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A Survey on Human Face Expression Recognition Techniques

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---ABSTRACT---
Facial expression Recognition is the challenging tasks in social context. Facial expressions are natural and is a mean of non-verbal communication. This paper focus on the survey of Face Expression Recognition (FER) techniques which include the three major stages such as preprocessing, feature extraction and classification. This survey is majorly focus on the various types of FER techniques and its contribution in this area. The performance of various FER techniques is compared considering the number of expressions, accuracy, complexity and efficiency of algorithms on Datasets like JAFFE, CK, CK+ The survey on classifiers is based upon recent papers and reveals an understanding and significance of the research in the field of automated facial expression recognition system.
KEYWORDS

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I. INTRODUCTION

Social context facilitates the human communication and facial expressions generally provide contextual information in social situations. Such information is very crucial when uncertainty-inducing conditions are encountered [1]. Automatic facial expression recognition (FER) allows the correct evaluation of such situations. FER is not limited to mental state identification but finds numerous applications in neuro marketing, robotics, medical field, security, automatic counselling systems, face expression synthesis, lie detection, music for mood, operator fatigue detection etc. It also allows effective communication of important information without speaking. Initially Aristotle and Stewart analysed the facial expressions, but after Darwin's work [2] it became empirical study.

Ekman [3] classified facial expressions into one of six universal emotions i.e. happiness, sadness, fear, disgust, surprise and anger. Perveen et. al [4] suggested spontaneous expression recognition using expression-vectors derived for different expressions. The technique performs better than other techniques based on class labels. Xie and Hu [5] proposed deep comprehensive multi-patches aggregation convolutional neural networks along with expressional transformation-invariant pooling, which provides superior performance in comparison to conventional FER systems. FER with high correct recognition rate is suggested in [6] by considering facial elements and muscle movement. The methodology provides improved performance in terms of face registration errors and processing time. A neural network based upper and lower facial action unit and FER analyzer [7] is developed to detect emotions from real-time posed affective facial expressions. The system effectively detects discussion topics from communicational inputs using latent semantic analysis to facilitate humanoid interaction. Rizwan Ahmed Khan [8] presented a memory and time efficient FER framework for low resolution real time facial images achieved average recognition rate for SVM, 2-nearest neighbour, random forest and decision tree using 10-fold cross validation technique. Ekman and Friesen [9] developed the Facial Action Coding System for describing facial expressions by action units.

The remaining paper is organized as follows. Section 2 presents the general idea of a facial expression recognition system. The literature survey is presented in the section 3. The performance comparison of various already published FER system is given in section 4 and final section 5 presents the conclusion based upon the literature survey presented in the paper.

II. FACE EXPRESSION RECOGNITION SYSTEM

The FER is carried out in five steps as shown in Fig.1. A facial expression recognition system has many stages which involves pre-processing, face detection or finding Region of interest, feature extraction and finally expression classification as shown in Fig. 1.

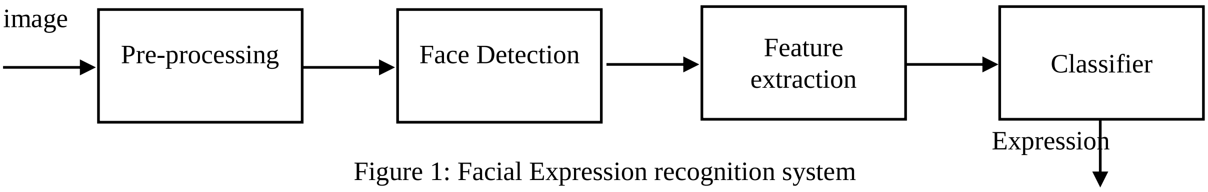

Figure 1: Facial Expression recognition system

Image Preprocessing

Pre-processing is carried before applying any feature extraction technique in FER. Image pre-processing includes processes such as image correction, enhancement, restoration, compression, scaling, cropping, resizing, and other image improvement processes along with face detection.

Face detection is the important phase in any FER system and is done in pre-processing phase. Types of Methods used in Face Detection are classified [10] into following types:

a. Knowledge-based methods.
b. Feature invariant methods.
c. Template matching methods.
d. Appearance-based methods.

The primary aim of face detection algorithms is to determine whether there is any face in an image or not. There are number of constraints associated with face detection like quality of image, smoothness, resolution, illumination, head pose, occlusion and camera errors due to orientation and local conditions etc. These constraints lead to performance degradation like Yuqian Zhou et al.,[11] has analysed the face detection on different level of blur, noise, and contrast on low quality images on traditional algorithm like Viola-Jones Haar AdaBoost [12] and HoG-SVM [13], and deep learning-based models. Performance degradation is noticed on low quality images by the authors.

To enhance face detection form input image normalization is done for reduction of illumination and extracting of eye position etc. Numerous algorithms like isotropic diffusion (IS)-based normalization, discrete cosine transform (DCT)-based normalization, difference of Gaussian (DoG) and homomorphic filtering-based normalization, can be used for normalization [14], [15]. The histogram equalization [16][17][18] method is widely used for contrast enhancement of the facial images and to improve the distinction between the intensities. Image enhancement which includes image brightness, contrast balancing etc. play vital role in detecting facial features therefore in pre-processing normalization is done. S. Kumar et.al.,[19] has analysed Filters like median filter and gaussian filters etc. for the smoothness of the facial images.

For effective face detection it is required to spot size and the face from the input image therefore localization is used. Localization is a pre-processing method and it uses the Viola-Jones algorithm to detect the facial images from the input image. Scaling and cropping of facial image is also done manually for feature detection taking nose as central point.

Face alignment [20] plays a significant role in face recognition, attribute computing, and expression recognition. Face alignment methods [21] can be classified by different ways Depending upon the number of landmark points, they are two categories sparse and dense alignment. Sparse alignment considers only few key points in a face. On the other hand, dense alignment methods focus on more key points. Depending upon information unit face alignment methods are categorized as global and local methods. Active appearance models [21] (AAM) and constrained local models (CLM) [21] have received more attention in global and local methods. In comparison to AAM, methods using CLM have many advantages. The popular technique to yield frontal face view was proposed by Hassner et al. [22]

The important factor along with accuracy which is desired is the performance of system in terms of its processing time. High resolution images have generally large size which is also a performance factor therefore down sampling is done for image size reduction like Bessel down-sampling [23] which also protects the worthy information of the original image. Similarly, to capture facial feature effectively up-sampling is done to for image enhancement. To capture only worthy information camera type and orientation of camera is also a major factor. To improve camera accuracy Taylor et.al,[24] used depth camera which automatically capture face image based upon the distance between face and camera.

Feature extraction

Feature extraction is locating and depicting of true features of interest from an input image for further processing. The feature extraction methods are categorized as texture feature-based method, edge-based method, global and local feature-based method geometric feature-based method and patch-based method. The descriptors which extract based on texture feature-based methods [25] are like Gabor filter, Local Binary Patter (LBP), Weber local descriptor (WLD), Discrete Contourlet Transform (DCT) etc. [25]. The descriptors which extract based Edge based methods Line edge Map (LEM), Histogram of Oriented Gradients (HOG) [25] is a window supported feature descriptor which uses the gradient filter. The extracted features are based on the edge information of the registered face images. The descriptors which extract based on the global and local feature-based methods are [25] Principal Component Analysis (PCA), Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA), Stepwise Linear Discriminant Analysis (SWLDA) etc. The descriptors which extract the features based on the geometric feature-based methods are [25] Local Curvelet Transform (LCT) etc.

Classification

Classification is last stage of any FER which classifies the features into the classes of respective facial expression like happy, sad, angry, disgust, neutral, surprised and fear. Commonly used classification methods are Support Vector Machine [26], Nearest Neighbor [26] and Convolution neural network etc.

III. LITERATURE REVIEW

The identification of facial emotions is a quite challenging task as the way of showing expressions is purely person dependent and in recent a lot has been contributed by authors in past. Abboud et al. [27] suggested an active appearance model for recognizing facial expressions, which is further used to create new expressions in an image using two approaches. The technique uses PCA to merge the shape and grey level appearance whereas linear regression allows the construction of expression models. Results prove that the artificial expressions synthetically created by the suggested technique are significantly close to the actual face expressions. Mlakar et al. [28] suggested histogram of oriented gradient and difference features vectors for recognizing facial emotions. The developed system reduces the size of feature vector and efficiency of sup-port vector machine classifier is also increased.

Kopaczka et al. [29] acquired a high-resolution infrared face image dataset with annotations which is used for emotion recognition. Face scrambling is used in image/ videos to be distributed over public network for privacy protection. Expression recognition of scrambled facial images is not feasible using conventional techniques due to the presence of chaotic signals. Jiang et al. [30] resolved this issue by recognizing expressions with the help of fuzzy combination from Many Graph Embedding. Results indicate that suggested scheme provides an enhanced recognition accuracy for scrambled im-ages. Meena et al. [31] represented facial regions by graph signals and facial information is extracted using spectral graph wavelet transform. The accuracy of recognition is investigated on benchmark datasets by proper choice of number of filter banks and their weights. Further wavelet entropy is also used for extracting features and classification of expressions is carried out using Jaya algorithm-based feedforward neural network [32]. The devised technique showed promising results for FER.

Mancini et al. [33] investigated the variation in expression recognition and affective ratings with age for different emotional face images. Results demonstrated that "happy" emotion is recognized more accurately in preadolescence. Further happy expressions are found more pleasing and arousing in comparison to others. Hui Fang [34] suggested a dynamic expression recognition system without using the action units. The important information is extracted from the video recordings by selecting frames having peak expressions without using any other information or subjective pre-processing. The presented method provides effective and robust facial expression recognition under slight uncontrolled variations. The facial characteristics i.e., emotion and pose details are used for adaptive initialization for face alignment problem [35]. The suggested technique proves to be more accurate and fast as compared to conventional regression techniques. Another work [36] based on video recordings uses multimodal approach to study learning emotions in an educational context. An annotation strategy is followed for labelling facial emotions and body movements to identify student's sentimental state changes so that required affective support is provided. The human expressions are also recognized by another multi model approach for a robotic system [37]. The approach uses GA designed artificial neural network and hidden Markov model. A bi-model approach based on optimal fusion of facial expression and speech features is also used to recognize human emotions [38].

FER techniques generally use local feature descriptors leading to instability in the presence of weak and distorted edges because of noisy environment. The limitation is overcome by Neighbourhood-aware Edge Directional Pattern method [39] based on gradient information of neighbouring pixels. Khan et al. [40] suggested a FER technique based on salient facial regions which mimics the human visual system. A pyramidal local binary pattern (PLBP) operator successfully discriminates the facial emotions in real time environment. Another local edge-based feature extractor called as Local Prominent Directional Pattern (LPDP) is proposed by Makhmudkhujaev et al. [41] where effect of local distortions is reduced by considering statistical information in the vicinity of a pixel. Lajevardi and Hussain [42] used Zernike moments, orthogonal invariant moment for feature extraction and classification is performed using Naive Bayes. The scheme proves to be a fast and robust method for automatic facial emotion recognition. A FER scheme is designed [43] based on texture information about centric pixel using spatial and temporal neighbouring pixels. The suggested scheme is a fast and effective recognition system in comparison to the conventional methods.

AI is the most commonly used technique to read, imitate, interpret and respond to human facial expressions with the help of extracted features. A 3-layer neural network trained using back-propagation algorithm [44] is utilized to classify facial expressions. The Viola-Jones descriptor detects face which is followed by Bessel transform and Gabor to extract features. Selecting lesser features via Adaboost enhances the speed of classification. Facial emotion recognition is carried out for discrete wavelet trans-form-fuzzy enhanced images [45]. The classification of facial geometric features is performed by neural network with TensorFlow central processing unit form. The scheme proves to be an efficient method for facial emotion detection. A new features set is suggested by Barman and Dutta [46] using distance and shape signatures for facial expression recognition. The features are further enhanced by augmenting statis-tical features like range, moment, entropy etc. Three combinations of features are test-ed on a Multilayer Perceptron to retrieve the corresponding facial expressions. Distance shape signature combination proves to be more promising than other feature sets for effective expression recognition. Deep neural networks (DNN) are widely used to learn and extract high-level features from a complex dataset. The hierarchical structure of DNN increases the computational burden and reduces the efficiency, these issues are overcome by a sparse autoencoder [47]. The obtained deep sparse autoencoder network with SoftMax regression classifier effectively recognizes the facial expressions. Jain et al. suggested a facial expression recognition model [48] using Single Deep convolutional neural networks comprising convolution layers and deep residual blocks. The designed model is successfully validated on Extended Cohn Kanade (CK+) and Japanese Female Facial Expression (JAFFE) Datasets. Deep convolutional neural network is also used by Li et al. [49]. Initially two CNNs are used for learning and feature identification, later on the two features are concatenated and given to fully connected layers which builds a new model. Results reveal the enhanced accuracy of facial expression identification. Other works of facial emotion recognition based on CNN include robust CNN using feedback method [50], two-part convolutional neural network using expressional vector [51], CNN for facial expression recognition to assess neonatal pain [52] etc. A fuzzy inference system is suggested [53] to identify facial expressions under partial occlusion conditions. The parameters of membership functions are optimized using genetic algorithm. The results reveal 93.96% average precision rate to recognize facial expressions. Ioannou et al. [54] used a neuro fuzzy network to extract and validate the emotional signs. The rule-base initialization is based on facial animation parameters of discrete and evaluation space, which are further fine-tuned using neural network. Results indicate a high estimation accuracy for recognizing facial expressions.

Recently, Generative adversarial networks (GAN) based methods have gain popularity in image synthesis to generate realistic faces, numbers, and other image types, which are enhancing data augmentation and recognition tasks also. Lai et al. [55] proposed a GAN-based face pose-invariant FER. In the proposed framework generator is use for pose correction in input face images along with preserving the identity and characteristics of features. Discriminator on the other hand distinguishes between real images and generated frontal face images. Zhang et al. [56] proposed a GAN-based model to generate images with various expressions under different poses for multiview FER.

IV. PERFORMANCE COMPARISON

The performance comparison of this survey is based on the complexity rate, recognition accuracy on different databases, availability of preprocessing and feature extraction methods, expression count analysis, major contribution and advantages of the various FER techniques.

Table 1: Performance analysis of FER techniques.

Author	Methodology	Dataset	Accuracy	Year
48	Histogram of oriented gradient descriptor (HOG) and difference feature vectors.	CK, JAFFE, MMI	98%, 92%, 84%	2017
50	Many Graph Embedding (MGE) to discover discriminative patterns from the subspaces of chaotic patterns	JAFFE, MUG and CK+	95&91%,40-42%,42-45%	2017
51	Graph signal processing (GSP)-based approach.	CK+, JAFFE	92%,96%	2019
52	Stationary wavelet entropy to extract features, and employed a single hidden layer feedforward neural network as the classifier	700-image dataset (Name not mentioned)	96%	2018
55	Expression and pose-based adaptive initialization (EXPAI)	300-W dataset	14% error reduction	2019
56	Facial Expression and Body Movement	Lab Experiment on recordings	Study only challenge no results reported	2014
58	Bimodal features-based emotion recognition - facial expression(CNN+RNN) and speech information (LST+CNN)	RML, AFEW6.0, eNTERFACE'05:	Better results than Unimodal	2020

59	Local descriptor named Neighborhood-aware Edge Directional Pattern (NEDP)	CK+, JAFFE , MMI, CMUPIE, , BU-3DFE , FACES, RaFD, ISED, and GEMEP-FERA datasets.	Performs better than other existing descriptors, and thereby, improves the overall performance of facial expression recognition.	2018
61	Edge-based descriptor, named Local Prominent Directional Pattern (LPDP)	CK+ , MMI, BU-3DFE , ISED, and GEMEP-FERA , and FACES	fairly better performance than other existing descriptors.	2019
63	TPOEM (Temporal Patterns of Oriented Edge Magnitudes) features,	CK+, MMI, KDEF	96.87	2018
65	Eye map–mouth map algorithm on an enhanced image	(KDEF), Oulu-CASIA NIR-VIS facial expression (Oulu-CASIA),CK+	98%, not calculated for (Oulu-CASIA),CK+	2019
66	Facial landmark Normalized distance and shape signatures	(CK+), JAFFE, MMI and MUG	100%, 96.4%, 81.9%, 97.7%	2017
67	Softmax regression-based deep sparse autoencoder network (SRDSAN)	JAFFE, CK+	98.59, 100%	2018
68	Deep Convolutional Neural Networks (DNNs), and deep residual blocks	CK+, JAFFE	Improved accuracy shown	2019
69	Identity and emotion joint learning approach with deep convolutional neural networks	CK+, FER+	99.31% and 84.29%	
71	Facial emotion recognition using convolutional neural networks (FERC) Based to two part CNN	CK, Caltech faces, CMU and NIST	FERC out-performs existing standard networks.	2020
72	Lightweight neonatal convolutional neural network as well as other popular CNN architectures for assessing neonatal pain	COPE and neonatal pain assessment dataset (NPAD)	neonatal pain using LBP features achieved 86.8%, g HOG features with SVM achieved 81.29%	2019
75	Multi-task learning approach based on the generative adversarial network (GAN)	Multi-PIE, BU-3DFE	very effective for expression recognition with large head pose variations.	2018
76	Joint Pose and Expression Modeling	Multi-PIE, BU-3DFE, SFEW	91.80%, 81.20%, .88% to 7.68% improvement	2018

V. CONCLUSION

The important future enhancements described from recent papers are FER for side view faces using the subjective information of facial sub-regions and use different parameters to represent the pose of the face for real-time applications. FER is used in real-time applications such as driver sate surveillance, medical, robotics interaction, forensic section, detecting deceptions. This survey paper is useful for software developers to develop algorithms

based on their accuracy and complexity. Also, it is helpful for hardware implementation to implement with low cost depends on their need. This survey compares algorithms based on preprocessing, feature extraction, classification and major contributions. The performance analysis is done based on the database, complexity rate, recognition accuracy and major contributions. This survey discusses the properties such as availability of preprocessing and feature extraction and expression count. The power of algorithms, advantages are discussed elaborately to reach the aim of this survey. ROI segmentation method is used for preprocessing and it gives the highest accuracy 99%. According to feature extraction GF have less complexity which gives the accuracy always between 82.5% and 99%. The highest recognition accuracy of 99% is provided by the SVM classifier and it recognizes the several expressions such as disgust, sad, smile, surprise, anger, fear, neutral effectively. In 2D
FER, mostly JAFFE and CK database are used for efficient performance than the other databases.

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