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MAXIMUM MARGIN ANALYSIS FOR INTERACTIVE SHAPE-BASED RETRIEVAL

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ABSTRACT:

With many potential practical applications, content- based image retrieval (CBIR) has attracted substantial attention during the past few years. 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. Among various RF approaches, support-vector-machine (SVM)-based RF is one of the most popular techniques in CBIR. Despite the success, directly using SVM as an RF scheme has two main drawbacks. 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.

INTRODUCTION

An **image retrieval** system is a computer system for browsing, searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords, or descriptions to the images so that retrieval can be performed over the annotation words. Manual image annotation is time-consuming, laborious and expensive; to address this, there has been a large amount of research done on automatic image annotation. Additionally, the increase in social web applicationsand the semantic web have inspired the development of several web-based image annotation tools.

The first microcomputer-based image database retrieval system was developed at MIT, in the 1980s, by Banireddy

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Prasaad, Amar Gupta, Hoo-min Toong, and Stuart Madnick.[1]A 2008 survey article documented progresses after 2007.[2]

RELATED INFORMATION

Search methods

Image search is a specialized data search used to find images. To search for images, a user may provide query terms such as keyword, image file/link, or click on some image, and the system will return images "similar" to the query. The similarity used for search criteria could be meta tags, color distribution in images, region/shape attributes, etc.

- Image meta search - search of images based on associated metadata such as keywords, text, etc.
- Content-based image retrieval (CBIR) – the application of computer vision to the image retrieval. CBIR aims at avoiding the use of textual descriptions and instead retrieves images based on similarities in their contents (textures, colors, shapes etc.) to a user-supplied query image or user-specified image features.
    - List of CBIR Engines - list of engines which search for images based image visual content such as color, texture, shape/object, etc.

Data Scope

It is crucial to understand the scope and nature of image data in order to determine the complexity of image search system design. The design is also largely influenced by factors such as the diversity of user-base and expected user traffic for a search system. Along this dimension, search data can be classified into the following categories:

- *Archives* - usually contain large volumes of structured or semi-structured homogeneous data pertaining to specific topics.
- *Domain-Specific Collection* - this is a homogeneous collection providing access to controlled users with very specific objectives. Examples of such a collection are biomedical and satellite image databases.
- *Enterprise Collection* - a heterogeneous collection of images that is accessible to users within an organization's intranet. Pictures may be stored in many different locations.
- *Personal Collection* - usually consists of a largely homogeneous

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collection and is generally small in size, accessible primarily to its owner, and usually stored on a local storage media.

- *Web* - World Wide Web images are accessible to everyone with an Internet connection. These image collections are semi-structured, non-homogeneous and massive in volume, and are usually stored in large disk arrays.

Multimedia Information Retrieval

(MMIR) is a research discipline of computer science that aims at extracting semantic information from multimedia data sources.[1] Data sources include directly perceivable media such as audio, image and video, indirectly perceivable sources such as text, biosignals as well as not perceivable sources such as bioinformation, stock prices, etc. The methodology of MMIR can be organized in three groups:

1. Methods for the summarization of media content (feature extraction). The result of feature extraction is a description.
2. Methods for the filtering of media descriptions (for example, elimination of redundancy)
3. Methods for the categorization of media descriptions into classes.

Feature Extraction Methods

Feature extraction is motivated by the sheer size of multimedia objects as well as their redundancy and, possibly, noisiness.[2] Generally, two possible goals can be achieved by feature extraction:

- Summarization of media content. Methods for summarization include in the audio domain, for example, Mel Frequency Cepstral Coefficients, Zero Crossings Rate, Short-Time Energy. In the visual domain, color histograms[3] such as the MPEG-7 Scalable Color Descriptor can be used for summarization.
- Detection of patterns by auto-correlation and/or cross-correlation. Patterns are recurring media chunks that can either be detected by comparing chunks over the media dimensions (time, space, etc.) or comparing media chunks to templates (e.g. face templates, phrases). Typical methods include Linear Predictive Coding in the audio/biosignal domain,[4] texture description in the visual domain and n-grams in text information retrieval.

Merging and Filtering Methods

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Multimedia Information Retrieval implies that multiple channels are employed for the understanding of media content.[5] Each of this channels is described by media-specific feature transformations. The resulting descriptions have to be merged to one description per media object. Merging can be performed by simple concatenation if the descriptions are of fixed size. Variable-sized descriptions - as they frequently occur in motion description - have to be normalized to a fixed length first.

Frequently used methods for description filtering include factor analysis (e.g. by PCA), singular value decomposition (e.g. as latent semantic indexing in text retrieval) and the extraction and testing of statistical moments. Advanced concepts such as the Kalman filter are used for merging of descriptions.

Categorization Methods

Generally, all forms of machine learning can be employed for the categorization of multimedia descriptions[6] though some methods are more frequently used in one area than another. For example, Hidden Markov models are state-of-the-art in speech recognition, while Dynamic Time Warping - a semantically related method - is state-of-the-art in gene sequence alignment. The list of applicable classifiers includes the following:

- Metric approaches (Cluster Analysis, Vector Space Model, Minkowski Distances, Dynamic Alignment)
- Nearest Neighbor methods (K-Nearest Neighbor, K-Means, Self-Organizing Map)
- Risk Minimization (Support Vector Regression, Support Vector Machine, Linear Discriminant Analysis)
- Density-based Methods (Bayes Nets, Markov Processes, Mixture Models)
- Neural Networks (Perceptron, Associative Memories, Spiking Nets)
- Heuristics (Decision Trees, Random Forests, etc.)

The selection of the best classifier for a given problem (test set with descriptions and class labels, so-called ground truth) can be performed automatically, for example, using the Weka Data Miner.

Open Problems

The quality of MMIR Systems[7] depends heavily on the quality of the training data. Discriminative descriptions can be extracted from media sources in various forms. Machine learning provides categorization methods for all types of data. However, the classifier can only be as good as the given training data. On the other hand, it requires considerable effort to provide class labels for large databases. The future success of MMIR will depend on the provision of such data.[8] The annual TRECVID competition is currently one of the most relevant sources of high-quality ground truth.

EXISTING SYSTEM:

Search by Image is optimized to work well for content that is reasonably well described on the web. For this reason, you'll likely get more relevant results for famous landmarks or paintings than you will for more personal images like your toddler's latest finger painting. Color representations based content based image retrieval.

PROPOSED SYSTEM:

To explore solutions to overcome these two drawbacks, in this paper, we propose a biased maximum margin analysis (BMMA) and a semi supervised BMMA (Semi BMMA) for integrating the distinct properties of feedbacks and utilizing the information of unlabeled samples for SVM-based RF schemes. The BMMA differentiates positive feedbacks from negative ones based on local analysis, whereas the Semi BMMA can effectively integrate information of unlabeled samples by introducing a Laplacian regularize to the BMMA. We formally formulate this problem into a general subspace learning task and then propose an automatic approach of determining the dimensionality of the embedded subspace for RF. Extensive experiments on a large real-world image database demonstrate that the proposed scheme combined with the SVM RF can significantly improve the performance of CBIR systems.

MODULES

1. **LOGIN MODULES.**
2. **POSITIVE MODULE.**
3. **NEGATIVE MODULE.**
4. **CBIR MODULE.**

MODULE DESCRIPTION:

LOGIN MODULES:

Login or logon (also called logging in or on and signing in or on) is the process by which individual access to a computer system is controlled by identification of the user using credentials provided by the user.

A user can log in to a system and can then log out or log off (perform a logout / logoff) when the access is no longer needed.

Logging out may be done explicitly by the user performing some action, such as entering the appropriate command, or clicking a website link labeled as such. It can also be done implicitly, such as by powering the machine off, closing a web browser window, leaving a website, or not refreshing a webpage within a defined period.

POSITIVE MODULE:

With the observation that "all positive examples are alike; each negative example is negative in its own way," the two groups of feedbacks have distinct properties for CBIR. However, the traditional SVM RF treats the positive and negative feedbacks equally. To alleviate the performance degradation when using SVM as an RF scheme for CBIR, we explore solutions based on the argument that different semantic concepts lie in different subspaces and each image can lie in many different concept subspaces .We formally formulate this problem into a general subspace learning problem and propose a BMMA for the SVM RF scheme..

NEGATIVE MODULE:

To utilize the information of unlabeled samples in the database, we introduced a Laplacian regularizer to the BMMA, which will lead to SemiBMMA for the SVM RF. The resultant Laplacian regularizer is largely based on the notion of local consistency, which was inspired by the recently emerging manifold learning community and can effectively depict the weak similarity relationship between unlabeled samples pairs. Then, the remaining images in the database are projected onto this resultant semantic subspace, and a similarity measure is applied to sort the images based on the new representations. For the SVM-based RFs, the distance to the hyperplane of the classifier is the criterion to discriminate the query-relevant samples from the query-irrelevant samples.

CBIR MODULE:

SVM-based RF has been widely used to bridge the semantic gap and enhance the performance of CBIR systems The novel approaches can distinguish the positive

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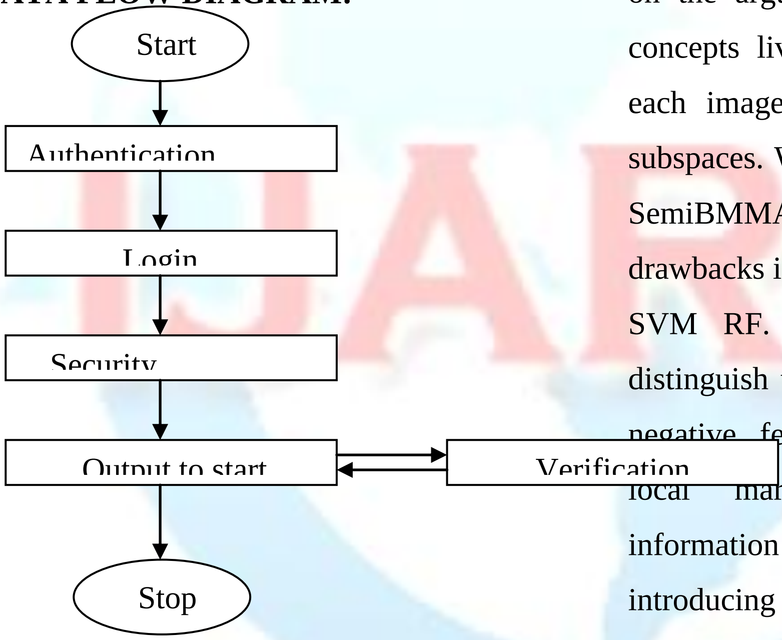
feedbacks and the negative feedbacks by maximizing the local margin and integrating the information of the unlabeled samples by introducing a Laplacian regularizer. Extensive experiments on a large real-world Corel image database have shown that the proposed scheme combined with the traditional SVM RF can significantly improve the performance of CBIR systems.

DATA FLOW DIAGRAM:



CONCLUSION AND FUTURE WORK

SVM-based RF has been widely used to bridge the semantic gap and enhance the performance of CBIR systems. However, directly using SVM as an RF scheme has two main drawbacks. First, it treats the positive and negative feedbacks equally, although this assumption is not appropriate since all positive feedbacks

share a common concept, while each negative feedback differs in diverse concepts. Second, it does not take into account the unlabeled samples, although they are very helpful

in constructing a good classifier. In this paper, we have explored solutions based on the argument that different semantic concepts live in different subspaces and each image can live in many different subspaces. We have designed BMMA and SemiBMMA to alleviate the two drawbacks in the traditional

SVM RF. The novel approaches can distinguish the positive feedbacks and the negative feedbacks by maximizing the local margin and integrating the information of the unlabeled samples by introducing a Laplacian regularizer. Extensive experiments on a large real-world Corel image database have shown that the proposed scheme combined with the traditional SVM RF can significantly improve the performance of CBIR systems.

Despite the promising results, several questions remain to be investigated in our future work. First, this approach involves dense-matrix eigen decomposition, which can be computationally expensive both in time and memory. Therefore, an effective technique for computation is required to alleviate the drawback. Second, theoretic questions need to be investigated regarding how the proposed scheme affects the generalization error of classification models. More specifically, we expect to get a better tradeoff between the integration of the distinct properties of feedbacks and the generalization error of the classifier

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