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SURVEY ON FACIAL EXPRESSION ANALYSIS AND RECOGNITION

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ABSTRACT: *Face and its features can be used to identify a person and to analyze the emotional state of a person. Facial expression analysis has been widely used and implemented across various fields such as computer technology, security, psychology, medicine, and pattern recognition [1, 2].*

Several literatures are reviewed which consists of blend shape regression, Vector Field Convolution (VFC) technique, multiple Radial Bases Functions neural networks, active patches, histogram of oriented gradient (HOG) filter, diffeomorphic growth model, sparse group wise image registration method, transductive transfer linear discriminant analysis (TTLDA) approach, Self-Organizing Map (SOM), Learning Vector Quantization (LVQ) Naive Bayes classifier, face quality assessment method, local binary pattern (LBP) and scale invariant feature transformation (SIFT) filters, bit plane specific local image description, Gabor filters, SVM, Active Shape Model, Facial Expression Generic Elastic Model, common and specific patches, Contourlet Transform and k nearest neighbor (KNN) classifier, face parsing, training expression images, cross-database facial expression recognition approach, temporal orthogonal locality preserved projection, principal component analysis, Local Phase Quantization, Random Forests, Local Binary Patterns (LBP), autoregressive (AR) models, median ternary pattern (MTP), Pyramid of Histogram of Gradients, Convolutional networks, graph-based spectral clustering, Supervised Locality Preserving Projection, geometrical feature-based approach, entropy based feature selection method, SUSAN operator (Smallest Univalue segment assimilating nucleus) and Bezier curve models. Several datasets are obtained from repositories and only few literatures have taken their own facial expression datasets. The performance metric accuracy is mainly taken for comparison. Most of the simulations are carried out using MATLAB tool.

Keywords: Image processing, pattern recognition, facial expression analysis, accuracy, time complexity.

1. INTRODUCTION

Face expression analysis and recognition has been one of the fast developing areas due to its wide range of application areas such as emotion analysis, biometrics, image retrieval and is one of the subjects on which lots of research has been done through solving the problems occurring in recognition of the face expressions under different illuminations, orientations and numerous other variations.

Face recognition is an important research problem spanning numerous fields and disciplines. This is because face recognition, in addition to having numerous practical applications such as bankcard identification, access control, mug shots searching, security monitoring, and surveillance system, is a fundamental human behavior that is essential for effective communications and interactions among people.

Generally facial expression recognition framework consists of three step: face detection, feature extraction and feature matching. In order to build robust facial expression recognition framework that is capable of producing reliable results, it is necessary to extract features (from the appropriate facial regions) that have strong discriminative abilities. Recently different methods for automatic facial expression recognition have been proposed, but invariably they all are computationally expensive and spend computational time on whole face image or divides the facial image based on some mathematical or geometrical heuristic for features extraction. None of them take inspiration from the human visual system in completing the same task. Many factors impinge upon the ability of an individual to identify emotional expression. Social factors, such as deception, and display rules, affect one's perception of another's emotional state. Therefore, there is a need to develop Face Expression Recognition System effectively.

2. RELATED WORK

S. Eleftheriadis et al.,2015 proposed a discriminative shared Gaussian process latent variable model (DS-GPLVM) for multiview and view-invariant classification of facial expressions from multiple views. In that a discriminative manifold shared by multiple views of a facial expression was learnt and performed a facial expression classification in the expression manifold. H. Yu and H. Liu.,2014 presented an approach for reproducing optimal 3-D facial expressions based on blendshape regression. It aimed to improve fidelity of facial expressions but maintain the efficiency of the blendshape method, which was necessary for applications such as human machine interaction and avatars. The method intends to optimize the given facial expression using action units (AUs) based on the facial action coding system recorded from human faces. To help capture facial movements for the target face, an intermediate model space was generated, where both the target and source AUs had the same mesh topology and vertex number.

N. Kulkarni et al.,2015 proposed a novel facial-expression analysis system design that focused on automatically recognize facial expressions and reducing the doubt and confusion between facial-expression classes. For that, a new Extraction method was introduced to segment efficiently facial feature contours or outline using Vector Field Convolution (VFC) technique. Depending on the detected contours or outlines, extracting facial feature points, that helps in facial-expression deformations. W. Zheng et al.,2015 proposed a method to deal with challenging cross-domain facial expression recognition problem, a novel transductive transfer subspace learning method. In that method, a labelled facial image set from source domain were combined with an unlabelled auxiliary facial image set from target domain to jointly learn a discriminative subspace and make the class labels prediction of the unlabelled facial images, where a transductive transfer regularized least-squares regression (TTRLSR) model was proposed to that end.

R. Saabni.,2015 proposed an Artificial Neural Network (ANN) of two hidden layers, based on multiple Radial Bases Functions Networks (RBFN's) to recognize facial expressions. The ANN, was trained on features extracted from images by applying a multi-scale and multi-orientation Gabor filters. They had considered the cases of subject independent/dependent facial expression recognition using The JAFFE and the CK+ benchmarks to evaluate the proposed model. M. C. Oveneke et al.,2015 proposed a framework for retrieving three-dimensional facial structure, motion and spatio-temporal features from monocular image sequences. First, they estimate monocular 3D scene flow by retrieving the facial structure using shape-from-shading (SFS) and combine it with 2D optical flow. Secondly, based on the retrieved structure and motion of the face, they extract spatio-temporal features for automated facial expression analysis.

In J. Jin et al.,2014 two different conditions (Pattern_1, Pattern_2) were used to compare across objective measures such as classification accuracy and information transfer rate as well as subjective measures. Pattern_1 was a “flash-only” pattern and Pattern_2 was a facial expression change of a dummy face. In the facial expression change patterns, the background was a positive facial expression and the stimulus was a negative facial expression. S. L. Happy and A. Routray.,2015 proposed a framework for expression recognition by using appearance features of selected facial patches. A few prominent facial patches, depending on the position of facial landmarks, were extracted which were active during emotion elicitation. These active patches were further processed to obtain the salient patches which contain discriminative features for classification of each pair of expressions, thereby selecting different facial patches as salient for different pair of expression classes.

Silva F. A. M. D. and Pedrini H.,2015 demonstrated that the histogram of oriented gradient (HOG) filter is a good technique for facial feature representation.

The HOG filter detect the appearance and shape of face by the distribution of local edge directions. The local features can be characterized without precise information of edge directions. Generally speaking, HOG filter is invariant to illumination, shadowing and changes in texture scale. Zheng-Hong Y., and Cong L.,2014 denoted that support vector machine is kind of classification technique with strong generalization ability. It has unique and prospective application areas in machine learning such as model prediction and function fitting. We believe that the combination of HOG and SVM can obtain the best expression recognition accuracy.

Y. Guo et al., 2016 proposed a dynamic facial expression recognition method. Dynamic facial expression recognition was formulated as a longitudinal groupwise registration problem. The main contributions of that method lie in the following aspects: 1) subject-specific facial feature movements of different expressions were described by a diffeomorphic growth model; 2) salient longitudinal facial expression atlas was built for each expression by a sparse groupwise image registration method, which can describe the overall facial feature changes among the whole population and can suppress the bias due to large intersubject facial variations; and 3) both the image appearance information in spatial domain and topological evolution information in temporal domain were used to guide recognition by a sparse representation method.

W. Zheng and X. Zhou., 2015 proposed a novel transductive transfer linear discriminant analysis (TTLDA) approach for cross-pose facial expression recognition (FER), in which training and testing facial images were taken under the two different facial views. The basic idea of the proposed expression recognition method was to choose a set of auxiliary unlabelled facial images from target facial pose and leverage it into the labelled training image set of source facial pose for discriminant analysis, where the labels of the auxiliary images were parameters of TTLDA to be optimized. In W. Zheng .,2014, a novel multi-view facial expression recognition method was presented. Different from most of the facial expression methods that use one view of facial feature vectors in the expression recognition, they synthesize multi-view facial feature vectors and combine them to that goal. In the facial feature extraction, they use the grids with multi-scale sizes to partition each facial image into a set of sub regions and carry out the feature extraction in each sub region.

M. I. H. Chowdhury and F. I. Alam., 2014 proposed a system for automatic facial expression recognition. A consistent combination of Self-Organizing Map (SOM), Learning Vector Quantization (LVQ) and Naive Bayes classifier was developed to recognize facial expression from Cohn Kanade (CK) and Japanese Female Facial Expression (JAFFE) database. Mao Xu et al.,2015 proposed a efficient facial expression recognition model based on transfer features from deep convolutional networks (ConvNets). They have trained the deep ConvNets through the task of 1580-class face identification on the MSRA-CFW database and transfer high-level features from the trained deep model to recognize expression.

M. A. Haque et al., 2014 proposed a system for constructing facial expression log by employing a face quality assessment method and investigates its influence on the representations of facial expression logs of long video sequences. A framework was defined to incorporate face quality assessment with facial expression recognition and logging system. M. Mandal et al.,2015 proposed a method to classify facial expression in two classes using the Zernike moments. The proposed system consists of two parts: facial feature extraction and facial expression classification. The facial features were extracted using higher order Zernike moments and the features were classified by an ANN based classifier. The facial expressions were classified into groups that represented either positive or non-positive emotion.

Mostafa K et al., 2014 used local binary pattern (LBP) and scale invariant feature transformation (SIFT) filters to represent primitive features of a face. The random forest collections were applied to learn the inter-expression similarity. Significant advantage of this approach was the use of SVM to learn the expression representation from random forest collections. However, the accuracy of this approach on cross datasets was very poor as compare to other approaches on same datasets.

Farajzadeh et al.,2014 used LBP and meta-probability codes to represent facial images and SVM to recognize the facial expressions from three datasets. In this approach the recognition accuracy was 87.2 % on CK dataset, but used only 30 individuals of CK dataset with six expressions. Lucey, P. et al.,2010 proposed a novel approach based on active shape model to locate facial features from dynamic face region. Multi class SVM was trained to detect the presence of an expression. This study demonstrated promising performance on clean and noisy facial images of CK dataset.

M. Dahmane and J. Meunier., 2014 introduced the concept of prototype-based model as anchor modeling through a SIFT-flow registration. A set of prototype facial expression models was generated as a reference space of emotions on which face images were projected to generate a set of registered faces. S. Mohseni.,2014 developed a method for facial movement recognition based on verifying movable facial elements and estimate the movements after any facial expressions. The algorithm plots a face model graph based on facial expression muscles in each frame and extracts features by measuring facial graph edges' size and angle variations.

F. Ahmed et al., 2015 presented a new facial expression recognition method that utilizes bit plane specific local image description in a weighted score level fusion. The motivation was to utilize bit plane slicing to highlight the contribution of a particular bit plane made to the holistic facial appearance, which was then used in a weighted score level fusion in order to boost the recognition performance. A new local image descriptor was proposed specifically to extract local features from bit plane representations that utilizes Fisher linear discriminant to maximize the inter-class distance, while minimizing the intra-class variance.

Dailey et al., 2010 made the first attempt to develop machine learning techniques for cross-cultural facial expression recognition. In this research the authors concluded that slight differences in cultural manifestation of facial expression are enough to confuse the classifier. It motivates to develop an efficient facial expression recognition system to deal with these expression representation differences. Gabor filters were used to represent a facial image, and extracted features were used to train the artificial neural networks.

Silva F. A. M. D. and Pedrini H., 2015 suggested that six basic facial expressions are universal with subtle differences. Experiments were performed on multi-culture facial expression dataset (different combinations of four databases). Gabor filters, histogram of oriented gradients and local binary patterns were used to highlight the edges and textures of the face. The extracted feature vectors were used to train the SVM, artificial neural network (ANN), and K nearest neighbour (KNN) classifiers. On the other hand, the authors were unable to represent an efficient combination of classifiers and feature extraction techniques, instead suggest the development of a vast dataset of multi-culture samples. Zia and Jaffar.,2015 proposed an incremental learning approach for cross-cultural facial expression recognition. The ability of incremental learning allows the classifier to accommodate the different cultures. The classifier was incrementally trained on JAFFE, CK, MUG and FEEDTUM databases subsequently. The major issue in this approach is the test dataset which is not a benchmark dataset. It would be better to evaluate the classifier's performance on cross-culture datasets by varying the training and testing databases.

D. J. Kim et al., 2014 proposed a robust facial expression recognition approach using ASM (Active Shape Model) based face normalization and embedded hidden Markov model (EHMM). Since the face region generally varies as different emotion states, the face alignment procedure was a vital step for successful facial expression recognition. Thus, they first proposed ASM-based facial region acquisition method for performance improvement. In addition, they also introduced the EHMM-based recognition method using two-dimensional discrete cosine transform (2D-DCT) feature vector.

A. Moeini et al., 2014 proposed a method for person-independent pose-invariant facial expression recognition based on 3D face reconstruction from only 2D frontal images in a training set. 3D Facial Expression Generic Elastic Model (3D FE-GEM) was proposed to reconstruct an expression-invariant 3D model of each human face in the present database using only a single 2D frontal image with/without facial expressions. Then, for each 7-class of facial expressions in the database, a Feature Library Matrix (FLM) was created from yaw face poses by the rotating the 3D reconstructed models and extracting features in rotated face. Each FLM was subsequently rendered based on yaw angles of face poses.

L. Zhong et al., 2015 presented a new idea to analyze facial expression by exploring some common and specific information among different expressions. Inspired by the observation that only a few facial parts were active in expression disclosure (e.g., around mouth, eye), they try to discover the common and specific patches which were important to discriminate all the expressions and only a particular expression, respectively. A two-stage multitask sparse learning (MTSL) framework was proposed to efficiently locate those discriminative patches. C. Quan et al.,2014 presented a model named K-order emotional intensity model (K-EIM) which was based on K-Means clustering. Different from other related works, the proposed approach can quantify emotional intensity in an unsupervised way. And then the output from K-EIM was encoded.

P. Dosodia et al.,2015 proposed Gabor DCT filters technique for Facial Expression recognition system reduces redundant features of Gabor matrices using average DCT filtering technique effectively and Gabor features were optimized towards enhancing the accuracy for facial expression recognition.In Y. Zheng-Hong and L. Cong.,2014, the support vector machine (SVM) was researched for the facial expression recognition, on the basis of the research SVM theory, thus a new and improved facial expression recognition method was proposed based on ASM and rough set SVM (RS-SVM). Firstly, the ASM algorithm was used for the facial features location, the features were extracted effectively. Moreover, the attribute reduction algorithm in the theory of rough set was introduced for the selection and classification of the extracted feature, the invalid and redundant features were filtered, finally, the classification was implemented with SVM algorithm.

R. Suresh and S. Audithan., 2014 proposed a automated recognition of facial expression system based on Contourlet Transform and k nearest neighbor (KNN) classifier. There were two types of filter banks were used for contourlet construction, which were Non Subsampled Pyramid Structure (NSPF) and Non Subsampled Directional Filters (NSDF). The energy features were extracted from each sub-band of contourlet decomposed image and then recognition was processed by KNN classifier. M. Xue et al.,2015 proposed a method to extract spatio-temporal features in 4D data (3D expression sequences changing over time) to represent 3D facial expression dynamics sufficiently, rather than extracting features frame-by-frame. It extracts local depth patch-sequences from consecutive expression frames based on the automatically detected facial landmarks. Three dimension discrete cosine transform (3D-DCT) was then applied on these patch-sequences to extract spatio-temporal features for facial expression dynamic representation.

Y. Lv et al., 2014 mainly studies facial expression recognition with the components by face parsing (FP). Considering the disadvantage that different parts of face contain different amount of information for facial expression and the weighted function were not the same for different faces, an idea was proposed to recognize facial expression using components which were active in expression disclosure. The face parsing detectors were trained via deep belief network and tuned by logistic regression. The detectors first detect face, and then detect nose, eyes and mouth hierarchically. L. T. Dang et al.,2014 described a study of the relation between facial expression and customer impression of service quality. Based on the results, a facial expression warning system will be designed to improve the service quality of the Customer Service Representative when they practice in training sessions. The system, based on existing systems, has three modules: facial recognition, feature extraction and facial expression recognition.

S. H. Lee et al., 2014 proposed a sparse representation based FER method, aiming to reduce the intra-class variation while emphasizing the facial expression in a query face image. To that end, they present a new method for generating an intra-class variation image of each expression by using training expression images. The appearance of each intra-class variation image could be close to the appearance of the query face image in identity and illumination. R. Zhu et al.,2015 attempted to apply transferring learning to cross-database facial expression recognition and proposed a transfer learning based cross-database facial expression recognition approach, in which two training stages were involved: One for learning knowledge from source data, and the other for adapting the learned knowledge to target data. That approach has been implemented based on Gabor features extracted from facial images, regression tree classifiers, the AdaBoosting algorithm, and support vector machines.

X. Huang et al., 2014 proposed the revised canonical correlation method to address the two above described issues for making FER be robust to false detection or mis-alignment. Firstly, it presents the local binary pattern to describe the appearance features for enhancing the spatial variations of facial expression. Secondly, it proposed the temporal orthogonal locality preserved projection for building a canonical subspace of a video clip, where it mostly captures the motion changes of facial expressions. D. Ghimire et al.,2015 proposed a method for the recognition of facial expressions from single image frame that uses combination of appearance and geometric features with support vector machines classification. In general, appearance features for the recognition of facial expressions were computed by dividing face region into regular grid (holistic representation).

N. Zainudin et al., 2015 applied optical flow technique to detect facial expression and aimed to investigate the use of optical flow techniques in detecting changes in facial expressions. H. Meng et al.,2016 proposed a two-stage automatic system to continuously predict affective dimension values from facial expression videos. In the first stage, traditional regression methods were used to classify each individual video frame, while in the second stage, a time-delay neural network (TDNN) was proposed to model the temporal relationships between consecutive predictions. A. Gruebler and K. Suzuki et al.,2014 presented the design of a wearable device that reads positive facial expressions using physiological signals. They first analyze facial morphology in 3 dimensions and facial electromyographic signals on different facial locations and show that they can detect electromyographic signals with high amplitude on areas of low facial mobility on the side of the face, which were correlated to ones obtained from electrodes on traditional surface electromyographic capturing positions on top of facial muscles on the front of the face.
S. Zhong et al., 2014 proposed a facial expression recognition method based on the selection of local Gabor features and the extended nearest neighbour algorithm. The Gabor filter and radial encode was used firstly to divide the expression image into local regions, then PCA and FLD was adopted for feature selection, finally the extended nearest neighbour algorithm was applied to classify the facial expression data. K. Li et al.,2014 presented a data-driven approach for facial expression retargeting in video, i.e., synthesizing a face video of a target subject that mimics the expressions of a source subject in the input video.

Y. Liu et al., 2014 proposed a method based on the combination of optical flow and a deep neural network - stacked sparse autoencoder (SAE). That method classifies facial expressions into six categories (i.e. happiness, sadness, anger, fear, disgust and surprise). In order to extract the representation of facial expressions, they choose the optical flow method because it could analyze video image sequences effectively and reduce the influence of personal appearance difference on facial expression recognition.

L. Li et al., 2014 proposed a novel algorithm for Facial Expression Recognition (FER) which was based on fusion of gabor texture features and Local Phase Quantization (LPQ). Firstly, the LPQ feature and gabor texture feature were respectively extracted from every expression image. LPQ features were histograms of LPQ transform. Five scales and eight orientations of gabor wavelet filters were used to extract gabor texture features and adaboost algorithm was used to select gabor features. Then they obtained two expression recognition results on both expression features by Sparse Representation-based Classification (SRC) method. Finally, the final expression recognition was performed by fusion of residuals of two SRC algorithms.
Li Wang et al., 2014 proposed a method for facial expression recognition to recognize expressions conveniently and effectively. Local binary pattern histogram Fourier (HF-LBP) features was used to represent facial expression features. Multiple HF-LBP features were extracted to form recognition vectors for facial expression recognition in the approach, which include sign and magnitude LBP in the completed LBP scheme with multiple radii and different size neighborhoods to achieve enough features. M. K. Abd El Meguid and M. D. Levine.,2014 discussed the design and implementation of a fully automated comprehensive facial expression detection and classification framework. It uses a proprietary face detector (PittPatt) and a novel classifier consisting of a set of Random Forests paired with support vector machine labellers. The system performs at real-time rates under imaging conditions, with no intermediate human intervention.

W. Wang et al., 2014 presented a novel 3D facial expression recognition algorithm using Local Binary Patterns (LBP) under expression variations, which has been extensively adopted for facial analysis. First, to preserve the main information and remove noises which will affect the discrimination, BDPCA reconstruction and Shape Index was utilized to depict the human face accurately. S. H. Lee and Y. M. Ro.,2015 proposed a partial matching framework that aims to overcome the temporal mismatch of expression transition. During the training stage, they construct an over-complete transition dictionary where many possible partial expression transitions were contained. During the test stage, they extract a number of partial expression transitions from a query video sequence. Each partial expression transition was analyzed individually.

S. M. Tabatabaei et al., 2015 proposed a method for image feature extraction using these new image texture descriptors (generalized LBP); then, the obtained results had been compared to the results produced when applying simple LBP descriptors. Furthermore, K-NN and SVM had been used as classifiers in the proposed approach. In C. H. Wu et al.,2014, the Error Weighted Cross-Correlation Model (EWCCM) was employed to predict the facial Action Unit (AU) under partial facial occlusion from non-occluded facial regions for facial geometric feature reconstruction. In EWCCM, a Gaussian Mixture Model (GMM)-based Cross-Correlation Model (CCM) was first adopted to construct the statistical dependency among features from paired facial components such as eyebrows-cheeks of the non-occluded regions for AU prediction of the occluded region. A Bayesian classifier weighting scheme was then used to enhance the AU prediction accuracy considering the contributions of the GMM-based CCMs.

X. Cheng, et al., 2014 proposed and established a Chinese subjects named Chinese Facial Expression Database (CFED). In that database, spontaneous expressions besides posed expressions were obtained across multiple poses besides frontal pose. M. Abdulrahman and A. Eleyan., 2015 proposed a facial expression recognition approach based on Principal Component Analysis (PCA) and Local Binary Pattern (LBP) algorithms. S. Aly et al., 2015 addressed publicly available RGBD+time facial expression recognition dataset using the Kinect 1.0 sensor in both scripted (acted) and unscripted (spontaneous) scenarios. Their fully annotated dataset includes seven expressions (happiness, sadness, surprise, disgust, fear, anger, and neutral) for 32 subjects (males and females) aged from 10 to 30 and with different skin tones. Both human and machine evaluations were conducted.

M. C. Chang and M. S. Lee., 2014 proposed a facial expression synthesis method which combines the advantages of 2D and 3D methods to synthesize expressions on an input neutral facial image. More accurate geometry information was exploited from 3D models by applying a time-saving face model reconstruction method. Expression on 2D was then synthesized using the information from 3D to produce a natural synthesized facial image with desired expression. Z. Su et al.,2014 proposed a dynamic facial expression recognition method based on the auto-regressive (AR) models using combined features of both shape and texture features. A. De and A. Saha studied the different approaches initiated for automatic real-time facial expression recognition which was undertaken along with their benefits and flaws.

W. Zheng et al., 2015 investigated the color facial expression recognition based on color local features, in which each color facial image was decomposed into three color component images. For each color component image, they extract a set of color local features to represent the color component image, where color local features could be either color local binary patterns (LBP) or color scale-invariant feature transform (SIFT). F. Bashar et al.,2014 proposed an appearance-based facial feature descriptor constructed with a new local texture pattern, namely the median ternary pattern (MTP) for facial expression recognition. The proposed MTP operator encodes the texture information of a local neighborhood by thresholding against a local median gray-scale value and quantizing the intensity values of the neighborhood around each pixel into three different levels.

S. L. Happy and A. Routray., 2015 represented an approach of combining the shape and appearance features to form a hybrid feature vector. They had extracted Pyramid of Histogram of Gradients (PHOG) as shape descriptors and Local Binary Patterns (LBP) as appearance features. K. Zhao et al.,2014 proposed an Adaptive Group Lasso based Multilabel Regression approach, which depicts each facial expression with multiple continuous values of predefined affective states. Adaptive Group Lasso was adopted to depict the relationship between different labels which different facial expressions share some same affective facial areas (patches).

A. T. Lopes et al., 2015 proposed a simple solution for facial expression recognition that uses a combination of standard methods, like Convolutional Network and specific image pre-processing steps. Convolutional networks, and the most machine learning methods, achieve better accuracy depending on a given feature set. A. Azazi et al.,2014 proposed a emotion marker identification algorithm for automatic and person-independent 3D facial expression recognition system. First, they mapped the 3D face images into the 2D plane via conformal geometry to reduce the dimensionality.

M. Hayat and M. Bennamoun., 2014 presented a fully automatic framework which exploits the dynamics of textured 3D videos for recognition of six discrete facial expressions. Local video-patches of variable lengths were extracted from numerous locations of the training videos and represented as points on the Grassmannian manifold. An efficient graph-based spectral clustering algorithm was used to separately cluster these points for every expression class. Using a valid Grassmannian kernel function, the resulting cluster centers were embedded into a Reproducing Kernel Hilbert Space (RKHS) where six binary SVM models were learnt.

Mingliang Xue et al., 2014 dealt with the problem of person-independent facial expression recognition from a single 3D scan. They consider only the 3D shape because facial expressions were mostly encoded in facial geometry deformations rather than textures. Unlike the majority of existing works, their method was fully automatic including the detection of landmarks. D. Han and Y. Ming.,2014 extended a combined strategy for Local Binary Patterns (LBP) and Supervised Locality Preserving Projection (SLPP) in facial expression recognition. First, they use LBP to get the histogram of the image. Then the SLPP method was used to reduce the dimension.

D. Das et al., 2014 proposed a real-time person independent facial expression recognition system using a geometrical feature-based approach. The face geometry was extracted using the modified active shape model. Each part of the face geometry was effectively represented by the Census Transformation (CT) based feature histogram. The facial expression was classified by the SVM classifier with exponential $\chi 2$ weighted merging kernel. Y. Nakashima et al.,2015 proposed an image melding-based method that modifies facial regions in a visually unintrusive way with preserving facial expression. Q. Rao et al.,2015 proposed a SURF (Speeded-Up Robust Features) boosting framework to address challenging issues in multi-pose facial expression recognition (FER). Local SURF features from different overlapping patches were selected by boosting in their model to focus on more discriminable representations of facial expression.

K. Yurtkan et al., 2015 presented a entropy based feature selection method applied to 3D facial feature distances for a facial expression recognition system classifying the expressions into 6 basic classes based on 3-Dimensional (3D) face geometry. V. Kumar and A. S. Ali Basha et al.,2014 presented a new approach to facial expression recognition, which uses Wavelet for reducing the high dimensional data of facial expression images into a relatively low dimension data and then uses K nearest neighbor(KNN) as the classifier for the expression classification afterwards. B. Romera-Paredes et al.,2014 presented a system for facial expression tracking based on head-mounted, inward looking cameras, such that the user can be represented with animated avatars at the remote party. The main challenge was that the cameras can only observe partial faces since they were very close to the face.

D. Thuthi., 2014 adopted the Gabor wavelet and SUSAN operator (Smallest Univalue segment assimilating nucleus) which will extracts various features from the faces that result in improved accuracy. In order to recognize their facial expression Adaboost classifier was adopted. N. Zheng et al.,2015 assumed that samples of different expressions reside on different manifolds and proposed a novel human emotion recognition framework named two-dimensional discriminant multi-manifolds locality preserving projection (2D-DMLPP). S. Wu et al.,2015 proposed a method to enhance expression recognition by age. Specifically, they proposed a three-node Bayesian network to incorporate age information as privileged information, which was only available during training. During training phase, a full probabilistic model was constructed to capture the joint probability among image features, age, and expression labels. During testing, the conditional probability of expression labels given image features was obtained by using the Bayesian rule and marginalizing over age.

H. Bao and T. Ma., 2014 proposed a new feature extraction method based on Bezier curve. On the basis of local feature representation and Bezier curves, that method can accurately portray the key parts with few Bezier control-points, and with less point tracking. With much less calculation and more accurate feature, they obtained ideal recognition rate through rigorous experiment.

3. CONCLUSION

This paper aims to conduct a literature review on facial expression recognition research work. In certain number of literatures, the image pre-processing tasks are carried out with the help of principal component analysis. Also three filters namely scale invariant feature transformation (SIFT) filters, histogram of oriented gradient (HOG) filter, and gabor filters are prevalently used to carry out the pre-processing task.

As far as feature selection task is concerned, entropy based method is used.

Machine learning algorithms namely support vector machine (SVM), artificial neural network, convolutional network are used for performing the FER task. Improved image processing techniques which includes autoregressive models, supervised locality preserving projection (SLPP), temporal orthogonal locality preserved projection and graph-based spectral clustering methods are used and attained better recognition accuracy. There are yet broad research dimensions such as feature extraction techniques, improved machine learning algorithms for carrying out facial expression recognition research.

REFERENCES

1. A.De and A. Saha, "A comparative study on different approaches of real time human emotion recognition based on facial expression detection," Computer Engineering and Applications (ICACEA), 2015 International Conference on Advances in, Ghaziabad, 2015, pp. 483-487.

2. A.T. Lopes, E. de Aguiar and T. Oliveira-Santos, "A Facial Expression Recognition System Using Convolutional Networks," 2015 28th SIBGRAPI Conference on Graphics, Patterns and Images, Salvador, 2015, pp. 273-280.

3. Apte, A. Basavaraj and Nithin R K, "Efficient Facial Expression Ecognition and classification system based on morphological processing of frontal face images," 2015 IEEE 10th International Conference on Industrial and Information Systems (ICIIS), Peradeniya, 2015, pp. 366-371.

4. Azazi, S. L. Lutfi and I. Venkat, "Identifying universal facial emotion markers for automatic 3D facial expression recognition," Computer and Information Sciences (ICCOINS), 2014 International Conference on, Kuala Lumpur, 2014, pp. 1-6.

5. Bashar, A. Khan, F. Ahmed and M. H. Kabir, "Robust facial expression recognition based on median ternary pattern (MTP)," Electrical Information and Communication Technology (EICT), 2013 International Conference on, Khulna, 2014, pp. 1-5.

6. C. H. Wu, J. C. Lin and W. L. Wei, "Action unit reconstruction of occluded facial expression," Orange Technologies (ICOT), 2014 IEEE International Conference on, Xian, 2014, pp. 177-180.

7. D. Das, M. M. Hoque, J. F. Ara, M. A. F. M. R. Hasan, Y. Kobayashi and Y. Kuno, "Automatic face parts extraction and facial expression recognition," Strategic Technology (IFOST), 2014 9th International Forum on, Cox's Bazar, 2014, pp. 128-131.

8. D. Han and Y. Ming, "Facial expression recognition with LBP and SLPP combined method," 2014 12th International Conference on Signal Processing (ICSP), Hangzhou, 2014, pp. 1418-1422.

9. D. J. Kim, M. K. Sohn, H. Kim and N. Ryu, "Geometric Feature-Based Face Normalization for Facial Expression Recognition," Artificial Intelligence, Modelling and Simulation (AIMS), 2014 2nd International Conference on, Madrid, 2014, pp. 172-175.

10. Dailey M. N., et al., "Evidence and a Computational Explanation of Cultural Differences in Facial Expression Recognition", Emotion, vol. 10, no. 6, pp. 874-893, 2010.

11. Ebenezer O., Yongzhao, Z., and Qi R. M., "A Neural-Adaboost Based Facial Expression Recognition System", Expert Systems with Applications, vol. 41, no. 7, pp. 3383-3390, 2014.

12. F. Ahmed, P. P. Paul, M. Gavrilova and R. Alhajj, "Weighted Fusion of Bit Plane-Specific Local Image Descriptors for Facial Expression Recognition," Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on, Kowloon, 2015, pp. 1852-1857.

13. Farajzadeh F., Pan G., and Wu Z., "Facial Expression Recognition Based on Meta Probability Codes", Pattern Analysis and Applications, vol. 17, no. 4, pp. 763-781, 2014.

14. Ghimire, S. Jeong, S. Yoon, J. Choi and J. Lee, "Facial expression recognition based on region specific appearance and geometric features," Digital Information Management (ICDIM), 2015 Tenth International Conference on, Jeju, 2015, pp. 142-147.

15. A. Gruebler and K. Suzuki, "Design of a Wearable Device for Reading Positive Expressions from Facial EMG Signals," in IEEE Transactions on Affective Computing, vol. 5, no. 3, pp. 227-237, July-Sept. 2014.

16. H. Bao and T. Ma, "Feature Extraction and Facial Expression Recognition Based on Bezier Curve," Computer and Information Technology (CIT), 2014 IEEE International Conference on, Xi'an, 2014, pp. 884-887.

17. H. Meng, N. Bianchi-Berthouze, Y. Deng, J. Cheng and J. P. Cosmas, "Time-Delay Neural Network for Continuous Emotional Dimension Prediction From Facial Expression Sequences," in IEEE Transactions on Cybernetics, vol. 46, no. 4, pp. 916-929, April 2016.

18. H. Yu and H. Liu, "Regression-Based Facial Expression Optimization," in IEEE Transactions on Human-Machine Systems, vol. 44, no. 3, pp. 386-394, June 2014.

19. J. Jin, Y. Zhang, X. Wang, I. Daly and A. Cichocki, "Decreasing the interference of visual-based P300 BCI using facial expression changes," Intelligent Control and Automation (WCICA), 2014 11th World Congress on, Shenyang, 2014, pp. 2407-2411.

20. K. Li, Q. Dai, R. Wang, Y. Liu, F. Xu and J. Wang, "A Data-Driven Approach for Facial Expression Retargeting in Video," in IEEE Transactions on Multimedia, vol. 16, no. 2, pp. 299-310, Feb. 2014.

21. K. Yurtkan, H. Soyel and H. Demirel, "Entropy driven feature selection for facial expression recognition based on 3-D facial feature distances," 2015 23nd Signal Processing and Communications Applications Conference (SIU), Malatya, 2015, pp. 2322-2325.

22. K. Zhao, H. Zhang and J. Guo, "An adaptive group lasso based multi-label regression approach for facial expression analysis," 2014 IEEE International Conference on Image Processing (ICIP), Paris, 2014, pp. 1435-1439.

23. L. Li, Z. Ying and T. Yang, "Facial expression recognition by fusion of gabor texture features and local phase quantization," 2014 12th International Conference on Signal Processing (ICSP), Hangzhou, 2014, pp. 1781-1784.

24. L. T. Dang, E. W. Cooper and K. Kamei, "Development of facial expression recognition for training video customer service representatives," 2014 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Beijing, 2014, pp. 1297-1303.

25. L. Zhong, Q. Liu, P. Yang, J. Huang and D. N. Metaxas, "Learning Multiscale Active Facial Patches for Expression Analysis," in IEEE Transactions on Cybernetics, vol. 45, no. 8, pp. 1499-1510, Aug. 2015.

26. Li Wang, Ruifeng Li and Ke Wang, "Features representation by multiple local binary patterns for facial expression recognition," Intelligent Control and Automation (WCICA), 2014 11th World Congress on, Shenyang, 2014, pp. 3369-3374.

27. Lucey, P. et al., "The Extended Cohn-Kanade Dataset (CK+): A Complete Expression Dataset for Action Unit and Emotion-Specified Expression", Third International Workshop on CVPR for Human Communicative Behaviour Analysis, San Francisco, USA, pp. 94-101, 2010.

28. M. A. Haque, K. Nasrollahi and T. B. Moeslund, "Constructing facial expression log from video sequences using face quality assessment," Computer Vision Theory and Applications (VISAPP), 2014 International Conference on, Lisbon, Portugal, 2014, pp. 517-525.

29. M. Abdulrahman and A. Eleyan, "Facial expression recognition using Support Vector Machines," 2015 23nd Signal Processing and Communications Applications Conference (SIU), Malatya, 2015, pp. 276-279.

30. M. C. Oveneke, I. Gonzalez, W. Wang, D. Jiang and H. Sahli, "Monocular 3D facial information retrieval for automated facial expression analysis," Affective Computing and Intelligent Interaction (ACII), 2015 International Conference on, Xi'an, 2015, pp. 623-629.

31. M. Dahmane and J. Meunier, "Prototype-Based Modeling for Facial Expression Analysis," in IEEE Transactions on Multimedia, vol. 16, no. 6, pp. 1574-1584, Oct. 2014.

32. M. Hayat and M. Bennamoun, "An Automatic Framework for Textured 3D Video-Based Facial Expression Recognition," in IEEE Transactions on Affective Computing, vol. 5, no. 3, pp. 301-313, July-Sept. 1 2014.

33. M. I. H. Chowdhury and F. I. Alam, "A probabilistic approach to support Self-Organizing Map (SOM) driven facial expression recognition," Computer and Information Technology (ICCIT), 2014 17th International Conference on, Dhaka, 2014, pp. 210-216.

34. M. K. Abd El Meguid and M. D. Levine, "Fully automated recognition of spontaneous facial expressions in videos using random forest classifiers," in IEEE Transactions on Affective Computing, vol. 5, no. 2, pp. 141-154, April-June 1 2014.

35. M. Mandal, S. Poddar and A. Das, "Comparison of human and machine based facial expression classification," Computing, Communication & Automation (ICCCA), 2015 International Conference on, Noida, 2015, pp. 1198-1203.

36. M. Xue, A. Mian, W. Liu and L. Li, "Automatic 4D Facial Expression Recognition Using DCT Features," 2015 IEEE Winter Conference on Applications of Computer Vision, Waikoloa, HI, 2015, pp. 199-206.

37. Mao Xu, Wei Cheng, Qian Zhao, Li Ma and Fang Xu, "Facial expression recognition based on transfer learning from deep convolutional networks," Natural Computation (ICNC), 2015 11th International Conference on, Zhangjiajie, 2015, pp. 702-708.

38. Mingliang Xue, A. Mian, Wanquan Liu and Ling Li, "Fully automatic 3D facial expression recognition using local depth features," IEEE Winter Conference on Applications of Computer Vision, Steamboat Springs, CO, 2014, pp. 1096-1103.

39. Moeini, H. Moeini and K. Faez, "Pose-Invariant Facial Expression Recognition Based on 3D Face Reconstruction and Synthesis from a Single 2D Image," Pattern Recognition (ICPR), 2014 22nd International Conference on, Stockholm, 2014, pp. 1746-1751.

40. Mostafa K., Meguid A. I., and Martin D. L., "Fully Automated Recognition of Spontaneous Facial Expressions in Videos using Random Forest Classifiers", IEEE Transactions on Affective Computing, vol. 5, no. 2, pp. 141-154, 2014.

41. N. Kulkarni, S. Kulkarni, M. Pardeshi, P. Sanap and N. D. Ghuse, "Facial expression recognition using VFC and snakes," Green Computing and Internet of Things (ICGCIoT), 2015 International Conference on, Noida, 2015, pp. 991-994.

42. N. Zainudin, S. Ramli, T. T. Zizi, N. A. Hasbullah and N. Ibrahim, "Facial expression change detection algorithm using optical flow technique," 2015 10th International Conference for Internet Technology and Secured Transactions (ICITST), London, 2015, pp. 332-335.

43. N. Zheng, X. Guo, L. Qi and L. Guan, "Two-dimensional discriminant multi-manifolds locality preserving projection for facial expression recognition," 2015 IEEE International Symposium on Circuits and Systems (ISCAS), Lisbon, 2015, pp. 2065-2068.

44. P. Dosodia, A. Poonia, S. K. Gupta and S. L. Agrwal, "New Gabor-DCT Feature Extraction Technique for Facial Expression Recognition," Communication Systems and Network Technologies (CSNT), 2015 Fifth International Conference on, Gwalior, 2015, pp. 546-549

45. Q. Rao, X. Qu, Q. Mao and Y. Zhan, "Multi-pose facial expression recognition based on SURF boosting," Affective Computing and Intelligent Interaction (ACII), 2015 International Conference on, Xi'an, 2015, pp. 630-635.

46. Quan, Y. Qian and F. Ren, "Dynamic facial expression recognition based on K-order emotional intensity model," Robotics and Biomimetics (ROBIO), 2014 IEEE International Conference on, Bali, 2014, pp. 1164-1168.

47. R. Saabni, "Facial expression recognition using multi Radial Bases Function Networks and 2-D Gabor filters," Digital Information Processing and Communications (ICDIPC), 2015 Fifth International Conference on, Sierre, 2015, pp. 225-230.

48. R. Zhu, T. Zhang, Q. Zhao and Z. Wu, "A transfer learning approach to cross-database facial expression recognition," 2015 International Conference on Biometrics (ICB), Phuket, 2015, pp. 293-298.

49. Romera-Paredes, C. Zhang and Z. Zhang, "Facial expression tracking from head-mounted, partially observing cameras," 2014 IEEE International Conference on Multimedia and Expo (ICME), Chengdu, 2014, pp. 1-6.

50. S. Aly, A. Trubanova, L. Abbott, S. White and A. Youssef, "VT-KFER: A Kinect-based RGBD+time dataset for spontaneous and non-spontaneous facial expression recognition," 2015 International Conference on Biometrics (ICB), Phuket, 2015, pp. 90-97.

51. M. C. Chang and M. S. Lee, "Facial expression synthesis from a single image," Consumer Electronics - Taiwan (ICCE-TW), 2014 IEEE International Conference on, Taipei, 2014, pp. 95-96.

52. S. Eleftheriadis, O. Rudovic and M. Pantic, "Discriminative Shared Gaussian Processes for Multiview and View-Invariant Facial Expression Recognition," in IEEE Transactions on Image Processing, vol. 24, no. 1, pp. 189-204, Jan. 2015.

53. S. H. Lee, K. N. Plataniotis and Y. M. Ro, "Intra-Class Variation Reduction Using Training Expression Images for Sparse Representation Based Facial Expression Recognition," in IEEE Transactions on Affective Computing, vol. 5, no. 3, pp. 340-351, July-Sept. 1 2014.

54. S. H. Lee; Y. M. Ro, "Partial Matching of Facial Expression Sequence Using Over-complete Transition Dictionary for Emotion Recognition," in IEEE Transactions on Affective Computing , vol.PP, no.99, 2015, pp.1-1

55. S. L. Happy and A. Routray, "Automatic facial expression recognition using features of salient facial patches," in IEEE Transactions on Affective Computing, vol. 6, no. 1, pp. 1-12, Jan.-March 1 2015.

56. S. L. Happy and A. Routray, "Robust facial expression classification using shape and appearance features," Advances in Pattern Recognition (ICAPR), 2015 Eighth International Conference on, Kolkata, 2015, pp. 1-5.

57. S. Liu, D. Y. Huang, W. Lin, M. Dong, H. Li and E. P. Ong, "Emotional facial expression transfer based on temporal restricted Boltzmann machines," Signal and Information Processing Association Annual Summit and Conference (APSIPA), 2014 Asia-Pacific, Siem Reap, 2014, pp. 1-7.

58. S. M. Tabatabaei, A. Chalechale and S. Moghimi, "Facial expression recognition using high order directional derivative local binary patterns," Pattern Recognition and Image Analysis (IPRIA), 2015 2nd International Conference on, Rasht, 2015, pp. 1-5.

59. S. Mohseni, N. Zarei and S. Ramazani, "Facial expression recognition using anatomy based facial graph," 2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC), San Diego, CA, 2014, pp. 3715-3719.

60. S. Wang, J. Sha, H. y. Wu and Y. Fu, "Hierarchical facial expression animation by motion capture data," 2014 IEEE International Conference on Multimedia and Expo (ICME), Chengdu, 2014, pp. 1-6.

61. S. Wu, S. Wang and J. Wang, "Enhanced facial expression recognition by age," Automatic Face and Gesture Recognition (FG), 2015 11th IEEE International Conference and Workshops on, Ljubljana, 2015, pp. 1-6.

62. S. Zhong, Y. Chen and S. Liu, "Facial Expression Recognition Using Local Feature Selection and the Extended Nearest Neighbor Algorithm," Computational Intelligence and Design (ISCID), 2014 Seventh International Symposium on, Hangzhou, 2014, pp. 328-331.

63. Silva F. A. M. D. and Pedrini H., "Effects of Cultural Characteristics on Building an Emotion Classifier through Facial Expression Analysis", Journal of Electronic Imaging, vol. 24, no. 2, pp. 1-17, 2015.

64. D. Thuthi, "Recognition of facial expression using action unit classification technique," Recent Trends in Information Technology (ICRTIT), 2014 International Conference on, Chennai, 2014, pp. 1-5.

65. V. Kumar and A. S. Ali Basha, "Facial expression recognition using wavelet and k-nearest neighbour," Current Trends in Engineering and Technology (ICCTET), 2014 2nd International Conference on, Coimbatore, 2014, pp. 48-52.

66. W. Wang, W. Zheng and Y. Ma, "3D Facial Expression Recognition Based on Combination of Local Features and Globe Information," Intelligent Human-Machine Systems and Cybernetics (IHMSC), 2014 Sixth International Conference on, Hangzhou, 2014, pp. 20-25.

67. W. Zheng and X. Zhou, "Cross-pose color facial expression recognition using transductive transfer linear discriminat analysis," Image Processing (ICIP), 2015 IEEE International Conference on, Quebec City, QC, 2015, pp. 1935-1939.

68. W. Zheng, "Multi-View Facial Expression Recognition Based on Group Sparse Reduced-Rank Regression," in IEEE Transactions on Affective Computing, vol. 5, no. 1, pp. 71-85, Jan.-March 2014.

69. W. Zheng, X. Zhou and M. Xin, "Color facial expression recognition based on color local features," 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), South Brisbane, QLD, 2015, pp. 1528-1532.

70. W. Zheng; Y. Zong; X. Zhou; M. Xin, "Cross-Domain Color Facial Expression Recognition Using Transductive Transfer Subspace Learning," in IEEE Transactions on Affective Computing , vol.PP, no.99, 2015, pp.1-1

71. X. Cheng, L. Xue, Y. Chen and L. Liu, "Chinese Facial Expression Database with spontaneous expressions across multiple poses," Computing, Communication and Networking Technologies (ICCCNT), 2014 International Conference on, Hefei, 2014, pp. 1-6.

72. X. Huang, G. Zhao, M. Pietikäinen and W. Zheng, "Robust Facial Expression Recognition Using Revised Canonical Correlation," Pattern Recognition (ICPR), 2014 22nd International Conference on, Stockholm, 2014, pp. 1734-1739.

73. Y. Guo, G. Zhao and M. Pietikäinen, "Dynamic Facial Expression Recognition With Atlas Construction and Sparse Representation," in IEEE

Transactions on Image Processing, vol. 25, no. 5, pp. 1977-1992, May 2016.

74. Y. Liu, X. Hou, J. Chen, C. Yang, G. Su and W. Dou, "Facial expression recognition and generation using sparse autoencoder," Smart Computing (SMARTCOMP), 2014 International Conference on, Hong Kong, 2014, pp. 125-130.

75. Y. Lv, Z. Feng and C. Xu, "Facial expression recognition via deep learning," Smart Computing (SMARTCOMP), 2014 International Conference on, Hong Kong, 2014, pp. 303-308.

76. Y. Nakashima, T. Koyama, N. Yokoya and N. Babaguchi, "Facial expression preserving privacy protection using image melding," 2015 IEEE International Conference on Multimedia and Expo (ICME), Turin, 2015, pp. 1-6.

77. Y. Zheng-Hong and L. Cong, "Research of Facial Expression Recognition Based on ASM Model and RS-SVM," Intelligent Systems Design and Engineering Applications (ISDEA), 2014 Fifth International Conference on, Hunan, 2014, pp. 772-777.

78. R. Suresh and S. Audithan, "Contourlets for facial expression analysis using one nearest neighbor classifier," Current Trends in Engineering and Technology (ICCTET), 2014 2nd International Conference on, Coimbatore, 2014, pp. 380-384.

79. Z. Su, J. Chen and H. Chen, "Dynamic facial expression recognition using autoregressive models," Image and Signal Processing (CISP), 2014 7th International Congress on, Dalian, 2014, pp. 475-479.

80. Zheng-Hong Y., and Cong L., “Research of Facial Expression Recognition Based on ASM Model and RS-SVM”, Fifth International Conference on Intelligent Systems Design and Engineering Applications, Hunan, pp. 772-777, 2014.