ELSEVIER

CrossMark

Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 84 (2016) 99 – 106

Procedia Computer Science

7th International conference on Intelligent Human Computer Interaction, IHCI 2015

An Approach for Automatic Pain Detection through Facial Expression

Sourav Dey Roy, Mrinal Kanti Bhowmik*, Priya Saha, Anjan Kumar Ghosh

Department of Computer Science & Engineering, Tripura University (A Central University), Suryamaninagar-799022, Tripura, India

Abstract

Automatic pain detection is an emerging area of investigation with convenient applications in health care. The variation in facial expression often provides a clue for occurrence of pain. It provides an important window for the person who cannot verbally describe or rate their level of pain. To meet up the specific necessities, a framework has been designed for extraction of features from the face for automatic pain detection through facial expression. In this framework, Gabor filtering and Principal Component Analysis (PCA) are used as contributive steps that improves the performance of the system in terms of accuracy. To verify the accuracy and robustness of the system, experiments have been conducted on UNBC-McMaster Shoulder Pain Expression Archive Database at both frame level (person dependent) and image level (person independent). The methodology achieves 87.23% accuracy for detection of pain at frame level. Also the methodology achieves 82.43% accuracy for classifying the frames between four pain level (i.e. PSPI of 0, 1, 2 and >=3). The success rate of the methodology for pain detection at image level is 95.5%.

Peer-review under responsibility of the Organizing Committee of IHCI 2015

Keywords: Pain; Pain Expression; Facial Action Coding System (FACS); Generalized Procrustes Analysis; Affine Warping; Gabor Filtering.

1. Introduction

Man-machine interface is one of the promising area from the beginning of computing machines and plays a crucial role for designing a system that could accurately distinguish and understand the human behavior. The present study focuses on one specific properties of pain behavior i.e. automatic pain detection through facial expression. Pain is a highly unpleasant sensation caused by illness or injury or it can be the mental distress or suffering [1]. It is

* Corresponding author. Tel.: +91-9436129933; fax: +0-381-237-4802.
*E-mail address:*mkb_cse@yahoo.co.in

Peer-review under responsibility of the Organizing Committee of IHCI 2015
doi:10.1016/j.procs.2016.04.072

often regarded as fifth vital sign in regard to healthcare because it is considered now in healthcare that pain, like other critical signs, is an objective sensation. According to National Centers for Health Statistics, about 76.2 millions of people in world suffer from pain.

Generally medical abnormalities are difficult to assess and manage and are typically measured by patients self-report [2]. This and analogous procedures are accepted because it is simple and easy to understand and often provide information that validates the level of pain that is experienced by the person. However these methods only work when the patient is sufficiently alert and cooperative, which is not always possible in the medical field. But beyond this pain assessment using self-report measures is a significant challenge and is not always reliable and valid in critically ill adults, especially those who are unable to communicate their pain level, e.g. with individuals of dementia and certain types of neurological disorder and also patients in Intensive Care Unit (ICU) needing oxygen mask for breathing. Furthermore, it cannot be applied for unconscious or new born patients. To overcome these restrictions observational and psychological measures has become indispensable.

Human face is a rich resource of nonverbal information that provides clues for understanding social emotions and can be helpful to reveal mental condition via social signals. The variation in facial expression often symbolizes the occurrence of pain. Clinicians and laypeople place great importance on the credibility of these behaviors and view them as consistent and convincing sign of pain. Facial activity has been in cooperated as a primary or major component of most multidimensional behavioral checklists or rating scales for assessing pain. There is a considerable amount of literature in which Facial Action Coding System (FACS) [2][3] has been applied to pain expression. Although the configuration displayed during pain shares the components with facial displays during pain and other negative emotional states have unique patterns that can be distinguished when the detail and configurations of actions are examined.

The paper mainly explores a newly framed approach for automatic pain detection through facial expression. The framework includes Gabor filtering as a contributive steps for extraction of features from faces and reducing dimensions using Principal Component Analysis (PCA) which increases the detection rate based on the comparative study described in section 5. The strength of the system is assessed by testing on UNBC-McMaster Shoulder Pain Expression Archive Database [3]. Also Graphical User Interface (GUI) based software is designed that could automatically detect and estimate four levels of pain at both frame level and image level.

The whole paper is organized as; section 2 describes the literature survey on pain detection. Section 3 explains the proposed methodology. In Section 4, a performance evaluation measure has been illustrated and reports the experimental results with discussion of the proposed methodology. In Section 5, a comparative study of the proposed methodology with respect to other techniques is provided. Also Section 5 gives an overview of Graphical User Interface (GUI) design of the proposed methodology for pain detection. And finally, section 6 concludes the paper.

2. Literature Review

From an arrangement of facial actions that signals pain through analyzing the presence of facial actions can reduce a difficulty of pattern recognition. In the recent year, the research communities have sparked off thunder for developing computed based techniques to advance this area. The analysis of these papers is shown in Table I. In [4], Ashraf et al. used Active Appearance Model (AAM) on digital videos containing pain expressions and then used machine learning procedure to classify between pain and no pain. With the advantage of representing dynamic alterations in pain-related actions the best performing predictive model gives a hit rate of 83%. In [5], Lucey et al. revised an AAM and Support Vector Machine (SVM) to develop an automatic system for frame level pain detection in two ways on the images of patients with rotator-cuff injuries: first straight from the facial features that is in a direct manner and second through the fusion of individual Action Unit (AU) detectors. In [3], Lucey et al. extended their work as described in [5] to detect pain from a patients face using an AAM approach on a frame-by-frame basis. They have shown that fusing all AAM representations together using linear logistical regression (LLR) provides a noticeable performance for detection of pain and action units in frame. In [6], Kaltwang et al. [6] proposed used a different shape of facial landmarks and appearance features i.e. Discrete Cosine Transformation (DCT), Relevance Vector Regression (RVR) and Local Binary Pattern (LBP) and then fused these features and thus showed that fusion of these features leads to better estimation of pain level as compared to feature specific estimation of pain intensity. In [7], Hammal et al. also used AAM to extract the canonical normalized appearance of the face (CAPP) and then passed through a set of Log-Normal filters. Finally SVM classifier is used to detect pain level on a frame-by-frame level and obtained 73% accuracy.

Table 1. Survey Tables of Different Techniques of Pain Expression Detection based on Automatic Approaches

Author/ Year	Method Used	Used Database	Accuracy
Ashraf et al./ 2009 [4]	AAM and SVM	UNBC-Mac Master Shoulder Pain Expression Archive Database	82% accuracy
Lucey et al./ 2009 [5]	AAM and SVM	UNBC-Mac Master Shoulder Pain Expression Archive Database	Not Provided
Lucey et al./ 2011 [3]	AAM, SVM, and LLR	UNBC-Mac Master Shoulder Pain Expression Archive Database	79.66% accuracy
Kaltwang et al./ 2012 [6]	DCT, LBP, RVR	UNBC-Mac Master Shoulder Pain Expression Archive Database	92% accuracy
Hammal et al./ 2012 [7]	AAM, Log-normal filters and SVM	UNBC-Mac Master Shoulder Pain Expression Archive Database	73% accuracy

3. Methodology

The proposed methodology has been illustrated in Fig.1 through the block diagram. The methodology is a combined approach of different techniques for extraction of features from image frames for automatic detection of pain. In the pre-processing stage all the image frames are converted into grayscale images. Then these gray scale images are used for further processing so as to detect pain. The brief details of all the steps are illustrated below.

3.1. Facial Region Extraction

Iterative Shape Alignment Using Procrustes Analysis:

The shapes of the faces are iteratively aligned so as to remove all geometric disparity i.e. scale, rotation and translation of the vertex location with respect to the base shape [8][9]. The alignment of multiple shapes is based on aligning pairs of shapes where one of them is a reference frame. For this Generalized Procrustes Analysis (GPA) is performed which consists of sequentially aligning pair of shapes with using the reference shape (the mean shape) and align the others to it. At the beginning of the procedure, any shape can be selected as the initial mean. After the alignment a new mean is recomputed, and again the shapes are aligned to this mean. This procedure is performed repeatedly until the mean shape doesn't change significantly within iterations.

Texture Warping

After aligning all the shapes, warping of texture is carried out using a piece-wise affine warping [11] to normalize all non-rigid texture samples with respect to the base shape. A piece-wise affine warping is a texture mapping procedure where convex hull of the mean shape and the sample shapes are partitioned using Delaunay

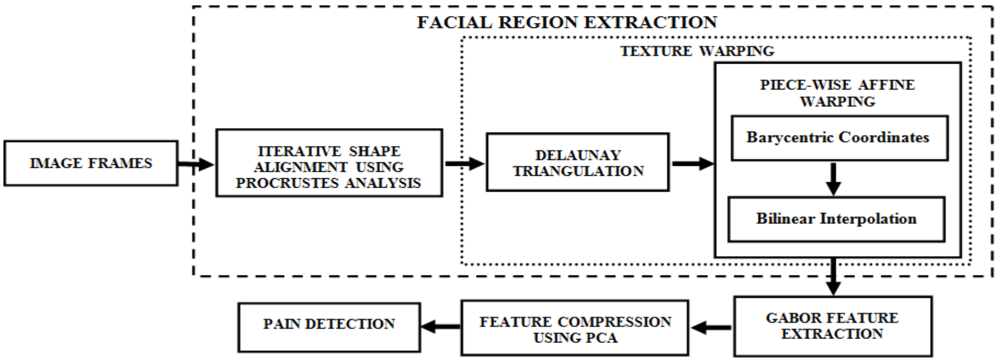

Fig. 1. Block diagram of the Proposed Automatic Pain Detection Method

triangulation [3][4][10]. Then each pixel from the training image, belonging to a specific triangle, is mapped into the respective destination triangle in the mean shape frame using barycentric coordinates with bilinear interpolation correction. The implementation of piecewise affine warp is illustrated below.

Any point, $\mathbf{x} = [x, y]^{\mathrm{T}}$, in a triangle can be defined as function of its three vertices x_1, x_2 and x_3 in a way that

$$\mathbf{x} = \mathbf{f}(\mathbf{x}) = \mathbf{x}_1 + \boldsymbol{\beta}(\mathbf{x}_2 - \mathbf{x}_1) + \boldsymbol{\gamma}(\mathbf{x}_3 - \mathbf{x}_1) = \boldsymbol{\alpha}\mathbf{x}_1 + \boldsymbol{\beta}\mathbf{x}_2 + \boldsymbol{\gamma}\mathbf{x}_3 \tag{1}$$

Where coefficients of **α, β** and **γ** are real numbers and are named barycentric coordinates of **x** such that $\boldsymbol{\alpha} + \boldsymbol{\beta} + \boldsymbol{\gamma} = 1$.

Here,

$$\begin{aligned}
\boldsymbol{\gamma} &= 1 - (\boldsymbol{\beta} + \boldsymbol{\alpha}) \\
\boldsymbol{\alpha} &= \frac{\mathbf{y}\mathbf{x}_3 - \mathbf{x}_1\mathbf{y} - \mathbf{x}_3\mathbf{y}_1 - \mathbf{y}_3\mathbf{x} + \mathbf{x}_1\mathbf{y}_3 + \mathbf{x}\mathbf{y}_1}{-\mathbf{x}_2\mathbf{y}_3 + \mathbf{x}_2\mathbf{y}_1 + \mathbf{x}_1\mathbf{y}_3 + \mathbf{x}_3\mathbf{y}_2 - \mathbf{x}_3\mathbf{y}_1 - \mathbf{x}_1\mathbf{y}_2} \\
\boldsymbol{\beta} &= \frac{\mathbf{x}\mathbf{y}_2 - \mathbf{x}\mathbf{y}_1 - \mathbf{x}_1\mathbf{y}_2 - \mathbf{x}_2\mathbf{y} + \mathbf{x}_2\mathbf{y}_1 + \mathbf{x}_1\mathbf{y}}{-\mathbf{x}_2\mathbf{y}_3 + \mathbf{x}_2\mathbf{y}_1 + \mathbf{x}_1\mathbf{y}_3 + \mathbf{x}_3\mathbf{y}_2 - \mathbf{x}_3\mathbf{y}_1 - \mathbf{x}_1\mathbf{y}_2}
\end{aligned} \tag{2}$$

So, the coordinate of pixels in the original image is recalculated by (1) and (2) as

$$W(x; p) = \mathbf{x}_1' + \boldsymbol{\beta}(\mathbf{x}_2' - \mathbf{x}_1') + \boldsymbol{\gamma}(\mathbf{x}_3' - \mathbf{x}_1') \tag{3}$$

3.2. Feature Extraction using Gabor Filtering

After extraction of facial regions, the next step is facial feature extraction to produce feature vectors. Gabor filters (also called as Gabor kernels) is an important method in the field of image analysis because of its optimal localization properties in both spatial and frequency domain. It is used to extract the changes in facial appearance as a set of multiscale and multiorientation coefficients. In the spatial domain, a 2D Gabor filter is a complex exponential modulated by a Gaussian function and can be defined as follows [12][13][14]:

$$g(x, y, \omega, \theta) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{(x\cos\theta + y\sin\theta)^2 + (-x\sin\theta + y\cos\theta)^2}{2\sigma^2}\right)} [e^{iw(x\cos\theta + y\sin\theta)} - e^{-\frac{w^2\sigma^2}{2}}] \tag{4}$$

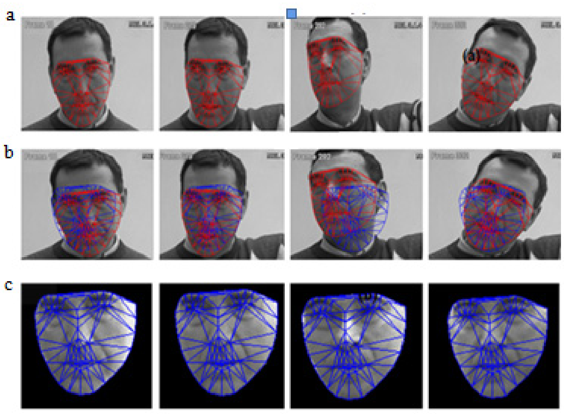

Fig.2. Samples of (a) Delaunay Triangulated Face Shapes; (b) Mean Shape over Original Shape; (c) Image Warping to the Mean Shape

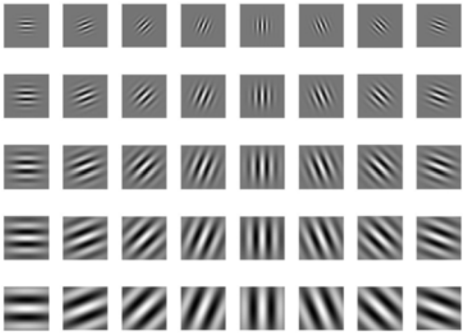

Fig.3. The Real Part of the Gabor Masks of Five Scales and Eight Orientation

where (x, y) denotes the pixel location of the image in the spatial domain, ω is the center frequency, θ represents the orientation and σ denotes the standard deviation of the round Gaussian function in x and y axes. The Gabor feature representation of an image $f(x, y)$ is given by:

$$r(x,y) = f(x,y) * g(x, y, \omega, \theta) \tag{5}$$

In this work, a Gabor mask with five scales and eight orientation is used to extract the Gabor feature vector from face. The real part of the Gabor filter of five scales and eight orientations is shown in Fig. 3.

3.3. Feature Compression using PCA

After facial feature extraction using Gabor kernel, Principal Component Analysis (PCA) is used for feature compression to overcome the problem and computational burden of high dimensionality by linear combination of features [15]. The dimensional reduced feature vectors y_i are defined by:

$$y_i = w_{PCA}^T x_i \text{ (Here, i=1, 2, ...N)} \tag{6}$$

Where w_{PCA} is the linear transformations matrix and the columns of w_{PCA} are the p Eigen vectors corresponds to the p largest Eigen values of the covariance matrix, which is defined as

$$Cov = \frac{1}{N-1}\sum_{i=1}^{N}(\mathrm{x}_i - \mu)(\mathrm{x}_i - \mu)^T \tag{7}$$

Here μ is the mean of all samples.

3.4. Classification using SVM

Based on the response of Gabor kernel and compression of features using PCA, SVMs are then used to classify between painful and non-painful faces as well as to classify four level of pain [16]. To correctly classify the images, the decision of linear SVM classification function decision is given by [16]:

$$\begin{aligned} &w^T x_i + b \geq 1 \text{ if } y_i = 1, \text{ and} \\ &w^T x_i + b \leq -1 \text{ if } y_i = -1 \end{aligned} \tag{8}$$

Where w denotes the weight vector partitioning the hyper plane, x_i is a N dimensional compressed Gabor feature vector, y_i is denoting the class to which the feature vector x_i belongs and b is the bias.

4. Performance Analysis and Experimental Results

The performance evaluation of proposed methodology in the literature has been given in terms of accuracy. It measures the proportion of true and false results those are detected correctly with respect to the total number of images. The formula for measuring accuracy (in %) is given by:

$$\text{Accuracy (in \%)} = \frac{\text{TP} \times 100}{\text{N}} \tag{9}$$

Where,

TP= Number of image frames correctly detected.
N= Total number of image frames.

To fully explore the system performance; experiments of the methodology was done for pain detection at both frame level as well as image level (i.e. pain and no pain detection) on UNBC-McMaster Shoulder Pain Expression Archive Database [7][8]. Also experiment of the methodology was conducted for four level pain detection at frame level.

4.1. Experimental Performance for Pain Detection at Frame Level

To assess the performance of the system for detection of pain at frame level, SVM was trained using positive examples which consisted of features of the frames that are labelled by the FACS coder having PSPI of 1 or more [7]. Also negative examples consisting of the features of the frames with PSPI of 0 (zero) was trained. And for testing the system, another set of frames of the same person that are not given for training the system are used. The average success rate of methodology for detection of pain at frame level is 87.23% and for no-pain is 89.19%.

Also to assess the performance of the system, experiment was conducted for four level pain detection at frame level (i.e. whether the frame is having no pain, tolerable pain, weak pain or strong pain). The performance of the methodology for four level pain detection is shown through bar diagram in Fig. 4. The average success rate of tolerable pain (PSPI=1), weak pain (PSPI=2) and strong pain (PSPI>=3) detection are 76.60%, 76.59% and 81.14% respectively whereas the accuracy of the no pain detection is 87.72%.

4.2. Experimental Performance for Pain Detection at Image Level

For conducting experiment of pain detection at image level, we have considered two sets of images for training and testing. Each set contains positive examples which consisted of images of several persons that are labelled by the FACS coder having PSPI of 1 or more. . Also negative examples consisting of the images of several persons that were labelled with PSPI of 0 (zero) was trained. The obtained performance of the system is listed in Table 2. The accuracy of the methodology for detection of pain and no pain at image level are 96.25% and 94.75% respectively.

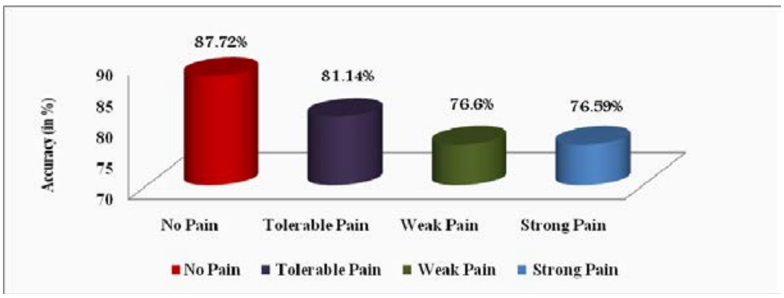

Fig. 4. Accuracy of the Methodology for Four Level Pain Detection at Frame Level

Table 2. Accuracy of the Methodology for Detection of Pain at Image Level

Pain Level	Associated PSPI	No. of Training Images	No. of Testing Images	No. of Images Correctly Detected	Accuracy (in %)
No Pain	0	500	400	379	94.75%
Pain	>=1	500	400	385	96.25%

5. Comparative Study and Graphical User Interface Design

In [4], Ashraf et al. reported the 79.5% accuracy for frame level pain detection with a false acceptance rate of 37% on UNBC-McMaster Shoulder Pain Expression Archive Database. Lucey et al. [3] and Hammal et al. [7] have also assess the performance of their automated system based on accuracy. So, by comparing success rate of our methodology with techniques developed by other researchers as shown in Table 3, we can say that our pain detection method generates noticeable results on the above mentioned database.

A Graphical User Interface (GUI) based prototype system has been designed for pain detection at both frame and image level as shown in Fig. 5. For performing all the required steps total three interfaces are designed. The first interface contains the “Menu Page” i.e. whether we want to detect pain at image level or frame level as shown in Fig. 5(a). The second interface shows all the intermediate steps for extraction of features from face as shown in Fig. 5(b) and finally if we click on push button “Classify Image” it classifies the image between painful and non painful faces. The interface for pain detection at image level are same as Fig. 5(b).

6. Conclusion and Future Work

Here we have presented a methodology for automatic pain detection that could alert hospital staffs timely and provide additional information for patient’s medical record. The methodology has experimental rate of 88.21% and 95.5% for pain detection at frame level and image level respectively and has success rate of 82.43% for four level pain detection. In future more emphasis will be given to integrate new techniques to extract more features from the image frames to enhance the performance of the system in terms of robustness, accuracy and adaptivity.

Table 3. Comparative Study of the Proposed Method with Other Methods

Author	Database	Pain Detection	Accuracy
Ashraf et al./ 2009 [4]	UNBC-Mac Master Shoulder Pain Expression Archive Database	Pain Detection at Frame Level	79.5%
Lucey et al./ 2011 [3]	UNBC-Mac Master Shoulder Pain Expression Archive Database	Pain Detection at Frame Level	79.66%
Hammal et al./ 2012 [7]	UNBC-Mac Master Shoulder Pain Expression Archive Database	Four Level Pain Detection at Frame Level	73%
Our Method	UNBC-Mac Master Shoulder Pain Expression Archive Database	Pain Detection at Frame Level	88.21%
		Four Level Pain Detection at Frame Level	82.43%
		Pain Detection at Image Level	95.5%

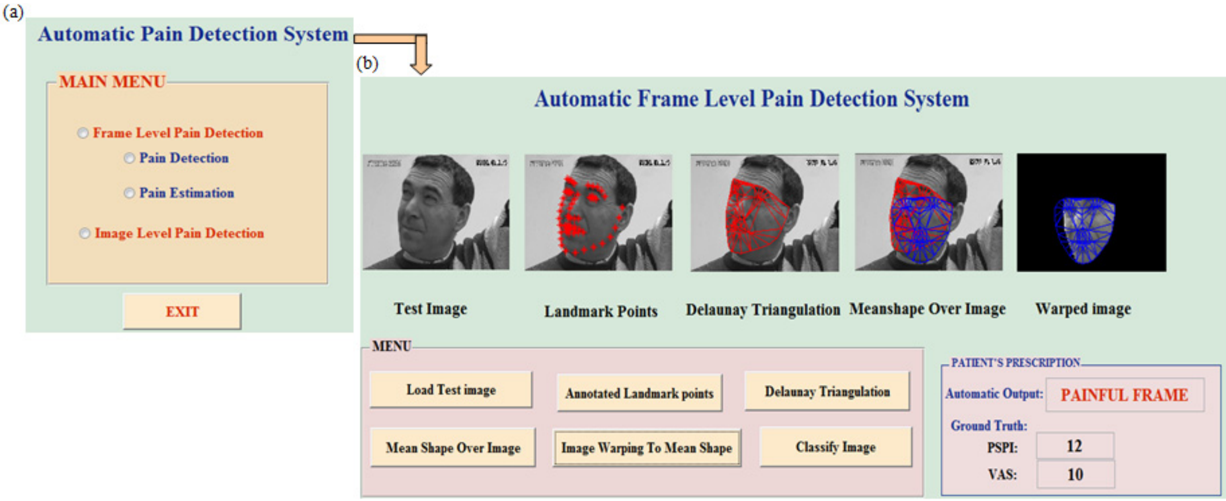

Fig.5. Overview of Graphical User Interface of the proposed System

Acknowledgements

The work presented here is being conducted in the Bio-Medical Infrared Image Processing Laboratory (B-MIRD), Department of Computer Science and Engineering, Tripura University (A Central University), Suryamaninagar-799022, Tripura(W). The research work was supported by the Grant No. BT/533/NE/TBP/2013, Dated 03/03/2014 from the Department of Biotechnology (DBT), Government of India.

References

1. Huskisson EC. Measurement of pain. *The Lancet* 1974; 304(7889): 1127-1131.
2. Prkachin KM, Solomon PE. The structure, reliability and validity of pain expression: Evidence from patients with shoulder pain. *Pain* 2008; 139(2): 267-274.
3. Lucey P, Cohn JF, Prkachin KM, Solomon PE, Matthews I. Painful data: The unbc-mcmaster shoulder pain expression archive database. *IEEE International Conference on Automatic Face & Gesture Recognition and Workshops (FG 2011)* 2011: 57-64.
4. Ashraf AB, Lucey S, Cohn JF, Chen T, Ambadar Z, Prkachin KM, Solomon PE. The painful face-pain expression recognition using active appearance models. *Image and vision computing 2009;* 27(12): 1788-1796.
5. Lucey P, Cohn J, Lucey S, Matthews I, Sridharan S, Prkachin KM. Automatically detecting pain using facial actions. *3rd International Conference on Affective Computing and Intelligent Interaction and Workshops (ACII 2009) 2009*; IEEE*:* 1-8.
6. Kaltwang S, Rudovic O, Pantic M. Continuous pain intensity estimation from facial expressions. *Advances in Visual Computing* 2012; Springer: 368-377.
7. Hammal Z, Cohn JF. Automatic detection of pain intensity. *Proceedings of the 14th ACM international conference on Multimodal interaction* 2012*:* 47-52.
8. Gower JC. Generalized procrustes analysis. *Psychometrika* 1975; 40(1): 33-51.
9. Cootes TF, Edwards GJ, Taylor CF. Active appearance models. *IEEE Transactions on pattern analysis and machine intelligence* 2001; 23(6): 681-685.
10. Zhu B. Voronoi diagram and delaunay triangulation: Applications and challenges in bioinformatics. *3rd International Symposium on Voronoi Diagrams in Science and Engineering (ISVD'06)* 2006; IEEE: 2-3.
11. Wang L, Li R, Wang K. A novel automatic facial expression recognition method based on aam. *Journal of Computers* 2014; 9(3): 608-617.
12. Deng HB, Jin LW, Zhen LX, Huang JC. A new facial expression recognition method based on local gabor filter bank and pca plus lda. *International Journal of Information Technology* 2005; 11(11): 86-96.
13. Lyons M, Akamatsu S, Kamachi M, Gyoba J. Coding facial expressions with gabor wavelets. *Proceedings of Third IEEE International Conference on Automatic Face and Gesture Recognition* 1998: 200-205.
14. Shan C, Gong S, McOwan PW. Facial expression recognition based on local binary patterns: A comprehensive study. *Image and Vision Computing* 2009; 27(6): 803-816.
15. Turk M, Pentland A. Eigenfaces for recognition. *Journal of cognitive neuroscience* 1991; 3(1): 71-86.
16. Li J, Zhao B, Zhang H, Jiao J. Face recognition system using svm classifier and feature extraction by pca and lda combination. *IEEE International Conference on Computational Intelligence and Software Engineering (CiSE 2009)* 2009: 1-4.