3.3.2 Number of books and chapters in edited volumes/books published and papers published in national/ international conference proceedings per teacher during last five year

Sl. No.	Name of the teacher	Title of the book/chapters published	Title of the paper	Title of the proceedings of the conference	Name of the conference	National / International	Calendar Year of publication	ISBN number of the proceeding	Affiliating Institute at the time of publication	Name of the publisher
1	Dr. N.V.Nagendram	A Text Book on Dr. Venkata Nagendram Near - Field Spaces Over - Field and Its Applications					2021	978-81-953717-6-1	Kakinada Institute of Technology & Science	Research India Publications
2	B.Veerendra		Information Retrieval Area Using Scalable Graph-based Ranking Model for Content-based System	Recent Advances in Computer Science and Engineering	3rd National Conference on Recent Advances in Computer Science and Engineering	National	2018	2455-3778	Kakinada Institute of Technology & Science	International Journal for Modern Trends in Science and Technology

2021 Edition

A Text Book on Dr. Venkata Nagendram Near–Field Spaces Over Near-Field and Its Applications

Dr. N. V. NAGENDRAM

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A Text Book on Dr. Venkata Nagendram Near–Field Spaces Over Near-Field and Its Applications

2021 EDITION

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RIP **Research India Publications**

B-2/84, Ground Floor, Rohini Sector-16, Delhi-110089, INDIA

Published by
Research India Publications
Head Office: B-2/84, Ground Floor,
Rohini Sector-16,
Delhi-110089, INDIA
Fax No.: +91-11-27297815
Email: ripublication@vsnl.net
Website: www.ripublication.com

Book Proposal No.: 1483

ISBN: 978-81-953717-6-1

Price: Within India: Rs. 900
Outside India: US$ 70

Typeset by RIP INFORMATION SERVICES
B-2/84, Ground Floor, Rohini Sector-16, Delhi-110089 INDIA

Printed in India

Available online at: http://www.ijmtst.com/ncracse2018.html

Special Issue from 3rd National Conference on Recent Advances in Computer Science and Engineering, 27th – 28th January 2018, Guntur, Andhra Pradesh, India

Information Retrieval Area Using Scalable Graph-based Ranking Model for Content-based System

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To Cite this Article

B.Veerendra, "Information Retrieval Area Using Scalable Graph-based Ranking Model for Content-based System", *International Journal for Modern Trends in Science and Technology*, Vol. 04, Special Issue 01, January 2018, pp. 19-23.

ABSTRACT

Graph-based ranking models have been widely applied in information retrieval area. In this paper, we focus on a well known graph-based model - the Ranking on Data Manifold model, or Manifold Ranking (MR). Particularly, it has been successfully applied to content-based image retrieval, because of its outstanding ability to discover underlying geometrical structure of the given image database. However, manifold ranking is computationally very expensive, which significantly limits its applicability to large databases especially for the cases that the queries are out of the database (new samples). We propose a novel scalable graph-based ranking model called Efficient Manifold Ranking (EMR), trying to address the shortcomings of MR from two main perspectives: scalable graph construction and efficient ranking computation. Specifically, we build an anchor graph on the database instead of a traditional k-nearest neighbor graph, and design a new form of adjacency matrix utilized to speed up the ranking. An approximate method is adopted for efficient out-of-sample retrieval. Experimental results on some large scale image databases demonstrate that EMR is a promising method for real world retrieval applications.

I. INTRODUCTION

GRAPH-BASED ranking models have been deeply studied and widely applied in information retrieval area. In this paper, we focus on the problem of applying a novel and efficient graph-based model for content based image retrieval (CBIR), especially for out-of-sample retrieval on large scale databases. Traditional image retrieval systems are based on keyword search, such as Google and Yahoo image search. In these systems, a user keyword (query) is matched with the context around an image including the title, manual annotation, web document, etc. These systems don't utilize information from images. However these systems suffer many problems, such as shortage of the text information and inconsistency of the meaning of the text and image. Content-based image retrieval is a considerable choice to overcome these difficulties. CBIR has drawn a great attention in the past two decades. Different from traditional keyword search systems, CBIR systems utilize the low-level features, including global features (*e.g.*, color moment, edge histogram, LBP [4]) and local features (*e.g.*, SIFT), automatically extracted from images. A great amount of researches have been performed for designing more informative low-level features to represent images, or better metrics (e.g., DPF [6]) to measure the perceptual similarity, but their performance is restricted by many conditions and is sensitive to the data. Relevance feedback [7] is a useful tool for interactive CBIR. Users High level perception is captured by dynamically updated weights based on the user's feedback. 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 [8], [9]. 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. Manifold Ranking (MR) [9], [10], a famous graph-based ranking model, ranks data samples with respect to the intrinsic geometrical structure collectively revealed by a large number of data. It is exactly in line with our consideration. MR has been widely applied in many applications, and shown to have excellent performance and feasibility on a variety of data types, such as the text [11], image and video. By taking the underlying structure into account, manifold ranking assigns each data sample a relative ranking score, instead of an absolute pair wise similarity as traditional ways. The score is treated as a similarity metric defined on the manifold, which is more meaningful to capturing the semantic relevance degree. He *et al.* [12] firstly applied MR to CBIR, and significantly improved image retrieval performance compared with state-of-the-art algorithms. However, manifold ranking has its own drawbacks to handle large scale databases – 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 (a new sample) efficiently under the existing framework. It is unacceptable to re compute 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. 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 1 million images and do the online retrieval in a short time. To the best of our knowledge, no previous manifold ranking based algorithm has run out-of-sample retrieval on a database in this scale. A preliminary version of this work previously appeared as.

1.2 Objective of the Project

Graph-based ranking models have been widely applied in information retrieval area. In this paper, we focus on a well known graph-based model - the Ranking on Data Manifold model, or Manifold Ranking (MR). Particularly, it has been successfully applied to content-based image retrieval, because of its outstanding ability to discover underlying geometrical structure of the given image database. However, manifold ranking is computationally very expensive, which significantly limits its applicability to large databases especially for the cases that the queries are out of the database (new samples). We propose a novel scalable graph-based ranking model called Efficient Manifold Ranking (EMR), trying to address the shortcomings of MR from two main perspectives: scalable graph construction and efficient ranking computation. Specifically, we build an anchor graph on the database instead of a traditional *k*-nearest neighbor graph, and design a new form of adjacency matrix utilized to speed up the ranking. An approximate method is adopted for efficient out-of-sample retrieval. Experimental results on some large scale image databases demonstrate that EMR is a promising method for real world retrieval applications.

1.3. 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.

DISADVANTAGESOF 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.

1.4. 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 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

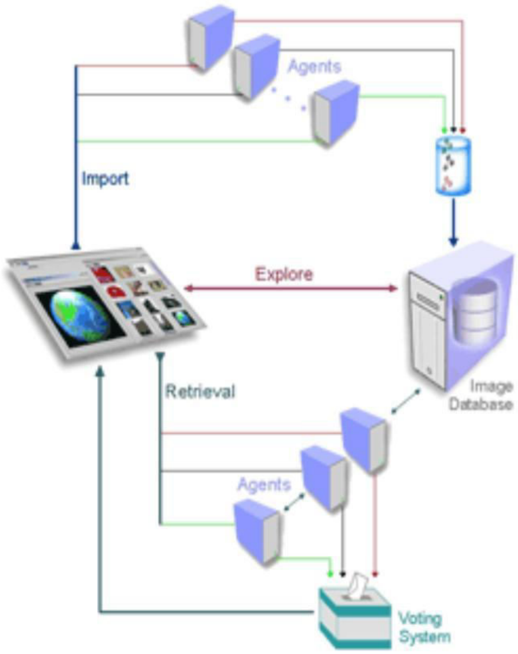
  scalable for large-scale image databases.

II. ANALYSIS

2.1. System Introduction

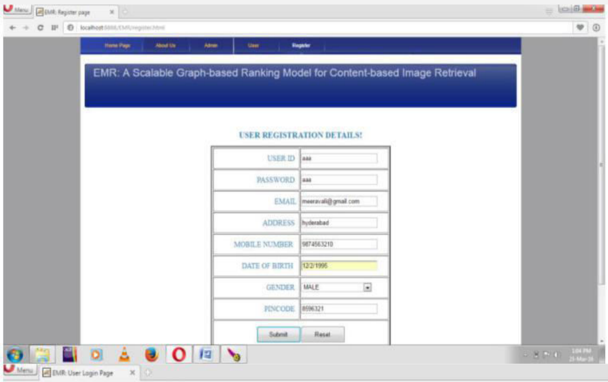
The Systems Development Life Cycle (SDLC), or Software Development Life Cycle in systems engineering, information systems and software engineering, is the process of creating or altering systems, and the models and methodologies that people use to develop these systems. In software engineering the SDLC concept underpins many kinds of software development methodologies. These methodologies form the framework for planning and controlling the creation of an information system the software development process.

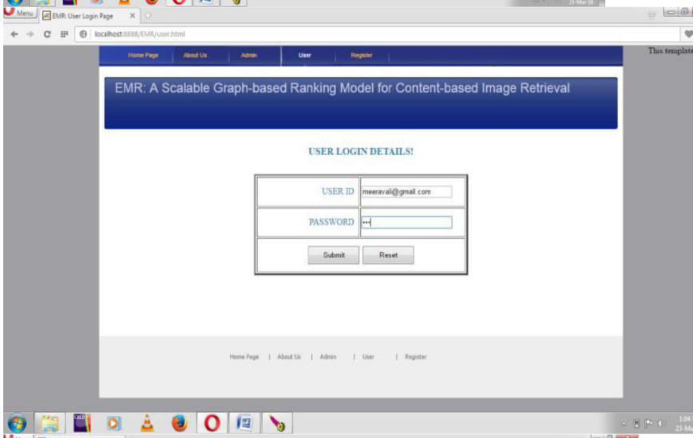
System Architecture

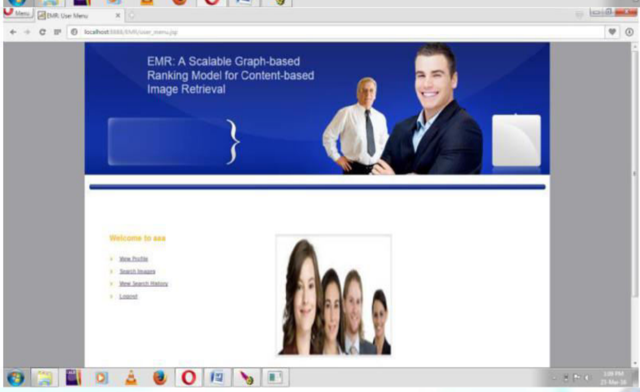


SCREEN SHOTS

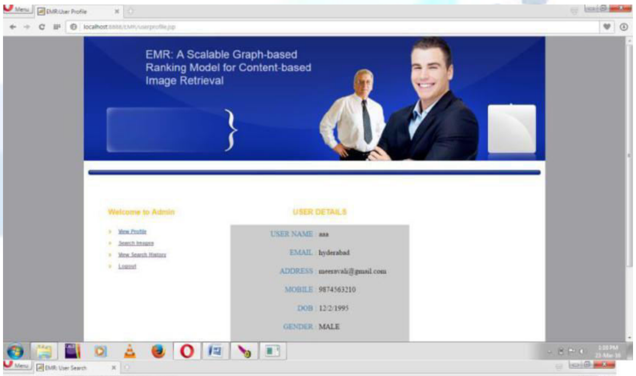
Home page:

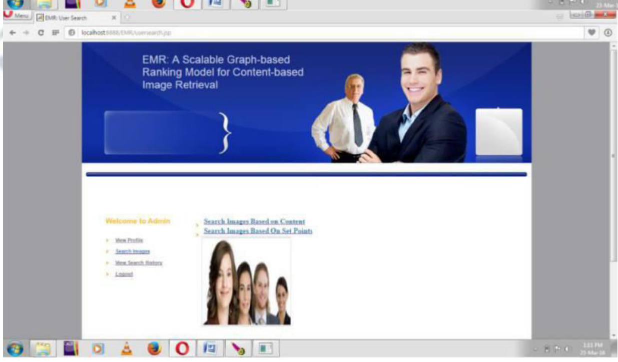






View Profile:





III. CONCLUSIONS

In this paper, we propose the Efficient Manifold Ranking algorithm which extends the original manifold ranking to handle large scale databases. EMR tries to address the shortcomings of original manifold ranking from two perspectives: the first is scalable graph construction; and the second is efficient computation, especially for out-of-sample retrieval. Experimental results demonstrate that EMR is feasible to large scale image retrieval systems – it significantly reduces the computational time.

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