Biased Maximum Margin Analysis for Content based Interactive Image Retrieval

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ABSTRACT
Content based image retrieval from large resources has become an area of wide interest now a days in many applications. 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. Content-based image retrieval system that uses colour, edge and texture as visual features to describe the content of an image region. 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. To explore solutions to overcome these two drawbacks, Biased maximum margin analysis and a semi supervised biased maximum margin analysis for integrating the distinct properties of feedbacks and utilizing the information of unlabeled samples for SVM-based RF schemes. The Biased maximum margin analysis differentiates positive feedbacks from negative ones based on local analysis; whereas the semi supervised biased maximum margin analysis can effectively integrate information of unlabeled samples by introducing a Laplacian regularizer to the biased maximum margin analysis

Keyword
Image retrieval, margin

1. Introduction

During the past few years, content-based image retrieval (CBIR) has gained much attention for its potential applications in multimedia management. It is motivated by the explosive growth of image records and the online accessibility of remotely stored images. An effective search scheme is urgently required to manage the huge image database. Different from the traditional search engine, in CBIR, an image query is described by using one or more example images, and low-level visual features (e.g., colour, texture, shape, etc.) are automatically extracted to represent the images in the database. However, the low-level features captured from the images may not accurately characterize the high-level semantic concepts. To narrow down the so-called semantic gap, relevance feedback (RF) was introduced as a powerful tool to enhance the performance of CBIR. Huang et al. introduced both the query movement and there weighting techniques. A self-organizing map was used to construct the RF algorithms. One-class support vector machine (SVM) estimated the density of positive feedback samples. Derived from one-class SVM, a biased SVM inherited the merits of one-class SVM but incorporated the negative feedback samples. Considering the geometry structure of image low-level visual features, With the observation that "all positive examples are alike; each negative example is negative in its own way," RF was formulated as a biased subspace learning problem, in which there is an unknown number of classes, but the user is only concerned about the positive class. However, all of these methods have some limitations. For example, the method is heuristically based, the density estimation method ignores any information contained in the negative feedback samples, and the discriminate subspace learning techniques often suffer from the so-called "small sample size" problem. Regarding the positive and negative feedbacks as two different groups, classification- based RFs have become a popular technique in the CBIR community.

However, RF is very different from the traditional classification problem because the feedbacks provided by the user are often limited in real-world image retrieval systems. Therefore, small sample learning methods are most promising for RF. Two-class SVM is one of the popular small sample learning methods widely used in recent years and obtains the state-of the-art performance in classification for its good generalization ability. The SVM can achieve a minimal structural risk by minimizing the Vapnik–Chervonenkis dimensions. Guo et al. developed a constrained similarity measure for image retrieval, which learns a boundary that divides the images into two groups, and samples inside the boundary are ranked by their Euclidean distance to the query image. The SVM active learning method selects samples close to the boundary as the most informative samples for the user to label. Random sampling techniques were applied to alleviate unstable, biased, and over fitting problems in SVM RF. Li et al. proposed multi-training SVM method by adapting a co-training technique and a random sampling method. Nevertheless, most of the SVM RF approaches ignore the basic difference between the two distinct groups of feedbacks, i.e., all positive feedbacks share a similar concept while each negative feedback usually varies with different concepts. For instance, a typical set of feedback

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samples in RF iteration is shown in Figure 1. All the samples labelled as positive feedbacks share a common concept (i.e., elephant), while each sample labelled as negative feedback varies with diverse concepts (i.e., flower, horse, banquet, hill, etc.).

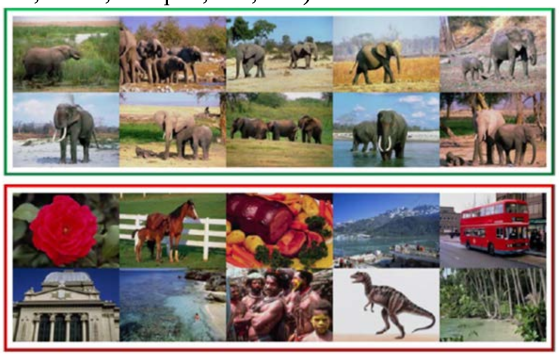


Figure 1 Typical set of positive & negative feedback samples in an RF iteration

Traditional SVMRF techniques treat positive and negative feedbacks equally. Directly using SVM as an RF scheme is potentially damaging to the performance of CBIR systems. One problem stems from the fact that different semantic concepts live in different subspaces and each image can live in many different subspaces, and it is the goal of RF schemes to figure out “which one”.
However, it will be a burden for traditional SVM-based RF schemes to tune the internal parameters to adapt to the changes of the subspace. Such difficulties have severely degraded the effectiveness of traditional SVM RF approaches for CBIR. Additionally, it is problem incorporate the information of unlabelled samples into traditional SVM-based RF schemes for CBIR, although unlabelled samples are very helpful in constructing the optimal classifier, alleviating noise and enhancing the performance of the system.

2. Existing System

Content-based image retrieval (CBIR) has gained much attention for its potential applications in multimedia management. It is motivated by most informative samples for the user to label. Random sampling techniques were applied to alleviate unstable, biased, and over fitting problems in SVM RF. Li et al. proposed multitraining SVM method by adapting a co training technique and a random sampling method. Nevertheless, most of the SVM RF approaches ignore the basic difference between the two distinct groups of feedbacks, i.e., all positive feedbacks share a similar concept while each negative feedback usually varies with different concepts. Traditional SVMRF techniques treat positive and negative feedbacks equally. Directly using SVM as an RF scheme is potentially damaging to the performance of CBIR systems. One problem stems from the fact that different Semantic concepts live in different subspaces and each image can live in many different subspaces, and it is the goal of RF Schemes to figure out “which one”. However, it will be a burden for traditional SVM-based RF schemes to tune the internal Parameters to adapt to the changes of the subspace. Such difficulties have severely degraded the effectiveness of traditional SVM RF approaches for CBIR. Additionally, it is problematic to incorporate the information of unlabeled samples into traditional SVM-based RF schemes for CBIR, although unlabeled Samples are very helpful in constructing the optimal classifier, Alleviating noise and enhancing the performance of the system

3. Proposed System

To explore solutions to these two aforementioned problems in the current technology, biased maximum margin analysis (BMMA) and a semi supervised BMMA (SemiBMMA) for the traditional SVM RF schemes were proposed, based on the graph-embedding framework. The proposed scheme is mainly based on the following:

- The effectiveness of treating positive examples and negative examples unequally.
- The significance of the optimal subspace or feature subset in interactive CBIR.
- The success of graph embedding in characterizing intrinsic geometric properties of the data set in high-dimensional space
- The convenience of the graph-embedding framework in constructing semi supervised learning techniques.

With the incorporation of BMMA, labelled positive feedbacks are mapped as close as possible, whereas labelled negative feedbacks are separated from labeled positive feedbacks by a maximum margin in the reduced subspace. The traditional SVM combined with BMMA can better model the RF process and reduce the performance degradation caused by distinct properties of the two groups of feedbacks. The SemiBMMA can incorporate the information of unlabeled samples into the RF and effectively alleviate the over fitting problem caused by the small size of labeled training samples. To show the effectiveness of the proposed scheme combined with the SVM RF, we will compare it with the traditional SVM RF and some other relevant existing techniques for RF on a real-world image collection.
Experimental results demonstrate that the proposed scheme can significantly improve the performance of the SVMRF for image retrieval.

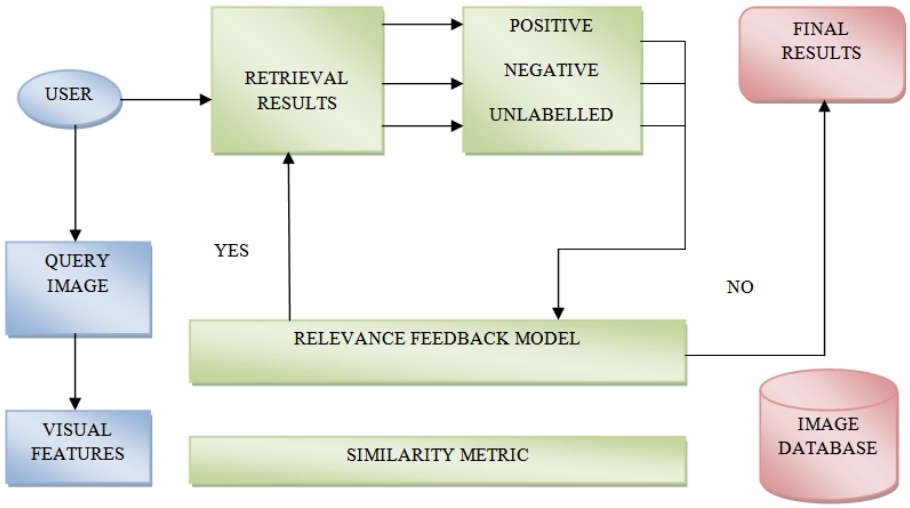


Fig 4 Flow chart of the CBIR System

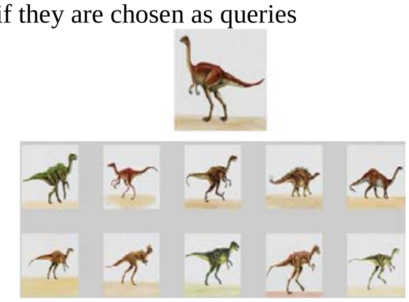
Figure 5.1 represents the flow chart of CBIR system, we can notice that, when a query image is provided by the user, the image retrieval system first extracts the low-level features. Then, all the images in the database are sorted based on a similarity metric, i.e., Euclidean distance. If the user is satisfied with the results, the retrieval process is ended, and the results are presented to the user. However, because of the semantic gap, most of the time, the user is not satisfied with the first retrieval results. Then, she/he will label the most semantically relevant images as positive feedbacks in top retrieval results. All of the remaining images in top results are automatically labelled by the system as the negative feedbacks. Based on the small-size positive and negative feedbacks, the RF model can be trained based on various existing techniques. Then, all the images in the database are resorted based on a new similarity metric. After each round of retrieval, the user will check whether the results are satisfied. If the user is satisfied with the results, then the process is ended; otherwise, the feedback process repeats until the user is satisfied with the retrieval results. Generally, the image representation is a crucial problem in CBIR.

The images are usually represented by low-level features, such as colour, texture, and shape, each of which can capture the content of an image to some extent. For colour, we extracted three moments, i.e., colour mean, colour variance, and colour skewness in each colour channel (L, U, and V, respectively). Thus, a 9-D colour moment is employed as the colour features in our experiments to represent the colour information. Then a 256-D HSV colour histogram is calculated. Both hue and saturation are quantized into eight bins, and the values are quantized into four bins. These two kinds of visual features are formed as colour features. Comparing with the classical global texture descriptors (e.g., Gabor features and wavelet features), the local dense features show good performance in describing the content of an image. The Weber local descriptors (WLDs) are adopted as feature descriptors, which are mainly based on the mechanism of the human perception of a pattern. The WLD local descriptor results in a feature vector of 240 values we employ the edge directional histogram from the Y component in YCrCb space to capture the spatial distribution of edges. The edge direction histogram is quantized into five categories including horizontal, 45 diagonal, and vertical, 135 diagonal and isotropic directions to represent the edge features.

4. Test Cases

To test the effectiveness of our algorithm, we randomly select 3 images from different classes, namely Flowers, Dinosaurs, Buses. Each query returns the top 10 images from the database. The four query retrievals are shown in Figure 5

As can be seen from Figure 5 our CBIR system has very good retrieving results over the randomly selected images as queries. It can be also shown that it has the same good retrieval results for most of the other images in the database if they are chosen as queries



a)Dinosaurs Query, 10 Matches from Top 10 Retrieved Images.

b)Buses Query, 8 Matches from Top 8 Retrieved Images.

c) Car Query, 10 Matches from Top 10 Retrieved Images.

Figure 5 Three Query Response Examples of CBIR.

Conclusion

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.

Future Enhancement

- Retrieval of required-query-similar images from abundantly available / accessible digital images is a challenging need of today.
- The revolutionary internet and digital technologies have imposed a need to have a system to organize abundantly available digital images for easy categorization and retrieval.
- The need to have a versatile and general purpose content based image retrieval (CBIR) system for a very large image database has attracted focus of many researchers of information-technology-giants and leading academic institutions for development of CBIR techniques.

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