International Journal of Research
Available at https://edupediapublications.org/journals
e-ISSN: 2348-6848
p-ISSN: 2348-795X
Volume 04 Issue 14
November 2017

Semantic-Based Image Retrieval by Visual Analytics Using Ranking Algorithm

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Abstract: *Now-a-days owing to syntax attributes and ability of compression of vast data, CBIR techniques are proving for useful. Semantic-based image retrieval (SBIR) is a retrieval technique based on the intuition of user most SBIR algorithms is explain and retrieved images are considered relevant to the user query, there is a chance that the user may miss out relevant images which may be outliers. Semantic technologies like ontology offers auspicious approach to image retrieval as it tries to map the low level image features to high level ontology concepts. So a tool called Visual Analytics Tool for Semantic Retrieval (VATSR) is proposed which allows user to visually interact and refine the query and/or search results. Our approach makes full use of the explanation in query sketches and the top ranked images of the initial results. Relevance feedback is applied to find more relevant images for the input query sketch. Color and texture features are normalized. Finally Ranking algorithm is used to rank the images for the order of retrieval. Benefits of our proposed system applied in flickr are experimentally shown in terms of both relevance and speed.*

Index Terms: CBIR, color space, color texture, similarity matching, feature extraction, re-ranking, image retrieval, relevance feedback

1. INTRODUCTION

Image mining denotes combination of data mining and image processing technology to aid in the analysis and understanding in an image-rich domain. Data mining and image processing are interdisciplinary that draws upon expertise in computer vision, image processing, image retrieval, data mining, machine learning, database, and artificial intelligence [1]. Clearly, image mining is different from computer vision and image processing techniques. This is because the focus of image mining is in the extraction of patterns from a large collection of images, whereas the focus of computer vision and image processing techniques is in understanding and/or extracting specific features from a single image [2]. Node similarity is computed based on the heterogeneous image rich networks such as

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PhotoBucket relation between two nodes as "two nodes are similar if and flickr are recommended with HMok-SimRank and they are linked by similar nodes in the network". SimRank IWSL. HMok-SimRank is derived from Link-based [3] is widely used for this purpose. The similarity score Similarity algorithm and IWSL is for the integration of link [4].

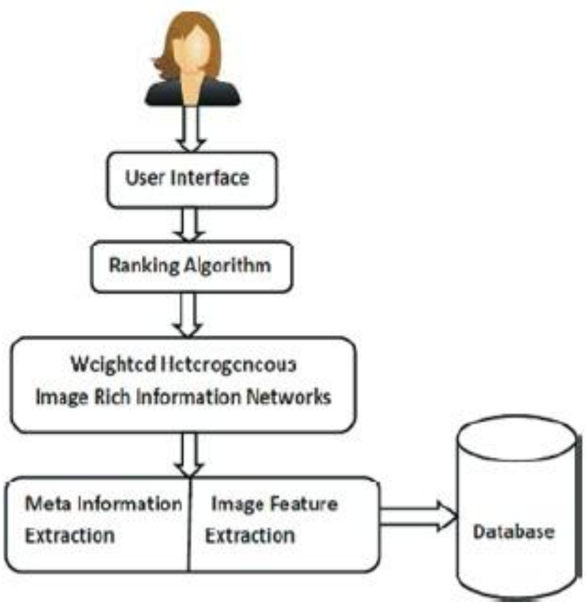

Fig. 1: Image search system architecture

Developments in Internet and mobile devices have increased the demand for powerful and efficient information retrieval tools. Content-based image retrieval (CBIR) mainly used for text and images in queries it is often not possible to precisely describe the content of the desired images using plain text. Additionally, obtaining image that exactly match a user's search intention is not a trivial task [5].

2. RELATED WORK

In a recent paper, Michael Lew et al proposed a principal of content based image retrieval, named query by image content and Content Based Visual Image Retrieval, which uses the computer vision techniques to solve the retrieval problems."Content-based" means that the search analyzes the contents of the image rather than the meta-data such as keywords, tags, or descriptions associated with the image [6]. The term content refers to colors, shapes, textures or any other information derived from the image itself. It is efficient but the evaluation of the effectiveness of keyword image search is subjective and has not been well-defined [7]. Many SBIR methods have been proposed over the past 20 years. Multimodal graph -based re-ranking[8],a web image search re-ranking approach that explores multiple modalities in a graph based learning scheme .This approach simultaneously learns relevance scores ,weights of modalities ,and the distance metric and its scaling for each modality. Image location estimation by salient region matching [9], A salient region mining and representation based image location estimation approach. To generate visual word groups by mean-shift clustering .To improve the retrieval performance , spatial

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constraint is utilized to code the relative position of visual words .To generate position descriptor for each visual word and build fast indexing structure for visual word groups. Hierarchical global feature clustering and local feature refinement.It consists of two parts: an offline system and an online system .A hierarchical structure is constructed for a large-scale offline social image set with GPS information.

Fig 2: sample input and output

3. PROSED SYSTEM

The top-ranked images obtained by the initial SBIR may contain irrelevant images. From the pool of images, he relevant images are obtained by grouping. By grouping, it improves the diversity of top-ranked results by finding near duplicated image groups. Further group the detected near-duplicate images into groups for the top-ranked images [10]. The score of relevant images are set to be maximum and minimum for irrelevant images. The relevant images are re-ranked using visual feature verification.

A. Content-based image retrieval (CBIR):

CBIR is defined as query by image content (QBIC), and it is also named as content based visual information retrieval (CBVIR) [11]. It uses a computer enabled program on to the retrieve the desired image from the database. To overcome the problem of traditional concept-based approaches, the content-based method is used. "Content-based" explained that the search which analyzes the texts/contents of the picture/image instead of the information such as tags, keywords or other methods of tagging the text with the image. Therefore, "content" defined to color, shape, texture, or any other related useful data that can be extracted from the image/picture [12]. The CBIR is used to avoid complete dependence on the quality of metadata and annotation tagged with the image..

B. Context-based image retrieval technique

The context-based image retrieval techniques mainly work on the information that is available within the image. The knowledge about the content of an image can come from other sources in addition to that of available in that very image [13]. The information about the image other than its visual attributes is the context of the image for example keywords, annotations, tag etc. At times the caption, subtitles or a text written nearby the image can also contribute in the retrieval. The standard text retrieval techniques can be used to create indexes [14].

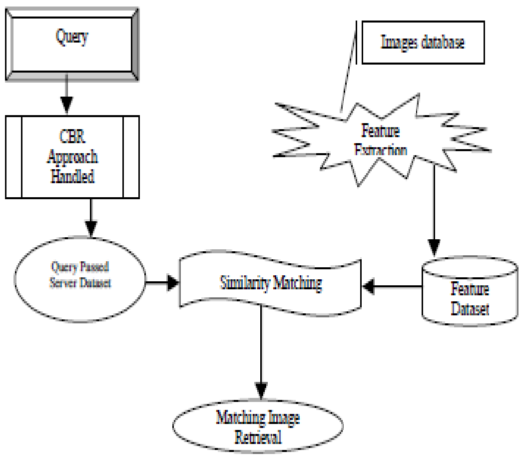

Figure 3. Content Based Image Retrieval System Flowchart

C. **Contour Based Relevance Feedback**

Contour based relevance feedback. To improve the final result query is expanded for image based retrieval. The contour of a top ranked image can also be regarded as sketch and return more relevant images. Relevance feedback algorithm consists of following steps [15]..

1. The verified images are used as query sketches.
2. Each image in the collection is given a score based on new query contours.
3. By combining the scores of initial and expanded retrievals final similarity score of each image is obtained.
4. Final ranked list is generated using initial system and combined to add weight to the initial result.
5. Obtaining the final ranked result. Using the contours CBRF finds more relevant images query expansion, ranks are provided for query expanded sketches. The relevance feedback scores of each image in collection for each expanded query are computed [16].

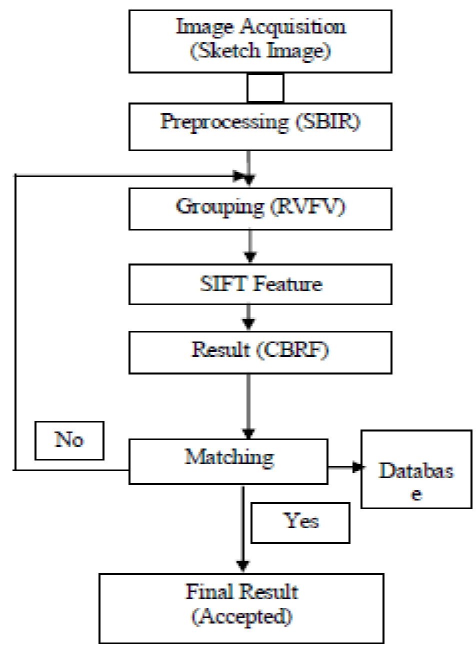

Figure 4.Over all Process of the System

4. RANKING AND VISUAL FEATURE VERIFICATION

The relevant image grouping approach can find more relevant images for the input query sketch,

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some irrelevant images may appear in the top N results. If we re-rank the top N results by measuring their similarities in the visual feature space [17] then the refined search results will be more satisfactory. Our aim is to filter out irrelevant images using content matching constraints which are often, used in retrieval result verifications. Thus, in this paper, we leverage the advantages of both retrieval result verification and relevance feedback to improve the retrieval performance. We select many relevant images from the top N-ranked images to expand the query and get more relevant results [18].

5. ASSOCIATION RULE MINING

Association rule mining generate rules that have support and confidence greater than some user specified minimum support and minimum confidence thresholds [19]. A typical association rule mining algorithm works in two steps. The first step finds all large item sets that meet the minimum support constraint. The second step generates rules from all the large item sets that satisfy the minimum confidence constraint. Association rule mining is frequently used in data mining to uncover interesting trends patterns and rules in large datasets. Recently, association rule mining has been applied to large image databases. Although the current image association rule mining approach is far from mature and perfection compared its application in data mining field, there opens up a very promising research direction and vast room for image association rule mining. There are two main approaches [20]. The first model is to mine from large collections of images alone, and the second approach is to mine from a combined collection of images and associated alphanumeric data.

6. EXPERIMENTAL RESULTS

Query Sketch

It was developed by Martin Wattenberg. This dataset was used in [4].It contains 101,240 images. There are 1240 benchmarked images for 31 query sketches, and 100,000 noise images. Query sketch may be of bitmap images. Query sketch can be in any form of clockwise and anticlockwise direction. Subjects are required to give a hand drawn sketch and comparing the sketch with databases.

	Initial SBIR	ours				
		clustering	RVFV1	CBRF	RVFV2	Total
Edgel	9.77	0.017	0.73	0.14	0.41	11.06
ARP	0.64	0.015	0.53	0.10	0.26	1.55

Edge and ARP are the two methods to measure the computational costs for the queries. Relative computational costs were different for the initial SBIR method. The average computational costs of the edge method was 9.77s.The total time taken by relevance feedback system was 1.28s.which was less than 1/7th of time taken by edge method. For the ARP method system took 0.91s to calculate the relevance feedback

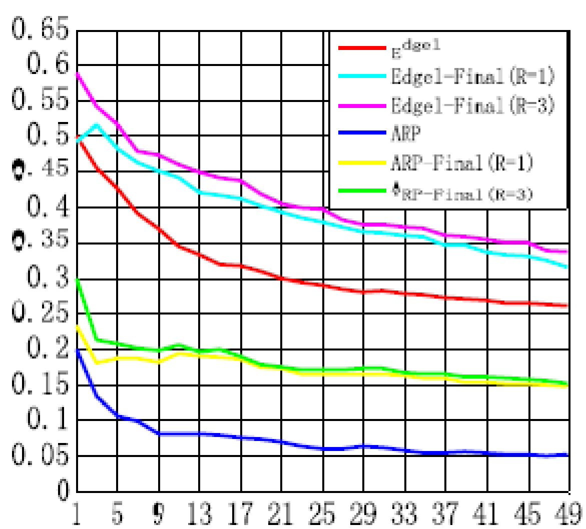

Fig No.5. Performance using SBIR&CBIR

7. CONCLUSION

SBIR method is uses initial result grouping re-ranking via visual analysis and relevance feedback model to search for more similar images. The initial result grouping helps our system find more relevant images for the relevance feedback. Content-based image retrieval (CBIR) has become a prominent research topic. Therefore an important problem that needs to be addressed is fast retrieval of images from large databases. Contour based relevance feedback (CBRF) is used to compute the similarity scores. Re-ranking via visual feature verification (RVFV) is used to determine the variation in similarity scores due to the combination of location and orientation differences and it is only applied to top ranked results. In this proposal we have portrayed only with small Data set excluding Big Data. We will very well implement our Knowledge Base into the Big Data in the future. As a final point we have combined here all the worked out and constructed biomedical domain based focused web crawler and even launched the Search engine for the end user(s).

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