iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 4 **Issue:** XI **Month of publication:** November 2016

DOI:

Volume 4 Issue XI, November 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

The Faces of Engagement: A Method to Infer Emotions from Facial Action Units

Thasneem PV
Department of Applied Electronics and Communication System
Cochin College of Engineering and Technology –Kerala

Abstract: We present a robust method to map detected facial Action Units (AUs) to six basic emotions. Automatic AU recognition is prone to errors due to illumination, tracking failures and occlusions. Hence, traditional rule based methods to map AUs to emotions are very sensitive to false positives and misses among the AUs. In our method, a set of chosen AUs are mapped to the six basic emotions using a learned statistical relationship and a suitable matching technique. Relationships between the AUs and emotions are captured as template strings comprising the most discriminative AUs for each emotion. The template strings are computed using a concept called discriminative power. The Longest Common Subsequence (LCS) distance, an approach for approximate string matching, is applied to calculate the closeness of a test string of AUs with the template strings, and hence infer the under lying emotions. LCS is found to be efficient in handling practical issues like erroneous AU detection and helps to reduce false predictions.
Keywords:-LBP-ICA-PCA-LDA-String Template

I. INTRODUCTION

Learning from intelligent educational interfaces elicits frequent affective responses from students and wide variations in their behavior. A variety of affective states occur frequently in learning contexts, and can have both positive and negative effects on students' learning For example, students often encounter exercises that require information or techniques with which they are not familiar. Confusion, frustration, boredom, and other affective states are elicited in response to how these impasses are resolved [14] These and other affective experiences are particularly important because they are inextricably bound to learning by coloring students' perceptions of a learning environment and changing how well they learn from it.Student engagement has been a key topic in the education literature since the 1980s. Early interest in engagement was driven in part by concerns about large drop-out rates and by statistics indicating that many students, estimated between 25 and 60 percent, reported being chronically bored and disengaged in the classroom. Statistics such as these led educational institutions to treat student engagement not just as a tool for improving grades but as an independent goal unto itself. Nowadays, fostering student engagement is relevant not just in traditional classrooms but also in other learning settings such as educational games, intelligent tutoring systems (ITS) and massively open online courses (MOOCs).

A huge population of users from all around the world with diverse contents, ranging from daily news feeds to entertainment feeds including music, videos, sports, and so forth is served, by using streaming transmission technologies. Also, with virtual private networks (VPNs), real-time video streaming communications such as web conference in intra company networks or via Internet are being widely deployed in a large number of corporations as a powerful means of efficiently promoting ditional costs. Rather than packet filtering by firewall-equipped way out nodes is an easy solution to avoid leakage of streaming contents to external networks.

The education research community has developed various taxonomies for describing student engagement. Fredricks et al. analyzed 44 studies and proposed that there are three different forms of engagement: behavioral, emotional, and cognitive. Anderson et al.[3] organized engagement into behavioral, academic, cognitive, and psychological dimensions. The term behavioral engagement is typically used to describe the student's willingness to participate in the learning process, e.g., attend class, stay on task, submit required work, and follow the teacher's direction

II. OBJECTIVE

A human teacher can observe students' affect in a classroom or one-on-one tutoring situation and use that information to determine who needs help and to adjust the pace or content of learning materials. On the other hand, computerized learning environments used in school computer labs rarely incorporate such accommodations into their instructional strategies. One of the many challenges of

Volume 4 Issue XI, November 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

creating intelligent educational interfaces is developing systems that can detect and respond to the affective states of students, though some initial progress has been made in laboratory settings (see [8] for a recent review The goal of these interfaces is to provide a computerized learning environment that responds to the affective needs of students, whether by redirecting off-task behavior, providing encouragement, or altering learning materials to better suit the student. Much work remains to be done for effective affect-sensitivity in learning environments in the wild, however. At the core of such systems is the ability to detect or anticipate the affective state and emotions of students, a proposition considered in this paper.

III. LITERATURE REVIEW

A literature survey is done for specified papers which are essential to know the existing techniques their significance and limitations. It also includes various supporting papers for the proposed technique and their advantages. Here all the papers are viewed based on its algorithm architectural flow.Automatic Prediction of Frustration And Multimodal Affect Recognition In Learning Environment:Kapoor et al. [11] developed the first system detecting affect in a learning environment. They used multimodal data channels including facial features (from Dynamic scalable service model for video conferencing video), a posture-sensing chair, a pressure-sensitive mouse, a skin conductance sensor, and interaction data to predict frustration in an automated learning companion. They were able to predict when a user would self-report frustration with 79% accuracy (chance being 58%). Furthermore, using similar multimodal sensor fusion techniques including facial features, Kapoor et al. [12] were able to classify interest/disinterest with 87% accuracy (chance being 52%).Exploring Temporal Patterns In Classifying Frustrated And Delighted Smiles**:**The Hoque et al. [13] used facial features and temporal information in videos to classify smiles as either frustrated or delighted – two states that are related to learning. They accurately distinguished between frustrated and delighted smiles correctly in 92% of cases. They also found differences between acted facial expressions and naturalistic facial expressions. In acted data only 10% of frustrated cases included a smile, whereas in naturally occurring frustration smiles were present in 90% of cases. These results illustrate the fact that there can be large differences between naturalistic and posed data.

The faces of engagement: automatic recognition of student engagement from facial expressions:In a more recent affect detection effort, Whitehill et al. [1] used Gabor features (appearance-based features capturing textures of various parts of the face) with a support vector machine (SVM) classifier to detect engagement as students interacted with cognitive skills training software. Labels used in their study were obtained from retrospective annotation of videos by human judges. Four levels of engagement were annotated, ranging from complete disengagement (not even looking at the material) to strong engagement. They were able to detect engagement with an Area Under the ROC Curve (AUC, averaged across all four levels of engagement) of .729 where AUC = .5 is chance level detection.It's written on your face: detecting affective states from facial expressions while learning computer programming: In another study using CERT, Bosch and D'Mello [6] used machine learning to build fine-grained detectors for learning-centered affective states of novice programming students using the likelihoods of AUs provided by CERT. The students took part in the study in a laboratory setting. Students made retrospective judgments of their own affective states. Confusion and frustration were detected at levels above chance (22.1% and 23.2% better than chance, respectively), but performance was much lower for other states (11.2% above chance for engagement, 3.8% above chance for boredom). Automatic local Gabor features extraction for face recognition

In this paper a biometric system of face detection and recognition in color images. The face detection technique is based on skin color information and fuzzy classification. A new algorithm is proposed in order to detect automatically face features (eyes, mouth and nose) and extract their correspondent geometrical points. These fiducial points are described by sets of wavelet components which are used for recognition. To achieve the face recognition, we use neural networks and we study its performances for different inputs. We compare the two types of features used for recognition: geometric distances and Gabor coefficients which can be used either independently or jointly. This comparison shows that Gabor coefficients are more powerful than geometric distances.

IV. PROPOSED SYSTEM

In this paper student engagement is calculated by frame by frame recognition. Many techniques developed for emotion and facial action unit classification can be applied to the engagement recognition problem

Proposed a three stage pipeline:

A. Face registration

The face and facial landmark (eyes, nose, and mouth) positions are localized automatically in the image; the face box coordinates

Volume 4 Issue XI, November 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

are computed; and the face patch is cropped from the image.

B. The cropped face patch is classified by four binary classifiers one for each engagement category $l \epsilon \{1,2,3,4\}$.
C. The outputs of the binary classifiers are fed to a regressor to estimate the image's engagement level.

For classification we use SVM classifier and use two alternative strategies:

1) Linear regression for real-valued engagement regression
2) Multinomial logistic regression for four-way discrete engagement level classification.

Two Modifications are done in this project.

D. Feature extraction using LBP(Local Binary Pattern)

Is a simple yet very efficient texture operator which labels the pixels of an image by threasholding the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity.

It is possible to implement this system on low resolution images, but make sure that the selected image is free from all forms of noises.

There are two common approaches to extract facial features:

1) *Geometric feature-based methods:* Geometric features present the shape and locations of facial components, which are extracted to form a feature vector that represents the face geometry. In image sequences, the facial movements can be qualified by measuring the geometrical displacement of facial feature points between the current frame and the initial frame.

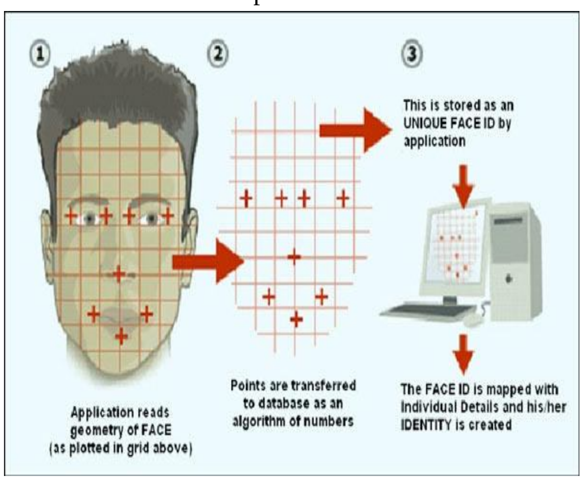


FIG 4.0:Geometric feature-based methods

FIG 4.1:Face Geometry Localisation

www.ijraset.com
IC Value: 13.98

Volume 4 Issue XI, November 2016
ISSN: 2321-9653

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

2) *Appearance-based methods:* With ***appearance-based methods***, Holistic spatial analysis including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) and Gabor wavelets, are applied to either the whole-face or specific face-regions to extract the appearance changes of the face. Due to their superior performance, the major works on appearance-based methods have focused on usingGabor-wavelet representations. However, the computation of **Gabor-wavelet** representations is both time and memory intensive. In image processing, a Gabor filter is a linear filter used for edge detection. The Gabor wavelet representation allows description of spatial frequency structure in the image while preserving information about spatial relations **LBP (Local Binary Pattern)** The generalization ability of LBP features across different databases are evaluated. Obviously low-resolution images in real world environments make real-life expression recognition much more difficult. So In this work, LBP features for low-resolution facial expression recognition are investigated. Experiments on different image resolutions show that LBP features perform stably and robustly over a useful range of low resolutions of face images. LBP features were proposed originally for texture analysis, and recently have been introduced to represent faces in facial images analysis. The most important properties of LBP features are their tolerance against illumination changes and their computational simplicity. Different machine learning methods, including template Matching, Support Vector Machine (SVM), Linear Discriminant Analysis (LDA) and the linear programming technique are examined to perform facial expression recognition using LBP features.

a) *Advantages of LBP:* Compared to other methods, LBP features can be derived very fast in a single scan through the raw image and lie in low-dimensional feature space, while still retaining discriminative facial information in a compact representation. Since it is both time and memory intensive to convolve face images with a bank of Gabor filters to extract multi-scale and multi-orientational coefficients. The generalization ability of LBP features across different databases are evaluated. Obviously low-resolution images in real world environments make real-life expression recognition much more difficult. So in this work, LBP features for low-resolution facial expression recognition are investigated. Experiments on different image resolutions show that LBP features perform stably and robustly over a useful range of low resolutions of face images.

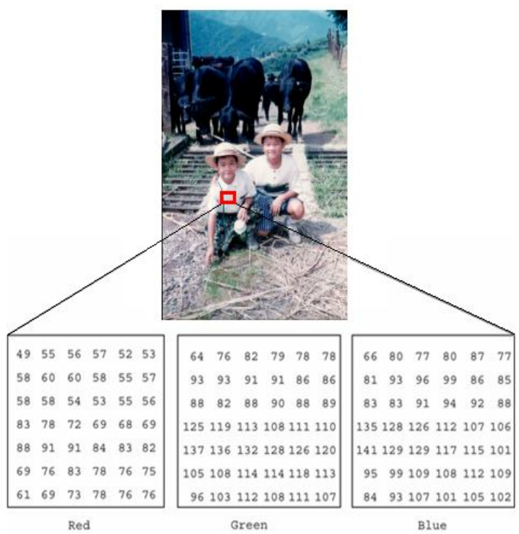


Fig 4.2: Image Data Representation Colour image

Fig 4.3 Grey image

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Basic Local Binary Patterns

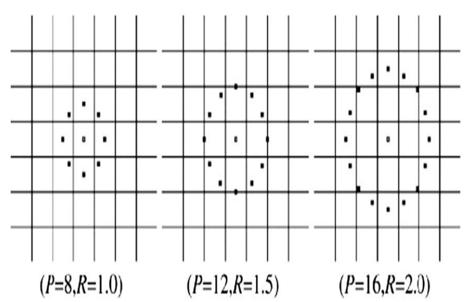
5	9	1		1	1	0
4	4	6		1		1
7	2	3		1	0	0

4<5 --------- 0
4<9 --------- 1
4>1 --------- 0
4<6 --------- 1
4>3 --------- 0
4>2 ----------0
4<7 ----------1
4=4 ----------1

Threshold

Binary: 11010011
Decimal:221

Extended Local Binary Patterns
Circular Neighborhoods



Uniformed Patterns

An important special case of LBP is the uniform LBP. A LBP descriptor is called uniform if and only if at most two bitwise transition between 0 and 1 over the circulated binary feature.Uniform LBP is used for compressing the histograms from 256 bins to 59, which gives quite some speedup when comparing them later.

For example:

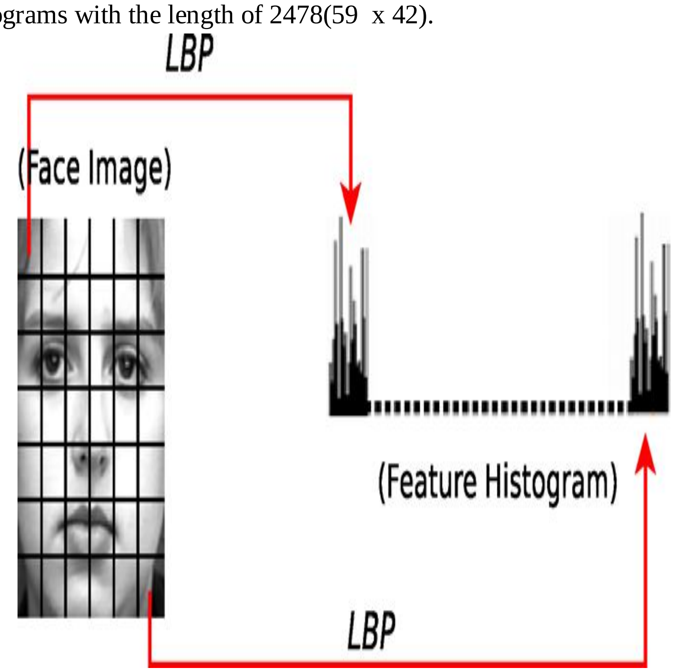
00000000 (0 transition), 11100011 (2 transitions) are uniform

01010000 (4 transitions) is non-uniform

Volume 4 Issue XI, November 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Constructing LBP Histograms

i) Some parameters can be optimized for better feature extraction
ii) 110 x150
iii) (Left) A face image divided into 6 X 7 sub-region.
iv) 378 histogram bin
v) 59 uniformed
vi) Represented by the LBP histograms with the length of 2478(59 x 42).



LBP Histograms

3) *Machine Learning:* Is a branch of artificial intelligence, concerns the construction and study of systems that can learn from data.

Types:

-Supervised Learning: Algorithms are trained on labelled examples, i.e., input where the desired output is known.

-Unsupervised Learning: Algorithms operate on unlabelled examples, i.e., input where the desired output is unknown. Here the objective is to discover structure in the data (e.g. through a cluster analysis), not to generalize a mapping from inputs t

Volume 4 Issue XI, November 2016
ISSN: 2321-9653

1	**1**	**1**	**0**
1	**1**	**1**	**0**
1	**1**	**1**	**0**

Templating matching

4) *Approaches:*

a) Template Matching: is a technique in digital image processing for finding small parts of an image which match a template image.

b) SVM:Gabor Energy Filters are bandpass filters with a tunable spatial orientation and frequency.

Methods(Feature+Classifiers)	7 class recognition(%)	6 class recognition (%)
LBP + Template matching Geometric feartures+TAN(11)	79.1±4.6\ 73.2	84.5 ± 5.2 --

Table 4.1:Comparison between geometric feature based and our LBP Template matching

	Anger (%)	Disgust (%)	Fear (%)	Joy (%)	Sadness (%)	Surprise (%)	Neutral (%)
Anger	58.7	5.5	0	0	26.7	0	9.1
Disgust	3.3	85.0	2.5	0	2.5	0	6.7
Fear	1.0	0	81.7	24.0	10.3	0	3.0
Joy	0	0	6.0	90.4	0	0	3.6
Sadness	4.9	0	0	0	72.4	1.7	21.0
Surprise	0	0	1.3	0	2.7	92.4	3.6
Neutral	2.0	0.8	0.4	0.8	25.7	0	70.3

Table 4.2: Confusion matrix of 7-class facial expressionrecognition using template matching with LBP featuresJoy and Surprise can be recognized with high accuracy (around 90–92%), but Anger and Fear are easily confused with others.

Volume 4 Issue XI, November 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	1	1	1	0	0
0	0	1	1	1	0	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

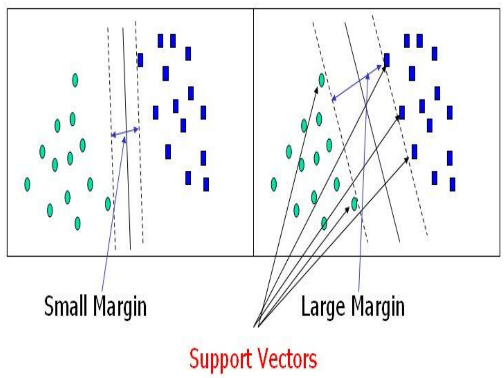


Fig 4.4:Support Vector Machine (S

Types of used SVM

i) *Linear*

ii) *Polynomial*

iii) *Radial basis function*

	Anger (%)	Disgust (%)	Fear (%)	Joy (%)	Sadness (%)	Surprise (%)
Anger	89.7	2.7	0	0	7.6	0
Disgust	0	97.5	2.5	0	0	0
Fear	0	2.0	73.0	22.0	3.0	0
Joy	0	0.4	0.7	97.9	1.0	0

Volume 4 Issue XI, November 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Sadness	10.3	0	0.8	0.8	83.5	4.7
Surprise	0	0	1.3	0	0	98.7

Table 4.3 Confusion matrix of 6-class facial expression recognition using SVM(RBF)

Feature comparisons LBP Vs. Gabor Using SVM

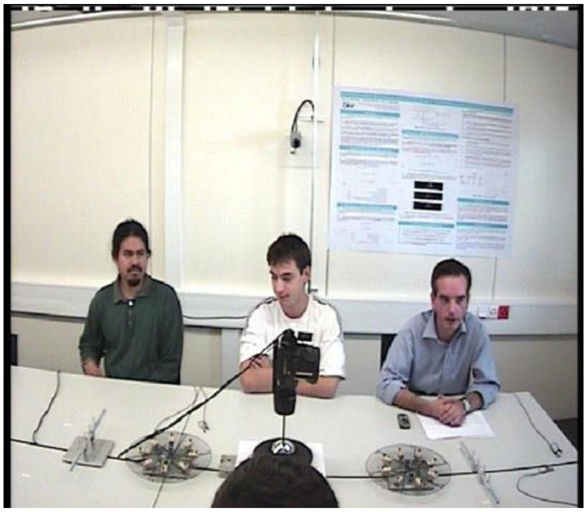
	6 Class		7 Class	
	LBP (%)	Gabor (%)	LBP (%)	Gabor (%)
SVM (Linear)	91.5±3.1	89.4±3.0	88.1±3.8	86.6±4.1
SVM (Polinomial)	91.5±3.1	89.4±3.0	88.1±3.8	86.6±4.1
SVM (RBF)	92.6±2.9	89.8±3.1	88.9±3.8	86.8±3.6

Table:4.4Comparison between LBP features with gabor filter features for facial expression recognition using SVM

Time and memory costs for extracting LBP featres and Gabornfilter features

	LBP	Gabor
Memory (feature dimension)	2478	42,650
Time(Feature extraction time)	0.03 s	30 s

5) *Low-resolution facial expression recognition:* In real-world environments such as smart meeting and visual surveillance, only low-resolution video input is available.

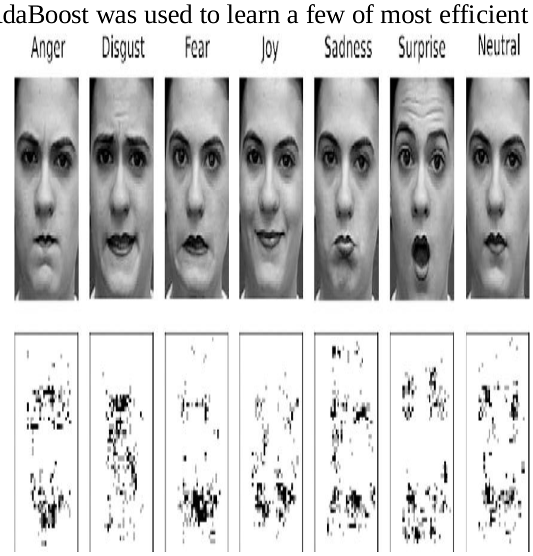


Volume 4 Issue XI, November 2016
ISSN: 2321-9653

Fig 4.5:We cropped the face region in frontal and near frontal view based on the location of two eyes from the input image sequence

6) Boosting LBP for facial expression recognition

The above experiments clearly demonstrate that the LBP features are effective for facial expression recognition, and performed just as well or better than reported existing techniques but with a significant low-computation advantage. In the above investigation, face images are equally divided into small sub-regions from which LBP histograms are extracted and concatenated into a single feature vector. However, apparently the extracted LBP features depend on the divided sub-regions, so this LBP feature extraction scheme suffers from fixed sub-region size and positions. By shifting and scaling a sub-window over face images, many more sub-regions can be obtained, bringing many more LBP histograms, which yield a more complete description of face images. To minimize a very large number of LBP histograms necessarily introduced by shifting and scaling a sub-window, boosting learning [can be used to learn the most effective LBP histograms that containing much discriminative information. In ,Zhang et al. presented an approach for face recognition by boosting LBP-based classifiers, where the distance between corresponding LBP histograms of two face images is used as a discriminative feature, and AdaBoost was used to learn a few of most efficient features.



Distributions of the top 50 sub-regions (LBP histograms) selected AdaBoost for each expression.As each LBP histogram is calculated from a sub-region, Ada- Boost is actually used to find the sub-regions that contain more discriminative information for facial expression classification in term of the LBP histogram. On selecting a weak classifier for Ada- Boost, we adopted the histogram-based template matching. For each sub-region, the LBP histograms in a given class are averaged to generate a template for this class

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

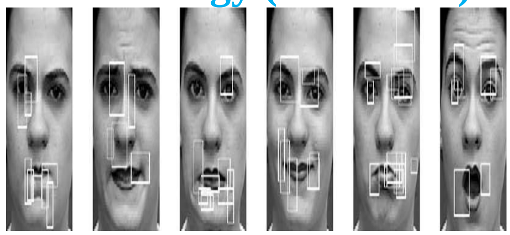


Fig 4.6: The sub-regions (LBP histograms) selected by AdaBoost for each emotion. from left to right: Anger, Disgust,Fear,Joy,Sadness,Surprise.

The trained weak classifier matches the input histogram with the closest template, and outputs the corresponding class label. The Chi square statistic ðv2Þ was used as the dissimilarity measure for histograms (Eq. (4)). As the traditional AdaBoost works on two-class problems, the multiclass problem here is accomplished by using the one-against-rest technique, which trains AdaBoost between one expression with all others. For each AdaBoost learner, the images of one expression were positive samples, while the images of all other expressions were negative samples. By shifting and scaling a sub-window, 16,640 sub-regions, i.e.,16,640 LBP histograms, in total were extracted from each face image. The sub-window was shifted in the whole image with the shifting step of 4 pixels, while its size was scaled between 10 _ 10 pixels and 25 _ 20 pixels with the scaling step of 5 pixels. AdaBoost was used to learn a small subset (in tens) of effective LBP histograms. we plot in Fig. 10 the spatial localization of the 50 subregions (i.e., the centers of the sub-regions) that corresponded by the top 50 LBP histograms selected by AdaBoost for each expression.

It is observed that different expressions have different key discriminant LBP features, and the discriminant features are mainly distributed in the eye and mouth regions. We performed facial expression recognition using the strong classifiers boosted by AdaBoost, and outputs the class with the largest positive output of binary classifiers. In our experiments, AdaBoost training continued until the classifier output distribution for the positive and negative samples were completely separated, so the number of LBP histograms selected for each expression was not pre-defined, but automatically decided by the AdaBoost learner itself. In the 10-fold experiments, the number of selected LBP histogram ranges 49–52 for 6-class expressions and 65–70 for 7-class expressions. For example, Fig. 11 displays the selected sub-regions (LBP histograms) for each basic expression in one trial of the 10-fold cross-validation. We can observe that the selected sub-regions have variable sizes and positions. Moreover, while the weights of sub-regions in the template matching were chosen empirically, the weights in boosted classifiers were learned by AdaBoost. The generalization performance of the boosted classifiers is 84.6% for 7-class recognition and 89.8% for 6-class recognition, respectively. As shown in Table 13, compared to the LBP based template matching in Section 5.1, AdaBoost (Boosted-LBP) provides improved performance. We also show the confusion matrix of 7-class recognition using AdaBoost in Table 14, where Disgust, Joy, Surprise and Neutral can be recognized with high accuracy. It can be seen that AdaBoost's performance is inferior to that of SVM (RBF) reported in Table 5 for most expressions except Fear and Neutral. We further combine feature selection by AdaBoost with classification by SVM. In particular, we train SVM with the Boosted- LBP features. In each trial of the 10-fold cross-validation, we applied AdaBoost to learn the discriminative LBP histograms for each expression, and then utilized the union of the selected LBP histograms as the input for SVMs. For example, in Fig. 11, the union of all sub-regions selected resulted in a total of 51 LBP histograms. The generalization performance of Boosted-LBP based SVM is summarized in Table 15, where the degree of the polynomial kernel is 1 and the standard deviation for the RBF kernel is 211. For comparison, we also include the recognition performance of LBP based SVMs (in Section 5.2) in Table 15. We observe that Boosted-LBP based SVMs outperform LBP-based SVMs by around 2.5–3.5% points. The 7-class expression recognition result of 91.4% is very encouraging, compared to the state of the art [11]. Bartlett et al. [19] obtained the best performance 93.3% by selecting a subset of Gabor filters using AdaBoost and then training SVM on the outputs of the selected filters. With regard to the 6-class recognition.

V. CONCLUSION

In this paper, we present a comprehensive empirical study of facial expression recognition based on Local Binary Patterns features.Different classification techniques are examined on several databases.The key issues of this work can be summarized as follows:

Deriving an effective facial representation from original face images is a vital step for successful facial expression recognition. We empirically evaluate LBP features to describe appearance changes of expression images. Extensive experiments illustrate that LBP features are effective and efficient for facial expression recognition.

One challenge for facial expression recognition is recognizing facial expressions at low resolutions, as only compressed lowresolution video input is available in real-world applications. We investigate LBP features on low-resolution images, and observe that LBP features perform stably and robustly over a useful range of low resolutions of face images.We adopt AdaBoost to learn the most discriminative LBP features from a large LBP feature pool. Best recognition performance is obtained by using SVM with Boosted-LBP features. However, this method has limitation on generalization to other datasets.Since the performance of the boosted strong classifier originates in the characteristics of its weak hypothesis space, we will evaluate other kinds of weak classifiers as alternative to template matching, in order to achieve better classification performance. One limitation of this work is that the recognition is performed by using static images without exploiting temporal behaviors of facial expressions. The psychological experiments by Bassili [15] have suggested that facial expressions are more accurately recognized from a dynamic image than from a single static image. We will explore temporal information in our future work. Recently volume LBP and LBP from three orthogonal planes have been introduced for dynamic texture recognition [16], showing promising performance on facial expression recognition in video sequences. Another limitation of the current work is that we do not consider head pose variations and occlusions, which will be addressed in our future work. We will also study the effect of imprecise face location on expression recognition results.

REFERENCES

[1] Whitehill, J., Serpell, Z., Lin, Y.-C., Foster, A., and Movellan, J.R. The faces of engagement: Automatic recognition of student engagement from facial expressions. IEEE Transactions on Affective Computing 5, 1 (2014), 86–98.

[2] Scientific Learning. (2012). [Online]. Available: www.scilearn.com.

[3] A. Anderson, S. Christenson, M. Sinclair, and C. Lehr, “Check and connect:The importance of relationships for promoting engagement with school,” J. School Psychol., vol. 42, pp. 95–113, 2004.

[4] J. R. Anderson, “Acquisition of cognitive skill,” Psychol. Rev., vol. 89, no. 4, pp. 369–406, 1982.

[5] I. Arroyo, K. Ferguson, J. Johns, T. Dragon, H. Meheranian, D. Fisher, A. Barto, S. Mahadevan, and B. Woolf, “Repairing disengagement with non-invasive interventions,” in Proc. Conf. Artif. ntell. Educ., 2007, pp. 195–202.

[6] Bosch, N., Chen, Y., and D’Mello, S. It’s written on your face: detecting affective states from facial expressions while learning computer programming. Proceedings of the 12th International Conference on Intelligent Tutoring Systems (ITS 2014), Switzerland: Springer International Publishing (2014), 39–44.

[7] Baker, R., Rodrigo, M.M.T., and Xolocotzin, U.E. The dynamics of affective transitions in simulation problem-solving environments. In A.C.R. Paiva, R. Prada and R.W. Picard, eds., Affective Computing and Intelligent Interaction. Springer, Berlin Heidelberg, 2007, 666–677.

[8] D’Mello, S. Dynamical emotions: bodily dynamics of affect during problem solving. Proceedings of the 33rd Annual Conference of the Cognitive Science Society,(2011).

[9] M. Chaouachi, P. Chalfoun, I. Jraidi, and C. Frasson, “Affect and mental engagement: Towards adaptability for intelligent systems,” presented at the 23rd Int. Florida Artificial Intelligence Research Society Conf., Daytona Beach, FL, USA, 2010.

[10] S. D’Mello, S. Craig, and A. Graesser, “Multimethod assessment of affective experience and expression during deep learning,” Int. J. Learn. Technol., vol. 4, no. 3, pp. 165–187, 2009.

[11] Kapoor, A., Burleson, W., and Picard, R.W. Automatic prediction of frustration. International Journal of Human-Computer Studies 65, 8 (2007), 724–736.

[12] Kapoor, A. and Picard, R.W. Multimodal affect recognition in learning environments. Proceedings of the 13th Annual ACM International Conference on Multimedia, ACM (2005), 677–682.

[13] Hoque, M.E., McDuff, D., and Picard, R.W. Exploring temporal patterns in classifying frustrated and delighted smiles. IEEE Transactions on Affective Computing 3, 3 (2012), 323–334.

[14] Chawla, N.V., Bowyer, K.W., Hall, L.O., and Kegelmeyer, W.P. SMOTE: synthetic minority oversampling technique. Journal of Artificial Intelligence Research 16, (2011), 321–357.

[15] J.N. Bassili, Emotion recognition: the role of facial movement and the relative importance of upper and lower area of the face, Journal of Personality and Social Psychology 37 (11) (1979) 2049–2058.

[16] G. Zhao, M. Pietikäinen, Dynamic texture recognition using local binary patterns with an application to facial expressions, IEEE Transactions on Pattern Analysis and Machine Intelligence 29 (6) (2007) 915–928.

[17] Yousra BEN JEMAA, Sana KHANFIR Automatic local Gabor features extraction for face recognition (IJCSIS) International Journal of Computer Science and Information Security, Vol. 3, No. 1, 2009