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A Review on EEG Signals Based Emotion Recognition

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Abstract
Emotion recognition has become a very controversial issue in brain-computer interfaces (BCIs). Moreover, numerous studies have been conducted in order to recognize emotions. Also, there are several important definitions and theories about human emotions. In this paper we try to cover important topics related to the field of emotion recognition. We review several studies which are based on analyzing electroencephalogram (EEG) signals as a biological marker in emotion changes. Considering low cost, good time and spatial resolution, EEG has become very common and is widely used in most BCI applications and studies. First, we state some theories and basic definitions related to emotions. Then some important steps of an emotion recognition system like different kinds of biologic measurements (EEG, electrocardiogram [EEG], respiration rate, etc), offline vs online recognition methods, emotion stimulation types and common emotion models are described. Finally, the recent and most important studies are reviewed.
Keywords: Emotion, affect; Recognition; Classification; Electroencephalogram

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Introduction

Everyone knows original and basic emotions such as happiness, fear, anger, disgust, sadness and surprise. But neuroscientists and researchers have no consensus about the nature of emotions. There are 2 opinions about emotions: one approach considers emotions as general states of individuals and the other one knows emotions as physiological interactions.[1] Imagine a person driving a car while another car approaches and causes him to deviate from the road. At first that individual probably experiences fear and anger. According to the first view, fear comes from the inference that one might be in anger and that anger is because of the driver who has just put him in danger. Thagard,[1] Oately[2] and Nussbaum[3] believe in the first approach. Oately demonstrated how original emotions have a strong relation with executing goals. In other words, people become happy while approaching their goals and sad when they fail. People become frightened when they experience trouble or feel threatened. Therefore, we can consider emotions a general representation of our problems.[1] In contrast to the first view, the second approach emphasis on physical and physiological interactions. When someone causes an individual driving a car to deviate off the road, their heart rate, blood pressure and respiration rate increase. Feelings (like fear or anger, etc) originate from the brain's responses to these physiological changes and not from the interpretation of the situation. James introduced this approach for the first time in 1884. Psychologically speaking, in terms of emotion classification there are 2 basic theories: Plutchik's theory and Ekman's theory. The first theory classifies emotions into 2 different categories: basic emotions and secondary ones. These emotions are as follows: anticipation, joy, trust, sadness, fear, surprise, anger, disgust. Secondary emotions come from a combination of these elementary feelings. These emotions are as follows: love, optimism, aggressiveness, submission, contempt, awe, remorse and disapproval. Ekman's theory is known as a discrete model. He introduced six basic emotions: fear, sadness, happiness, surprise, disgust, anger.[4] After that, the number of these emotions increased to 15. James and Lange in the 19th century introduced another theory. In this theory environmental variations cause physiological changes in our autonomous nervous system and consequently cause different emotions. On the other hand, physiological changes cause emotions. Therefore, researchers analyze signals and images related to these physiological changes in order to recognize feelings and classify emotions. However, physiological signals introduce some problems like noise, artifacts, etc. Another problem is that we cannot visually recognize emotions from physiological signals and need computerized processes.[5-11] Also, there are other factors which affect emotions, such as sex, age and race. Usually, researchers consider these parameters while studying emotions. Besides the discrete model of emotions, there is another model which Lang proposed and called valence-arousal model. In this model, valence and arousal values are assigned to each emotion. In other words, in this model emotions are a continuous spectrum of valence and arousal values and generally emotions are plotted in a 2D coordination called valence-arousal plane.

There are 4 important steps in emotion recognition systems: physiologic records, emotion stimulation, online or offline recognition and stimulated emotions and emotion models.

Physiologic Records

Emotion status is reflected by physiological changes, which is why biological signals and images are recorded in order to recognize emotions. Some biological systems in the human body and their indexes are described as follows:

1-Cardiovascular system: electrocardiogram (ECG), heart rate variability (HRV), cardiac output, blood pressure, etc.
2- Respiratory system: respiration rate, etc.
3- Muscular system: electromyogram (EMG) signals, etc.
4- Brain activity: EEG signals, etc.

Figure 1 shows some types of these signals.

EEG signals due to their simplicity to analyze and good time and spatial resolution have become common and useful in most BCI applications such as emotion recognition. Also, EEG recording systems are cheap and accessible. Previous studies show that by recording and processing EEG signals we can achieve very good results in terms of emotion classification. So a decision was made to explain and review some previous studies related to emotion classification through EEG signals.

Emotion Stimulation

The way emotions are evoked plays an important role in emotion recognition systems. Some believe that video clips can stimulate human emotions the best while others find music or memories the most effective way. What is clear is that the stronger the stimulation is the richer the database will be. By using good and strong stimulation, emotion recognition is more likely to be performed with better results and higher accuracy. There are some types of stimulation as follow: pictures,[12-43] video clips,[44-60] music,[61-76] memories,[77] self-induction,[78,80,81] environment elicitation like light, humidity and temperature,[79] games,[82] etc.

Some ways of eliciting emotions and some induced emotions are listed in Table 1.

Offline or Online Recognition

In some studies, emotion recognition on the spot is really important such as monitoring patients while taking medicine, so online methods are of importance in those applications. For example, Iacoviello et al[81] an effective, general and complete classification method for EEG signals was introduced. In this study, self-induction was used as emotion elicitation. Wavelet transform (WT), principle component analysis (PCA) and support vector machine (SVM) were used to process and classify EEG signals. Also, Sourina et al[83] introduced an online emotion recognition study which used spatial time fractal to characterize brain states. A vital issue in online recognition systems is that processing methods must be fast and precise. Fractal transform is one of these methods that was used in several related studies. Sourina et al[86] determined brain responses using fractal transform following stimulation by music. Also they calculated Renyi entropy as well. Liu et al[55] calculated Higuchi's fractal dimension. They processed EEG signals while participants were listening to music.

The other type of emotion recognition systems is offline. For example, Zhang and Li[85] recognized positive and negative emotions using neuro fuzzy method offline. In this study, an unsupervised clustering method and adaptive neuro fuzzy inference system (ANFIS) were used. Clustering was used in early steps for creating primary information related to emotions. Emotions were elicited by International Affective Picture System (IAPS)

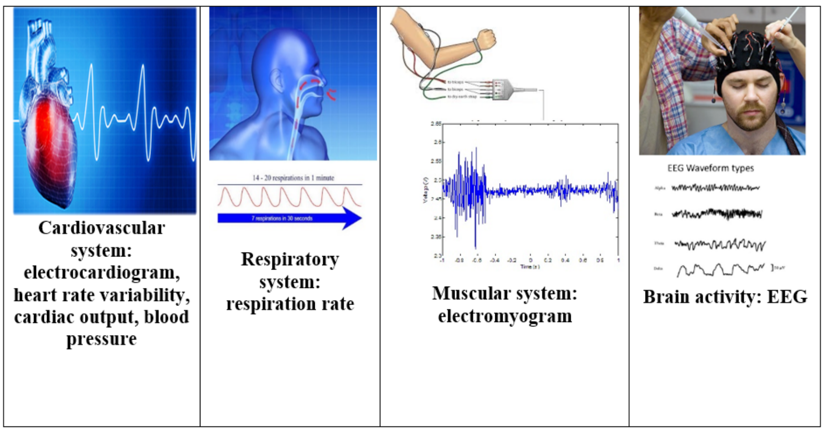

Figure 1. Types of Physiologic Records.

Table 1. Different Kinds of Emotion Stimulation

Stimulation	Emotion	Ref.
Pictures	Valence-arousal model	19
	Negative and positive emotions	54
	Happiness, fear, neutral, sadness	27
	Valence-arousal model	17
	Happiness, fear, neutral, sadness, anger	43
	Negative and positive emotions	42
	Negative and positive emotions	97
Video clips	Happiness, sadness, disgust, amusement, fear, surprise, anxiety, anger, neutral	96
	Valence-arousal model	44
	Happiness, disgust, fear, surprise, anger, neutral	45
	Valence-arousal model	57
	Valence-arousal model	58
Music	Valence-arousal model	61
	Happiness, sadness, fear, surprise, anger	62
	Positive and negative emotions	63

images. In this study, EEG signals and visual information were recorded.

Emotion Models

Another problem in emotion recognition studies is the number of elicited emotions and the emotion model. Some studies, according to discrete model of emotions, consider a specific number of emotions and others according to valence-arousal model suppose more emotions. For example, Murugappan et al[45,48,52] studied anger, fear, surprise, happiness emotions according to discrete emotion model, while Koelstra et al,[51] Koelstra and Patras,[53] and Hidalgo-Munoz et al[24] studied emotions according to the valence-arousal model.

Public Databases

There are some public emotion databases which can be used by researchers for free. The advantage of public databases is that researchers do not need any laboratory and specific recording systems, appropriate condition, shield environment, etc. Also, they do not need participants and they will have reliable and free databases. In this section, some available databases are described.

DEAP Database

This multimodal database was recorded by Koelstra et al,[51] in 2 laboratories (Geneva and Twente) in 2012. In this database, 40 video clips were used to elicit emotions according to valence arousal model. Thirty-two individuals participated and 32-channel EEG signals, 4-channel EMGs, 4 EOG signals, 2-channel GSR signal, 2 ERG signals, temperature in a single channel, single channel respiration rate and 1-channel blood volume pressure were recorded. Five indexes including arousal, valence, like/dislike, dominance and familiarity were reported by each participant. Raw and preprocessed signals from all participants and also face videos from 22 of them are available in this dataset. More detailed descriptions can be found in https://www.eecs.qmul.ac.uk/mmv/datasets/deap/index.html. Figure 2 shows selected emotional videos in valence arousal plane.

SJTU Emotion EEG Dataset (SEED)

Zheng and Lu[98] recorded SJTU emotion EEG Dataset. This dataset contains EEG signals from 15 individuals while watching Chinese video clips. Figure 3 shows a participant while watching clips. Emotions were considered as positive, negative and natural. Participants filled a questionnaire after watching videos. EEGs were recorded in three sessions to evaluate stability of patterns and neural signatures among participants and sessions, the interval between 2 sessions was one or more weeks. EEG signals were recorded according to the 10-20 international standard system. Raw and preprocessed signals and also face videos are available. For more details refer to http://bcmi.sjtu.edu.cn/~seed/index.html.

MAHNOB-HCI database

Soleymani et al[96] recorded MAHNOB-HCI database, a multimodal database in 2012. This database included several multimodal signals, 32 channels EEG signals, 3 channels ECG signals, 2 channels ERG, 2 channels GSR, respiration amplitude and skin temperature signals. Multimodal signals were recorded from 27 individuals while watching video clips and pictures. This database included

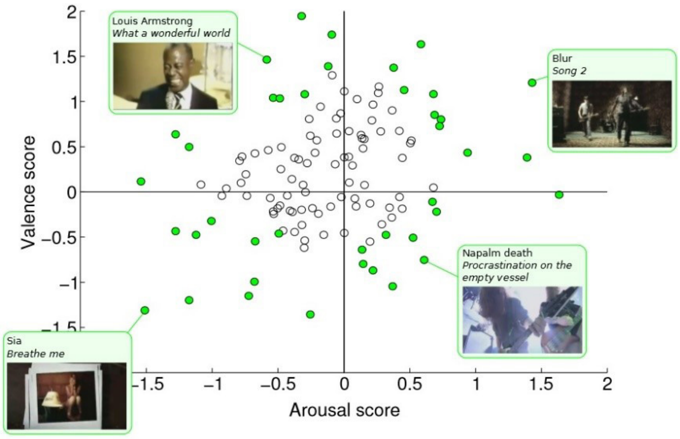

Figure 2. Valence and Arousal Values of Video Clips in DEAP Database. Included video clips are shown in green.[51]

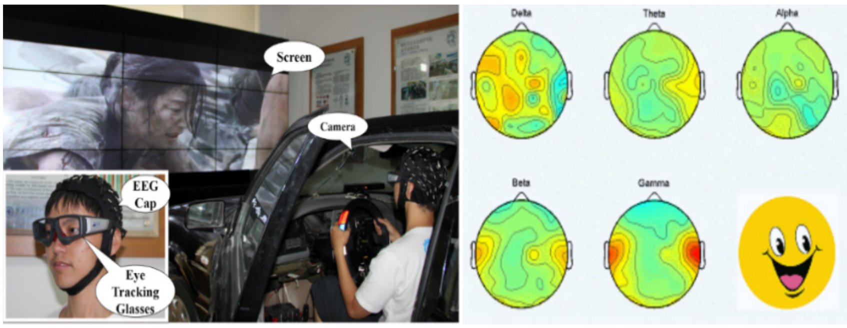

Figure 3. SJTU Emotion EEG Dataset (SEED) setup.[98]

2 separate sessions, in the first session video clips were displayed and participants immediately filled a questionnaire about their feelings after watching clips. In the second session, short videos and pictures were displayed once with right and wrong labels and once without labels. Their comments about their feelings were evaluated. Signals were recorded according to the 10-20 international standard system. For more details about this database refer to https://mahnob-db.eu/hci-tagging/.

These databases have been used in several studies, Table 2 shows a brief description and references which have used biological signals in these databases so far.

Previous Emotion Studies

Emotion and Normal Cases

In this section we review previous studies which evaluate emotions in normal individuals. Weinreich et al[26] measured variations of alpha frequency band in frontal lobe from an oddball paradigm. Participants were asked to describe each image regardless of the emotion of the image. 16-channel EEG signals were recorded from 20 female and 8 male participants.

Hidalgo-Munoz et al[24] studied EEG signals of 26 females while watching emotional images from IAPS. This study considered emotions according to the valence-arousal model. In the processing step, they used spectral turbulence (ST), a method which was inspired by ECG studies. Results show that the left temporal lobe has considerable activity during emotion elicitation. Koelstra and Patras[53] recorded EEG signals from several participants according to the valence-arousal model. They showed video clips in order to evoke emotions. The details are described in section 1.5 and Table 2. In this study, power spectral density of EEG sub-bands was calculated and active units (AU) were detected from face videos of participants. Then a combination of features was applied. Hidden Markov Model (HMM) and GentleBoost were used as the classifiers. Results showed that the combination of face videos and EEG signals improved the accuracy.

Lee et al[54] proposed an emotion recognition system based on fuzzy logic. They used video clips to elicit emotions and recorded EEG signals from 12 participants. They extracted dynamic features from emotional states and 3D fuzzy GIST and 3D fuzzy tensor to extract brain features in a semantic level. Independent component analysis (ICA) was used to remove artifacts. ANFIS was used to classify emotions, results showed the performance of the proposed method.

Haung et al[60] presented a multimodal approach to recognize emotions. In this study EEG signals from MAHNOB-HCI database were used. Discriminant power spectrum and difference power spectrum were extracted from EEG signals of 27 participants. Local binary patterns (LBP) were extracted from videos of participants' faces. Then fusion in features and decisions were applied. Finally, SVM and KNN were used as classifiers. Results showed that using multimodal data, gives better recognition results.

Bozhkov et al[31] considered valence-arousal model for emotions and recorded EEG signals from 26 females viewing IAPS pictures. They used Echo state networks (ESN) to cluster and classify positive and negative emotions. They obtained the desired results and demonstrated the performance of their proposed method.

Mavratzakis et al[36] evaluated event related potentials (ERPs) of 27 individuals during watching pictures. In this study, three picture databases were used as stimuli: KDEF (Karolinska Directed Emotional Faces Database), RAFD (Radboud Faces Database) and IAPS. After statistical analysis of ERP components, results showed that emotions did not influence on P1 component. Also, N170 increased during watching emotional pictures but N100 was not sensitive to emotion changes. Moreover, early posterior negativity (EPN) increased during watching fearful images.

Emotions and Neural Disorders

An interesting part of emotion studies is studies which evaluate psychological diseases and disorders through emotion recognition. In this section, studies about some disorders such as Parkinson's disorder (PD), autism spectrum disorder (ASD), schizophrenia, depression, etc. were reviewed. Yuvaraja et al[88] extracted higher order spectral features from EEG signals and evaluated emotion changes between PD patients and normal individuals. EEG signals were recorded from 20 PD patients and 20 normal participants while watching video clips. Samples were classified into six basic emotions (sadness, happiness, fear, anger, surprise and disgust)

Table 2. Description of Public Databases

Name	Participants	Signals	Stimulation	Emotion	Supplementary Files	Ref.
DEAP	32	32 EEGs, 4 EMGs, 4 EOGs, 1 GSR, 1 RR, 1 Plethy[a], 1 Temp[b]	40 video clips	40 emotions according to valence arousal model	Face videos	44,51,57,58,87
MAHNOB-HCI	30	16 EEGs, 3 ECGs, 2 GSRs, 1 RR, 1 Temp	20 Video clips and pictures	Happiness, Sadness, disgust, amusement, fear, surprise, anxiety, anger, neutral	Face videos (522), eye gaze	53,60,96
SEED	15	15 EEGs	15 video clips	Positive, neutral and negative emotions	Face videos	59,98

[a] Plethysmograph, [b] Temperature.

through SVM classifier. Results showed PD patients have weaker emotions in comparison with normal individuals, especially for negative emotions. Yeung et al[90] examined cortical connectivity of autistic children while watching KDEF face pictures and compared them with normal children. EEG signals of 18 autistic children and 18 normal children were recorded during stimuli and then analyzed using theta coherence index (cortical connectivity index). This study showed that autistic children have deficiency in emotion recognition. Also, there was no theta coherence modulation while normal children had theta coherence modulation in the right frontal lobe in response to emotional faces. Theta coherence modulation in response to emotions is related to social deficiency of autistic children.

Schizophrenia can be detected by emotion stimulation. Brennan et al[89] examined this hypothesis by processing ERP signals. This study used international BRAINnet database, including 108 schizophrenic patients and 108 normal cases. All individuals watched emotional pictures including sadness, fear, anger, disgust and happiness and simultaneously ERPs were recorded in conscious and non-conscious conditions. Then significant differences among 2 groups were achieved through analysis of variance (ANOVA). Results showed that schizophrenic patients had shorter brain activity, about 70 ms. Also, schizophrenic patients in response to disgust had positive shifts after 70 ms and normal people had negative shifts in response to fear and anger in comparison with happiness in temporal-occipital regions.

Croft et al[95] detected emotion deficiency in Huntington's patients via ERPs. In this study, EEG signals from 11 Huntington's patients and 11 normal individuals were recorded while participants expressed emotions such as scramble, neutral, happiness, anger and disgust. Results showed lower accuracies for negative emotions such as disgust, neutral and anger due to decreased functionality.

Psychogenic non-epileptic seizures (PNES) are unknown among epileptic seizures. Recent studies showed that PNES patients have impairments in control of their emotions. Urbanek et al[94] evaluated this hypothesis. In this study, EEG signals from 56 patients and 68 normal individuals during emotion stimulation were recorded. Results demonstrated that these patients have weaker emotions, more negative feelings and stronger control on their emotions than normal people.

Tseng et al evaluated phase synchrony and EEG activation oscillation in Asperger syndrome (AS) patients while they were recognizing emotions from face images.[40] AS group included 10 individuals and the normal group consisted of 10 individuals. Emotions were stimulated by pictures. Results demonstrated that AS group had no determined N400 in response to pictures, also, they showed lower synchrony in temporal and parietal-occipital lobes at delta/theta and weaker phase synchronization in separate regions of brain.

Akar et al examined brain dynamics of major depressive disorder (MDD) patients during stimulation using positive and negative emotions.[72] They used music as stimulation. Three different situations including noisy environment, relaxation and listening to music were considered. EEG signals from 15 MDD patients and 15 normal people were recorded and analyzed using non-linear methods. Some kinds of complexity measures such as Lempel-Ziv, Kolmogorov were calculated and then significant differences were evaluated by ANOVA measure. This study demonstrated that MDD patients have more complex EEG signals in parietal and frontal lobes comparing to normal people. Also EEG signals of these individuals had lower complexity in frontal and parietal lobes while listening to music compared to other situations.

Li et al evaluated large scale functional brain networks of depressed people and normal ones using graph theory.[34] Participants' emotions were elicited by Ekman pictures including positive, negative and neutral emotions. Simultaneously, EEG signals were recorded from 16 depressed and 14 normal participants. In this study, EEG signals were processed by extracting coherence in frequency bands such as delta, theta, alpha, beta and gamma. Results showed that for depressed participants total coherence values in gamma band were higher than normal people. Also, total coherence among normal participants for negative emotions was higher in gamma band. Moreover, there were abnormal networks in prefrontal and occipital lobes for depressed participants. Table 3 describes recent studies related to emotion recognition.

Conclusion

In this paper, we reviewed several emotion recognition studies from EEG signals. First, we stated some emotion

Table 3. Recent Emotion Recognition and Evaluation Studies From EEGs

Emotions	Stimulation	Recorded signals	Method	Results	Ref
Positive and negative valence	Music	EEG signals from 5 women	Correlation dimension, ANOVA	Lower correlation dimension while listening to music	69
Valence arousal model	Video clips	MAHNOB-HCI	PSD sub bands (EEGs), AU (face pictures) detection, fusion in feature and decision levels, HMM, GentleBoost	Better results using 2 modalities (EEG signals and face pictures)	53
rSASM (recalibrated Speech Affective Space Model), 12-PAC (12-Point Affective Circumplex)	Pictures (RAFD database)	EEG signals from 5 children	KSDE (Kernel Density Estimation), MFCC (Mel-Frequency Cepstral Coefficients), MLP	MFCC-rSASM has lower MSE vs MFCC-12PAC and KSDE-12-PAC was lower than KSDE-rSASM	27
Happiness, sadness	Self-induction	EEG signals	Signal velocity	Sadness has faster velocity than happiness	78
Three levels of arousal	Pictures (IAPS database) and transcutaneous electric nerve stimulation (TENS)	EEGs, SC, HR and acoustic startle amplitude from 30 individuals	Frontal alpha asymmetry	Relative activity in left frontal lobe plays an important role in emotion controlling	25
Valence-arousal model	Pictures (IAPS database)	EEGs from 26 females	ST, SVM-RFE	Left temporal lobe activated during emotional stimulation	24
Neutral, erotic, aversive, pleasant, unpleasant	Pictures (IAPS database)	EEGs from 73 individuals	Spectral analysis, ANOVA	Increase of upper alpha power in central lobe	92
Neutral, unpleasant	Pictures (IAPS database)	EEGs from 18 individuals	Dynamic theta in occipital region, spectral analysis, ANOVA	2 peaks in early theta power increase	93
Negative and positive	Video clips	EEGs from 12 individuals	3D fuzzy GIST, 3D fuzzy tensor, FCM, ICA, STFT, ANFIS	Effectiveness of 3D fuzzy, derived EEG features and ANFIS	54
Very happy, somewhat happy, neutral, sadness, anger, fear	Pictures	EEGs from 29 individuals	ERP amplitude, delay interval theta power, ANOVA	Higher N170 component and higher theta power in the delay in response to negative facial expression	39
Pleasant and unpleasant	Direct and indirect lightening environment	EEGs from 28 individuals	Spectral analysis, t-test, Pearson's correlation coefficient	-Correlation between pleasant score and theta power in F8 channel-theta frequency band as emotion biomarker in different lightening conditions	79
Neutral, anger, happiness, disgust	Picture (KDEF database)	EEGs from 11 Huntington's disease patients and 11 normal individuals	ERP analysis, statistical analysis	Lower emotion recognition accuracy for HD patients due to decreased emotional function (neutral, disgust and anger)	95
Pleasantness, tension, happiness, anger, fear, energy, sadness, tenderness	Music	EEGs from 31 individuals	ICA, connectivity, asymmetry, PCA	Correlation between nervous and evoked emotions	70
Positive, negative, low level and high level	Video clips	EEGs from 36 individuals	Higuchi fractal dimension, MANOVA	More complexity for EEGs following (while) high level emotion stimulation	55
Anger, neutral, happiness	Pictures	EEGs from 31 children	FFT, EEG asymmetry, ANOVA	Attention decreased in children with right temporal-anterior EEG asymmetry	38
Negative, positive, neutral	Pictures (Ekman emotion database)	EEGs from 16 depressed patients and 14 normal individuals	Sub band coherence, graph theory	-Higher coherence of depressed patients at gamma frequency band -Higher coherence of normal individual in negative stimulation compared to positive	34
Neutral, happiness, anger,	Pictures (Ekman emotion database)	EEGs from 10 Asperger's syndrome (AS) patients and 10 normal individuals	ERP and ERSP analysis, phase synchronization, MANOVA	The AS group had no visible N400 component and lower delta/theta synchronization (350–450ms post-stimulus onset) in the temporal and occipital–parietal regions	40

Table 1. Continued

Pleasantness, tension, happiness, anger, fear, energy, sadness, tenderness	Music	EEGs from 31 individuals	Acoustic features (music), frequency band power and asymmetry (EEGs), PCA, regression model, correlation	Prediction of emotions using neural activity of individuals	71
4 emotions from valence arousal model	Pictures (IAPS database)	EEGs	ICA, modified kernel density estimation (KDE), artificial neural networks	Improvement in recognition using modified KDE	28
Negative and positive	Pictures (IAPS database)	EEGs from 26 women	Amplitude and latency of ERPs, Neural networks, logistic regression, naïve Bayes, linear discriminant analysis	P300 and P200 from parietal and occipital regions play role in emotion recognition	29
Negative and positive	Music	EEGs from 15 MDD patients and 15 normal individuals	Katz fractal dimension, Higuchi fractal dimension, Shannon entropy, Lempel-Ziv complexity, Kolmogorov complexity (KC), ANOVA	More EEG complexity in parietal and frontal of MDDs	72
Valence arousal emotions	Pictures (IAPS database)	EEGs, HR, SCR, Near-Infrared Spectroscopy (NIRS) from 20 subjects	EEG power, correlation analysis, ANOVA	Significant difference in right and anterior region following emotion stimulation (negative valence vs arousal)	30
Disgust	Self- induction (remembering unpleasant smell)	EEGs from 10 men	WT, PCA, SVM	Right hemisphere and T8 play important role in emotion recognition	81
Unpleasantness	Self- induction (remembering unpleasant smell)	EEG from C4, P4, T8 and P8 from 28 individuals	STFT (gamma and alpha frequency bands), similarity measure	Sensitivity of right hemisphere in gamma frequency band following negative emotion stimulation	80
Relaxation	Music (Tanpura drone)	EEGs from 10 individuals	WT, Empirical Mode Decomposition (EMD), Multifractal detrended fluctuation analysis (MFDFA)	Music affect alpha and theta frequency bands	73
Fear, happiness, neutral	Pictures (MacBrain Face Stimulus set)	EEGs from 47 individuals	ERP analysis, ANOVA	Sensitivity of N170 component during emotion stimulation	37
Happiness, anger, fear, sadness, disgust, surprise	Video clips	Forehead EEGs, SC, BVP, RR from 25 individuals	Adaptive weighted linear model, KNN, SVM,	EEG forehead signals are sufficient for emotion recognition	56
Very happiness, somewhat happiness, neutral, sadness, anger, fear	Pictures (MacBrain Face Stimulus set)	EEGs from 38 schizophrenic patients and 42 normal individuals	ERP analysis, ANOVA	Higher N170 for 2 groups at negative emotions vs neutral but higher theta power in schizophrenic patients in delay interval	41
Reappraisal and suppression of negative emotion	Pictures (IAPS database)	EEGs from 102 individuals	Frontal alpha asymmetry (FAA), ANOVA	Greater relative activity in left frontal as reappraisal negative emotions vs normal view of negative emotions	33
Valence arousal emotions	Pictures (IAPS database)	EEGs from 28 individuals	WT, ANOVA,	Reduction of frontal alpha oscillation following higher arousal	26
Valence arousal emotions	Video clips	EEGs from 32 individuals (DEAP database)	Bispectrum analysis, LS-SVM, ANN (Linear and RBF kernels)	Sub bands had better results than EEGs	57
Valence arousal emotions	Video clips	DEAP database	Minimum-Redundancy-Maximum-Relevance(mRMR), SVM, genetic algorithm-SVM	Preference of mRMR vs SVM and GA-SVM	58
Relaxation	Music	EEGs from F3 and F4 from 10 men	WT, fractal dimension	Increased alpha fractal dimension following listening to sad and happy songs	74

Table 1. Continued

Happiness, sadness, anger, love	Music	EEGs from 30 individuals	Time and spectral features, WT, SVM, KNN, Multilayer perceptron (MLP),	Higher accuracy using fusion of features and MLP classifier	75
Negative, neutral and positive	Video clips	EEGs from 15 subjects (SEED database)	Domain adaptation, subspace alignment auto-encoder (SAAE)	Effectiveness of SAAE in emotion recognition	59
Valence arousal emotions	Video clips	EEGs and face expression from 30 subjects (MAHNOB-HCI database)	multimodal approach, Spectral power difference, discriminant spectral power, KNN, ANOVA, fusion	Effectiveness of multimodal approach	60
Happiness, fear, neutral	Pictures (Ekman database)	EEG and Transcranial magnetic stimulation (TMS) from 12 individuals	P1-N1 component, ANOVA	P1-N1 component reduction in medial prefrontal cortex, first P1-N1 in right hemisphere and second in left	35
Happiness, fear, neutral	Pictures (RAFD, KDEF, IAPS, GAPED[1] databases)	EEGs and facial electromyography (fEMG) from 27 individuals	ERP, statistical analysis	-Emotion had no effect on P1 component -Increase of N170 amplitude with emotion stimulation	36
Happiness, sadness, neutral	Music	EEGs from 19 individuals	Multi variation autoregressive model, connectivity, SVM	-Positive correlation between valence and frontal inter-hemispheric stream -Negative correlation between bilateral connectivity in parietal lobe	76
Negative	Pictures (IAPS database)	EEGs from 25 individuals	ERP analysis, statistical analysis	P3 component amplitude was modulated following emotional stimulation in parietal lobe	32
Valence arousal emotions	Pictures (IAPS database)	EEGs from 26 subjects	Clustering and classification by Echo state networks (ESN)	Echo state networks were better than classic networks	31
Valence arousal emotions	Video clips	EEG signals and peripheral signals (DEAP database)	Spectral and time features, multiple-fusion-layer based ensemble classifier of stacked auto-encoder (MESAE)	Preference of MESAE method vs classic methods	87
Fear, anger	Pictures (POFA[2])	High density EEGs from 11 young women and 11 adult women	ERP analysis (N170 modulation), brain source localization	Change in N170 amplitude, age effects on emotions	91
Anger, happiness, neutral	Pictures (Ekman and Friesen's collection)	EEG signals from 46 subjects	Event-related spectral perturbations, ANOVA	-Theta synchronization lead to increase in low depression patients following happiness stimulation -Increase of theta synchronization due to anger elicitation in high depression patients	99
Sad, disgust, fear, anger, happy and surprise	Pictures (IAPS database), sounds (IADS[3] database), video clips	EEG signals from 57 subjects	Wavelet packet transform, Hurst exponent, K-nearest Neighbour (KNN), Probabilistic Neural Network (PNN)	-Beta as the most discriminative frequency band -Sad emotion had higher accuracy (82.32%)	100
Valence arousal emotions	Video clips	EEG signals and peripheral signals (DEAP database)	Reinforcement online learning (ROL), support vector regression (SVR), least square regression (LS)	Reduced learning time for Least square reinforcement learning and support vector reinforcement learning methods	101
Positive and negative	Pictures (GAPED database)	EEG signals from 12 subjects	Power Spectral Density (PSD), Signal Power (SP) and Common Spatial Pattern (CSP), Linear Discrimination Analysis (LDA)	Higher accuracy for finding better electrode arrangement	102

[1]Geneva affective picture database = GAPED, [2] Pictures of Facial Affect=POFA, [3]Inter-national Affective Digitized Sounds = IADS.

approaches and theories. Then we described different components of emotion recognition systems: different kinds of biologic measurements (EEG, ECG, etc) offline vs online recognition systems, different types of emotional stimulation, and the specific emotion models which have been used in studies (valence-arousal model and discrete model). Since EEG has become more and more common in emotion recognition applications in recent years, our main focus was on the subject of emotion recognition through EEG signals. So different papers and studies were reviewed in order to cover this issue. Attempts were also made to support recent, valid and reliable studies for young researchers who are interested in this field.

Conflict of Interest Disclosures

The authors declare that they have no conflict of interests.

Ethical Statement

Not applicable.

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