International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 6, Issue 3, March 2017, ISSN: 2278 – 1323

An Efficient Sketch Based Image Retrieval Using Re-Ranking Method

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Abstract—**A sketch based image retrieval often needs to optimize the trade off between efficiency and precision. Index structures are typically applied to large-scale databases to realize efficient retrievals. However, the quantization errors will affect the performance. Moreover, the uncertainty of user provided examples may also reduce the performance, when compared with traditional image retrieval methods. Sketch based image retrieval systems that preserve the index structure are challenging. In this paper, we propose an effective sketch based image retrieval approach with re-ranking and relevance feedback schemes. 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. The integration of the two schemes results in mutual benefits and improves the performance of the sketch based image retrieval.**

Keywords-Sketch,Sketch Based Image Retrieval (SBIR), Relevance Feedback, Image Retrieval, Contour Matching,Reranking via Visual Feature Verification(RVFV),Contour Based Relevance Feedback(CBRF).

1.Introduction

1.1Background

The Image processing is processing of images by using any form of signal processing for which the input is an image, a series of images, or a video, such as a photograph or video frame and the output may be either an image or a set of characteristics or values related to the image.

1.2Digital Image Processing

A digital image is a statistical representation of a two-dimensional image. Depending on whether the image resolution is fixed, it may be grid of pixels. Digital image refers to bitmap images. Image processing is a algorithm to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. The image processing toolbox provides a stable, well supported software environment for addressing a broad range of applications in digital image processing.

Image processing basically includes the following three steps:

1. Transporting the image with optical scanner or by digital photography.
2. Analyzing and manipulating the image which includes data compression and image complement and spotting patterns that are not to human eyes like satellite photographs.
3. Output is the last stage in which result can vary image or report that is based on image analysis.

Methods for efficiently searching images are an important research topic. 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. However, 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. Query sketches drawn by users can effectively describe the aim of a search. Therefore, query by sketch is an effective method when text description and query examples are unavailable. Sketch based image retrieval (SBIR) method use a hand drawn sketch composed of simple strokes or lines to fulfill the image retrieval task.

1.3Image Recognition

An image is a geometric representation of any objects. It may be of two dimensional or three dimensional which are captured by optical devices. Query sketches drawn by users does not require any prior knowledge or training to draw the hand drawn image according to the users intension. The sketch is a drawing that uses different words to represent diverse objects. Their locations and sizes are represented by the words. Global features are used to match sketch and an image. The matching algorithm uses a predefined tolerance, because the sketches drawn by users are often not precise. Local feature matching is used to solve this problem.

Figure 1.Input Image

2.Related Works

In this section, we discuss existing solutions for image recognition and several state of image recognition methods are reviewed.

2.1Content Based Method

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. 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.

2.2Bayesian Visual Re-ranking

I. J. Cox, M. L. Miller [7] proposed a Bayesian visual Re-ranking to refine text-based video and image that utilizes visual information to recover “true” ranking list from the noisy one generated by text-based search, by organizing both textual and visual information. In this method, the textual information is modeled as a likelihood, to reflect the disagreement between re-ranked results and text-based search results which is called ranking distance [8]. The visual information is modeled as a conditional prior, to indicate the ranking score consistency among visually similar samples which is called visual consistency. Bayesian visual re-ranking acquires the best re-ranking results by maximizing visual consistency while minimizing ranking distance. To model the ranking distance more precisely, [7] proposed a novel pair-wise method which measure the ranking distance based on the disagreement in terms of pair-wise orders. It provides more useful information in the ranking distance term but too much noise is contained in the pseudo-positive samples which lead unsatisfactory re-ranking performance.

2.3Contour Based Image Retrieval

In recent papers Zhiyong Zhang proposed a principal of CBIR method to retrieve multi texture images. The contour of each texture primitive is extracted from an image and the contours of the texture primitives in the original image are clustered. Then Gabor wavelet transform is applied to extract the features of texture primitives for each group so that the images can be represented by a set of features. It is efficient and has higher retrieval precision but contains some irrelevant images. Relevance Feedback method is used to filter out those irrelevant images and to improve the performance.

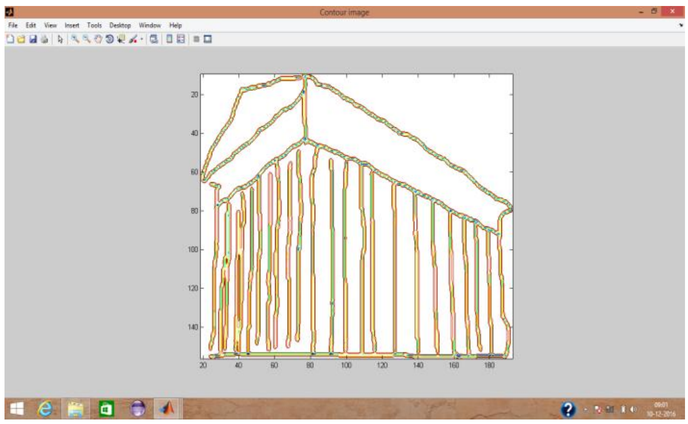


Figure 2.Contour Image

2.4Sketch Based Image Retrieval

SBIR method uses initial result grouping, re-ranking via visual verification, and a relevance feedback system to search for more similar images. SBIR uses relevance feedback to improve performance. In this method, SIFT features are extracted for each image. The locations and orientations of those images are recorded and finally contour similarity index for each image is builded. It can find many relevant images when the initial results are sufficient, but the proposed method can't find the images with differently size and rotation.

2.5Motivation

In previously discussed methods, different extraction schemes are used, each method extracts a different features. The Existing system may not be efficient to find the image with different orientations. These method lacks in accuracy when it couldn't be able to extract the features of the image. To rectify the disadvantages, the proposed scheme uses Bag Based Re-ranking approach to avoid the ambiguities and to achieve an effective and efficient re-ranking process.

3.Proposed Scheme

3.1Grouping of relevant images

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. 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.

3.2Re-ranking via visual verification

The relevancy of image results is maximized by re-ranking. Although grouping can find more relevant images some irrelevant images may appear in the top ranked results. Based on similarities of visual feature space re-ranking is done. The main aim of re-ranking is to filter out irrelevant images using content matching or spatial constraints. It reduces the number of false positive results at the first time and optimizes the final result at last time. RVFV consists of two steps

1. Finding SIFT pairs for all images
2. Re-ranking is done using similarity scores.

3.2.1Feature Matching

RVFV is only applied to top ranked initial results. It is used to match features of one image with other images. From the top ranked images ,the relevant images are selected to expand the query. Then find SIFT pairs of all images. By using matched SIFT point pairs the similarity scores are measured. SIFT descriptor is used to extract some features from images and describe them in a standard way. In this SIFT feature we can compare images to each other or find a visual query image within the target image.

3.2.2Similarity Based Re-ranking

Based on spatial location and orientations matching performance is improved. SIFT feature matching has been extensively applied to image classification. Spatial locations and orientations are used to add weights to the matched SIFT pairs. Similarities can be determined by summing the weighted scores of the matched SIFT point pairs. It describes about how similar the images in the initial result is to the standard image and checks it satisfies a minimum matching requirement.

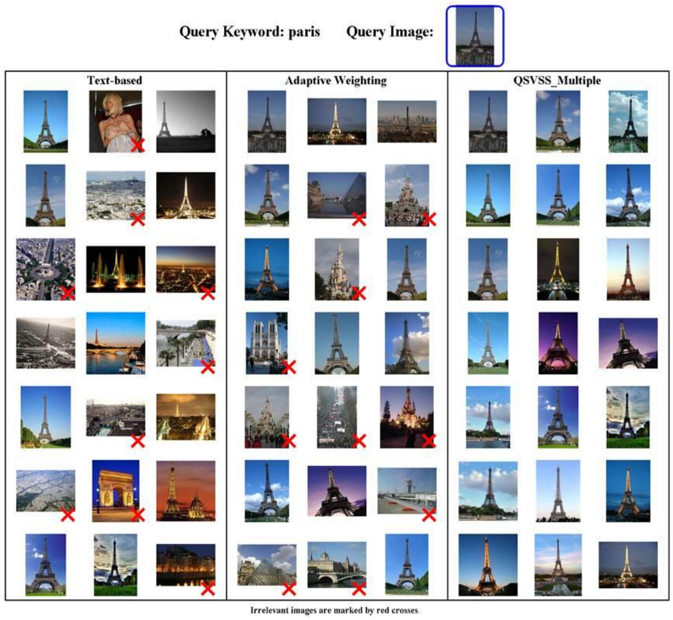


Figure 3.Comparison of database image with query image based on the similarity.

3.3Contour 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:

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. By query expansion, ranks are provided for query expanded sketches. The relevance feedback scores of each image in collection for each expanded query are computed. Scores and images are determined using the contour similarity index structure. Higher ranked image in the initial results has more influence on feedback. It is used to Generate final ranked results and ensure the feedback is positive. After re-ranking in CBRF new ranked list will be done. Some irrelevant queries are produced by expanded queries. So RVFV is applied to re-rank the top results. Images verified in the first RVFV are recorded. Second RVFV is much faster than first.

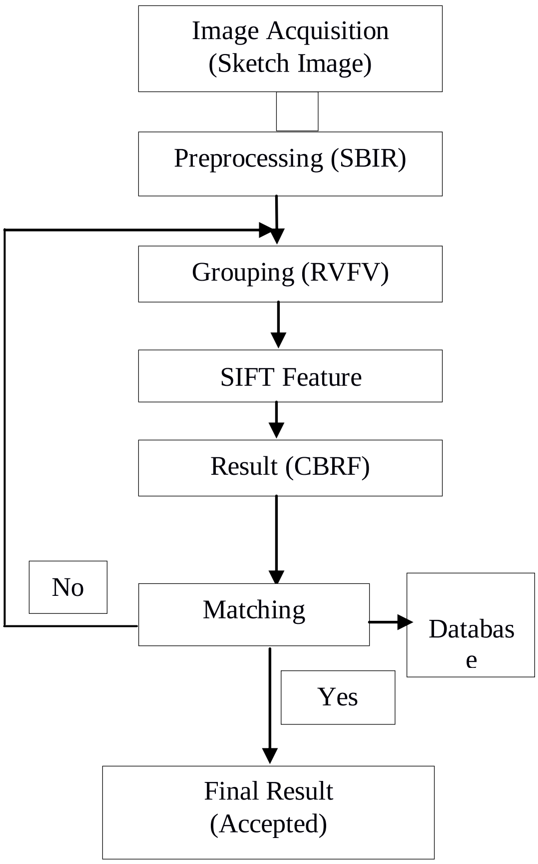


Figure 3.Over all Process of the System

4.Experimental Results

4.1Query 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.

4.2Sketch Based Image Retrieval

The performance of the proposed system is demonstrated using a MATLAB. A dataset consists of 296,562 images. It consists of sketch describable dataset of 68,647 images. The query sketch is given as SBIR (initial result).The initial results are clustered and ranked according to the similarities. The relevant images are converted to contour based image and finding the SIFT features. The contour images are re-ranked through contour similarity index and relevance feedback algorithm is applied. By comparing the initial result and RVFV image the sketch based image is retrieved

4.3Performance Analysis

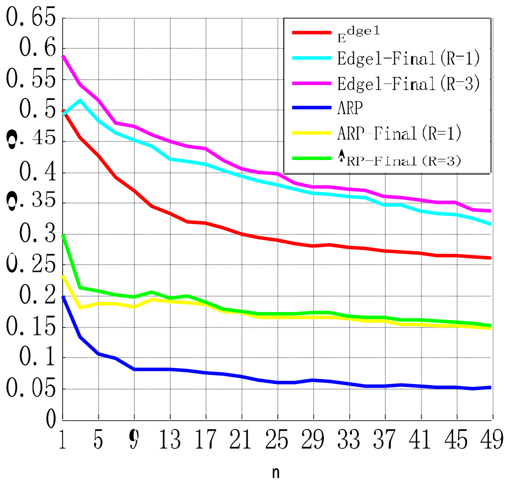
In this section, we discuss about the performance analysis in terms of SIFT matching, Location matching, object weighting.

SIFT Matching: It is an image descriptor for image matching and recognition. It converts grey level image to colour image. SIFT descriptor is very useful in practice for image matching and object recognition under real world conditions. Finding SIFT features for the contour images and compare the images within the database images.

Location Matching: It is used to match the SIFT Feature images based on location or pixels arranged. Mostly matching is compared by matrix formation. It will improve the performances and add weights to matched SIFT pairs.

Object Weighting: Object Weighting includes location and orientation weights. It is calculated by similarity between two images and summing the weighted scores. The minimum difference of SIFT pair and sum of orientations should be in range. It is computed by similarity of image to the standard image. A vocabulary tree is established and uses scheme to determine weights.

Performance using SBIR



	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

Edgel 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 edgel 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 edgel method. For the ARP method system took 0.91s to calculate the relevance feedback.

5.Conclusion and Future Work

The proposed system is used to find the relevant image among the database images for the initial query sketch. The image is retrieved by re-ranking via visual feature verification (RVFV), contour based relevance feedback method(CBRF).It compares more images among database and extract SIFT features for the relevant images. 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. By applying RVFV to the CBRF irrelevant images are removed and improves the performance. Our approach finds out more relevant images by combining it with other SBIR methods and it it improves the accuracy.In the future work, we will work hard to find the images with differently size and rotation.

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