InSide: interactive sketching for image database exploration

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***Abstract*—We propose an interactive sketching tool for exploring image database, called *InSide*. Our main contribution is a new solution of interactive image exploration that dynamically adapts to users sketching and provides mixed feedback. A position-aware matching approach is proposed for InSide in order to support translation-free sketch searching. Based on demonstrated results, our method outperforms state-of-the-art approaches in aspects of user interface and matching results.**

***Index Terms*—Sketching; interactive image search**

I. Introduction

Sketch-based image retrieval (SBIR) receives much research attention recently because of its interaction manner [1] and the booming market of mobile devices. SBIR provides a freeform drawing interface for searching from scratch. But the key difficulty of sketching is that not all people can draw sketches as exactly as the idea in their mind, which makes the quality of queried results varying. In this paper, we propose an interactive tool for exploring image database, called *InSide*. Our main contribution is a new solution of interactive image search engine that dynamically adapts to the users sketching and provides real-time feedback. InSide is made unique by a number of technical contributions. Although portions of InSide follow the basic framework of CBIR, we proposed a new technique of position-aware matching for InSide, in which it allows for multiple matching images based on different sub-regions of the image. In addition, the user interface for progressive image searching is unique to this work. While there have been previous works that are pure SBIR [2] or help users draw basic shapes [3], to our knowledge, we are the first to develop an interactive user interface to assist image database exploration with guided sketching.

II. InSide Approach

InSide consists of three main components: (1) we construct an index structure of edge pixel (edgel) for a given image database and their edge maps by performing LSD [4]; (2) an contour image matching method that, given user sketching, rapidly retrieves matching images based on a position-aware matching score; and (3) an intuitive user interface, which displays a shadow of weighted edge maps beneath the users sketching to help guide the searching process which is similar to [3]. The user interface of InSide is shown in Fig. 1.

After finishing the edgel index, Inside is ready to accept queries of sketching from users and return matching feedbacks

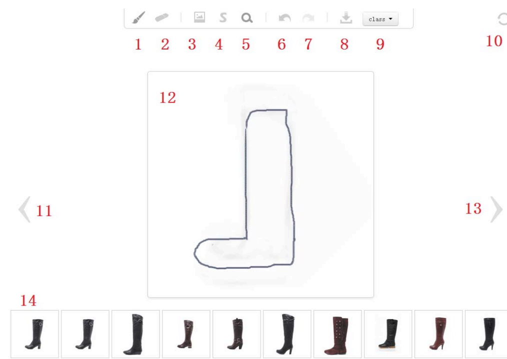

Fig. 1. InSide user interface.

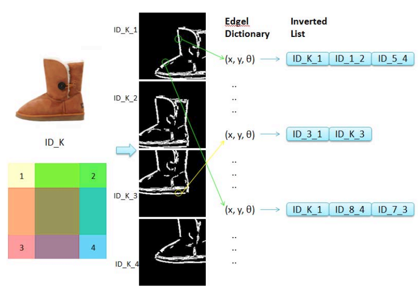

Fig. 2. Position-aware edgel indexing.

for image database exploration. We now discuss about how to search the images in database user expected most. Given a database image D and a query sketch image Q which is scaled to the same size of D, we first define a hit counter

$$h(p;Q) := \begin{cases} 1 & \exists q \in N_Q(p,r) \text{ and } \theta_p = \theta_q, \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

to test whether pixel p in D maintains the same edgel in Q as near the position v_p, where $N_Q(p)$ is a neighborhood edgel set of Q centered at v_p with radius r. For the good performance of oriented Chamfer matching (OCM) on comparing contours of objects, we choose it as a basic matching score to measure the similarity between D and Q,

$$M(D;Q) := \frac{1}{|D|} \sum_{p \in D} h(p;Q) \quad (2)$$

However, in our paper, instead of matching the total sketch

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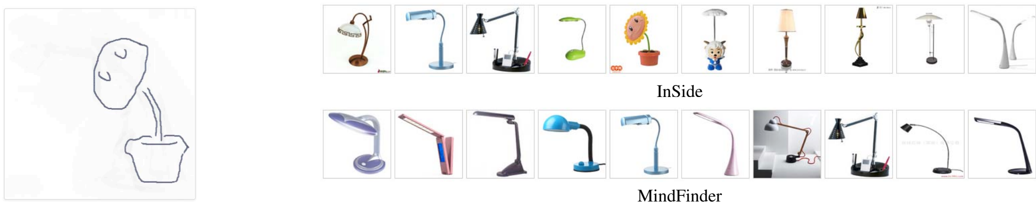
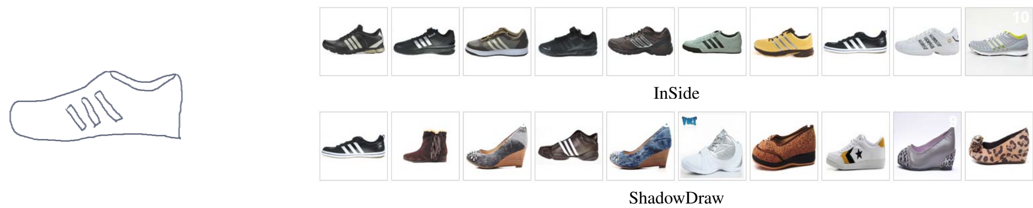
DOI 10.1109/CADGraphics.2013.78



(a) Displaced sketch (b) Searching results of (a).

Fig. 3. Illustration of lamp searching. Comparison with MindFinder [2].



(a) Sketch (b) Searching results

Fig. 4. Illustration of Shoes searching. Comparison with ShadowDraw [3].

image Q directly, we adopt K overlapped sub-images $I^{(j)}$ $(j = 1, \ldots, K)$ which cover the total image for similarity computing. To efficiently computing out the score $M(D^{(j)}; Q)$, firstly, we should take full advantage of index structure to calculate sub-image similarity $M(D^{(j)}; Q)$ in Eqn. 2. And then we calculate the total similarity integrating different parts

$$\tilde{M}(D; Q) := \sum_{i=1}^{K} \max_{j=1,\ldots,K} P(i,j) M(D^{(i)}; Q^{(j)}) \qquad (3)$$

where is $P(i, j)$ is a position-aware punish function. A reasonable choice of $P(i, j)$ could be

$$P(i,j) = \frac{1 + \delta_{i,j}}{2} \qquad (4)$$

where notation $\delta_{i,j}$ is the Kronecker's delta, i.e., $\delta_{i,j} = 1$ when $i = j$ and otherwise $\delta_{i,j} = 0$. Thus, the symmetric Oriented Chamfer Matching with position-aware punishment (OCM-P) is given by:

$$Sim(D, Q) := \sqrt{\tilde{M}(D; Q) * \tilde{M}(Q; D)} \qquad (5)$$

To rapidly execute matching, we adopt an efficient ranking algorithm with the help of edgel index structure. As shown in Fig. 2, given a query sketch and its pre-generated hit map, we first generate K sub-images. Similar to [2], our method use inverted list in the index structure to computing the matching score for each sub-image defined in Eqn. 3. After that, by dividing the number of total edgels $|D^{(\cdot)}|$ for each sub-image as in Eqn. 2, we obtain $K \times K$ similarity scores. Finally, we can rank database images based on these normalized similarity scores and select the top 10 images.

For working efficiently with large database, the actual ranking is performed by two side filtering. That is we first compute $\tilde{M}(D_k; Q)$ for all images to find top 30 images. And then perform $\tilde{M}(Q; D_k)$ calculation in this small image set. In order to avoid the degenerate matching and to obtain a more reasonable and accurate score, an additional step is performed to get final $M(Q^{(i)}; D_k^{(j)})$. Note that the output LSD is a set of line segments [4]. For those line segment whose number of $hit(p) > 0$ exceed 30% of the segment length, we accumulate those hits to the final $M(Q^{(i)}; D_k^{(j)})$.

III. Results and Conclusion

Two results are demonstrated in Fig. 3 and Fig. 4. It shows that our method can retrieve relevant images in real time based on incomplete and evolving sketches by user, and it outperforms previous approaches. Although our method can be viewed as a coupling of MindFinder and ShadowDraw, our presented user interface provides outperform experiences of image data exploration.

Acknowledgment

This work was supported by the National Natural Science Foundation of China (Grant No. 61070073) and the key Natural Science Foundation of Zhejiang Province, China (Grant No. LZ12F02002).

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