IJCSN International Journal of Computer Science and Network, Volume 4, Issue 1, February 2015
ISSN (Online) : 2277-5420 www.IJCSN.org
Impact Factor: 0.417

An Efficient Methodology for Image Rich Information Retrieval

[1] Ashwini Jaid, [2] Komal Savant, [3] Sonali Varma, [4] Pushpa Jat, [5] Prof. Sushama Shinde

[1,2,3,4] Computer Department, Siddhant College of Engineering, Pune, Maharashtra, India

[5] Assistant Professor, Computer Department, Siddhant College of Engineering, Pune, Maharashtra, India

Abstract - Social multimedia sharing and hosting websites, such as Flickr and Facebook, contain billions of user-submitted images. Popular Internet commerce websites such as Amazon.com are also furnished with tremendous amounts of product-related images. In addition, images in such social networks are also accompanied by annotations, comments, and other information, thus forming heterogeneous image-rich information networks. In this paper, the concept of (heterogeneous) image-rich information network and the problem of how to perform information retrieval and recommendation in such networks is introduced. A fast algorithm, heterogeneous minimum order k-SimRank (HMok-SimRank) is proposed to compute link-based similarity in weighted heterogeneous information networks. Then, we propose an algorithm Integrated Weighted Similarity Learning (IWSL) to account for both link-based and content based similarities by considering the network structure and mutually reinforcing link similarity and feature weight learning. Both local and global feature learning methods are designed. Experimental results on Flickr and Amazon data sets show that our approach is significantly better than traditional methods in terms of both relevance and speed. A new product search and recommendation system for e-commerce has been implemented based on our algorithm.

Keywords - *Information Retrieval, Image Mining, Information Network, Ranking.*

1. Introduction

Social multimedia (photo and video) sharing and hosting websites, such as Flickr, Facebook, YouTube, Picasa, ImageShack, and Photo bucket, are popular around the world, with over billions of photos uploaded by users. Popular Internet commerce websites such as Amazon are also furnished with tremendous amounts of product-related images. In addition, many images in such social networks are accompanied by information such as owner, consumer, producer, annotations, and comments. They can be modeled as heterogeneous image-rich information networks. Fig. 1 shows an example of the Flickr information network, where images are tagged by the users and image owners contribute images to topic groups. Fig. 2 shows an Amazon information network of product images, categories, and consumer tags. Conducting information retrieval in such large image rich information networks is a very useful but also very challenging task, because there exists a lot of information such as text, image feature, user, group, and most importantly the network structure. In text-based retrieval, estimating the similarity of the words in the context is useful for returning more relevant images. Word Net manually groups words into synonym sets, Google Distance computes word similarity by co-occurrence in search results. Flickr Distance considers visual relationship. In image content-based retrieval, most methods (such as Google's Visual Rank) and systems compute image similarity based on image content features. Hybrid approach combine text features and image content features together. Most commercial image search engines use textual similarity to return semantically relevant images and then use visual similarity to search for visually relevant images. Integration-based approaches use linear or nonlinear combination of the textual and visual features. However, existing works cannot handle the link structure.

2. Proposed System

In this paper, we propose an image-rich information network model where the similarities between same type of nodes and different types of nodes can be better estimated based on the mutual impact under the network structure. Among algorithms that compute object similarity in information networks, SimRank is one of the most popular, but it is very expensive to calculate and the similarity is only based on the link information. When consider the images in the network, image similarity can actually also be judged by content features, such as RGB histogram and SIFT.

In this paper, we propose an efficient approach called MoK-SimRank to significantly improve the speed of SimRank, and introduce its extension HMok-SimRank to work on weighted heterogeneous information networks. Then, we propose algorithm IWSL to provide a novel way of integrating both link and content information. IWSL performs content and link reinforcement style learning with either global or local feature weight learning.

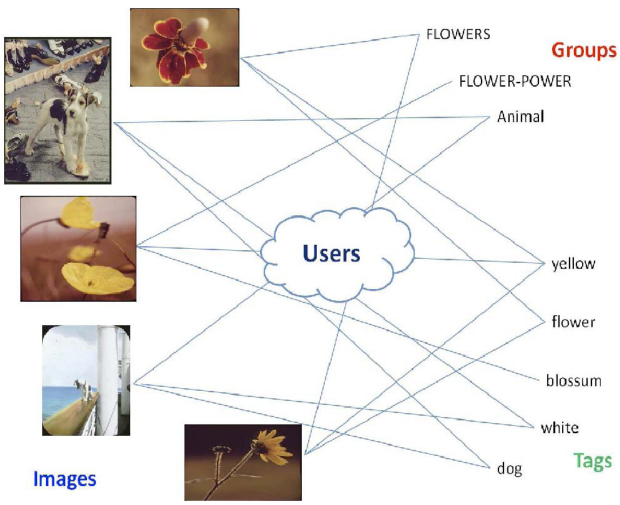

Fig.1 Information network for Flickr, connected by images, user tags and groups.

3. Proposed System

Fig 2. shows the of structure of proposed system.
Following are the modules in the system:

1] Instantiation Module - This has two sub modules

a) Simrank Instantiation Module - Here we create and initialize the image tag matrix
b) CBIR Instantiation Module - Here we create and initialize image feature vectors (contains values for all color moments, texture extraction for all images in a file)

2] Input Module - This module reads input string from user Simrank Module - This module displays images after receiving input query string. It finds the images and relevant images tagged by query string

3] Feedback Module - This module works on result of simrank module. User clicks in one image as feedback to system.

4] CBIR Module - This module works after feedback is given. The image received as feedback from user is now considered as reference and contents are compared with resultant images obtained by simrank module.

5] Display Module - This module is used by both Simrank Module and CBIR Module. Both use this module to display resultant images.

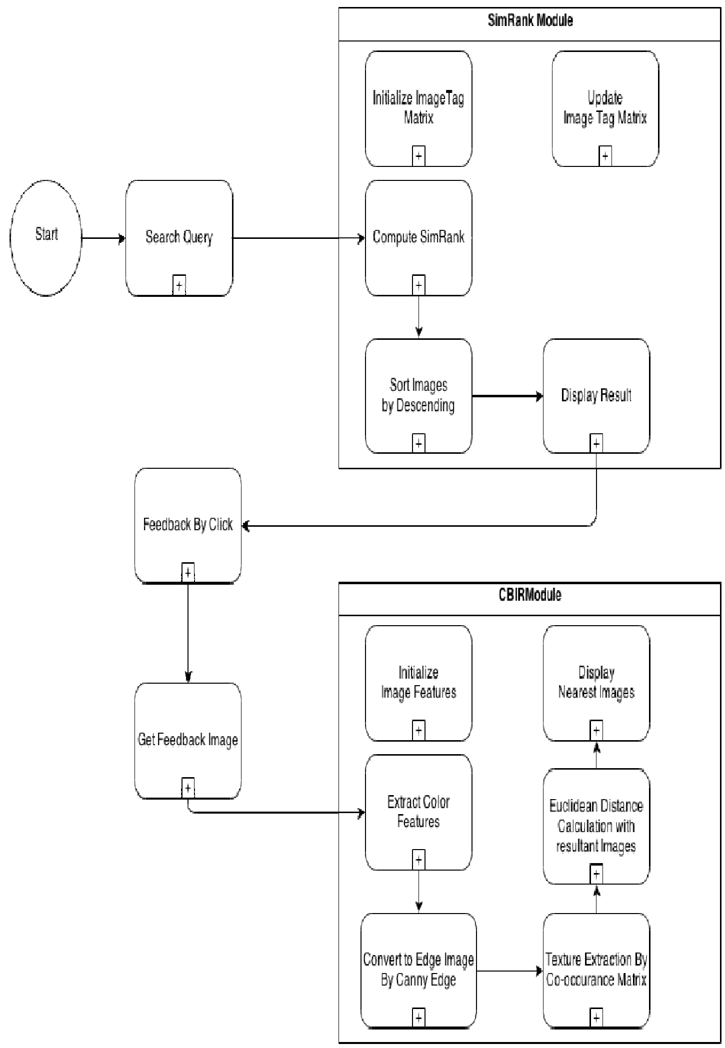

Fig.2 Structure of Proposed System

IJCSN International Journal of Computer Science and Network, Volume 4, Issue 1, February 2015
ISSN (Online) : 2277-5420 www.IJCSN.org
Impact Factor: 0.417

4. Techniques Used

1] SimRank:

$$s(a,b)=\begin{cases}1 & (\text{if } a=b)\\ \dfrac{C}{|I(a)||I(b)|}\displaystyle\sum_{i=1}^{|I(a)|}\sum_{j=1}^{|I(b)|}s(I_i(a),I_j(b)) & (\text{if } a\neq b)\end{cases} \qquad \ldots\ldots\ldots..(1)$$

The similarity between objects *a* and *b*: $s(a, b) \in [0, 1]$

- *C* is a constant between 0 and 1
  - • Confidence level or decay factor
  - • C gives the rate of decay as similarity flows across edges (since $C < 1$)

If *a* or *b* may not have any in-neighbors, $s(a,b) = 0$
SimRank scores are symmetric, i.e., $s(a,b) = s(b,a)$
Similarity between *a* and *b* is the average similarity between in-neighbors of *a* and in-neighbors of *b*

2] Content Based Image Retrieval (CBIR):
Content Based Image Retrieval (CBIR), uses the visual contents of an image such as Color, Shape, Texture and spatial layout to represent and index and index the image. The CBIR technology uses the basic idea of-
Feature Extraction of Images Based on-
1) Color
2) Sketch

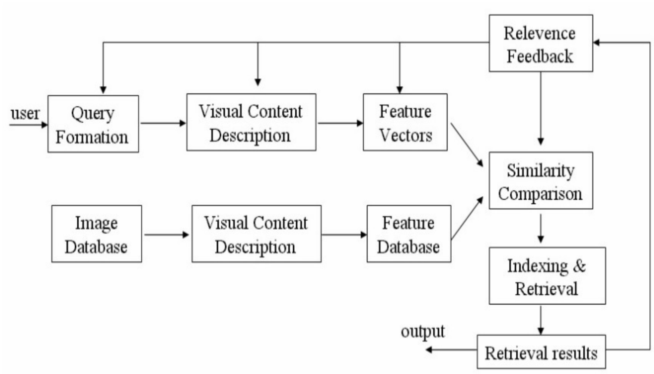

Fig.3 CBIR Architecture

As shown in above architecture user will give the input and one query will form using input attributes. After that we extract visual content like color, coordinates, pixels, etc. After this feature vector is from. Now we combine all above steps with existing image database feature and give it to similarity comparison module. After this we do indexing and retrieval of images in database. And from this we retrieve result and give you an appropriate output. CBIR is basically a two step process which is Feature Extraction and Image Matching (also known as feature matching). Feature Extraction is the process to extract image features to a distinguishable extent. Information extracted from images such as colour, texture and shape are known as feature vectors. The extraction process is done on both queries images and images in the database. Image matching involves using the features of both images and comparing them to search for similar features of the images in the database.

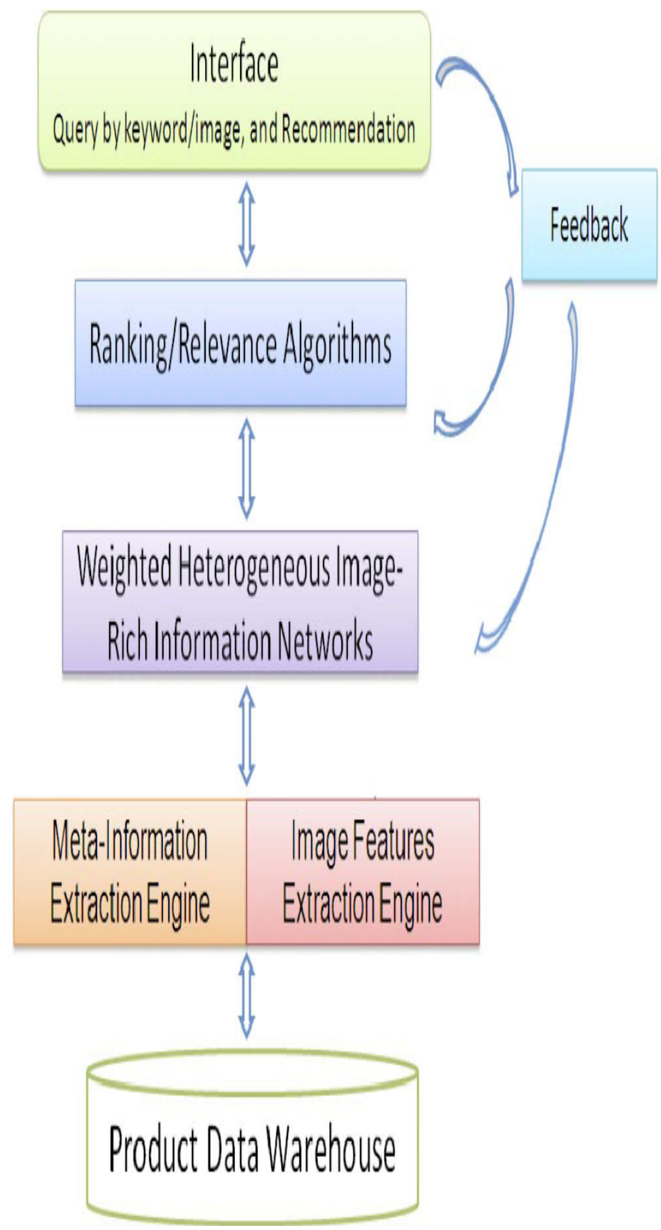

Fig.4 System Architecture

Fig.4 describes the system architecture of proposed system. The bottom layer contains the product data warehouse which includes product images and related product information. The second layer performs meta information extraction and image feature extraction. The third layer builds a weighted heterogeneous image-rich information network. The fourth layer performs information network analysis based ranking to find relevant results for a query. The top layer contains a user-friendly interface, which interacts with users, responds to their requests, and collects feedback.

5. Survey and Comparison between RGB and HSV

The performance of retrieval system can be measured in terms of its recall and precision. Recall measure the ability of the system to retrieve all the models that are relevant, while precision measures the ability of the system to retrieve only models that are relevant. This HSV values has a high recall and precision of retrieval, and is effectively used in content based image retrieval systems. They are defined as:

Precision = Number of Relevant images retrieved /Total Number of images retrieved.

Recall = Number of Relevant images Retrieved/Number Of relevant images in the database.

It is observed that for lower values of recall, the precision is getting higher, this is greater than 65%. Similarly, for higher value of recall, the precision is comparable and the performance of the proposed method is good.

Here in table 1.Theay have taken different images of Nature, Red Flower, and Beach and from this we have calculated the parameters Precision and Recall. Precision is given by number of relevant images retrieved to the total number of images retrieved, whereas Recall is the number of relevant images retrieved to the number of relevant images in the database. After calculating Precision and Recall, Accuracy for the RGB model is calculated which the average value of Precision and Recall.

Table 1. Accuracy of CBIR with RGB Color Model

Images	No. of Images in Database	No. of Retrieve images	No. of relevant images	Precision	Recall	Accuracy
Nature	12	10	6	0.6	0.5	0.575
	15	10	7	0.7	0.46	0.58
	20	12	9	0.75	0.45	0.6
Red Flower	12	10	7	0.7	0.58	0.64
	15	10	8	0.8	0.53	0.665
	20	10	9	0.9	0.45	0.675
Beach	12	10	5	0.5	0.41	0.455
	15	10	6	0.6	0.4	0.5
	20	10	7	0.7	0.35	0.525

Here, In table 2.Similar images are taken as in RGB model and as compare to that Precision, Recall and accuracy is calculated but this time it is calculated for HSV model and accuracy obtained for HSV model is higher and better as compared to RGB model less Faulty images are retrieved in HSV model as compared to RGB model.

Table 2. Accuracy of CBIR with HSV Color Model

Images	No. of Images in Database	No. of Retrieve images	No. of relevant images	Precision	Recall	Accuracy
Nature	12	10	8	0.8	0.66	0.73
	15	12	10	0.83	0.66	0.75
	20	14	12	0.86	0.6	0.73
Red Flower	12	10	8	0.8	0.66	0.73
	15	10	9	0.9	0.55	0.725
	20	12	11	0.91	0.45	0.68
Beach	12	10	8	0.8	0.66	0.73
	15	10	8	0.8	0.54	0.67
	20	10	9	0.9	0.45	0.675

6. Conclusions

In this paper efficient way of finding similar objects (such as photos and products) is presented by modeling major social sharing and e-commerce websites as image rich information networks. The algorithm minimum order

SimRank is proposed which efficiently computes weighted link-based similarity in weighted heterogeneous image-rich information networks. In future, under the concept of heterogeneous image rich information network, the study can be performed how such kind of network structure may benefit various image mining and computer vision tasks, such as image categorization, image segmentation, tag annotation, and collaborative filtering.

References

[1] Xin Jin, Jiebo Luo,"Reinforced Similarity Integration in Image-Rich Information Networks", IEEE Transactions on knowledge and data engineering, February 2013.

[2] X. Jin, J. Luo, J. Yu, G. Wang, D. Joshi, and J. Han, "iRIN: Image Retrieval in Image-Rich Information Networks," Proc. 19th Int'l Conf. World Wide Web (WWW '10), 2010.

[3] J. Yu, X. Jin, J. Han, and J. Luo, "Collection-Based Sparse Label Propagation and Its Application on Social Group Suggestion from Photos," ACM Trans. Intelligent Systems Technology, Feb. 2011.

[4] Z. Ye, X. Huang, Q. Hu, and H. Lin, "An Integrated Approach for Medical Image Retrieval through Combining Textual and Visual Features," Proc. 10th Int'l Conf. Cross-Language Evaluation Forum: Multimedia Experiments (CLEF '09), 2010.

[5] J. Tang, H. Li, G.-J. Qi, and T.-S. Chua, "Image Annotation by Graph-Based Inference with Integrated Multiple/Single Instance Representations," IEEE Trans. Multimedia, Feb. 2010.

[6] L. Yang, R. Jin, L. Mummert, R. Sukthankar, A. Goode, B. Zheng, S.C. Hoi, and M. Satyanarayanan, "A Boosting Framework for Visuality-Preserving Distance Metric Learning and its Application to Medical Image Retrieval," IEEE Trans. Pattern Analysis and Machine Intelligence, Jan. 2010.

[7] Savvas A. and Chatzichristofis, "Color and Edge Directivity Descriptor: Descriptor for Image indexing and Retrieval", Springer, 2008.

[8] A.Vijay, k.Jayarajan, "Image Similarity Measurements Using HmokSimrank ", IJLTET, Vol. 4 Issue 1 May 2014.

[9] Hui Hui Wang, Dzulkifli Mohamad, N.A. Ismail, "Approaches, Challenges and Future Direction of Image Retrieval", Journal Of Computing, June 2010.

[10] Mehwish Rehman, Muhammad Iqbal, Muhammad Sharif and Mudassar Raza,"Content Based image Retrieval: Survey", World Applied Sciences Journal, IDOSI Publications, 2012.