

# Face recognition based on improved artificial bee colony algorithm

Qi Yang\*

College of Electronic Engineering (College of Artificial Intelligence), South China Agricultural University, Guangzhou, China

\*Corresponding author: youngseven77@163.com

**Abstract:** Under different environments, the accuracy of face recognition will be affected. For face image recognition, principal component analysis is used to extract the main features of face. Based on the classical bee colony algorithm, a preferred multi-objective bee colony algorithm is proposed in face image recognition. The algorithm has the ability of distinguishing and recognition, and the recognition accuracy reaches 96.7% in practical application. It has the characteristics of effectiveness and adaptability.

**Keywords:** PCA, image recognition, multi - target colony algorithm

## 1. Introduction

Face recognition is a kind of biometric identification technology based on people's facial features. A series of related technologies, also known as portrait recognition and face recognition, are used to collect images containing faces with cameras [1], automatically detect and track faces in the images, and then carry out face recognition on the detected faces. There are many methods applied to face recognition, such as BP neural network [2] algorithm to build a model. There are two - dimensional face reconstruction technology. How to accurately recognize faces in different environments has become the core problem of face recognition.

## 2. Construction of an improved artificial bee colony algorithm

### 2.1 Facial feature extraction with PCA

Usually in face recognition, the image is regarded as a pixel matrix, a face image size of  $w \times h$ , according to the column expansion, it can be regarded as the length of  $w \times h$  column vector, equivalent to the image in a high dimensional space, the need to through some transformation to project the data in the high dimensional space to the low dimensional subspace, the redundant information to get rid of, so as to better classification.

Principal component analysis is used to extract facial features (eyes, nose, mouth, etc.). The  $N$  features of the original data are replaced by fewer  $M$  features, so as to make the  $M$  features uncorrelated to each other as far as possible, and then the original  $N$  features are represented by the linear combination of  $M$  features. In the recognition process, the feature face is first formed into a space, and then the face image to be recognized is mapped to the feature face space. The specific steps are as follows:

① Calculate the mean value  $\mu$  and covariance matrix  $S$  of all samples, as shown in equations (1) and (2).

$$\mu = \frac{1}{N} \sum_{i=1}^N X_i \quad (1)$$

$$S = \sum_{i=1}^N (X_i - \mu)(X_i - \mu)^T \quad (2)$$

② Calculate the eigenvalues of the covariance matrix  $S$ , denoting the eigenvalues of the matrix as  $\lambda_1, \lambda_2, \dots, \lambda_n$ , and order from largest to smallest, as in Equation (3).

$$\lambda_1 > \lambda_2 > \dots > \lambda_n \quad (3)$$

③ The vector corresponding to the first  $m$  eigenvalues is constructed into a matrix  $R$ . In general, if

the eigenvalue is smaller, the eigenvector is more likely to contain noise. Therefore, in practical application, the first  $m$  feature vectors are selected as the principal components extracted from PCA.

## 2.2 Construction of preferred multi-objective bee colony algorithm

The traditional ABC algorithm [3-4] mainly has the convergence defect of "precocious". Although it has good exploration ability, it lacks development ability, weak local search ability and relatively slow convergence speed.

### 2.2.1 Multiple evolutionary goal setting

In the artificial bee colony algorithm, according to the characteristics of the multi-objective evolution problem[5], the whole evolutionary population problem is divided into several subpopulation evolution problems, and each subpopulation corresponds to a human face feature for optimization calculation, so as to realize the evolution of the whole bee colony algorithm. A multi-objective optimization problem (MOP) is generally defined as follows:

$$\begin{aligned} \min f(x) &= \{f_1(x), f_2(x), \dots, f_k(x)\} \\ \text{s. t. } &\begin{cases} g_i(x) \leq 0 & i = 1, 2, \dots, m \\ h_j(x) = 0 & j = 1, 2, \dots, q \\ x \in D \subset \mathbb{R}^n \end{cases} \end{aligned}$$

Where:  $x$  is the decision variable in  $\mathbb{R}^n$  space;  $D$  is its domain of definition;  $f$  of  $x$  is the target function;  $g(x)$  and  $h(x)$  are constraint functions. The preference region is added to the solution set, and then the Pareto optimal solution set with multiple objectives is found to determine the Pareto<sub>true</sub> set, so as to determine whether it is the target face region.

### 2.2.2 The setting of the preference information area

In the face recognition problem, the parameter range of a certain face feature is used as the Pareto frontier input multi-objective artificial bee colony algorithm as the face preference information region. Preference areas are defined as follows:

$$S = \pi \left( \frac{||x_H - x_L|| + ||y_H - y_L||}{4} \right)^2 \quad (4)$$

Where:  $S$  is the area of preference parameter;  $x_H, x_L$  are the upper and lower bounds of parametric Euclidean space abscissa;  $y_H, y_L$  are the upper and lower bounds of parametric Euclidean space ordinate. Therefore, the preferred multi-objective artificial bee colony algorithm is constructed.

The advantage of this search method is that the algorithm only needs to search the optimal solution near the preference region, but does not need to obtain the complete Pareto frontier, so the algorithm search scope is reduced, so it has higher recognition rate and convergence speed than the common multi-objective algorithm.

### 2.2.3 Steps of Preferred multi-objective swarm algorithm

①  $kN$  initial positions are randomly generated in  $k$  different face parameter data to be searched according to Formula (5).

$$v_{ij} = x_{jL} + \text{rand}(0, 1) \times (x_{jH} - x_{jL}) \quad (5)$$

Where  $v_{ij}$  is the position after the  $i$ th only searches for the  $J$ TH dimension;  $x_{jL}, x_{jH}$  are the lower bound and upper bound of the  $j$ -th dimension variable, respectively;  $\text{rand}(0, 1)$  is a random number ranging from 0 to 1.

② Input the preference parameter region, and guide the bees to search for the matching new honey source near the preference region according to formula (6).

$$v_{ij} = x_{ij} + r(x_{ij} - x_{kj}) \quad (6)$$

Where  $v_{ij}$  is the location of the new nectar source;  $r \in [-1, 1]$  is a random variable;  $x_{ij}$  is the  $j$ -dimension position of nectar source  $i$ ;  $x_{kj}$  is the  $j$ -th-dimension position of nectar source  $k$ , which is not  $i$ .

- ③ Compare the nectar source information after searching and select the better nectar source.
- ④ The follower bees selected the nectar source leading the search according to the roulette strategy, and searched for new nectar sources near the nectar source according to Formula (6).
- ⑤ Compare the quantity of nectar, and choose the best as the position of leading bees and nectar source, and the rest as the position of following bees.
- ⑥ If the honey source remains unchanged after the set limit cycle, the honey source will be abandoned and the leading bees will turn into reconnaissance bees, generating a new honey source according to Formula (5).
- ⑦ Return to step ② until the termination condition is met.

According to the definition of multi-objective optimization problem, the objective function for each leader bee is:

$$\min f(x) = f_1(x) - f_2(x) \quad (7)$$

Where  $f_2(x)$  is the initial position of the face parameter, and  $f_1(x)$  is the position of the leading bee. Take its nearest value as the optimal objective function. The constraint conditions of the above objective function in the preference region are:

$$||\min f(x)||^2 \leq S \quad (8)$$

Where S is the area of the preferred region, which is equivalent to limiting the positions of the leading and following bees to the preferred region, so as to repeatedly search for the optimal value within this range. The flow chart of the improved algorithm is shown in figure 1.

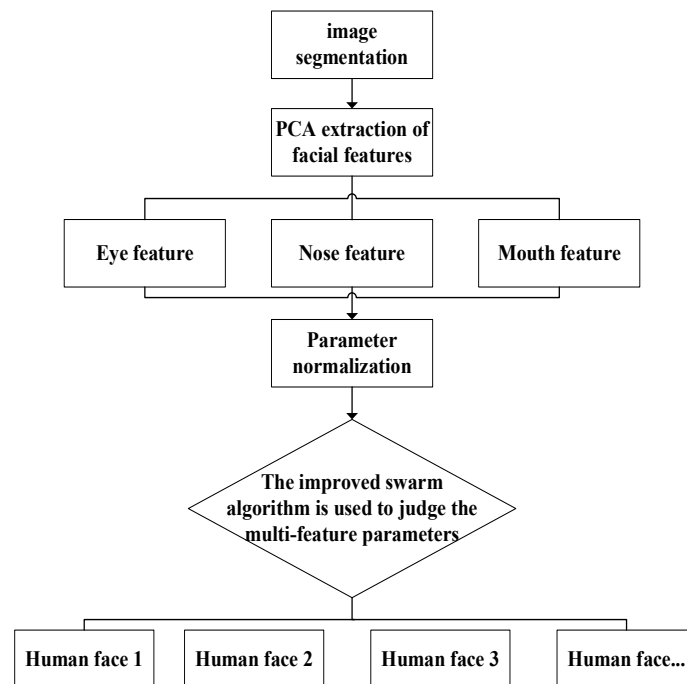


Figure 1: Face recognition process

### 3. Results

#### 3.1 Comparative analysis of algorithms

Iris data set was used to compare the recognition rate and recognition time between the preferred multi-objective bee colony algorithm and the classical artificial bee colony algorithm. The results show that when Versicolor data is used as the preferred region, the recognition rate of the improved preferred multi-objective colony algorithm is 12.57%, 7.98% and 6.87% higher than that of the classical artificial colony algorithm under no interference, mild random interference and random high interference, respectively. The average recognition rate increased by 9.14%. The time complexity decreases by 1.39 s,

1.19 s and 0.48 s, and the average clustering time decreases by 1.02 s, which proves the effectiveness of the improved algorithm. The algorithm comparison is shown in figure 2.

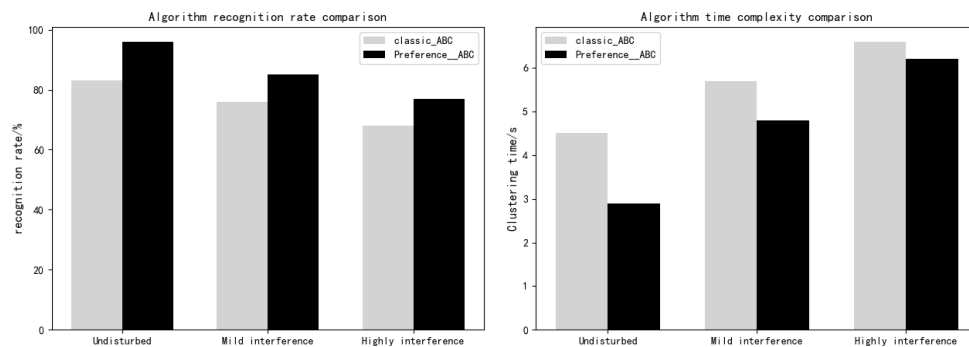


Figure 2: Algorithm recognition rate and time complexity comparison

### 3.2 Result analysis

In this experiment, the ORL YALE database is used to collect the face images of 15 people, each person has 10 images, the image size is  $112 \times 92$ , a total of 150 images. Details of the images include whether or not a frame is worn, the Angle of the eyes, the length of the hair, and the different expressions. In addition, the posture of human face also changes greatly. For example, the rotation Angle of human face can reach about  $30^\circ$ , and the size will also vary by 10%. A total of 60 groups of face recognition were carried out in the simulation experiment, among which 58 groups were correctly identified with an accuracy of 96.7%.

## 4. Conclusions

In this paper, PCA method is used to extract the main features in the face image, and then the improved artificial bee colony algorithm is used for iterative calculation. Finally, the matching speed is fast and the robustness is good.

## References

- [1] Zhao Shanghui. *Based on the depth study of dynamic facial recognition technology research [D]*. Nanjing University of posts and telecommunications, 2022. The DOI: 10.27251 /, dc nki. Gnjdc. 2022.001110.
- [2] Wei Dahuan, Su Yan. *Research on Face recognition System based on BP Neural Network [J]*. Wireless Internet Technology, 2021, 18(10):116-117.
- [3] Gao Chenyang, Yu Xiaojun, Yan Yan. *A review of swarm algorithms [J]*. Information and Computer (Theoretical Edition), 2021, 33(22):63-65.
- [4] Bai Huilin, Qu Na, Chen Shaojie, Liu Tiantian. *Face recognition based on artificial colony algorithm [J]*. Journal of shenyang institute of engineering (natural science edition) 2019, 15 (01): 88-92, DOI: 10.13888 / j.carol carroll nki jsie (ns).
- [5] Ma Shijing. *Multi-objective artificial colony algorithm and its application [D]*. The northeast normal university, 2019. The DOI: 10.27011 /, dc nki. Gdbsu. 2019.000082.