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Using Feed Forward Network to Increase the Accuracy in Face Emotion Recognition

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Abstract: One of best and easiest methods for emotion recognition is facial expressions. Facial expression gives important information about emotion of a person. Face emotion recognition is one of main applications machine vision that widely attended in recent years. It can be used in areas of security, entertainment and human machine interface (HMI). Emotion recognition usually uses of science image processing, speech processing, gesture signal processing and physiological signal processing. In this paper a new algorithm using feed forward neural network based on a set of images to face emotion recognition has been proposed. We recommend use of eyes and lip as biometric elements for face emotion recognition. Face emotion recognition process involves three stages pre-processing, feature extraction and classification. One of biggest problems in classification emotions is overlap in range of values. To increase accuracy in face emotion recognition we recommend use of feed forward neural network. The obtained results show that success rate and running speed in PSO algorithm has improved with feed forward neural network.

Keywords: Face Emotion Recognition, Projection Profile, Particle Swarm Optimization (PSO), Feed Forward Neural Network.

I. INTRODUCTION

Facial expression gives us valuable information about emotion of a person. The important parts for express emotion a person are biometric elements such as eyes and lip. Ekman classifications for emotion recognition are sadness, angry, joy, fear, disgust and surprise without consider natural emotion. In this paper a new algorithm using feed forward neural network based on a set of images to face emotion recognition has been proposed. 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 use in feature extraction. Secondly Particle Swarm Optimization (PSO) algorithm uses to optimize characteristics ellipse eyes and lip. In the third stage by using features obtained from optimal ellipse eye and lip can be classified emotion a person according to experimental results and emotions represented by Ekman. In this study for the validity of research a collection of Indian images including 350 training images and 350 non-training images in seven emotions are used [20].The obtained results show that success rate and running speed in PSO algorithm has improved with feed forward neural network. The rest of this paper organized as follows. Section 2 is an overview of related works. Parameter setting for PSO 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 with88% 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]. Performance optimization algorithms in the classification face emotion recognition are described in Manuscript Acceptance Letter from IJARCS) [9]. Comparing Face Emotions with Genetic Algorithm and Particle Swarm Optimization are described in Manuscript

Acceptance Letter from IJARCS) [10]. Evaluation of Optimization Methods Ant Colony and Imperialist Competitive Algorithm in Face Emotion Recognition are described in Manuscript Acceptance Letter from IJARCS) [11].

III. THE PROPOSED METHOD

To get good results we should similar eye and lip to regular and irregular ellipse. The main objective of this paper is to introduce PSO algorithm to optimize characteristics ellipse eye and lip. Finally we compare the results for this algorithm with use of feed forward neural network and without use of feed forward neural network. One of main reasons for using sobel edge detection filter is high speed and high accuracy. Sobel relations are shown in (1), (2), (3).

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * A \quad , \quad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * A \quad (1)$$

$$G = \sqrt{G_x^2 + G_y^2} \qquad (2)$$

$$\alpha = \arctan\left(\frac{G_y}{G_x}\right) \qquad (3)$$

Sobel filter on the sample image is shown in Fig.1.

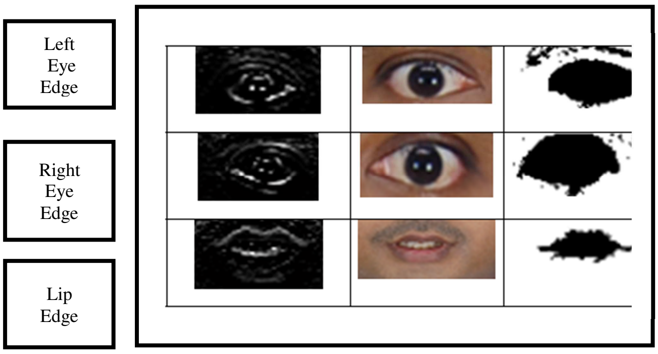

Figure1. Edge Detected of Person Image

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 (4) [8].

$$\mathbf{Mvj} = \sum_{i=1}^{m} f(i,j) \quad \mathbf{j = 1, 2, 3 \ldots n} \qquad (4)$$

The horizontal (M_h) with size m is shown by (5) [8].

$$\mathbf{Mhi} = \sum_{j=1}^{n} f(i,j) \quad \mathbf{i = 1, 2, 3 \ldots m} \qquad (5)$$

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 (6) [8].

$$\frac{\mathbf{x^2}}{\mathbf{a^2}} + \frac{\mathbf{y^2}}{\mathbf{b^2}} = \mathbf{1} \qquad (6)$$

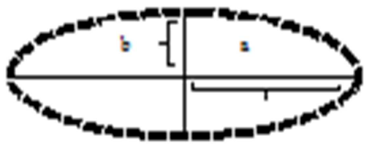

Figure2. The regular ellipse

Person 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_1" and "b_2" are calculated. In the next section PSO algorithm adopted to optimize these features.

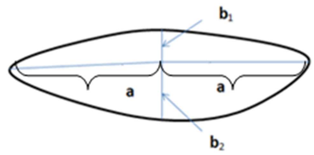

Figure3. The irregular ellipse

For the binary image 8*8 eye or lip horizontal and vertical features extracted are shown in Fig.4.

4	2	2	2	2	2	2	4

0
0
8
2
2
8
0
0

4	2	2	2	2	2	2	4	
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	8
1	0	0	0	0	0	0	1	2
1	0	0	0	0	0	0	1	2
1	1	1	1	1	1	1	1	8
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0

Figure4. Horizontal and vertical features extracted

B. *Proposed Model for Feed Forward Neural Network:*

Classification using standard parameter is shown in Fig.5.Three bits output shows the seven emotions.

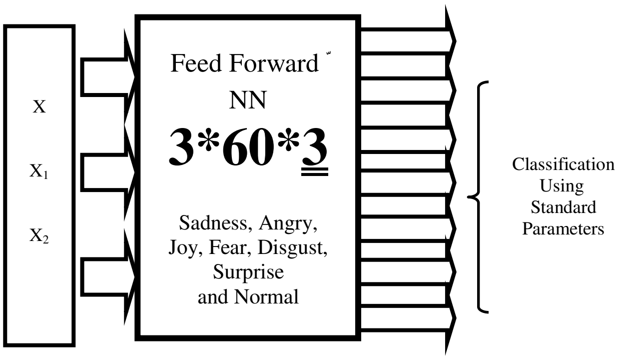

Figure5. Proposed Model for Feed Forward Neural Network

C. *Parameter Setting for PSO 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
V_{max}=20	Variable
Learning factor	[0-2]
stop conditions	500(maximum repetition) , minimum accuracy for ellipse axes
version	local
inertia weight	W_{max}=0.9 , W_{min}=0.4
max iteration	500
W(iteration)	W_{max}-((W_{max}- W_{min})/ max iteration)* iteration

IV. EXPERIMENTAL RESULTS

In this study for the validity of research a collection of Indian images including 350 training images and 350 non-training images in seven emotions are used [20].The eye and lip features have been given as input 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 of optimal ellipsoid axes. Manual and PSO optimal measured parameters without use of feed forward neural network are shown in Table II. Manual and PSO optimal measured parameters with use of feed forward neural network is shown in Table III. One of biggest problems in classification of emotions is overlap in range of values. To increase accuracy in face emotion recognition we recommend use of feed forward neural network. By comparing Table II and Table III we see that success rate and running speed in PSO algorithm has improved with use of feed forward neural network.

V. CONCLUSION AND FUTURE WORKS

An important area, practical, low cost and rapid in emotion recognition is facial expression. Emotion recognition usually uses of science image processing, speech processing, gesture signal processing and physiological signal processing. In this paper a new algorithm with use of feed forward neural network based on a set of images to face emotion recognition has been proposed. We use of eyes and lip as biometric elements for face emotion recognition. Face emotion recognition process involves three stages pre-processing, feature extraction and classification. One of biggest problems in classification emotions is overlap in the range of values. To increase accuracy in face emotion recognition we recommend use of feed forward neural network. The obtained results show that success rate and running speed in PSO algorithm has improved with use of feed forward neural network.

Table II. Manual and PSO optimal measured parameters without use of feed forward neural network

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	43.6355	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 PSO optimal measured parameters with use of feed forward neural network

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	39.5625	43.7856	24.7854	98%	120
Fear	27	44	21	26.4785	43.6524	20.1245	94%	97
Happy	27	50	20	26.1452	49.7842	19.1450	96%	115
Sad	28	37	22	27.4785	36.1021	21.1450	97%	145
Angry	27	36	19	26.2562	35.4582	18.1452	96%	128
Dislike	37	32	18	36.7855	31.7854	17.1201	94%	146
Surprise	46	60	20	45.0125	59.1450	19.1452	98%	135

VI. REFERENCES

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