Systematic review of various feature extraction techniques for facial emotion recognition system

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Abstract: Facial emotion recognition (FER) is the task of recognising human emotions from images and videos. Communicating through facial emotions is a kind of non-verbal communication and it reflects a person's inner thoughts and mental states. In the present study, various existing geometric and appearance based feature extraction techniques used in FER are reviewed in tabular form. The main motive of this paper is to analyse the performance of these techniques on the bases of accuracy on different datasets like JAFFE, CK+, CK and MMI. After extensive research on feature extraction techniques for FERS, it is found that the appearance feature-based techniques achieved maximum accuracy and more favourable as compared to geometric feature-based techniques. Finally, the paper concludes with the various challenges encountered for feature extraction in the field of FERS which need to be addressed in the future.

Keywords: emotions; FERS; facial emotion recognition system; geometric feature based techniques; appearance feature based techniques; classification.

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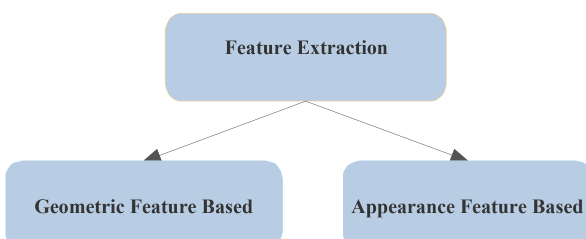
1 Introduction

In recent years, the Facial emotion recognition system(FERS) has become an open and wide research area due to the advancement of its related research fields especially machine learning, computer vision, pattern recognition, image processing, and cognitive science (Kar et al., 2017). In social communication, human facial expressions are extremely essential. Communication includes both verbal and non-verbal communication. Non-verbal communication accurately conveys human emotions but verbal communication cannot find a person's exact emotion. Non-verbal communication includes body language, facial expression and human behaviour. Recognition of human emotions is a very interesting and challenging problem in FER because human faces vary from one person to another due to different ages, races, skin colour and facial hair. Most of the FERSs focus on recognising six basic emotions (Ekman and Friesen, 1971) i.e., anger, disgust, fear, happiness, sadness and surprise. Emotion Recognition is mostly performed in three stages consisting of image pre-processing, feature extraction of images, and classification. This review paper is focused on the feature extraction step. The feature extraction is a very important task in FER. The feature extraction is divided into two categories (Wang, 2018) and they are geometric feature-based technique and appearance feature-based technique. Figure 1 shows two types of feature extraction techniques for FERS. The geometric feature-based techniques comprise mouth, eyes, eyebrows, nose and geometric relationships from face images. The geometric based technique is also known as feature-based technique. In a geometric feature-based technique, the facial points in a single image or image sequences are used in different ways to form a feature vector for recognition of facial emotions. For example, the distance between feature points and the relative sizes of the major face components are computed to form a feature vector. The feature points can also form a geometric graph representation of the face.

Figure 1 Feature extraction technique for facial emotion recognition system (see online version for colours)



The appearance feature-based technique describes the skin texture caused by expression, e.g., wrinkles, furrows and texture of facial images. The Appearance feature-based extraction techniques (Turan and Lam, 2018) extract image features from the whole face or some part of the face without any previous knowledge. This research paper is dedicated to a systematic review of feature extraction techniques for the recognition of facial emotions. Various types of feature extraction techniques are discussed and reviewed in literature to recognise the human emotions for FERS. Different types of human emotion, numbers of facial emotion database and few challenges faced by researchers in the field of FER are presented in this paper.

1.1 Abbreviations

All the abbreviations used in this review paper are listed alphabetically in Table 1.

Table 1 List of abbreviations

Abbreviation	*Full name*	*Abbreviation*	*Full name*
AAM	Appearance active model	JAFFE	Japanese female facial expression
AFEW	Acted facial expressions in the wild	KDEF	Karolinska directed emotional face
ANN	Artificial neural network	K-ELM	Kernel extreme learning machine
ARFD	Aleix Robert face database	KNN	K-nearest neighbours
BU –3DFE	Binghamton university 3D facial expression	LBP	Local binary pattern
CE	Compond emotion	LDA	Linear discriminant analysis
CK	Cohn Kanade	LDN	Local directional number
CK+	Extended Cohn Kanade	LDTP	Local directional ternary pattern
CNN	Convolutional neural network	LGBP	Local gabor binary patterns
DBN	Deep belief network	LPQ	Local phase quantisation
DCLBP	Diagonal crisscross local binary pattern	LS-SVM	Least square support vector machine
DCT	Discrete cosine transform	LTP	Local ternary pattern
DISFA	Denver intensity of spontaneous facial action database	MLP	Multi layer perceptron
DWT	Discrete wavelet transform	MUG	Multimedia understanding group
EXPW	Expression in-the-wild database	PCA	Principal component analysis
FER	Facial emotion recognition	RF	Random forest
FERG-DB	Facial expression research group 3D database	RWAF	Real-world affective faces RWAF
FERS	Facial emotion recognition system	SFEW	Static facial expressions in the wild
FFNN	Feed forward neural network	SPO	Spider monkey optimisation
GF	Gabor filter (GF)	SVM	Support vector machine
HDL	Hierarchical deep learning	SWT	Stationary wavelet transform
HMM	Hidden Markov model	TFD	Toronto face database
HOG	Histogram of oriented gradients	TFEID	Taiwanese facial expression image database
IALTP	Improved adaptive local ternary pattern	WLD	Weber local descriptor
ICA	Independent component analysis		

1.2 Emotions

There are different types of emotions that can be easily detected on the human face (Kumari and Bhatia, 2020). Table 2 shows a summary of different types of facial emotions.

Table 2 Different types of emotions (see online version for colours)

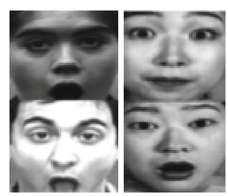
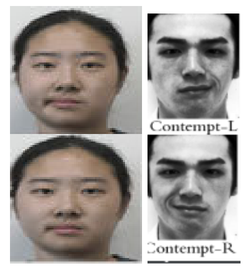
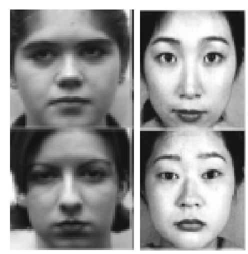
S. No.	*Emotion*	*Facial muscles movements*	*Sample images*
1	Happiness	Happy expression is symbolised by the smile of Joy. The mouth may be open or closed. Cheeks have been raised. The eyelids are tightened and the eyebrows are drawn down	 CK JAFFE
2	Sad	Sad expression is usually seen as a corner of lips pulled down, raised cheeks, likely slipped down jaw. Upper eyelids Drop, Inner corner of eyebrows raised and joined together	 CK JAFFE
3	Surprise	Surprise expression is symbolised by the jaw-drop, wrinkled nose, eyes that look far wider than usual ones and eyebrows that look a little higher. Extreme surprise can lead to larger eyes and higher brows	 CK JAFFE
4	Anger	Angry expression is represents by a firmly clenched jaw. If the teeth are clenched, the mouth has a rectangular shape. Thinning of the lips, the lower jaw may be forward, the upper eyelids raised, the skin around the eyes squeezed. The eyebrows were lowered and pulled together	 CK JAFFE
5	Fear	A Fear expression is normally joined by lips extended horizontally. Possibly dropped jaw raised upper eyelids as high as possible, raised eyebrows and slightly closer together. Eyes staring straight at the head	 CK JAFFE

Table 2 Different types of emotions (see online version for colours) (continued)

S. No.	*Emotion*	*Facial muscles movements*	*Sample images*
6	Disgust	The eyebrows and eyelids are calm. The upper lip is raised and curled, the mouth is open, the lower lip is flattened and the upper lip is raised	 CK JAFFE
7	Contempt	Contempt expression is the upper lip raised, the lip lifted to one side, the nose wrinkled and the eyes turned away	 CK+ TFEID
8	Neutral	Neutral is relaxed facial muscles. Eyelids are iris-tangent. The mouth is closed and the lips in touch	 CK+ JAFFE

1.3 FER datasets

In the field of FERS, number of databases has been used for comparative and extensive experiments. Table 3 shows the name of the dataset, number of images/videos, resolution details, emotions, environment, subject of the FER databases.

1.4 Organisation of the paper

The paper is structured as follows. Section 2 presents a literature review of feature extraction techniques. Section 3 elaborates on the detail study of facial emotion recognition. Section 4 provides a result analysis of various existing feature extraction techniques for recognition of facial emotions. Section 5 presents some challenges and future scope. Section 6 discusses the conclusion of the survey.

Table 3 Datasets for FERS

Dataset	*Images/ Videos*	*Resolution*	*Emotions*	*Environment used*	*Subject*
JAFFE (Poursaberi et al., 2012)	213 Images	256 × 256	7 (6 Basic + Neutral)	Lab	10
CK+ (Lucey et al., 2010)	593 video Sequences	640 × 490	7 (6 Basic + Contempt)	Lab	123
FER+ (GitHub, 2013)	35,685 Images	48 × 48	8 (6 Basic + Neutral + Contempt)	Web	N/A
CK (Cohn, 2001)	500 Image Sequences.	640 × 490	6 Basic	Lab	100
MUG (Zia and Jaffar, 2013)	1462 Sequences	896 × 896	7 (6 Basic + Neutral)	Lab	86
ARFD (Martinez and Benavente, 1998)	4000 Images	768 × 576	4 Neutral, Smile, Anger and Scream	Lab	126
MMI (Ryu et al., 2017)	238 Videos Sequences	720 × 576	7 (6 Basic + Neutral)	Lab	28
TFEID (Chen and Yu Shiuan, 2007)	7200 mages	600 × 480	8 (6 Basic + Neutral + Contempt)	Lab	40
KDEF (Lundqvist et al., 1998)	4900 Images	762 × 562	7 (6 Basic + Neutral)	Lab	70
Yale (Georghiades, 2001)	165 Images	168 × 192	6 Basic	Lab	11
CMU Multi – Pie (Gross et al., 2008)	750,000 Images	3072 × 2048	6 Basic	Lab	337
CE (Du et al., 2014)	5060 Images	3000 × 4000	22 (Basic + Compound Emotions)	Lab	230
Extended Yale B Face (B+) (Kuang chih et al., 2005)	16,128 Images	320 × 243	6 Basic	Lab	28
DISFA (Mavadati et al., 2013)	130,000 Stereo Frames	1024 × 768	5 Happy, Surprise, Fear, Disgust and Sadness	Lab	27
BU –3DFE (Ko, 2018)	2500	1040 × 1329	6 Basic	Lab	100
FERG-DB (Aneja et al., 2017)	55767 Annotated Face	–	7 (6 Basic + Neutral)	Lab	6

Table 3 Datasets for FERS (continued)

Dataset	*Images/ Videos*	*Resolution*	*Emotions*	*Environment used*	*Subject*
AFEW (Samadiani et al., 2020)	1809 Videos	-	7 (6 Basic + Neutral)	Movie	220
TFD (Susskind et al., 2010)	112,234 Images	48*48	7 (6 Basic + Neutral)	Lab	4178
SFEW (Dhall et al., 2015)	1635 Images	720×576	7 (6 Basic + Neutral)	Movie	–
Oulu-CASIA Database (Zhao et al., 2011)	2880 Image Sequences	320×240	6 Basic	Lab	80
Radboud Faces Database (Langner et al., 2010)	1608 Images	681*1024	8 (6 Basic + Neutral + Contempt)	Lab	67
Emotionet (Benitez Quiroz, Srinivasan and Martinez, 2016)	950,000 Images	Not Given	6 Basic 5 Compound (Happily and Sad) (Happily and Surprised) (Happily and Disgust) (Sadly and Fearful) (Sadly and Surprised)	Web	N/A
Affectnet (Mollahosseini et al., 2019)	450,000	Various	8 (6 Basic + Neutral + Contempt)	Web	N/A
EXPW (Zhao et al., 2011)	91,793	Various	7 (6 Basic + Neutral)	Web	N/A
Real-World Affective Face Database (Shan and Weihong, 2019)	29672 Images	Not given	8+12 (compound)	Web	–
BU-4DFE (Yin et al., 2008)	60,600 Frame (Dynamic data)	1040×1329	6 Basic	Lab	101
Gemep-Fera (Anziger and Scherer, 2010)	2500 Video clips	N/A	7 (6 Basic + Neutral)	Lab	100
Bosphorous (Savran et al., 2008)	4666 Images	1600 * 1200	35 Expressions	Lab	105

2 Literature review

Different feature extraction techniques have been suggested in the literature work for FERS. Shan and Weihong (2019) proposed the artificial neural network (ANN) based technique to recognise facial emotions. Spatial-temporal recurrent neural network (Zhang et al., 2019) has been designed to recognise the human facial emotions. It also uses sparse projection to enhance the model discriminant ability. Authors (Kim et al., 2019) used the Hierarchical deep learning (HDL) method to recognise facial expressions. HDL can extract the dynamic facial features between the neutral and emotional images without sequence data. Authors (Rajpurohit et al., 2020) proposed an attention based word-level contextual feature extraction approach for emotion classification. The Author (Li and Xu, 2020) discussed a deep reinforcement learning framework for robust emotion classification in facial expression recognition. The Distinctiveness of human footprints features (Nagwanshi and Dubey, 2020) was estimated using G-mean clusters, segmentation, and rule based techniques. Authors (Chifu et al., 2019) proposed evolutionary based approach. Fast Fourier Transformation and principal component analysis techniques (Arabaci and Mohamed, 2020) were used for feature extraction. Authors (Ratnoo et al., 2018) proposed clustering-based method for data reduction. Decision trees (j48), multi-layer perceptron, random forest and naive Bayes classifiers were discussed for the classification task (Mahmoud et al., 2018).

2.1 Appearance based feature extraction techniques

The Most common existing appearance based feature extraction techniques used for emotion recognition are gabor filter (GF) (Revina and Emmanuel, 2018), principal component analysis (PCA) (Franco and Treves, 2001), independent component analysis (ICA) (Uddin et al., 2009), local binary pattern (LBP) (Shan et al., 2009), local directional ternary pattern (LDTP) (Ramírez Rivera et al., 2015), gabor wavelets (Zhang and Ma, 2007), histogram of oriented gradients (HOG) (Mlakar and Potocnik, 2015), discrete wavelet transform (DWT) (Nayak et al., 2016), discrete cosine transform (DCT) (Vedantham and Reddy, 2020) and stationary wavelet transform (SWT) (Nayak et al., 2017). The Comparative review of these appearance feature extraction techniques used for feature extraction in FERS is reviewed in Table 4. It includes various fields such as dataset, feature extraction technique, classifier and test accuracy.

2.2 Geometric based feature extraction techniques

From existing literature, it is found that geometric feature extraction techniques used for emotion recognition in FERS are normalised central moments descriptor (Ghimire et al., 2016b), AAM (Liliana et al., 2018; Zangeneh and Moradi, 2018), active shape model (Natarajan and Muthuswamy, 2014), point distribution model (Saeed et al., 2014), elastic bunch graph (Ghimire and Lee, 2013), T-stochastic embedding (Yu and Zhang, 2015), QuadTree Decomposition (Sandbach et al., 2012), Bezier Curve (Zhao-yi et al., 2010), local curvelet transform (Ucar et al., 2014) and canny edge detection (Vishnu, 2017). Table 5 presents a comparative review of various existing geometric feature extraction techniques for emotion recognition in FERS.

Table 4 Comparative review of various appearance-based feature extraction techniques for FER

S. No.	*References*	*Dataset*	*Appearance based-feature extraction technique*	*Classifier*	*Test Accuracy*
1	Vedantham and Reddy (2020)	KDEF CK+ MMI DISFA+ Oulu-CASIA	LPQ WLD LBP and DCT	DBN with SMO Algorithm	97.93%, 95.42%, 97.58%, 95.76%, 92.38%
2	Dosi et al. (2019)	KDEF	LBP, LGBP and DCLBP	SVM	82.38% 79.44% 73.80%
3	Varma et al. (2019)	Two Own Datasets	PCA and LDA	HMM and SVM	(87.50% and 98.40%) (84.97% and 92.90%)
4	Saurav et al. (2019)	CK, JAFFE and Radboud Faces	IALTP, LTP and PCA	K-ELM	99.5%, 95.9% and 97.8%
5	Dino and Abdulrazzaq (2019)	CK+	HOG and PCA	SVM, KNN and MLP	82.97% 93.53% 79.97%
6	Vishnu (2017)	CK JAFFE ISED	Quadrilateral Shape Model used for Feature Extraction	SVM, MLP, and RF	96.69% 97.8% 97.3%
7	Nigam et al. (2018)	CK+ JAFFE Yale	DWT and HOG	Multi Class SVM	97.2% 71.43% 75%
8	Rahul et al. (2018)	JAFFE	Partition-Based Method	Multi Stage HMM	85%
9	Islam et al. (2018,)	JAFFE	2D-PCA	Minimum Distance Classifier	89.86%.
10	Arora et al. (2018)	JAFFE	Gradient Filter, PCA and PSO	RF	93.1%
11	Ryu et al. (2017)	CK+ JAFFE MMI CMU-PIE BU-3DFE GEMEP-FERA	LDTP	SVM	94.2% 93.2% 99.8% 89.5% 72.5% 81.8%
12	Shan et al. (2017)	JAFFE CK+	Haar like Features	CNN	76.7442% 80.303%

Table 4 Comparative review of various appearance-based feature extraction techniques for FER (continued)

S. No.	*References*	*Dataset*	*Appearance based-feature extraction technique*	*Classifier*	*Test Accuracy*
13	Nazir et al. (2017)	MMI	HOG and DCT	KNN	95.2%
		CK+			99.6%
14	Tsai and Chang (2017)	JAFFE	DCT and GF	SVM	97.10%
15	Sharma and Rameshan (2017)	JAFFE	HOG, LBP and Eigen Faces	Fisher Discrimination Dictionary	95.23%
		CK+			93.33%
16	Ab., A. and E. (2017)	Self dataset	Gabor Feature	SVM and KNN	90%
17	Chen et al. (2012)	Cohn	PCA and LDA	SVM	90.1%
		JAFFE			81.5%
		Self			85.1%
18	Qayyum et al. (2017)	JAFFE	DCT	FFNN	98.83%
		CK+			96.61%
19	Wang et al. (2018)	Own dataset	Stationary wavelet entropy and Jaya algorithm	FFNN	96.80%
20	Kar et al. (2017)	JAFFE	Ripplet-II + PCA + LDA	LS- SVM and	99.46%
		CK+		Radial Basis Function	98.97%
21	Guo et al. (2016)	JAFFE	Extended LBP	SVM	93.3%
		CK+			92.3%
22	Zhang et al. (2016)	JAFFE	LBP, LPQ, Gabor Wavelet, PCA and LDA	SVM	85.94%
24	Mehta and Jadhav (2016)	JAFFE	Log-Gabor Filter and PCA	Euclidean Distance Metric	93.7%
23	Rejila and Menon (2015)	JAFFE	LDA, LBP, PCA	SVM and ANN	97%
25	Mannan et al. (2015)	CK+	LDN	Multiple SVM and Decision Level Fusion	96.38%
26	Happy and Routray (2015)	KDEF	LBP	SVM	93.3%
27	Biswas and Sil (2015)	JAFFE	Discrete Contourlet Transform	SVM	98.63%
		CK			98.06%

Table 4 Comparative review of various appearance-based feature extraction techniques for FER (continued)

S. No.	*References*	*Dataset*	*Appearance based-feature extraction technique*	*Classifier*	*Test accuracy*
28	Kumari Shah and Khanna (2015)	Self database	PCA, LDA and Gabor Wavelet	SVM	86.7%
29	Dixit and Gaikwad (2015)	JAFFE	Zernike Moments	Naive Bayesian	81.66%
30	Dahmane and Meunier (2014)	JAFFE	HOG	SVM	85%
31	Zhang et al. (2014)	JAFFE, CK	GF	SVM	82.5%
32	Siddiqi et al. (2014)	Own	PCA and ICA	HMM	98%
33	Owusu et al. (2014)	JAFFE, Yale	GF	Multi feed-forward neural network	94.16%
34	Deepthi (2013)	JAFFE	2D – DCT	Artificial neural networks	–
35	Li et al. (2013)	JAFFE	LBP	Sparse Representation Classification	69.52%
36	Ji and Idrissi (2012)	CK, MMI	LBP	SVM	95.8% 97%
37	Poursaberi et al. (2012)	JAFFE, CK and MMI	Gauss-Laguerre Wavelet	KNN	96.71% 92.20% 87.66%
38	Weifeng et al. (2012)	JAFFE	LBP and GF	Sparse Representation Classification and Discriminative Dictionary Learning	85.7% 78.6% 94.3%
39	Song et al. (2010)	JAFFE, CK and Realtime	Graphics-processing unit based active shape model	SVM	86.85%

Table 5 Comparative review of various geometric-based feature extraction techniques for FER

S. No.	*References*	*Dataset*	*Geometric based-feature extraction technique*	*Classifier*	*Test accuracy*
1	Ngoc et al. (2020)	CK+	Conventional deep learning-based landmark extractor	Directed graph neural network	96.02%
2	Krithika and Priya (2020)	MMI	Edge-based Invariant Transform	Neural network-based self-organising classifer	96.47%
3	Alreshidi and Ullah (2020)	SFEW	Neighbourhood difference features	RF	57.7%
		RWAF			59.0%
4	Jarraya et al. (2020)	Meltdown Crisis	Deep spatio-temporal feature extraction	Recurrent neural network	85.5%
5	Samadiani et al. (2020)	AFEW (Acted facial expressions in the Wild)	Generalised procrustes analysis	RF	39.71%
6	Agarwal et al. (2019)	JAFFE	Linear geometric features derived from images like diameter, physiological length, physiological width, face area etc.	HMM	84.7%
7	Kathy et al. (2018)	CK+	Layer based	CNN	93.3%
8	Wang and Ni (2018)	JAFFE	Generative adversarial networks	CNN	59.62%
9	Zangeneh and Moradi (2018)	CK +	AAM algorithm	SVM	96.44%
10	Michael Revina and Sam Emmanuel (2018)	JAFFE CK	LDN, dominant gradient local ternary pattern descriptor	SVM	88%
11	Liliana et al. (2018)	CK+	AAM and geometry facial component feature extraction	Fuzzy rule based	93.67%
12	Chanti and Caplier (2017)	JAFFE	Random face feature descriptor algorithm	SVM	88.4%

Table 5 Comparative review of various geometric-based feature extraction techniques for FER (continued)

S. No.	*References*	*Dataset*	*Geometric based-feature extraction technique*	*Classifier*	*Test accuracy*
13	Benitez-Garcia et al. (2017)	CK+	Fourier descriptors for feature extraction	SVM	92.5%
14	Yang et al. (2017)	JAFFE	Haar cascades method for feature extraction	FFNN	Surprise Happy Anger Disgust Fear 93.26% 95.25% 91.22% 84.32% 82.58%
15	Goyani and Patel (2017)	CK JAFFE TFEID (Taiwanese Facial Expression Image Database)	Haar wavelet	Logistic Regression	96.84% and 98.73% 90.48% and 90.56% 88.57% and 89.58%
16	Vishnu (2017)	JAFFE	Facial fiducial points selection through Adaboost classifiers	Decision tree algorithm	78.4%
17	Ghimire et al. (2016a)	CK+ MMI MUG	Selective multi-class AdaBoost and Extreme Learning Machine	SVM	97.8 % 77.22 % 95.5 %
18	Rejila and Menon (2016)	JAFFE	Learning free facial landmark detection technique and active patch extraction	SVM	97.8%
19	Sexana et al. (2016)	CMU MultiPIE	Active shape model	Adaboost	94%
20	Maximiano da Silva and Pedrini (2016)	CK+ MUG BOSPHOR US 3D	AAMs to position the fiducial points	SVM	63% 74% 90%

Table 5 Comparative review of various geometric-based feature extraction techniques for FER (continued)

S. No.	*References*	*Dataset*	*Geometric based-feature extraction technique*	*Classifier*	*Test accuracy*
21	Ghimire et al. (2016b)	CK+	Normalised central moments descriptors	SVM	Neural Angry Disgust Fear Happy Sad 83.3% 78.8% 90% 82% 100% 73.3% 98.8%
22	Yu and Zhang (2015)	FER-2013 SFEW	Hinge Loss	CNN	72% 61.29%
23	Bavkar et al. (2015)	CK	Lucas Kanade optical flow tracker	SVM and radial basis function neural network	91%
24	Hernandez Matamoros et al. (2016)	KDEF	Gabor function	SVM	99%
25	Natarajan and Muthuswamy (2014)	CK + and FERT	Active shape model	Ada-Boost and temporal rule-based	93.6% and 94.4%
26	Ucar et al. (2014)	JAFFE, CK	Linear curvelet transform	Online sequential extreme learning machine	94.41%
27	Hsieh et al. (2015)	CK	Active shape model, GF and Laplacian of Gaussian	Multi-class SVM	94.7%
28	Suk and Prabhakaran (2014)	CK+	Active shape model (ASM)	SVM	86%
29	Saeed et al. (2014)	CK+	Point distribution model	SVM	83.15%

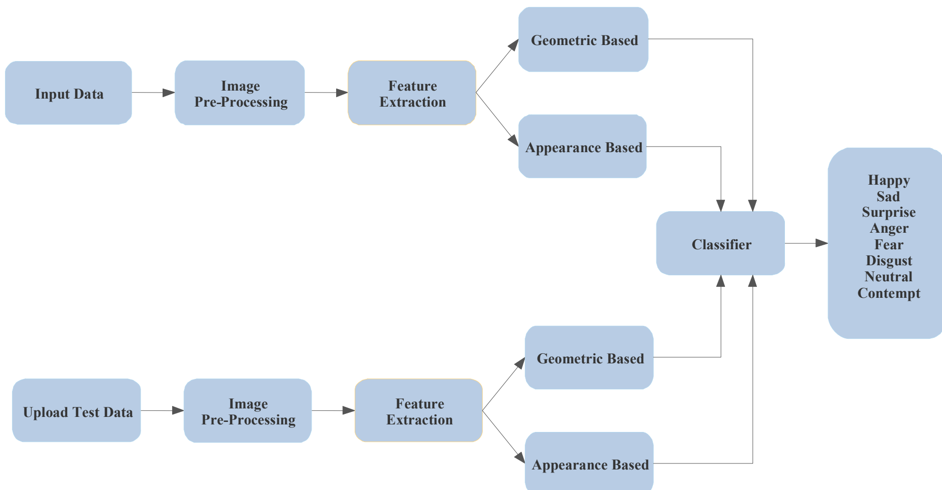
Table 5 Comparative review of various geometric-based feature extraction techniques for FER (continued)

S. No.	*References*	*Dataset*	*Geometric based-feature extraction technique*	*Classifier*	*Test accuracy*
30	Dhavalikar and Kulkarni (2014)	OWN dataset	AAM	Euclidean distance method and adaptive neural fuzzy inference system	90–95% 99%
31	Miranda et al. (2014)	Own dataset	Eccentricity features determined using specific facial landmarks	k-NN, SVM and RF	85%, 88% and 89%,
32	Lin et al. (2014)	Yale faces	Geodesic distance	Mahalanobis distance	90%
33	Ghimire and Lee (2013)	CK+	Elastic Bunch Graph	Multi-Class AdaBoost SVM	95.17% and 97.35%
34	Yi et al. (2014)	CK Beihang University (BHU) database	Feature point distance ratio coefficient, connection angle ratio coefficient and skin deformation energy parameter	Radial basis function neural network	88.7% and 87.8%
35	Yi et al. (2013)	JAFFE	T-Stochastic neighbour embedding	SVM Ada-Boost M2	90.3% 94.5%
36	Sandbach et al. (2012)	BU-4DFE	Quad tree decomposition	Gentle boost and HMM	76.5%
37	Chen et al. (2012)	CK	Facial points and local textures	Radial basis functions and SVM	95%
38	Banu et al. (2012a)	Own dataset	Bezier Curves	FFNN	85%
39	Zhao-yi et al. (2010)	JAFFE	Adaptive Canny operator edge detection and AAM	Least-squares method	85%
40	Wang et al. (2010)	JAFFE	Static facial expression features, motion-dependent facial expression features	SVM	87.5%

3 Facial emotion recognition system

In this section, Figure 2 shows the overall framework of the FERS. The three main steps that are common in the FERS, i.e., image pre-processing, feature extraction and classification.

Figure 2 Overview of facial emotion recognition system (see online version for colours)



Step 1: The image pre-processing step is used to prepare the raw data for further processing which includes different types of activities such as face images that are converted to a grey-scale image, cropping, scaling, detecting the face region from the image, remove other objects (e.g., hair), background from the image and noise-removal/enhancement. The most popular and effective pre-processing techniques are viola-jones algorithm for face detection (Benitez-Garcia et al., 2017; Salmam et al., 2016; Ucar et al., 2014; Zhang and Liu, 2016), normalisation (Ji and Idrissi, 2012), segmentation (Hernandez-Matamoros et al., 2016) and histogram equalization (Cossetin et al., 2016; Happy and Routray, 2015; Ucar et al., 2014). Analysing raw data without any kind of screening can lead to unwanted results.

Step 2: The feature extraction is the next step for emotion recognition. Data presented in an image is very complex and high dimensional; it is a necessary step to extract the informative feature from an image. The feature extraction technique is divided into two types: appearance based and geometric based feature extraction technique. Various feature extraction techniques used for FERS are discussed in the literature review.

Step 3: Classification is the last step for emotion recognition in FERS. A classifier is used to recognise the various emotions such as happiness, sadness, anger, fear, surprise, disgust, contempt and neutral. The most commonly used and widely applied classifier in FER systems are SVM (Dosi et al., 2019; Ghimire et al., 2016b; Vishnu, 2017), k-NN (Poursaberi et al., 2012), Naive Bayesian (Dixit and Gaikwad, 2015), Ada-boost (Sexana et al., 2016), CNN (Wang and Ni, 2018; Yu and Zhang, 2015), HMM (Siddiqi et al., 2014), decision tree (Vishnu, 2017), RF (Samadiani et al., 2020) and MFFNN (Owusu et al., 2014)

4 Result analysis

In the literature review, various existing feature extraction techniques implemented by different researchers in the field of emotion recognition are discussed in detail. In this review paper, the comparative analysis of these techniques is analysed on the basis of accuracy on different datasets like JAFFE, CK, CK+ and MMI are shown in Figures 3–10. From comparative analysis, It is found that Researchers achieved maximum accuracy 99.4%, 99.6%, 99.5% and 99.8% on JAFFE, Ck+, Ck and MMI datasets using appearance based feature extraction techniques for emotion recognition. Whereas in geometric based feature techniques researchers have achieved maximum accuracy 97.8%, 97.8%, 98.7% and 96.47% on JAFFE, Ck+, Ck and MMI datasets for emotion recognition. Table 6 shows the result analysis of feature extraction techniques on the different dataset for FERS.

Figure 3 Test accuracy of appearance feature extraction technique rate for JAFFE dataset (see online version for colours)

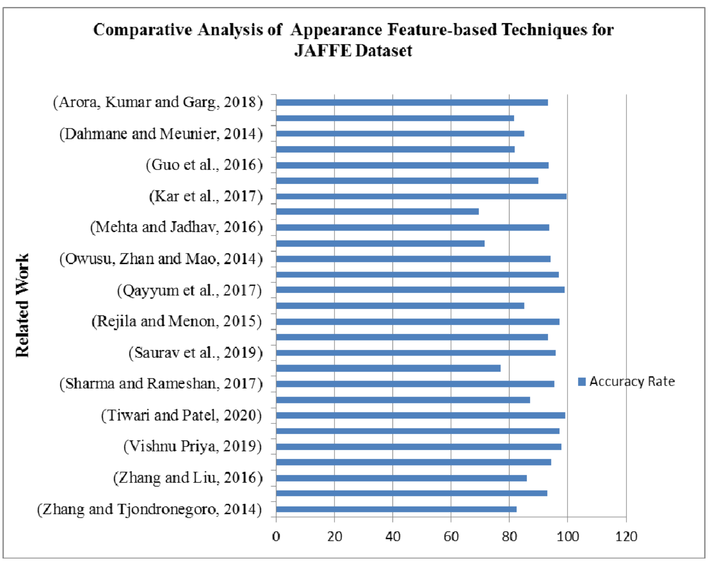


Figure 4 Test accuracy rate of appearance feature based techniques for CK + dataset (see online version for colours)

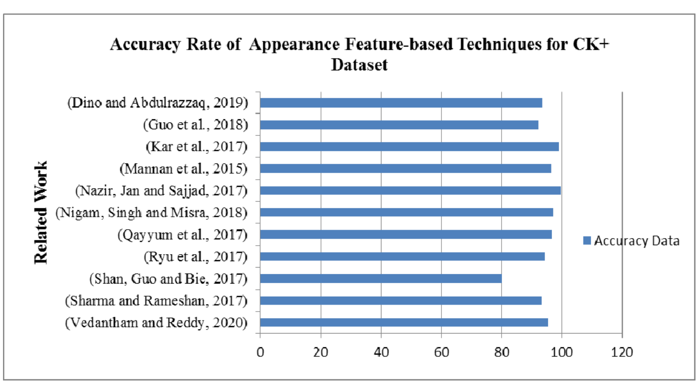


Figure 5 Test accuracy rate of appearance based feature extraction techniques for CK dataset (see online version for colours)

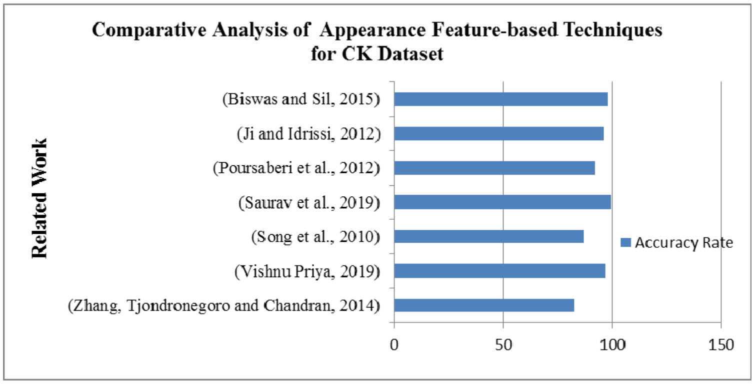


Figure 6 Test accuracy rate of appearance based feature extraction techniques for MMI dataset (see online version for colours)

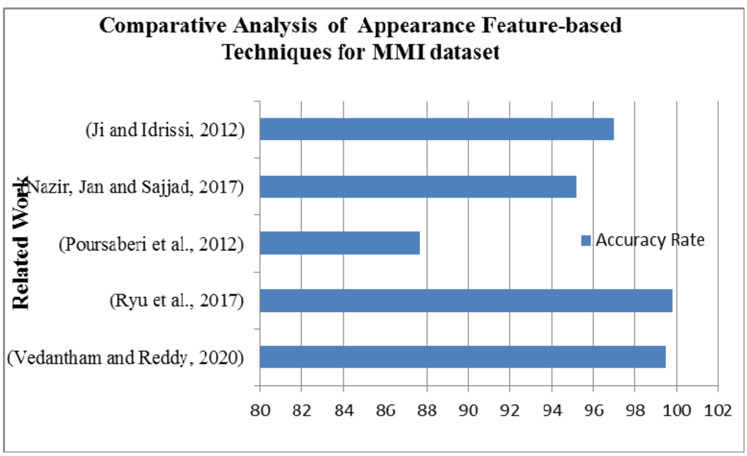


Figure 7 Test accuracy rate of geometric based feature extraction techniques for JAFFE dataset (see online version for colours)

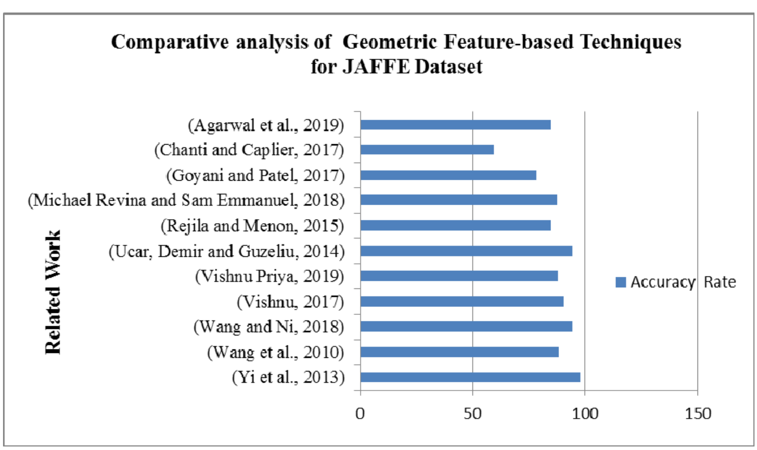


Figure 8 Test accuracy rate of geometric based feature extraction techniques for CK + dataset (see online version for colours)

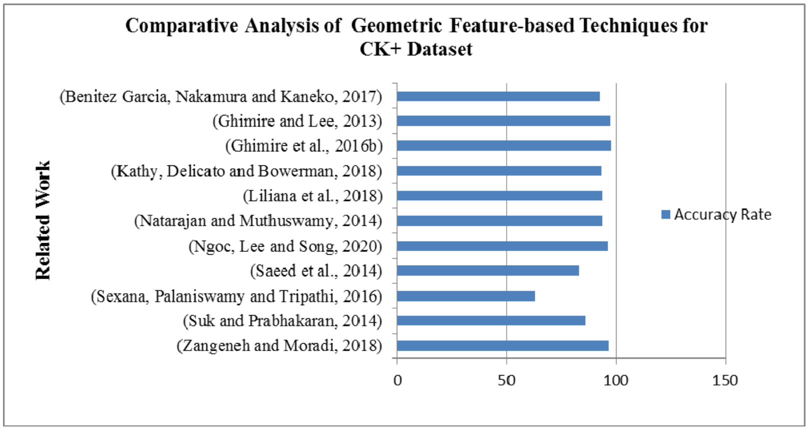


Figure 9 Test accuracy rate of geometric based feature extraction techniques for CK dataset (see online version for colours)

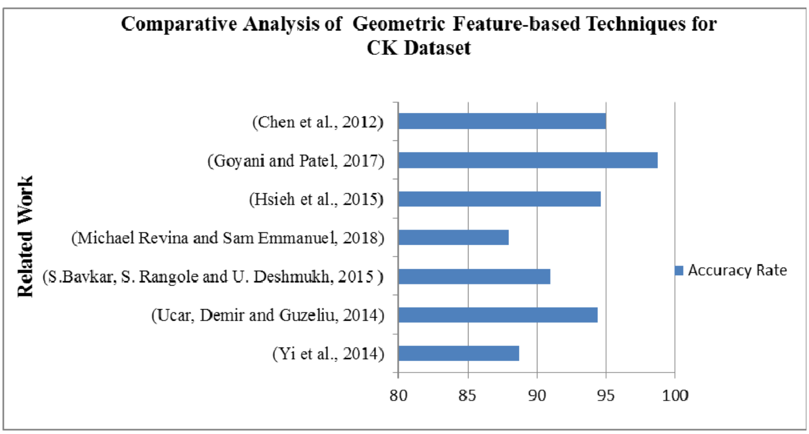


Figure 10 Test accuracy rate of geometric based feature extraction techniques for MMI dataset (see online version for colours)

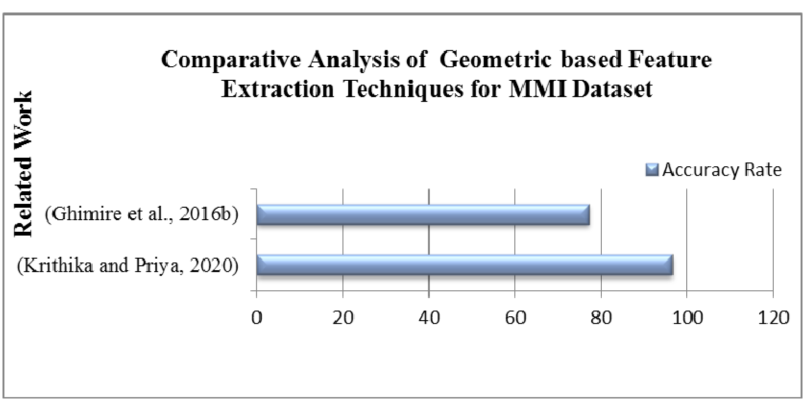


Table 6 Result analysis of various feature extraction techniques on JAFFE, CK+, CK and MMI dataset

Technique	*Author*	*Dataset*	*Appearance based feature extraction technique*	*Maximum accuracy achieved*
Analysis of Existing Appearance Based Feature Extraction Technique	Kar et al. (2017)	JAFFE	Ripplet-II, PCA and LDA	99.4%
	Nazir et al. (2017)	CK+	HOG and DCT	99.6%
	Saurav et al. (2019)	CK	IALTP and PCA	99.5%
	Ryu et al. (2017)	MMI	LDTP	99.8%
Analysis of Existing Geometric Based Feature Extraction Technique	Rejila and Menon (2015)	JAFFE	Learning free facial landmark detection technique and active patch extraction	97.8%
	Ghimire et al. (2016a)	CK+	Selective multi-class AdaBoost and extreme learning machine	97.8%
	Goyani and Patel (2017)	CK	Haar wavelet	98.7%
	Krithika and Priya (2020)	MMI	Edge-based invariant transform	96.47%

5 Challenges and future scope

The most common challenges faced by researchers in the field of FER system for image feature extraction are as following:

1. The current databases available on the internet include posture based facial expressions.
2. Facial expressions based images included in the commonly available datasets generally do not consider the temporal effects as well as effects due to aging.
3. In real-time applications of facial emotion recognition, high pixel resolution data is required which is generally measured in TBs and poses a challenge for data storage, data- transmission as well as data processing.
4. The facial images datasets generally take images in an unconstrained environment which many-a-times include faces with camouflage or faces covered by accessories/occlusions.
5. Due to overwhelming growth in the size of datasets, it is now a challenge to run conventional feature extraction algorithms efficiently on these huge datasets.
6. If face images are taken in different illumination then expression features can be detected inaccurately and hence recognition rate of facial emotions is low.

7 With the advancements in multi-core architectures, there is a growing demand for feature extraction algorithms that can run in parallel.

8 Humans lost natural facial expressions due to some medical problems like facial Paralysis, autistic disorder, asperger syndrome, hepatolenticular degeneration, depressive disorders, Depression, facial weakness (Jameel et al., 2016).

9 There is a lack of standard protocols for the FER system's performance comparison and fair evaluation.

10 The quality of prominently available datasets with regard to proportionate representation of various facial emotions is still a challenge. For example, the datasets generally contain comparatively less number of images for the emotion labelled as 'disgust' as compared to the emotion 'happy' or 'sad'.

11 Certain emotions like 'disgust' and 'anger' have too much similarity index. It is very challenging to accurately classify such types of emotions.

12 Most of the available datasets suffer from the problems of gender biases, cultural variations and are not diverse. Due to this reason, the FER models are unable to generalise or have low performance.

13 Many times, it is difficult to determine whether the facial emotions are 'subtle' or 'acted out', i.e., whether the images contained in the datasets are of real emotions or forced fake emotions.

14 The machine can correctly recognise or classify expressions only for the human face for which it is trained, due to the great variations in the nature of the facial data.

15 Human visual scanning system can work on images belonging to a different sex, age groups, ethnicity and can classify a single emotion into more than one class whereas till now no automatic FER system has this capability. Neither any such datasets exist having multiple emotions for a single image. Another noticeable point is that most of the time people do not produce exact emotion, for example, 'hundred percent angry', rather they produce bent emotions.

6 Conclusion

The purpose of this review paper is to provide a structured and thorough analysis of the work carried out in the field of FER and to further encourage research in this area. After extensive research on feature extraction techniques for FER system, it is found that geometric based feature extraction techniques provides table and scale-invariant features but appearance feature-based technique gives optimal feature points which can represent global face structure. The appearance-based feature extraction techniques do not require the accurate reconstruction of all the facial landmarks but only need emotion labels of the samples for the training process. From comparative analysis, researchers achieved maximum accuracy of 99.4%, 99.6%, 99.5% and 99.8% on JAFFE, Ck+, Ck and MMI datasets respectively using appearance based feature extraction techniques for emotion recognition. Whereas in geometric based feature techniques researchers have achieved maximum accuracy 97.8%, 97.8%, 98.7% and 96.47% on JAFFE, CK+, CK and MMI datasets respectively for emotion recognition in FERS.

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