Image Retrieval Using Bilinear Similarities for Large Datasets

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Abstract
It is an image retrieval approach which provides a method of retrieving an image from the large dataset by using an image as query which selects all of its variants which are more relevant to the query image. It makes use of a single bi-linear similarity measure for image retrieval. Content based image retrieval extracts the Images as per their features. Because it is a huge problem to retrieve the required images from the image database very frequently. We the users are always not satisfied with the given technologies they used in present time they always look forward for further improvement in the image retrieval process. The CBIR focuses on image features. It retrieves images from the database which are semantically correct based on the query image.

Keywords
Image Retrieval, Bi-linear Similarity Measure, Angular Regularization, K-means Clustering

I. Introduction

Recently, digital content has become a significant and inevitable asset for any enterprise and the need for visual content management is on the rise as well. There has been an increase in attention towards the automated management and retrieval of digital images owing to the drastic development in the number and size of image databases. Due to exponential increase of the size of the so-called multimedia files in recent years because of the substantial increase of affordable memory storage on one hand and the wide spread of the World Wide Web (www) on the other hand, the need for efficient tool to retrieve images from large dataset becomes crucial. This motivates the extensive research into image retrieval systems.

In large scale image retrieval systems, a single similarity measure is often defined globally to allow the deployment of an efficient indexing data structure (e.g., inverted file, hashing, or hierarchical search). There should be some similarity measures between them i.e., query dependent similarity measures should be applied on the large scale image retrieval system. We have to address the following two main issues in this system. First, indexing schemes like hashing, or hierarchical Search may not support query dependent similarity measure .so to solve this issue we use bilinear similarity measure that shows similarity between two images (query image, database image) in a bilinear form. Second, there are limited training samples, which may considers negative samples for retrieving an image based on single query image .So to solve this issue we should train lots of samples by considering a set of reference queries.

We should collect training samples for each reference query. Existing works commonly choose the queries and their variants [1, 2, 3] as positive samples. However, generating negative samples [1, 2] requires either user interactions or time-consuming mining which greatly affect the user experience. To address the first issue, we introduce the use of a bilinear similarity model which expresses the similarity between two images in a bilinear form. This model allows the similarity be computed by first transforming one image by a linear transformation and then evaluating its Euclidian distance to the other image.

II. Proposed Method

This image retrieval approach consists of an off-line module to learn a bilinear similarity measure for each query in the reference set, and an online module to perform search by a query dependent similarity measure for each online query. The main contributions of this system are: We introduce the use of a bilinear similarity model in a large scale image retrieval system to achieve search by query-dependent similarity measure without sacrificing any efficiency of indexing and retrieval. We propose an angular regularization for learning the bilinear similarity measure that can greatly reduce the risk of over fitting under limited training data. To solve the second issue, we leverage a reference set consisting of a number of reference queries. We collect training samples and learn a linear transformation for each reference query off-line. To reduce the risk of over-fitting under limited training samples (especially negative samples), we propose a novel angular regularization to encourage the learned transformation to be not too far away from an identity matrix(i.e., we respect the original similarity to a certain extent).
There are 4 basic modules in this system.
They are:

1. Query dependent similarity measure.
2. Bi-linear similarity measure
3. Angular Regularization
4. Optimization Methods

1. Query-Dependent Similarities

In a search by query-dependent similarity measure scenario, different queries have different similarity measures, which require building different indexes for fast retrieval. However, this is not feasible in practice as the online queries and hence their similarity measures are not known beforehand, and it is not sensible or even possible to exhaust the space of similarity measures and build an index for each measure. If only one index is built, the returned images for ranking may contain few relevant images and this result in a low recall rate.

In image retrieval, Mahalanobis distance [10,6] is commonly used to measure similarity between images. Let an image be represented by a d-dimensional feature vector xi, and let D ={xi} denote the image database. The Mahalanobis distance between a query image xq and a database image xi € D is defined as d_M (xq, xi)=(xq-xi) ^{T}M(xq-xi),where M is a positive definite matrix.

2. Bilinear Similarity

To avoid the aforementioned indexing problem, we consider a bilinear similarity model [7,8]. The bilinear similarity is between a query image x_q and a database image x_i € D.

$$
\begin{aligned}
s_{\mathbf{W}_q}(\mathbf{x}_q, \mathbf{x}_i) &= \mathbf{x}_q^{\mathrm{T}} \mathbf{W}_q \mathbf{x}_i \\
&\propto \hat{\mathbf{x}}_q^{\mathrm{T}} \mathbf{x}_i \\
&= \frac{1}{2}(\hat{\mathbf{x}}_q^{\mathrm{T}} \hat{\mathbf{x}}_q + \mathbf{x}_i^{\mathrm{T}} \mathbf{x}_i - \|\hat{\mathbf{x}}_q - \mathbf{x}_i\|^2) \\
&= 1 - \frac{1}{2} d_{\mathbf{I}}(\hat{\mathbf{x}}_q, \mathbf{x}_i),
\end{aligned}
$$

Here, we assume x_i is a L2-normalized. Finding an image x_i that is most similar to the query x_q under the query-dependent measure s_{Wq} is therefore equivalent to finding an image x_i that is closest to $\hat{x}_q$ in terms of Euclidean distance. It follows that we can build a static index for the database images using Euclidean distance and uses it for fast retrieval without inducing any efficiency loss. Since the query dependent similarity measure is more specific to the query than the indexing similarity measure, the surrogate query has more relevant images than the original query in their corresponding neighborhoods. This has been validated in our experiments.

III. Angular Regularization

Actually the time taken for collecting sufficient training samples for each reference query is very high and laborious. So we need to find better way. Meanwhile, similarity measure learned from limited training samples suffers from the over-fitting problem and has poor generalization ability. In this paper we introduce a novel angular regularization to tackle the issue of limited training samples.

In image retrieval, a similarity measure with $w_q = I_d$ (i.e., cosine similarity) [4] performs reasonably well in most cases. Therefore, similarity measures with wq deviating slightly from Id are desirable. Note that w*q* and swq, where s is an arbitrary positive scalar, are equivalent under the bilinear similarity model. Therefore, the angle between w_q and I_d (denoted by $< w_q, I_d >$) is much more crucial than the magnitude of their difference. This angle can be measured by the minus cosine value:

$$
-\frac{\mathbf{w}_q^{\mathrm{T}} \mathbf{I}_d}{\|\mathbf{w}_q\| \, \|\mathbf{I}_d\|}.
$$

4 .Optimization Methods

The regularized bilinear model here is convex, its energy function is not differentiable at some points as it contains the hinge loss term. For the first two datasets, we exhaustively searched query-relevant images to evaluate the performance of learning regularized query-dependent bilinear similarity measures. For the third one web image dataset, the performance was evaluated in a large scale image retrieval scenario, and multi-probe k-mean trees were employed to search approximate nearest neighbors efficiently. K-Means strategy can help us in both efficiency and quality. Clustering is very efficient and powerful technology to handle large data sets. It assists faster image retrieval and also allows the search for most relevant images in large image database. K-means is a clustering method based on the optimization of an overall measure of clustering quality is known for its efficiency in producing accurate results in image retrieval. By using k-means user can select the closer group of image so that they gate fast result. K-means[5,6] is sensitive to noise and thus to get better result we will try k-Centroid clustering in future and for faster we use hierarchical clustering same time.

IV. Evaluation

We used two commonly employed protocols like MAP (Mean Average Precision) and average precision of top R-ranked images for each test query to evaluate this approach of image retrieval. The area under the recall precision curve is called as MAP. We compared the bilinear similarity measure used here with the following two baseline methods and one state-of-the-art method:

1. Euclidean distance

It is used to evaluate the similarities between query and database images.

2. Query-Independent Ranking SVM (QI-RSVM)

Ranking SVM is used to learn a ranking function from the training samples of all reference queries, which is then applied to all queries.

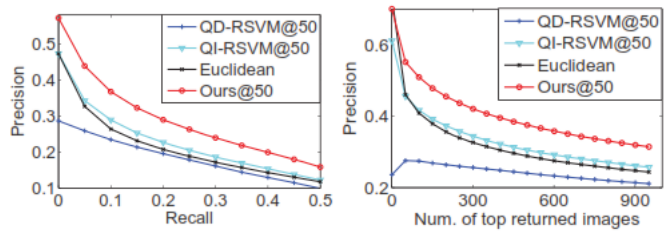
3. Query-Dependent Ranking SVM (QD-RSVM)

Query dependent Ranking SVMs are learned. It is equivalent to our similarity measure with $\sigma = 0$. For a fair comparison, all other parameters we

V. Results

About thousands of images were crawled from the Web image dataset and were tested to calculate the performance of this image retrieval approach and it gives good results and performance was increased as it gives relevant images related to the query image based on ranking. And proposed method is far superior to other image retrieval methods. We clustered the data set into number of clusters after indexing using k-mean trees [5-6].The method based on Euclidian distance used the original queries, while others used the surrogate queries.

Methods \ K	5	10	15	20
Ours@50	**0.371**	**0.451**	**0.506**	**0.545**
QD-RSVM@50	0.221	0.275	0.321	0.350
QI-RSVM@50	0.311	0.409	0.474	0.518
Euclidean	0.328	0.412	0.468	0.511



(a) Recall precision curve (b) Precision@R

Fig. 1: Performance on the Web Image Dataset

VI. Conclusion

In this paper, we have proposed a method of image retrieval for large scale image datasets which is based on a query dependent bilinear similarity measure. In this model query image is placed and searching of relevant images is carried out using a surrogate query which is generated from the query image which does not happens with existing method. It leads to search by query-dependent similarity measure possible without sacrificing any efficiency of indexing and retrieval. As there are limited training samples, to avoid this problem similarity transformation of an

online query is approximated by a linear combination of the similarity measure matrices associated with its nearest neighbors in a reference query set. As it deals with large scale image dataset there is over-fitting problem in learning the similarity measure for each reference query with limited training data novel angular regularization constraint is proposed to. Experimental results on lot of web-image datasets demonstrate that this proposed method of image retrieval performs well compared with other methods in terms of precisions and recall rates.

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