 2 until the variance in each sub cluster is below a variance threshold.

Splitting process of FC and VC is similar to the splitting process of a binary tree. Splitting process of clusters resembles with a splitting process of a leaf node in a binary tree. The root corresponds to the initial multiset of all pixels. For each non leaf node, its left child stands for the split sub cluster whose representative is Z_0 and its right child stands for the other sub cluster whose representative Z_1 .FC and VC differ from each other in their conditions to terminate the extraction process. FC completes this process when a definite number of pixel clusters have been extracted. VC completes this process when the number of pixel clusters extracted so far is adequate to represent the image. We define such a adequacy by the condition that the variance in each pixel cluster is below a variance threshold T_v, where the value of T_v is predefined and empirically obtained.

Algorithm for QMP based feature extraction:
Input: type of extraction method M_T, multiset S and termination parameter τ

c. Comparison QMP with the Binning Methods

FC and VC are able to preserve the color distribution of images, and therefore, color features extracted by them are less distorted than those extracted by the binning method. FC and VC determine the representative colors based on the color distribution of an image while the binning methods do not provide such flexibility. An image is usually divided into several sub blocks and regional color features are extracted. In this case, our extraction methods will be even more preferable to the binning methods because the color content in a sub block tends to be dominated by only a few colors. Our extraction methods are able to flexibly extract those dominated colors while there is no clear extension that will enable the binning methods to do that.

For a binning method, the extraction can complete in one scan and has a running time of O(S). In contrast, FC extracts color features in time O (NS). However, as pointed out earlier, the average computing time of FC is in fact much smaller than that in the worst case. Moreover, when the regional color features, whose color content tends to be highly homogeneous, are extracted, the computing time of FC and VC will be further closer to that of the binning method.

III. RELEVANCE FEEDBACK FOR CBIR

In content-based image retrieval, the search is initiated using a query as an example. The top rank similar images are then presented to the user. Then, the interactive process allows the user to refine his request as much as necessary in a relevance feedback loop [21].such a human computer interaction improves the usability and retrieval precision.

Relevance feedback (RF) is a query modification technique which attempts to capture the user's precise needs through iterative feedback and query refinement. Many kinds of interaction between the user and system have been proposed, most of the time, user information consists of binary labels indicating whether or not the image belongs to the desired concept. The positive labels indicate relevant images for the current concept, and the negative labels indicate irrelevant images. To achieve the relevance feedback process, the general strategy focuses on the query concept updating. The aim of this strategy is to refine the query according to the user labeling. A simple approach, called query modification [21], computes a new query by averaging the feature vectors of relevant images.

A. Uncertainty based sampling for relevance feedback

In CBIR, the whole set of images is considered as the pool of unlabeled data, during the selective sampling process. User information consists of binary labels indicating whether or not the image belongs to the desired concept. In our context the image retrieval task is considered as a classification problem in which the learner of the relevance function has to classify data as relevant or irrelevant. Any data in the pool of unlabeled samples may be evaluated by the learner. Some are definitively relevant, others irrelevant, but some may be more difficult to classify. Uncertainty-based sampling strategy aims at selecting unlabeled samples that the learner is the most uncertain about. It is observed in the literature that such uncertainty corrects the classification boundary and improves the precision of classification. To achieve this strategy, a first approach proposed by Cohn [23] uses several classifiers with the same training set, and selects samples whose classifications are the most contradictory. This approach requires many iteration of retrieval, every time with different classifiers. This is very time consuming. We proposed solution in which we compute probabilistic output for each sample, and we select the unlabeled samples with the probabilities closest to 0.5. This probability values is decided based on the extent of similarity of a query image with the image in a dataset. Similar strategies have also been proposed with SVM classifier [24], with a theoretical justification [24].This approach to find the uncertain class of image is quite simple to compute and it requires only one classifier. Thus it significantly reduces the time of boundary correction and improves the precision of classification significantly. As very large number of images are present in a dataset. Initially classification boundary divides the dataset into imbalance classes. During the first steps of relevance feedback, classifiers are trained with very few data, about 0.1% of the database size. At this stage, classifiers are not even able to perform a good estimation of the size of the concept. Their natural behavior in this case is to divide the database into two parts of almost the same size. Each new sample changes the estimated class of hundreds, sometimes thousands of images. Selection is then close to a random selection.

A solution is to ensure that the retrieval session is initialized with minimum examples. For instance, Tong proposes to initialize with 20 examples [26]. It is also found that initial examples can be preferably given with third-party knowledge (for instance, keywords).

IV. EXPERIMENTAL RESULTS

To evaluate the performance of a CBIR system, we have used a database which consists of images solely from landscape scenes. There are total 1000 images in our database collected from image albums published by Corel Corp. These images comprise of six image classes, each of which contains around 150-200 images. In other words, each image has a known class identity. Such as (a) red roses (b) seas, (c) farms, (d) mountains (e) lands & skies. The experiments are conducted on a PC with a Pentium-I5 with 2.8 GHz CPU and 2 GBytes RAM running the Windows-XP OS.

The performance of a color extraction method is measured in terms of evaluation measures such as F-measure, NDCG and average retrieval precision [26]. Each time a query image is selected from the database to retrieve 25 best matched images, excluding the query image itself, from the database. Table 1 summarized the performance of fixed clustering method, where N is the fixed number of clusters formed during feature extraction process.

Table 1. Performance of Fixed clustering method

Parameters/N	**16**	**32**	**64**	**128**	**256**
Precision	0.52	0.56	0.56	0.56	0.60
Recall	0.81	0.88	0.88	0.88	0.90
F measure	0.63	0.68	0.68	0.68	0.73
$\mathbf{f_\beta}$	0.56	0.60	0.60	0.60	0.65
Average Precision	0.58	0.65	0.71	0.74	0.79
Execution time(ms)	6	7.2	9.45	12.32	14.20
Ndcg	0.84	0.85	0.88	0.88	0.89

Table 2 summarized the performance of variable clustering method with measure such as precision, recall, F-measure Ndcg etc .Which is calculated on different concepts such as red rose, sea, farms, mountains & rivers and lands and skies.

Table 2. Performance of Variable Clustering Method

Parameter/ Concept	**Red Rose**	**Sea**	**Farms**	**Mountain & Rivers**	**Land & Skies**
Precision	0.56	0.60	0.68	0.40	0.44
Recall	0.88	0.83	0.85	0.83	0.85
F measure	0.68	0.7	0.76	0.54	0.58
fB	0.60	0.64	0.71	0.45	0.49
Average Precision	0.73	0.67	0.79	0.69	0.74
NDCG	0.88	0.90	0.89	0.92	0.88
Average Threshold	110	102	154	132	122
Execution Time	10.2	9.88	11	10.8	10.3

The quadratic-form distance [5] is chosen to be the distance measure for color histograms obtained by the binning method. As suggested in [24], the L1 metric is chosen to be the distance measure for color channel moments. We set the diameter threshold of CBHC as 30 when the cardinality and 32, and as 20 when, 128 and 256.It is observed that FC improves the precision rate by the factor of 25 % as compare to the binning method when 16 bins are extracted. Even when 256 colors are extracted, FC still achieves a higher precision rate than the binning method by 13%. Therefore, the precision rate is mainly dominated by the extraction methods instead of the distance measures. This result implies that representing color features in a precise manner is indeed very helpful for the image retrieval applications. When cardinality is below 64, the method of channel moments outperforms the binning method. These shows that the moments are a compact representation for color features and that the binning method tends to heavily distort color features when coarse quantization is used.

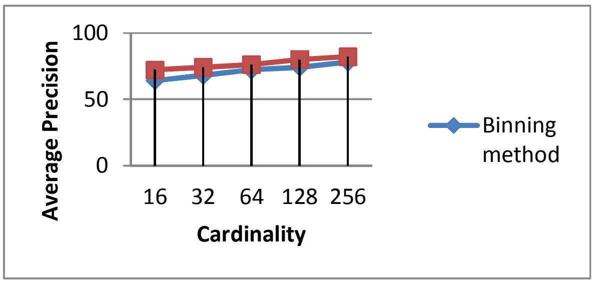

Fig. 1 Comparison of average precision of Binning method and fixed cardinality approach

Table 3 shows the retrieval performance of a system with 4 iteration of relevance feedbacks. The samples for feedback are selected with the proposed approach of uncertainty based sampling. A result shows that average precision is improved by the factor of 8 % after the 4 iterations.

Table 3.Retrieval performance of variable cardinality approach after 4 iterations of relevance feedback

Parameter/Query Concept	**Red Rose**	**Sea**	**farms**	**Mountain & Rivers**	**Land & Skies**
Precision	0.62	0.64	0.71	0.46	0.48
Recall	0.89	0.86	0.88	0.89	0.88
F measure	0.72	0.73	0.78	0.58	0.60
fB	0.64	0.68	0.73	0.58	0.55
Average Precision	0.77	0.69	0.83	0.72	0.78
NDCG	0.88	0.90	0.89	0.94	0.88

V. CONCLUSION

A color feature extraction scheme (QMP), which preserves the color distributions up to the third moment, is proposed. It is observed that minimizing the distortion incurred in the feature extraction process can enhance the accuracy of image retrieval system. The experimental results have shown that the new extraction methods can achieve a substantial improvement over the traditional color feature extraction methods.

An image is usually divided into several sub blocks and the regional color features are extracted. In this case, our extraction method and distance is observed o be more effective than the traditional binning methods because the color content in a sub block tends to be dominated by only few colors. Further, the variable clustering extraction method, which terminates the extraction process based on the heterogeneity of the pixel values, is achieving a balance between expressiveness and compactness.

It is observed that the usability of a system and the average precision of retrieval can be improved with a human computer interaction based techniques such as relevance feedback. We proposed novel technique to find the uncertain class of images which can be used to modify a query in successive iterations of relevance feedback.

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