ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Implementation of Efficient Manifold Ranking (EMR) Model for Content-Based Image Retrieval

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ABSTRACT

Hybrid wireless networks combining the advantages of both mobile ad-hoc networks and infrastructure wireless networks have been receiving increased attention due to their ultra-high performance. An efficient data routing protocol is important in such networks for high network capacity and scalability.

However, most routing protocols for these networks simply combine the ad-hoc transmission mode with the cellular transmission mode, which inherits the drawbacks of ad-hoc transmission. This paper presents a Distributed Three-hop Routing protocol (DTR) for hybrid wireless networks. To take full advantage of the widespread base stations, DTR divides a message data stream into segments and transmits the segments in a distributed manner. It makes full spatial reuse of a system via its high speed ad-hoc interface and alleviates mobile gateway congestion via its cellular interface. Furthermore, sending segments to a number of base stations simultaneously increases throughput and makes full use of widespread base stations. In addition, DTR significantly reduces overhead due to short path lengths and the elimination of route discovery and maintenance. DTR also has a congestion control algorithm to avoid overloading base stations.

Theoretical analysis and simulation results show the superiority of DTR in comparison with other routing protocols in terms of throughput capacity, scalability and mobility resilience. The results also show the effectiveness of the congestion control algorithm in balancing the load between base stations.

INTRODUCTION

The traditional methods for image retrieval are based on the data features but they do not use the underlying structure information. It has been observed that databases have unde lying cluster or manifold structure. Under such cases, it is possible that we can assume label consistency. It means that those nearby data points or points that belong to the same cluster are likely to have the same semantic label. Such phenomenon is very important to explore the semantic relevance in the absence of label information.

Objectives

We have identified following objectives for the proposed work. These objectives are useful to enhance retrieval process.

1. To learn various ranking methods used for content based image retrieval (CBIR).
2. To understand the details of Manifold Ranking methodology.
3. To propose a technique to resolve ambiguity present in existing technique.

LITERATURE SURVEY

The retrieval of images started back in the late 1970s. The aim is to provide an effective and efficient way tool for retrieving images from large databases. Till this date due to development of internet the number of digital images used for various purposes has grown tremendously. Many researchers have put their attention to the development of an image retrieval system which works better for specific contexts.

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In the initial stage image retrieval is based on keyword annotation. This is a similar mechanism used in text retrieval methods. In this approach images in the database are first annotated manually by keywords. It is then retrieved according to their annotations.

However this approach has following difficulties for e.g. it requires large amount of workers required to tag the entire database. It is possible that such manual annotations may introduce the inconsistency among different annotations in perceiving the same image. The problem is serious in case of real world applications where the size of the data is very large.

The generalized manifold ranking approach suggested by Jingrui He, Mingjing Li, Hong-Jiang Zhang, Hanghang Tong and Changshui Zhang to tackle these issues. They have proposed general manifold ranking model which works better as compared to Support Vector Machine (SVM).

Bin Xu, Jiajun Bu, Chun Chen, Deng Cai, Xiaofei He, Wei Liu and Jiebo Luo extended previous work by addressing issues in manifold ranking by two ways in terms of graph construction and computation of ranking score.
Wei Liu applied the idea of large graph construction for semi-supervised approach. He showed anchor graph works well as compared to traditional KNN strategy.

Xue-Qi Cheng, Pan Du, Jiafeng Guo, Xiaofei Zhu and Yixin Chen suggested the concept of sink points in manifold ranking. They covered relevance along with diversity in raking. They converted ranked objects (points) into sink points preventing redundant objects from receiving higher rank. They applied this approach to query recommendation and update summarization tasks.

We revisit existing manifold ranking algorithm which we are using a base point for our proposed work.

EXISTING SYSTEM:

Most traditional methods focus on the data features too much but they ignore the underlying structure information, which is of great importance for semantic discovery, especially when the label information is unknown.

Many databases have underlying cluster or manifold structure. Under such circumstances, the assumption of label consistency is reasonable. It means that those nearby data points, or points belong to the same cluster or manifold, are very likely to share the same semantic label. This phenomenon is extremely important to explore the semantic relevance when the label information is unknown. In our opinion, a good CBIR system should consider images' low-level features as well as the intrinsic structure of the image database.

DISADVANTAGES OF EXISTING SYSTEM:

- It has expensive computational cost, both in graph construction and ranking computation stages.
- Particularly, it is unknown how to handle an out-of-sample query efficiently under the existing framework.
- It is unacceptable to recompute the model for a new query. That means, original manifold ranking is inadequate for a real world CBIR system, in which the user provided query is always an out-of-sample.

PROPOSED SYSTEM:

In this paper, we extend the original manifold ranking and propose a novel framework named Efficient Manifold Ranking (EMR).

We try to address the shortcomings of manifold ranking from two perspectives: the first is scalable graph construction; and the second is efficient computation, especially for out-of-sample retrieval.

Specifically, we build an anchor graph on the database instead of the traditional k-nearest neighbor graph, and design a new form of adjacency matrix utilized to speed up the ranking computation.
The model has two separate stages: an offline stage for building (or learning) the ranking model and an online stage for handling a new query.

With EMR, we can handle a database with many images and do the online retrieval in a short time. To

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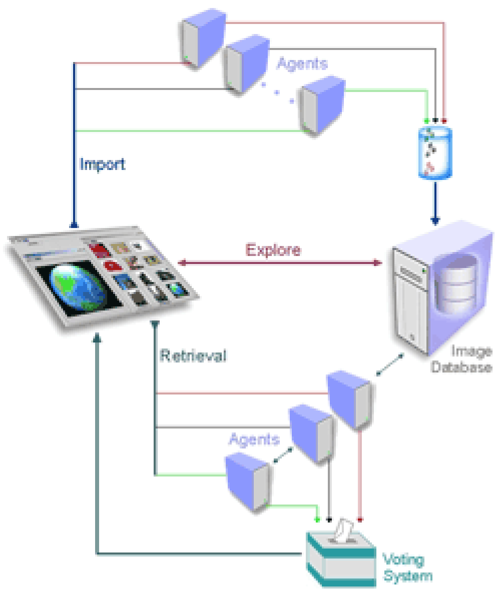
the best of our knowledge, no previous manifold ranking based algorithm has run out-of-sample retrieval on a database in this scale.

ADVANTAGES OF PROPOSED SYSTEM:

- We show several experimental results and comparisons to evaluate the effectiveness and efficiency of our proposed method EMR on many real time images.
- We can run out-of sample retrieval on a large scale database in a short time.
- Our model EMR can efficiently handle the new sample as a query for retrieval. In this subsection, we describe the light-weight computation of EMR for a new sample query. We want to emphasize that this is a big improvement over our previous conference version of this work, which makes EMR scalable for large-scale image databases.

SYSTEM ARCHITECTURE:



We have identified following key points about ranking models Manifold Ranking and Enhanced Manifold Ranking respectively. [1, 2]

Manifold Ranking Model:

1. Manifold Ranking creates a kNN graph for each data sample. It calculates the relationships to its k-nearest neighbours.
2. In the ranking computation step the important part is to perform the matrix inversion operation.

Enhanced Manifold Ranking Model:

1. EMR step creates an anchor graph for each data sample. It calculates the relationships to its s-nearest anchors. Anchor point can be selected using k-means method.
2. The ranking computation stage performed at reduced complexity.

Modules

1. Image Search
2. Query Categorization
3. Visual Query Expansion
4. Images Retrieved by Expanded Keywords

Image Search

In this module, Many Internet scale image search methods are text-based and are limited by the fact that query keywords cannot describe image content accurately. Content-based image retrieval uses visual features to evaluate image similarity.
One of the major challenges of content-based image retrieval is to learn the visual similarities which well reflect the semantic relevance of images. Image similarities can be learned from a large training set where the relevance of pairs of images.

Query Categorization

In this module, the query categories we considered are: General Object, Object with Simple Background, Scenery Images, Portrait, and People. We use 500 manually labeled images, 100 for each category, to train a C4.5 decision tree for query categorization. The features we used for query categorization are: existence of faces, the number of faces in the image, the percentage of the image frame taken up by the face region, the coordinate of the face center relative to the center of the image.

Visual Query Expansion

In this module, the goal of visual query expansion is to obtain multiple positive example images to learn a visual similarity metric which is more robust and more specific to the query image. The query keyword is “Paris” and the query image is an image of “eiffel

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tower". The image re-ranking result based on visual similarities without visual expansion. And there are many irrelevant images among the top-ranked images. This is because the visual similarity metric learned from one query example image is not robust enough. By adding more positive examples to learn a more robust similarity metric, such irrelevant images can be filtered out. In a traditional way, adding additional positive examples was typically done through relevance feedback, which required more users' labeling burden. We aim at developing an image re-ranking method which only requires one-click on the query image and thus positive examples have to be obtained automatically.

Images Retrieved by Expanded Keywords

In this module, considering efficiency, image search engines, such as Bing image search, only re-rank the top N images of the text-based image search result. If the query keywords do not capture the user's search intention accurately, there are only a small number of relevant images with the same semantic meanings as the query image in the image pool. Visual query expansion and combining it with the query specific visual similarity metric can further improve the performance of image reranking.

Implementation Steps

1. We extract low level features of images in a database and use them as coordinates of data points in the graph.
2. We select representative anchor points and construct the weight matrix Z by kernel regression with small neighborhood size s.
3. The user uploads an image as a query. We extract its low level features and update the weight matrix Z.
4. We combine image features and tag information to compute ranking score given by equation

$$r^* = (I_n - \alpha H^T H)^{-1} y$$

5. Images with highest ranking score are selected as most relevant image(s) to given query image and return to the user.

RESULTS AND CONCLUSIONS

We have collected images for five categories i.e. beach, boat, cherry, crater, sunset. We have considered that images in the same category belong to the same semantic concept. It means that images from the same category are judged relevant and otherwise irrelevant. We use each image as a query for testing the in-sample retrieval performance. We have extracted colour features for learning semantic concept. The results for retrieval performance are as shown in Figure 4.1.

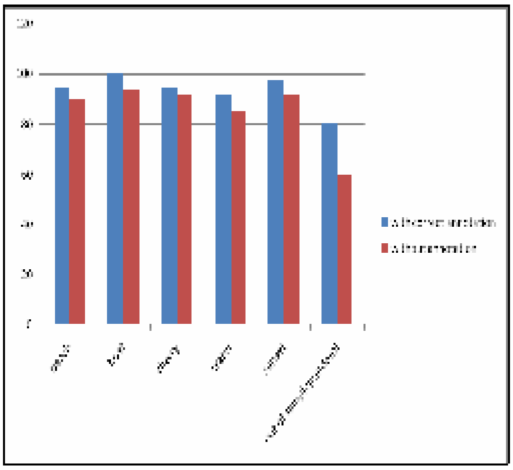

Figure: Showing the results of proposed Retrieval System

The Efficient Manifold Ranking algorithm extends the original manifold ranking model to handle scalable data sets. The application of EMR to a content based image retrieval used for real world image databases.
Our proposed method deals with resolution of ambiguity present in Image Retrieval. It tries to reduce computational complexity and decides a strategy about an anchor graph construction.

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