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RESEARCH PAPER

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Optimization Eye and Lip Curves with Minimization Euclidean Distance and Use Learning Vector Quantization (LVQ) Network for Classification Face Emotion

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Abstract: One of simplest and most commonly methods for emotion recognition is facial expressions. Facial expression gives important information about emotion of a person. Face emotion recognition is one of important issues that widely attended in recent years. It can be used in areas of security, control, entertainment and machine vision. Nowadays for emotion recognition is used of science image processing, speech signal processing, gesture signal processing and physiological signal processing. Our proposal uses of an objective function for minimization sum of Euclidean distance from the given points to the eye and lip curve that PSO algorithm will be used to optimize objective function. We recommend use of ellipse form as eye and lip in face emotion recognition. Face emotion recognition process like presented previous papers involves three stages pre-processing, feature extraction and classification. One of biggest problems in classification emotions is overlap in range of values. To increase success rate and running speed in face emotion recognition we used in this paper for another experience of neural networks with name LVQ neural network. We also show our experiments, we want obtain better results than those previously reported. Additionally our solutions have a low error in success rate.

Keywords: Projection profile, Particle Swarm Optimization (PSO), Euclidean Distance Measurement LVQ Network.

I. INTRODUCTION

Eyes and lips give us important parameters about emotion of a person. The important parts for express emotion a person are biometric elements such as eyes, lips, hands and legs move, how to stand and other cases. Ekman classifications for emotion recognition are sadness, angry, joy, fear, disgust and surprise without consider natural emotion. Our proposal uses of an objective function for minimization sum of Euclidean distance from the given points to eye and lip curve that PSO algorithm will be used to optimize objective function. 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 lips with using minimize the Euclidean distance. 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 particularly success rate has improved. 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 this paper with way Euclidean distance.

III. THE PROPOSED METHOD

To get good results we should similar eye and lip to regular and irregular ellipse. The main purpose of this paper is introducing PSO algorithm to optimize eye and lip curve with using minimize Euclidean distance. Finally, we will show influence minimize the Euclidean distance in optimize Eye and lip curve. One of main reasons for using sobel edge detection filter is high speed and high accuracy. Sobel relations are shown in (1), (2), (3).

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

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

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

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

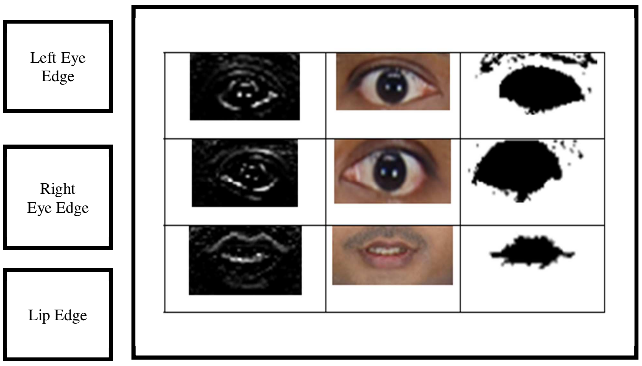

Figure1. Edge Detected of Person Image

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].

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

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

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

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 emotion each person. 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].

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

Note: Eq. (6) can be written in implicit from as:

$$f(x, y) = (a^2y^2+b^2x^2-a^2b^2) = 0 \qquad (7)$$

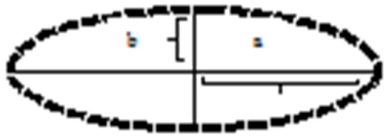

Figure2. The regular ellipse

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.

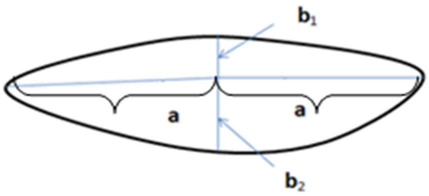

Figure3. The irregular ellipse

The Euclidean distance d, from a point x, to another point y, in R^2 is represented by (8):

$$d = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \quad (8)$$

The squared distance is d^2.

$$E=\sum_{i=1}^{N} d_i \quad (9)$$

This error (E) is calculated as the sum of the Euclidean distances that N points and d as Euclidean distance.

Our method is based on Ellipse fitted according to Fig.4. using Euclidean distance.

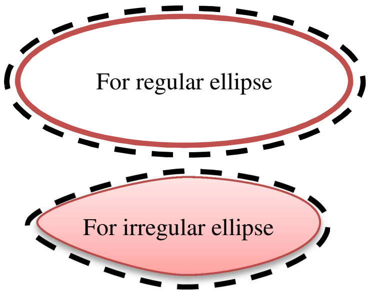

Figure4. Ellipse fitted

For the binary image 8*8 eye or lip horizontal and vertical features extracted are shown in Fig.5.

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

Figure5. Horizontal and vertical features extracted

B. *Proposed Model for LVQ Neural Network:*

Classification using standard parameter is shown in Fig.6.Three bits output shows the seven emotions.

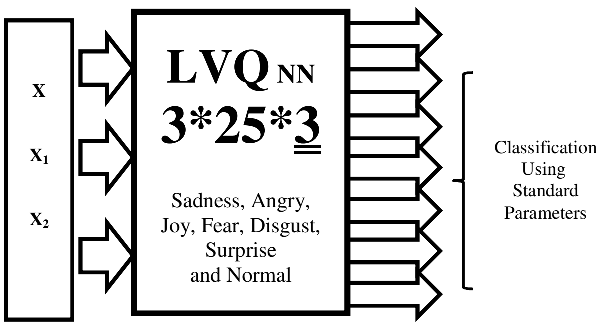

Figure6. Proposed Model for LVQ Neural Network

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 curve optimized 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. PSO optimal measured parameters without use of LVQ neural network and Euclidean Distance is shown in Table II.PSO optimal measured parameters with use of LVQ neural network and Euclidean Distance is shown in Table III. One of biggest problems in classification emotions is overlap in range of values. To increase accuracy in face emotion recognition, we recommend use of LVQ neural network. By comparing Table II and Table III we see that the obtained results show that success rate and running speed particularly success rate has improved.

V. CONCLUSION AND FUTURE WORKS

Eyes and lips give us important parameters about emotion of a person. An important field, 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. Our proposal uses of an objective function for minimization sum of Euclidean distance from the given points to the eye and lip curve that PSO algorithm will be used to optimize objective function. 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 LVQ neural network. We will also show our experiments, we want obtain better results than those previously reported. Additionally our solutions have a low error in success rate

Table II. PSO optimal measured parameters without use of LVQ neural network and Euclidean Distance.

Emotion	**Manually Computed Mean Value (in pixels)**			**Optimized Mean Value by PSO (in pixels)**			**50Images 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	39.4512	43.3636	24.1425	91%	52
Fear	27	44	21	26.7854	43.0145	19.7855	86%	47
Happy	27	50	20	26.1254	48.7855	19.1250	91%	65
Sad	28	37	22	27.4525	36.2785	21.3652	89%	53
Angry	27	36	19	26.1452	35.8965	18.7855	92%	49
Dislike	37	32	18	35.7845	31.1452	17.2541	91%	46
Surprise	46	60	20	45.2514	58.4585	19.7811	94%	65

Table III. PSO optimal measured parameters with use of LVQ neural network and Euclidean Distance.

Emotion	**Manually Computed Mean Value (in pixels)**			**Optimized Mean Value by PSO (in pixels)**			**50Images 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	39.9845	43.9741	24.8969	99%	32
Fear	27	44	21	26.9765	43.8410	20.8748	97%	28
Happy	27	50	20	26.9635	49.9714	19.9630	98%	46
Sad	28	37	22	27.8745	36.7452	21.8749	97%	56
Angry	27	36	19	26.8745	35.8745	18.8741	98%	49
Dislike	37	32	18	36.9741	31.8745	17.8745	97%	46
Surprise	46	60	20	45.6874	59.6978	19.9636	97%	51

VI. REFERENCES

[1] Pantic, M., Rothkrantz, L.J.M. Toward an affect-sensitive multimodal human-computer interaction. Proceedings of the IEEE , Volume: 91 Issue: 9 , Sept. 2003. Page(s): 1370 – Volume: 91 Issue: 9 , Sept. 2003. Page(s): 1370 –1390.

[2] Mase K. Recognition of facial expression from optical flow. IEICE Transc., E. 74(10):3474–3483, 0ctober 1991.

[3] Yacoob, Y., Davis, L. Computing spatio-temporal representations of human faces. Computer Vision and Pattern Recognition, 1994. Proceedings CVPR '94., 1994 IEEE Computer Society Conference on , 21-23 June 1994 Page(s): 70 –75.

[4] Black, M. J. and Yacoob, Y. Tracking and recognizing rigid and non-rigid facial motions using local parametric model of image motion. In Proceedings of the International Conference on Computer Vision, pages 374–381. IEEE Computer Society, Cambridge, MA, 1995.Ekman, P., Friesen, W. V. Facial Action Coding System: A Technique for Measurement of Facial Movement

[5] Consulting Psychologists Press Palo Alto, California, 1978.

[6] Tian, Ying-li, Kanade, T. and Cohn, J. Recognizing Lower Face Action Units for Facial Expression Analysis. Proceedings of the 4th IEEE International Conference on Automatic Face and Gesture Recognition (FG'00), March, 2000, pp. 484 – 490.

[7] Essa, Pentland, A. P. Coding, analysis, interpretation, and recognition of facial expressions. IEEE Transc. On Pattern Analysis and Machine Intelligence, 19(7):757–763, JULY 1997.

[8] Hideaki Tani, Kenji Terada, Shunichiro Oe and Junichi Yamaguchi, "Detecting of one's eye from facial image by using genetic algorithm", The 27thAnnual Conference of the IEEE Industrial Electronics Society, 2001, pp.1937-1940.

[9] Akhari Oskuyee, M. (2011a). Performance Optimization Algorithms In The Classification Face Emotion Recognition. International Journal Of Advanced Research In Computer Science (Ijarcs), 1-4.

[10] Akhari Oskuyee, M. (2011a). Comparing Face Emotions with Genetic Algorithm and Particle Swarm Optimization. International Journal Of Advanced Research In Computer Science (Ijarcs), 1-4.

[11] Akhari Oskuyee, M. (2011a). Evaluation of Optimization Methods Ant Colony and Imperialist Competitive Algorithm in Face Emotion Recognition. International Journal Of Advanced Research In Computer Science (Ijarcs), 1-4.

[12] Rafael C Gonzalez and Richard E Woods, "Digital Image Processing", Pearson Education, Inc, India, 2002.

[13] Keith Anderson and Peter W. McOwan, "A Real-Time Automated System for the Recognition of Human Facial Expressions", IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetics, February 2006, 36(1), pp.96-105.

[14] Maja Panti and Ioannis Patras, "Dynamics of facial expression: recognition of facial actions and their temporal segments from face profile image sequences", IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetics, April 2006, 36(2), , pp.433-449.

[15] Hironori Takimoto, Yasue Mitsukura, Minoru Fukumi and Norio Akamatsu, "Face Detection And Emotional Extraction System Using Double Structure Neural Network", Proc. of the International Joint Conference on Neural Networks, 20-24 July 2003, pp.53-57.

[16] Picard, R., & Klein, J. (2002). Computers that recognize and respond to user emotion: Theoretical and practical implications. Interacting With Computers, 14, 141-169.

[17] Zeng, Z. et al. 2004. Bimodal HCI-related Affect Recognition. ICMI'04, October 13–15, 2004, State College, Pennsylvania, USA.

[18] Rafael A. Calvo, Sidney D'Mello, "Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications," IEEE Transactions on Affective Computing, pp. 18-37, January-June, 2010.

[19] Zhihong Zeng; Pantic, M.; Roisman, G.I.; Huang, T.S.; , "A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions," Pattern Analysis and Machine Intelligence, IEEE Transactions on , vol.31, no.1, pp.39-58, Jan. 2009.

[20] Images Dataset From : sadegnet@yahoo.com

[21] Images Dataset From : sadegnet@yahoo.com