Comparing Frei-Chen & Sobel Edge Detector in Face Emotion Recognition with Euclidean Distance and LVQ Network

Mehdi Akhari Oskuyee *
Master of Science in Mechatronics and Robotics
Tabriz Branch, Islamic Azad University, Tabriz, Iran
sadegnet@yahoo.com

Abstract: In this paper, to increase the execution speed in face emotion recognition instead Sobel edge detector of Frei-Chen edge detector is used. The advantages Frei-Chen method are accurate and better detection, low overhead, detect corners beside with edges and less sensitive to noise than other edge detector. The Frei-Chen algorithm works on a part of image with size 3*3 similarly like the Sobel filter but instead of two masks of 4 masks are used. Of important characteristics this filter can be pointed to 4 masks of unique. For edge detection suitable masks are selected and selected mask is applied on image. This filter such as sobel filter can be used for multi-channel images. Furthermore we know 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 use of science image processing, speech signal processing, gesture signal processing and physiological signal processing. Use of image processing science than other methods can be very useful and helpful. Our proposal uses of an objective function for minimization of 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 of emotions is overlap in range of values. To increase success rate in face emotion recognition we in this paper for another experience of neural networks use of LVQ neural network. We also show experiments face emotion recognition with Sobel filter and Frei-Chen filter. The results show that using Frei-Chen filter against Sobel filter reduces run time.

Keywords: Projection Profile, Particle Swarm Optimization (PSO), Euclidean Distance Measurement LVQ Network and Frei-Chen Edge Detector.

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 positions. 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 of 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 and also using Frei-Chen filter against Sobel filter reduces run time. 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 to 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 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 eye and lip of facial image by genetic algorithm has been suggested recently [8].

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. The main goal in this paper is comparing two methods edge detector Sobel and Frei-Chen. Frei-chen masks are shown in G_{1-4} (1-4).

$$G_1 = \begin{bmatrix} +2 & +3 & +4 \\ 0 & 0 & 0 \\ -2 & -3 & -2 \end{bmatrix} \quad (1)$$

$$G_2 = \begin{bmatrix} +2 & 0 & -2 \\ 0 & -2 & +3 \\ +3 & -2 & 0 \end{bmatrix} \quad (2)$$

$$G_3 = \begin{bmatrix} +3 & 0 & -3 \\ +2 & 0 & -2 \\ -2 & 0 & +2 \end{bmatrix} \quad (3)$$

$$G_4 = \begin{bmatrix} +2 & 0 & -2 \\ -3 & +2 & 0 \\ 0 & +2 & -3 \end{bmatrix} \quad (4)$$

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

Figure1. Edge Detected of Person Image

Frei-chen filter on the sample image is shown in Fig.2.

Figure2. 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 and Frei-Chen 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 (5) [8].

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

The horizontal (M_h) with size m is shown by (6) [8].

$$\mathbf{Mhi} = \sum_{j=1}^{n} f(i,j) \qquad i = 1, 2, 3 \dots m \qquad (6)$$

The human eye shape is more like an ellipse (we call this as a regular ellipse) and shown in Fig.3.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 (7) [8].

$$\frac{x^2}{a^2} + \frac{y^2}{b^2} = 1 \qquad (7)$$

Note: Eq. (7) can be written in implicit from as:

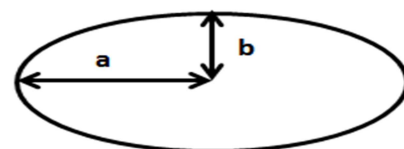F(x, y) = ($a^2y^2+b^2x^2-a^2b^2$) =0 (8)

Figure3. The regular ellipse

Person lip is an irregular ellipse and shown in Fig.4. 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.
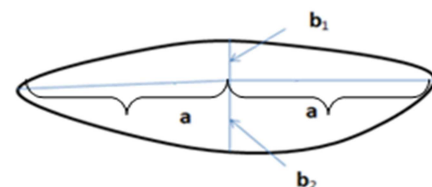

Figure4. The irregular ellipse

The Euclidean distance d, from a point x, to another point y, in R^2 is represented by (9):

$$d = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \qquad (9)$$

The squared distance is d^2.

$$E = \sum_{i=1}^{N} d_i \qquad (10)$$

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.5. by using Euclidean distance.
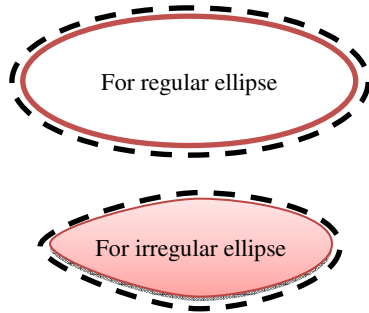

Figure5. Ellipse fitted

For the binary image 8*8 eye or lip horizontal and vertical features extracted are shown in Fig.6.
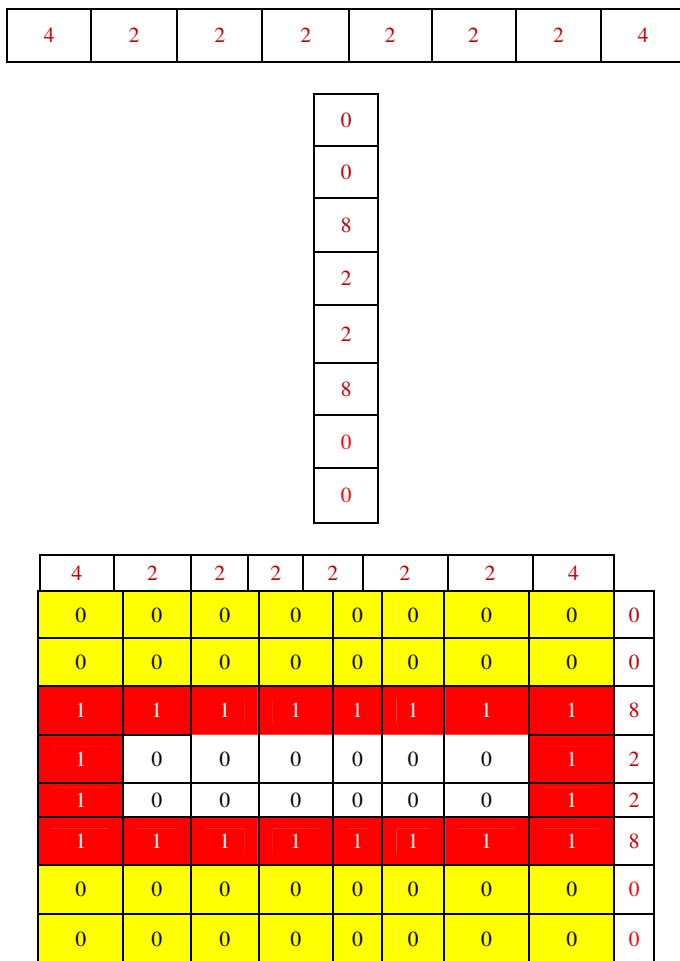

Figure6. Horizontal and vertical features extracted

B. *Proposed Model for LVQ Neural Network:*

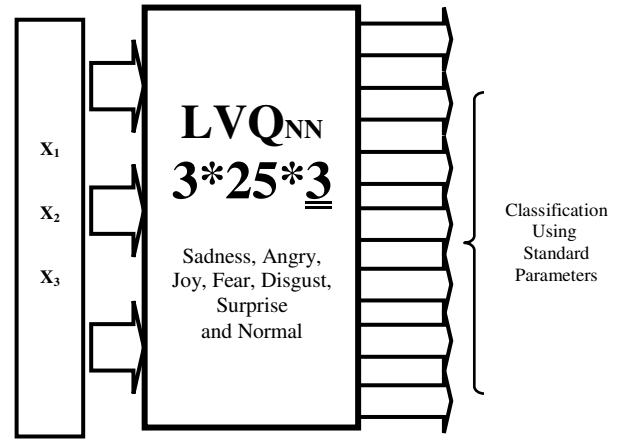Classification using standard parameter is shown in Fig.7.Three bits output shows the seven emotions.

Figure7. Proposed Model for LVQ Neural Network

C. *Parameter Setting for PSO Algorithm:*

Table I. Parameter setting for PSO algorithm

Parameter	Value
Defined particle	(x_1, x_2, x_3)
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_1, x_2, x_3) 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 and use the Sobel filter is shown in Table III. PSO optimal measured parameters with use of LVQ neural network and Euclidean Distance and use the Frei-Chen filter is shown in Table IV. 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 LVQ neural network and Frei-Chen filter against Sobel filter for reduces run time. By comparing Table III and Table IV we see that the obtained results show that success rate and run time has improved and running speed particularly with Frei-Chen filter is acceptable.

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 of emotions is overlap in the range of values. To increase accuracy in face emotion recognition we recommend use of LVQ neural network and Frei-Chen filter against Sobel filter that reduces run time. We also show our experiments in Table II, Table III and Table IV.

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 (**Sobel Filter**).

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

Table IV.PSO optimal measured parameters with use of LVQ neural network and Euclidean Distance (**Frei-Chen Filter**).

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	24.9898	99%	20
Fear	27	44	21	26.9765	43.9859	20.9898	98%	23
Happy	27	50	20	26.9635	49.9714	19.9630	98%	35
Sad	28	37	22	27.9875	36.9858	21.9898	98%	42
Angry	27	36	19	26.9898	35.9858	18.9898	98%	39
Dislike	37	32	18	36.9741	31.9874	17.9898	97%	36
Surprise	46	60	20	45.9858	59.9854	19.9636	99%	41

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