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A Coherent Line-based Image Search using User Sketch

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Abstract

We present an improved sketch-based image search framework through which users can search their target images from the images in database. Our basic approach is to search the database by comparing the user-created sketch with the graph extracted from the images in the database and estimating the similarity. The images of high similarities are suggested as the candidates that match the target image. To improve the accuracy of the matching process, we substitute the graph-based representation of images with vectorized coherent lines, which are known as one of the most precise schemes in extracting and describing important features in an image. By the experiments on 820 images of 32 categories, we prove that our scheme shows higher matching accuracy than the existing schemes.

Keywords: *Kinect sketch-based search, coherent line, features, vectorization*

1. Introduction

The shape information is one of the most important components in human visual perception. In computer vision, many techniques such as object extraction and feature recognition have been proposed to process the shape information in understanding the contents of an image. Recently, the progress of technologies such as digital camera, smart phone and cloud system, accelerate sharing of images in internet environment. Therefore, it becomes more important to search the users' desired images among the huge storage of images in internet environment.

The most frequently used image search technique is developed based on text-based approach. In this approach, the keywords tagged on the images are compared with the search word from a user and the search operation is executed. This approach requires a tremendous pre-computation on the images for tagging proper keywords. Since this scheme does not consider the shape information in the image and human visual perception, this scheme often produces wrong search results.

Many researchers have presented various sketch-based search algorithms by using human visual perception process. They focused on how to construct sketch-based index on the images, since the index is compared with user-created sketch. The key point of these schemes is how to construct the sketch-based index. If the index is not properly constructed, the search process produces wrong results.

In our paper, we present a coherent line-based scheme for constructing the sketch-based index structure on the images of the database. The coherent line is recognized as the most effective scheme for describing the shape of an object in a image. We apply coherent line

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algorithm to the images in the database and build index from the shape of the model. In the first step of the search process, users are asked to draw a sketch that describes the primal shape of a model to search. Then, we compare the user-created sketch with the sketches constructed in the images by coherent line algorithm and measure the similarity. The result of the search process is illustrated as a list of images sorted in the descending order of similarity.

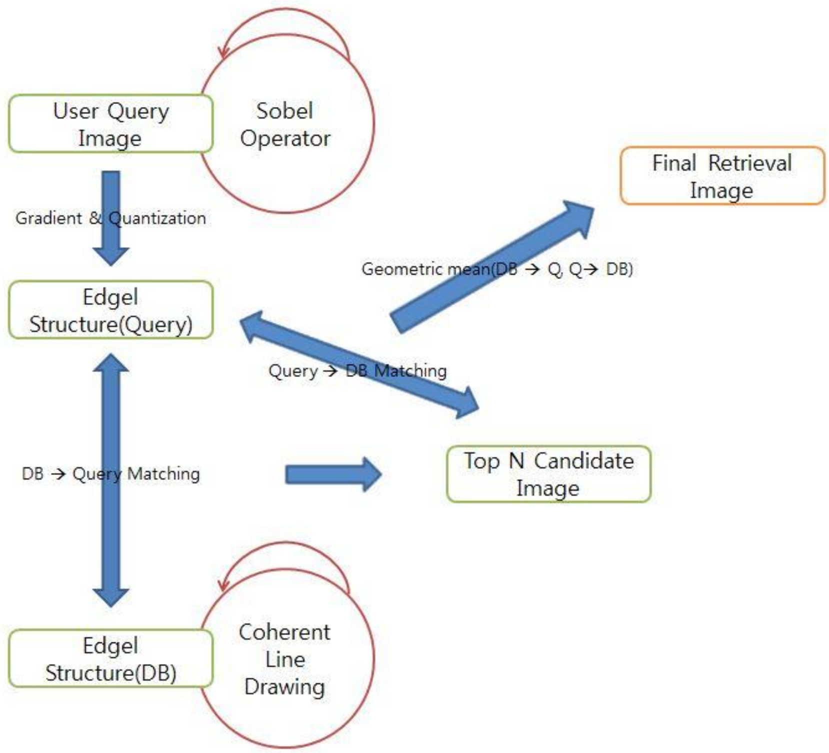

Figure 1. Overview

2. Related Work

Many researches have presented schemes that match a shape and objects in an image. Eitz *et al.* [5] have presented a scheme that computes edge histogram cna Canny edge detector [3] from images for correct shape matching process. They segment images into blocks of same numbers and represent them in one-dimensional vector with same size. Their scheme has a problem that the shape information inside a block is not available. Fonseca *et al.* [6] proposed a sketch-based system for retrieving complex drawings by organizing the hierarchical structure of the shape according to topology and geometry. Sousa and Fonseca [12] also presented a scheme that retrieves similar images using topological proximity. Fonseca *et al.* [13] proposed a sketch-based retrieval for simple drawings such as clipart images. These schemes use a complex model based on topology, which results in a heavy computational loads.

Leung and Chen [8] proposed a simple matching scheme for sketch-based image search. They extract stroke information from the shape of an object and compared the spatial relation between the strokes from both images. Liang and Sun [9] presented a pattern matching algorithm based on biased singular vector machine (SVM) method. They assigned different weights to the features in the image and combined them to compare with sketch patterns.

Chalechale *et al.* [4] utilized thinned contour image, which is extracted by applying morphology operations on the edges detected from the image. They applied Fourier transform to the images in the database and the user-created sketch image and executed image matching using the distribution of angle space. Sousa and Fonseca [12] combined text information and saliency estimated from the images in database. The text information specified by users are compared with the saliency precomputed.

3. Overview of the System

Our sketch-based image search is designed by applying contours extracted by coherent line algorithm [16] to Edgel Index Structure and EI-2 matching scheme [15]. The overview of our system is illustrated in Figure 1. The input images are re-sized as 200x200 resolution. We apply Sobel operator to the re-sized input images to extract contour lines, whose gradient vectors are further quantized. These images are organized into Edgel Index Structure. In contrast to the input images, the contours from the images in the database are extracted by applying Coherent Line Algorithm. The extracted contours are organized according to Edgel information. The EI-2 matching scheme that utilizes Edgel Index Structure is a two-way scheme. The similarity of the images in the database to the input image is estimated. We reversely compute the similarity of the highly-ranked images to the input image. Finally, we estimate the geometric average of two similarities and show the images of high scores.

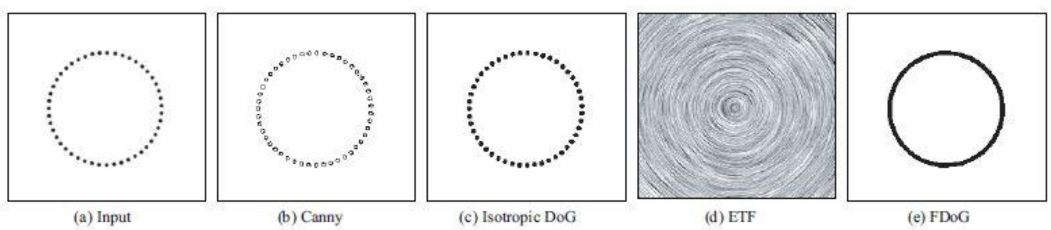

Figure 2. Line Construction from Isolated Points

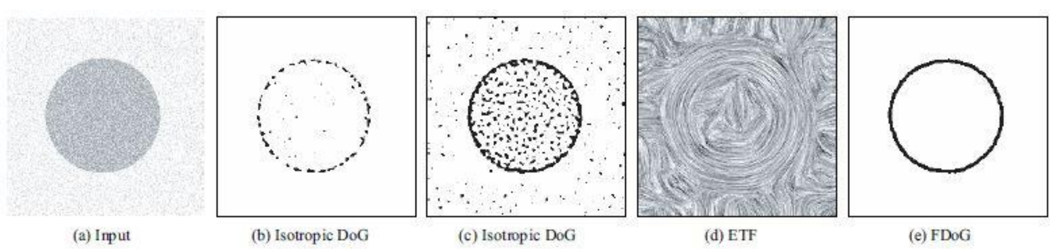

Figure 3. Noise Suppression by FDoG

4. Algorithm

4.1. Coherent Line Drawing

We apply the coherent line algorithm proposed by Kang *et al.* [16] to extract contours from images. This algorithm applies difference of Gaussian (DoG) scheme [18] along the edge tangent flow (ETF) in an anisotropic way. This scheme reduces noise (see Figure 2 (a)) and produces spatially coherent lines (see Figure 2 (b)). These benefits are key reasons why we apply this algorithm to our work. One drawback of the coherent line algorithm is that the extracted contours are thick. We further apply Zhang-Seun's thinning algorithm to the contours and produce thin contour lines.

4.2. Indexiable Oriented Chamfer Matching

We apply indexiable oriented chamfer matching (IOCM) [15] to construct efficient index structure (see Figure 3). The IOCM scheme improves chamfer matching [2], which requires distance map on the target image to compute the distance of chamfer matching. Therefore, it requires a heavy space complexity. Another problem of the chamfer matching is the distortion of the user-created sketch image when they are compared with the images in the database. Due to this property of sketch images, the chamfer matching is not proper in comparing images. To remedy this problem, we represent the distance between two images as a kind of binary similarity map, which is denoted as Hit map. The hit map of the input image, denoted as Q, has N_θ channels, which denotes the quantized angle information. In this paper, we assign 6 for N_θ.

The six channels are composed of [-15 ~ 15], [15 ~ 45], ..., and [135 ~ 165]. The angle information at each pixel is computed to form the Edgel Index Structure information. Edgel at a pixel p is composed of (x, y, θ). This information is used to define the hit function between two images. A hit function at X_P of the map computed in Q is represented as follows:

$$Hit_Q(p) = \begin{cases} 1, \exists q \in Q \left(\left\| X_q - X_p \right\|_2 \leq r \theta_p = \theta_q \right) \\ 0, \qquad \qquad otherwise \end{cases} \tag{1}$$

In the above formula, the hit function at p has 1, if the Euclidean distance between the pixel p and the pixel q at Q is less than or equal to the threshold value r and the quantized angles between p and q are same. In other cases, the hit function fails.

The metric for computing similarity between Q and D, the image in database, is as follows:

$$Sim_{D \to Q} = \frac{1}{|D|} \sum_{p \in D} Hit_Q(p) \tag{2}$$

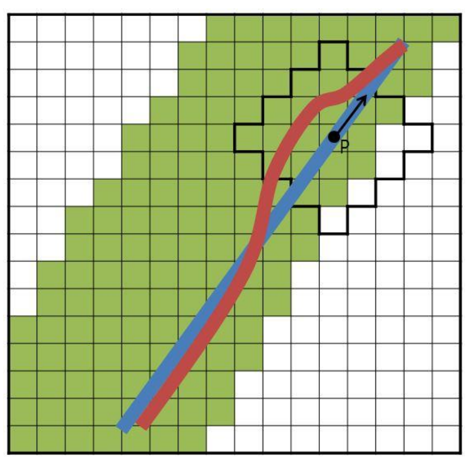

Figure 4. Indexible Oriented Chamfer Matching (Query Sketch: Red line, Object Contour: Blue line)

The above formula computes the similarity of D to Q as the sum of hit functions computed on the edgel information comprising D. The sum is further normalized by dividing |D|, the number of edgels. To raise the rate of recall, we use |sqrt(D)| instead of |D|.

4.3. Two-way Matching

Using a one-way IOCM matching from D to Q, the case when all the edgels of D hits Q makes the normalized hit ratio as 1, which results in the highest similarity. This case, however, may produce unwanted matching. Therefore, we add another IOCM matching from Q to D based on the formula (2). The geometric average of the results of two-way matching produces the final similarity (see formula (3)).

The IOCM matching from Q to D is executed only for first N% images which are sorted in the descending order of IOCM matching results from D to Q. We test N as 2.5% in this paper.

$$Sim_{Q \cdot D} = \left(Sim_{Q \to D} \cdot Sim_{D \to Q}\right)^{\frac{1}{2}} \tag{3}$$

5. Experiments and Results

5.1. Parameters

Table 1 suggests the parameters for coherent line algorithm we used in this paper. σ_M denotes the coherence of the line and σ_C determines the width of line. We repeat the coherent line algorithm three times and set the threshold as 0.997. Table 2 shows the information of the image database. We use 840 images and 32 categories. The number of sketches we use is 65.

Table 1. Coherent Line Drawing Parameter

	σ_M	σ_C	Repetition	Threshold
value	6.0	0.35	3	0.997

5.2. Comparison of the Experiments

Figure 5 illustrates the EI-2 matching scheme proposed in [15] and our matching scheme based on coherent lines. In the experiments, we compute precision per rank for 65 sketch input images and average them. The experiment shows that the EI-2 scheme with coherent line shows greater precision than the existing scheme in [15]. This result is due to the coherent line algorithm that reduces noise and produces spatially coherent line.

Table 2. Experiment Data Set

	No. of images	No. of categories	No. of sketches
value	840	32	65

5.3. Results

We illustrate the matching results in Figures 6-8. The image in the rightmost column is the input sketch user created. The image of highest similarity is given in the upper leftmost column. The images are sorted in the descending order of the similarity from left to right and upper to bottom.

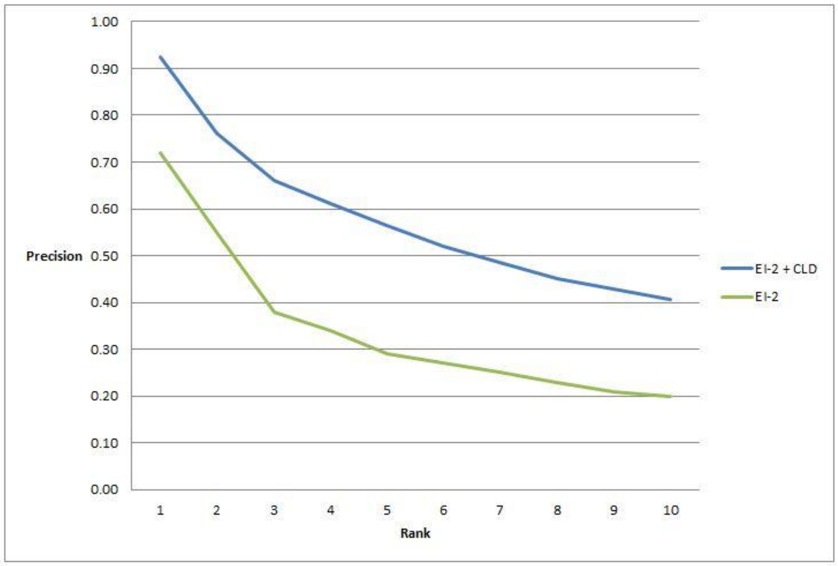

Figure 5. Performance Comparison for EI-2 Matching

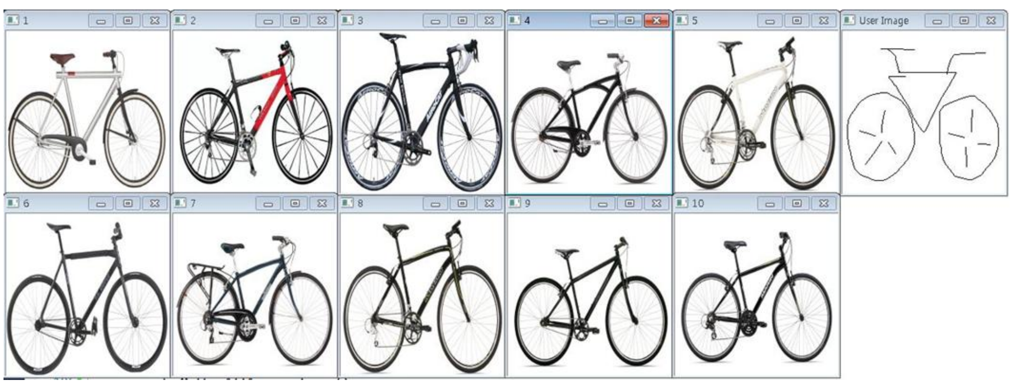

Figure 6. Results (1)

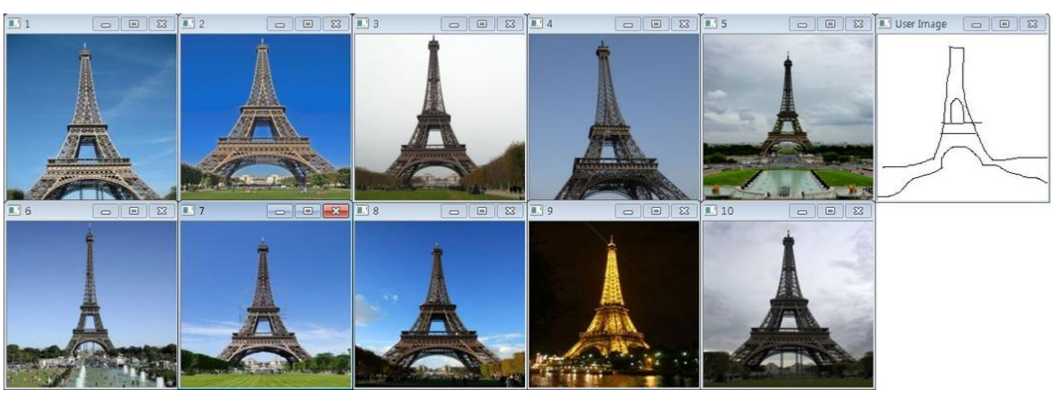

Figure 7. Results (2)

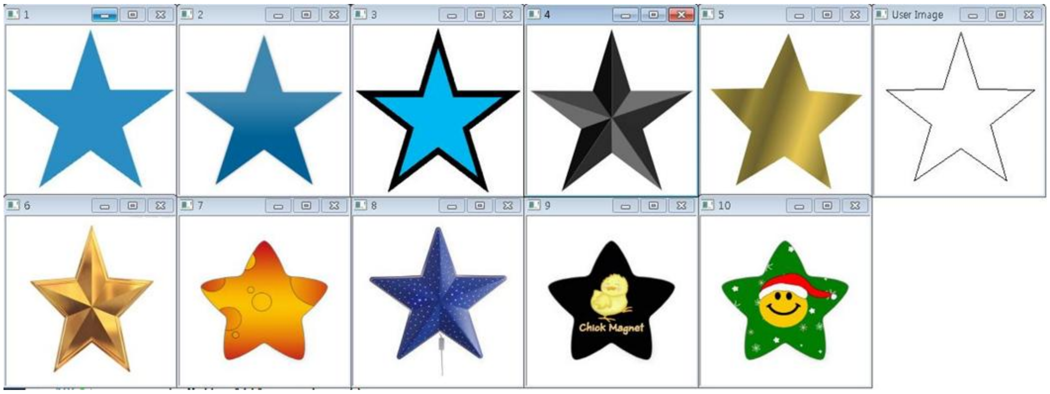

Figure 8. Results (3)

6. Conclusion and Future Work

In this paper, we present a sketch-based image matching algorithm using coherent line algorithm. Our scheme improves the exactness of the algorithm by extracting contours from the images in the database based on coherent line algorithm.

Our plan to future work is to extend the image database and perform very extensive experiment about image matching process. Another plan is to apply intelligent thinning algorithm to the coherent lines for effective image matching.

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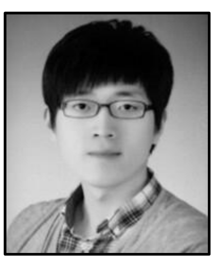

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