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A Comprehensive Survey of Emotion Recognition System in Facial Expression

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Abstract: *Affective computing is one of the emerging topics and has several applications in health care, e-Learning and in general in human computer interaction. Facial expression is an important feature to discern the emotion of the user. It is used to discover the inner feelings and thoughts. Emotion recognition involves several phases. Several works are available in the literature to improve the performance of emotion recognition system. The QoS metrics used to measure the performance of various techniques are extent of emotions covered, response time and accuracy of emotion recognition. This study compares the different emotion recognition techniques based on facial expressions and analyses their performance and suitability for various applications.*

Key words: Accuracy rate, basic emotions, affective computing, emotion recognition technique, facial expression

INTRODUCTION

Emotion Recognition System play significant role in Human Computer Interaction. Dr. Rosalind Picard of MIT Media Laboratory coined the term Affective Computing in 1994 and published the first book on Affective Computing in 1997 (Picard, 2000). This field is related to Artificial Intelligence (AI), Virtual Reality (VR) and Human Computer interaction (HCI). Many researchers are interested to detect and synthesize the human emotion and mood. In the past few decades many researches were done in the field of emotion recognition system. A machine can predict the user emotion by facial expression, voice, hand gesture and body gesture represented in the form of images, videos, movies, audio, etc., then machine can be trained to understand the user emotion and give the correct response for those emotion states.

Emotion detection is currently popular area in the research of medical and computer science field. Many researchers are doing research for helping patient's psychological problem speech-impaired children and lonely persons. Human computer interactions are required in many applications. In past few years HCI has improved rapidly. Online tutoring systems are designed to predict the emotions of the students and change the teaching methodology accordingly. For example in MOOC (Massive Open Online Course) production system, tutor is able to predict the student mood and doubt can be clarified. Tutoring system recognizes the emotion and make positive attitude to maximize the learning process. Thus it provides more interactive and effective way of learning, then give feedback and guide towards a solution to student problem (Leony *et al*., 2015).

Smart home with intelligent robot is a recent trending application. In this application based on user mood, robot operates light settings, smart kitchen, smart interactive mirror, smart air-conditioner and music system to provide a better ambience. Robot recognizes the user emotion by facial expression, body gesture and bio-signals to predict the health and feelings of the user. Interactive mirror is a smart artifact, developed for smart home applications. It supports face recognition and emotion recognition and measurement of physiological parameters like body weight, height and display health progress chart (Body Mass Index, Body metabolic Rate) (Augusto *et al*., 2010).

In medical field, to reduce stress, depression and anxiety in patients, systems are developed to recognize emotion and treat by music therapy. They have found positive effects on Alzheimer disease (Drapeau *et al*., 2009). In call centers, voice is used to detect the emotion of customer. After recognizing the voice of angry or happy customer, system can prioritize the angry calls to satisfy the customer needs and improve sale. In marketing side, emotion recognition process has more impact on advertisement in supporting purchasing decisions (Payne *et al*., 2008).

Emotion recognition system uses facial expression, speech (audio and voice), body gesture, keystroke dynamics, mouse movements, physiological signals, Bio-signals (Brain signal, skin temperature, blood

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pressure, heart rate, respiration rate) and body movements (for example limbic movement) for identifying emotional states (Wioleta, 2013). Devices used to capture the emotion are mobile phones, camera, surveillance camera, FLIR thermal camera, desktop webcam, Electro Encephalo Gram (EEG) (Soleymani *et al*., 2015), Electro Cardio Graphy (ECG), Electro Dermal Activity (EDA) (Kim *et al*., 2004), respirator change, skin conductivity, Electro Myo Gram (EMG) (Wagner *et al*., 2005), speaker, microphone, keyboard and mouse movements.

Researchers classify basic emotion states as happy, sad, fear, surprise, disgust and anger. In facial expression the positive and negative states of emotions are classified as happy and anger, respectively (Batty and Taylor, 2003). The first step of emotion detection is face detection in the image. Face detection is complex task because it depends on face gesture, pose and lighting condition. Some of the challenges in face detection are variation in shape, color, size, structural component, imaging condition, lighting direction, camera position, wearing glasses, different make up in face, direction of image noisy image acquisition, facial expression, occlusion in group of people.

Emotion classifiers are used to detect the accurate emotion state. So selecting the appropriate classifier is the most important process because successful classifiers are used to detect accurate and quick emotion detection. Some of the popular classifiers are Linear Discriminant Classifiers (LDC), k-Nearest Neighbour (k-NN), Gaussian Mixture Model (GMM), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Tree Algorithms and Hidden Markov Models (HMMs).

RELATED WORKS

From 1970 onwards, research work has been done in recognizing the human emotions by facial expressions. Face detection is done by many features like presence eye, nose, mouth, eyebrow, lip, etc. Real value parameters are eyebrow raise distance, upper eyelid to eyebrow distance, inter-eyebrow distance, upper eyelid-lower eyelid distance, upper lip thickness, lower lip thickness, mouth width and mouth opening. The binary parameters are upper teeth visible, lower teeth visible, forehead lines, eyebrow lines, nose lines, chin lines, nasolabial lines (Kulkarni *et al*., 2009). To recognise the emotion of user by image acquisition, face detection, feature extraction and classification of emotion.

In the image acquisition process are in different ways are static and dynamic capture system. In the form of images or video types taken by camera or webcam. Image acquisition processed by webcam in laptop and Camera such as DSLR, Kinect camera (Hu and Chen, 2015). Image or set of images and videos are taken in image acquisition process. Pre-processing is the important steps in image acquisition process. After capturing a image or videos (converted into frames and taken image only) pre-processing method will occur. Pre-processing step is mainly improve image quality in unvaried shape, size and normalized intensity.

Pre-processing image by median filter, Gaussian filter (Neeru and Kaur, 2016), average filter, adaptive mean filter, image normalization. These are some of the filters used in pre-processing to remove noise and improve the quality of image. Next face detection method is used to detect the face images. Main purpose is localizing and extracting the important features in the face region from the background of images. Some techniques are knowledge based, feature invariant, template matching, appearance based (Hjelmas and Low, 2001).

Feature extraction means extracting feature from whole face regions(like action units) or some face regions are taken (eyes, mouth, lips, forehead). Shape and color important feature are used to detection features. Some techniques are Gabor filter (Kung *et al*., 2015), sobel filter, canny edge detection and prewitt edge detection (Maini and Aggarwal, 2009). To classify the moods by emotion recognition techniques. Person emotion is vary from person to person, place to place and different in many situation.

Chavan *et al*. (2013) present dynamic response for basic emotions such as happy, sad, fear, disgust, surprise, neutral and anger using facial expressions. Using the Bezier curve recognize the emotion dynamic manner. It provides best results for single user and average result for multiple users.

Goyal *et al*. (2016) suggested the mixture of expert model for multimodal emotion prediction in movies. It is a dynamic way of predicting emotion in movies by facial expression and audio (music). Histogram of face area and video compression are used to recognize the face expression. First audio only and video only format are separately used for emotion detection. Later fusion method combining audio and video make mixture modal in multimodal system. It is unable to predict sub types of emotions.

Mistry *et al*. (2016) proposed the micro genetic algorithm embedded with particle swarm optimization. He used different classifiers to detect the seven dimension of emotion state and proposed hvnLB operator performs horizontal and vertical neighborhood pixel comparison to retrieve the initial discriminative facial features. It gives better performance compared with other classical algorithm present in that paper.

Malassiotis and Tsalakanidou (2011) present emotion detection method by facial expression recognition in the sequence of 2D and 3D image. Emotion are happy, sad, disgust, surprise and neutral. Facial action unit and facial expression recognition by 3D sensors. Active shape model technique used in 3D face tracker. Sequence of 3D images are more accurate to detect the emotion by different pose variation. This supports real time emotion classification.

Lee *et al*. (2014) uses mobile camera to detect the facial expression emotion recognition system. Weighted fuzzy k-NN Classification is used to compare the result. Delaunay triangulation form triangle meshes to map the vectors in face image. Active Appearance model is used in this paper to extract feature set of input. It is dynamic process taking image in sequence of video. Only happy, sad and neutral emotions can be recognized by this method.

Zen *et al*. (2016) propose the personalized model for facial recognition. Transductive Parameter Transfer (TPT), a framework for building personalized classification models and define some application. It is using the visual data and the gesture movements to detect the user emotion. It is user-independent. It provide accuracy at low computational cost. Gesture recognition and facial expression are assumed to "one size fit all". It is mainly designed for the average person applicable for action unit, pain detection and smart watch based gesture recognition.

Liu and Yin (2015) has proposed spontaneous facial expression analysis. In this study, infra-red thermal video descriptor is used in order to improve spontaneous emotion recognition. It represents image as thermal video clips. It is mainly based on temperature generated by movement of body and muscle movement that produces heat. It captures the emotion by FLIR thermal camera. This method is used to identify the low back pain as real or fake. It is useful to detect spontaneous changes of emotions.

Table 1 shows survey of face emotion recognition systems. Study refers contributors. Face images or video

Table 1: Survey of emotion recognition techniques

Study	Technique	Classifier	Attribute	Input Format	Database used
Lee *et al*. (2014)	AAM and Fuzzy K-NN	No preprocessing (template Matching Method)	Face	MPEG-4	Recorder Mobile video
Liu and Yin (2015)	SIFT (Scale Feature Invariant Transform)	SVM as classifier	Face (skin temp and head motion)	FLIR thermal camera videos	USTC-NVIE and thermal database
Georgakis *et al*. (2016)	DICA (Discriminant Independent Coherent analysis	Linear Regression Classifier	Face	Database images (32x32 pixel)	CK+ Dataset, CMU, Multi-PIE AR, GEMER-FERA
Le Ngo *et al*. (2016)	EMM	SVM	Face	Short movies	CASME II Corpus
Sarma and Bhattacharyya (2016)	ANN	LDA	Face	Image	Own database
Li and Nan (2011)	BLD, FLD	KPCA	Face	Images	CED-WYU(1.0)
Zen *et al*. (2016)	Novel transfer learning Framework	SVM as classifier	Face, Gesture	Video	PAINFUL Dataset CK+, SWGR Dataset
Zhao *et al*. (2015)	Space Based FER	2-D median filter	Face	2.5 D Facial Data	EURECOM, FRGC Bosphorus
Zhang *et al*. (2016)	Discrete Wavelet Transform and Biorthogonal Wavelet Transform	SVM	Face	Image	JFFE
Shojaeilangari *et al*. (2015)	Extreme sparse learning	Non-Linear classifier	Face	Videos	CK+, ECK+, AVEC 2011
Lee and Ro (2015)	Partial matching	Sparse representation classifier	Face	Video	(CK++), MMI, Natural visible and infrared facial expression (NVIFE)
Agarwal and Mukherjee (2017)	Local motion pattern	Motion descripts/SVM classifiers	Face	Video	CK++, MMI,MUG
Kung *et al*. (2015)	3D HMM	Histogram, Gaussian	Face	Video	CK database, MMI
Mistry *et al*. (2016)	Micro GA Embedded PSO	Ensemble classifier/	Face	Image	CK++, MMI
Goyal *et al*. (2016)	Mixture of experts based fusion model	MFCC and HOF (Histogram of optical flow)	Face, Audio	Video	Movies and animated movie as dataset
Reney and Tripathi (2015)	KNN and multi resolution decomposition	Violo Jones and Mel frequency component	Face, Voice	Sound file and image	Features dataset
Shah and Kaushik (2015)	Euclidian distance and neural networks	DCT and canny edge detection	Face	Images	JAFFE, IFE (Indian Facial Expression)
Oh *et al*. (2016)	Higher Order Riesz Transforms	SVM classifier	Face	Videos	CASME II and SMIC
Qayyum *et al*. (2017)	Stationary Wavelet Transform (SWT)	DCT	Face	Videos	JAFFE,CK+, data set from MS-Kinect device
Liong *et al*. (2014)	Optical strain	LOSOCV and SVM	Face	Videos	CASME II & SMIC

taken as input and can be test data set or training set. Techniques are referred as RGB, thermal images, grayscale images and classifier used. Input format refers to audio, video and image.

TECHNIQUES

Facial expressions are important features to detect the mood of the user. First phase involves capturing image from video or camera followed by image preprocessing. Normalization process is done after the pre-processing. Then different facial features are extracted to detect the emotions. Different techniques are used to detect state of person’s emotion. Different techniques are used to classify test data compare to trained data in database. **Table 2** refers response time can be static or dynamic. Static represents the still images or videos used to detect the emotion recognition system.

Table 2: Performance comparison of emotion recognition techniques

Study	Response time	Accuracy	Best features	Limitation	Application
Lee *et al*. (2014)	Dynamic	76%	Beneficial for quick application in phone	Happy, sad and neutral emotions are identified Difficult to differentiate false dismissals	Iphone and mobile application
Liu and Yin (2015)	Dynamic	91%	Eight spontaneous expressions are educed	Cannot differentiate real/ fake expression	To find chronic low back pain
Georgakis *et al*. (2016)	Static	95.4%	Subject independent. Expression recognition Training set may have scarf, sunglass and occlusion	Different accuracy database AU detection gives low performance	Biometric. Face analysis
Li and Nan (2011)	Static	83.55%	Seven basic emotion classify. Inducement intersection of facial expression find	Person dependent. It is hard to differentiate the inducement expression	Find the inducement of facial expression
Zen *et al*. (2016)	Static	90.0%	User independent. Computational time reduced Increase accuracy. Computational cost is low because of pre trained regression	Accuracy based on user independent classifier.	Used in smart watch. AU (Action Unit) detection Pain detection
Zhao *et al*. (2015)	Dynamic	91.6%	Trained AU detection. AU computation and evaluation	2.5 D kinetic camera and RGB-D camera images used	Wearable Social Assistant device. 2.5 D video chatting
Zhang *et al*. (2016)	Dynamic	96.77%	Improve accuracy	Not focus on the geometric face images Only uses the image not considering the video images	Used in MR images, CR images, remote sensing images. To identify autism person and AD
Shojaeilangar *et al*. (2015)	Static	92.74%	Increases the accuracy or the acted and self-generated facial expression Head pose variation and occlusion images are used to detect emotion	Failure in optical flow. Fail in face detection. Fail to detect. Reference point in face	Driver warning system Real world application
Lee and Ro (2015)	Static	92.08%	Computation time is been reduced Performance increased due to temporal mismatch and geometric displacement solved	Subject independent. Limited number of frames are used to recognize the emotion	FER application
Agarwal and Mukherjee (2017)	Static	94.2%	High accuracy. Time and space complexity is been reduced	Difficult to detect anger and sadness	Emotion recognize application
Kung *et al*. (2015)	Static	92.7%	Three dimensional spatio-temporal is applied to locate the motion and changes in video	Hard to find chin part in face	Applied in spatial temporal domain

Table 2: Continue

Study	Response time	Accuracy	Best features	Limitation	Application
Mistry *et al*. (2016)	Static	94.66%	Compare with other heuristic algorithm m-GA give better accuracy	Different to identify neighboring pixel by LBP	Human robot in real world application
Reney and Tripathi (2015)	Dynamic	94.5%	Accuracy rate increase because face and audio	Audio file are not matched correctly for all time	Biometric surveillance camera
Oh *et al*. (2016)	Dynamic	90%	use intrinsic two-dimensional (i2D)	i2D feature not improve accuracy rate for all emotions	To detect micro expression Signal processing
Qayyum *et al*. (2017)	Dynamic	98.83%	Better performance in accuracy and classification	Use kinect camera	Kinect based application

Dynamic response represents the real time response to user. For example surveillance camera detects person emotion from crowd dynamically taking input from the user. All these algorithms have some merits at the cost of some limitations.

Table 2 refer performance analysis accuracy rate limitation, best feature and application. Different techniques used to high accuracy rate detection. Response time as dynamic and static process. In dynamic (Liong *et al*., 2014; Qayyum *et al*., 2017; Oh *et al*., 2016; Reney and Tripathi, 2015; Goyal *et al*., 2016; Zhao *et al*., 2015; Zhang *et al*., 2016; Lee *et al*., 2014; Liu and Yin, 2015; Sarma and Bhattacharyya, 2016) process real time images and videos are test data compare with trained database. In static process trained database data are used to classify emotion (Georgakis *et al*., 2016; Le Ngo *et al*., 2016; Shojaeilangari *et al*., 2015; Lee and Ro, 2015; Agarwal and Mukherjee, 2017; Kung *et al*., 2015; Mistry *et al*., 2016; Shah and Kaushik, 2015; Zen *et al*., 2016). It has different accuracy rate and application.

CONCLUSION

Several emotion recognition systems are available in the literature. These recognition systems are unimodal or multimodal. In this study, a survey of emotion recognition systems is based on facial expression alone is done. These papers provide a tradeoff between accuracy and response time and range of emotions. The appropriate emotions recognition system depends on the application chosen.

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