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Image Retrieval Relevance Feedback algorithms: Trends and Techniques

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Abstract: With many applications, Content based Image Retrieval (CBIR) has come into the attention in recent decades. To reduce the schematic gap a wide variety of relevance feedback (RF) algorithms have been developed in recent years to improve the performance of CBIR systems. These RF algorithms capture user's preferences and bridge the semantic gap. Many schemes and techniques of relevance feedback exist with many assumptions and operating criteria. Yet there exist few ways of quantitatively measuring and comparing different relevance feedback algorithms. Such analysis is necessary if a CBIR system is to perform consistently. In this paper, different RF techniques are reviewed. The selection of papers include sources from image processing journals, conferences, books, dissertations and thesis out of more than 500 journals, books and online research databases. The state of art research on each category is provided with emphasis on developed technologies and image properties used by them. Finally, conclusions are drawn summarizing commonly used techniques and their complexities in applications.

I. Introduction

Content-based Image Retrieval (CBIR) [1][2][3][4] has gained much attention in the past decades. CBIR is a technique to retrieve images from an image database such that the retrieved images are semantically relevant to a query image provided by a user. It is based on representing images by using low-level visual features, which can be automatically extracted from images, to reflect the color, texture, and shape information of the image. However, the gap [5] between the low-level visual features and the high-level semantic meanings usually leads to poor performance. Also, different users or the same user at different times may have different viewpoints on an identical image.

The visual features of the old lady image and the dog image are very similar, but their semantic meanings are totally different as shown in fig 1.

Another kind of example for semantic gap is shown in fig 2.For the left query image of fig 2, some users focus on the sea beach so the best match could be a sea beach like the one in the middle image; while others may focus on the coconut tree, so the rightmost image is the best match. These problems are come under semantic gap.

Fig 1. Examples of semantic gap

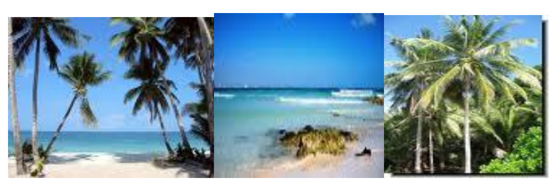

Fig 2

A question that naturally emerges is, what can we do to deal with these problems? The answer is to introduce the users in the process, having them interacting and telling what is really relevant for the images being retrieved and analyzed. Therefore, by gathering the user's indications, algorithms can be developed to change the placement of the query, or to change the similarity function employed in order to better comply with the user's expectations. The approach that asks to

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the user to set the relevance of the images to a given query and to reprocess it based on the users´ feedback is called ***relevance feedback*** (***RF***) [6], and is been proven to be quite effective in bridging the semantic gap.

The conventional process of RF is as follows:

1. from the retrieved images, the user labels a number of relevant samples as positive feedbacks, and a number of irrelevant samples as negative feedbacks;
2. The CBIR system then refines its retrieval procedure based on these labeled feedback samples to improve retrieval performance.

Recently, many RF methods have been introduced and we classify them into the following groups.

1. **Subspace learning based methods** [7][8][9] define a ( )-class problem and find a subspace within which to separate the one positive class from the unknown number of negative classes. Few of the methods come under this category are: biased discriminant analysis or BDA[12], the direct kernel biased discriminant analysis (DKBDA) [11], marginal biased analysis (MBA) [10]
2. **Support vector machine (SVM) based methods** [13] [14] either estimate the density of positive instances or regard RF as a classification problem with the positive and negative samples as training sets. SVM active learning selects the samples near the SVM boundary and queries the user for labels. After training, the points near the SVM boundary are regarded as the most informative images while the most-positive images are the farthest ones from the boundary on the positive side.
3. **Random sampling-based methods** [6]apply statistical sampling techniques to reduce particular problems in RF which occurs in previous two methods. For example, the asymmetric bagging random subspace scheme [15][16].
4. **Feature selection-based methods** [5] [17] adjust weights associated with various dimensions of the feature space to enhance the importance of those dimensions that help in retrieving the relevant images and to reduce the importance of those dimensions that hinder the retrieval performance. Alternatively, features can be selected by the boosting technique, e.g., AdaBoost,[18], in which a strong classifier can be obtained as a weighted sum of weak classifiers along different feature dimensions.

All CBIR systems face two main problems:

a) Producing low level image features that accurately describe human visual perception.
b) Computational complexity
The high dimensional feature vector gives better information about the image content. It increases the computational complexity when working with high dimensional vectors. Thus CBIR suffers with 'curse of dimensionality'.

II. Existing CBIR With Relevance Feedback

In some CBIR systems, users are asked to provide the system, as a part of the query, with some extra information such as the level of importance for each feature, or suggesting a set of features to be used in image retrieval. It seems to be an efficient way to help the user modeling his query; however, different users (or the same user at different instances) may have a different perception of the notion of similarity between image properties. Moreover, it may not even be feasible to express the information need of a user exactly as a weighted combination of features of a single query image.

According to relevance feedback technique in CBIR [20], an image object model O(D, F, R) together with a set of similarity measures M = $\{m_{ij}\}$,specifies a CBIR model O(D, F, R, M).

- D is the raw image data e.g., JPEG image
- F = $\{f_i\}$ is a set of low level visual features associated with the image object such as color, texture and shape.
- R = $\{r_{ij}\}$ is a set of representations for a given feature e.g., both color histogram and color moments are representations for the color feature. Note that each representation rij itself may be a vector consisting of multiple components i.e., $r_{ij} = \{r_{ij1}, \ldots\ldots., r_{ijk}, \ldots..,r_{ijK}\}$

Based on the image object model and the set of similarity

Based on the image object model and the set of similarity measures the retrieval process is described below:

1) Initialize the weights $W = [W_i, W_{ij}, W_{ijk}]$ to W_0 which is a set of no bias weights. That is every entity is initially of the same importance.

2) The user's information need, represented by the query object Q, is distributed among different features f_i according to their corresponding weights W_i.

3) Within each feature f_i the information need is further distributed among different feature representations r_{ij} according to the weights W_{ij} .

4) The objects similarity to the query in terms of r_{ij}, f_i is calculated according to the similarity measure mij and the weights W_i, W_{ij}, and W_{ijk}. .

5) The objects in the database are ordered by their overall similarity to Q . The N_{RT} most similar ones are returned to the user where N_{RT} is the number of objects the user wants to retrieve.

6) For each of the retrieved objects the user marks it as highly relevant, relevant, no opinion, non relevant or highly non relevant according to his information need and perception subjectivity.

7) The system updates the weights according to the user's feedback such that the adjusted Q is a better approximation to the user's information need.

8) Go to Step 2 with the adjusted Q and start a new iteration of retrieval.

Support vector machines are a core machine learning technology [14]. They have been successfully applied to tasks such as handwritten digit recognition, object recognition, and text classification. In the area of image retrieval, SVMs have been used for feature weighting. SVMs are basically used for binary classification.

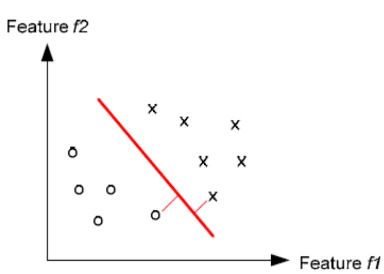

Fig 3 SVM classification: supports and margins

In the simplest form, SVMs are hyper-plains that separate the training data {x1, …, xn} in a data space by a maximal margin rule as shown in fig 3 .

All vectors lying on one side of the hyper-plain are labeled as +1, and all vectors lying on the other side are labeled as -1. The training instances that lie closest to the hyper-plain on each side of it are called support vectors, and a margin is defined as the minimum distance of support vectors from the hyper-plain. Therefore, the best hyper-plain is the one that maximizes the margins in the data space. SVMs project the original training data in the input space to a higher dimensional feature space via a kernel operator K. Data points (xi) are presented as $\Phi(xi)$ in feature space and define a set of classifiers as $D(xi) = \mathbf{w}.\Phi(xi) + w0$ where $\mathbf{w}$ is the vector of dimension weights in the feature space. The classifier D(xi) classifies data point xi as +1 or -1 according to the following relations:

$$\mathbf{w}.\Phi(xi) + w0 \geq +1; \text{ if } yi = +1$$

$$\mathbf{w}.\Phi(xi) + w0 \leq -1; \text{ if } yi = -1$$

In image retrieval by relevance feedback, SVMs can be applied to the image features space. Data points are images which are labeled as positive (+1) or negative (-1). The task of SVMs is to create a hyper-plain to separate all images in the database to two group of relevant (+1) and irrelevant (-1) images. During the relevance feedback process, an SVM is constructed in each dimension of the feature space and the generalization error is computed and features with smaller generalization error are assigned larger weights. Generalization error measures how good a classifier can classify training data. In another SVM method [89], weights are assigned to each types of feature rather than each dimension of the features so that only a few weights need to be estimated which may have less risk in relevance feedback problems with high dimensionality on the features and small size of training samples.

In relevance feedback another algorithm has been adopted known as **Bayesian network** [21][22]. It explored Bayesian network as a relevant image adoption model to select a number of good points composing the positive feedback information. It is based on the evaluation of the belief values

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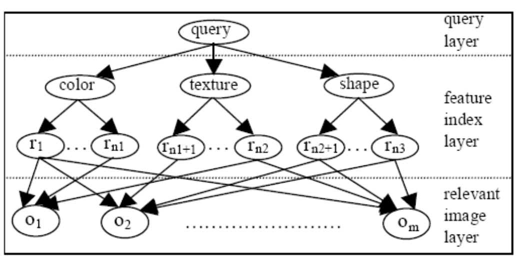
of the relevant image nodes in the network such that these belief values can be used as probabilistic measure of usability of the relevant images. By this approach, objects deemed relevant during previous iterations are reasonably incorporated and the chosen relevant images can better capture user's information need than former methods. A Bayesian belief network is a graphical representation of a set of random variables and their dependencies. It provides an effective knowledge representation which imitates knowledge structures used by the human mind. Bayesian network models the probabilistic relationships among the objects, which make it suitable to handles situation relating to probability distributions over variables. Furthermore, the architecture representation of Bayesian network is highly adaptive and easy to build. Bayesian network provides a good framework for integrating the feature representations and it offers easy maintenance when adding new features. The flexibility of feature incorporation is preferable in our application. In [23] they proposed a Bayesian network image retrieval engine searching the whole image database to find the retrieval results. In our work, we build a similar network, but only to process the relevant images. In this network aggregates all the features compared with their separate networks for each feature in the feature set. Moreover, proposed Bayesian network model is a dynamic model which can be adjusted with different relevant images specified by the user. it also developed a different mechanism for the updating of conditional probabilities associated with the direct links in the network for our purpose. The diagram of the proposed Bayesian network is shown below.



In [21] a Bayesian active learning (BAL) mechanism has proposed to overcome semantic gap problems using relevance feedback.

Several key elements in this scheme:

(i) Based on Bayesian rule, a new classifier is constructed, which produce a rank of images instead of return a binary decision.

(ii) By defining the confidence of learner, a new sample selection strategy is proposed, and the most informative samples obtained by using this strategy are helpful to refine the learner.

(iii) Two different methods are used to estimate the positive and negative samples, and thus the accuracy of learner is improved.

Another approach in relevance feedback is **feature reweighing**. [24] have presented a feature re-weighting approach using relevant images as well as irrelevant ones in the relevance feedback. They have presented a feature re-weighting approach using the standard deviation of feature values from relevant images as well as the distribution pattern of irrelevant images on the axis of each feature component. As far as feature re-weighting approaches are concerned, one of their common drawbacks is that the feature re-weighting process is prone to be trapped by suboptimal states. To overcome this problem, this paper introduced a disturbing factor, which is based on the Fisher criterion, to push the feature weights out of sub-optimum.

Feature selection approach in relevance feedback is given in [25]. This paper has introduced the relevance feedback mechanism into the region-based image retrieval with online feature selection during each feedback round. This contribution has two folds. (1) A novel region-based image representation is proposed. Based on a generative model, a fuzzy codebook is extracted from the original region-based features, which represents the images in a uniform real-value feature space. (2) A feature selection criterion is developed and an effective relevance feedback algorithm is implemented in a boosting manner to simultaneously select the optimal features from the fuzzy codebook, and generate a strong ensemble classifier over the selected features. They proposed an effective relevance feedback method with online feature selection in the RBIR context. Based on the generative model, a fuzzy codebook is extracted to represent the images in a uniform fuzzy feature space. And based on the feature selection criterion to measurement the similarity between the positive and negative training sets, an RF algorithm is implemented in a boosting manner to select the optimal features and generate an ensemble classifier during each feedback round.

Researchers proposed Query Refinement framework in [27] that utilizes feedback from users to support:

- Query Modification allows users to refine the query representation. A user may start from a query object that approximately captures his information need. In each iteration of feedback, the system modifies the representation of the query to a more suitable representation.
- Query weighting changes the relative weights of different features in the query representation. The re-weighting mechanism allows the system to learn the user's interpretation of similarity/distance function.

Researchers have used *Image Relevance Reinforcement Learning* (IRRL) [26] ,that can integrate multiple RF techniques and makes use of their advantages. They believe that most researchers strive to develop a new RF technique which can attain better retrieval performance than the existing ones. However, they ignore the fact that, for a given image database, an RF technique that brings the best retrievals to a certain class of query images may be inferior to other RF approaches for another class of query images. Even for a specific query, we may need to apply different RF techniques at various feedback iterations to achieve the highest retrieval performance. By integrating existing RF algorithms, this paper demonstrates that a superior performance can be obtained. This paper has developed a new model, named image relevance reinforcement learning (IRRL), that can integrate multiple RF techniques and makes use of their advantages. The IRRL model automatically chooses the best RF approaches at various feedback iterations for a given query. It integrated three major existing RF techniques, namely, the Query Vector Modification (QVM), Feature Relevance Estimation (FRE), and Bayesian Inference (BI).

This technique includes :

1. It presents two integration schemes, a) combination and b) hybridization, to achieve the maximum synergism between different RF techniques.

2. The system is the first one that can automatically choose the optimal RF approach for a given query at particular feedback iteration.

3. This used a shared long-term memory to accumulate the relevance knowledge acquired from multiple users' experiences. The long-term relevance knowledge significantly improves the retrieval performance.

Another approach is **subspace learning using Discriminant Analysis**. The objective of discriminant analysis is to find the most discriminant features of data (*xi*) in the original high-dimensional space, and map data points to a projected low - dimensional space in a way that discriminant features are preserved. Linear discriminant analysis (LDA) is a popular method in CBIR area. LDA tries to find the transformation matrix *W* that maximizes the separation between different classes while minimizing within-class scatters in the new subspace.

It can be mathematically formulated as:

$$S_b = \sum_{i=1}^{C} p_i (m_i - m_G)(m_i - m_G)^T$$

$$S_w = \sum_{i=1}^{C} \sum_{x_j \in Class_i} (x_j - m_i)(x_j - m_i)^T$$

$$W_{LDA} = \arg\max_{W} \frac{| W^T S_b W |}{| W^T S_w W |}$$

where S_b is called between-class scatter matrix, S_w is within-class scatter matrix, C is total number of classes, and P_i is the prior probability of class *i* which is sometimes simply the number of data points in class *i*. The mean of class *i* is represented by *mi*, and m_G is the global average of all data points. The optimum *W* is obtained by solving the following generalized maximum eigenvalue problem:

$$S_b W = \lambda S_w W$$

There is an issue in computing LDA. To solve the above equation, the inverse of S_w should be obtained. However, when the rank of S_w is less than the number of dimensions, it is singular and has no inverse. In such situations, a common approach called Regularization is used to make S_w a full rank matrix by adding small quantities to its diagonal elements. Another approach is projecting feature vectors into a subspace of only a few of its principal components (PCA) or applying a null-space.

When there are only two classes, the process is known as **Fisher Discriminant Analysis** (FDA) [28]. A significant problem with FDA is its assumption that negative examples are drawn from the same distribution, which is not usually true in the case of image data. Another choice is **Multiple Discriminant Analysis** (MDA) that considers each negative example as a different class and creates a (NN+1)-class discriminant analysis problem where NN is the number of negative examples. Again, this assumption may not be true and some of negative examples do belong to the same distribution. Biased Discriminant Analysis (BDA) [11] keeps negative examples away from positive examples, and clusters only positive examples.

It assumes that "all positive examples are alike; each negative example is negative in its own way" [11]. This means that all positive examples should be located loosely in the same area in the feature space. However, semantically similar images may not be close to each other in the feature space, especially when their relations are defined based on high levels of semantic concepts. Discriminant analysis can be expressed as a combination of informative and discriminative learning with compactness and discrimination factors respectively. Compactness factor is related to minimizing within-class variations. BDA compacts only positive examples while LDA compacts both positive and negative points. Discrimination is maximizing between classes variations, and can be done by keeping negative examples away from the mean of positive examples or vice versa. LDA applies both strategies by maximizing class means from the global average (m_G) as it assumes there is the same distribution for all data points. BDA keeps only negative examples away from positive ones by maximizing the total distances of negative examples from the mean of positive examples (m_P). Empirical experiments with synthesized data shows that when the number of positive examples (N_P) is much higher than the number of negative examples (N_N), compacting negative examples, and discriminating negative examples from positive examples is the most efficient

strategy. On the other hand, when $N_N >> N_P$, it would be better to compact positive examples and keep them away from the mean of negative points. The reason is when the number of positive examples is much higher, it would be a heavy burden to compact them or discriminate them from negative examples. It would be the same for negative examples when their number is much higher than positive points.

There are various type of feature subspace selection discriminant analysis such as biased discriminant analysis (BDA), kernel bias discriminant analysis (KBDA) and nonparametric discriminant analysis (NDA).

Statistical discriminant analysis (SDA) [29] is a pattern recognition approach that attempts to maximize the distances between different labeled data samples. A eight matrix can be finding by using the discriminant analysis such that the distance between the two scatter class matrixes are maximized.

The KBDA and NDA methods had been implemented with and without feature selection framework. The result show the feature selection approach is more superior without feature selection framework when the training samples are small.

The **biased discriminant analysis** (BDA) is an approach tries to find the subspace to discriminate the positive (relevant images that concerned by user) and negatives (irrelevant images) samples. To do this, BDA minimize the variance of the positive samples. Then, it maximizes the distance between the center of the positive feedbacks and all negatives feedback. There are occurs a problem in biased discriminant analysis approach, which is it assumes all positive samples from a single Gaussian distribution, which means all positive samples should be similar view angle, similar illumination.

In [11] author has proposes biased discriminant analysis and transforms specifically designed to address the asymmetry between the positive and negative examples, and to trade off generalization for robustness under a small training sample in relevance feedback . The kernel version, namely .BiasMap., is derived to facilitate nonlinear biased discrimination. BiasMap can deal with positive and negative examples with non-linear densities asymmetrically in a principled way. Instead of confining to the traditional settings of the discriminant analysis, a better way is to use a new form of the discriminant analysis for which it believe that the relevance feedback problem is better cast as a .biased learning problem.: $(1+ x)$-*class learning* or *biased learning* can be defined as the learning problem in which there are an unknown number of classes but the user is only interested in one class, i.e., the user is biased toward one class. And the training samples are labeled by the user as only .positive. or .negative. as to whether they belong to the target class or not. Thus the negative examples can come from an uncertain number of classes. Past research has addressed this problem simply as a two-class classification problem with symmetric treatment on positive and negative examples, which makes sense only when sufficient negative examples are available. However the situation for relevance feedback during information retrieval is that the negative examples are too few to be of representative power for the true distribution. While the positive examples may have a better chance since in reality the class-ofinterest usually has compact support, the intuition is that all positive examples are alike, each negative example is negative in its own way. When the negative examples are too few to be representative of their true distribution, the (1+*x*)-class assumption becomes critical. It also proposed discriminating transform.

Kernel bias discriminant analysis (KBDA) [11], is the kernel version of the biased discriminant analysis. This kernel-based approach had been introduced to eliminate the problem on BDA, which is assumes Gaussian distribution on positive examples. Besides, it was used to perform non-linear discrimination for non-linear data distributions. However, the approach has been created a few disadvantages. The kernel based learning has to rely on parameter tuning, which makes the online learning unfeasible. In [31], the authors mentioned that there are two drawbacks on this approach. Firstly, the regularization method as used by [11] for avoiding matrix singularity problem is often unstable. To solve this problem, Tao and Tang [32] have been proposed nonparametric discriminant analysis method. The second problem is parameters used in the kernel function require to be manually tuned for maximum retrieval accuracy. This problem was suggested solved by maximizing the discriminant ratio of inter and intra covariant matrix in [30].

Among various RF schemes, biased discriminant analysis (BDA) based RF is one of the most promising [12]. The small sample size (SSS) problem is a big challenge, as users tend to give a small number of feedback samples. To explore solutions to this issue, paper [12] proposed a direct kernel BDA (DKBDA), which is less sensitive to SSS. An incremental DKBDA (IDKBDA) is also developed to speed up the analysis. Usually data is in a non-linear space, in which the kernel method is successfully used. Therefore, BDA is generalized to its kernel version, named as KBDA. To obtain the non-linear generalization, the linear input space is mapped to a non-linear kernel feature space. The aim is to significantly improve the performance of CBIR RF and utilize the direct idea to the BDA algorithm in the kernel feature space. This direct method is proposed based on *all positive examples are alike and each negative example is negative in its own way*. They name the approach as the direct kernel BDA (DKBDA). DKBDA can be regarded as an enhanced KBDA. According to the kernel trick idea, the original input space is first nonlinearly mapped to an arbitrarily high dimension feature space, in which the distribution of the images' patterns is linearized. Then, the DLDA idea is used to obtain a set of optimal discriminant basis vectors in the kernel feature space.

Nonparametric Discriminant Analysis

The nonparametric discriminant analysis (NDA) is an approach to finds the optimal feature set to maximize the margin between all positive feedbacks and all negative feedbacks in the input feature space [30]. NDA has an advantage which is the approach does not require all positive samples to be based on a single Gaussian distribution. In additional, it was used to solve the problem in kernel-bias discriminant analysis, Tao and Tang [30] have been reported a full rank null-space method for calculating the Eigen values and vectors of inter and intra covariant scatter matrix. The sss (small sample- size) problems also can be solving by three method which are regularization method, null-space method and full-space method. In Relevance Feedback, BDA assumes all positive feedbacks form a single Gaussian distribution [32] which may not be the case for CBIR. Although kernel BDA can overcome the drawback to some extent, the kernel parameter tuning makes the online learning unfeasible. To avoid the parameter tuning problem and the single Gaussian distribution assumption in BDA, In [32] authors construct a new nonparametric discriminant analysis (NDA). To address the small sample size problem in NDA, we introduce the regularization method and the null-space method. Because the regularization method may meet the ill-posed problem and the null space method will lose some discriminant information, they proposed here a full-space method. The proposed nonparametric discriminant analysis (NDA) has the following properties: 1. NDA assumes all positive samples are alike and each negative sample is negative in its own way; 2. NDA does not require all positive samples form a single Gaussian distribution. 3. NDA, similar to BDA and KBDA, may meet the Small-Sample-Size (SSS) problem. In this paper, authors solved the SSS problem with three methods: 1. The regularization method, which is used by Zhou in BDA [11]; 2. the null-space method [33], which is a popular method to solve the SSS problem in linear discriminant analysis for face recognition; 3. the full-space method, which is proposed to preserve all discriminant information of NDA.

In [34] for relevance feedback, Biased Discriminant Euclidean Embedding technique has been used which parameterizes samples in the original high-dimensional ambient space to discover the intrinsic coordinate of image low-level visual features. BDEE precisely models both the intra class geometry and interclass discrimination and never meets the under sampled problem. To consider unlabelled samples, a manifold regularization-based item is introduced and combined with BDEE to form the semi-supervised BDEE, or semi-BDEE for short. Images are represented by low-level visual features. These can be deemed as samples drawn from a low-dimensional manifold and artificially embedded in a high-dimensional ambient space. Here, the high-dimensional ambient space is $R^{H,}$ the low-level visual feature space and the low-dimensional smooth manifold is R^{L}. Therefore, our objective is to find a mapping F to select the effective subspace R^{L} from R^{H} for separating positive samples from negative samples based on a number of observations

To reduce the complexity of the problem, assume that the mapping is linear and then can find low-dimensional representations

There is a growing interest in subspace learning techniques for face recognition; however, the excessive dimension of the data space often brings the algorithms into the curse of dimensionality dilemma. In paper [35], authors had presented a novel approach to solve the supervised dimensionality reduction problem by encoding an image object as a general tensor of second or even higher order.

First, it proposed a discriminant tensor criterion, whereby multiple interrelated lower dimensional discriminative subspaces are derived for feature extraction. Then, a novel approach, called k-mode optimization, is presented to iteratively learn these subspaces by unfolding the tensor along different tensor directions. This algorithm is **multilinear discriminant analysis** (MDA), which has the following characteristics:

1) Multiple interrelated subspaces can collaborate to discriminate different classes, 2) for classification problems involving higher order tensors, the MDA algorithm can avoid the curse of dimensionality dilemma and alleviate the small sample size problem, and

3) The computational cost in the learning stage is reduced to a large extent owing to the reduced data dimensions in k-mode optimization.

More specifically, contributions in [35] is as follows. First, it proposed a novel criterion for dimensionality reduction, called ***discriminant tensor criterion (DTC)*** which maximizes the interclass scatter and at the same time minimizes the intraclass scatter both measured in the tensor-based metric. Different from the traditional subspace learning criterion which derives only *one* subspace, in our approach *multiple* interrelated subspaces are obtained through the optimization of the criterion where the number of the subspaces is determined by the order of the feature tensor used. Second, they presented a procedure to iteratively learn these interrelated discriminant subspaces via a novel tensor analysis approach, called k-*mode optimization* approach. They also explored the foundation of the k-*mode optimization* approach to show that it unfolds the tensors into matrices along the th direction. When the column vectors of the unfolded matrices are considered as the new objects to be analyzed, a special discriminant analysis is performed by computing the scatter as the sums of the scatter computed from the new samples with the same column indices. This explanation provides an intuitive explanation for the superiority of proposed algorithm in comparison with other vector-based approaches.

III. Conclusion And Future Work

As we know, CBIR suffers with 'curse of dimensionality'.

Several Dimension reduction methods are suggested for CBIR system. These methods are based mainly on

1. Principal component analysis (PCA)
2. Linear discriminant Analysis (LDA)

PCA → PCA finds the low dimensional subspace that captures the most variance of original data sheet i.e., this method extracts the most descriptive features.

LDA → The objective of LDA is to perform dimensionality reduction while preserving as much of the clad discriminatory information as possible. Thus LDA constructs most discriminative features.

PCA and LDA are linear algorithms that operate on 1-D objects, i.e., first-order tensors (vectors). To apply these linear algorithms to higher order (greater than one) tensor objects, such as images and videos, these tensor objects have to be reshaped (vectorized) into vectors first. However, it is well understood that such reshaping (vectorization) breaks the natural structure and correlation in the original data, reducing redundancies and/or higher order dependencies present in the original data set, and losing potentially more compact or useful representations that can be obtained in the original tensorial forms [36]. Thus, dimensionality reduction algorithms operating directly on the tensor objects rather than their vectorized versions are desirable.

Recently, multilinear subspace feature extraction algorithms [35], [36], [38], [39] operating directly on the tensorial representations rather than their vectorized versions are emerging. The multilinear principal component analysis (MPCA) framework [36], a multilinear extension of the PCA, determines a multilinear projection that projects the original tensor objects into a lower dimensional tensor subspace while preserving the variation in the original data. Similar to PCA, MPCA is an unsupervised method as well and the feature extraction process does not make use of the class information. Since LDA is a classical algorithm that has been very successful and applied widely in various applications, there have been several variants of its multilinear extension proposed, named multilinear discriminant analysis (MLDA). In the existing MLDA variants [35], [39], [37], [40], the attention focused mainly on the objective criterion in terms of (either the ratio of or the difference between) the between-class scatter and the within-class scatter since it is well known that the classical LDA aims to maximize Fisher's discrimination criterion (FDC). However, they did not take the correlations among features into account. So we can aim to consider un-correlated features in MLDA.

For future work we can incorporate multilinear discriminant analysis (MLDA) technique with relevance feedback. Removal of redundancy is very important in relevance feedback. The set of sampled images provided after each irritation shouldn't contain any redundant image sample. So by considering un-correlated features we can reduce the amount of redundancy present in samples given for feedback.

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