Judgmental Feature Based Facial Expression Recognition Systems and FER Datasets - A Comprehensive Study

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Facial expressions play an equally important role as the verbal communication and tonal expressions. They echo the mental state of the person. Expressions can be modeled either by using *descriptive features* - coded using facial muscles, or *judgmental features* - coded using texture information. In this paper, we surveyed mainly judgmental feature based prominent methods. An image is rich and high dimensional data structure, which can result into considerable computation when processed directly. Various feature extraction techniques have been proposed to represent the image efficiently in lower dimensions which can be easily processed by a machine. Until now, most of the research was centered around the recognition of frontal face expressions. Recent work has been targeted on processing profile faces and spontaneous expressions by treatment of multimodal fusion. In addition to features, the dataset is another major aspect of pattern recognition. Multidimensional comparison of various facial expression databases is also derived in this paper. Moreover, the survey presents scientific challenges touching the performance of the system.

Keywords: Affective computing, facial expression recognition, judgmental features, local binary pattern, Gabor filter.

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1. INTRODUCTION

Affective computing is the next generation computing, in which an automated response is generated from human behavior and expressions. It focuses on recording, interpreting and modeling the users' mental state into appropriate computer actions. Pantic et al. [2006] described Facial Expression Recognition (FER) as a process of finding the emotional state of the person from the facial images. Bit by bit, future of computation will be humanistic instead of computer focused. Automatic facial expression recognition can act as a component of the natural human-machine interfaces. Synthetic speech with expressions sounds more pleasing and convincing than a monotonous voice. Fasel and Luettin [2003] and Kanade et al. [2000] have shown that talking heads, avatars, computer agents can be trained to learn user preferences through the user's expressions.

Facial expression is the most grounded segment which mirrors the mental state of an individual. And as per the studies of Donato et al. [1999], it provides an important behavioral measure to study emotion, cognitive processes, and social interaction. Human-Computer Interaction (HCI) is getting key attention in automation of computer-based activities such as motion based gadget controlling, security frameworks, medical, and entertainment. Customary HCI frameworks do not account the mental state of the individual. Precise recognition of the facial expressions can revolutionize human-machine interfaces.

Facial expressions are not just a physical change on the face, rather it is a physio-psychological process, which emerges from the mind and reflected on the face in the form of contraction of muscles. Fasel and Luettin [2003] identified that this adjustment in muscles keeps going for limited focus period, roughly from 250 ms to 5 sec. Expressions are not always in peak intensity, 18 unique classes of *smile* are noted by Schmidt and Cohn [2001]. Also, other expressions may have a number of variants - *gentle to peak*. Thus, recognition of facial expression is not an easy task. The intensity of expressions varies over the time for an individual and between two different persons. Subsequently, it is difficult to determine precise facial expression intensities, without referring to the neutral face of a given subject. Recognizing expressions from the spontaneous image is harder as compared to posed still images, which are usually captured in a controlled environment with peak expression intensity and thus can be identified more easily.

Investigation of the Physiognomy and facial expression dates back to the era of Aristotle (4^{th} century). *Physiognomy* is the Greek word, in which *physis* means "nature" and *gnomon* means "judge". Highfield et al. [2009] defined it as the branch of assessing peoples' character from their outer appearance, especially from the face. Over the period, interest in Physiognomy faded out but the facial expression has been an active area for artists, physicians, and researchers. In 1649, Bulwer [1649] discussed about effects of expressions on facial muscles movement in his well-known book "Pathomyotomia". This can be considered as foundation study in the field. Another interesting study on facial expressions was performed by French Painter Brun [1698]. He promoted the expression of emotions in his article published in 1698. His lecture at the *Royal Academy of Painting* in 1667 on facial expressions and their effects on the painting was reproduced in the form of book Brun [1734]. Many of the 18^{th}-century artists had been referring this book for imitating the expressions in different conditions. The most important work which has had a direct influence on modern FER research was done by Darvin [1872] in the nineteenth century. In 1872, he studied the generality of facial expressions across human and animals in his well-known book *"The Expression of the Emotions in Man and Animal"*. That was the preliminary experiment on facial expression. He observed how humans and animals exhibit the common characteristics while expressing their emotions. Both have a tendency to show their ocular muscles and tighten their teeth when they are in anger state.

Till then, a lot of work has been done in the field of facial expression recognition. It has played a vital role in social communication and in conveying emotions. According to Mehrabian [1968], facial expressions alone convey 55% of the information, while vocal and verbal channel together carry only 45%. Darvins claim of universality in expression was reinforced by the series of experiments conducted by Ekman and Friesen [1971]. They postulated a range of expressions into six judgmental classes - anger, disgust, fear, happy, sad and surprise, which are portrayed in Figure 1. These prototypic expressions are universal across all human ethnicities, cultures, race, age, gender and locality. Later, Ekman and Friesen [1978] introduced descriptive coding, known as *Facial Action Coding System* (FACS). FACS represents the expression in terms of Action Units (AU), which is a visible measurable change in facial muscles.

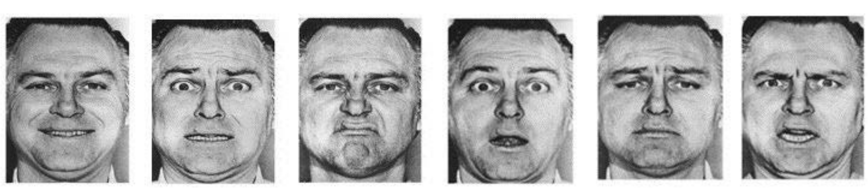

Figure 1. Six basic expressions postulated by Ekman and Friesen. From left to right: happy, fear, disgust, surprise, sad and anger

Suwa et al. [1978] offered pioneer study on auto facial expression analysis from the sequence of images. In their presented work, they tracked the motion of 20 facial points on image sequence. Since then, both face and facial expression recognition continue to attract researchers from various fields like image processing, pattern recognition, machine learning, and computer vision. By the time, processing power had grown unexpectedly and became less expensive. Face detection and face tracking studies, which are required for FERS, had already made significant progress. Research on facial expression recognition got the real attention after the modality of six expressions and experiment by Suwa. Historical developments in facial expression recognition are summarized in Table 1.

Reference	**Contribution**
Darvin [1872]	He established the historical background for the study of facial expressions
Mehrabian [1968]	Claimed that the expressions contribute 55% in social communication
Ekman and Friesen [1971]	Classified range of expressions into six basic prototypic expressions
Ekman and Friesen [1978]	Developed FACS to model the facial muscle change in terms of AUs
Suwa et al. [1978]	Proposed first computerized FER system by tracking 20 facial locations
Sirovich and Kirby [1987]	Presented an idea to represent a face as an *eigenpicture*
Daugman [1988]	Presented a Gabor texture descriptor with neural network for face analysis
Turk and Pentland [1991]	Implemented first facial expression recognition system based on PCA
Chellappa et al. [1995]	Their survey on *face recognition using machine* has given a new direction to the field of face recognition
Ojala et al. [1996]	Proposed a powerful texture descriptor called Local Binary Pattern
Yacoob and Davis [1996]	Designed a facial expression recognition system by extracting dynamic temporal features from image sequence using optical flow
Swets and Weng [1996]	Presented an idea of automatic selection of most discriminative features and most expressive features using PCA and LDA
Belhumeur et al. [1997]	Designed fisherface based facial expression recognition using LDA. PCA and LDA are highly used in facial expression recognition for optimal feature selection by dimension reduction.
Bartlett and Sejnowski [1997]	Proposed a way of representing a face as a set of independent uncorrelated components.
Lyons and Akamatsu [1998]	Prepared JAFFE dataset and implemented Gabor wavelet based FERS. Through experiment they showed that mouth and eye region are the most promising areas for feature extraction.
Cootes et al. [2001]	Designed Active Appearance Model for efficiently locating fiducial points on face
Ojala et al. [2001]	Authors extended the functionality of basic LBP to multi-resolution LBP
Fasel and Luettin [2003]	Published a remarkable survey on facial expression recognition
Yang et al. [2004]	Implemented 2D-PCA to overcome the limitations of PCA
Viola and Jones [2004]	Designed Viola-Jones algorithm for face detection
Shan et al. [2009]	Compared performance of various classifiers for LBP features and evaluated performance of facial expression in low resolution
Guo et al. [2010]	Extended LBP to completed LBP by incorporating sign and magnitude of LBP response
Moore and Bowden [2011]	Investigated intrinsic potential of different poses for facial expression recognition. Using variants of LBPs, implemented FER for multi-view non-frontal faces.
Almaev and Valstar [2013]	Presented Local Gabor Binary Pattern (GLBP) which finds LBP pattern of Gabor convolved image.
Huang et al. [2015]	Proposed spatio-temporal feature extractor LBP-TOP for efficient facial representation
Corneanu et al. [2016]	Published remarkable survey on facial expression recognition using multimodality.

Table I: Timeline of facial expression research

Rest of the paper is organized as follow. Generic framework of FER system is discussed in section 2. Section 3 covers the fundamental aspect of the study, various feature extraction techniques, classifiers, comparisons etc. Detail study of facial expression dataset is outlined in section 4. Section 5 covers conclusion and discussion followed by references.

2. FACIAL EXPRESSION RECOGNITION FRAMEWORK

Corneanu et al. [2016] classified coding of expression in two categories: descriptive and judgmental. *Descriptive* coding scheme defines the expression in terms of position and relation between facial muscles. The face is described by the set of facial muscle configuration, called Action Units (AUs). For a given expression, the presence of AU may be independent or in combination. Ekman reported more than 7000 different AU combinations. Facial Action Coding Scheme (FACS) and Facial Animation Parameter (FAP) are widely used descriptive coding schemes. Conventionally, FACS code is manually labeled by trained observers while viewing videotaped facial behavior in slow motion. Few of the descriptive features of upper and lower face are portrayed in Figure 2.

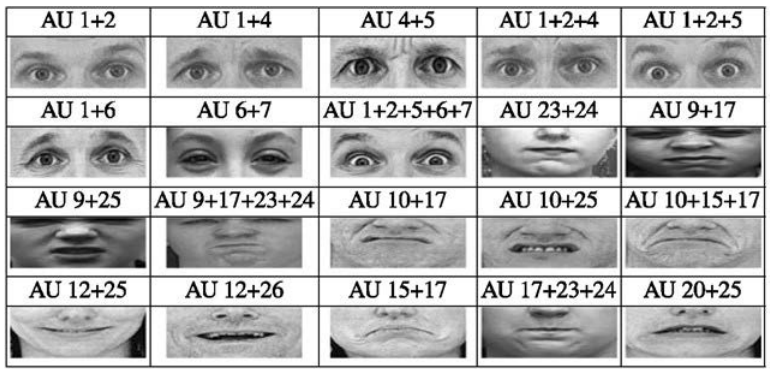

Figure 2. Descriptive facial features: upper face features (top half), lower face features (bottom half)

On the other hand, *judgmental* coding scheme describes the emotion based on subtle details present on the face, like texture, wrinkles, bulges etc. Typically, judgmental features are extracted using filter or kernel function. If features are extracted holistically, it is known as *appearance* based approach. In *geometric* feature based methods, major face components and/or feature points are used for feature extraction. Appearance/texture features are more suitable for capturing subtle changes in appearance (e.g. wrinkles) of the face, while geometric features are more capable of representing shape and location information of facial components (e.g. mouth, eye, nose etc.). Normally, texture features require a face normalization to handle errors caused by variations in pose, size and location of the face, while geometric features have a better tolerance to a reasonable amount of these variations. However, geometric features have the weakness of losing regional texture and they also require accurate location and robust tracking of facial landmarks. Geometric and appearance based judgmental features are demonstrated in Figure 3.

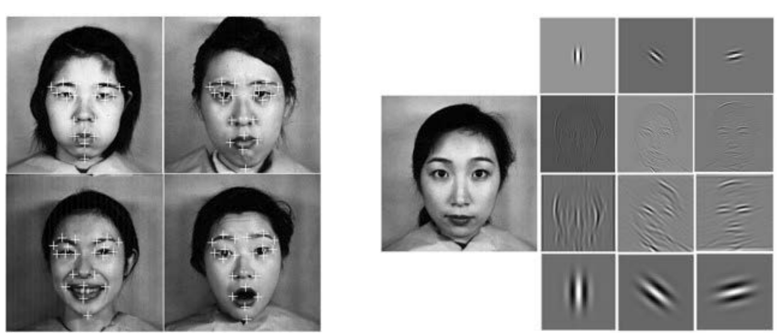

Figure 3. Judgmental features: Geometry-based (left) vs. Appearance-based (right)

Tian et al. [2005] reported that fundamentally FER system consists of three steps: preprocessing, feature extraction and classification . FER can be performed on still images or image sequence, classified as a static or dynamic method. Input samples are often pre-processed for better performance. Face detection and face registration brings up uniformity in samples. Face registration is often performed using various methods like Eight eye segmentation by Luo et al. [2013], manual eye localization by Shan et al. [2009], Shih et al. [2008], Yan et al. [2012] or Viola-Jones face detector by Oliveira et al. [2011], Nagi et al. [2013], Zhang et al. [2012]. A generic framework for FER system is shown in Figure 4.

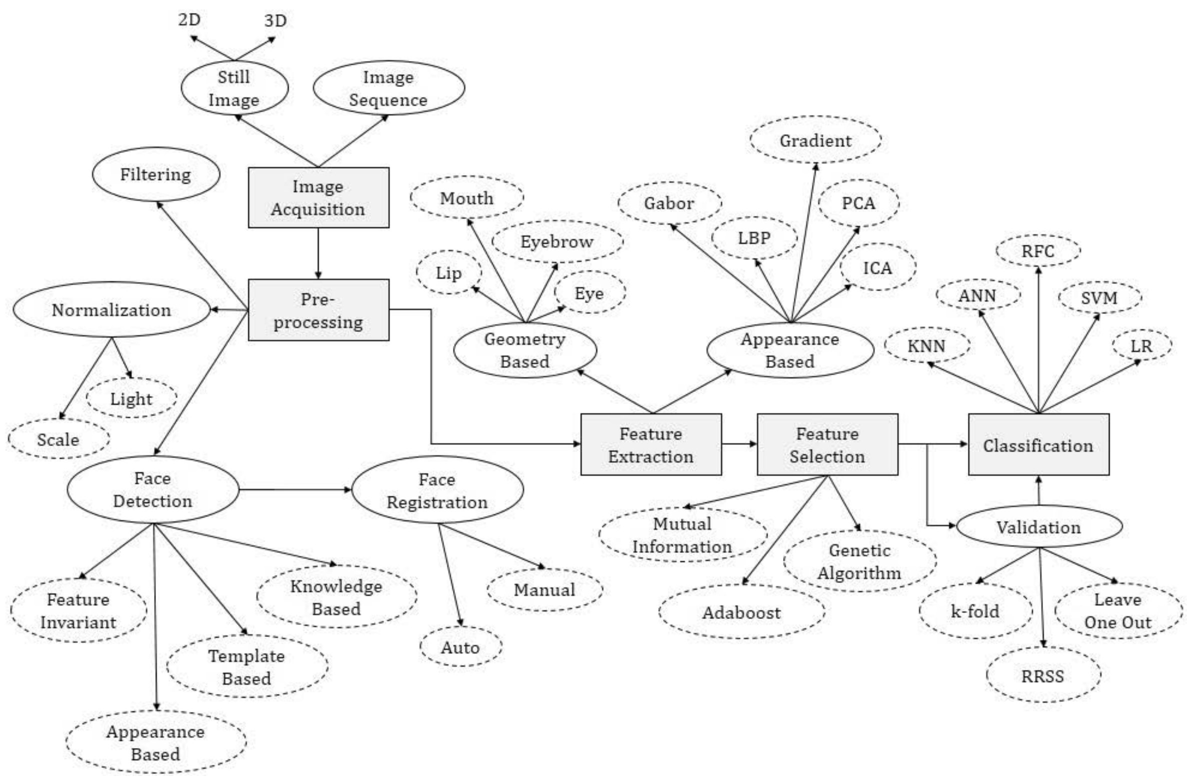

Figure 4. Generic framework for facial expression recognition

As reported by Tian et al. [2005], expression recognition may be performed on 2D images or 3D models, known as *image based* or *model based* approach, respectively. Image based approach considers the intensity values of spatial coordinates of the image plane and extracts expression representative information. Model-based approach considers the depth as well as intensity value of the face points. Added third dimension adds the robustness with elevated complexity. Image based approaches fail to handle in-plane or out of the plane rotation of face, while model-based approaches can deal with such problems by performing affine transformations. In holistic approaches, features are extracted holistically. In geometry-based methods, individual face components like an eye, cheeks, lip, eyebrow, nose tip etc. are detected and expression is classified based on the relation between those local components.

Principal Component Analysis (Turk and Pentland [1991], Sirovich and Kirby [1987], Swets and Weng [1996]), Linear Discriminant Analysis (Swets and Weng [1996], Belhumeur et al. [1997], Lyons [1999]), Gabor wavelet (Lyons [1999]), Local Binary Pattern (LBP) (Ojala et al. [1996]), Line Edge Map descriptor (Gao et al. [2003]), 2D PCA (Yang et al. [2004]), $(2D)^2$ PCA (Oliveira et al. [2011]) etc. have proved good mark in pattern recognition problem.

2.1 Scope and Challenges

Facial expression is intensively studied topic however, there are certain open issues. Expression recognition in low-resolution environment is almost unaddressed. Real time videos like conference recordings, surveillance videos are normally available in low resolution. Precise recognition of expression in such environment is a challenging task. Tian [2004] used geometric and appearance based features to perform expression recognition in low-resolution images. Bartlett et al. [2005] evaluated the performance of Gabor features and achieved noticeable accuracy. Later Shan et al. [2009] investigated Gabor and LBP features for FER in a similar environment. Jabid et al. [2010] evaluated the performance of Local Directional Pattern (LDP) features for low-resolution images. Results of an experiment on low-resolution images are compared in Table 2.

Descriptor	**Reference**	**150 × 110**	**75 × 55**	**48 × 36**	**37 × 27**
Gabor	Tian [2004]	92.2	91.6	-	77.6
Gabor	Bartlett et al. [2005]	89.1 ± 3.1	89.2 ± 3.0	86.4 ± 3.3	83.0 ± 4.3
LBP	Shan et al. [2009]	92.6 ± 2.9	89.9 ± 3.1	87.3 ± 3.4	84.3 ± 4.1
Gabor	Shan et al. [2009]	89.8 ± 3.1	89.2 ± 3.0	86.4 ± 3.3	83.0 ± 4.3
LDP	Jabid et al. [2010]	96.4 ± 0.9	95.5 ± 1.6	93.1 ± 2.2	90.6 ± 2.7

Table II: Performance comparison of different methods in low-resolution environment

Still, accuracy on low-resolution environment is far from acceptable level for the implementation of realistic system. Accurate detection and tracking of geometric features in such images is always a difficult task.

Many standard datasets are published for research, but most of them are designed under controlled environment with fake expressions, which makes the trained model vulnerable to real-time images. None of the dataset addressed all essential variability required to implement a real time FER system. Different facial views, in-plane and out of the plane head rotation, illumination variation, age difference, ethnicity, race, gender etc. are the few factors affecting the performance, and almost all datasets lack one or more of them. The design of a comprehensive large size dataset is essential and yet unaddressed.

Expressions in recorded datasets are fake and in their full intensity. Many a times, expressions appear in mixed state, and intensity of spontaneous expressions may not always be at peak, so estimation of the exact intensity of expression is also challenging.

Research till date focuses on recognition of expression from frontal pose with single face in the image. Non-frontal faces and multiple faces in a frame is a realistic scenario but nobody addressed such issues.

Many appearances based and geometry-based methods have achieved remarkable accuracy on a certain type of dataset. Very little work is addressed for cross-dataset experiments, and the reported results are also very poor. Nowadays, standardization and comparability has also got serious attention from the research community. Lack of commonly accepted evaluation parameter makes the comparison difficult.

Many efforts have been made towards improving effectiveness of FER, but still there is a need for common performance evaluation strategies. To provide the standardized platform, Facial Expression Recognition Analysis (FERA) challenge events are being held by Social Signal Processing Network (SSPNET) in conjunction with Face and Gesture Recognition Group. Two such editions of FERA were held in 2011 at Santa Barbara, California by Valstar et al. [2011] and in 2015 at Ljubljana, Slovenia by Valstar et al. [2015]. FERA 2017 is to be held in Washington, USA after March 2017. FERA brings the researchers across globe under common roof to understand and solve the issues of FER.

2.2 Applications

FER plays a vital role in many applications, such as human-computer interaction, indexing and retrieving images based on expressions, emotion analysis, image understanding, synthetic face animation etc. Even it is possible to instruct a robot to behave according to the person's emotion. It can also be used in various medical domains like behavioral affective state and clinical practice. Computer animated characters are now necessary components of many applications, including computer games, movies, web pages, communication and psychological studies. They are used in place of actual human performers for many reasons, including freedom to change an appearance of the characters, simulating a crowd scene, and issues with privacy.

Online Multiplayer Games (MOG) are increasingly becoming popular. Many FER based MOGs have been studied and proposed by Zhan et al. [2006] and Zhan et al. [2008]. Application of FER is not just limited to the physiological domain, rather it has touched many aspects of engineering, medical, social communication, entertainment, and automation. Since the last decade, research on FER has transformed from simply expression recognition to more complex systems. Application area of FER covers a wide spectrum, including grading of physical pain, smile detection (Freire [2002], Whitehill et al. [2009], Shan [2012]), driver fatigue detection (Ji et al. [2004]), patient pain assessment (Gholami et al. [2010]), video indexing, robotics and virtual reality (Fasel and Luettin [2003]), depression detection (Zeng et al. [2009]) etc. Recently, Microsoft [2016] developed a very interesting Emotion API , which detects the face from an image and finds the weight of each expression. The API can handle an image with size not larger than 4 MB and can operate on the resolution of 36×36 to 4096×4096. It can detect up to 64 faces from the query image. However, it suffers from some technical challenges like large face angle, non-frontal face, and occlusion.

3. STATE OF THE ART METHODS

Since the last decade, LBP has emerged as a powerful non-parametric descriptor, which efficiently represents the local structure of the image. Ojala et al. [1996] presented the LBP operator. The strength of LBP lies in its tolerance against non-monotonic change in illumination and its computational simplicity. Originally, LBP was proposed for texture analysis, but it is being used extensively in applications like face analysis (Ahonen et al. [2006], Abdenour et al. [2004]), facial expression recognition (Shan et al. [2009], Liao et al. [2006], Luo et al. [2013]), image retrieval and classification (Lin et al. [2012]), sign language recognition (Hruz et al. [2012]), image forgery detection (Muhammad et al. [2014]), smile detection (Freire [2002]), texture analysis (Maenappa et al. [2000]) etc. A brief survey on LBP can be found in literature by Shan et al. [2009] and D. Huang and Chen [2011].

LBP establishes the binary relationship with the neighbor pixels and its response is weighted by the decimal weight matrix. Feature descriptor is derived by generating histogram from these weighted values. Let i_c be the intensity of center pixel (x_c, y_c) of 3×3 local region and intensity of remaining eight neighbors $[i_0, i_1, , i_7]$ describes the local structure of image. Binary relationship with neighbor is established as: $F = (S(i_0 - i_c), S(i_1 - i_c), , S(i_7 - i_c))$, where,

$$S(x) = \begin{cases} 0, & \text{if } x < 0 \\ 1, & \text{Otherwise} \end{cases} \tag{1}$$

Binary numbers are read out in clockwise direction and converted into decimal as,

$$LBP_{P,R}(x_c, y_c) = \sum_{n=0}^{P-1} 2^n * S(i_n - i_c) \tag{2}$$

Due to its small neighbor size, basic LBP operator failed to capture large structure. Ojala et al. [2001] presented multi-resolution LBP which can work with any size of neighborhood by bilinear pixel interpolation. Survey on recent work on LBP in the context of facial expression recognition is outlined in Table 3.

Reference	LBP Variants	Remark
Zhao and Pietikainen [2007]	VLBP + LBP-TOP	The dynamic texture is modeled using volume LBP. LBP-TOP is applied to reduce the computation by selecting local binary pattern on three orthogonal planes.
Shan et al. [2009]	Boosted LBP	Conditional mutual information based feature selection technique has been proposed for selecting most discriminative LBP features, in conjunction with SVM for classification.
Guo et al. [2010]	Completed LBP	CLBP_S and CLBP_M represent sign and magnitude part of the difference of center and neighbor pixels, respectively. CLBP_S is identical to basic LBP operator
Smith [2010]	LBP + FCBF	Promising candidate features from LBP is selected using Fast Correlation-Based Filtering.
Moore and Bowden [2011]	Magnitude LBP	$\mathrm{LBP}^{u,2}$ is applied to gradient of face image
Azmi and Yegane [2012]	Local Gabor binary pattern (LGBP)	$\mathrm{LBP}^{u,2}$ is applied to Gabor convolved images with five scales and eight orientations. It provides multiscale, multi-oriented features
Zhang et al. [2012]	LBP + FLDA	High dimensional LBP features are projected on fisher space and tested using SVM classifier.
Luo et al. [2013]	Fusion of PCA and LBP	PCA of full face and basic LBP of mouth and cheek is given to SVM
Almaev and Valstar [2013]	LGBP-TOP	LBP pattern of Gabor convoluted Three Orthogonal Plane (TOP) is used to combine spatial and temporal features. Results confirm the improved recognition rate of AU.
Ouyang et al. [2013]	LBP map + SRC	Sparse representation based classification is applied to LBP map. Proposed scheme operates in modest time compare to other discussed approaches.
Connor and Roy [2013]	Modified LBP	Concatenated vector of local magnitude and the local sign is presented to Random Forest for feature selection.
Ahmed et al. [2014]	Compound LBP	Each neighbor is encoded with two bits, one represents basic LBP code and second bit represents a sign of the difference of average magnitude and magnitude of the neighbor pixel.
Satyanarayanamurty [2014]	Distinct LBP	5×5 sub-images are compressed to 3 x 3 sub-images. Two DLBPs are derived by triangular pattern between upper and lower parts of 3×3 sub-images.
Abdulrahman et al. [2014]	Gabor LBP + Gabo PCA	LBP is applied on Gabor transformed image. LBP and PCA is applied on this transformed image for feature computation
Chao et al. [117]	es-LBP + cr-LPP	es-LBP is improved version of LBP, it emphasizes the partial information of human face by computing LBP at specific fiducial points. Class regularized locality preserving projection is proposed to minimize interclass variation and maximize the class independence.
Huang et al. [2015]	STLBP-IP	Spatio-Temporal LBP with Integral Projection is computed by finding LBP of horizontal and vertical projection of integral images.
Werghi et al. [2015]	Mesh LBP	Basic LBP code is computed for triangular mesh manifold for the surface. Mesh LBP operates on 3D triangular meshes and simplifies the computation by eliminating preprocessing like registration and normalization.
Patela et al. [2016]	Compass LBP	Proposed operator effectively combines properties of LBP and Kirsch masks, and performs gender classification on sketch images

Table III: Comparative study of LBP variants for facial expression recognition

Gabor filter is another powerful texture analysis tool, which was first conceptualized by Jones and Palmer in 1987 Palmer [1987]. For a long time, Gabor dominated the field of texture analysis and pattern recognition. The behavior of Gabor filter is similar to that of the human visual system and it has been found to be appropriate for texture representation and classification. Palmer [1987], Lyons [1999], Zhang et al. [2014], Liu and Wechsler [2002]. Survey on texture feature based on Gabor is illustrated in Grigorescu et al. [2002]. In the spatial domain, Gabor function can be viewed as a sinusoidal plane modulated by a Gaussian envelope. The spatial summation property of simple cells can be modeled by a family of two-dimensional Gabor functions. Gabor kernel centered at (x_c, y_c) in spatial domain is defined as Lyons and Akamatsu [1998], Bashyal and Venayagamoorthy [2008], Oshidarit and Babak [2010], Zhang et al. [1998]:

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\left(i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right) \tag{3}$$

Where, (x', y') is the polar representation of spatial coordinate (x, y). σ_x and σ_y are the standard deviations of Gaussian function, and it is assumed that $\sigma_x = \sigma_y = \sigma$. Parameters λ, θ, ψ and γ represents wavelength of cosine factor, orientation of kernel, phase offset of sinusoidal, and spatial aspect ratio, respectively. Response of Gabor kernel is computed by its 2D convolution with input image. Response of imaginary part of Gabor response is useful in efficient edge detection Oshidarit and Babak [2010]. Generally real part of the convolved image makes sense for the feature extraction. Survey on Gabor based FER system is presented in Table 4.

Reference	**Gabor Variants**	**Remark**
Lyons [1999]	Gabor + Elastic graph	Features are computed from auto and manual grid setup on amplitude response of Gabor. Saliency map proved that mouth and eye are a most discriminative facial component for expression recognition.
Deng et al. [2005]	Local Gabor and PCA + LDA	High dimensional local Gabor filter response are compressed using PCA + LDA approach to take care of matrix non-singularity
Chen [2007]	2-stage classifier on Gabor	Uses first tier and second tier fiducial points to convolve Gabor jet. Elastic Bunch Graph Model is created for the feature extraction.
Bashyal and Venayagamoorthy [2008]	Gabor + LVQ	34 fiducial points are used to get Gabor filter bank response. The performance of Learning Vector Quantization is compared with MLP.
Oshidarit and Babak [2010]	Adaptive Gabor	A fuzzy controller is used to tune the orientation parameter.
Moore and Bowden [2011]	Local Gabor binary pattern (LGBP)	LBP^{u,2} is applied to Gabor convolved images with five scales and eight orientations. It provides multiscale, multi-oriented features
Xibin et al. [2013]	Block Gabor fusion	The face is divided into blocks and each block is weighted according to the presence of expression in it.
Reddy and Sravanthi [2013]	Log-Gabor + LDA	Representative features are selected using mutual information quotient from the log-Gabor features.
Almaev and Valstar [2013]	LGBP-TOP	LBP pattern of Gabor convoluted Three Orthogonal Plane (TOP) is used to combine spatial and temporal features. Results confirm the improved recognition rate of AU.
Zhang et al. [2014]	Random Gabor	Monte Carlo algorithm is used to select set of Gabor convolved occluded faces. SVM followed by template matching is employed for nearest expression identification.
Abdulrahman et al. [2014]	Gabor LBP + Gabo PCA	LBP is applied on Gabor transformed image. LBP and PCA is applied on this transformed image for feature computation

Table IV: Comparative study of Gabor variants for facial expression recognition

According to input sequence, FER methods can be divided into two groups: image sequence based methods (Kenji [1991], Yacoob and Davis [1996], Otsuka and Ohya [1997], Essa and Pentland [1995], Essa and Pentland [1997]), and still image based methods (Shan et al. [2009], Tian et al. [2001], Zeng et al. [2006]). The former method deals with sequence of images to extract the dynamics for efficient facial expression representation. The promising methods include Optical Flow (Kenji [1991], Yacoob and Davis [1996], Essa and Pentland [1997], Black and Yacoob [1997]), and Hidden Markov Model (HMM) (Otsuka and Ohya [1997], Otsuka and Ohya [1998], Cohen et al. [2000]). The latter methods operate on single image for feature extraction. These methods may be holistic or it may be local. Optical flow (Yacoob and Davis [1996], Rosenblum et al. [1996]), Eigenface (Sirovich and Kirby [1987], Turk and Pentland [1991]), Fisherface (Belhumeur et al. [1997]), Laplacianface (He et al. [2005]), Neural networks (Tan et al. [2005]), Independent Component Analysis (Bartlett and Sejnowski [1997]), Line Edge Map (Gao and Leung [2002]), 2D PCA (Yang et al. [2004]) are few of the widely used holistic methods. Even though these methods have been significantly used and explored, local descriptors have gained the attention of researchers because of robustness and invariance property. Local feature extraction methods operate on local region or small neighborhood of the pixel. Feature descriptor is obtained by collecting features computed locally. Few well studied local feature extraction methods are Local Binary Pattern (Ojala et al. [1996]), multi-resolution LBP (Ojala et al. [2001]), Weber Local Descriptor (WLD) (Chen and Shan [2010]), Local Directional Pattern (Jabid et al. [2010]), Gabor filter (Lyons and Akamatsu [1998]), Local Gabor Binary Pattern (LGBP) (Almaev and Valstar [2013]).Feature extraction techniques can be categorized as image based vs model based, appearance based vs. geometry based, local vs. global, or static vs. dynamic. Research is either feature centric or classifier centric. SVM (Shan et al. [2009], Shih et al. [2008], Oliveira et al. [2011], Nagi et al. [2013], Luo et al. [2013]), KNN (Oliveira et al. [2011], Nagi et al. [2013], Taheri et al. [2014], Ahmed et al. [2013]), ANN (Owusu et al. [2014], Zhang et al. [2012]), Linear Programming (Shan et al. [2009]), Nave Byse Classifier (Ahmed et al. [2013], Cohen et al. [2003]), Random Forest Classifier (Ahmed et al. [2013]), HMM (Cohen et al. [2003]), Decision Tree (Ahmed et al. [2013]) etc. classifiers are extensively investigated by the researchers. The face is a complex entity and possesses massive dimensions. Many feature extraction techniques produce a large number of features. All features are not of equal importance; some are dominating while some are little effective. To select the most discriminative features, NSGA (Oliveira et al. [2011]), Boosted LBP (Shan et al. [2009]), 2D LDA (Shih et al. [2008]), Adaboost (Owusu et al. [2014], Yang et al. [2009]), mutual information (Zhang et al. [2012]), PSO (Tang and Chen [2013]) etc. methods have been widely used. Multidimensional survey of recent prominent facial expression research is summarized in Table 5.

4. FACIAL EXPRESSION DATASETS

Expression dataset is another important aspect of FER research. Datasets are classified based on various characteristics such as modalities, frame/image sequence, age group, coding scheme, illumination conditions and ethnicity. Some datasets contain temporal data, taken over a period of time to add diversity in age. Few of them include variation in illumination, race, view, gender etc. We categorized databases based on the information available on subject, content, and modality. Most of the dataset contains basic six expressions postulated by Ekman and Friesen [1971]. CK dataset is one of the most widely used publically available datasets designed by Kanade et al. [2000]. CK database set up the modern research in FER. Images and expressions in CK database are more controlled with categorical labels. CK+ database was published later covering more number of images with spontaneous expressions, and AU coded images. Lyons [1999] published Japanese Female Facial Expression Database (JAFFE) dataset which is another widely used FE database, representing 10 Japanese female models. Images in JAFFE are captured under uniform lighting condition and have a limited number of subjects with frontal view only. Chen [2007] designed Taiwanese Facial Expression Image Database (TFEID), which consists of 40 models, including 50% male and 50% female. Subjects of JAFFE and TFEID belong to a single ethnicity. Recently, Yin et al. [2006] built 3D facial expression databases of 3D static images and 3D image sequences, and these two databases are called BU-3DFE (Binghamton University

Ref.	G/ L	Preprocessing	Features	FS	DB	Classifier	VM	MRR (%)
Oliveira et al. [2011]	G	Face detection using Adaboost	2DPCA	NSGA	JAFFE	KNN SVM	10F	KNN:91 SVM: 94
Yan et al. [2012]	G	Manual eye localization	-	-	JAFFE CK Feedtum	ADM	-	J: 96 CK: 96.9 Fed: 88.5
Shan et al. [2009]	L	Face cropping using manual eye labeling	LBP	Boosted LBP	JAFFE CK	SVM LP	10F	LP: 82.3 SVM: 86.0
Gao et al. [2003]	G	Faces are manually cropped such that distance between eye remains 80 pixel	LEM	-	AR	-	-	86.6
Rahulamathavan et al. [2013]	G	Images are rescaled to size 51 x 51 pixels	PCA, FLDA LFDA	-	JAFFE MUG	NN	-	95.24
Shih et al. [2008]	G	Face is manually cropped and rescaled to size 168 x 120, Histogram equalization	DWT	2DLDA	JAFFE	SVM	LOO	LOO: 95.71 CV: 94.13
Nagi et al. [2013]	L	Eye, nose and mouth are cropped using Adaboost detector	LBP		CK JAFFE 3DBFU	1VA SVM KNN	10F	SVM: 77.81 KNN: 77.65
Taheri et al. [2014]	L	Prepared AU Dictionary, Faces are cropped and resized to 128 x 128	SIFT	-	Bosph. CK+	NN	-	88.52
Owusu et al. [2014]	L	Face components are selected using Viola-Jones descriptor	Bessel Transform + Gabor	Ada boost	JAFFE YALE	ML FFNN	-	J: 96.83 Y: 92.22
Luo et al. [2016]	H	-	PCA + LDP	-	-	SVM	-	91.61
Zhang et al. [2012]	G	Face detection using Viola-Jones detector	AAM	QMI	CAS-PEAL	SVM ANN	-	SVM: 87.33 ANN: 66.67
Ji and Idrissi [2012]	G	-	LBP + VTB	-	MMI CK	SVM	10F 2F	2F: 94.00 10F: 97.00
Yang et al. [2009]	L	Face images are cropped and normalized	Dynamic Haar like features	Ada boost	CMU	Ada boost	-	95.00
Majumder et al. [2014]	L	Top 1/5th part was removed to locate eye	Shape of lip, eye and eyebrow	-	MMI	KSOM	-	93.53
Luo et al. [2013]	L	Eight eye segmentation	LBP + PCA	-	InHouse	SVM	-	SVM: 71.5 PCA + SVM: 91.5 PCA + LBP + SVM: 94
Tang and Chen [2013]	G	Images are rescaled to 100 x 100	Curvelet	PSO	JAFFE	SVM	-	LibSVM: 87.01 PSOSVM: 94.94
Zhi and Ruan [2008]	L	Images are manually cropped	2D-DLPP	-	JAFFE CK	NN	-	96.00
Cohen et al. [2003]	L	-	PBVD + AUs	-	Inhouse video	Naive Bayes HMM	-	NB: 81.31 HMM: 82.46
Ahmed et al. [2013]	L	Lip and mouth are extracted for feature extraction	LBP	-	CK+ MMI FEED	SVM, 2NN, RF, DT, NB	2F 10F	2F: 95.2 10F: 96.7
Wang et al. [2015]	G	Face is cropped and resized to 30 x 24	PCA	-	JAFFE	FSVM KNN	-	KNN: 83.91 SVM: 85.74 FSVM: 87.75
Huang et al. [2012]	L	Image is divided in different size of overlapping blocks	Variations of spatio temporal LBP Gabor	-	CK Oulu CASIA	-	CK: LOO CASIA: 10F	CK: 81.54

G: Global, **L**: Local, **H**: Hybrid **F**: Fold, **LOO**: Leave One Out, **FS**: Feature Selection, **MRR**: Maximum Recognition Rate, **CV**: Cross Validation

Table V: Comprehensive survey of recent promising appearance based FER approaches

3D Facial Expression) database and BU-4DFE (3D + time), respectively. BU-3DFE database presently contains 100 subjects (56% female, 44% male), age ranging from 18 - 70 year, with a variety of ethnic/racial ancestries, including White, Black, East-Asian, Middle-east Asian, Indian, and Hispanic-Latino.

Figure 5 shows random samples of happy expression from JAFFE, CK, TFEID and BU-3DFE.

AR dataset designed by Martinez and Benavente [1998] consists of only four expression - angry, neutral, scream and smile. It contains 4000+ static color images of 70 males and 56 females. MMI

Figure 5. Snapshots of happy expression from various facial expression recognition datasets. JAFFE (top row), CK (second row), TFEID (third row), BU-3DFE (bottom row).

is image/video database, designed by Pantic et al. [2005]. The database contains more than 1500 images plus video sequences, with frontal and profile view. Age group of subjects covers a wide range, 19 to 62 years. Belfast Naturalistic Database (BND) is created by Douglas-Cowie et al. [2003] at Queen's University of Belfast. BND covers 250 wide range of expression videos, each expression considers neutral as ground truth and reaches to the apex and again comes back to neutral. Savran et al. [2010] designed Bosporus dataset which is also 3D dataset with a wide range of subjects, head pose and a number of expressions. Natural Visible and Infrared facial Expression Database (NVIE) (Wang et al. [2010], Wang et al. [2013]) contain visible and infrared images. It contains 412 static images of 215 subjects having age group 17-31 years. A comprehensive survey on facial expression datasets is described in Table 6.

5. CONCLUSIONS AND FUTURE SCOPES

In this paper, we present the recent advances in facial expression recognition and associated applications which will create interest to the novice and researchers. In order to do so, we conducted the survey on FER from its historical origin to recent innovations. We highlighted the timeline of work on facial expression recognition. We also present the general framework for facial expression recognition with scopes and challenges affecting the performance along with its interesting applications. We surveyed various judgmental feature extraction methods which are extensively used in the research.

Expression evolves from the deformation of the facial muscle groups, that are accountable to change in facial additives like eye, eyebrow, cheek, mouth etc. Research has shown that both texture and geometry of face delivers complementary but quite beneficial information for FER. Certain expressions may have distinctive texture, however, similar geometric features, and vice versa. Use of both kinds of features might be the better choice. Dataset is another important aspect of the pattern recognition problems. In this paper, we discussed and compared various aspects of FER datasets. A comprehensive survey enables the user to make a choice of the appropriate dataset for his/her research. Almost all the databases described in the survey are captured under controlled environment and subjects are well posed with fake expressions. None of the above databases addressed the spontaneous expressions with the non-standard background. The intensity of spontaneous expressions varies on large scale, as well as cluttered background, low resolution, pose variation, improper illumination etc. makes real-time facial expression recognition even more challenging. Expression recognition from the frontal pose and spontaneous facial expression recognition continues to be an open area for improvement and research. CK and JAFFE datasets are rigorously exploited by researchers. None of the work has achieved accept-

	CK	JAFFE	TFEID	AR	BU-3DFE	Bosphorus	MMI	BND	NVIE
SUBJECT									
#Subject	97	10	40	126	100	105	19	125	215
#Male	34	0	20	70	44	60	11	31	157
#Female	63	10	20	56	56	45	8	94	58
Age Group	18-30	N/A	N/A	N/A	18-70	25-35	19-62	N/A	17-31
Ethnicity	Y	N	N	N/A	Y	N	Y	N	N
CONTENT									
#Img / #Vid	486	213	1975	4000+	2500	4666	V:848 I:740	250	412
Ima / Vid	V	I	I	I	I	I	V + I	V	I
Frame Rate	12 fps	-	-	-	-	-	24 fps	-	-
Single / Multi Face	M	S	M	S	M	M	S	S	S
Coding Scheme	G	G	G + C	C	C	C	C	C	C
3D Data	N	N	N	N	Y	Y	N	N	N
Resolution	640 × 480 640 x × 490	256 × 256	600 × 480	768 × 576	512 × 512	N/A	720 × 576	N/A	1920 × 1080
MODALITY									
Face Pose	F	F	F captured at 00 and 450	F	F	Y, P, CR	F + F captured by two cameras	Various	F, L, R
Expressions	23 facial display + combination of AUS	AN, DI, FE, HA, NE, SA, SU	AN, DI, FE, HA, NE, SA, SU, CO	AN, NE, SC, SM	AN, DI, FE, HA, NE, SA, SU	AN, DI, FE, HA, SA, SU, + 25 pure and 3 combination of AUs	79 facial displays	Wide range of FE	AN, DI, FE, HA, SA, SU
Intensity	Neutral to Apex	N/A	Slight and High	With & W/o Occlusion	NE to AP	Head Posses & Occlusion	NE-AP-NE	NE-AP-NE	N/A
Posed / Sponteneous	PO	PO	PO	PO	PO	PO	PO	SP	PO + SP
Light	Uniform	N/A	N/A	L, R & All	N/A	N/A	Uniform	Indoor	L & R

N/A: Not Available or Not Applicable, **Y**: Yes, **N**: No, **I**: Image, **V**: Video, **AN**: Anger, **AP**: Apex, **CO**: Contempt, **DI**: Disgust, **FE**: Fear, **HA**: Happy, **NE**: Neutral, **SA**: Sad, **SC**: Scream, **SM**: Smile, **SU**: Surprise, **O**: Onset, **FP**: Frontal and Profile, **PO**: Posed, **SP**: Spontaneous, **S**: Single, **M**: Multiple

Table VI: Comparison of state-of-the-art facial expression recognition databases

able recognition rate for cross database testing. Shan et al. [2009] reported 51.1% and 41.3% highest generalization performance for CK-MMI and CK-JAFFE datasets, respectively. In both cases, CK database was used for training, MMI and JAFFE datasets were used for testing in respective experiment. Generalization of FER system is still an open area to work upon.

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