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# Performance Optimization Algorithms in the Classification Face Emotion Recognition

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*Abstract:* The work areas for emotion recognition are facial expressions, vocal, gesture and physiology signal. Facial expressions are one of most functional areas for faceemotion recognition. For best results we should similareye and lip as regular and irregular ellipse. The main purpose of this paper is introducing an Imperialist Competitive Algorithm (ICA) to optimize eye and lip ellipse characteristics. Then performance of three optimization methods including Imperialist Competitive Algorithm (ICA), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for this issue will be discussed. This process involves three stages pre-processing, feature extraction and classification. Firstly a series of pre-processing tasks such as adjusting contrast, filtering, skin color segmentation and edge detection are done. One of important tasks at this stage after pre-processing is feature extraction. Projection profile method to reason has high speed and high precision used in feature extraction. Secondly ICA, GA and PSO are used to optimize eye and lip ellipse characteristics. Finally in the third stage with using features obtained on optimal ellipseeye and lip, emotion a person according to experimental results have been classified. The obtained results show that success rate and running speed in ICA is better than PSO and these two parameters for PSO are better than GA.

*Keywords:* Face emotion recognition, Projection profile, Imperialist Competitive Algorithm (ICA), Particle Swarm Optimization (PSO) algorithm and Genetic algorithm (GA).

# I. INTRODUCTION

Facial expressions are one of important concepts for emotion recognition. You can express emotion a human with (her /his) face in comparing with other body parts. The eyes and lip are important elements in facial expression. A category of emotions which universally developed by Ekman are sadness, angry, joy, fear, disgust and surprise without consider natural emotion. The main purpose of this paper is introducing an Imperialist Competitive Algorithm (ICA) to optimize eye and lip ellipse characteristics. Then performance of three optimization methods including Imperialist Competitive Algorithm (ICA), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for this issue will be discussed. The obtained results show that success rate and running speed in ICA is better than PSO and these two parameters for PSO are better than GA. In this study for the validity of research a collection of Indian images including 350 images in seven emotions are used [17]. This method consists of three main parts. The first part describes various stages in image processing include preprocessing, filtering, edge detection. Projection profile method to reason has high speed and high precision usedin feature extraction. The second part discusses an ICA-based approach to optimize eye and lip ellipse characteristics. In the third part we used of eye and lip optimal parameters to classify the emotions. The rest of this paper organized as follows. Section 2 is an overview of related works. The method with ICA, PSO and GA algorithm is described in section 3. Efficiency analysis and results of the method is discussed in section 4 and section 5 contains conclusions.

# II. RELATED WORKS

Facial expressions afford important information about emotions. Therefore, several approaches have been proposed to classify human affective states. The features used are typically based on local spatial position or displacement of specific points and regions of the face, unlike the approaches based on audio, which use global statistics of the acoustic features. For a complete review of recent emotion recognition systems based on facial expression the readers are referred to [1]. Mase proposed an emotion recognition system that uses the major directions of specific facial muscles [2]. With 11 windows manually located in the face, the muscle movements were extracted by the use of optical flow. For classification, K-nearest neighbor rule was used, with an accuracy of 80% with four emotions: happiness, anger, disgust and surprise. Yacoob et al. proposed a similar method [3]. Instead of using facial muscle actions, they built a dictionary to convert motions associated with edge of the mouth, eyes and eyebrows, into a linguistic, per- frame, mid-level representation. They classified the six basic emotions by the used of a rule-based system with 88% of accuracy. Black et al. used parametric models to extract the shape and movements of the mouse, eye and eyebrows [4]. They also built a mid- and high-level representation of facial actions by using a similar approach employed in [3], with 89% of accuracy. Tian et al. attempted to recognize Actions Units (AU), developed by Ekman and Friesen in 1978 [5], using permanent and transient facial features such as lip, Nasolabial furrow and wrinkles [6].

Geometrical models were used to locate the shapes and appearances of these features. They achieved a 96% of accuracy. Essa et al. developed a system that quantified facial movements based on parametric models of independent facial muscle groups [7]. They modeled the face by the use of an optical flow method coupled with geometric, physical and motion-based dynamic models. They generated spatial-temporal templates that were used for emotion recognition. Without considering sadness that was not included in their work, a recognition accuracy rate of 98% was achieved. A method that extracts region of eye and lip of facial image by genetic algorithm has been suggested recently [8].

## **III. THE PROPOSED METHOD**

In this paper we want similar eye and lip to regular and irregular ellipse. The main purpose of this paper is introducing an Imperialist Competitive Algorithm (ICA) to optimizeeye and lip ellipse characteristics. Then performance of three optimization methods including Imperialist Competitive Algorithm (ICA), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for this issue will be discussed. The obtained results show that success rate and running speed in ICA is better than PSO and these two parameters for PSO are better than GA.One of main reasons for using sobel edge detection filter is high speed and high accuracy andit is shown in Fig.1.





Figure 1. The surprise emotion [17]

#### A. Feature Extraction:

Projection profile is a rapid method for feature extraction. This feature extraction method is implemented with the row-sum and column-sum of white pixels in the image was obtained by sobel filter [8]. The template of row-sum along the column show with ( $M_h$ ) and template of column-sum along the row show with ( $M_v$ ) and these features defined for each region [8]. These features are defined as projection profile. Allow f (m, n) is shown with a binary image of m rows and n columns [8]. The vertical profile ( $M_v$ ) with size n is shown by (1) [8].  $\mathbf{Mvj} = \sum_{i=1}^{m} f(i,j) \mathbf{j} = \mathbf{1}, \mathbf{2}, \mathbf{3} \dots \mathbf{n}$  (1)

The horizontal (M<sub>h</sub>) with size m is shown by (2) [8].  $\mathbf{Mhi} = \sum_{j=1}^{n} f(i, j) \mathbf{i} = \mathbf{1}, \mathbf{2}, \mathbf{3} \dots \mathbf{m} \quad (2)$ 

The human eye shape is more like an ellipse (we call this as a regular ellipse) and shown in Fig.2.The minor axis of ellipse is a feature of eye and different for each person emotion. The major axis of ellipse with name "a" is different for each person. The regular ellipse is displayed with its minor and major axes and also parameter "a" fixed and "b" calculated by (3) [8].



Figure2. The regular ellipse

Human lip is an irregular ellipse and shown in Fig.3.An irregular ellipse has two variable axes. In the irregular ellipse parameter "a" fixed and parameters "b<sub>1</sub>" and "b<sub>2</sub>" are calculated. In the next section ICA algorithm adopted to optimize these features.



Figure3. The irregular ellipse

#### B. Imperialist Competitive Algorithm (ICA):

In this algorithm a random number of solutions in search space are generated. The initial generated solutions are called as initial countries. Countries in ICA, chromosomes in GA and particles in PSO have a mean. In ICA cost function shows power a country.

### **IV. EXPERIMENTAL RESULTS**

In this study we worked on Indian images with seven emotions and 350 images. Sample images are shown in [17]. The eye and lip features have been given as input to ICA, PSO and GA algorithm to find optimized values (ellipse optimum). Optimization process was repeated 20 times for each emotion. Thereupon optimal parameters  $(x, x_1, x_2)$ come from optimal ellipsoid axes. TableI, Table II and Table III show settings for ICA, PSO and GA algorithm. In Table IV manual measured parameters from 350 images and ICA optimized parameters (The mean of parameters) are shown. Table V and Table VI show the same calculation with PSO and GA. By comparing Table IV, Table V and Table VIwe observe that success rate and running speed in ICA is better than PSO and these two parameters for PSO are better than GA.

Table 1. Parameter setting for ICA algorithm

| ICA Parameters         |     |  |  |  |  |  |
|------------------------|-----|--|--|--|--|--|
| #Countries             | 200 |  |  |  |  |  |
| #Imperialists          | 20  |  |  |  |  |  |
| <b>Revolution Rate</b> | 0.3 |  |  |  |  |  |
| Г                      | 0.5 |  |  |  |  |  |
| В                      | 2   |  |  |  |  |  |
| #Iterations            | 500 |  |  |  |  |  |

Table 2. Parameter setting for PSO algorithm

| Parameter              | Description   |
|------------------------|---|
| Particle               | $(x, x_1, x_2)$   |
| number of particles    | 200   |
| Dimension of particles | 3   |
| Range of particles     | $X_1 \ge 0$ and $X_2 \le 0$   |
| $V_{max}=20$           | variable  |
| Learning factors       | [0,3]   |
| stop condition         | 500(maximum repetition)   |
| Version                | local   |
| inertia weight         | W <sub>max</sub> =0.9, W <sub>min</sub> =0.4                                |
| max iteration number   | 500   |
| W(iteration)           | W <sub>max</sub> -(( W <sub>max</sub> - W <sub>min</sub> )/ max iteration)* |
|                        | iteration   |

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## Table 3.Parameter setting for GA algorithm

| Generation      | 500  |
|-----------------|------|
| Population size | 200  |
| Fitness scaling | Rank |

| Selection Function | Roulette  |
|--------------------|-----------|
| Mutation           | Gaussian  |
| Crossover          | Scattered |

#### Table 4. Manual and ICA optimal measured parameters

| Emotion  | Manu<br>Mean          | ally Com<br>Value (in | puted<br>pixels) | Optimized :                     | Mean Value by ICA | (in pixels) | 50<br>Images<br>For each<br>emotion | Duration of<br>Emotion Recognition<br>(sec) |
|----------|-----------------------|-----------------------|------------------|---------------------------------|-------------------|-------------|-------------------------------------|---|
|          | <b>b</b> <sub>1</sub> | <b>b</b> <sub>2</sub> | b                | x <sub>1</sub> x <sub>2</sub> X |                   |             | Success Rate                        | Mean Time                                   |
| Natural  | 40                    | 44                    | 25               | 39.2644                         | 43.2531           | 24.6188     | 96%                                 | 35  |
| Fear     | 27                    | 44                    | 21               | 26.0287                         | 43.9529           | 20.7024     | 91%                                 | 31  |
| Нарру    | 27                    | 50                    | 20               | 26.5929                         | 49.4742           | 19.0393     | 94%                                 | 42  |
| Sad      | 28                    | 37                    | 22               | 27.9104                         | 36.4511           | 21.9633     | 92%                                 | 36  |
| Angry    | 27                    | 36                    | 19               | 26.2781                         | 35.8381           | 18.4120     | 90%                                 | 29  |
| Dislike  | 37                    | 32                    | 18               | 36.3409                         | 31.6276           | 17.8353     | 95%                                 | 33  |
| Surprise | 46                    | 60                    | 20               | 45.6892                         | 59.0180           | 19.0701     | 93%                                 | 42  |

#### Table 5. Manual and PSO optimal measured parameters

| Emotion  | Manually Computed<br>Mean Value (in pixels) |                       |    | Optimized 1 | Mean Value by PSC     | ) (in pixels) | 50<br>Images<br>For each<br>emotion | Duration of<br>Emotion Recognition<br>(sec) |
|----------|---|-----------------------|----|-------------|-----------------------|---------------|-------------------------------------|---|
|          | <b>b</b> 1                                  | <b>b</b> <sub>2</sub> | b  | <b>X</b> 1  | <b>X</b> <sub>2</sub> | Х             | Success Rate                        | Mean Time                                   |
| Natural  | 40  | 44                    | 25 | 39.8165     | 43.2366               | 24.9852       | 93%                                 | 48  |
| Fear     | 27  | 44                    | 21 | 26.2525     | 42.6355               | 19.6565       | 89%                                 | 39  |
| Нарру    | 27  | 50                    | 20 | 26.9612     | 48.2256               | 19.6353       | 92%                                 | 51  |
| Sad      | 28  | 37                    | 22 | 27.1464     | 36.5598               | 21.9751       | 88%                                 | 49  |
| Angry    | 27  | 36                    | 19 | 26.1256     | 35.2684               | 18.6521       | 94%                                 | 53  |
| Dislike  | 37  | 32                    | 18 | 35.2565     | 31.2255               | 17.9850       | 87%                                 | 39  |
| Surprise | 46  | 60                    | 20 | 45.9680     | 58.2685               | 19.1451       | 94%                                 | 52  |

Table 6. Manual and GA optimal measured parameters

| Emotion  | Manually Computed<br>Mean Value (in<br>pixels) |                       |    | Optimized I    | Mean Value by G | A (in pixels) | 50<br>Images<br>For each<br>emotion | Duration of<br>Emotion<br>Recognition<br>(sec) |
|----------|--|-----------------------|----|----------------|-----------------|---------------|-------------------------------------|--|
|          | <b>b</b> <sub>1</sub>                          | <b>b</b> <sub>2</sub> | b  | x <sub>1</sub> | X2              | х             | Success Rate                        | Mean Time                                      |
| Natural  | 40   | 44                    | 25 | 37.2644        | 41.2531         | 23.6188       | 68%                                 | 118  |
| Fear     | 27   | 44                    | 21 | 25.0287        | 40.9529         | 19.7024       | 73%                                 | 185  |
| Нарру    | 27   | 50                    | 20 | 25.5929        | 46.4742         | 18.0393       | 81%                                 | 146  |
| Sad      | 28   | 37                    | 22 | 26.9104        | 35.4511         | 18.9633       | 68%                                 | 135  |
| Angry    | 27   | 36                    | 19 | 25.2781        | 35.8381         | 16.4120       | 72%                                 | 115  |
| Dislike  | 37   | 32                    | 18 | 34.3409        | 31.6276         | 15.8353       | 74%                                 | 120  |
| Surprise | 46   | 60                    | 20 | 44.6892        | 57.0180         | 17.0701       | 76%                                 | 112  |

## V. CONCLUSION AND FUTURE WORKS

Methods used for emotion recognition are facial expressions, vocal, gesture and physiology signal. For have high speed, low cost, ability tohigh implement and have less time to emotion recognitionwe used from facial expression on static images. The main purpose of this paper is introducing an Imperialist Competitive Algorithm (ICA) to optimizeeve and lip ellipse characteristics. Then performance of three optimization methods including Imperialist Competitive Algorithm (ICA), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for this issue will be addressed. The obtained results show that success rate and running speed in ICA is better than PSO and these two parameters for PSO are better than GA.In total a series of pre-processing tasks such as adjusting contrast, filtering, skin color segmentation and edge detection are done. One of important tasks at this stage after pre-processing is feature extraction. Projection profile method to reason has high speed and high precision

usedinfeature extraction. Secondlyeye and lip features are given as input to ICA, PSO and GA to compute optimized values of b,  $b_1$  and  $b_2$ .Finally in the third stage with using features obtained on optimal ellipse eye and lip, emotion a person according to results Table IV, Table V and Table VIhave been classified. They are exhibit eye and lip ellipses with different parameters in each emotion. On average, by comparing Table IV, Table V and Table VIweobserve that success rate and running speed in ICA is better than PSO and these two parameters for PSO are better than GA.

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