*International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)*
*Volume 7, Issue 11, November 2018, ISSN: 2278 – 1323*

# Facial Emotion Recognition: A Survey

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***Abstract*— Emotion could be expressed through unimodal social behaviour's or bimodal or it could be expressed through multimodal. This survey describes the background of facial emotion recognition and surveys the emotion recognition using visual modality. Some publicly available datasets are covered for performance evaluation. A summary of some of the research efforts to classify emotion using visual modality for the last five years from 2013 to 2018 is given in a tabular form.**

***Index Terms*— Visual, Emotion Recognition, Deep Learning, Facial Expressions.**

## I. Introduction

Facial expressions convey emotions and provide evidence about people's personality and intentions. Studying and understanding facial expressions returns to the first reported scientific to Duchenne who wanted to fix how the muscles in the human face produce facial expressions. Charles Darwin also studied facial expressions and body gestures in mammals[1]. An influential milestone in the analysis of facial expression is the work of Paul Ekman [2], who described a set of 6-basic emotions (fear, sad, anger, surprise, disgust and happy) that are universal in terms of expressing, and understanding them.

Emotion is a fundamental component of being human [3]. In human daily social life, knowing the emotional feeling of the counterpart is intuitive, but, when it comes to the computer, this is much harder [4]. Emotion recognition finds its extensive applications in the area of human-computer interaction (HCI) since the information about emotional states could be used to make communication with computers in a more human-like manner [5, 6]. Emotion could be expressed through unimodal social behaviours, including speech, facial expressions, text, gesture, etc., or bimodal such as speech and facial, brain signals and facial, speech and text etc., or it could be expressed through multimodal such as audio, video, physiological signals and so on [7] as shown in Fig. 1. The main part of the overall impression of the message is the facial expression 55% while the audio part and semantic content contribute 38% and 7% respectively [8].

This paper aims to present a survey of emotion recognition using visual modality to identify the latest methods used by researchers to detect human emotions using computers.

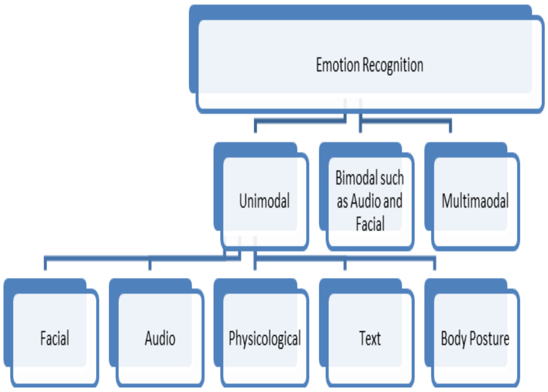


Fig. 1 Emotion recognition types.

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## II. FACIAL EMOTION RECOGNITION

A. Important evidence about a person's emotion can be obtained from facial expressions[9]. The Facial Action Coding System (FACS) describes all facial muscle movements that can be perceived in terms of predefined Action Units(AUs), which are encoded numerically and facial expressions correspond to one or more of these AUs [10].

Recognizing emotion from facial expressions has several advantages such as:

- It considers a natural way to identify emotional states.
- Many datasets available for facial expression.
- Many tools support facial recognition are available to researchers.

Recognizing emotion from facial expressions has also some disadvantages such as:

- Cannot provide context information thus sometimes results are misleading.
- Detection results dependent on image or video quality [11].
- Motions involved in facial emotions can be faked by actors [12].

The general stages of facial emotion recognition are:

Collecting data means getting static images or sequences of video images that provide more information because they are capable of representing the temporal characteristics of an expression [13].

Pre-processing It's an important step that aims to enhance the quality of the image to make it ready for other processing by for example removing the noise, or changing the contrast and brightness. Solve illumination problems, e.g. by using histogram equalization [14], and find faces in the images using a face detection algorithm [15]. Viola-Jones is the most famous face detection algorithms. It is widely used for real-time face detection purposes [16]

Feature extraction plays an important role in emotion recognition [17]. Different techniques were used to extract the features like Gabor-wavelets and Principal Component Analysis (PCA) [18].

Classification can be done in different methods in terms of facial actions that cause expression, in terms of some unusual expressions. Ekman defined 6-categories, referred to as basic emotions [19] as shown in Fig. 3. All basic emotions are described in terms of facial expressions that characterize unique emotion [20].


**Fig. 4.**The 6-basic facial emotions (a) Anger (b) Disgust (c) Fear (d) Happiness (e) Sadness (f) Surprise [21]**.**

Several machine-learning techniques can be used for FER, the majority of these methods use manually extracted features, and hence require certain efforts in terms of computation cost and programming [22]. A new kind of learning based on DL, comes to challenge the above framework, e.g., DCNN [23]. The individual steps in such systems can be combined into a single learning procedure.

## III. FACIAL EMOTION RECOGNITION TECHNIQUES

Different techniques used in previous literature as will be shown in table 2. The trend in recent research is towards the use of Deep Learning (DL) and the results reached in their experiments are actually encouraging [24-31]. DL is capable of addressing the challenges of unlabeled, noisy, missing and/or conflicting data [32]. It is a self-learning tool designed to identify patterns in several sets of data samples, extracted from multiple processing layers [33]. The concept of it comes from the study of artificial neural network multilayer perceptron which contains more hidden layers. One of the main strengths of using DL techniques is that there is no need for extracting features manually instead it is able to learn features over basic representations [12, 34].

## IV. DATASETS

One of the important requirements to develop facial emotion recognition system is the acquisition and validation of emotion data. The performance of the recognition system are easily affected if it is not well-trained with sufficient data in the datasets. Therefore, we need publicly available datasets to evaluate the performance [35]. Some of the these publicly available datasets used for this purpose are summarized with a simple description about it in Table 1.

## V. LITERATURE SURVEY

As it is difficult to include all of these studies, this paper introduces and surveys some of the recent research papers from 2013 to 2018 as shown in Table 2.

## VI. CONCLUSIONS

Facial modality have the core position in emotion recognition, however audio, text, psychological, body posture could also play an important role. Much progress has been made in the facial emotion recognition, but more work is still necessary to get a satisfactory framework. This survey describes the background of facial emotion recognition and presents the related works. Some of the publicly available datasets for researchers are also covered. A summary of some of the last five years papers from 2013 to 2018 show that there are many different techniques used for feature extraction and classification which some researchers use individually; others use a combination of these techniques to get a benefit of more than one of them. There are no unified methods defined in this field. The trend in recent research is towards the use of DL especially CNN and results reached in their experiments are actually encouraging.

Table 1: Facial emotion recognition datasets

| Dataset | Simple Description |
|---|---|
| Amsterdam Dynamic Facial Expression Set (ADFES) | 1- Contains 648 - emotional expressions illustrated which are the dynamic events that unfold in a certain way over time.<br>2- Contains the 6-basic emotions beside contempt, pride, and embarrassment.<br>3- 22 subjects (12 males, 10 females) from Northern Europe and the Mediterranean.<br>4- Uses an active turning head to illustrate the orientation of the expressions.<br>5- It is publicly available to researchers under request [36]. |
| Amsterdam Dynamic Facial Expression Set Bath Intensity Variations (ADFES-BIV) | 1. It is an extension of the ADFES [37].<br>2. It is acted by 12 North European subjects (5 female, 7 male) and 10 Mediterranean actors (5 female, 5 male) expressing the 6-basic emotions plus 3-complex emotions of contempt, pride, and embarrassment, beside neutral.<br>3. Wingenbach et al. created the ADFES-BIV dataset by editing the 120 videos played by the 12 North European actors to add three levels of intensities by created three new videos, displaying the same emotion at three different degrees of intensity: low, medium and high, for a total of 360 videos [38].<br>4. It is free available for a scientific research purposes under request. |
| Binghamton University 3D Facial Expression (BU-3DFE) | 1- The three dimensional models of facial tissue and facial texture of two dimensions of 2500 models of 100 substances (44 male, 56 female), and their ages from 18 - 70 years.<br>2- Expressions of happiness, disgust, fear, anger, surprise, and sadness include four levels of distress.<br>3- It contains posed expression.<br>4- It is the first attempt at making a 3D facial expression dataset available for the research community [39]. |
| Binghamton University 4D Facial Expression (BU-4DFE) | 1- 3D video dataset for recognition facial expression.<br>2- Comprises 101 subjects (43 male, 58 female) with an age range of 18 - 45 years, belonging to various ethical and racial groups including Asian (28), black (8), Latino (3) and white (6).<br>3- Contains the 6-basic emotions. |

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| | 4- Each facial expression was captured to produce a four seconds video sequence of temporally varying 2D texture and 3D shapes at the rate of 25 frames per second.<br>5- It is publicly available [40]. |
| Cohn-Kanade (CK) | 1- Is the most widely used dataset, includes 388 image sequences from 100 subjects. Each sequence contained 12–16 frames.<br>2- The subject's age range of 18 - 30 years (35% male, 65% female). 50% of subjects came from the African-American background, and 3% from the Asian or the Latino-American background.<br>3- Contains the 6-basic emotions beside neutral.<br>4- Contains posed expressions.<br>5- Some subjects did not have image sequences corresponding to all of the expressions, and in some cases, only one image sequence per expression was available [41].<br>6- It's available but under certain conditions. |
| Extended Cohn-Kanade (CK+) | 1- Contains 593 sequences from 123 subjects. These are not fixed length sequences and the duration varies from 10 to 60 frames.<br>2- All the sequences start from the neutral pose to the peak formation of the expression.<br>3- The locations of facial landmarks are provided along with the dataset.<br>4- It contains both spontaneous and poses expression.<br>5- Contains the 6-basic emotions beside neutral.<br>6- Out of the 593 sequences in the dataset, only 309 were labelled as one of the 6-basic emotions.<br>7- It's available to the research community [42, 43] |
| FACES | 1- Comprising 171 naturalistic faces of young, middle-aged, and older women and men.<br>2- Contains the 6-basic emotions beside neutral, bringing about 2,052 individual images.<br>3- Contains 154 subjects of different age.<br>4- It's available free to scientific research [44]. |
| Facial Expression Recognition (FER-2013) | 1- It contains 35,887 images.<br>2- The dataset is split into 28,709 samples for training, 3,589 for validation, and 3,589 for test sets with basic expression labels provided for all samples.<br>3- Grayscale images with a resolution of 48 x 48 pixels.<br>4- The dataset was created using the Google image search API to search for images of faces that match a set of 184 emotion-related keywords like "blissful", "enraged," etc.<br>5- It is available for download [45, 46] |
| Japanese Female Facial Expression (JAFFE) | 1- Contains 213 images of female facial expressions expressed by 10 subjects.<br>2- Each image has a resolution of 256×256 pixels with almost the same number of images for each category of expression.<br>3- The head in each image is usually in a frontal pose, and the subject's hair was tied back to expose all the expressive zones of her face.<br>4- Tungsten lights were positioned to create an even illumination on the face.<br>5- Contains the 6-basic emotions beside neutral [47].<br>6- It's is available free for use in non-commercial research [48]. |
| Multimedia Understanding Group (MUG) | 1- Collection of posed and induced facial expression image sequences.<br>2- All sequences were captured in a controlled laboratory environment with high resolution and no occlusions.<br>3- Image resolution 896×896 pixels.<br>4- The collection consists of two parts: The first part depicts 86 subjects (51 |

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| | male, 35 female) performing the 6-basic emotions beside neutral. The second part contains the same subjects recorded while watching a video that stimulates emotion.<br>5- Contains manual and automatic explanation of 80 points facial features of a large number of frames.<br>6- Most of the dataset recordings are available to the scientific community [49]. |
| Warsaw Set of Emotional Facial Expression Pictures (WSEFEP) | 1- is a high quality photograph of genuine facial expressions with 210 high quality photographs of 30 subjects.<br>2- It is available for free to the scientific researcher under request [50]. |

Table 2: A summary of some of the recent papers (2013 - 2018)

| **Paper Reference** | **Dataset** | **Feature Extraction Technique** | **Classification Technique** | **Recognition Rates** |
|---|---|---|---|---|
| [51] | JAFFE, and MUG | Local Fisher Discriminant Analysis (LFDA) | 1-nearest-neighb or | JAFFE: 94:37%<br>MUG: 95.24% |
| [52] | JAFFE | Gabor filter | Bayesian | 96.73 % |
| [53] | JAFFE, and Yale | Gabor techniques | Neural network back-propagation algorithm | JAFFE: 96.83%<br>Yale: 92.22% |
| [54] | JAFFE | Gabor wavelet transform, PCA and LBP | k-NN | 90% |
| [55] | CK+ | kernel PCA (KPCA) | KPCA | KPCA: 76.5%<br>PCA: 72.3% |
| [56] | Private | Eigen face approach | Euclidean distance | Average of recognition rate: 85.38% |
| [57] | CK+ | Active Shape Models (ASM) | RBF kernel SVM, HMM | SVM: 70.6%<br>HMM: 65.2% |
| [58] | Private | Biorthogonal Wavelet Entropy (BWE) | Fuzzy Multiclass SVM (FMSVM) | 96.77+_0.10% |
| [59] | CK, and Berlin | Gabor filter for images, and Mel-Frequency Cepstral Coefficients (MFCC) for audio signals | SVM | CK: 84.68%<br>Berlin: 80.68%<br>In Real-Time: 81.58% |
| [31] | JAFFE, and CK+ | CNN | | JAFFE: 76.7442%<br>CK+: 80.303% |
| [60] | CK+ | Gabor, and LBP | Linear, RBF and polynomial kernel SVM | Gabor+LBP 6-class: (linear SVM: 97.10% RBF SVM: 97.42% polynomial SVM: 96.45%)<br>7-class (linear SVM: 95.45% RBF SVM: 95.45% polynomial SVM: 94.45%) |
| [61] | CK+, JAFFE and BU-3DFE | CNN | | CK+: 96.76<br>JAFFE: 82.10,<br>BU-3DFE: 82 |
| [62] | Private | DWT | Single-hidden-lay er NN | 89.49  0.76% |
| [63] | ADFES-BIV | Extracting temporal information | sparse representation was used | Low intensity: 66.9 , 79.6 for middle , and 80.3 for high intensity |

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