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SURVEY ON SOCIAL IMAGE RETRIEVING TECHNIQUES

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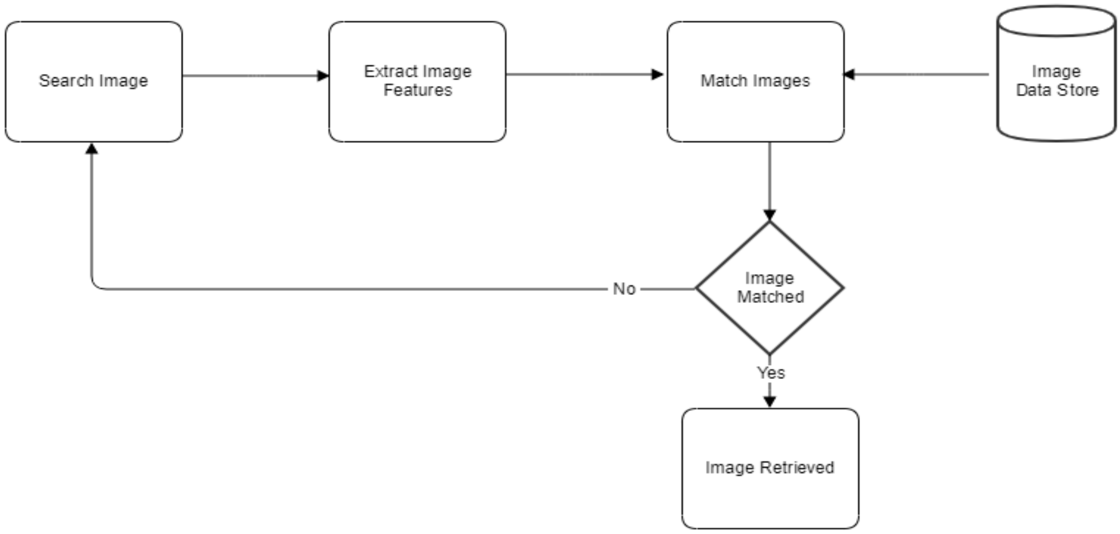
Abstract: *In the era of digital communication, there is tremendous increase in use of digital images on social media sites for sharing or interpreting the information. It makes the task of retrieving images from millions of stored images is very complex and challenging. Basically, image retrieval can be done using methods like Content based Image Retrieval (CBIR) and Tag/keyword based Image Retrieval (TBIR). CBIR is common method of image retrieval depends on visual content of an image. In TBIR method, images are retrieved based on the tag information associated with it. Most of the time, the tags associated with the images aren't adequate and are very context specific and hence poses limitation with the TBIR method. There are some good techniques proposed by various researchers for efficient retrieval of images. The focus here is to understand the techniques and problems associated with the social image understanding viz. tag/keyword assignment, tag/keyword refinement and retrieval of images.*

Keywords*: Tag Refinement, Tag Assignment, Tag Expansion, Image Understanding, Retrieval of Image.*

1. INTRODUCTION

With the recent increase in the usage of social media, sharing of images and pictures have increased dramatically on social websites, that poses challenges to the image search engines. Generally, retrieval of image is classified into Content based (CBIR) or tag based (TBIR). Content based image retrieval takes an image as a query and compares the uploaded image with the stored image based on the visual similarities (viz. characteristics of images). Although, the performance of the CBIR system is limited due to the quality of the visuals uploaded versus that are available in data store. Whereas, TBIR uses the tags to represent the visual features of the image to overcome the limitation posed by CBIR. It allows to present the information in the form of textual query and the results are found based on the comparison between textual query and the tags / notes associated with the images.

TBIR provides better results and is more efficient in identifying images when compared to CBIR. Having said that, the performance of TBIR depends on the quality of the tags associated with the uploaded image. Most of the times, tags are provided by the user who uploads the images on the social sites and hence it is mostly inaccurate or contains insufficient information in describing visual content of images. We have carried a survey by referring multiple papers to identify different techniques which are efficient for social image understanding and add scope for achieving better results. Our focus is to look after the problem of social image understanding i.e. tag/keyword Assignment, tag/ keyword Refinement, tag/ keyword expansion and retrieval of Images.



2. LITERATURE SURVEY

Tag Completion for Image Retrieval

Study shows that many social image retrieval engine works on keyword or tag matching as it is observed that Keyword or Tag based image retrieval is more efficient and convenient than any other way of social image retrieval. However, the performance of tag based image retrieval mostly depends on the quality of manual tags associated with the images. In recent studies it is observed that in general manual tags associated with the images are unreliable and improper and many users provides incorrect tags to the image and some user uploads image without any tags , which leads to performance degradation of TBIR. To overcome this impediment, In [5] author studies the problem of tag completion, where the goal is to correct improper and noisy tags associated with the images and also automatically assign tags to the images which are uploaded without any tag or keyword, for that authors shows Tag image relationship by tag matrix .They proposed new algorithm for solving optimization problem and specifies that this algorithm is efficient for large database.

Projective matrix factorization with unified embedding for social image tagging

Performance of TBIR is limited due to incorrect or noisy tag associated with the image uploaded on social websites. To overcome the performance issues some previous image retagging techniques are proposed to fine tune the tag information of social image in transductive learning manner. However, most of the techniques are unable to handle the images which are not part of sampling data. In [3] author proposed an approach of novel factorization called as Projective matrix factorization with unified embedding for tag learning and retagging. In learning phase, the previously tagging information of social images is applied to find the image and tag correlation matrix. This can handle huge number of social image retagging tasks.

Unsupervised Feature Selection via Non-negative Spectral Analysis and Redundancy Control

An image can be represented by attributes of its features .Extraction of the features from images are done with the help of different image processing techniques. Feature selection reduces the feature space which helps in prediction accuracy and also minimizes computational time. In [2] most of the image processing problems and pattern recognition and images mostly represented by their high dimensional visual features or parameters. All features that characterized images are not equally important for the entire task. Most of the features are redundant and noisy. Toward this end, authors proposed an unsupervised feature selection scheme, called, non-negative spectral analysis with constrained redundancy, by jointly leveraging non-negative spectral clustering and redundancy analysis.

Image Tag Completion via Image-Specific and Tag-Specific Linear Sparse Reconstructions

As user-provided tags with images are mostly incomplete and inadequate which is unable to describe the content of related images, which cause degradation in performance of tag dependent image retrieving application and which increase the necessity of tag completion techniques. In [6] authors proposed LSR scheme for automatic tag completion of image via image and tag specific linear sparse reconstructions which merges various contextual information. Considering an initial incomplete tagging matrix in which rows represents an images and columns represents tags given LSR optimally reconstruct each image and each tag (i.e. row and column) with remaining ones under constraints of deficiency considering image to image similarity, image to tag association and tag to tag concurrence.

3. TAXONOMY CHART

Sr. No	Paper Name	Author	Technique	Result
1.	Multi-task Rank Learning for Image Quality Assessment	Long Xu, Jia Li, Weisi Lin, Yongbing Zhang, Lin Ma, Yuming Fang, Yihua Yan	Pairwise rank learning and multi-task learning for IQA.	Efficient approach for image retrieval.
2.	Unsupervised Feature Selection via Nonnegative Spectral Analysis and Redundancy Control	Zechao Li and Jinhui Tang	Unsupervised feature selection approach (non-negative spectral analysis with constrained redundancy)	Reduce redundancy constraints.
3.	Projective matrix factorization with unified embedding for social image Tagging	Z. Li, J. Liu, J. Tang, and H. Lu	Matrix factorization approach for social image retagging.	Effectively handle large amount of social image retagging task.
4.	Tag Completion for Image Retrieval	L. Wu, R. Jin, and A. K. Jain	Tag matrix completion method for image tagging and image retrieval.	Highly effective method of retagging.
5.	Image tag completion via image specific and tag-specific linear sparse reconstructions	Z. Lin, G. Ding, M. Hu, J.Wang, and X. Ye	LSR scheme for automatic tag completion for image, using image and tag-specific linear sparse reconstructions.	Shows good result for tag completion.

4. CONCLUSION AND FUTURE WORK

We did the survey on various research papers on social Image understanding and Image retrieval by various methods and identified the scope for more proper and effective image retrieval using tag/keyword expansion. To achieve that we need to focus on Novel Deep

Collaborative Embedding (DCE) model for social image understanding. It incorporates the end-to-end learning and bring together related structure with representation similarity and inactive space revelation. To mutually investigate the rich logical data of social images, it factorizes various correlation matrices at the same time and flawlessly. A refined tagging matrix with nonnegative and discrete properties is specifically figured out how to deal with the noisy tags. The proposed strategy is connected to social image tag/keyword refinement and tag/keyword assignment, content-based image recovery, tag/keyword-based image recovery and tag/ keyword expansion.

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