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SURVEY OF AUTOMATIC FACIAL EXPRESSION RECOGNITION BASED ON CLASSIFICATION SCHEMES

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Abstract: Automated facial identification and facial expression recognition have topics of active research over the past few decades. Facial and expression recognition finds applications in human-computer interfaces, subject tracking, real-time security surveillance systems and social networking. Several holistic and geometric methods have been developed to identify faces and expressions using public and local facial image databases. While facial expressions are naturally dynamic, they are not easy to detect so the focus of the study is now shifted to find new methods which would be helpful to improveaccuracy, lower computational cost, and less memory consumption. This paper demonstrates a quick survey of facial expression recognition by analyzing various classification algorithms; evaluated by comparing their results in general which in turn broadened the scope for other researchers and they could efficiently offer a solution to related problems.

Keywords: Facial recognition, expression recognition, classification, feature extraction and feature selection.

I. INTRODUCTION

Judging mental state of a person is one of the difficult tasks. The Best way to understand an emotional state of a person is through facial expressions like happy, sad, fear, disgust, surprise and anger [1-3]. The automated analysis of facial expression (FER) is a challenging task in the field of computer vision. Its implementation is not restricted to mental state identification only [4], it is also applicable in the security domain [5], automatic counselling systems, face expression synthesis, lie detection, music for mood [6], automated tutoring systems [7], operator fatigue detection [8]etc.

Facial expression is a natural nonverbal communication language. A person can express his or her sentiments/ state of mind through facial expressions but sometimes these expressions are not good enough for recognition systems. They have to be more refined to get right results. This issue still needs attention, but many algorithms have been proposed so far to handle these vague expressions [9].

Facial expression is formed by relaxing or contracting different muscles of human face [10] which results in deformed facial features [11]. According to [10, 12] facial expression are rapid signals which differs with change in facial features like open mouth, raising eyebrows, lips, eyes, cheeks etc., and these features affect the accuracy of a system.

Whereas skin color, gender, age etc., and slow signals affect rapid signals. As shown in Fig. 1, FER process consists of five phases. The noise is reduced and enhanced in the pre-processing phase by taking image or sequence of images (series of images from neutral face to peak expression of face) as an input and returns the face for more processing.

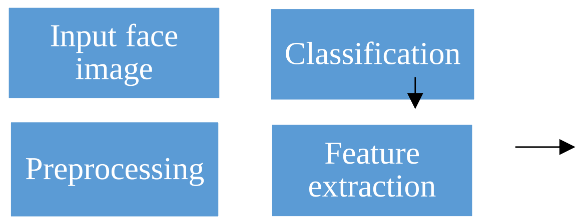

Figure 1: Flow diagram of Facial expression recognition

Region of interest (ROI) is extracted from facial components i.e. nose, mouth, eyes, cheeks, eyebrows, forehead, ear, etc. Extractions of ROIs are performed in feature extraction phase. Techniques which are used for feature extraction are Local Binary Patterns (LBP) [13], Independent Component Analysis (ICA) [14], Principal Component Analysis (PCA) [15], Local Gradient Code (LGC) [16], Linear Discriminant Analysis (LDA) [17], and Local Directional Pattern (LDP) [18]. In next phase of classification, classifier classifies the features into their respective classes based on facial expressions with the help of defined classification methods which include SVM (Support Vector Machine) [19] and NN (Nearest Neighbor) [20].

This paper provides a survey based timeline view which performs an analysis on different technique to handle facial expressions to recognize faces. Lastly the evolution has been done by comparing the results of recognition with different algorithms. The rest of the phases are placed as: section 2 discusses certain earlier researches based on FER methods. Section 3 explains the limitations of the existing schemes 4. Lastly, this work is concluded and gives future idea.

II. LITERATURE SURVEY

In this survey, the existing Facial Expression Recognition (FER) schemes and their merits and limitations has been discussed.

In 2017, Goyani, & Patel [21] proposed a multilevel haar wavelet-based approach to extract presence features from protuberant face regions at two different scales. First, the method segments most useful geometric modules like mouth, eye, eyebrows etc. by the Viola-Jones force object finder. Haar features of segmented components are extracted. For classification, one among all logistic regression method was used. Also, the Haar features are simply computed and it can efficiently signify the signal in low dimension, however reserves the energy of the signal. The presented scheme performance was evaluated by using available datasets like CK, JAFFE and TFEID and it attains 90.48%, 88.57% and 96.84% accuracy for relevant datasets.

In 2017, Qayyum et al., [22] proposed a Stationary Wavelet Transform (SWT) to extract features for FER owing to its decent localization features, in both spectral and spatial domains. Additionally, a mixture of horizontal and vertical subbands of SWT was practiced as these subbands include muscle measure information for mainstream of the FE. Further, feature dimensionality was reduced through applying Discrete Cosine Transform (DCT) on these subbands. Then, the selected features are transformed into Feed Forward Neural Network (FFNN), which was trained by Back Propagation (BP) algorithm. The presented scheme performance was evaluated by using available datasets like JAFFE, CK+ and MS-Kinect datasets. It attains 98.83%, 96.61% and 94.28% accuracy for relevant dataseta.

In 2016, Radlak and Smolka [23] proposed a joined two facial detection methods like tree models and gradient boosting. First, face detection was done through Dlib library. Then, gradient boosting method was used for noticing facial landmarks. If Dlib fails, trees model method was used identified face normalization was complete by Affine Transformation (AT), which excluded face contour. Eliminating the contextual nearby detected face will detained to reduce its properties in facial classification. Before perceived facial landmarks were practised as center point to extract multi scale patches for producing feature vectors for classification. Uniform Local Binary Pattern (ULBP) histogram was calculated for every area inside this piece. Finally, all histogram were united to make high dimensional feature vector. Random Frog (RF) used for feature extraction and fast feature selection was used. Finally, Support Vector Machine (SVM) "one-on-one" technique for multiclass classifier was used. This method attained the finest classification accuracy of 36.93% on validation set.

In 2016, Kamarol et al. [24] used 3D method and proposed framework which takes communication of time and space with less computational cost. Spatio-Temporal Texture Map (STTM) was applied for feature extraction which captures continuous and perfect motion of facial expressions which in turns provide special information. It generates 2D textured map. Has very low computational cost by giving accurate temporal and spatial variations of face expressions. In proposed framework firstly viola and jones face detector detects face then crop out background. After that STTM extract and modeled facial features by using spatiotemporal information gathered from 3 dimensional Harris corner function. Features are extracted and represented in form of histograms this was done by using block-based method. Support vector machine classifier classifies features into emotions. Following results showed strength of proposed framework: recognition rate recorded was 95.37%, 98.56% and 84.52% for different datasets having spontaneous expressions, posed expressions and close to real world expressions.

In 2016, Mistry et al., [25] proposed Micro Generic Algorithm embedded with Particle swarm optimization (mGA embedded PSO) to optimize the features. It also solves local optimum problem and premature convergence by introducing non replaceable memory, a secondary swarm having 5 participants with a leader and 4 followers, new velocity updating strategy, sub dimension-based regional facial feature searching and global exploration searching. For Emotion recognition, features generated from mGA embedded PSO algorithm are classified with multiclass SVM and ensemble classifier for improved accuracy. Results from the paper shows that hvn LBP based feature extraction surpassed most recent Local Binary Pattern variants. For expression recognition, 100% accuracy was achieved in case of CK+ and 94.66% in case of MMI database for mGA embedded POS and diverse classifier. Assessment was done around of 30 trails.

In 2016, Imran et al., [26] proposed a novel expression recognition method by describing images in form of high order two dimensional orthogonal Gaussian-Hermite moments (GHMs). Set of features are selected on the bases of instants having high discrimination power. The discriminative GHMs are casted on the new expression-invariants subspace using association among regular faces to get differentially expressive elements of the instances. Features attained from the differentially expressive elements of the instances and discriminative instances are applied to identify an expression using the SVM classifier. Experiments were conducted on commonly used databases, achieved resulted in overall batter performance of expression recognition than similar or existing methods.

In 2016, Patil et al. [27], presented a scheme to overcome the challenge of feature extraction from images taken in uncontrolled environment. the proposed method uses contourlet transformation and spatial domain to create feature vector unlike current working system that work on Local binary pattern or steerable pyramid that create feature vector only from transformation and spatial domain. As contourlet transform utilizes properties of directionality and anisotropy, it extracts important features. For contour subbands, they suggested a new coefficient enhancement algorithm which enhances skin region features to make system more vigorous. They also tested feature level fusion on multiple databases that showed face recognition rate was competitive. In 2015, Pu et al. [28] used Action Units for Facial Expression recognition and analysis by using random forest classifier in a video. First random frog will detect action units and these detected AUs are classified by second random forest which detects expressions. On first frame Facial Landmarks are generated by active appearance Model (AAM) landmarks are tracked throughout the sequence of frames in a video by Lucas-Kanade optical Flow tracker. A displacement vector was created between natural and Peak expression. First Random forest detects Action units from DNNP features and these AUs are sent to 2nd Random Forest as an input that then process these AUs into Facial Expressions. The proposed methods of facial expression recognition achieve the accuracy rate of 89.37% for the two-fold Random Forest classifier. It can achieve accuracy rate of 96.38%. The results have been achieved by randomly selecting training and testing sets from the database 9 times.

In 2015, Carcagnì et al. [29] proposed a system which implements Histograms of oriented gradients (HOG) on FER system. HOG was dense feature extraction method for single image. It extracts all regions of interests from image through gradients. This technique was pretty fast. Paper describes about how to set perimeters of HOG so it could distinguish the facial expression traits to its best. Algorithmic pipeline pattern splits the system in 3 phases. In 1st phase input frontal face in system which then performs registration of face after that HOG was applied on face. Support Vector Machine (SVM) technique was applied for classification. Phase 2 applies HOG perimeters which are then tested on datasets; sequence of input faces starts with neutral face and ends with expressive face. Phase 3 validates system in real world. This system gave performance for edge and shape molding up to 95.8% accurate. Strength of applied technique lies in choice of parameters plus it gives performance 95.9%, a precision 98%, and accuracy of 98.9%. In 2015, Manisha et al., [30] explored the use of Artificial Neural Network and machine learning. Facial Expression Recognition System was developed to analyze four type of human expressions- happy, sad, Angry and surprised. Jaffe and Paul Ekman database was used for training the database. This facial expression recognition system was found to be 76% accurate in analyzing the human emotion.

In 2014, Saini et al., [31] implemented facial expression recognition techniques using Principal Component analysis (PCA) with Singular Value Decomposition (SVD). Experiments are performed using Real database images. Support Vector Machine (SVM) classifier was used for face classification. Emotion detection was performed using Regression Algorithm with SURF (Speed Up Robust Feature).The universally accepted five principal emotions to be recognized are: Angry, Happy, Sad, Disgust and Surprise along with neutral.

In 2013, Yu et al. [32] presented a semiautomatic way of creating a dataset containing facial expression. First a web search was performed for a certain emotion keyword; search engine returns a raw dataset which was very noisy. To remove non face images, Voila Jones facial detector was used. Images relevant to the query are selected by binary support vector machine. SVM was trained by pool base active learning method to make it able to predict existence of a facial expression matching the query keyword. SVM selected images are final expression data. Furthermore they presented a new facial feature based on WLD and histogram contextualization for multi-resolution analysis of faces. Experiment show that the suggested frame work was fast and accurate, and a diverse dataset for facial expression can be created by this framework. Limitation of this approach was that WLD produces lot of dimensions that needs to be reduced once we have applied this technique. That makes it a bit slow and unreliable. In 2013, Dornaika et al. [33] exploited head poses, 3D head pose and facial actions are provided with an appearance based 3D face tracker, Principal component analysis (PCA) which reduced noise, Latent Dirichlet allocations (LDA) which enhanced the

Discrimination between expressions. Two schemes to implement these algorithms for facial expression recognition are mentioned Scheme 1: Dynamic time wrapping technique in which trained data was given by temporal signature associated with facial expressions. Scheme 2: modeled temporal signature facial actions with constant length feature vector and to recognize expressions used machine learning algorithms. Experiments were conducted on CMU (database) and self-made video frames. It improved classification by applying dimensionality reduction technique. Maximum recognition it gave was 90%.

In 2013, Khan et al. [34] proposed an FER system that would be able to work with images and has less resolution plus for high quality images too which could manages illuminations. It will be memory and time efficient, Features will be extracted from salient regions of face by using Pyramid feature extraction approach Pyramid of Local Binary Pattern (PLBP), after that proposed framework was tested on different databases and obtained very good results i.e. Cohan Kanad CK+, MMI FE database. Generally face recognition systems are divided in 3 phases. Phase 1: Face detection which applies Viola jones object detection. Phase 2: Feature extraction best features are minimized with the change in expressions. Algorithms used in this phase are PLBP for facial feature extractions. It was spatial representation of LBP, takes texture resolution variations into account. For extraction of salient features psycho-visual experiment was implemented using tracker of eyes, conducted on 6 universal expressions. Phase 3: Expression classification. Now let’s talk about strength. Strength of paper is PLBP. It was simple yet computationally efficient. It performs efficiently for high resolution images and has improved performance on images with lower resolution. Framework gave illumination which remain unchanged. It was good for posed as well as for abrupt expressions. Proposed framework proposes silent regions of face only which in turn have less memory consumption and was computationally efficient plus it was useful for real world applications.

In 2013, Ramirez Rivera et al., [35] proposed a novel local feature descriptor, Local Directional Number pattern (LDN), for face analysis, i.e., face and expression recognition. LDN encodes the directional information of the face's textures (i.e., the texture's structure) in a compact way, producing a more discriminative code than current methods. To compute the structure of each micro-pattern with the aid of a compass mask that extracts directional information, and can encode such information using the prominent direction indices (directional numbers) and sign-which allows to distinguish among similar structural patterns that have different intensity transitions. Each face divide into several regions, and extract the distribution of the LDN features from them. Then, concatenate these features into a feature vector, and use it as a face descriptor and should perform several experiments in which descriptor performs consistently under illumination, noise, expression, and time lapse variations. Moreover, test descriptor with different masks to analyse its performance in different face analysis tasks.

In 2012, Liton Chandra Paul & Abdulla Al Sumam [36] addressed the building of face recognition system by using Principal Component Analysis (PCA). PCA was a statistical approach used for reducing the number of variables in face recognition. In PCA, every image in the training set was represented as a linear combination of weighted eigenvectors called eigenfaces. These eigenvectors are obtained from covariance matrix of a training image set. The weights are found out after selecting a set of most relevant Eigenfaces. Recognition was performed by projecting a test image onto the subspace spanned by the eigenfaces and then classification was done by measuring minimum Euclidean distance. A number of experiments were done to evaluate the performance of the face recognition system. In 2012, Kittusamy & Chakrapani [37] recognized the user’s facial expressions from the input images, using a method that was customized from eigenface recognition. Evaluation was done for this method in terms of identification correctness using two different Facial Expressions databases, Cohn-Kanade facial expression database and Japanese Female Facial Expression database. The results show the effectiveness of proposed method. 1n 2011, Khandait et al., [38] proposed a Feed forward back propagation neural network for classifying the expressions of supplied face into seven basic categories like surprise, neutral, sad, disgust, fear, happy and angry. For face portion segmentation and localization, morphological image processing operations are used. Permanent facial features like eyebrows, eyes, mouth and nose are extracted using SUSAN edge detection operator, facial geometry, edge projection analysis. Experiments are carried out on JAFFE facial expression database and gives better performance in terms of 100% accuracy for training set and 95.26% accuracy for test set. In 2011, Living Lang & Zuntao Hu [39] proposed a conventional Adaboost algorithm for local features of face such as eyes and mouth are separated as mutual independent elements for facial feature extraction and classification. The multi-expression classification algorithm which was based on Ad boost and mutual independent feature was proposed. In order to effectively and quickly train threshold values of weak classifiers of features, Sample of training was carried out and to obtain good classification results through experiments. In 2010, Hsieh et al., [9] proposed an integrated face recognition system that was robust against facial expressions by combining information from the computed intraperson optical flow and the synthesized face image in a probabilistic framework. It was proposed to exploit the two different types of information, i.e., the computed optical flow and the synthesized image, to improve the accuracy of face recognition. Experimental validation on the Binghamton University 3-D Face Experssion (BU-3DFE) Database was given to show the improved performance of the proposed face recognition system. The experimental results show that the proposed system improves the accuracy of face recognition from expressional face images. In this section, the existing FER algorithm has been discussed.

Table 1: State-of-the-art among various facial expression recognition schemes

Author Name	Methodology	Advantages	disadvantages
Goyani, & Patel (2017)	• Multilevel Haar wavelet-based approach	• It achieves 90.48%, 88.57% and 96.84% accuracy for the respective dataset.	• It has computational complexity.
Qayyum et al., (2017)	• Stationary Wavelet Transform (SWT)	• An average recognition rate of 98.83% and 96.61% is achieved for JAFFE and CK+ dataset, respectively.	• The face recognition computation time was high.
Radlak and Smolka (2016)	• Dlib detector, • Gradient boosting	• Tests performed on real time settings • Best Accuracy 36.93%	• Bad Results in Disgust and Fear expressions
Kamarol et al. (2016)	STTM (Spatiotemporal texture map) is applied for feature extraction • Generates 2D textured Map.	• Recognition rate recorded was 95.37%, 98.56% and 84.52% for different datasets.	• In AFEW, STTM have accuracy of 90% for most of expressions. 71.43% was lowest for fear which was confused with disgust most of the time.

	• viola and jones face detector for face detection • Harris corner function • Support vector machine classifier classifies features into emotions	• Overall STTM achieved highest performance with low computational cost. • For CK+ datasets high recognition rate was 100%	
Mistry et al. (2016)	•Modified LBP (hvnLBP) • mGA-embedded POS • SVM	• 100% accuracy over CK+ database • 94.66% accuracy for MMI database	• Further work needed in mGA embedded POS
Imran et al. (2016)	•orthogonal Gaussian-Hermite moments • SVM classifier	•Overall Accuracy of 92.13 % in all databases	• When feature extraction is automatic, it diminishes the accuracy. • Neutral images are often confused with Happy or Smile and Sad images
Patil et al. (2016)	• Contourlet transformation and spatial domain to create feature vector. • New coefficient enhancement algorithm	• 99+% accuracy on multiple databases	• The average recognition time for a single query face is 0.949s
Pu et al. (2015)	• Two Fold Random Forest • Active Appearance Model • Lucas-Knade Optical Flow Tracker	• Action Unit Detection Accuracy up to 100% • Expression Recognition Accuracy up to 96.38%	• Not tested on real time environment
Carcagnì et al. (2015)	• Algorithmic pipeline pattern is used • Histogram of gradient(HOG) applied on registered face • SVM(support vector Machine) performs classification • HOG perimeters	• Proposed pipeline is able to classify image correctly with average performance of 95.9%, • Performance 95.9%, precision 98%, and accuracy of 98.9% • Processes 7fps	• It can’t detect emotional state of person • Non-frontal face issue • Work only in range of [-30, 30] degree
Manisha et al., (2015)	• Artificial Neural Network	• It found to be 76% accurate in analyzing the human emotion.	• The training time was high and it was not suitable for large dataset.
Saini et al., (2014)	• Principal Component analysis (PCA) • Singular Value Decomposition (SVD).	• It gives good classification accuracy.	• Time complexity was a big problem.
Yu et al. (2013)	• Voila Jones	• A semiautomatic way of creating a dataset containing facial expression	• WLD produces a lot of dimensions that needs to be reduced latter

	• Support vector machine • Multiscale-WLD based facial expression feature	• Robust Framework	
Dornaika et al. (2013)	• Tracked system is used for recognition to detect head movement with the help of 3D face and facial actions. • Exploited head poses, 3D head pose and facial actions are provided with an appearance based 3D face tracker • Principal component analysis (PCA) • Latent Dirichlet allocations (LDA). Dynamic time wrapping • Modeled temporal signature facial actions	• It improved classification by applying dimensionality reduction technique. • Maximum recognition was 90%. • dynamically learns online face appearance • PCA+LDA have provided better performance. Its classification accuracy is 90.10% • Overall recognition rate was 90.4% in CMU	• Disgust expression gave 44% accuracy • Face detection, facial action and 3D face tracking is not in scope of paper
Khan et al. (2013)	• Features extraction by PLBP • Framework was tested on different databases • Best features are minimized with the change in expressions • For extraction of salient features psycho-visual experiment was implemented using tracker of eyes	• PLBP was simple yet computationally efficient. • Performs efficiently for high resolution images and has improved performance on images with lower resolution	• Change in camera angles and effect of system jamming was not catered.
Liton Chandra Paul & Abdulla Al Sumam (2012)	• Principal Component Analysis (PCA)	• It provides accurate dimensionality reduction and accuracy was high.	• But, the FER accuracy rate was not good.
Kittusamy & Chakrapani (2012)	• Examine the facial expression recognition based on static image using eigen faces	• It provides good performance result.	• It doesn't concentrate any classification schemes like neural network and wavelet transformations
Khandait et al., (2011)	• Feed forward back propagation neural network	• In training set, 100% accuracy and in testing set, 95.26% accuracy.	• But, the training time was high.
Liying Lang & Zuntao Hu (2011)	• Conventional Adaboost algorithm	• Good classification results	• The FER classification accuracy was not good.

Hsieh et al., (2010)	• The computed optical flow and the synthesized image	• The accuracy of this scheme was good.	• It was computationally Costly.

III. CONCLUSION

Facial expressions are fabricated during communication transmission so images may be acquired in uncontrollable condition like occlusion (glasses, scarf, facial hair, cosmetics and it also effects recognition rate), pose, illumination and expression variation etc. This paper has presented a survey on facial expression recognition. Recent feature extraction techniques are covered along with comparison which are very helpful for other researchers to enhance the existing techniques in order to get better and accurate results. In future, to improve the expression classification accuracy, the Hybrid Kernel Function with Relevance Vector Machine (HKF-RVM) based classification schemes will be proposed. In this process, the face will be detected by using Steerable Wavelet Transform (SWT) and the Gray Level Co-occurrence Matrices (GLCM) and statistical features are extracted for classification. This will be improve the classification accuracy and it will suitable for large database.

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