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Sketch Based Image Retrieval using Saliency Matching

Safiya P.C[1], Niyas N[2,]

M.Tech Student, Department of Computer Science, KMCT College of Engineering, Kozhikode, Kerala, India[1]

Assistant Professor, Department of Computer Science, KMCT College of Engineering, Kozhikode, Kerala, India[2]

ABSTRACT: Sketch based image retrieval systems takes sketches that are roughly drawn by the user as the input and retrieves similar image from a large data base of images. Ability to deal with sketches is the main advantage of this system over existing image retrieval systems. Similarity measurement between a sketch and an image is one of the main challenges of this system for which we propose a novel SBIR system which utilizes Saliency Matching. The system uses the outlines in the image known as contour maps. Here we use the Salient contour map (SCM) for shape matching. SCM is utilized to identify salient objects inside the natural images with backgrounds and matches with the query sketch. Along with SCM, we propose another feature known as Angular Radial Partitioning with Orientation (ARPO) feature. ARPO feature utilizes the edge pixels in SCM to extract the feature vectors. Sketch Based Image Retrieval systems are very much helpful in the medical field, digital libraries, photo sharing library etc.

KEYWORDS*:* SBIR, Salient Contour, ARPO feature, Saliency

I. Introduction

Image retrieval process is an inevitable part of the Digital Image Processing and it includes image search and image retrieval. Image search needs some information as input based on which the similarity measurement and retrieval process is done. The input information may be an image, a sketch or a textual description. The image retrieval system returns the most similar images after searching and similarity measurement. The similarity measurement can be done using any of the properties of input data like description, content or shape.

Due to the boom in digital imaging and archiving, the need for effective and efficient searching algorithms is increased. There are different types of image retrieval systems which can be used for online searching and filtering of images from large digital image database. State of the art image retrieval systems are Text based image retrieval systems in which the input must be a textual description about the desired image, Content based image retrieval systems in which the input must be an image, and Sketch based image retrieval systems in which the input can be a rough outline of the image drawn by the user. When the user is not sure about the the description of the intended image or lacking of similar images to be given as input, then both text based and content based systems wont be of much use. In such cases user can use the Sketch based systems in which the user can draw the outline of the images which needs to be retrieved from database. The system utilizes shape matching algorithms to compare the similarity between an image and an input query. To address this challenge, we propose a new matching algorithm which utilizes a new feature ARPO (Angular Radial Partitioning with Orientation).

II. Related Work

One of the earlier techniques used for SBIR is QVE proposed in [6] which works in such a way that the images get re-sized and the edges are extracted by using gradient operator. The EHD [2] and the HoG [10] are two important methods used for implementing the SBIR system [8]. They both are based on features of image edges as whole. The author suggest a way in [4] to attains improved precision by using local features also.

In an earlier work [12], re-ranking and feedback of relevance are proposed to accomplish SBIR. Performance improvement is achieved using initial results which gives top ranked images. Then the results are refined using relevance feedback. Another SBIR approach proposed in [14] in which free hand sketches and their labels are taken as input and realistic pictures are composed from these sketches. In this approach searching is done using text labels and the results are tuned for sketch similarity using segmentation. After searching the blending boundary is optimized and blending results are computed by combining different blending techniques.

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Edgel Index method [15] converts a shape image into a document like representation and uses a shape based indexing method. Pixel level matching is employed to perform shape-to-image matching. Indexing is done using OCM to find out the distance of contours. They also propose a binary similarity map as an alternative to Oriented chamfer matching. This hit map is created for each input sketch for each of the orientations considered. They also propose a hit function which can be used to define the shape to image similarity as the sum of all the hits. Then they indexes the position values of the hit maps. Then the similarity score is calculated as the product of the similarities measured in forward and backward directions.

Another SBIR system is detailed in [3] which uses Angular and Radial Partitioning which is an enhancement to the angular partitioning feature [3] using radial partitioning. In ARP, the Edge detection and extraction is done and then abstract image is obtained using thinning of edges. Here they first divide the image into sectors, and then the statistics of true edges in each sector is taken as the feature to represent the sector. If we have M angle partition and N radius partitions, then the image will have $M \times N$ sectors and it can be represented using an $M \times N$ dimensional vector. Range of angle for angular partitioning is $\theta = 2\pi / M$ and radius of radial partitioning is $\phi = r / N$, where r is the radius of the image. One of the recent work [9] uses contour maps based on global as well as salient regions. In the proposed method which uses only the salient contour map, shape matching is done for salient regions to calculate the similarity between image and sketch.

Sketch retrieval performance can be improved using spectral residual approach[5] for saliency detection. Another SBIR system which uses color contrast based saliency and achieves scale and translation invariance is proposed in [9]. Retrieval efficiency is also improved since they extract the salient region and then prioritize resources for this salient region.

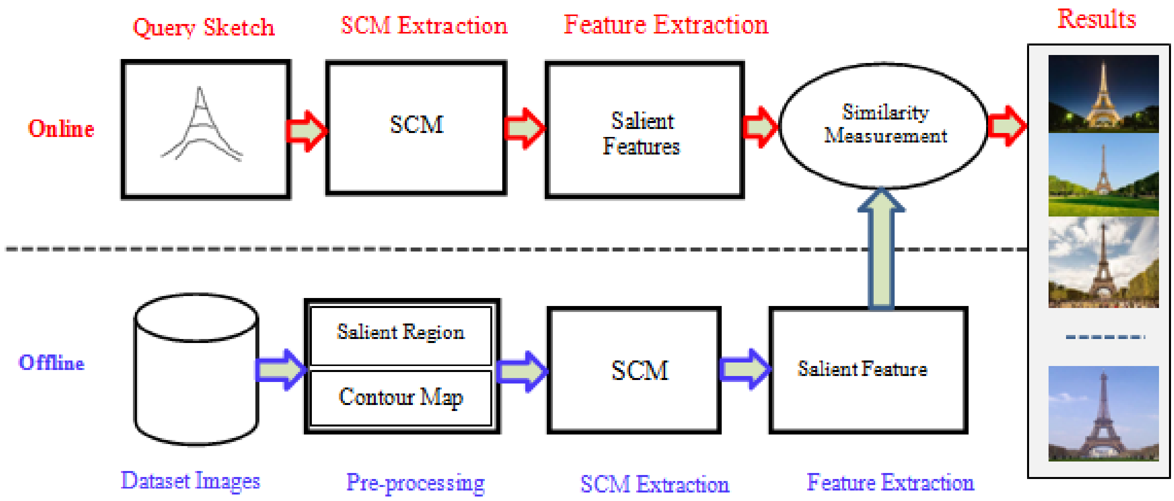

Figure 1. Proposed Framework

One of the important SBIR approach[16] generates a set of images from the set of sketches. They extract patches from binary images or sketches and those patches with a labeled center pixel are clustered using k-means algorithm. Each class of sketch tokens is detected for their occurrence in color images and the feature is extracted from the patches of color from training images. Since this is a multi-class problem,they uses Random Forest Classifier

III. Proposed Algorithm

One of the recent works in the area of SBIR proposes an approach based on two contour maps namely Global contour map(GCM) as well as Salient contour map(SCM) and also utilizes salient contour reinforcement[1] to address the problem of shape-to-image matching. Since the state of the art techniques in SBIR lacks an effective and efficient solution to tackle the problem of real time SBIR, we have reattempted to solve the problem of sketch based image

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retrieval. Here we propose a new approach for the similarity measurement between an image and a input query sketch which uses the proposed ARPO feature.

Proposed system architecture is depicted in Figure 1. The framework have an online and offline parts. In the offline phase, for the data set images, we perform the following steps: 1) Pre-processing stage in which all the images are processed to identify the salient regions as well as contour maps; 2) SCM Extraction step in which the identified salient region and contour maps are utilized to generate the Salient Contour Map; 3) Feature Extraction step in which the ARPO features are extracted from Salient Contour maps.

Online phase is for processing the query. When an input query sketch is to be searched for, Salient contour map and ARPO features are extracted using SCM extraction and Feature Extraction steps. Then, the similarity of the image to the query sketch is calculated as the euclidean distance between the ARPO features of corresponding image and query sketches. Finally, the similarity measures are sorted to get the top matching images. Following sections details the proposed methodology in detail.

Salient Region and Contour Map Detection

Spectral residual approach method in [5] is applied to each of the images in the database to compute the saliency map. Saliency map is binarized using a threshold T and a segmentation is initialized. Then the largest connected region with most salient other regions are combined to get the candidate region using bounding boxes. All other regions are considered as background and ignored. The main advantage of the SRA method over state of the art RC is that SRA can extract the most dominant object [5] with a better performance. Here we have utilized the parameters suggested in [5] to compute the SRA Saliency map. The saliency map is computed using :

$$SR(x,y)=\begin{cases}1, & if\ T_b>70\\ 0, & otherwise\end{cases} \qquad (1)$$

where $SR=1$ means that the pixel (x,y) is inside the salient region, otherwise out side the salient region.

Popular edge detection algorithms doesn't provide image contours that alleviates the noise in the images. So we use the Berkeley detector[7] for edge detection and contour extraction. Berkeley edge detector algorithm re-sizes the image fist into 200x200 and find out the probability of potential edges. The raw contour map(CM) is calculated as $B(x,y)$ under the threshold th.

$$B_{th}(x,y)=\begin{cases}1, & p(x,y)>th\\ 0, & otherwise\end{cases} \qquad (2)$$

The value of th decides the complexity of the contour map. We choose the parameter values as suggested in [4], [2] where they choose the edge set with threshold 0.5 as the contour map of an image. We have set $CM(x,y)=B_{0.5}(x,y)$ and $CM(x,y)$ is taken as the contour map. In Figure. 2, Natural images are in the first row, and corresponding SRs are in the second row. Figure. 2 shows that the SRA saliency method extracts dominant object in the scene.

Salient Contour Map Extraction

Image contour map may be of salient or global contour maps. We are only using the Salient contour map which finds the matching objects in the query sketch and in the image. As the users are more focused in the salient region of an image, the system retrieves the images that contain the same object in it. Also the system should be simple and easy for use to meet the requirements of the user. These purposes are accomplished by using Salient Contour Map.

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Figure 2. Contour map examples: First row shows the image. Second row gives the salient region , and the third row shows corresponding SCM..

Salient Contour Map is extracted as follows. Firstly, the SRA saliency algorithm is applied to generate the saliency map. Bounding box is used to get the minimum rectangle of each SRA salient map. Secondly, saliency map is refined to get the candidate rectangle. Thirdly, contour map $CM(x,y)$ is used to generate Salient Contour Map of the image $SCM(x,y)$ by using image candidate rectangle. The SCM is defined as

$$SCM(x,y) = CM(x,y) \times SR(x,y) \qquad (3)$$

Figure 2. shows the natural images and salient regions as well as their contour maps. Third row shows the SCM corresponding to the natural images shown in first row.

ARPO Feature Extraction

ARP [3] is a rough representation as it counts the number of edges. In angular radial partition, radial partition can be done in two ways. Uniform and nonuniform. In nonuniform method,radius of each partition can be decided using some functions where as in uniform method, the radius of each partition is equal. In this paper, we adopt the uniform partition. To extract the Angular Radial Partitioning with Orientation Feature , $M \times N$ sectors of each image contour is determined, where M is the number of angle partitions and N is the number of radius partitions and then the number of edge pixels for each of the sectors in different orientation channels are counted to represent the sector. Number of orientation channels are defined as O. Each sector is represented using (O+1) dimensional vector and the image is represented using an $M \times N \times (O+1)$ dimensional vector. To extract the ARPO features, we first extract the O dimensional AROP features[1] of each sector and combine it with one dimensional ARP features[3]. Thus the ARPO feature of a sector is an (O+1) dimensional vector. The ARPO features are extracted for the salient contour map and is named as salient ARPO feature. The salient ARPO feature helps to determine the images that contains the regions similar to the input query sketch. We denote the salient ARPO feature of images in dataset as ft.

Feature Matching for Query sketch

Now we explain the online part. For an input query sketch, salient ARPO features are extracted as described in offline part. Then, the similarity measurement is done using the euclidean distance of the ARPO features of data set images and that of the query sketch. Since the sketch contains only clear lines drawn on a white background, the region of interest is computed as the smallest bounding box which contains the maximum pixel value. Bounding box is used to obtain the $SCM_q(x,y)$ for the input. Thus we can compute the ARPO features for the salient contour map f_q for the input query q.

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In both the offline and online stages, we represent images or sketches by their ARPO features. So, we can compute the similarity scores using Euclidean distance. F we denote the salient contour similarity of query q and an image t as $S(t)$.

$$S(t) = \| f_t - f_q \|_2 \qquad (4)$$

where $\|\cdot\|_2$ gives the distance of two vectors. The similarity of the query and the image is given by the salient similarity measure.

IV. EXPERIMENTS

The proposed approach with ARPO features is compared with the approaches with ARP features[3] and with AROP features[1]. Retrievals are done from both the dataset using same input query and the output precision are compared.

A. Datasets

SBIR_100K dataset : This is the dataset used in [1] (denoted as dataset_100k) and it has 10,240 images. It contains 1240 bench marked images corresponding to 31 query sketches, and there are 100,000 noise images also.

THUR15000 : Dataset for image retrieval using randomly selected internet images, corresponding to five keywords: butterfly, coffee mug, dog jump, giraffe and plane. Salient regions for the downloaded images also are included in the dataset.

B. Performance Evaluation

In this paper, the performance evaluation of the proposed method is done using the precision under depth n (denoted as Precision@n) measure. The objective performance is measured using the mentioned measure is defined as follows:

$$precision@n = \frac{1}{Z}\sum_{m=1}^{Z}\frac{1}{n}\sum_{i=1}^{n} R_m(i) \qquad (5)$$

where $R_m(i)$ takes value 0 or 1 depending on the relevance of the *i*-th result for query m, $i \in [1..n]$ and $m \in [1..Z]$. $R_m(i) = 1$ if it is relevant to the query sketch, then , otherwise $R_m(i) = 0$.

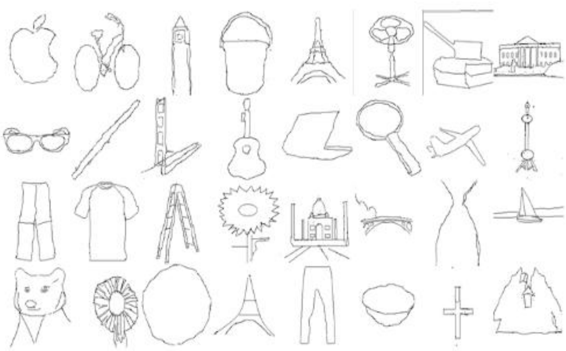

Figure 3. Some examples of input sketches

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C. Objective Comparisons

Since both AROP[1] and ARP [3] methods employ angular and radial partitioning of the image contour, these methods are selected for comparison with the proposed approach. The precision@n curves for ARP[3] and AROP[1] methods and the proposed method for depth n varying for 1 to 50 are plotted in Figure. 4(a) (THUR15000 dataset) and Figure. 4(b) (SBIR_100K dataset). As suggested in [1], we have set the values of M to 8 and of N to 4 for ARP[3] and AROP[1], and uniform radial partitioning is employed. The number of orientations considered in the proposed method is 4 and in the AROP method it is 8.

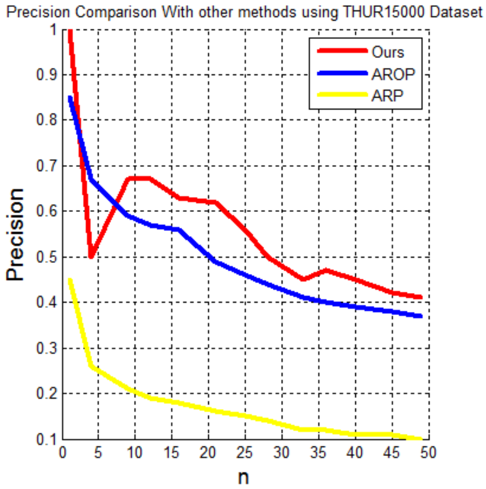

Figure 4a. Precision Comparison with ARP and AROP for THUR15000

While comparing with other methods, it is found that the proposed method with ARPO features is 12% more accurate on an average than the AROP methods for depth varying from 1 to 50. When compared the results with that of ARP method, it is concluded that the proposed ARPO method outperforms the ARP by 69% for 1 to 50 results. For $n = 25$, proposed method shows a better result by 73% than the ARP method and shows 21% more accuracy than the AROP method. Since we propose the ARPO method based only on the local contour maps, the proposed method retrieves the relevant image quickly than the others.

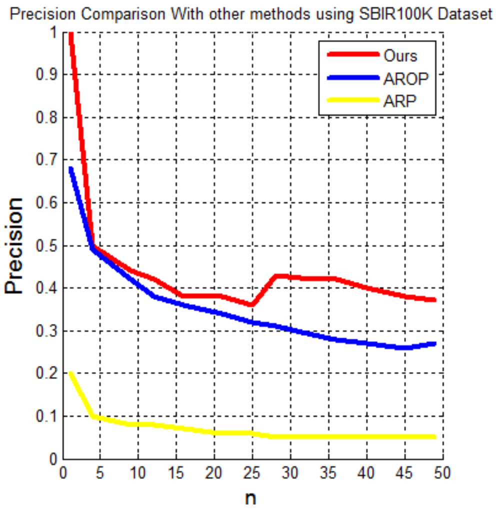

Figure 4b. Precision Comparison of ARP and AROP for SBIR_100K

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Figure 5(a) and Figure 5(b) is plotted with the precision@n curves of the proposed ARPO method for the query sketches selected from database as well as for free hand drawn sketches. Precision comparison is also done for sketches from the database as well as sketches drawn by users. While using THUR15000 dataset, hand drawn sketches provide 33% more accurate result but with the SBIR_100K data set precision is reduced for hand drawn sketches by 22% when compared to sketches taken from the database.

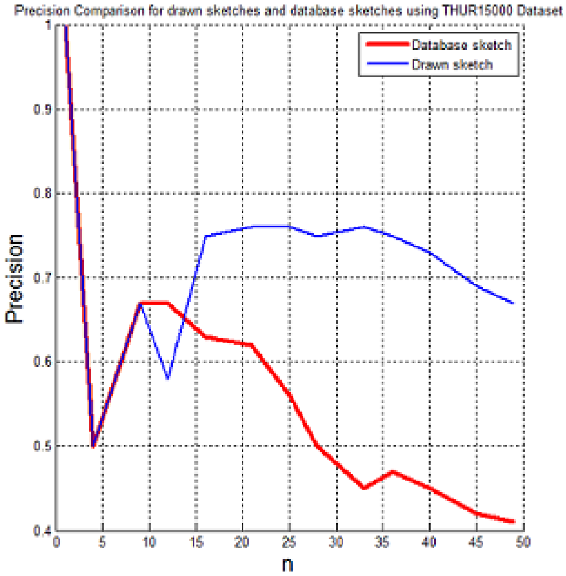

Figure 5a. Precision Comparison of sketches drawn by user and sketches from database using THUR15000

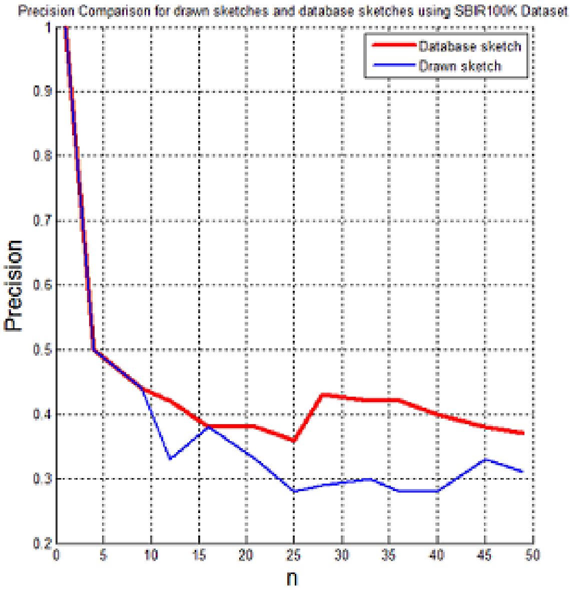

Figure 5b. Precision Comparison of sketches drawn by user and sketches from database using SBIR_100

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The average response time of image retrieval process of the three methods are compared in Table 1. The AROP based methods are time consuming. But the relative performance are obviously different. AROP method takes 1.42s on an average to process a query and retrieve similar images which is higher than the proposed ARPO method. The ARP method takes only 0.635s, which is less than the proposed approach. The reason is that the ARPO features dimension is (O+1) times than ARP features dimension.

TABLE I. RESPONSE TIME COMPARISON OF ARP,AROP AND ARPO METHODS

Method	ARP	AROP	ARPO (Ours)
Time(s)	0.64	1.42	0.72

V. CONCLUSIONS

Sketch Based Image Retrieval is one of the leading research area in which shape to image comparison remains a great challenge. Here we propose a method as a solution to this problem by combining ARP features with orientation namely ARPO features. In order to enhance the performance of the system, the similarity measurement based on salient contour maps is introduced. SRA saliency map generation algorithm is used for detecting salient regions which has a great performance enhancement over state of the art RC method . We have conducted experiments using THUR15000 and SBIR_100K datasets. On THUR15000 dataset, ARPO feature exhibits better performance when compared to existing ARP and AROP features. From the extensive result analysis done, we conclude that the proposed approach has a great improvement over the existing image retrieval methods.

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BIOGRAPHY

Safiya PC received her B.Tech. degree in Computer Science and engineering from University of Calicut, and currently pursuing MTech in Computer Science at KMCT College of Engineering, Calicut. She has seven years of IT industrial experience as a software performance tester . Her research interest include Computer Vision, Image Processing and Image Retrieval.

Niyas N received his B.Tech. degree in Computer Science and engineering from Cochin University for Science and Technology and MTech degree in Computer Science from University of Calicut. He has a broad span of experience in IT industry as well as Teaching. He is currently working as Assistant Professor in KMCT College of Engineering, Kozhikode. His research interest has a wide range including Image Processing and Supervised Machine Learning .