Extraction of Feature Subspaces for Content-Based Retrieval Using Relevance Feedback

Zhong Su
State Key Lab of Intelligent Technology and Systems
CS department, Tsinghua University
Beijing 100084, China
suzhong_bj@hotmail.com

Stan Li, Hongjiang Zhang
Microsoft Research China
5F, Beijing Sigma Center, 49 Zhichun Road
Beijing 100080, China
szli, hjzhang@microsoft.com

ABSTRACT
In the past few years, relevance feedback (RF) has been used as an effective solution for content-based image retrieval (CBIR). Although effective, the RF-CBIR framework does not address the issue of feature extraction for dimension reduction and noise reduction. In this paper, we propose a novel method for extracting features for the class of images represented by the positive images provided by subjective RF. Principal Component Analysis (PCA) is used to reduce both noise contained in the original image features and dimensionality of feature spaces. The method increases the retrieval speed and reduces the memory significantly without sacrificing the retrieval accuracy.

Keywords
Content-based image retrieval (CBIR), Bayesian estimation, principal component analysis (PCA), relevance feedback.

1. INTRODUCTION
Content-based image retrieval (CBIR) is a technique for finding, from an image database, images similar in content to the given query. It is usually performance based on comparison of low level features, such as colour, texture or shape features, extracted from the images themselves.

A problem in CBIR is the disparity between semantic concepts and low-level image features. For example, for different queries, different types of features have different significance; an issue is how to derive a weighting scheme to balance the relative importance of different feature types; there is no universal formula for all queries. The relevance feedback (RF) technique can be used to shorten or bridge the gap [3][10][11][14][20][22].

RF, originally developed for Information Retrieval (IR)[14], is an active supervised learning technique. Positive and negative examples provided by the user are used to improve system's performance. The key issue is how to incorporate positive and negative examples to refine the query and to adjusting the similarity measure according to the feedback examples.

Generally speaking, previous RF methods can be classified into two categories: "re-weighing approach" and "probability approach". Most of existing works in CBIR use the former approach, notably based on a popular model in information retrieval called the vector model [1][17][18], which is adopted in some systems [11][14][16] [7][10]. The idea is to associate larger weights with more important dimensions and small weights with unimportant ones. This can be illustrated by the Rocchio's formula. For a set of relevant documents and non-relevant documents given by the user, the new query is moved towards good example points and away from bad example ones.

Bayesian estimation methods have been used in the latter approach. Cox [3] and Vasconcelos [22] used Bayesian learning to incorporate user's feedback to update the probability distribution of all the images in the database. They consider the positive examples as a sequence of independent query and try to minimize the retrieval error by Bayesian rules.

A new algorithm, which belongs to the second approach, is one based on Gaussian Estimator and Bayesian Classifier [20][21], recently proposed by the authors. By assuming (1) that all positive examples in one retrieval iteration belong to the same semantic class with common semantic object(s) or meaning(s) and (2) that the features from the same semantic class follows the Gaussian distribution, we can use all positive feedbacks of this query iteration to calculate and update the parameters of the corresponding semantic Gaussian class. Then we use a Bayesian classifier to re-rank the images in database. Such process is progressive so that every feedback can have impact on the latter retrieval processes.

However, both pervious RF approaches assume that image features have been given. Neither considers the problem of feature selection. Moreover, they need large memory and storage cost, which slows down retrieval speed.

Research has been done to deal with the problem of slow response time in CBIR caused mainly by the high dimensionality of the feature space, typically hundreds to thousands. Ng and Sedighian [12] made direct use of eigenimages, a method for face recognition [8], to carry out the dimension reduction. Faloutsos and Lin [5], Chandrasekaren et al. [2], and Brunelli and Mich [13] used principal component analysis (PCA) to perform dimension reduction in feature spaces. Experimental results in these works showed that most real image feature set could be considerably reduced in dimension without significant degradation in retrieval quality. However, there are two problems with the use of PCA in these works: First, they adopted a fixed dimensionality. This strategy is questionable because intrinsic dimensions are usually different for images of different types or complexities. Second, the subspaces are fixed once the PCA is performed without considering users' subjectivity. Such dimension reduction could be undesirable.

The objective in this paper is to perform feature dimension reduction more effectively according to user's feedbacks. We address the following issue: How to derive from user's subjectivity transforms of original features, to improve CBIR performance.

We propose a novel method to incorporate PCA into the RF framework to extract feature subspaces in order to represent the subjective class implied in the positive examples. To derive a more effective, efficient and compact feature representation, different types of features are allowed to have different dimensionalities according their significances and distributions as implied in RF. A procedure is provided to achieve this.

The proposed method has the following advantages: (1) whitened feature distributions on which distance metrics can be rationally defined, (2) reduced noise in the resulting feature set, (3) reduced dimensionality of feature spaces, (4) reduced amount of training data needed to estimate the parameters of the Gaussian semantic class during feedback iteration.

The time and memory complexities in online retrieval are linear with the total feature dimension. When only about ψ = 30% of the original total dimension is used, which is the case in our system, only 30% of the memory is needed and the speed of the proposed method is 3 times of that of the methods without the PCA dimension reduction. In other words, by applying PCA dimension reduction, the retrieval system allows 9 times more images. The reduced information is most likely due to noise in the original feature and so it causes little decrease in performance. According to our experimental results on large amount of data, dropping 80% of dimensions leads to only about 5% reconstruction error; dropping 90% dimensions only about 10% reconstruction error. These are evidenced by experiments performed on more than 10,000 Corel images.

This paper is organized as follows. Section 2 introduces the PCA process. Section 3 describes our method of RF based on Bayesian estimation. Section 4 presents Bayesian RF in PCA feature subspaces. Section 5 performs a complexity analysis. The experimental results are shown in Section 6. The concluding remarks and future work will be given in the final section.

2. PRINCIPAL COMPONENT ANALYSIS

PCA [4] is a statistical tool for data analysis [6]. It decorrelates second order moments corresponding to low frequency property, and identifies directions of principal variations in the data. Consider an ensemble of n-dimensional vectors $\{x = [x_1,\ldots,x_n]^T\}$ whose distribution is centered at the origin , $E(x) = 0$. The covariance between each pair of variables: $r_{ij} = E\{(x_i - \bar{x}_i)(x_j - \bar{x}_j)\} = E\{x_i x_j\}$, where E is the expectation operator. The parameters r_{ij} can be arranged to form the n $\times$n covariance matrix

$$R_x = E\{(x-\bar{x})(x-\bar{x})^T\} = E\{xx^T\} \tag{1}$$

Assuming $\det(R_x) \neq 0$, then by applying eigenvector decomposition, R_x can be decomposed into the product of three matrices:

$$R_x = W\Lambda W^{-1} \tag{2}$$

where $\Lambda = diag\{\lambda_1,\ldots,\lambda_n\}$ are the eigenvalues and W = $[w_1,\ldots,w_n]^T$ are the corresponding eigenvectors. W is orthonormal in that $W^TW = I$. The columns of W form a set of orthonormal basis vectors which spans a linear space.

The eigenvalue decomposition result can be used to whiten the feature distributions as follows: Project the original feature vectors x onto the PCA space (without dimension reduction), obtaining the coordinates x' in the latter space, which is equivalent to rotating the feature space; then re-scalar the obtained coordinates x_j' by the factor of $\sqrt{\lambda_j}$ to obtain the whitened feature vector y. After the whitening, we are able to calculate the Mahalanobis distance between x_1 and x_2 in the original feature space by the simple Euclidean distance between the corresponding y_1 and y_2, in the whitened feature space, ie:

$$dist(x_1, x_2) = (x_1 - x_2)^T \Sigma^{-1}(x_1 - x_2) = \| y_1 - y_2 \| \tag{3}$$

If we select only m eigenvector as the orthonormal basis vectors to form subspace L = span (W'), then any vector x in the original space can be linear transformed to L with the new representation y:

$$y = W'x, \tag{4}$$

The original x can be reconstructed from the projection y as $x' = W'^T y = W'^t W'x$. The mean squared reconstruction error is

$$J_e\,(m) = E\{\, ||x-x'||^2 \} = \sum_{i=m+1}^{n} \lambda_i \tag{5}$$

The mean square reconstruction error J_e can thus be minimized by choosing the eigenvectors corresponding to the largest eigenvalues.

There are two advantages brought about by PCA: (1) Dimension reduction is achieved when $k<n$ and x is represented by the

projected coefficients. (2) Noise reduction is achieved because noise corresponds to high frequency components correspond to the components of the smallest eigenvalues.

3. RELEVENCE FEEDBACK BASED ON BAYESIAN ESTIMATION

The Gaussian density is often used for characterizing probability for its computational tractability and the fact that it models adequately a large number of cases. Consider vector x in R^n that obeys Gaussian distribution; then, the probability density function of x is (6):

$$p(x) = \frac{1}{(2\pi)^{d/2} |R_x|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\bar{x})^T R_x^{-1}(x-\bar{x})} \quad (6)$$

Denote the image database by D. Suppose that m types of features are used in the retrieval and so an image is represented by $\vec{x} = [\vec{x_1},...,\vec{x_m}]$, where $\vec{x_i}$ is the feature vector in the n_i-dimensional feature space S_i for type i features. We assume that each type of features is a Gaussian distribution, $\vec{x_i} \sim N(\varepsilon_i, \Sigma_i)$ where Σ_i is the $n_i \times n_i$ dimension covariance matrix and ε_i is the n_i dimensional mean vector. Let n be the number of positive feedbacks for image P. We use a diagonal block matrix $diag\{\sigma_i^2\}$, where $\sigma_i(m) = \Sigma_i(m,m)$, to represent the inter-feature correlation, for simplicity reason. This is because the inter-feature correlation cannot be estimated practically and reliably, especially when there are not enough feedbacks.

Our idea about relevance feedback is the following: It is reasonable to assume that all the positive examples belong to the class of images containing the desired object or semantic meaning. The parameters for the semantic Gaussian class can be estimated from the positive examples. The log posterior probability that the feature vector x belongs to the subjective class c_i implied in the positive examples is estimated using the following Bayesian formulation

$$\begin{aligned} g_i(x) &= \ln P(c_i \mid x) \propto \ln p(x \mid c_i) + \ln P(c_i) \\ &= -\frac{1}{2}(x-\varepsilon_i)^T \Sigma_i^{-1}(x-\varepsilon_i) + \ln P(c_i) + const \end{aligned} \quad (7)$$

where *const* are fixed in one RF iteration. This formula is for one feature type. Assuming that different feature types are independent of each other, the log posterior is calculated as the sum of individual $g_i(x)$'s. Experiment shows that the use of this posterior as the ranking metric improves the RF-CBIR performance [15] [16] and [22].

There are three parameters in the Bayesian estimate in Eq.(8): ε_i, Σ_i and the probability of the semantic class $P(c_i)$. They need to be updated when more positive examples are provided by the user through relevance feedback. Actually such process could be considered as the combination of two Gaussian classes. So it is easy to get the updating process. Denote the current set of positive examples by U. The updating can be performed as follows:

$$\sigma_i^2 = n\sigma_i^2 + \frac{n|U|\varepsilon_i^2 - 2n\varepsilon_i \sum_{u\in U} u}{n+|U|} + \sum_{u\in U} u^2 - \frac{(\sum_{u\in U} u)^2}{n+|U|} \quad (8)$$

$$\varepsilon_i = \frac{n\times\varepsilon_i + \sum_{u\in U} u}{n_k+|U|} \quad (9)$$

$$n = n + |U| \quad (10)$$

The following describes how positive feedbacks are performed:

Initialization of System

1. Feature Normalization: This allows equal emphasis on all the feature components. For $\vec{x_i}$ the normalized vector is $\vec{x_i}' = \lfloor x_{i1},...,x_{in_i} \rfloor$, where $x'_{i_m} = \dfrac{x''_{i_m} - \varepsilon(x''_{i_m})}{3\sigma(x_{i_m})}$ and $x''_{i_m} = \dfrac{x''_{i_m} - \min(X_{i_m})}{\max(X_{i_m}) - \min(X_{i_m})}$. If x_{im} satisfies the Gaussian distribution, it is easy to prove that the probability of x'_{im} being in the range of [-1,1] is 99%.

2. Initialization: Initialize $\sigma_i = \mathbf{I}$ (identity matrix) and $\varepsilon_i = \vec{x_i}$, $n = 1$.

Retrieval and Feedback

1. Update the retrieval parameters σ_i, ε_i, and n according to Equation (8)-(10) using the information provided by the current set of positive examples U.

2. Distance Calculation: For each image P, $P \in D$, its distance d_i is calculated using Equation (7) in the retrieval after the feedback. $d_i = -g(P)$, That is, the similarity of each image in the database to be refined query is determined by Equation (7) based on the positive examples.

3. Sorting by distances and provide the new ranking list to the user.

Our feedback algorithm is incremental, which has the following advantages: Not only the retrieval performance could be improved for the current user, but also the improvements also help the subsequent users. The parameters of the Gaussian semantic class corresponding to each query will be refined by its positive examples according to Equation (8) -- (10), and could be used for other users. The updating process is an online process, so the computation complexity is quite important. However, such updating process needs to take care only of the current positive examples. So the computation cost could be negligent as compared with the whole retrieval process.

4. BAYESIAN RELEVENCE FEEDBACK IN THE PCA FEATURE SUBSPACES

Our method performs subspace feature extraction while allowing varying dimensions for different types of features. We propose to use the following idea to perform the PCA in the feedback framework.

In the first round of retrieval, we use only a few significant components for each feature. That is, for each feature type i, select the first m_i most significant eigenvectors for type i feature, where m_i is quite small comparing with its original feature dimension n_i. The initial value of m_i can be calculated by: $m_i = \psi \times n_i$ where ψ is the dimension reduction rate; e.g, en ψ = 10%.

For the subsequent iterations, we propose the following scheme for the determination of dimensions of feature subspaces: Let the sum of dimensions over all the types be a fixed integer, e.g., ψ = 10% of the original number. As iterative relevance feedback continues, the dimensions to be retained for good feature types are increased the dimensions for bad types are decreased. This is achieved by adjust m_i according to a goodness measure for a feature type as follows.

Let Q be the query, let the current set of positive examples be U, such evaluation measurement can be defined as follows:

$$M_i = \frac{\sum_{p_i \in D} \frac{d(p_i, Q)}{|D|}}{\sum_{u \in U} \frac{d(u,Q)}{|U|} \times (1-\alpha_i)} \tag{11}$$

where $d(x,y)$ refer to the distance between x and y in PCA subspace. We can see from the above equation that the *good* feature will has small distances from its positive examples to the query class center comparing to other images in databases.

After calculating M_i for each type i sorting the M_i in the descending order, then we can get the rank r_i of M_i. Such rank can reflect the effectiveness of the feature in current retrieval session relative to the others. It will be high for a good feature type and low for a bad one. So we can update the m_i based on the calculated rank value by equation (12).

$$m_i = (m_i + \tau \times (\left\lfloor \frac{m}{2} \right\rfloor - r_i - 1)) \tag{12}$$

where τ is a constant factor. From the above equation we can see that for good feature, its corresponding m_i will be increased so that more dimensionality could be evolved in next retrieval iteration. In our experiment, we set τ to 1. The following describes the PCA embedded algorithm:

<u>Initialization of System</u>

For each feature type *i=1,…m*, do the following:

1. Perform PCA to all the images in the original feature space S_i, obtaining the eigenvalues and the corresponding eigenvectors calculated by (1) and (2). Sort the eigenvectors in the order of descending eigenvalues.

2. Whiten the distribution of the feature vectors by first Rotating the feature space and then dividing the coordinate by the square root of the corresponding eigenvalues (refer to Section 2). Such pre-processing does not lose any information because the dimensionalities are not reduced in the process.

3. Initialize the parameters of σ_i ε_i and n as before.

The following describes how to update the retrieval and feedback Process.

<u>Retrieval and Feedback</u>

1. Update the parameter of the Gaussian class according to Equation (8)(9) and (10).
2. Calculate M_i according to equation (11), where i = 1,..,m. Sorting the M_i in decreasing order to get the rank r_i of M_i.
3. Update the m_i according equation (12)
4. Calculate the distance between all image in the database D to current query Q in the m_i dimensional feature subspace.
5. Sort by distances and provide the new ranking list to the user.

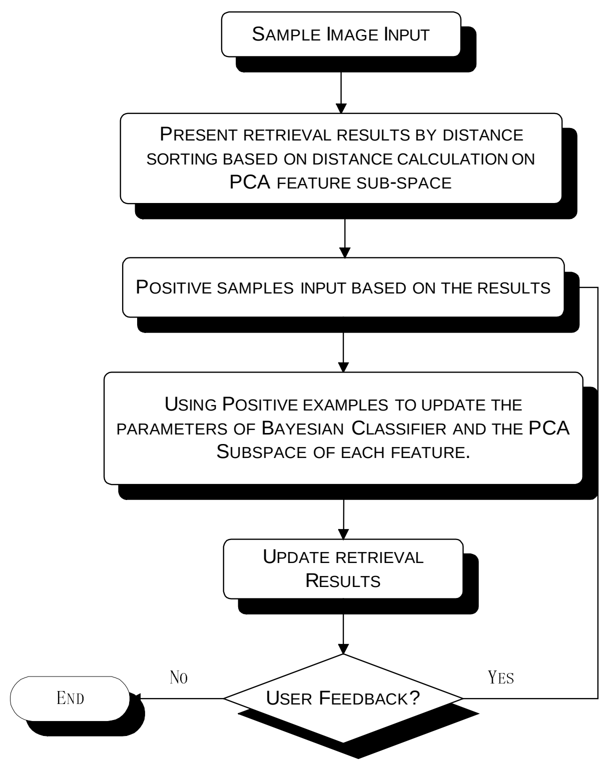

Fig. 1: Diagram of the proposed positive feedback process

Fig. 1 shows the feedback process. The differences between the current retrieval/feedback method and the previous one are listed as the following:

1. The retrieval and feedback are performed based on the features in the extracted feature subspaces. For type *I* features, we only use first m_i dimensions to do the retrieval and feedback process.

2. In addition to updating the parameters of Gaussian class as before (this costs a little because the number of positive examples is usually small), the m_i are also updated so that better features will have more impacts than the bad ones.

In this way, the system learns from the user's feedback in a feature-based manner. The dimensionalities of the individual feature subspaces are adjusted dynamically according to goodness of the corresponding features at current RF session.

5. COMPLEXITY ANALYSIS

The proposed PCA subspace method can save memory and speed up the computation significantly. The requirements for memory come from two parts: the basis vectors and the feature coordinates in the feature subspaces. The size of the former part is fixed and regardless of the database size. It can be ignored when the database is large. Therefore, the memory requirement depends on the total number of images in the database, which in turn depends, linearly, on the total dimensionality of the feature vectors.

Now let us look at the time complexity. The PCA learning involves two stages: calculating R_x and performing eigenvalue decomposition. The R_x calculation process is very time consuming, which is O(*Total_image_number* * n_i * n_i). The computation complexity of eigenvalue decomposition process is O($n_i * n_i$). So the covariance matrix computation is the dominant factor for the complexity. Fortunately, such process is an offline procedure. If the previously calculated covariance matrix R_x is retained together with the number of samples, the covariance matrix may be updated in a more efficient way.

The bottleneck of online retrieval is the distance calculation and sorting. Because no addition and multiplication operations are needed, sorting could be optimized by compiler and would be very fast. So, the true bottleneck is the distance calculation. The computation complexity of distance measure is O(n) where n is the number of the vector dimension. For example, the Euclidean distance needs O(n) times multiplication and O(n) addition operation, which is same as our method. Therefore, the total computation complexity in the online retrieval is $\sum_{i=1}^{m} \mathrm{O}(\mathrm{Total\_image\_number} \times \mathrm{n_i}) = O(Total\_image\_number \times n)$, where $\mathrm{n} = \sum_{i=1}^{m} \mathrm{n_i}$.

From these, we can see that the time and memory costs are linear with the total feature dimension. More specifically, if we use only about ψ = 10% of the original total dimension, only 10% of the memory is needed and the speed of a PCA method is 9 times faster than methods without PCA dimension reduction. In other words, by applying PCA dimension reduction, the retrieval system can afford 9 times more images.

6. EXPERIMENTAL RESULTS

6.1 Retrieval Interface

Our *MiAlbum* image retrieval system implements the framework discussed in this paper. It is an image retrieval system for PC users. In this paper, we only focus on the retrieval based on low-level feature and the "search by example" mode of interaction as shown in Fig. 2 (The *MiAlbum* system also supports other two modes of interaction: keyword based search and browsing the entire image database). Search results are returned as a ranked list show in the right image view. The ranking sequence is from left to right, from top to bottom. During the retrieval process user can provide relevance feedback by click the 'Yes' or 'No' sign below the results. As we can see from Fig. 2, there is an Option Dialog in the main interface. User can select the features and methods, as well as the selection between original features space and PCA feature space.

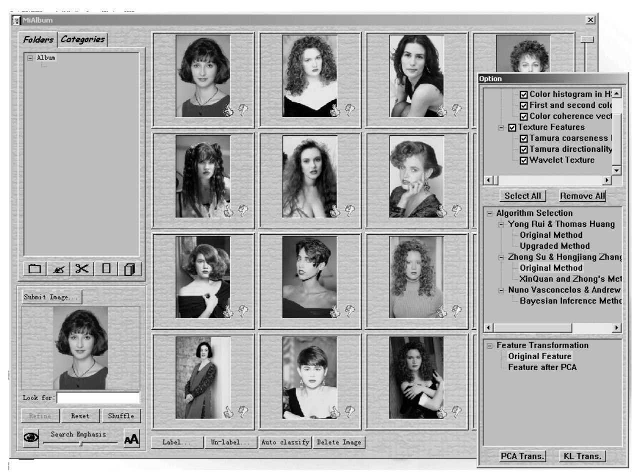

Fig. 2: Retrieval and feedback interface of *MiAlbum*. Example image is shown on the left of the bottom.

6.2 Results

The image set we used is the Corel Image Gallery. 10,009 images of 79 semantic categories are selected to calculate the performance statistics, of which 80% are for learning PCA basis vectors and 20% for testing. Whether a retrieved image is correct or not is judged according to the ground truth class. Three types of color features and three types of texture features are used in our system, as shown in Table 1. The total dimension is 435.

Table 1: Low level features used in '*MiAlbum*'.

Features	Dimension
Color histogram in HSV space with quantization 256	256
First and second color moments in Lab space	9
Color coherence vector in LUV space with quantization 64	128
Tamura coarseness histogram	10
Tamura directionality	8
Pyramid wavelet texture feature	24

The feedback process runs as follows: Given a query example from the test set, one different test image of the same category as the query is used in each round of feedback iteration as the positive example for updating the Gaussian parameters. The accuracy is defined as:

$$Accuracy = \frac{\text{relevant images retrieved in top } N \text{ returns}}{N} \quad (13)$$

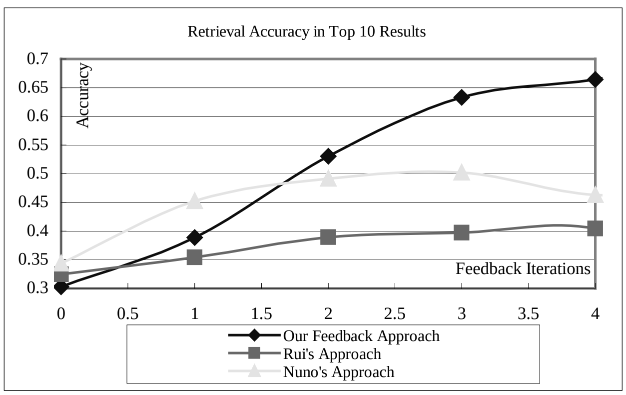

Fig. 3: retrieval accuracy for top 10 results in original feature space.

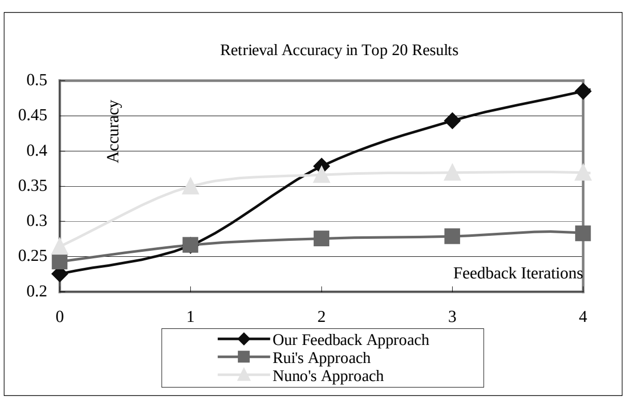

Fig. 4: retrieval accuracy for top 20 results in original feature space.

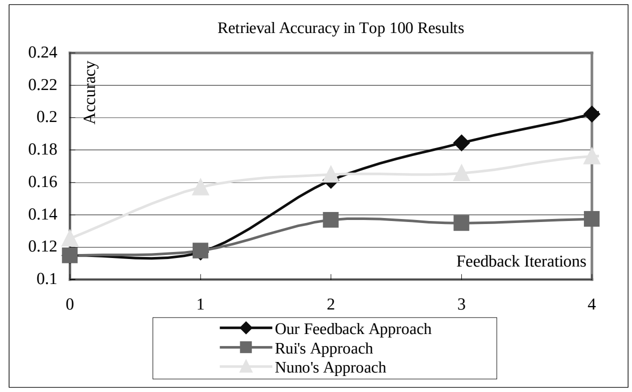

Fig. 5: retrieval accuracy for top 100 results in original feature space.

Several experiments are performed as follows.

First, our Bayesian feedback scheme is compared with previous feedback approaches presented by Vasconcelos [22] and Rui [15] [16] in the original feature space without dimension reduction. **Fig. 3** show that the accuracy of our Bayesian feedback method becomes higher than the other two methods after two RF iterations. This demonstrates that the incorporated Bayesian estimation with the Gaussian parameter updating scheme can improve RF-based retrieval.

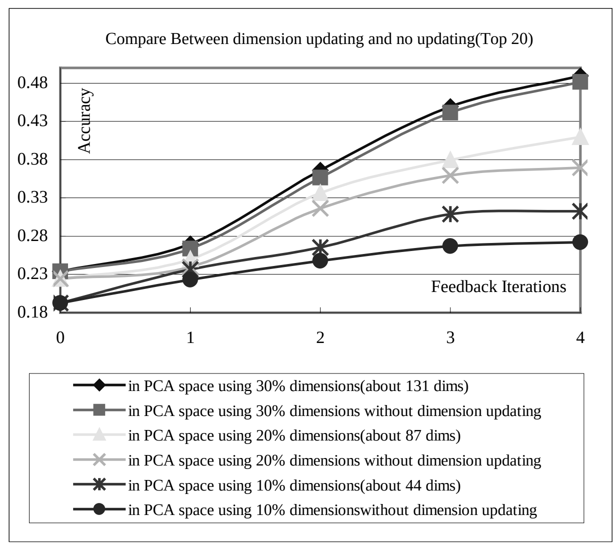

Fig. 6: comparing the retrieval accuracy of top 20 results in PCA feature space between the dimension updating and no dimension updating method.

Fig. 10 demonstrates the quality of reconstructions in the PCA subspace, which can be defined as $\sum_{i=1}^{m} \lambda_i$ (see Section 2), as a function of retained dimension *m*, for the 6 types of features. It is shown that significant dimension reductions cause little reconstruction errors, for all the 6 cases: Dropping 80% of the dimensions causes only about 5% reconstruction error; cutting off 90% of the dimensions causes about 10% of loss. The discarded information can be due to noise because it corresponds to the least significant or high frequency components. However, given the reconstruction fidelity (or the α parameter, or the total dimension) fixed, the minimum dimension for an individual subspace can vary when the type of the features is different, as can be seen from the differences of the 6 plots. Also, the dimensions should be adjusted dynamically according to the evidences gathered thus far. Therefore, the PCA dimension reduction must be completed by an appropriate method for the dynamic adjustment of subspace dimensions in order achieving significant reduction with little loss in the accuracy.

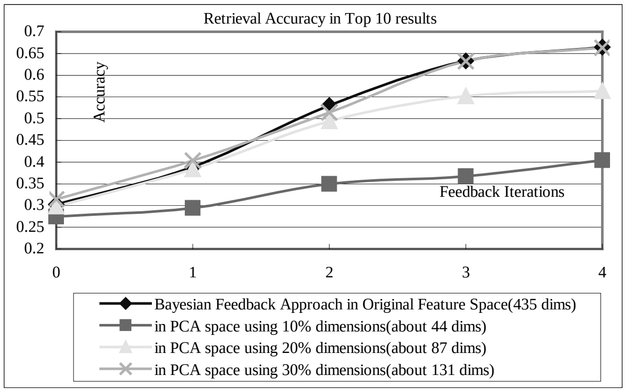

Fig. 7: comparing the retrieval accuracy in top 10 results between the original feature space and PCA feature space.

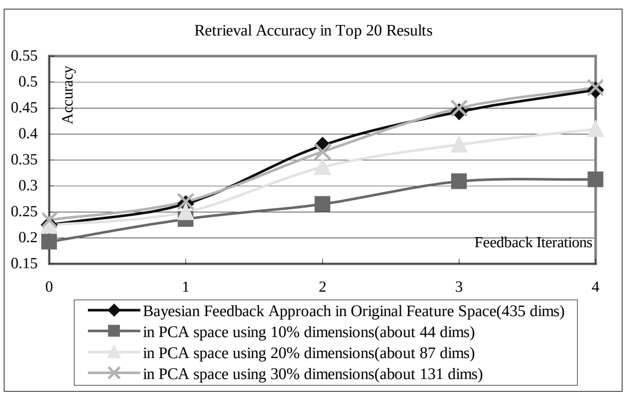

Fig. 8: comparing the retrieval accuracy in top 20 results between the original feature space and PCA feature space.

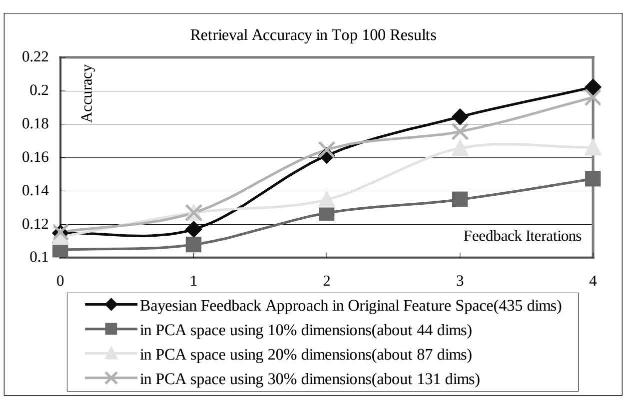

Fig. 9: comparing the retrieval accuracy in top 100 results between the original feature space and PCA feature space.

Next, we compare the results obtained with and without the dynamic adjustment of the dimensionalities of feature subspaces. As we can see from Fig. 6, the retrieval accuracy can be improved by the dynamic adjustment scheme, especially when the dimension retention rate ψ is small.

Finally, the accuracy after PCA reduction is compared with that obtained in the original feature space. The results in **Fig. 7** -- 10 show that the accuracy can be maintained when the retained total dimension is 30% of the original or above; the benefit brought about by this reduction is that the retrieval speed is tripled and that the memory requirement is 1/3 of the original.

7. CONCLUSIONS AND FUTURE WORK

In this paper, we have presented a new method for relevance feedback (RF) based content-based image retrieval (CBIR). Principal Component Analysis (PCA) is incorporated into a Bayesian feedback process to extract efficient features of reduced dimensionalities.

The RF process plays two roles: providing information for updating the Gaussian parameters in the Bayesian feedback, and providing evidences for the adjustment of feature subspace dimensionalities. When multiple types of features (e.g., color and texture) are used, a method is proposed to allow different subspace dimensionalities for different features. This accounts for differences between individual feature subspaces as based on evidences obtained so far from recent RF.

Results show that the proposed method can significantly improve the retrieval performance in speed and memory without sacrificing the accuracy. In principle, the proposed feature subspace extraction method can be incorporated to any other content-based retrieval methods to save memory and to speed-up computation.

We use a single Gaussian to estimate the user's intention in one feedback iteration which is described in this paper. However, in many cases, images of user's interest may correspond to several distinct clusters in feature spaces. To solve this problem, currently we are working on using mixture Gaussian estimation in feedback process based on the pre-clustered feature space. Hopefully, we could achieve better performance.

8. ACKNOWLEDGMENTS

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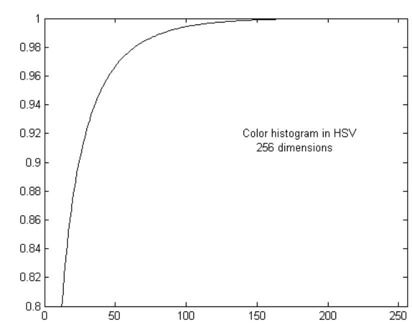

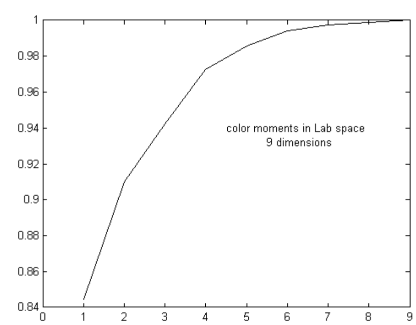

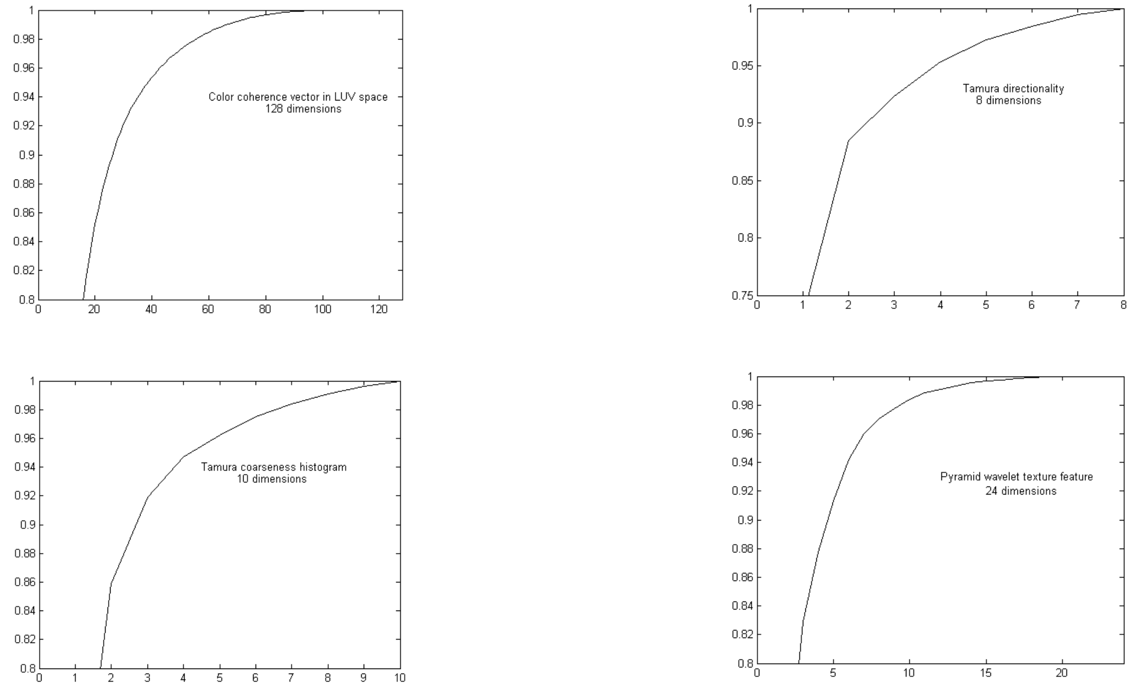

Fig. 10: Accumulate eigenvalues of individual low-level features after PCA process.