OPTIMAL SKETCH BASED IMAGE RETREIVAL USING PSO BASED IMAGE RERANKING

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Abstract

A sketch-based image retrieval often needs to optimize the trade-off between efficiency and precision. Index structures are typically applied to large-scale databases to realize efficient retrievals. However, the performance can be affected by quantization errors. Moreover, the ambiguousness of user-provided examples may also degrade the performance, when compared with traditional image retrieval methods. Sketch-based image retrieval systems that preserve the index structure are challenging. In this paper, we propose an effective sketch-based image retrieval approach with re-ranking and further optimize the results of SBIR using Particle Swarm Optimization (PSO). Our approach makes full use of the semantics in query sketches and the top ranked images of the initial results. The optimal images are retrieved by the utilization of PSO with feature matching. The integration of the two schemes results in mutual benefits and improves the performance of the sketch-based image retrieval.

Keywords: - *Sketch Based Image Retrieval (SBIR), Relevance Feedback, Re-Ranking, Feature matching, Particle Swarm Optimization (PSO).*

I. INTRODUCTION

With the improvement of the Internet, and the accessibility of image catching devices, for example, computerized cameras, image scanners, the span of advanced image gathering is expanding quickly [1]. It is essential to productively store and recover images for various application, for example, fashion design, crime anticipation, drug, engineering, and so forth [2]. For this reason, many universally useful image recovery frameworks, for example, content based and substance based have been created [3]. Distinctive sorts of substance based image queries have been proposed and analysed: case images; rough, blurry drawings of the coveted colors; straightforward layout sketches; and combinations or augmentations thereof [4]. We trust that blueprint sketches are normally less demanding and quicker to produce than an entire shading depiction of the scene. What's more, they can be produced for arbitrary coveted images, while case images may or may not be at hand when searching [5]. Furthermore, input devices change for sketching as touch-empowered devices turn out to be more normal. In other words, sketch-based image retrieval (SBIR) is an applicable method for querying vast image databases [6]. The principle favourable position of sketch based image retrieval instead of content based retrieval is that it is simpler to express the orientation and stance in the query sketch to locate the required image rather than determining these qualities in content [7]. The fundamental test in sketch based image retrieval framework is the manner by which to measure the importance of an image and an inquiry sketch and furthermore it requires understanding of both sketch and image area and after that do comparison [8]. Traditional approaches have depended on hand outlined components which utilize the slopes or edges as elements which are generally invariant crosswise over both image and sketch areas however such systems can be bettered a considerable measure [9]. With the approach of profound convolutional systems, there has been a change in image acknowledgment assignments in both image and sketch area [10]. Effective matching algorithms have received much research consideration [11]. Analysts frequently utilize worldwide elements to coordinate a sketch and an image [12]. The coordinating calculation or matching algorithm normally utilizes a predefined resistance, on the grounds that the sketches drawn by users are regularly not exact [13]. Be that as it may, the worldwide similarity of the sketch and image does not really reflect content comparability. Neighbourhood highlight coordinating could take care of this issue [14]. In any case, it is computationally intensive. A strategy presented in [15] that sets up an edge list structure, which solves the sketch retrieval issue on expansive scale datasets by drastically lessening the computational cost. Some irrelevant images may show up in the top-positioned comes about. To solve these problems, we propose to optimize the search results at the end of a SBIR system, such as the ARP (angular radial partitioning) or edgel, by verifying the top-ranked results and implementing a relevance feedback.

II. SYSTEM MODEL

To improve the performance and to reduce the computational time of the SBIR system introduced in [15] we propose a novel SBIR system with Particle Swarm Optimization (PSO). The utilization of PSO in the proposed SBIR system reduces the multiple use of re-ranking and contour based relevance feedback used in [15]. Thus leads to improve the system performance and reduces the computational time. The proposed SBIR system model is shown in Fig. 2.1.

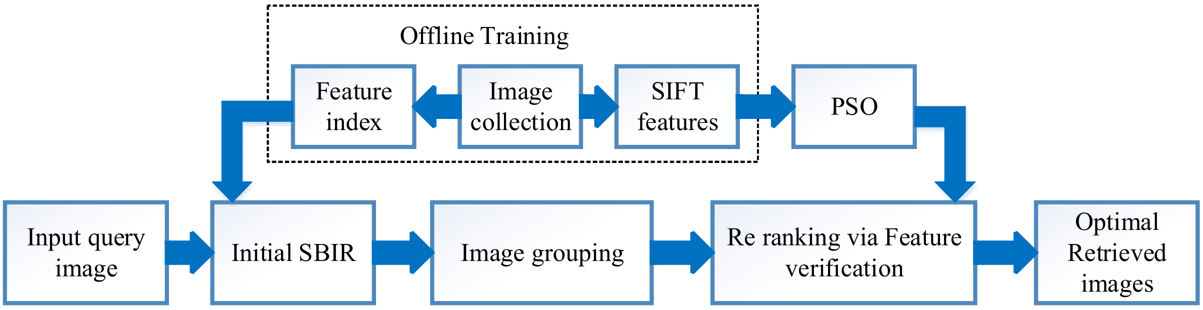

Figure 2.1: Process flow of the proposed work

The proposed system consists of two parts: the offline part and the online part. Our approach can be included at the back end of any initial SBIR system (such as the edgel and ARP methods) using relevance feedback to improve performance. We now focus on an edgel SBIR system to illustrate our approach. In the offline part of the method, we must build an edgel index structure for each image based on the Berkeley edge detector. 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 online part, for a given input query sketch, we sequentially execute four 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) optimal feature selection using PSO and re-rank using SIFT matching.

III. OPTIMAL SKETCH BASED IMAGE RETRIEVAL BY PSO & RELEVANCE FEEDBACK

This section presents a detailed description of our proposed framework on sketch based image retrieval (SBIR) using Particle Swarm Optimization (PSO) and relevance feedback.

3.1 Initial SBIR

In this section we have considered the edgel as an initial SBIR system in order to show the significance of the proposed work. The initial SBIR system produces the initial results for the proposed system by means of the following steps proposed in [11]: 1) For an image database with T images, we apply the Berkeley detector to each image (resized to 200×200). This produces hit maps with six orientation channels ($\theta = 6$). Thus, for each image, we build an index structure with 200×200×6 entries for the six orientation channels. 2) The Berkeley detector extracts contours. It uses the brightness, color, and texture gradients to accurately detect and localize the boundaries of images. 3) For each point at a certain orientation, we build an inverted list for fast indexing. For each edgel point in the contours, the position (x,y) and quantized orientation channel θ are combined to (x,y,θ). For each entry (x,y,θ), we build an inverted list of images (IDs). 4) When a query sketch Q (normalized to 200×200 entries) is input to the system, six hit maps are generated by marking the regions surrounding the sketch lines within a certain radius, and quantizing each edge orientation into six channels. By comparing the edgels (x,y,θ) of the hit maps of the query sketch and the edges extracted from the database images, we can measure the similarities between the sketch and images. Each edgel marked in the hit maps is used to search the inverted list for corresponding image IDs. Finally, the similarity between the query sketch *(Q)* and the image *(D)* in the database is computed by counting how many times *D* appears during the search.

3.2 Relevant Images Grouping

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. We apply near-duplicate image clustering to the top ranked R images to find similar images from the top *N* initial SBIR results. This approach consists of the following steps. 1) For each image, we record the SIFT descriptors together with their locations *(x,y)* and orientations. The SIFT feature extraction is carried out off-line for the dataset images. 2) We first find near-duplicated images for the top *R* images of the top *N* images returned by the initial SBIR. We use the similarity measurement (i.e., near-duplicate image detection) with the existing image matching approach. In this paper, we use binary edge-SIFT to carry out the near-duplicate image retrieval approach and find near-duplicate image groups. 3) We further cluster the detected near-duplicate images into groups for the top ranked *R* images. Assume that the group number is *K (K ≤ R)* and we record the corresponding image numbers.4) we use the cluster with the most near duplicate images as relevant image group for the query sketch.

3.3 Re-Ranking via Visual Feature Verification

Although the relevant image grouping approach can find more relevant images for the 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 with PSO to improve the retrieval performance. RVFV consists of two steps: 1) finding SIFT pairs of the standard image and other images; and 2) re-ranking using the similarity scores.

- Feature Matching

In this paper, RVFV is only applied to the top *N* initial results. Select some of the relevant images from the top *N*-ranked images to expand the query and get more relevant results. Find SIFT pairs of the standard image (the top-ranked image after relevant image grouping of the initial SBIR results, I_S) and other images (the top-ranked *N* images, but not including duplicates of the standard image). The similarity scores are measured using matched SIFT point pairs. P_A is a SIFT point in image I_A, and P_B is a SIFT point in image *IB*. Define ($P_A P_B$) as a SIFT pair, if and only if, the best-matched SIFT point of P_A of image I_A in image I_B is P_B, and vice versa. The similarity of two SIFT descriptors (d_1 and d_2) is measured using the *L*2-norm. That is,

$$(d_1,d_2) = \| d_1 - d_2 \|_2^2 = \sum_i | d_1^i - d_2^i |^2 = \sum_{i|d_2^i=00} | d_1^i |^2 + \sum_{i|d_1^i=00} | d_2^i |^2 + \sum_{i|d_1^i \neq 0, d_2^i \neq 0} | d_1^i - d_2^i |^2$$
$$= 2 - \sum_{i|d_1^i \neq 0, d_2^i \neq 0} d_1^i d_2^i \quad \rightarrow (1)$$

Where d^i is the value of *d* in the *i*-th dimension for *i=1,2,....128.* d^i is normalized using

$$d_*^i = d_*^i / \| d_* \|_2^2 \quad \rightarrow (2)$$

Thus in Eqn. (1) have $\| d_1 \|_2^2 + \| d_2 \|_2^2 = 2$. According to the similarity score between image I_A and d_{Bj} of image I_B is defined as

$$sim\,(d_{Ai},d_{Bj}) = \sum_{l|d^{l}_{Ai}\neq 0, d^{l}_{Bj}\neq 0} d^{l}_{Ai}\, d^{l}_{Bj} \qquad \rightarrow(3)$$

Where dl denotes the value of the *l*-th dimension of the descriptor on Eqn. (3) the similarity score is

$$sim\,(d_{Ai},d_{Bj}) = \frac{sim^{2}(d_{Ai},d_{Bj})}{\frac{1}{L_B}\sum_{k=1}^{L_B} sim\,(d_{Ai},d_{Bk}) * \frac{1}{L_A}\sum_{k=1}^{L_A} sim\,(d_{Ak},d_{Bj})} \qquad \rightarrow(4)$$

Where L_A and L_B are the number of SIFT points in image I_A and I_B, respectively. The denominator serves as a normalization, considering the average similarity between d_{Ai} and all other descriptors in image I_B, and the average similarity between d_{Bj} and all other descriptors in image I_A.

- Optimal Feature Selection using PSO

The optimal SIFT features are selected using PSO from the grouped images. PSO is a stochastic optimization algorithm in which the members of the population are called “particles”. In this algorithm, each particle flies in a multi-dimensional search space, where its velocity is constantly updated by the particle's own experience and the experience of the neighbouring particles.

In this algorithm, each particle flies in a multidimensional search space, where its movement is constantly updated by the particle's own experience and the experience of the neighbouring particles. In the proposed PSO, the movement vector is defined as:

$$v_I(t+1) = wv_i(t) + c_1 r_1 \left(Pbest_i - x_i(t)\right) + c_2 r_2 \left(Gbest - x_i(t)\right) \qquad \rightarrow(5)$$

Where $v_i = \left(v_{i1}, v_{i2}, \ldots\ldots, v_{im}\right) \in R^m$ is the movement vector of particle *i* at the *(t+1)*th iteration, *w* is the inertia weight, c_1 and c_2 are the acceleration coefficients, r_1 and r_2 are two randomly generated values in [0,1]. The location of particle *i* is updated by using the following equation:

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad \rightarrow(6)$$

Where $x_i(t+1)$ indicates the location of particle *i* at the *(t+1)*th iteration, That is, adding the particle i’s current location and it's movement vector obtains the particle i’s new location. The steps in PSO can be simply defined as follows:

PSO Algorithm
Initialize the swarm size, weight, range of movement for particles, and the number of iterations. ***Determine the fitness function.*** ***Store G_{best} and P_{best} locations for all particles.*** ***Calculate the movement vectors for all particles*** ***Update the locations for all particles.*** ***Continue step 3 until maximum iterations reached.*** ***Output G_{best} and P_{best} locations.***

- Similarity-Based Re-Ranking

SIFT feature matching has been extensively applied to image classification. Considering the spatial locations, orientation, or other geometric constraints can improve matching performances. Sketch-based image retrieval has strong spatial constraints. Therefore, use SIFT locations *(L)* and orientations *(O)* to add weights to matched SIFT pairs. The weight is defined as

$$W(m) = \exp(-\alpha \times (W_L(m) + \beta \times W_o(m)) \qquad \rightarrow(7)$$

Where m denotes the m-th SIFT pair between I_A and I_B. α controls the convergence of the exponential function, and β balances the two parts. $W_L(m)$ and $W_O(m)$ are the location and orientation weights, respectively. They are defined as

$$W_L(m) = \| L(A_m) - L(B_m) \|_2^2 \qquad \rightarrow(8)$$

$$W_o(m) = \min(|O(A_m) + O(B_m)|) \qquad \rightarrow(9)$$

Where $L(.)$ and $O(.)$ are the location and orientation of a SIFT point, and (A_m, B_m) is the m-th SIFT pair of I_A and I_B. Use the minimum of the difference and the sum of orientations so that $W_O(m)$ is in the range $[-\pi, \pi]$. Then, the similarity between two images can be determined by summing the weighted scores of the matched SIFT point pairs. That is,

$$SIM(I_A, I_B) = sim(d_{Am}, d_{Bm})W(m) \qquad \rightarrow(10)$$

For the top N results of the initial retrieval ($N = 100$ in experiments), compute the similarity of image I_k to the standard image I_S using

$$S_k = SIM(I_S, I_k), k = 1 \sim N \qquad \rightarrow(11)$$

When $k = 1$, have $S_k = 1$. S_k indicates how similar an image in the initial result is to the standard image. Evaluate if it satisfies a minimum matching requirement (i.e., S_k is larger than a cut-off threshold), or sort S_k in descending order and select the top M images. The selected images are retrieved as optimal output images which match the input query images more accurately.

IV. SIMULATION RESULTS

This section presents the dataset description with the proposed simulation results obtained for the taken dataset and the performance analysis of the proposed SBIR system.

4.1 Dataset Description

The dataset consists of 296,562 images. There were approximately 1000 images in each topic. The dataset contains some query images, relevant images to the query sketch with some irrelevant images which are used to confuse the proposed system results. It mostly contained images with different topics to the images gathered from Google. We drew 361 query sketches, including 162 good sketches drawn by 10 students with excellent drawing skills and 199 inferior sketches drawn by students in our lab. Some of the sample query images presented in the database is shown in figure 4.1.

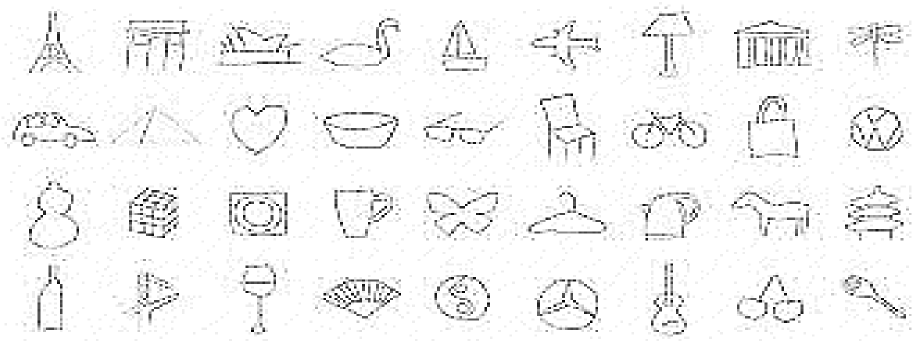

Figure 4.1: Sample query images

4.2 Proposed simulation results

The simulation results of the proposed SBIR system depends on the result of the initial SBIR system (such as edgel or ARP). The images retrieved by the initial SBIR system (edgel) is shown in figure 4.2.

Figure 4.2: Initial SBIR results (edgel)

From the initial SBIR results the proposed system selects the most optimal images via re-ranking and PSO optimization with SIFT feature matching in order to retrieve the accurate images from the database. The optimally retrieved images using the proposed SBIR system is shown in figure 4.3

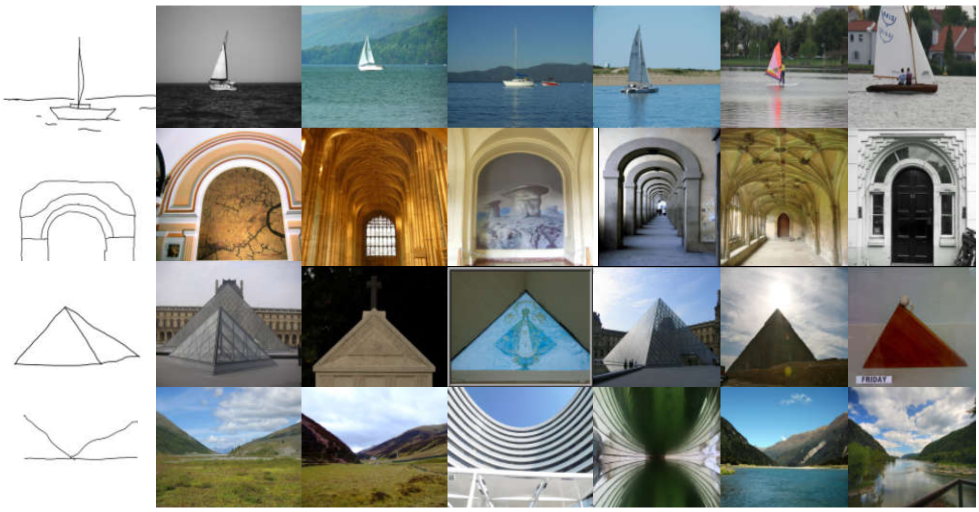

Figure 4.3 optimally retrieved images using proposed system

4.3 Performance Analysis & Comparison

The performance of the SBIR can be evaluated using precision and Recall. Both precision and recall are therefore based on an understanding and measure of relevance. We used the precision under depth n to measure the objective performance defined as,

$$\Pr ecision = \frac{n(RI_{RE})}{n(I_{RE})} \quad \rightarrow (12)$$

Recall can be defined as,

$$\mathrm{Re}\,call = \frac{n(I_{RE})}{n(I_{RD})} \quad \rightarrow(13)$$

Where $n(I_{RE})$ is the number of retrieved images, $n(RI_{RE})$ is the number of relevant images retrieved, $n(I_{RD})$ is the total number of relevant images in the database. Figure 4.4 to figure 4.6 shows the comparison of different SBIR methods with the proposed SBIR method. Figure 4.4 shows the comparison of proposed PSO based SBIR when Edgel is used as an initial SBIR.

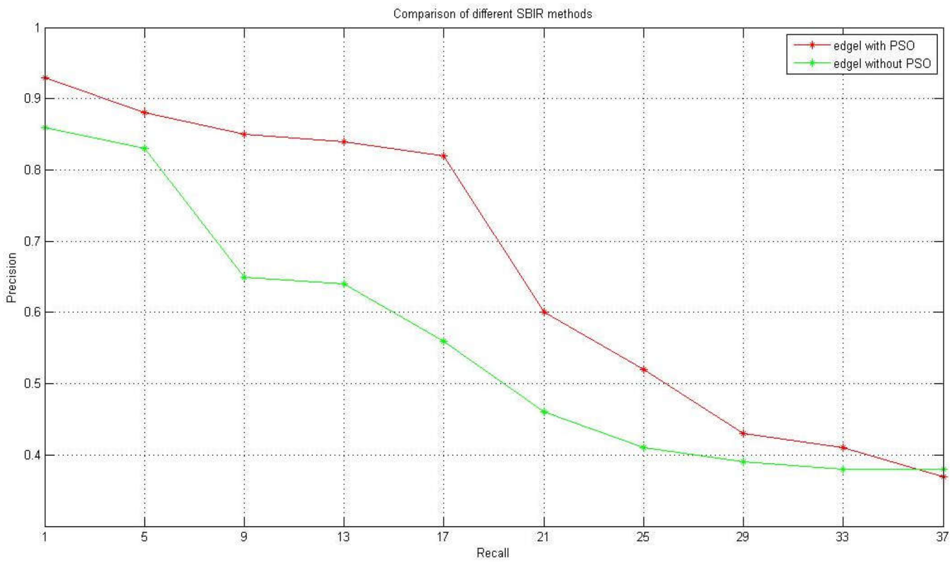

Figure 4.4: Comparison of proposed PSO based SBIR with Edgel

Figure 4.5 shows the comparison of proposed PSO based SBIR when ARP is used as an initial SBIR.

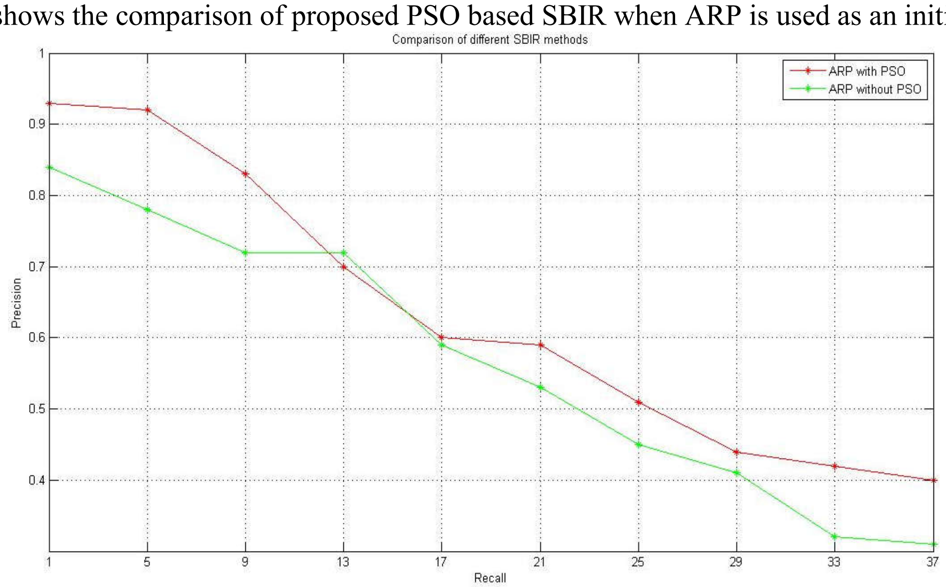

Figure 4.5: Comparison of proposed PSO based SBIR with ARP

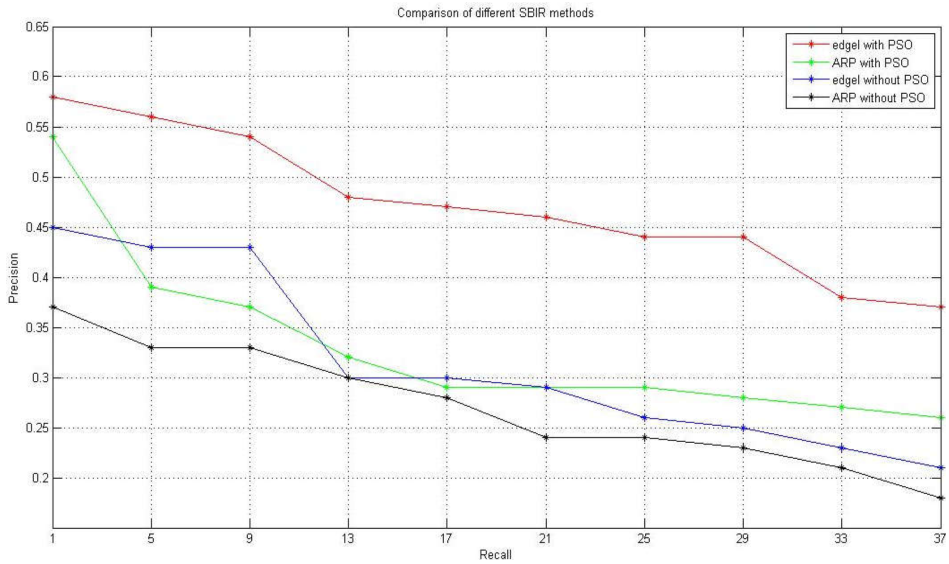

Figure 4.6: Comparison of proposed SBIR with PSO

From the above comparison graphs it is clear that the proposed SBIR method with PSO results in high precision value at low recall. This proves the efficiency of our proposed work than the existing SBIR methods. In addition to that table 4.1 shows the comparison of proposed SBIR and the SBIR introduced in [15] in terms of computational cost.

Table 4.1: Computational costs of the SBIR with and without PSO compared with the initial SBIR approaches using the Edgel and ARP methods

	INITIAL SBIR	SBIR WITHOUT PSO [15]				
		RVFV1	CLUSTERING	CBRF	RVFV2	TOTAL
Edgel	9.77	0.73	0.017	0.14	0.41	11.06
ARP	0.64	0.53	0.015	0.10	0.26	1.55
	INITIAL SBIR	**PROPOSED SBIR WITH PSO**				
		RVFV1	**CLUSTERING**	**PSO-RVFV**		**TOTAL**
Edgel	9.77	0.73	0.017	0.17		10.687
ARP	0.64	0.53	0.015	0.14		1.325

From the knowledge gained from table 4.1 it is clear that the proposed SBIR not only efficiently retrieves the images but also reduces the computational cost than the existing SBIR methods.

V. CONCLUSION

We proposed a SBIR method that uses initial result grouping, re-ranking via visual verification, and particle swarm optimization to search for more optimal images. Our approach does not destroy the original index structure, and does not significantly increase time or storage costs. The simulation results and comparison of the proposed SBIR system with some conventional SBIR system is presented in this paper which shows the significance of the proposed work. The proposed SBIR system retrieves the optimal images from the database when compared to the method introduced in [15]. The proposed method also eliminates the multiple use of re-ranking and contour based relevance feedback utilized in

[15] and produce better results in terms of precision and computational cost. This make us to conclude that the proposed method will be a better choice for future SBIRs.

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