ISSN No. 0976-5697

Volume 3, No. 1, Jan-Feb 2012

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

Comparing Face Emotions with Genetic Algorithm and Particle Swarm Optimization

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Abstract: Emotion recognition in branches facial expressions, vocal, gesture and physiology signal recognition are study. Facial expressions play an important role in personality communication. In this paper we want similar eye and lip to regular and irregular ellipse. The main purpose of this paper is introducing a Particle Swarm Optimization (PSO) algorithm to optimize eye and lip ellipse characteristics. Then the performance two optimization methods including Particle Swarm Optimization (PSO) algorithm and Genetic Algorithm (GA) for this issue will be discussed. The obtained results show that success rate and running speed in PSO algorithm is better than Genetic algorithm.

Keywords: Feature extraction, Projection profile, Eye and lip ellipse, Particle Swarm Optimization algorithm and Genetic algorithm.

I. INTRODUCTION

There are many ways that humans can express their emotions. The most common natural way to express emotions is facial expression. A human can express his/her emotion through lip and eye. A category of emotions which universally developed by Ekman are sadness, angry, joy, fear, disgust and surprise without consider natural emotion. The main goal of this paper is introducing a method to assign an image to one of these categories by using PSO algorithm. In this study for the validity of research a collection of Indian images including 350 images in 7 emotions have been used [9]. 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 used in feature extraction. The second part discusses a PSO-based approach to optimize eye and lip ellipse characteristics. In the third part we use of eye and lip optimal parameters for emotions classification. The rest of this paper organized as follows. Section 2 is an overview of related works. The method with PSO algorithm is described in section 3. Efficiency analysis and results of the method is discussed in section 4 and section 5 contains conclusion.

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 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. Yacoobet 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

The main purpose of this paper is introducing a Particle Swarm Optimization algorithm to optimize eye and lip ellipse characteristics. Then performance of two optimization methods including Particle Swarm Optimization (PSO) Algorithm and Genetic Algorithm (GA) for this issue will be addressed. The obtained results show that success rate and running speed in PSO algorithm is better than Genetic algorithm. Sobel edge detection method due to high speed and small volume of calculations and applied to eye and lip images. The sobel edge detection region for images lip and eye are shown in Fig.1.

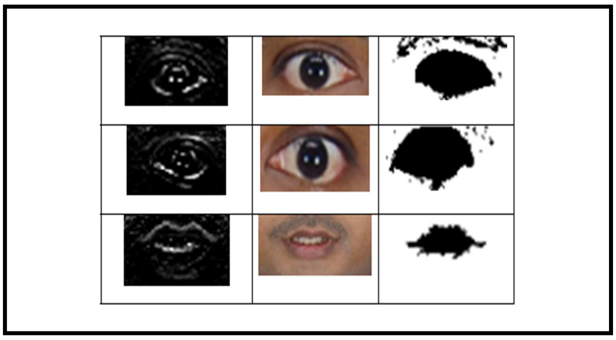

Figure1.Sobel filter for image lip and eye [9]

A. Feature Extraction:

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].

$$\mathbf{Mvj} = \sum_{i=1}^{m} f(i,j) \quad \mathbf{j} = 1,2,3 \ldots n \qquad (1)$$

The horizontal (M_h) with size m is shown by (2) [8].

$$\mathbf{Mhi} = \sum_{j=1}^{n} f(i,j) \quad \mathbf{i} = 1,2,3 \ldots m \qquad (2)$$

The human eye shape is very similar to 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].

$$\frac{\mathbf{x}^2}{\mathbf{a}^2} + \frac{\mathbf{y}^2}{\mathbf{b}^2} = 1 \qquad (3)$$

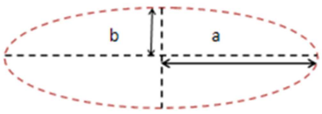

Figure2. The regular ellipse

Human lip is an irregular ellipse and shown in Fig.3.An irregular ellipse has two variable axes. In irregular ellipse parameter "a" fixed and parameters "b_1" and "b_2" are calculated. In the next section PSO algorithm adopted to optimize these features.

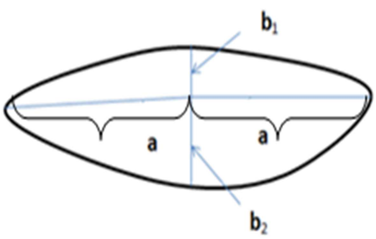

Figure3. The irregular ellipse

B. Particle Swarm Optimization:

The global best, local best, personal best, particle velocity vector, particle position vector and a random number in range(0, 1) respectively are shown with gbest, lbest, pbest, v [], x [] and rand ().To update position and velocity of particles we use of following relations (4) and (5). PSO algorithm parameters are shown in Table I.

v [] = v [] + c_1 * rand () * (pbest [] - x []) + c_2 * rand () * (gbest [] - x []) (4)

x [] = x [] + v [] (5)

IV. EXPERIMENTAL RESULTS

In this study on an Indian subject seven emotions and 350 images were examined [9]. The eye and lip features have been given as input to PSO 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. In Table II manual measured parameters from 350 images and PSO optimized parameters (The mean of parameters) are shown. Table III shows the same calculation with Genetic algorithm. By comparing Table II and Table III we observe that success rate and running speed in PSO algorithm is better than Genetic algorithm.

V. CONCLUSION AND FUTURE WORKS

Current methods for emotion recognition are facial expressions, vocal, gesture and physiology signal recognition. In related works several method were investigated for facial expressions. In this paper we proposed a method based on facial expressions with a new optimization algorithm. 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 eye and lip features are given as input to PSO to compute optimized values of b, b_1 and b_2. Finally in the third stage with using features obtained of optimal ellipse eye and lip, emotion a person according to results Table II is classified. Observation of various emotions leads to a unique characteristic of eye and lip. They are exhibit the eye and lip ellipses with different parameters in each emotion. On average, by comparing PSO and Genetic algorithm for this problem we observe that success rate and running speed in PSO algorithm is better than Genetic algorithm.

Table I. Parameter setting for PSO algorithm

Parameter	***Value***
Defined particle	(x, x_1, x_2)
Number of particles	200
Particle dimension	3
Particle dimension Range	x_1>=0 and x_2<=0
inertia weight	W_{max}=0.9 , W_{min}=0.4
max iteration	500
W(iteration)	W_{max}-((W_{max}- W_{min})/ max iteration)* iteration

Table II. Manual and PSO optimal measured parameters

Emotion	Manually Computed Mean Value (in pixels)			Optimized Mean Value by PSO (in pixels)			50 Images For each emotion	Duration of Emotion Recognition (sec)
	b_1	b_2	b	x_1	x_2	x	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
Happy	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 III. Manual and genetic algorithm optimal measured parameters

Emotion	Manually Computed Mean Value (in pixels)			Optimized Mean Value by GA (in pixels)			50 Images For each emotion	Duration of Emotion Recognition (sec)
	b_1	b_2	b	x_1	x_2	x	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
Happy	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

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