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3D Facial Expression Analysis – A Review

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Abstract— Automatic facial expression recognition (FER) is a sub-area of face analysis research that is based heavily on methods of computer vision, machine learning, and image processing and plays an important role in human computer interaction, biometric security, social interaction, emotional intelligence and social intelligence. The 3D dynamic facial geometry contains ample information about human facial expressions. Such information is invariant to pose and lighting conditions, occlusion, and time delay which have imposed serious hurdles on many 2D facial analysis problems .These considerations motivated a progressive shift from 2D to 3D in performing facial shape analysis. This paper focuses a brief review on automatic systems used in facial expression detection by using 3D/4D face database and summarized research trends to date.

Index Terms— Facial expression recognition (FER) ,Facial Action Coding System (FACS), Action unit (AU), Support vector machine (SVM), Artificial Neural Network (ANN), Principal Component Analysis(PCA), Linear Discriminate Analysis(LDA), Independent Component Analysis.

1 Introduction

Facial expression recognition has interested many researchers due to its various purposes and applications. It plays a key role in emotion recognition and thus contributes to the development of human computer interaction systems. It can also reinforce face recognition systems by providing prior knowledge on the facial motions and facial feature deformations. It is a medium of expression of one's perspective or his mental state to others. Other applications include but are not limited to psychological studies, tiredness detection, facial animation, robotics as well as virtual reality [1].

Facial emotion recognition involves three main stages: face detection, information extraction and expression classification. Expressions on the face are the result of distortions of facial features due to the constriction of facial muscles. During last two decades, various techniques have been presented by many researchers in the areas of facial expression detection/recognition. G. N. Matre et. al. [2], compares various 1D, 2D methods for FER. Approaches like Principal Component Analysis, Linear Discriminate Analysis, and Independent Component Analysis constitute a major part in the 1-dimensional facial expression representation techniques. 1D technique is applicable only in gray scale images. 2- Dimensional representation methods include Principal Component Analysis. As these methods are applicable only for black and white gray scale images, Global Eigen Approach and Sub pattern extended 2-dimensional Principal Component Analysis (E2DPCA) are extended by traditional approaches to color space. Multilinear Image Analysis introduced tensor concept which allows more than one factor variation in contradiction to PCA. Tensor concept is also used in Color Subspace Linear Discriminant Analysis but in color space it simply improves the accuracy. In order to achieve greater performance, the other technique called Gabor Filer Bank is mostly used to outperform over all present methods. The Local Gabor Binary Pattern technique has significantly improved recognition rate as compare to gabor filter bank method. If RGB color space is used, then the accuracy depends on the angle and light source which in turn reduces the recognition performance. Therefore RGB color space is not always suitable for color information processing. To overcome the said problem, a novel tensor perceptual framework for facial expression recognition achieve better accuracy. This is done on perceptual color space and can be examined under slight variations in illuminations.

More properly, facial expressions can be seen as dynamical processes that involve the 3D space and the temporal dimension (3D plus time, referred to as 4D), rather than being just a static or dynamic 2D behavior. In addition, 3D face scans are expected to feature less sensitivity to lighting conditions and pose variations. These considerations motivated a progressive shift from 2D to 3D in performing facial shape analysis, with BU-3DFE, BU-4DFE and BOSPHORUS publicly available database[3][4][5]. Since the accuracy of the face expression recognition systems depends solemnly on the effectiveness of the adopted feature extractions techniques, The goal of this paper is to survey the various FER methods on 3D/4D image database. Here, we discuss few systems and compare their performance.

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2. LITERATURE SURVEY

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Despite considerable progress on the automatic detection using 2D image data, several challenges remain. Jun Wang et. al. [05], conducted geometric feature based facial expression descriptor in 3D Euclidean space on BU-3DFE database using elaborately extracted primitive facial surface features and an LDA classifier based on the Principal curvature information based on 3D triangle based model. The highest average recognition rate obtained was 83.6 % on this database.

H. Tang et. al. [06] , measured the normalized distances and slopes of the lines segments comprise a set of 96 distinguishing features. The performance of the system were tested on the BU-3DFE database.The average recognition rate obtained was 87.1% using multi-class SVM classifier .

Arman Savran et. al. [03], proved that 3D face data can alleviate difficulties inherent in 2D modality since 3D enables true facial surface measurements and investigated the use of 3D data for the facial action. Naive Bayes and linear SVM have scores of 95.3% and 95.4% respectively. The feature fusion of the two modalities proved advantageous as the average AU recognition performance rises from 95.4% to 97.1%. All of the classifiers used 200 Gabor features that are selected by AdaBoost, except the fusion where concatenated 400 length feature vector is employed.

T. Fang et. al. (2011)[01], surveyed the existing works in 3D FER and also explained different featured base and model based FER systems with BU-3DFE, BU-4DFE and BOSPHORUS database. Feature-based 3D FER methods focus on the extraction of facial features directly from the input scan while model-based approaches usually involve a generic face model as an intermediate to bring input scans into correspondence by means of registration and/or deformation. Gabor wavelets with AdaBoost for feature selection and SVM for classification obtained high recognition rate of 97.1%

Le et. al. [07](2011) proposed an approach based on facial level curves for expression recognition from 3D videos. The spatiotemporal features were extracted by comparing the curves across frames using chamfer distances and an HMM based decision boundary focus algorithm was used for classification . Experiment was carried out on BU4DFE with 92.22% recognition rate.

Omar Ocegueda et.al.(2011) [8] presented a semi-automatic 3D Facial Expression Recognition system based on geometric facial information. In which, the 3D facial meshes were first fitted to an Annotated Face Model (AFM). Then, the Expressive Maps were computed, which indicate the parts of the face that are most expressive according to a particular geometric feature (e.g., vertex coordinates, normals, and local curvature).Using the selected features a simple linear classifier was trained and yielded a very competitive average recognition rate of 90.4% when evaluated using ten-fold cross validation on the publicly available BU-3DFE database.

Laszlo A. Jenia et. al.[09](2012) investigated person independent and pose invariant facial emotion classification and action unit intensity estimation. 3D shape information was computed by means of constrained local models (CLM) on video sequences. They computed a time averaged Personal Mean Shape from the estimated shapes, which ensures person independent performance. Results on BU-4DFE dataset show that shape estimation alone can be used for robust pose invariant emotion and AU estimation with close to 100% performance.

Georgia Sandbach, et. al. (2012)[10], proposed a fully automatic method for facial expression recognition that exploits the dynamics of 3D facial motion. The system developed consists of several stages. Firstly the 3D motion of the face appearing between frames in each image sequence was captured using Free-Form Deformations (FFDs). They extracted features by applying quad tree decomposition. Features were then collected using a GentleBoost feature selection method for the onset and offset temporal segments of the expression and frame classification. Dimensionality reduction was applied via Linear Discriminant Analysis (LDA), Temporal modeling of the full expression is performed via neutral-onset-apex-offset HMM models. These models were finally used for dynamic expression recognition and expression Results was 83.03%.

Hassen Drira et. al. [11](2013) proposed framework for analyzing 3D faces. He represented facial surfaces by radial curves emanating from the nose tips and use elastic shape analysis of these curves to develop a Riemannian framework for analyzing shapes of full facial surfaces with the elastic Riemannian metric, seems natural for measuring facial deformations and was robust to challenges such as large facial expressions (especially those with open mouths), large pose variations, missing parts, and partial occlusions due to glasses, hair, and so on. This framework allows for formal statistical inferences, such as the estimation of missing facial parts using PCA on tangent spaces and computing average shapes. Expression Results was 97 %.

Mohamed Daoudi et. al. [12] (2013) presented a fully automatic approach for identity independent facial expression recognition from 3D video sequences. He extracted relevant features from deformations between faces using LDA and then trains a dynamic model on these features using HMM. Experiments conducted on Binghamton University BU-3DFE, and the Bosphorus database BU-4DFE with an average accuracy of 93.83%.

Munawar Hayat et. al. [13](2013), presented a fully automatic system with 100 % accuracy which exploits the dynamics of 3D videos and was capable of recognizing six basic facial expressions. Local video patches of variable lengths were extracted from different locations of the training videos and represented as points on the Grassmannian manifold. An efficient spectral clustering based algorithm was used to separately cluster points for each of the six expression classes. The proposed system was tested on 3D video database, BU4DFE.

Yun Tie et al [14](2013),presented a fully automatic method for emotion recognition that exploits the Elastic Body

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Spline technology (EBS) features between neutral and expressional faces based on a 3-D deformable mesh (DM) model. The facial region was first detected automatically in the input frames using the local normalization based method. They then locate 26 fiducial points over the facial region using The fiducial points were tracked continuously by multiple particle filters throughout the video sequences. EBS was used to extract the deformation features and the D-Isomap algorithm was then applied for the final decision. Expression Results was 88.02%.

Author	Algorithms	database	Recognition rate
Jun.wang et.al. [05]	Extracted primitive facial surface features and an LDA classfier.	BU-3DFE	83.6%
HaoTangand Thomas et.al. [06]	Video-patches considered to be points on the Grassmanian manifold algoithm and spectral clustering for matching .	BU-3DFE BU 4DFE	87.1%
Arman Savran et.al. [03]	Gabor features selected by AdaBoost,The feature fusion of Naive Bayes and linear SVM as classifier .	BU-3DFE	97.1%
Omar ocegueda et.al. [08] (2011)	Mesh fitting algorithm UV parametrization expressive maps.	BU-3DFE	90:4%
Le et al. [07]	Facial level curves for expression recognition and an HMM-based decision boundary focus algorithm is used for classification	BU-4DFE	92.22%
T. Fang et al [01]	Gabor wavelets with AdaBoost for feature selection and SVM for classification.	BU-3DFE BU-4DFE BOSPHORUS	97.1%
László A. Jeni et.al. [09]	Constrained local models (CLM) method, SVM regression using the different emotions classes or AU values.	BU- 4DFE , CK+ dataset	100%
Sandbach et. al.[10]	Iterative closed point (ICP) , Free Form Deformations (FFDs) , quad-tree decomposition, HMMs were used .	BU-3DFE, BU4DFE	90.44%
Yun Tie, et.al. [14]	Elastic body spline technology Discriminative Isomap based classification was used. The final decision was made by computing the nearest class center of the feature space.	RML	88.2% .
Mohamed Doudi et.al. [12]	LDA and dynamic model on these features using HMM.	BU-4DFE	93.83%
Hassen Drira, et.al. [11]	Elastic Riemannian metric.	FRGCv2, GavabDB , and Bosphorus	97%

scale space extrema and scale invariant feature examination.

TABLE 1-SUMMARY OF THE VARIOUS 3D/4DFER STUDIES

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3. CONCLUSION

Automatic recognition of facial expressions is still a challenging due to high variability in the types of faces. 3D face scans are expected to feature less sensitivity to lighting conditions and pose variations. Existing works in 3D /4D FER shown promising results in specific experimental conditions. How to reduce the computational complexity of this system is yet another intriguing problem. According to survey of 3D/4D FER, constrained local models (CLM) method with SVM regression gave 100% accuracy on BU- 4DFE.

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