Feature Selection Based-On Swarm Particle Optimization And Genetic Algorithms For Image Retrieval

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ABSTRACT:
This paper proposes a genetic algorithm feature selection (GAFS) and Particle Swarm Optimization Feature Selection (PSOFS) are utilized to optimize the image retrieval system. Three image feature include color features of HSV color histogram (HCH), Shape features of Zernike moments (ZM) and texture features of Local Binary Pattern (LBP) were used in this paper. The simulation results showed that by applying GAFS and PSOFS to image retrieval systems, not only could the number of features be effectively reduced, but higher image retrieval accuracy is achieved. At the end, the performances retrieval of GAFS and PSOFS were compared. The simulation results showed that GAFS has better retrieval performance than PSOFS but need longer running time than PSOFS.

Keywords: Feature selection, PSO, Genetic Algorithm, Image Retrieval, Feature extraction

1. INTRODUCTION
Due to the explosive growth of digital and multimedia technologies, people increasingly come into contact with a lot of Digital images. The digital images include images of textures, animals and plants, Signs, fingerprint, face, medical, tourism and so on [1]–[5]. To store and manage these images, large image databases need to be created. Various image databases have led to the rapid growth of the content based image retrieval (CBIR) field, a challenging and expanding research area. Therefore, determining how to effectively and precisely retrieve a desired image from a constantly growing image database has become an important question. Traditional text-based image retrieval technology has been unable to satisfy people’s needs; therefore, CBIR method is become a hot research topics [6]–[8]. Features that use in CBIR are color, texture, shape and other basic features. These three low level features, are so popular since they are easy to extract, and many methods have been proposed for extracting these low level features [4], [9], [10]. Color feature is the most intuitive and obvious feature of the image, it has certain stability, and shows a very strong robustness to the change of noise, image size, direction and resolution [2]. Color histogram [11] is one technique which is commonly used in CBIR [2]. Shape is one of the basic characteristics of depicting the objects; shape features in image retrieval can improve the efficiency and accuracy of image retrieval [12], [13]. Texture is one the most important feature for CBIR; Texture features reflect the homogeneity and contain the surface information as well as surrounding environment of the image, and spatial information of the image can be described quantitatively [14], [15]. Ojala et al. [16] contributed the new texture descriptor called as local binary pattern (LBP) for texture categorization which encodes the association among the middle pixel and its bordering pixels for a particular center pixel of sub-region of an image. Feature selection is a problem that has to be addressed in artificial intelligence [17]. The main
problem in developing feature selection methods are choosing a small number of feature set in order to minimum the cost and computation time of a given system, as well as achieving an acceptably high retrieval rate. However in general that a better image retrieval rate can be achieved with more feature descriptors used, this is not always and absolutely true. in image retrieval all features of image are not helpful. Many feature selection techniques from a larger set of possible features have been proposed. Despite the extensive applications of colors, textures and shapes in image retrieval, image retrieval results are still unsatisfactory [18]. In order to overcome this problems and improve the retrieval accuracy, an image retrieval method which combines color, shape and texture features (CST) is proposed in this study and in continue this paper proposes genetic algorithms feature selection (GAFS) and Particle Swarm Optimization Feature Selection (PSOFS) for better retrieval performance. These methods choose a small number feature set and improve the retrieval accuracy. Fig. 1 shows the general framework of studied CBIR in this paper. The rest of the paper is organized as follows: in Section II, a brief review of color shape and texture feature extraction is described. The image retrieval system is introduced in Section III. Section IV describes the feature selection based on GA and PSO. Experimental results and discussions are given in Section V. Conclusions are described in Section VI.

II. FEATURES FOR IMAGE RETRIEVAL

The features that used in this paper for image retrieval are HSV color histogram, a color feature, Local Binary Pattern (LBP), a texture feature and Zernike Moments, a shape feature. They are summarized as follows.

2.1. HSV Color Histogram

The method used in this paper is color histogram in HSV color space with 32bin color histogram. The specific quantitative rules are defined as follows [12]:

$$H = \begin{cases} 0, & h \in [315,20] \\ 1, & h \in [20,40] \\ 2, & h \in [40,75] \\ 3, & h \in [75,155] \\ 4, & h \in [155,190] \\ 5, & h \in [190,271] \\ 6, & h \in [271,295] \\ 7, & h \in [295,315] \end{cases}$$

When using this method to quantify the color value in quantitative critical edge, it will produce certain quantitative error, in order to minimize this error, introducing a kind of non-truncated quantitative method, the calculation formula of L can be rewritten as Eq.(2), in which round is the rounding function, and then carrying on normalization processing.

$$H_{HSV_{Feature}} = round(9H + 3S + V)$$

2.2. Zernike moments

In this paper, the Zernike moments are selected for shape feature extraction; they have good rotation invariance and simple calculation, at the same time they are widely used as a kind of shape descriptor. Zernike moments are a special kind of complex moments, they are orthogonal functions based on Zernike polynomials, Zernike polynomials are orthogonal in the unit circle, and their orthogonalities make Zernike moments independent, they have large superiority in characteristic expression ability [12]. The Zernike orthogonal polynomials are defined as follows:

$$V_{nm}(x,y) = V_{nm}(|\rho|,\phi) = R_{nm}(\rho)e^{in\phi}$$

where $n$ and $m$ are the orders of the orthogonal Zernike polynomials, $n$ is a positive integer or
zero, $m$ is a positive or negative integer, they are subject to the conditions $n - |m| = even$ and $n \geq |m|$; is the vector length between circle dot and the pixel $(x, y)$, is the angle between vector and the x-axis of counterclockwise direction; $R_{nm}(\rho)$ is an orthogonal radial polynomial of real value, it is defined as follows:

$$R_{nm}(\rho) = \left(\frac{\rho}{2}\right)^m \sum_{s=0}^{\left\lceil \frac{\rho+1}{2} \right\rceil} (\frac{\rho+1}{2})^s (-1)^s \binom{n-m}{s} \binom{n+m}{2s} \rho^{n-2s}$$

Zernike moments of the image refer to the projection of image function $f(x,y)$ on the orthogonal polynomial $V_{nm}(x,y)$, $n$ order Zernike moment with the repetition of $m$ is defined as:

$$Z_{nm} = \frac{n+1}{\pi} \int_{-1}^{1} \int_{-1}^{1} f(x,y)V_{nm}^*(x,y)dx\,dy$$

For two dimensional images, the integrals in above equation are replaced by summations and the Zernike moments can be defined as [19]:

$$Z_{nm} = \frac{n+1}{\pi} \sum_x \sum_y f(x,y)V_{nm}(x,y), x^2 + y^2 \leq 1$$

Table 1 shows the studied Zernike moments in this paper and applying of ZM on an example image is shown in fig.2.

**Table 1.** The List of Studied Zernike Moments in this paper

<table>
<thead>
<tr>
<th>Order (n)</th>
<th>Zernike Moments Amplitude</th>
<th>Number of Moments</th>
<th>Total Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>$</td>
<td>Z_{2,0}</td>
<td>,</td>
</tr>
<tr>
<td>3</td>
<td>$</td>
<td>Z_{3,1}</td>
<td>,</td>
</tr>
<tr>
<td>....</td>
<td>....</td>
<td>....</td>
<td>....</td>
</tr>
<tr>
<td>9</td>
<td>$</td>
<td>Z_{9,0}</td>
<td>,</td>
</tr>
<tr>
<td>10</td>
<td>$</td>
<td>Z_{10,0}</td>
<td>,</td>
</tr>
</tbody>
</table>

![Fig. 2](image1.png)

Fig.2. The steps calculation of Zernike Moments (n=4, m=2) for a sample image. (a) Original Image (b) Complement Image. (c) Binary Image (A=0.98199, q=-29.9071)

### 1.3. Local Binary Pattern

Local binary pattern (LBP) is created by the difference of local pixels. For calculation of method, Each pixel is considered as a center pixel, then the comparisons of center pixel with local surrounding pixels are obtained. On the basis of the comparison, a binary value is assigned to each surrounding pixel and these binary values multiplied by specific weights and summed up. This summation value is called binary pattern value for that center pixel. For each pixel of the image, a binary pattern value is obtained and all pattern value together called the local binary map of the image. For feature vector, histogram of this local binary map is created. Mathematically, LBP has been defined as follows [15]:

$$LBP_{P,R} = \sum_{x,y} 2^7 \times T_i(a_i,b_i)$$

$$T_i(a_i,b_i) = \begin{cases} 1 & a_i \geq 0 \\ 0 & \text{else} \end{cases}$$

$$H(L)_{LBP} = \sum_{i=0}^{2^P-1} \sum_{x,y} T_i(LBP(x_i,x_j),L), L \in [0,2^P-1]$$

$$T_i(a_i,b_i) = \begin{cases} 1 & a_i = b_i \\ 0 & \text{else} \end{cases}$$

where $P$ and $R$, are the number of neighboring pixels and radius for neighboring pixels. Center pixel and surrounding pixels are denoted as $I_c$ and $I_i$. Final histogram of pattern map is computed by Eq. (8). An example window of LBP calculation and histogram of LBP are shown in Fig. 3 and

![Fig. 3](image2.png)

Fig. 3. Local binary pattern computation sample window
the denominator = 0. In all our experiments we consider \( \varepsilon = 1 \).

the Euclidian distance between query image \( Q \) and database images \( D \) is defined as:

\[
\Delta_{HCH} = \sum_{i=1}^{32} \sqrt{(c_i^q - c_i^d)^2} 
\]

(11)

the Zernike moments (ZM), \( s_1^q, s_2^q, ..., s_{34}^q \) and \( s_1^d, s_2^d, ..., s_{34}^d \) of images \( Q \) and \( D \) are obtained from following equations. so the image similarity distance \( \Delta_{ZM} \) according to d1 and Euclidian distance between \( Q \) and \( D \) based on ZM can be formulated as:

\[
\Delta_{ZM} = \sum_{i=1}^{32} \frac{s_i^q - s_i^d}{s_i^q + s_i^d + \varepsilon} 
\]

(12)

\[
\Delta_{ZM} = \sum_{i=1}^{32} \frac{s_i^q - s_i^d}{s_i^q + s_i^d + \varepsilon} 
\]

(13)

The local Binary patterns(LBP), \( t_1^q, t_2^q, ..., t_{59}^q \) and \( t_1^d, t_2^d, ..., t_{59}^d \) of images \( Q \) and \( D \) are obtained from following Equations, so the image matching according to d1 and Euclidian distances between \( Q \) and \( D \) based on LBP can be defined as:

\[
\Delta_{LBP} = \sum_{i=1}^{59} \frac{t_i^q - t_i^d}{t_i^q + t_i^d + \varepsilon} 
\]

(14)

\[
\Delta_{LBP} = \sum_{i=1}^{59} (t_i^q - t_i^d)^2 
\]

(15)

The proposed CST system combines the HCH, ZM and LBP to reduce the similarity between \( Q \) and \( D \). To determine the similarity of images using the fusing of color, shape and texture (CST) system, the image matching according to d1 distance \( \Delta_{CST} \) between \( Q \) and \( D \) is defined as:

\[
\Delta_{CST} = w_1\Delta_{HCH} + w_2\Delta_{ZM} + w_3\Delta_{LBP} 
\]

(16)

where \( w_1 \), \( w_2 \) and \( w_3 \) are the weights decided by the importance of each component for HCH, ZM and LBP, respectively. HCH is based on color distribution, whereas ZM and LBP are based on shape and texture features. Generally, \( \Delta_{CST} \) decreases with the increase of similarity between \( Q \) and \( D \). Hence, the CST system can deliver the image from the database with the minimal \( \Delta_{CST} \).
3.2. Evaluation Measure

Many evaluation measures have been used in content based image retrieval history. Precision and recall of Mehtre and et al [22] are well-known performance measure, which has been used to describe the performance of an image retrieval system. For each database, every image is treated as query image and image retrieval process has been performed. In this study, each $I_{i}^{j}$ is used as the query image, but this query image is not in database image D. For each query, the system responds to the L retrieved images with the minimal $\Delta^{CST}$ from the database image D. If the similarity of $I_{i}^{j}$ exists among the L database images, we say the system correctly finds the desired image. Otherwise, the system is considered to have failed in finding the desired database image. In the following, the precision ($P$) and recall ($R$) of $i^{th}$ query image are defined as:

$$P(i) = \frac{n_{i}}{L} \quad \text{and} \quad R(i) = \frac{n_{i}}{N_{d}}$$  \hspace{1cm} (17)

Where $L$ is the number of retrieved images, $n_{i}$ is the number of relevant images in the retrieved images and $N_{d}$ is the number of all relevant images in the database.

IV. FEATURE SELECTION

The aim of feature selection is to select the best features that can not only achieve the maximum retrieval rate but can also simplify the calculation of image retrieval.

4.1. Particle Swarm Optimization Feature Selection method

PSO is a stochastic optimization algorithm which was presented by Kennedy in 1995 [23]. Where 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 neighboring particles. It is employed to solve the optimization problems in many applications, such as, image processing and vehicle routing problem. More specifically, the training procedure of the PSO algorithm is shortly described as follows [24];

1. define the initial PSO parameters, include: swarm size, weight, range of movement for particles, and the number for training iterations. In addition, the particles are randomly located and the movement vector is randomly assigned.
2. Store $Gbest$ and all $Pbest$ locations at the current iteration according to an evaluation process by utilizing the fitness function for all particles.
3. If the number of training iterations is expired or the accuracy is satisfied, then $Gbest$ and $Pbest$ locations are obtained, and the algorithm terminates. Otherwise, go to Step 4.
4. Calculate the movement vectors for all particles by Eq. (18).
5. Update the locations for all particles by applying Eq. (19) and then go to stage 2.

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

$$V_{i}(t+1) = wV_{i}(t) + c_{1} \times r_{1} \times (Pbest_{i} - X_{i}(t)) + c_{2} \times r_{2} \times (Gbest - X_{i}(t)),$$

Where $V_{i} = (V_{i1}, V_{i2}, ..., V_{im}) \in R^{m}$ is the movement vector of particle $i$ at the $(t+1)^{th}$ iteration, $w$ denotes the inertia weight, $c_{1}$ and $c_{2}$ represent the acceleration coefficients which are random numbers in [0,1], $r_{1}$ and $r_{2}$ are two randomly generated values in [0,1]. Moreover, in Eq. (18), the first term indicates the particle’s inertia, the second term $c_{1} \times r_{1} \times (Pbest_{i} - X_{i}(t))$ shows the particle’s cognition only model, and the third term $c_{2} \times r_{2} \times (Gbest - X_{i}(t))$ indicates the particle’s social-only model. Additionally, $Pbest \in R^{m}$ presents the nearly optimal position for the $i^{th}$ individual particle’s path of movement and $Gbest \in R^{m}$ indicates the position closest to the nearly optimal solution in the group. Finally, the
location of particle $i$ is modified by using following equation:

$$X_i(t+1) = X_i(t) + V_i(t+1),$$

(19)

where $X_i(t+1)$ indicates the location of particle $i$ at the $(t+1)^{th}$ iteration, $V_i(t+1)$ represents the movement vector 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. Fig.5 illustrates a schematic view of updating the position of a particle in two successive iterations [24].

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**4.2. Genetic algorithms feature selection (GAFS) method**

The basic theory of genetic algorithms is based on the Darwinian theory of evolution, i.e., survival of the fittest. Notably, this method can be applied to solve optimization problems. The genetic algorithm simulates evolution within a biosphere where the main expressions include concepts such as reproduction, crossover and mutation, etc. Through the evolutionary simulation and suitable species generation (the simulated living environment is called fitness function), all of the species evolve with respect to the fitness function. After the completion of genetic algorithms in accordance with expressions of reproduction, crossover etc., a new generation of the best gene combination may be obtained. We used MATLAB for implementation of genetic and PSO algorithm in the study. The genetic algorithm optimization and search technology adopted genes and natural selection mechanics. The flow of genetic algorithm is illustrated in Fig. 6; the general steps of Genetic Algorithms are as follows:

- **Selection:** in this stage the first quarter of the remaining chromosomes according to the assessed values are Selected and the good chromosomes are chosen.
- **Crossover:** in this stage two chromosomes are chosen from the group sequentially to perform the crossover process.
- **Mutation:** one chromosome sequentially is chosen from the group after Crossover and then one gene from the chromosome is chosen sequentially. At the same time, a random variable is generated. If its value is less than or equal to the mutation rate, the value of this gene will be changed from 0 to 1 or from 1 to 0.
- **Iteration:** in this stage two better chromosomes from Fitness Functions are taken to bond with the chromosome after mutation. Then, repeat the steps from Fitness Functions to Iteration until the maximum iteration is achieved (Stop1). Then, go to Evaluation.

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![Fig.5: Illustration of particle’s position update in PSO.](image_url)

In this paper we set the PSO’s parameters as Table 2.

**Table 2. the parameters of PSO**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population Size</td>
<td>20</td>
</tr>
<tr>
<td>Maximum Iteration</td>
<td>25</td>
</tr>
<tr>
<td>$c_1$, $c_2$</td>
<td>2</td>
</tr>
<tr>
<td>$r_1$, $r_2$</td>
<td>2.05</td>
</tr>
<tr>
<td>$w$</td>
<td>0.99</td>
</tr>
</tbody>
</table>
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**Evolution:** In this stage the best feature set of the genetic algorithm are Recorded. Finally, the best feature set from the optimal feature set generated in each stage are selected until the maximum iteration is achieved (Stop2).

**Fitness Functions for GAFS and PSOFS:** In this section the fitness function of GAFS and PSOFS is introduced. For GAFS denote the chromosome within the population initialization as a feature set. Then, match each gene to the respective feature; the value 0 for the gene means that the corresponding feature was not included in the calculation And the value 1 for the gene means that the feature was included in the calculation. Similarity this process can used for each particle in PSOFS.

Then, the image similarity distances between a query and other images in the image database are sorted descending. In this study we used only d1 distance metric in feature selection calculation. Therefore, for each query image, the image retrieval system responds to the first L retrieved images. If a similarity of query exists among the L retrieved image in database, the precision $P(i)$ of $i^{th}$ query image is corrected, and $P(i) = 1$. Otherwise, the precision of this query image is considered to have failed, and $P(i) = 0$. Therefore, the fitness function value can be derived by the precision P from Eq. (17), and then the average precision $\overline{P(i)}$ in $i^{th}$ feature set of the all of the images is as follows:

$$\overline{P(i)} = \frac{1}{N_i} \sum_{j=1}^{N_i} p(i), i = 1,2,...,N_i$$

where $N_i$ is the total image number. The optimum feature number $M^*$ and the best precision $\overline{P}(i)$ of GAFS and PSOFS can be written by the following equation:

$$\overline{P}(i) = \max\{\overline{P(i)}\},$$

$$M^* = \arg\max\{\overline{P(i)}\}$$

**Table 3.** The Parameters of Genetic Algorithms

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population Size</td>
<td>20</td>
</tr>
<tr>
<td>Maximum Iteration</td>
<td>25</td>
</tr>
<tr>
<td>Mutation rate</td>
<td>0.8</td>
</tr>
</tbody>
</table>

**V. RESULTS**

**5.1. Dataset**

In this study we use Corel_1k dataset [26], which consists of 1000 images with 384 ×256 pixels, all images are grouped into 10 class, each containing 100 images. The images in the same class are considered to be similar images. Fig. 7 shows some of these images. This 10 Classes are shown in Table 4.

**Table 4.** Ten classes of Corel_1k Image dataset

<table>
<thead>
<tr>
<th>Class</th>
<th>Class Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>African people and village</td>
</tr>
<tr>
<td>2</td>
<td>Beach</td>
</tr>
<tr>
<td>3</td>
<td>Building</td>
</tr>
<tr>
<td>4</td>
<td>Buses</td>
</tr>
<tr>
<td>5</td>
<td>Dinosaurs</td>
</tr>
<tr>
<td>6</td>
<td>Elephants</td>
</tr>
</tbody>
</table>

Fig. 6. The flowchart of Genetic Algorithms [25]

Fig. 7. Some examples of Corel_1k dataset
5.2. Experiment Results
The experiments results are compiled with MATLAB R2015a in this paper. Table 5 shows the total number of extracted features of all studied methods.

Table 5. The Number of Extracted Feature in Each Image

<table>
<thead>
<tr>
<th>Method</th>
<th>Number of Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>HSV color Histogram</td>
<td>32</td>
</tr>
<tr>
<td>Zernike Moments</td>
<td>34</td>
</tr>
<tr>
<td>LBP</td>
<td>59</td>
</tr>
<tr>
<td>ALL=HCH+ZM+LBP</td>
<td>125</td>
</tr>
</tbody>
</table>

5.3 Retrieval performance
Table 6. comparison results of all features

<table>
<thead>
<tr>
<th>Distance Metric</th>
<th>Average Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HCH</td>
</tr>
<tr>
<td>L=20</td>
<td></td>
</tr>
<tr>
<td>D1</td>
<td>0.774</td>
</tr>
<tr>
<td>Euclidian</td>
<td>0.725</td>
</tr>
<tr>
<td>L=50</td>
<td></td>
</tr>
<tr>
<td>D1</td>
<td>0.678</td>
</tr>
<tr>
<td>Euclidian</td>
<td>0.625</td>
</tr>
<tr>
<td>L=100</td>
<td></td>
</tr>
<tr>
<td>D1</td>
<td>0.605</td>
</tr>
<tr>
<td>Euclidian</td>
<td>0.540</td>
</tr>
</tbody>
</table>

5.4. The performance of PSOFS and GAFS
In this section, the performance of image retrieval using color, shape and texture features are presented. A comparison of the results of all features based on d1 distance and Euclidian distance for L retrieved images is given in Table 6. As we can see from Table 6, the LBP method provides higher average precision in various retrieved images than the other two methods and it is clear that d1 distance metric provide better performance from Euclidian distance. The LBP consider both of color and texture of image and apply to color image, but ZM has the minimum retrieval rate, because it consider only the shape feature of a grayscale image and the HCH has close average precision to LBP.

Table 7. the compared results of feature selection for GAFS and PSFS

<table>
<thead>
<tr>
<th>Retrieval Method</th>
<th>GAFS</th>
<th>PSOFS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Feature Number</td>
<td>Average Precision</td>
</tr>
<tr>
<td>HCH</td>
<td>15</td>
<td>0.824</td>
</tr>
<tr>
<td>ZM</td>
<td>14</td>
<td>0.590</td>
</tr>
<tr>
<td>LBP</td>
<td>17</td>
<td>0.833</td>
</tr>
<tr>
<td>HCH+ZM+LBP</td>
<td>15.33</td>
<td>0.749</td>
</tr>
</tbody>
</table>
Table 8. the compared results of GAFS and PSOFS using Eq. (16)

<table>
<thead>
<tr>
<th>Feature Selection Method</th>
<th>Total Feature Number</th>
<th>Average Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAFS</td>
<td>48.8</td>
<td>0.943</td>
</tr>
<tr>
<td>PSOFS</td>
<td>70.7</td>
<td>0.913</td>
</tr>
</tbody>
</table>

VI. CONCLUSION
In this paper, we proposed the Genetic and PSO feature selection techniques in order to achieve an acceptably high retrieval performance. The features of the CST system integrated the three color, shape and texture features of image. The performance of the proposed method for Genetic algorithm feature selection (GAFS) and particle swarm optimization feature selection (PSOFS), image retrieval was evaluated using Corel_1k dataset. In our experiments regarding feature selections have shown that GAFS and PSOFS can not only decrease feature numbers, but also increase the retrieval accuracy. Although the average precision obtained by GAFS is close to PSOFS, the GAFS method require longer computation time than PSOFS and the feature number of GAFS are less than PSOFS.

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