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An Efficient 3D image retrieval with 2D sketch using AROP feature

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Abstract

The paper presents a sketch-based image retrieval algorithmic rule. one in all the most challenges in sketch-based image retrieval (SBIR) is to live the similarity between a sketch and a picture. To tackle this drawback, we tend to propose a SBIR primarily based approach by salient contour reinforcement. In our approach, we tend to divide the image contour into 2 sorts. the primary is that the international relief map. The second that's referred to as the salient relief map is useful to search out out the item in pictures the same as the question. additionally, supported the 2 contour maps, we tend to propose a replacement descriptor, particularly angular radial orientation partitioning (AROP) feature. It totally utilizes the sting pixels' orientation data in contour maps to spot the spacial relationships. Our AROP feature supported the 2 candidate contour maps is each economical and effective to find false matches of native options between sketch and pictures, and may greatly improve the retrieval performance. the appliance of retrieval system supported this algorithmic rule is established. The experiments on the image dataset with zero.3 million pictures show the effectiveness of the planned methodology and comparisons with different algorithms also are given. Compared to baseline performance, the planned methodology achieves 100% higher preciseness in top5.

Keywords-

Sketch based Image Retrieval, SBIR, Image Retrieval, Contour Matching, Salient Contour

1. Introduction

Developments in internet and mobile devices have increased the demand for powerful and efficient image retrieval tools. How to find the images we need from large scale datasets? In order to answer this question, content-based image retrieval (CBIR) develops rapidly and works well. The existing CBIR systems [2, 31, 32, 40] still mainly use keywords or images as the query, which still can't fulfill all user demands. It is often difficult to precisely describe the content of the desired images using plain text. When the user does not have the natural scene images and accurate textual descriptions to justify his/her search intention, there are some difficulties in obtaining relevant images. To avoid these problems, the sketch-based image retrieval (SBIR) system is generated. This system is more convenient for users, because the end user could simply draw a sketch and then use the sketch as the input for effective image retrieval.In real life, we can draw a contour

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or a shape to represent the relevant image. In addition, sometimes a sketch produced by a user will look rough because of poor drawing skills or limited time for drawing. So it is possible that the sketches are different from natural scene images in some aspects. Considering this factor, an effective SBIR systems must be able to deal with the ambiguousness existed between the simple stroke and the natural scene images. This brings great challenges for solving the problem.

SBIR based approach using the extracted salient contour feature, which makes full use of contour and orientation to improve the accuracy. To solve the representation gap, we use Berkeley detector [12] to extract the images contour maps and propose two contour maps (the global contour map and the salient contour map). The global contour map is defined to find the relevant image with a simple background. The salient contour map is defined to tackle the problem that an object is similar to the query. In order to solve the matching problem, we propose a novel angular radial orientation partitioning (AROP) feature. It is an enhanced angular radial partitioning (ARP) feature [3]. With the reinforcement of the salient contour, this feature uses contour and orientation to constrain the spatial information.

When extracting the descriptor, some works focus on global descriptors, and other focus on local descriptors. Global features [1-3, 53] can be better used in image analysis, matching, and classification. However, global features are unreliable to deal with local affine variations. To overcome such drawback, many local descriptors are proposed [4, 5].

In a sketch-based image retrieval system, users care more about search precision than recall. The main directions in sketch retrieval are sketch querying [42-45] and fusion sketch and tag [27, 46, 47] querying. To find more relevant images in SBIR system, we need to overcome the following two challenges: representing and matching. Contour based retrieval is important because contour provides information about image structure and texture. In addition, orientation has been exploited widely in the computer vision community [24, 39, 48-52]. Orientation shows outperforming results in tasks such as object recognition and object categorization. In general, all these stages, including image segmentation, contour extraction and image saliency, are difficult and extensively researched. Here, we do not claim to solve these challenging problems in general.

In this paper, we propose a SBIR based approach using the extracted salient contour feature, which makes full use of contour and orientation to improve the accuracy. To solve the representation gap, we use Berkeley detector [12] to extract the images contour maps and propose two contour maps (the global contour map and the salient contour map). The global contour map is defined to find the relevant image with a simple background. The salient contour map is defined to tackle the problem that an object is similar to the query. In order to solve the matching problem, we propose a novel angular radial orientation partitioning (AROP) feature. It is an enhanced angular radial partitioning (ARP) feature [3]. With the reinforcement of the salient contour, this feature uses contour and orientation to constrain the spatial information.

The main contributions of this paper are summarized as follows: 1) We propose a global contour map (GCM) to describe the background contour. The GCM has impact to the main object contour by adjusting its weight. Compared to the contour map, the proposed GCM is more reliable and better suited to SBIR. It demonstrates superior performance and is helpful for reducing the impact of complex background. Our experiments demonstrate that the proposed GCM plays a key role in significantly improving retrieval performance.

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2) We propose a salient contour map (SCM) to increase the impact of the main object contour, corresponding to the object contour of all extracted edges. Our experiment demonstrates that SCM is helpful to filter out false matches and alleviate the impact of noisy edges.

3) Based on our candidate contour maps, we propose a new global descriptor, angular radial orientation partitioning (AROP) feature, to describe the spatial information of contours within each block. Compared to image patch-based descriptor, our AROP feature contains more information, which makes the retrieval result more accurate and reliable.

Compared with our preliminary work [55], several enhancements have been made in this paper. We summarize them as the follows: 1) we enhance global and salient feature for feature extraction by reinforcing the saliency map to improve their robustness in SBIR; 2) we propose an effective approach to rank the feature, based on which we can reduce the computation time; 3) more extensive experiments and comparisons are conducted. The remainder of this paper is organized as follows. Works related to sketch-based retrieval are reviewed in Section II. We describe the proposed approach in Section III, our experiments are presented in Section IV, and the discussion is given in Section V. Finally, we present our conclusions in Section VI.

2. Related Work

There have been a lot of studies in sketch-based image retrieval system recently. In the following, we briefly describe some approaches which are widely used in SBIR systems.

The query by visual example (QVE) is one of the earliest approaches in SBIR [6]. In this approach, they resize the query and the database images to 64*64 pixels and then they use the proposed gradient operator to extract edges. The correlation is calculated by shifting these blocks. The edge histogram descriptor [2] and the histogram of oriented gradients (HoG) [1] are also used to establish the SBIR system [14]. They are both global features extracted from the edges of images. Eitz et al. [4], [5] use local descriptors to achieve state-of-the-art retrieval precision. And QVE (query by visual example) [6] is a typical method by using blocks and local features. Cao et al. propose a local feature method, edgel index method [7], for sketch-based image search by converting a shape image to a document-like representation.

In our previous work [24], we propose a SBIR approach with re-ranking and relevance feedback schemes. We make full use of the semantics in query sketches and the top ranked images of the initial results to improve retrieval performance. We further apply relevance feedback to find more relevant images for the input query sketch. The integration of the re-ranking and relevance feedback results in mutual benefits and improves the performance of SBIR.

Chen et al. [46] present a system that composes a realistic picture from a simple freehand sketch annotated with text labels. Firstly, they use the text label to search the relevance item and background. And then they choose candidate images for each scene item and background. During filtering, each image is segmented to find the scenic elements corresponding to the sketch. Finally, they optimize the combination of filtered images into a picture by two steps. Firstly, they optimize the blending boundary and assign each pixel within the boundary a set, indicating whether the texture and color of that pixel are consistent or not. Secondly, they compute the blending result by combining improved position blending and alpha blending.

The edgel index approach is a shape-based indexing method [7]. It solves the shape-to-image matching problem using pixel-level matching. Its Mind Finder system [7, 27] is a real-time image retrieval system. Oriented chamfer

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matching is used to compute the distance between contours to conveniently build the index structure [8]. Cao et al. use a binary similarity map (a hit map) instead of the distance map [7]. For each input sketch, a set of hit maps is created, which correspond to the number of orientations. They also design a simple hit function. Specifically, if a point falls in the valid region on a hit map in the same channel, it is considered as one hit. The sum of all the hits is the similarity between a database image *D* (represents the contours of an image) and the query sketch *Q*. Then, they build an edgel index structure for fast retrieval, which records the value of position and channel of the hit map. And last they use two-way matching. The one-way often leads to trivial results. Unsatisfactory results could be filtered out by combining the opposite direction matching . Then, they multiply these two similarity scores to obtain a final score that reduces the influence of trivial results.

3. The Proposed Approach

The framework of the proposed SBIR system is shown in Fig.1, which consists of the offline part and the online part. In the offline part, for the dataset images, we sequentially execute three steps: 1) we first carry out preprocessing for dataset images to extract image salient regions and contour maps by RC [10] and Berkeley detector [12] respectively; 2) we use salient contour reinforcement method to extract candidate contour maps containing the global contour map and the salient contour map; 3) we extract AROP features based on the candidate maps named global features and salient features.

In the online part, for a given input query sketch, we extract the global contour map and the salient contour map based on the contour map. Then, similar to the offline, we extract AROP feature based on the two candidate maps.

After we extract these two types of features, we measure the similarity between the query sketch features and the dataset image features. Finally, we sort the similarity score to get the result. In the following sub-sections we firstly introduce the offline system and then the online system step by step.

A. Salient Region and Contour Map Extraction

In our offline system, we use RC [10] method to extract the saliency map for each dataset image, and we use the Berkeley detector to extract contour map [12].

1) Salient region extraction

We apply region-based contrast (RC) method in [10] to get the RC saliency map. Cheng et al., initialize a segmentation obtained by binarizing the RC saliency map using a fixed threshold . And then the largest connected region is considered as the initial candidate region of the most dominant salient object. The other regions are labeled as background. In this paper, we utilize the suggested parameter according to [10] to get the RC saliency map. The saliency map for an image is defined as follows:

( ) { (1)

where ( ) denotes the pixel ( ) belonging to the salient region, otherwise belonging to the background region.

For the input natural scene images as showed in the first row of Fig.2, the corresponding salient regions are shown in the second row. From Fig. 2, we can know that the RC method can extract the main object or scene well.

2) Contour map extraction

Common edge detection algorithm cannot meet the requirements for better generating contours that vividly reflect objects' shapes and suppress the influence by textures and noise in images. Therefore, researchers often adopt the Berkeley detector [12] to extract object contours. In the proposed method, we use Berkeley detector to extract contour map and edge's gradient.

For an image, we apply the Berkeley detector to each image (resize to) as that utilized in our previous work [24]. Thus we will get the true posterior probability (defined as ( )) and

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orientation at every potential edge. We define ( ) as the raw contour map under the cut-off threshold *th*

( ) { ( ) (2)

4. Experiments

In order to show the effectiveness of the proposed approach, we compare our algorithm AROP with the method Edgel [7], the method ARP [3], the SHoG method in [4], and the method in [9] on our crawled dataset. We also use the SBIR system in [10] as a comparison. They use shape contexts method [11] to compute the similarity of two outlines of the object (named RC-SC). All experiments were carried out in the same environment.

A. Datasets

1) SBIR_100K dataset

This dataset was used in [4] (denoted as dataset_100k) and contains 101,240 images. There are 1240 benchmarked images for 31 query sketches, and 100,000 noise images.

2) Our Dataset

The experimental dataset consists of 293,215 images, and the storage cost is 119 GB. Our dataset consists of two parts. One is called Sketch-describable Dataset with 65,366 images collected from Google using keywords.

There are a total of 81 topics and each topic approximately consists of 1000 images. Another part is GOLD [2,24,40,55] set , which is mainly about landmarks and landscapes.

We select 162 sketches which cover most of 81 topics in the Sketch-describable Dataset as queries to sketch retrieval systems. Some of them are shown in Fig. 5.

B. Performance Evaluation

We use the precision under depth n (denoted as Precion@n) to measure the objective performance, defined as follows:

Σ Σ ( ) (8)

where ( ) is the relevance of the *i-th*result for query m, , and . If it is relevant to the query sketch, then ( ) , otherwise, ( ) .

C. Objective Comparisons

MSF [9], HoG [1], SHoG [4] and ARP [3] methods are all proposed by calculating the histogram in each image contour partition. RC-SC method [10] is the method using shape contexts[11] directly based on salient region. Edgel method [7] compares edge pixel similarity and performs better in big dataset. Considering this, we select these methods as comparison methods. Correspondingly, *Precision@n*curves of other methods and the proposed method with the depth varying in the range [1, 50] are shown in Fig. 6(a) (our dataset) and Fig. 6(b) (SBIR_100K dataset). The curves are drawn by the average results of the query sketches on our database. For fair comparison, the parameters *M* and *N* are set to 8 and 4 respectively for both ARP and AROP, and the partition of radius is uniform. The orientation channels in the proposed method and edgel method are both set to 8.

In our objective comparison, we find that the proposed algorithm is 10% more accurate than the other methods for the range from top-5 to top-40 results. For , our method is 5% more accurate than the edgel method and 10% more accurate than the other methods. Because we propose the AROP feature based on the global and local contour maps, our method makes the relevant image more similar and irrelevant image more different.

The average computational costs of the three methods are shown in Table 1. The HoG and RC+SC based approaches are time consuming. These experiments were implemented using Matlab on Linux, and the code was only optimized in Matlab. But the relative computational costs are obviously different. Edgel method costs 9.077s and the MSF method

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costs 4.478s. The costs are all more than the proposed method. The ARP method costs 0.635s, which is less than ours. The reason is that the AROP features dimensionality is O times than ARP features dimensionality.

6. Conclusion

To address the SBIR, we first proposed two contour maps: global contour map and saliency map. The global contour map is used to filter the complex background and the saliency map is used to find the image of a common object. Then, we introduced an AROP (Angular Radial Orientation Partitioning) feature that has higher performance between the sketch and profile based on two types of contours. In order to reduce searching time, firstly, we filtered the complicated images using contour segment. Secondly, we chose top 5000 in the result based on global contour map feature similarity score. Then, we computed the saliency map feature's similarity. In the experiments, the weight of AROP features has been discussed in detail. On our image dataset, AROP feature has certain advantages over the other methods in retrieval precision. Various experiments proved that sketch retrieval algorithm outperforms the other methods.

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