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Sketch-Based Image Retrieval and Enhancement by Re-Ranking and Relevance Feedback

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Abstract* — A sketch -based image retrieval often needs to find the tradeoff between efficiency and precision. Preserve the index structure are challenging in sketch-based image retrieval approach. The repetition of user-provided examples may degrade the performance .The system that uses many techniques, including relevant image grouping, re-ranking via visual feature verification, and contour-based relevance feedback. The objective of grouping approach is to find more suitable images. We are searching for an initial result grouping (Re-Ranking) or visual verification and relevant feedback system search for more similar images .We need more deeply explores relevant images, to find those that were not found original image retrieval system. Also need not to destroy the original index structure and does not increase time or storage cost. So here propose sketch-based image retrieval system with re-ranking and relevance feedback scheme. The combination of the two schemes results in mutual benefits and improves the performance.

Key words: SBIR, sketch, re-ranking,image retrieval,relevance feedback.

I. INTRODUCTION

Sketch-based communication is the oldest form of writing. In which sketch depicts rough shape of object. Sketch-based image retrieval (SBIR) can therefore be a very valuable information search tool. Although sketch is good way to express people’s thoughts, there is a large gap in the appearance of user sketches and photorealistic images, when people draw a sketch they usually focus on the main structure of an object and only draw the semantic contour boundary. In contrast, photo-realistic images contain the color, texture and detailed shape of an object, which makes it very difficult to directly match a sketch and the corresponding photo-realistic image. Therefore, this is fundamental challenge in SBIR.

Digital Image processing is the manipulation of images from a digital camera. Image retrieval means retrieving images from digital image database by searching for desired images. In order to search for an image, we need to provide an image or an image description as a search query. The image retrieval system will return images "similar" to the query after searching in the digital database. The similarity can be measured based on metadata, the contents or the shape of an image.

Traditional draw-and sketch systems need to have an input query which is similar to natural scene image to be searched. That is the sketch should be similar in color shape and texture. This converts the problem of sketch based image retrieval to content based image retrieval (CBIR). The major goal of SBIR technology is to measure the similarity between a hand drawn sketch and an image. That is by measuring the contour similarity between input query sketch and the database image. Thus the problem of SBIR is converted to contour matching. Shape of an object have an important role in image comparison and is used in object detection and object comparison. Shape of an object can be described using shape descriptor or shape contexts. Shape descriptors can be global or local. Global descriptor plays a major role in image analysis.

SBIR systems can be used to take a hand drawn [7] sketch as the input query and retrieve the similar images from large scale digital database. Human brain recognizes an object based on its shape or contour. We can draw the shape of an object in simple strokes for any of the natural scene images. But there may presence some ambiguities in sketches due to poor drawing skills. To remove these ambiguities the image retrieval system should be able to deal with the ambiguity existing if any.

In order to retrieve images from databases, there is a need for efficient methods for retrieval. The most common method used for image retrieval is Content Based Image Retrieval (CBIR) in which the output images are similar to a user provided query image. The main advantages of using Content Based Image Retrieval (CBIR) are (i) Fast Retrieval (ii) Ease of implementation. The main disadvantages in Content Based Image Retrieval system (i) time consumption to tag all available data (ii) results user subjective. However, there can be a lack in clarity of information if images are tried to be communicated through words. Sketch based image retrieval approach was used where the input is given as a hand drawn sketch using software like paint. Since this technique requires a particular amount of basic artistic skills, some people may refrain from using this.

Relevance feedback has been extensively applied to better interpret users’ search intentions in an interactive way [1]. There are generally two challenges when applying the relevance feedback technique to SBIR. The first is that the query sketch and returned images do not have the same style. The second is that the scarcity and inaccuracy of a query sketch may mean that many noisy images appear in the top-ranked search results. The system that uses several techniques: including relevant image grouping, re-ranking via visual feature verification (RVFV), and contour-based relevance feedback (CBRF). The aim of grouping approach is to find more relevant images to produce relevant feedback. The RVFV approach removes noisy images and makes the top ranked images more relevant to the input query sketch. The CBRF approach uses the contours of the top-ranked images obtained by the SBIR system as new queries to find more relevant images. We apply RVFV again to remove irrelevant images that introduced in the CBRF stage. The two systems are both offline and are considerable enhancements on SBIR.

Fig 1: sample input and output

The main contributions of this paper are summarized as follows[1].

1) We propose an effective sketch-based image retrieval approach with relevant image grouping, verification and re-ranking. The semantics explored from the sketch and the local features of the verified relevant images are fused to reduce the user's search intention gap in SBIR. 2) We propose mining relevant images in the top-ranked results from the initial SBIR system using relevant image grouping, and using them in the relevance feedback. 3) We propose a visual verification system that re-ranks the results to improve the overall performance. 4) We integrate a contour-based relevance feedback system into the SBIR system to improve the retrieval performance. This method uses contours as sketches to carry out the relevance feedback in SBIR. We test our relevance feedback based SBIR approach on the ARP and edgel based SBIR system. Fig 1 is the sample input and output.

II. RELATED WORK

Many SBIR methods have been proposed over the past 20 years. Multimodal graph -based re-ranking[2],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[3], 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 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.

GPS estimation for places of interest from social user[4], An unsupervised image GPS location estimation approach with 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.

III. PROPOSED SYSTEM

The proposed system in this project is relevant image grouping, re-ranking via visual feature verification (RVFV)[1], and contour-based relevance feedback (CBRF). The aim of grouping approach is to find more relevant images to produce relevant feedback. The RVFV approach removes noisy images and makes the top ranked images more relevant to the input query sketch. The CBRF approach uses the contours of the top-ranked images obtained by the SBIR system as new queries to find more relevant images. We apply RVFV again to remove irrelevant images that introduced in the CBRF stage. The two systems are both offline and are considerable enhancements on SBIR. With small increase in complexity, the sketch retrieval system can retrieve more desired images

Advantages

- The semantics explored from the sketch and the local features of the verified relevant images are fused to reduce the user's search intention gap in SBIR.
- Mining relevant images in the top-ranked results from the initial SBIR system using relevant image grouping, and using them in the relevance feedback.
- We propose a visual verification system that re-ranks the results to improve the overall performance.
- We integrate a contour-based relevance feedback system into the SBIR system to improve the retrieval performance.

This approach can be included at the back end of any initial SBIR system using relevance feedback to improve performance. We now focus on an edgel SBIR system to illustrate our approach. In the first part of the method, we must build an edgel index structure for each image. Then, we extract SIFT features and record the SIFT descriptors with their locations and orientations. Finally, we build a contour similarity index for each image. In the second part, for a given input query sketch, we sequentially execute five stages: 1) the initial SBIR, which obtains the initial result; 2) relevant image grouping for the initial results, which finds the relevant images from the top *R* images in the top *N* ranked results; 3) re-rank and verify the results using SIFT matching; 4) contour-based relevant feedback to find more relevant images; and 5) re-rank the results of the relevant feedback to improve the performance.

The Modules Are:

A. Sketch-Based Image Retrieval
B. Relevant Images Grouping For Relevant Feedback
C. Contour-Based Relevance Feedback
D. Re-ranking via Visual Feature Verification

A. Sketch-Based Image Retrieval

Sketch-based image retrieval (SBIR) methods use a hand-drawn sketch composed of simple strokes or lines to fulfill the image retrieval task [7]. In a user's visual perception, the most informative lines in an image are the contours. A sketch is generally a rough description of an object's shape and contours. The sketch does not need to be artistic, and is simply the user's rough impression of the intended object. Traditional draw and search systems require that the input sketch is colored and similar to a real photo [9]. This approach converts sketch-based retrieval to content-based image retrieval. The user must draw the sketch carefully and color it to make the sketch visually similar to the natural scene images. Then, CBIR fuses different features (such as shape, color, and texture) together to perform retrieval. However, this method will burden users by requiring detailed drawings, and most importantly, it does not solve the core problem of SBIR, i.e., matching a line-formed sketch and colored images. In system ,we build a feature index structure for each image [8].Finally ,the similarity between the query sketch(Q) and the image(D) in the database is computed by counting how many times D appear during the search.

B. Relevant Images Grouping For Relevant Feedback

The top-ranked images obtained by the initial SBIR may contain irrelevant images. In our approach, the relevant images are the ones that occur most in the top N images. We make full use of the top R images ($R<N$) to find relevant images for CBRF. Our approach is motivated by retrieval results clustering, which improves the diversity of top-ranked results by finding near duplicated image group.Using relevant image grouping we can roughly eliminate the noisy images from the top-ranked results. Then, we further use the top N images with RVFV to obtain more relevant images. We use the duplicate image group from the top R-ranked images (denoted by top-R+top-N), rather than the top N images to eliminate noise. Generally, a higher-ranked image is more relevant to the query sketch. If we use the top-ranked N images directly in RVFV, we will include some noise. This would negatively impact the final CBRF.

C. Contour-Based Relevance Feedback

The contour based image retrieval is useful to expand the query for image-based retrieval to improve the final result. A sketch is a description of contours. The contour of a top-ranked image can also be regarded as a sketch and used to return more relevant images. The contours of the verified images are used as new query sketches. Each image in the corpus is given a score based on each of the new query contours. The final similarity score of each image in the corpus is obtained by combining the scores of the initial and expanded retrievals. The final ranked list is generated using the initial system for each new query. These ranked lists are combined and used to add weight to the initial result and obtain the final ranked list. Relevance feedback algorithm contains the following steps.

1) The contours of the verified images are used as new query sketches.
2) Each image in the corpus is given a score based on each of the new query contours.
3) The final similarity score of each image in the corpus is obtained by combining the scores of the initial and expanded retrievals.
4) The final ranked list is generated using the initial system for each new query. These ranked lists are combined and used to add weight to the initial result and obtain the final ranked list.

D. Re-Ranking via Visual Feature Verification

The relevant image grouping approach can find more relevant images for the input query sketch, 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, then the refined search results will be more satisfactory. Our aim is to filter out irrelevant images using content matching or spatial 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.RVFV is only applied to the top N initial results. We select some of the relevant images from the top N-ranked images to expand the query and get more relevant results. We find SIFT pairs of the standard image (the top-ranked image after relevant image grouping of the initial SBIR results, IS) and other images (the top-ranked N images, but not including duplicates of the standard image).And perform re-ranking using the similarity scores.

IV. CONCLUSION

SBIR method that uses initial result grouping, re-ranking via visual verification, and a relevance feedback system to search for more similar images. The initial result grouping helps our system find more relevant images for the relevance feedback. Our RVFV approach filters out irrelevant images to improve the relevance feedback, and to find more relevant images for the top-ranked images. The proposed CBRF more deeply explores relevant images, to find those that were not found in the original SBIR. These systems work well when compared with other methods, and can find many relevant images when the initial results are sufficient. Note that our approach does not destroy the original index structure, and does not significantly increase time or storage costs. But the proposed method can't find the images with differently size and rotation. In the future work, we will work hard to solve this problem. Theoretically, this method can be combined with a wide range of existing SBIR methods to improve the final retrieval results.

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