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A Dynamic System to Determine Dimensionality of the Embedded Subspace for Relevance Feedback In Order To Improve the Performance of Content-Based Image Retrieval Systems

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Abstract:

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. Content-based image retrieval is opposed to traditional concept-based approaches. In this paper CBIR is used for efficient retrieval of relevant images from a large image database based on automatically derived from the image feature. The features are extracted based on color, shape and texture. One fundamental problem in CBIR is the semantic gap between low level visual features and the high level semantic concepts.

To reduce this semantic gap relevance feedback was introduced.A variety of relevance feedback (RF) schemes have been developed as a powerful tool to bridge the semantic gap between low-level visual features and high-level semantic concepts, and thus to improve the performance of CBIR systems. First, it treats the positive and negative feedbacks equally, which is not appropriate since the two groups of training feedbacks have distinct properties. Second, most of the SVM-based RF techniques do not take into account the unlabeled samples, although they are very helpful in constructing a good classifier. To explore solutions to overcome these two drawbacks, in this paper, we explore and implement a biased maximum margin analysis and a semi-supervised BMMA for integrating the distinct properties of feedbacks and utilizing the information of unlabeled samples for SVM-based RF schemes.

Keywords:

Image Retrieval, Relevance feedback, Support Vector Machine, Clustering Techniques, Image Database.

Introduction:

“Content-based” means that the search analyzes the contents of the image rather than the metadata such as keywords, tags, or descriptions associated with the image. The term “content” in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. CBIR is desirable because searches that rely purely on metadata are dependent on annotation quality and completeness. Having humans manually annotate images by entering keywords or metadata in a large database can be time consuming and may not capture the keywords desired to describe the image. The evaluation of the effectiveness of keyword image search is subjective and has not been well-defined. In the same regard, CBIR systems have similar challenges in defining success.

The term “content-based image retrieval” seems to have originated in 1992 when it was used by T. Kato to describe experiments into automatic retrieval of images from a database, based on the colors and shapes present. Since then, the term has been used to describe the process of retrieving desired images from a large collection on the basis of syntactical image features. The techniques, tools, and algorithms that are used originate from fields such as statistics, pattern recognition, signal processing, and computer vision. The earliest commercial CBIR system was developed by IBM and was called QBIC (Query by Image Content).

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The interest in CBIR has grown because of the limitations inherent in metadata-based systems, as well as the large range of possible uses for efficient image retrieval. Textual information about images can be easily searched using existing technology, but this requires humans to manually describe each image in the database. This can be impractical for very large databases or for images that are generated automatically, e.g. those from surveillance cameras.

It is also possible to miss images that use different synonyms in their descriptions. Systems based on categorizing images in semantic classes like “cat” as a subclass of “animal” can avoid the miscategorization problem, but will require more effort by a user to find images that might be “cats”, but are only classified as an “animal”. Many standards have been developed to categorize images, but all still face scaling and miscategorization issues.

Initial CBIR systems were developed to search databases based on image color, texture, and shape properties. After these systems were developed, the need for user-friendly interfaces became apparent. Therefore, efforts in the CBIR field started to include human-centered design that tried to meet the needs of the user performing the search.

This typically means inclusion of: query methods that may allow descriptive semantics, queries that may involve user feedback, systems that may include machine learning, and systems that may understand user satisfaction levels.

CBIR techniques:

Many CBIR systems have been developed, but the problem of retrieving images on the basis of their pixel content remains largely unsolved.

Query techniques:

Different implementations of CBIR make use of different types of user queries.Query by example is a query technique that involves providing the CBIR system with an example image that it will then base its search upon. The underlying search algorithms may vary depending on the application, but result images should all share common elements with the provided example.

Semantic retrieval:

Semantic retrieval starts with a user making a request like “find pictures of Abraham Lincoln”. This type of open-ended task is very difficult for computers to perform - Lincoln may not always be facing the camera or in the same pose. Many CBIR systems therefore generally make use of lower-level features like texture, color, and shape. These features are either used in combination with interfaces that allow easier input of the criteria or with databases that have already been trained to match features (such as faces, fingerprints, or shape matching). However, in general, image retrieval requires human feedback in order to identify higher-level concepts.

Relevance Feedback (Human Interaction):

Combining CBIR search techniques available with the wide range of potential users and their intent can be a difficult task. An aspect of making CBIR successful relies entirely on the ability to understand the user intent. CBIR systems can make use of relevance feedback, where the user progressively refines the search results by marking images in the results as “relevant”, “not relevant”, or “neutral” to the search query, then repeating the search with the new information. Examples of this type of interface have been developed.

Iterative/Machine Learning:

Machine learning and application of iterative techniques are becoming more common in CBIR.

Other query methods:

Other query methods include browsing for example images, navigating customized/hierarchical categories, querying by image region (rather than the entire image), querying by multiple example images, querying by visual sketch, querying by direct specification of image features, and multimodal queries (e.g. combining touch, voice, etc.).

Content comparison using image distance measures:

The most common method for comparing two images in content-based image retrieval (typically an example

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image and an image from the database) is using an image distance measure. An image distance measure compares the similarity of two images in various dimensions such as color, texture, shape, and others. For example a distance of 0 signifies an exact match with the query, with respect to the dimensions that were considered.

As one may intuitively gather, a value greater than 0 indicates various degrees of similarities between the images. Search results then can be sorted based on their distance to the queried image. Many measures of image distance (Similarity Models) have been developed.

Color:

Computing distance measures based on color similarity is achieved by computing a color histogram for each image that identifies the proportion of pixels within an image holding specific values. Examining images based on the colors they contain is one of the most widely used techniques because it can be completed without regard to image size or orientation. However, research has also attempted to segment color proportion by region and by spatial relationship among several color regions.

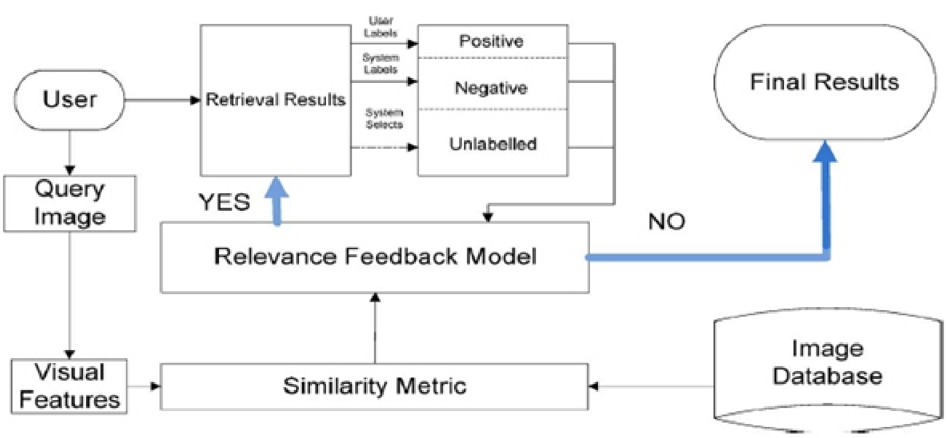
Texture:

Texture measures look for visual patterns in images and how they are spatially defined. Textures are represented by texels which are then placed into a number of sets, depending on how many textures are detected in the image. These sets not only define the texture, but also where in the image the texture is located.Texture is a difficult concept to represent. The identification of specific textures in an image is achieved primarily by modeling texture as a two-dimensional gray level variation. The relative brightness of pairs of pixels is computed such that degree of contrast, regularity, coarseness and directionality may be estimated. The problem is in identifying patterns of co-pixel variation and associating them with particular classes of textures such as silky, or rough.

Shape:

Shape does not refer to the shape of an image but to the shape of a particular region that is being sought out. Shapes will often be determined first applying segmentation or edge detection to an image. Other methods use shape filters to identify given shapes of an image. Shape descriptors may also need to be invariant to translation, rotation, and scale.

SYSTEM ARCHITECTURE:



EXISTING SYSTEM:

A variety of relevance feedback(RF) schemes have been developed as a powerful tool to bridgethe semantic gap between low-level visual features and high-levelsemantic concepts, and thus to improve the performance of CBIRsystems. Among various RF approaches, support-vector-machine(SVM)-based RF is one of the most popular techniques in CBIR.

DISADVANTAGES OF EXISTING SYSTEM:

Despite the success, directly using SVM as an RF scheme hastwo main drawbacks. First, it treats the positive and negativefeedbacks equally, which is not appropriate since the two groupsof training feedbacks have distinct properties. Second, most of theSVM-based RF techniques do not take into account the unlabeledsamples, although they are very helpful in constructing a goodclassifier.

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The low-level featurescaptured from the images may not accurately characterize thehigh-level semantic concepts

PROPOSED SYSTEM:

The proposed scheme is mainly basedon the following:

1) The effectiveness of treating positive examples and negative examples unequally.

2) The significanceof the optimal subspace or feature subset in interactiveCBIR;

3) The success of graph embedding in characterizing intrinsicgeometric properties of the data set in high-dimensionalspace

4) The convenience of the graph-embedding framework in constructing semi-supervised learning techniques.

ADVANTAGES OF PROPOSED SYSTEM:

To explore solutions to these two aforementioned problems inthe current technology, we propose a biased maximum marginanalysis (BMMA)and a semisupervised BMMA(SemiBMMA)for the traditional SVM RF schemes, based on the graph-embeddingframeworkWith the incorporation ofBMMA, labeled positive feedbacksare mapped as close as possible, whereas labeled negative feedbacks are separated from labeled positive feedbacks by amaximum margin in the reduced subspace. The traditional SVMcombined with BMMA can better model the RF process and reducethe performance degradation caused by distinctpropertiesof the two groups of feedbacks.

The SemiBMMA can incorporatethe information of unlabeled samples into the RF and effectivelyalleviate the overfitting problem caused by the small sizeof labeled training samples. To show the effectiveness of theproposed scheme combined with the SVM RF, we will compareit with the traditional SVM RF and some other relevantexisting techniques for RF on a real-world image collection.Experimental results demonstrate that the proposed scheme cansignificantly improve the performance of the SVMRF for imageretrieval.

MODULES:

Training and Indexing Module

Graph-Embedding Framework

Features Extraction Based on Different Methods

Visualization of the Retrieval Results

Experiments on a Large-Scale Image Database:

Experiments on a Small-Scale Image Database

MODULES DESCRIPTION:

Training and Indexing Module:

In this module, we index and train the system. Indexing the whole set of images is done for making the search efficient and time consuming. If we don't index the system, then it takes more time as it searches the whole disk space..Indexing is done using an implementation of the Document Builder Interface. A simple approach is to use the Document Builder Factory, which creates Document Builder instances for all available features as well as popular combinations of features (e.g. all JPEG features or all avail-able features).

In a content based image retrieval system, target images are sorted by feature similarities with respect to the query (CBIR).In this indexing, we propose to classification of feature set obtained from the CBIR.First, it randomly selects k of the objects, each of which initially represents a cluster mean or center. For each of the remaining objects, an object is assigned to the cluster to which it is the most similar, based on the distance between the object and the cluster mean. It then computes the new mean for each cluster.

Graph-Embedding Framework:

In order to describe our proposed approach clearly,we firstreviewthe graph-embeddingframework Generally, for a classification problem, the sample set can be representedas matrix , whereindicates the total number of the samples and is the featuredimensionality. Let be an undirected similaritygraph, which is called an intrinsic graph, with vertices setand similarity matrix.

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The similarity matrix isreal and symmetric, and measures the similarity between a pairof vertices; can be formed using various similarity criteria.The corresponding diagonal matrix and the Laplacian matrixof graph can G. Graph embedding of graph is defined as an algorithmto determine the low-dimensional vector representationsof the vertex set, where islower than for dimensionality.

The column vector is theembedding vector for vertex, which preserves the similaritiesbetween pairs of vertices in the original high-dimensionalspace. Then, in order to characterize the difference betweenpairs of vertices in the original high-dimensional space, apenalty graph is also defined, where verticesare the same as those of, but the edge weight matrixcorresponds to the similarity characteristics that are tobe suppressed in the low-dimensional feature space. For adimensionality reduction problem, direct graph embeddingrequires an intrinsic graph, whereas a penalty graph isnot a necessary input.

Features Extraction Based on Different Methods:

Six experiments are conducted for comparing the BMMAwith the traditional LDA, the BDA method, and a graph-embeddingapproach, i.e., MFA, in finding the most discriminativedirections. We plot the directions that correspond to the largest Eigenvalue of the decomposed matrices for LDA, BDA,MFA, and BMMA, respectively. From these examples, we canclearly notice that LDA can find the best discriminative directionwhen the data from each class are distributed as Gaussianwith similar covariance matrices Biased toward thepositive samples, BDA can find the direction that the positivesamples are well separated with the negative samples when thepositive samples have a Gaussian distribution, but it may alsoconfuse when the distribution of the positive samples is morecomplicated.

Biased towardpositive samples, the BMMA method can find the mostdiscriminative direction for all the six experiments based onlocal analysis, since it does not make any assumptions on thedistributions of the positive and negative samples. It shouldbe noted that BMMA is a linear method, and therefore, weonly gave the comparison results of the aforementioned linearmethods.

Visualization of the Retrieval Results:

In the previous subsections,we have presented some statistically quantitative resultsof the proposed scheme. Here, we show the visualizationof retrieval results.In experiments, we randomly select some images (e.g., bobsled,cloud, cat, and car) as the queries and perform the RFprocess based on the ground truth. For each query image, wedo four RF iterations. For each RF iteration, we randomly selectsome relevant and irrelevant images as positive and negativefeedbacks from the first screen, which contains 20 images intotal. The number of selected positive and negative feedbacks isabout 4, respectively.

We choose them according to the ground truth of the images, i.e., whether they share the same conceptwith the query image or not. The query images are given as the first image of each row.We show the top one to ten images of initial results without feedbackand SemiBMMA SVM after four feedback iterations, respectively,and incorrect results are highlighted by green boxes.From the results, we can notice that our proposed scheme cansignificantly improve the performance of the system. For thefirst,second, and fourth query images, our system produces tenrelevant images out of the top ten retrieved images. For the thirdquery image, our system produces nine relevant images out ofthe top ten retrieved images. Therefore, SemiBMMA SVM caneffectively detect the homogeneous concept shared by the positivesamples and hence improve the performance of the retrievalsystem.

Experiments on a Large-Scale Image Database:

Here, we evaluate the performance of the proposed schemeon a real-world image database. We use precision–scope curve,precision rate, and standard deviation to evaluate the effectivenessof the image retrieval algorithms. The scope is specifiedby number of top-ranked images presented to the user. Theprecision is the major evaluation criterion, which evaluates the effectiveness of the algorithms. The precision–scope curvedescribes the precision with various scopes and can give theoverall performance evaluation of the approaches. The precisionrate is the ratio of the number of relevant images retrievedto the top retrieved images, which emphasizes the precisionat a particular value of scope.

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Standard deviation describesthe stability of different algorithms. Therefore, the precisionevaluates the effectiveness of a given algorithm, and the correspondingstandard deviation evaluates the robustness of thealgorithm. We designeda slightly different feedback scheme to model the realworldretrieval process. In a real image retrieval system, a queryimage is usually not in the image database. To simulate such anenvironment, we use fivefold cross validation to evaluate the algorithms.More precisely, we divide the whole image databaseinto five subsets of equal size. Thus, there are 20% images percategory in each subset. At each run of cross validation, onesubset is selected as the query set, and the other four subsetsare used as the database for retrieval. Then, 400 query samplesare randomly selected from the query subset, and the RF is automaticallyimplemented by the system. For each query image,the system retrieves and ranks the images in the database, andnine RF iterations are automatically executed.

Experiments on a Small-Scale Image Database:

In orderto show how efficient the proposed BMMA combined withSVM is in dealing with the asymmetric properties of feedbacksamples, the first evaluation experiment is executed ona small-scale database, which includes 3899 images with 30different categories. We use all 3899 images in 30 categoriesas queries. Some example categories used in experiments. To avoid the potential problemcaused by the asymmetric amount of positive and negative feedbacks, weselected an equal number of positive and negative feedbackshere. In practice, the first five query-relevant images and firstfive irrelevant images in the top 20 retrieved images in theprevious iterations were automatically selected as positive andnegative feedbacks, respectively.

Conclusion:

The image retrieval is done by considering color, Texture, and Edge features in the proposed technique. The color and bitmap method involves extracting only the local and global features such as mean and standard deviation. But in the proposed technique, color, texture, and Edge features are extracted and then Interactive Genetic Algorithm is applied on these image features. The estimated parameters in the proposed technique include the Precision and Recall values.

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