Cognitive Robotics 1 (2021) 29–40

Contents lists available at ScienceDirect

Cognitive Robotics

journal homepage: http://www.keaipublishing.com/en/journals/cognitive-robotics/

Review of the emotional feature extraction and classification using EEG signals

Jiang Wang, Mei Wang*

Xi'an University of Science and Technology, Xian 710054, China

ARTICLE INFO

Keywords:
Emotion
EEG signals
Feature extraction
Classification

ABSTRACT

As a subjectively psychological and physiological response to external stimuli, emotion is ubiquitous in our daily life. With the continuous development of the artificial intelligence and brain science, emotion recognition rapidly becomes a multiple discipline research field through EEG signals. This paper investigates the relevantly scientific literature in the past five years and reviews the emotional feature extraction methods and the classification methods using EEG signals. Commonly used feature extraction analysis methods include time domain analysis, frequency domain analysis, and time-frequency domain analysis. The widely used classification methods include machine learning algorithms based on Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Naive Bayes (NB), etc., and their classification accuracy ranges from 57.50% to 95.70%. The classification accuracy of the deep learning algorithms based on Neural Network (NN), Long and Short-Term Memory (LSTM), and Deep Belief Network (DBN) ranges from 63.38% to 97.56%.

Introduction

Emotion is the behavioral response of a person to objective things mediated by individual needs. It influences a person's psychological and behavioral activities, such as processing information and making decisions. In recent years, the field of the brain-computer interfaces (BCIs) [1] has been continuously developed and gradually applied in many areas, for instance, medicine, psychology, education, and military affairs [2].

Some neuroscientists, psychologists, and engineers have carried out a series of studies on emotion recognition in computer science [3–5]. The research on emotion recognition through the electroencephalogram (EEG) signals has extensively promoted the development of the BCIs. Emotion recognition can generally be analyzed through non-physiological signals and physiological signals.

Non-physiological signals are often referred to as facial expressions, actions, voices, etc., only relying on these non-physiological signals cannot accurately identify human emotions in disguise [6–9]. It is precise because EEG signals are different from other non-physiological signals in objectivity and difficult to hide [10].

EEG signals have been proved to have a strong relationship with emotional states in [11,12]. It has higher classification accuracy for emotion recognition by analyzing EEG signals and reacts faster to the emotion changes [13,14]. Therefore, analyzing EEG signals is more reliable and effective for emotion recognition.

This paper reviews the emotional feature extraction methods and classification based on EEG signals proposed in the past five years, as shown in Fig. 1. We focus on the emotional characteristics based on EEG signals, proving the EEG signals' scientific nature on the emotions' classification.

* Corresponding author.
E-mail address: wangm@xust.edu.cn (M. Wang).

https://doi.org/10.1016/j.cogr.2021.04.001
Received 30 December 2020; Received in revised form 26 March 2021; Accepted 2 April 2021
Available online 20 April 2021

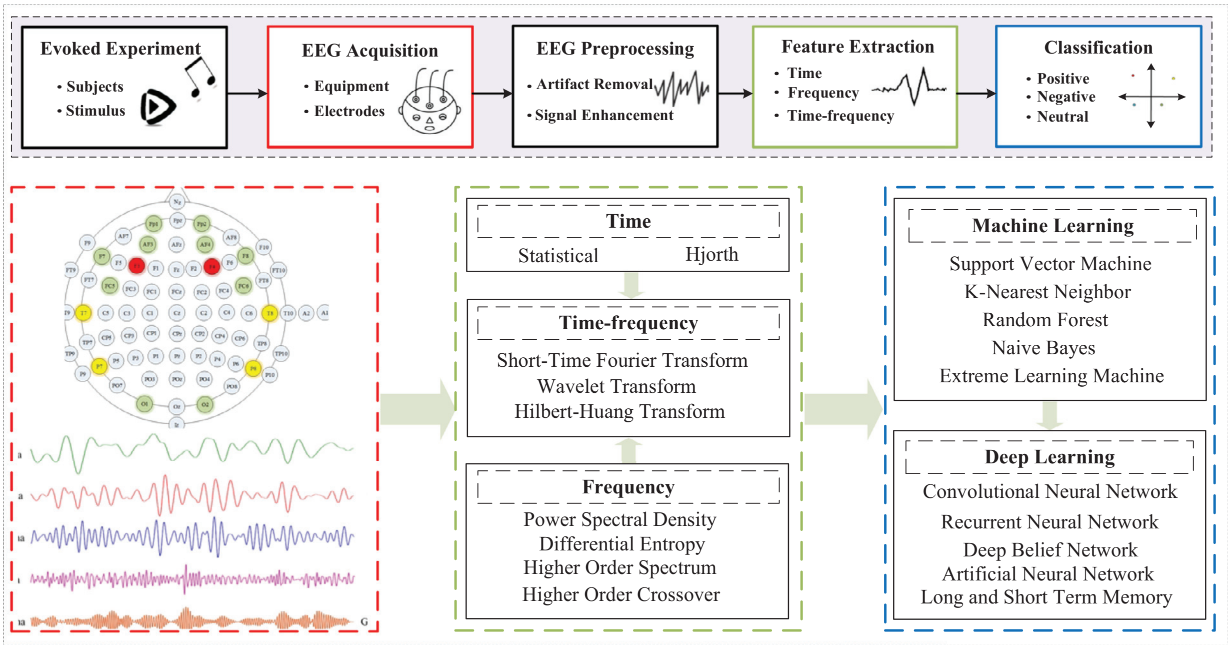


Fig. 1. Overview diagram of the emotional feature extraction and classification using EEG signals.

Our analysis is roughly based on the process of the EEG-based emotion classification. First of all, we introduce the commonly emotional evocation experiments and EEG datasets for emotion recognition. Secondly, the EEG signals acquisition equipment and electrode distribution in different experimental studies are carried out.

After the comparison, the EEG feature analysis methods commonly used in current studies are explained. Finally, the different feature extraction and classification methods to distinguish valences on commonly used EEG datasets are analyzed and evaluated.

Relevant theories

In the following, we will briefly introduce the Emotion-related theories and the emotion representation models, and the emotion-evoked experiments and commonly used datasets give background knowledge about the relationship between emotion changes and EEG signal characteristics.

Theory of the emotion

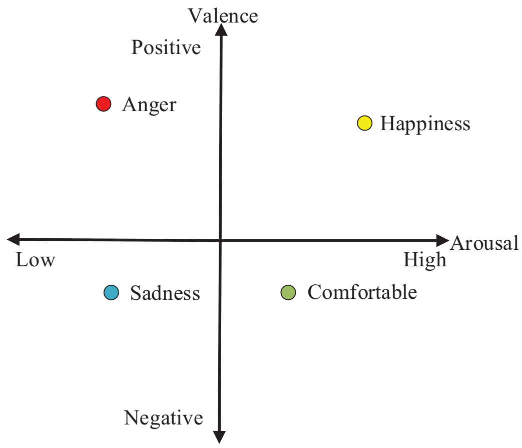
Emotion is a psychological phenomenon mediated by the organism's need tendency, which contains three components: physiological arousal, subjective experience, and external performance [15]. Physiological arousal refers to the physiological response to emotions.

The physiological reactions of the different emotions are different, such as normal heartbeat rhythm when satisfied and happy; when fear or anger, the heartbeat speeds up, blood pressure rises, breathing rate increases and even intermittent or pause occurs; blood vessel volume decreases when painful. Relevant studies have shown that women are more likely to evoke emotions than men, and the degree of physiological arousal is more evident [16].

Subjective experience is the individual's feelings about different emotional states. Other people may have different emotions to the same stimulus. The external manifestation of emotions is what we often call expressions. It generally includes facial expressions, gesture expressions, and intonation expressions [17]. The correctness of the emotion representation is the crucial point of the emotion recognition research.

Different emotion representation methods have been proposed by other researchers, which can be roughly divided into discrete model theory and dimensional model theory. P. Ekman proposed six primary emotional states of happiness, anger, fear, disgust, sadness, and surprise [18]. Other complex emotions can be composed of these basic emotions [19]. Simultaneously, the discrete model represents the natural attributes of the emotions with suitable identification.

According to the cognitive evaluation, the dimensional model theory maps emotions to the two-dimensional model space of valence and arousal, or the three-dimensional model space of the valence, arousal, and dominance. Valence refers to the degree of positive and negative emotions; arousal is the intensity of the emotions; the degree of dominance describes emotional control.



wrong axis?

Fig. 2. Two-dimensional model.

Fig. 2 shows the three categories of the discrete emotions: positive, neutral, and negative, using the two-dimensional model. The emotions are vectorized by the dimensional model theory, which becomes more operable. Recently, the two-dimensional model has become more and more dominant in emotional representation.

Emotions evoked

At present, there are two common ways to evoke emotions: subject evocation and external event evocation. Subject evocation refers to the need for subjects to recall specific emotional memory fragments or scenes to stimulate them to produce corresponding emotions. This evocation method belongs to internal evocation with uncertainty and uncontrollability, and the subject evocation is generally not used to conduct emotion evocation-related experiments.

We often use the external events to evoke the subjects to produce corresponding emotions through different stimulation methods, such as video, audio, and images. According to the existing emotional evocation experiments, the commonly used EEG datasets for emotional recognition include the database for emotion analysis using EEG, Physiological and video signals (DEAP), the SJTU emotion EEG dataset (SEED), the International Affective Picture System (IAPS), the International Affective Digitized Sounds (IADS), and Mahnob HCI, etc.

The DEAP dataset was initially established by Korlstra et al. [20] for the study of the physiological signals and emotional analysis, which includes EEG signals collected from 32 subjects (16 males and 16 females) watching a one-minute music video [21]. The SEED dataset was provided by BCMI Laboratory of the Shanghai Jiao Tong University, which includes EEG signals collected from 15 subjects (7 males and 8 females) watching Chinese films showing positive, neutral, and negative emotions [22,23].

The IAPS [24] and the IADS were developed by the National Mental Health Center for Emotion and Attention, University of Florida. IAPS contains many color images labeled with valence, arousal, and dominance levels, while IADS provides an auditory emotional stimulation system [25]. The Mahnob HCI dataset was created by M. Soleymani et al. [26] of the Imperial College London and contains experimental data from 27 subjects (11 males and 16 females) on emotion recognition and implicit labeling [27].

Meanwhile, the standardized Chinese Emotional Video System (CEVS) can also evoke emotions [16]. Y. J. Liu et al. [28] proposed a real-time EEG emotion recognition system through the standardized film dataset.

EEG signals and emotions

In biomedical research, the brain is the most complex organ in the human body. The cerebral cortex is the largest part of the brain, on which there is a kind of bioelectric signal, the brain electrical signal, whose amplitude is about 10 V $\sim$ 100 V [29]. The cerebral cortex can be divided into the frontal lobe, parietal lobe, temporal lobe, and occipital lobe, as shown in Fig. 3 [5].

The primary function of the frontal lobe is cognitive thinking and emotional needs. The parietal lobe responds to human tactile sensation and is related to the human body's balance and coordination. The temporal lobe is mainly responsible for hearing and smell and is related to emotional and mental activities. Finally, the occipital lobe is responsible for processing visual information.

According to the difference of the EEG signal frequency bands, EEG signals can be divided into five types: the delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (>30 Hz), as shown in Fig. 4. In the different studies, the specific range of each frequency band is slightly different.

The EEG signals of the different frequency bands are related to conscious human activities [30]. Delta waves often occur in the unconscious state of deep, dreamless sleep. Theta waves appear in sleep, dreaming, and sleepiness and are associated with subconsciousness. When the positive emotions are evoked, the Theta waves on the frontal midline will increase.

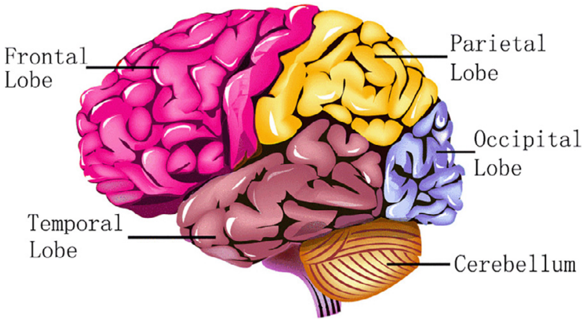


Fig. 3. Physiological structure of the cerebral cortex.

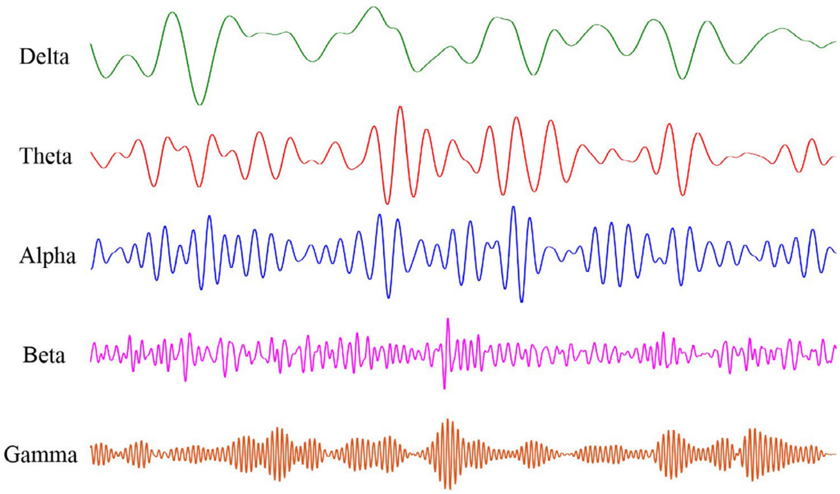


Fig. 4. EEG Rhythm waveforms.

Alpha waves arise when a person is relaxed but conscious. The asymmetry of the alpha waves in the frontal lobe reflects the valence of the emotions, and the midline sagittal channel plays an essential role in the study of the EEG signals [31]. In neutral and negative emotions, alpha waves have higher oscillatory energy than beta and gamma waves.

Beta waves occur when the human mind is active and highly concentrated. The significant beta waves in the frontal lobe can reflect emotional valence. The average power ratio of the beta and alpha waves can reflect the active state of the brain. Gamma waves are associated with hyperactivity in the brain [32,33]. Studies have shown that simultaneous use of the alpha, beta, and gamma waves for emotion recognition is more reliable [31].

The emotion recognition research based on EEG signals shows that EEG signals have non-stationary properties in the emotions [22]. Besides, the emotion's valence is asymmetric in the forehead area, and arousal is related to the forehead area's activity. Emotional EEG is more fully evoked in the low-frequency band than in the high-frequency band, and negative emotions have a wider distribution and higher intensity than positive emotions [34].

The average power of the Theta waves, Alpha waves, and Beta waves on the midline of the brain will be significantly different in the presence of the happy, sad, and fearful emotions, which indicates that the midline power spectrum of the EEG is one of the effective features of the emotion classification [16].

P. Li et al. [35] combined the functional connection network with local activation to demonstrate the local brain areas' activity that responds to emotions and reflects the interaction between relevant brain areas. These studies reveal the relationship between emotional changes and the corresponding EEG signals' characteristics, which is more beneficial for studying EEG signals' emotion classification.

EEG signals acquisition

In the EEG signals acquisition process, the EEG acquisition equipment and electrode distribution selection play an essential role in emotion feature extraction, analysis, and classification. The statistics of the acquisition equipment and electrodes commonly used in some emotional EEG experiments are shown in Table 1.

The collection of EEG signals can be divided into invasive and non-invasive methods. The invasive collection method has a high signal-to-noise ratio and high signal intensity. Still, it needs to be implanted into the skull cavity through medical surgery, and the

Table 1
EEG acquisition equipment and the distribution of the electrodes.

Reference	Equipment (frequency)	Electrodes Distribution (#)
J. Liu et al. [28]	Emotiv EPOC (128 Hz)	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 (14)
Z. Liu et al. [30]		
R. Nawaz et al. [45]		
T. Chen et al. [46]		
T. B. Alakus et al. [47]	Emotiv EPOC (2048 Hz)	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, P3, P4 (16)
Zamanian et al. [48]	Biosemi Active Two (128 Hz)	P7, P3, PZ, PO3, O1, CP2, C4 (7)
E. S. Pane et al. [49]		T7-T8, F7-F8, O1-O2, C3-C4, CP5-CP6, P7-P8 (6)
L. Piho et al. [38]	Biosemi Active Two (512 Hz)	International 10–20 System (32)
H. Dabas et al. [50]		
L. Zhu et al. [51]	Biosemi Active Two (1000 Hz)	FP1, FPZ, FP2, AF3, AF4, F5, F3, F1, FZ, F2, F4, F6 (12)
L. Zheng et al. [52]	ESI NeuroScan System (1000 Hz)	International 10–20 System (62)
W. Zheng [53]		International 10–20 System (20)
T. Zhang et al. [54]		International 10–20 System (62)
T. Song et al. [23]	62-Channel Cap (1000 Hz)	International 10–20 System (62)
W. L. Zheng et al. [12]		
S. K. Khare et al. [55]	24-Channel EEG Device (256 Hz)	FP1, FP2, F3, F4, F7, F8 (6)
Z. Li et al. [56]	Neuroscan Quik-Cap (250 Hz)	International 10–20 System (32)
K. Yang et al. [57]	g.HIamp System (512 Hz)	International 10–20 System (62)

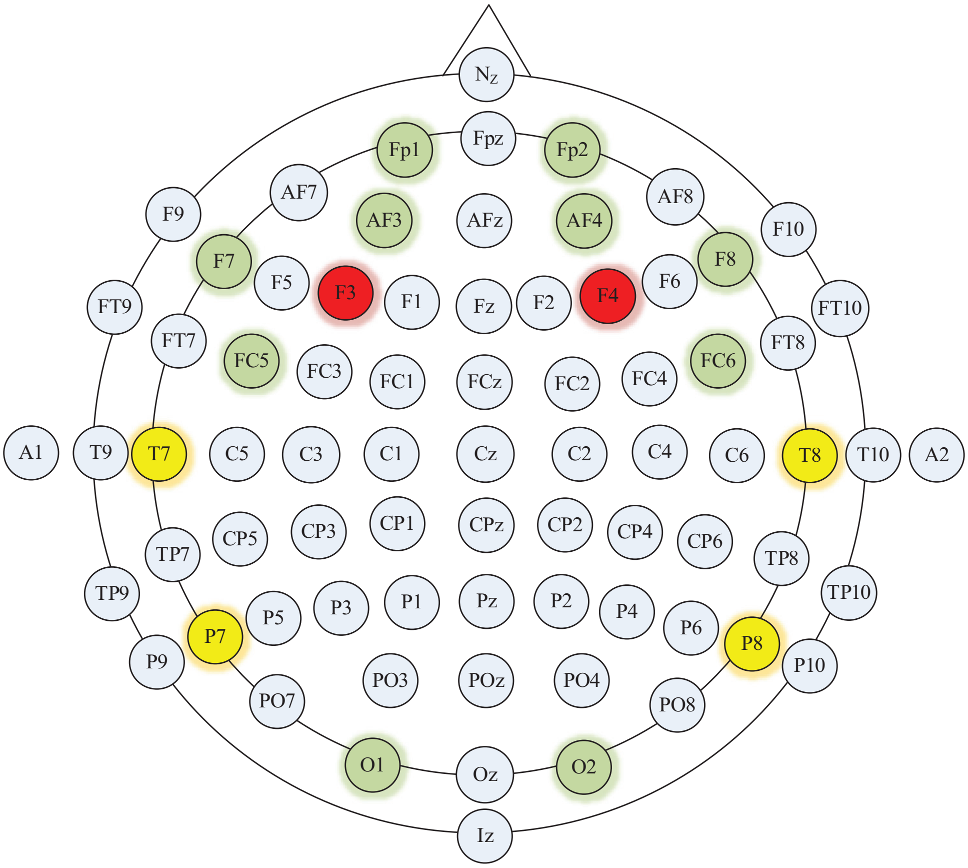


Fig. 5. 10–10 standard electrodes lead system.

electrode invades into the cortex of the brain, so it is not easy to operate. The non-invasive acquisition method is to contact the acquisition electrode on the subject's scalp, which is simple to use and is the mainstream acquisition method in the brain-computer interface's current research.

According to Fig. 5 found that emotion-related EEG electrodes were mainly distributed in the prefrontal lobe, temporal lobe margin, and posterior occipital lobe. These regions were precisely in line with the physiological principle of emotion generation. By selecting the electrode distribution, the extracted feature dimension can be greatly reduced. The complexity of calculation can be diminished, and the experiment is simpler and easy to carry out.

Acquisition equipment

In the emotional EEG experimental study, the EEG acquisition equipment is different due to the various practical needs. Common ones include Biosemi Active Two, Emotiv EPOC, and Neuroscan Quik-Cap.

The Biosemi Active Two is the second-generation and high-resolution EEG analysis system developed by the Biosemi in the Netherlands based on the Active One. It is in the industry's leading position regarding the sampling rate, bandwidth, and common-mode rejection ratio. The high electrode impedance under the active electrode does not affect the signal quality. Therefore, there is no need for any skin preparation work at all so that the experiment operation is more convenient and faster.

The Emotiv EPOC is the non-implantable electrode equipment developed by Emotiv Systems for five years to obtain brain waves. There are 16 sensors inside. The position should be adjusted well, and the movement should not be too large when worn. The Quik-Cap electrode cap of the Neuroscan is easy to wear and comfortable and uses a standard EEG electrodes positioning system. The EEG sampling rate is different for the different emotion EEG experiments. It can be seen from Table 1 that the typical sampling rate is 1000 Hz, 128 Hz, 512 Hz, and so on.

Electrodes distribution

The emotional EEG experiment differs in the collected EEG signals due to different specific research contents, and the corresponding number and location of the electrodes are also different. We use the 10–10 standard electrodes lead system to demonstrate the commonly used electrodes' statistical distribution, as shown in Fig. 5.

As shown in Table 1, most emotional EEG experiments adopt the International 10–20 System's brain electrodes distribution. The number of electrodes ranges from 6 to 62. The most commonly used electrodes are located in the frontal lobe, as shown in Fig. 5, F3 and F4 in the red area, which is related to the function of the human brain's frontal lobe.

In addition, there are FP1, FP2, AF3, AF4, F7, F8, FC5, FC6, O1, and O2 in the green area and T7/T8, P7/P8 in the yellow area in Fig. 5. A total of 16 electrodes are often used for emotional EEG experiments. T7/T8 in the yellow area is T3/T4, and P7/P8 is T5/T6 [36,37]. Regarding the electrodes' name, FP, AF, F, FC, T, P, and O represent frontopolar, anterior frontal, frontal, frontocentral, temporal, parietal, and occipital, respectively. The odd number suffix indicates the left hemisphere, and the even number indicates the right hemisphere.

Features extraction and analyses

In the emotion recognition process through EEG signals, feature extraction is the crucial part of the emotion classification. The quality of the feature extraction will directly affect the accuracy of the emotion classification. Traditional EEG emotion research mainly uses artificial extraction of the emotion-related EEG features, such as extracting the power spectrum of a specific frequency band and the energy ratio of the different frequency bands.

This kind of method is simple and easy to implement. Still, it requires EEG analysts to have rich experience and knowledge, the extracted feature level is low, the generalization ability is poor, and the classification accuracy cannot be improved. In recent years, many EEG emotion studies have proposed different new EEG signal feature extraction methods. The most commonly used methods are Short-Time Fourier Transform (STFT), Power Spectral Density (PSD), statistical, Wavelet Transform (WT), Differential Entropy (DE), sample entropy (SE), wavelet entropy (WE), and empirical mode decomposition (EMD), as shown in Table 2.

Besides, L. Piho et al. [38] proposed extracting information EEG features based on the window of subjects' mutual information, which realized the robust and accurate classification of the related emotions. S. Liu et al. [39] combined the advantages of the EMD and DE and proposed a dynamic differential entropy (DDE) algorithm to extract the EEG signals' features.

C. Wei et al. [40] took advantage of the dual tree-complex wavelet transform (DT-CWT) to extract features of the EEG signals under different emotions. Compared with the traditional wavelet transform, this algorithm has a good anti-aliasing effect and translation invariance. H. Li et al. [41] combined DE and Pearson correlation coefficient matrix (PCCM) to construct a new feature extraction method for DE-PCCM, which can measure the correlation between different brain nodes in different emotional states, effectively improving the accuracy of the multiple emotional classifications.

X. F. Liu [42] combined the multi-scale entropy and permutation entropy to obtain a new multi-scale permutation entropy non-linear analysis method. When the scale factor is 2, this method has a noticeable effect on the emotional EEG classification. G. K. P. Veeramallu et al. [43] made use of the EMD method to decompose the non-stationary and non-linear EEG signals to obtain intrinsic mode functions (IMFs), from which different non-linear features are extracted. Finally, the random forest classifier is used to complete the automatic classification of the EEG emotions [44].

Generally, the traditional EEG feature analyses are mainly carried out in the time domain, frequency domain, and time and frequency domain. However, considering the EEG signals' non-linear characteristics, the EEG signals' analyses through non-linear dynamics can be used for more profound research. This section will introduce the EEG feature analysis methods for emotion recognition from four perspectives: time domain analyses, frequency domain analyses, time-frequency domain analyses, and non-linear feature analyses.

Table 2
Methods of the Emotional Feature Extraction and Classification Using EEG Signals.

Reference	Classification Methods	Feature Extraction	Accuracy (%)
G. Zhao et al. [13]	SVM	STFT	81.08 Extraversion; 86.11 Agreeableness; 80.56 Conscientiousness; 83.78 Openness
J. Liu et al. [28]			86.43 Amusement VS. Joy VS. Tenderness; 65.09 Anger VS. Disgust VS. Fear VS. Sadness; 92.26 Non-Neutrality VS. Neutrality; 86.63 Positive VS. Negative
R. Nawaz et al. [45]			77.62 Valence; 78.96 Arousal; 77.60 Dominance
Z. Li et al. [56]		MLDW-PSO	89.50
Zhang et al. [66]		EMD, SE	94.98
Q. Gao et al. [67]		STFT, PS, WT, WEE	85.67 Neutral; 87.11 Happiness; 89.17 Sadness
T. B. Alakus et al. [47]	SVM (RBF)	DWT, Statistical	75.00 HAPV; 96.00 HANV; 71.00 LAPV; 79.00 LANV
H. Zamanian et al. [48]		EMD, Gabor Wavelet	93.86
N. Zhuang et al. [44]		EMD	69.10 Valence; 71.99 Arousal
H. Chao et al. [68]	SVM (Linear)	MIC	70.21 Valence; 71.85 Arousal
S. K. Khare et al. [55]	MC-LSSVM (RBF)	Adaptive TQWT	95.70
T. Chen et al. [46]	LIBSVM (Gaussian)	EMD	82.63 Valence; 74.88 Arousal
Z.Yin et al. [69]	LSSVM	PSD, Statistical	70.00 Valence; 67.00 Arousal
S. Taran et al. [70]	MC-LSSVM	EMD, VMD	92.79 Happiness; 87.62 Fear; 88.98 Sadness; 93.13 Relax
T. Song et al. [23]	DGCNN	DE	90.40
T. Zhang et al. [54]	STRNN	DE	89.50
S. Liu et al. [39]	DECNN	DDE	97.56
H. Cui et al. [71]	RACNN	Temporal, Regional, Asymmetric	96.65 Valence; 97.11 Arousal
A. Rahman et al. [72]	ANN	PCA, t-statistics	86.57
Alnafjan et al. [73]	NeuCube-Based SNN	–	84.62
S. K. Khare et al. [74]	Configurable CNN	SPWVD	96.71 Fear; 86.08 Happy; 93.83 Relax; 95.45 Sadness
Z. Liu et al. [30]	KNN	EMD	86.46 Valence; 84.90 Arousal
L. Piho et al. [38]		WT, SF, PSE, HOS, HOC	86.00 Valence; 87.20 Arousal
M. A. Ashar et al. [75]		DFC, DE	92.30
A. E. Putra et al. [76]	KNN (k = 21)	WD	57.50 Valence; 64.00 Arousal
D. Nath et al. [77]	LSTM	PSD	94.69 Valence; 93.13 Arousal (Subject-Dependent)
Y. Q. Yin et al. [78]		DE	90.45 Valence; 90.60 Arousal (Subject-Dependent) 84.81 Valence; 85.27 Arousal (Subject-Independent)
J. Yang et al. [79]	BiLSTM	DE	84.21
A. Garg et al. [80]	Merged LSTM	WT, Statistical	84.89 Valence; 83.85 Arousal; 84.37 Dominance
W. L. Zheng et al. [12]	DBN	DE	86.08
Y. Huang et al. [81]		W-WPCC	74.84 Anger; 71.91 Boredom; 66.32 Fear; 63.38 Joy; 69.98 Neutral; 72.68 Sadness
L. Zheng et al. [52]	GELM	STFT, PSD, DE, DASM, RASM	91.07
W. Zheng [53]	GSCCA	DE	82.45
E. S. Pane et al. [49]	RF	PSD, Statistical, DWT	75.60
H. Dabas et al. [50]	NB	PSD	78.06

Feature Extraction: Power Spectral Density (PSD), Short-Time Fourier Transform (STFT), Adaptive Tunable Q Wavelet Transform (ATQWT), Differential Entropy (DE), Wavelet Transform (WT), Statistical Features (SF), Power Spectral Entropy (PSE), Higher-Order Spectral (HOS), Higher-Order Crossing (HOC), Empirical Mode Decomposition (EMD), Wavelet Energy Entropy (WEE), Deep Feature Clustering (DFC), Fractal Dimension (FD), Differential Asymmetry (DASM), Rational Asymmetry (RASM), Wavelet Energy (WE), Multi-Stage Linearly-Decreasing Inertia Weight-Particle Swarm Optimization (MLDW-PSO), Discrete Wavelet Transform (DWT), Principal Components Analysis (PCA), Weighted Wavelet Packets Cepstral Coefficients (W-WPCC), Maximal Information Coefficient (MIC), Dynamic Differential Entropy (DDE), Smoothed Pseudo Wigner Ville Distribution (SPWVD), Variational Mode Decomposition (VMD), Wavelet Decomposition (WD).
Classification Methods: Support Vector Machines (SVM), Multi Class Least-Squares Support Vector Machine (MC-LSSVM), Radial Basis Function (RBF), Graph Regularized Extreme Learning Machine (GELM), Deep Belief Network (DBN), Dynamical Graph Convolutional Neural Networks (DGCNN), Group Sparse Canonical Correlation Analysis (GSCCA), Spatial-Temporal Recurrent Neural Network (STRNN), K-Nearest Neighbors (KNN), Random Forest (RF), Least-Squares Support Vector Machine (LSSVM), Regional-Asymmetric Convolutional Neural Network (RACNN), Artificial Neutral Network (ANN), Spiking Neural Network (SNN), Dynamic Empirical Convolutional Neural Network (DECNN), Graph Convolutional Neural Networks (GCNN), Bidirectional Long Short-Term Memory Network (BiLSTM), Naive Bayes (NB).
Accuracy: L - Low, H - High, P - Positive, N - Negative, A - Arousal, V - Valence, VS. – Versus.

Time domain analyses

Time domain analyses have been used in the study of brain function for a long time. Most of the existing EEG acquisition equipment collects EEG signals in the time domain. Commonly used time-domain analysis methods are histogram analysis method, statistical characteristics [58], Hjorth parameter [59], fractal dimension, event-related potential (ERP), etc.

This kind of method mainly starts with the EEG signals' geometric features, and the EEG analyst can accurately and intuitively perform statistical analyses on its features. Its features include the EEG signals with less information loss. However, due to the EEG signals' complex waveform, there is no unified standard for analyzing the EEG time-domain characteristics, so EEG analysts need to have rich experience and knowledge.

Frequency domain analyses

The frequency domain analysis methods transform the EEG signals in the time domain to the frequency domain to analyze and extract the frequency domain features. Usually, the acquired spectrum is decomposed into multiple sub-bands, and features such as logarithm energy spectrum, power spectral density (PSD), differential entropy (DE), higher-order spectrum (HOS), and higher-order crossover (HOC) are extracted for analysis. C. P. Panagiotis et al. [60] and others first proposed HOC to reflect the EEG signals' fluctuation characteristics.

For a fixed-length EEG sequence, the DE is equivalent to the logarithm energy spectrum in a certain frequency band [61]. Differential entropy, as the entropy for measuring the complexity of the continuous random variables, can be expressed as:

$$DE = -\int_X f(x)\log(f(x))dx \tag{1}$$

Where X is a random variable and $f(x)$ is the probability density function of the experimental studies show that a series of the sub-frequency bands of the EEG signals after band-pass filtering approximately obey Gauss distribution $N(\mu, \sigma^2)$, and its differential entropy can be defined as:

$$\begin{aligned} DE &= -\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma_i{}^2}} e^{-\frac{(x-\mu)^2}{2\sigma_i{}^2}} \log\left(\frac{1}{\sqrt{2\pi\sigma_i{}^2}} e^{-\frac{(x-\mu)^2}{2\sigma_i{}^2}}\right) dx \\ &= \frac{1}{2}\log(2\pi e\sigma_i{}^2) \end{aligned} \tag{2}$$

Time-Frequency domain analyses

The time-frequency domain analysis method integrates the time domain and frequency domain information and has localized analysis capabilities in the time-frequency domain simultaneously.

The analyses of the EEG signals in the frequency domain will not lose the original signal's time-domain information, and it can be guaranteed during the analyses process higher resolution. Short-time Fourier transform (STFT) is commonly used to add a fixed window function to the time. The non-stationary process is regarded as a superposition of a series of short-time stationary signals. Its calculation formula can be expressed as:

$$X(\mathrm{t}, f) = \int_{-\infty}^{+\infty} x(u)w(u-t)e^{-j2\pi f u}du \tag{3}$$

Where $w(u-t)$ is the short-time window function. The window function's fixed size and shape cannot meet the high-frequency time subdivision requirements and the low-frequency subdivision. The wavelet transform (WT) inherits the ability of the STFT local analysis.

Simultaneously, the window function that can change with frequency is introduced, which has a higher resolution to analyze time-varying and non-stationary signals. Besides, the wavelet packet transform (WPT) and Hilbert-Huang transform (HHT) [62] are also important methods of time-frequency domain analysis.

Non-linear characteristic analyses

Many studies have shown that the EEG signals have non-linear and non-periodic characteristics [63–64]. The EEG signals with chaotic characteristics can be further studied by non-linear dynamic analysis.

The non-linear feature analyses mainly include chaos theory and information theory. Chaos theory methods include correlation dimension, maximum Lyapunov index, and Hurst index. Information theory methods include permutation entropy, power spectrum entropy, singular value decomposition entropy, sample entropy, and so on.

EEG emotion classification

The EEG emotion classification research generally includes five parts: emotion evoked experiment, EEG signals acquisition, EEG preprocessing, feature extraction, and emotion classification, as shown in Fig. 6.

Among them, classification is the final step in emotion recognition. At present, some popular machine learning algorithms, such as the Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Random Forest (RF), Naive Bayes (NB), and Extreme Learning

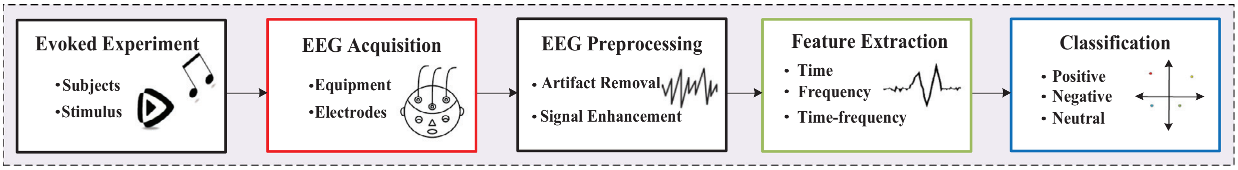


Fig. 6. Emotional classification process based on EEG signals.

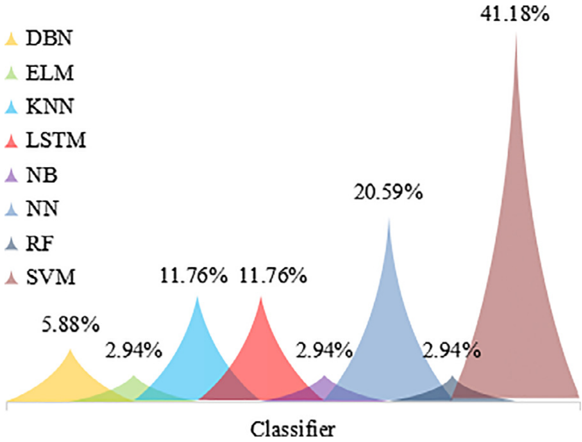


Fig. 7. Methods of the emotional classification using EEG signals.

Machine (ELM), are widely used in the study of the EEG emotion classification. These shallow classification models all directly use EEG signals characteristics for classification [5] without considering the EEG signals' internal temporal dynamic information.

In recent years, deep learning methods have been favored by the majority of researchers. The Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Generative Adversarial Network (GAN), Deep Belief Network (DBN), Artificial Neural Network (ANN), and Long and Short Term Memory (LSTM) can be applied to classify more complex situations due to their advantages of the relatively shallow models in representational learning ability and high classification accuracy [65].

Therefore, more and more researchers regard deep learning as an essential research method for EEG emotion classification. The Emotional Classification methods using EEG Signals in recent years are summarized as shown in Table 2.

From Table 2, we roughly analyze and compare the classification accuracy ranges of the different machine learning algorithms and deep learning algorithms that appear in this paper: the classification accuracy of the traditional machine learning algorithms ranges from 57.50% to 95.70%. The classification accuracy of the deep learning algorithms ranges from 63.38% to 97.56%. It can be seen that the classification effect of the traditional machine learning algorithms is generally not as good as the deep learning algorithms.

The traditional machine learning algorithms require a large amount of prior knowledge to find EEG signals' characteristics. However, in the complex cognitive process, different subjects have great differences, and it isn't easy to find representative and effective characteristics. All make it very difficult to improve the accuracy of the EEG signal classification. Compared with the traditional machine learning algorithms, deep learning does not require a lot of prior knowledge and manual feature extraction. It can directly extract features from the complex data level by level.

Most of the above studies are based on public datasets such as DEAP, SEED, Mahnob HCI, etc. Since more than one classification method is used, we select the classifier with a better classification effect for analysis and summary. As shown in Fig. 7, SVM and its variants MC-LSSVM, LSSVM, etc., are used the most often, accounting for 41.18%, and the corresponding kernel functions are radial basis functions (RBF), linear, Gaussian, etc.

Neural Networks (NN), for example, CNN, RNN, AAN, SNN, and their variants are the second most frequently used, accounting for 20.59%. The usage of the LSTM and its variants is similar to that of the KNN, each accounting for 11.76%. DBN is chosen by 5.88% of the researchers. NB, RF, and ELM are the least frequently used, each accounting for 2.94%.

As a representative of the traditional machine learning algorithms, SVM has the advantage that it can use different kernel functions to perform class separation in a higher-dimensional space, and most researchers have favored it for a long time. Therefore, it ranks first in the frequency of the use of the algorithm in this paper. As a branch of machine learning, deep learning is an algorithm that uses artificial neural networks as a framework and uses multiple processing layers to characterize and learn data. It can automatically extract advanced features for classification directly from the original signals.

Based on the big data and graphics processing units' mighty computing power, deep learning is significantly better than traditional machine learning algorithms. In this paper, the dynamic empirical convolutional neural network (DECNN) algorithm is used, and the classification accuracy is 97.56%. Therefore, the frequency of the use of the NN is second only to SVM.

Although these classifiers are better than traditional methods in the emotion classification tasks based on EEG, the classification calculation complexity is very high due to the high dimension of the EEG data and few samples. Therefore, we need to further optimize the classification algorithm, reduce the computational complexity, improve the classification accuracy, and build a better and more general classification model.

To overcome the shortcomings of the excessive super parameters and large amounts of the training data, J. Cheng et al. [82] proposed a deep forest-based multi-channel EEG emotion classification method. Used on the DEAP dataset, the average accuracy of valence and arousal reach 97.69% and 97.53%, respectively. H. Yang et al. [83] adopted the CNN model with a multi-column structure to conduct the emotion classification on the DEAP database with a final accuracy of 90%.

J. Chen et al. [84] classified the EEG signals' binary emotion using a hybrid convolution recurrent neural network, and the final accuracy of classification was 93.64% and 93.26%, separately. To solve the problem that the EEG signals are dependent on time, L. Yang et al. [85] proposed a sequence model based on deep learning to construct a time sequence of fixed length time window data and input it into a temporal convolutional network to classify it.

As for the lack of the EEG data, Y. Luo et al. [86] introduced the conditional Wasserstein GAN model for the EEG data enhancement, which significantly improved the emotion classification DEAP and SEED datasets. E. S. Pane et al. [49] were the first to implement RF in the EEG emotion classification, and its highest accuracy rate was 75.6%. C. Y. Liu et al. [87] used the SVM after optimizing parameters with a genetic algorithm to classify different emotions, with an accuracy of 93.75%.

In emotion recognition tasks, the EEG temporal information is often neglected, which leads to insufficient use of the EEG's time and space-frequency domain information. Z. Q. Li [88] put forward an emotion classification algorithm based on long and short-term memory recurrent neural networks on the emotional time series model and achieved an average accuracy of 78.44% in the emotional pleasure classification experiment.

B. H. Kim et al. [89] proposed a model based on convolutional long and short-term memory networks and a loss function based on time edges. The DEAP public dataset experiment showed that the recognition accuracy was improved by 15.96% compared with the most advanced technology. On the other hand, S. Sheykhivand et al. [90] directly applied the original EEG signals to the convolutional neural network and the long and short-term memory network without involving the feature extraction methods.

Conclusions

This paper mainly investigates and analyzes some literature in the past five years, in which the new method of extracting and classifying emotional features by EEG signals is proposed. Our analysis of these studies shows the scientific nature of the emotion classification study's research through EEG signals. This paper introduces experimental and standard datasets from the emotions, EEG signals acquisition equipment and electrode distribution, and EEG analysis methods.

For the emotional feature extraction and classification of the EEG research, different feature extractions and classification methods have been expounded with a comparison system from several aspects. It is hoped that this paper can provide some help on ideas for researchers, especially those who are about to enter the field, to understand the current situation of the research on the extraction and classification of the emotional-oriented electroencephalogram features.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by Scientific and Technological Projects of Shaanxi Province under Grant 2016GY-040 and 2020JM-525.

Reference

[1] R. Cowie, et al., Emotion recognition in human-computer interaction, IEEE Signal Proc. Mag. 18 (1) (2001) 32–80.
[2] J. Joshi, et al., Multimodal assistive technologies for depression diagnosis and monitoring, J. Multimodal User In. 7 (3) (2013) 217–228.
[3] J. Frey, C. Mühl, F. Lotte, M. Hachet, Review of the use of electroencephalography as an evaluation method for human-computer interaction, Int. Conf. Physiol. Comput. Syst. (2014) 214–223.
[4] J.H. Gruzelier, EEG-neurofeedback for optimising performance. I: a review of cognitive and affective outcome in healthy participants, Neurosci. Biobehav. Rev. 44 (2014) 124–141.
[5] S.M. Alarcão, M.J. Fonseca, Emotions recognition using EEG signals: a survey, IEEE Trans. Affect. Comput. 10 (3) (2019) 374–393.
[6] T. Zhang, W. Zheng, Z. Cui, Y. Zong, J. Yan, K. Yan, A deep neural network-driven feature learning method for multi-view facial expression recognition, IEEE T. Multimedia 18 (12) (2016) 2528–2536.
[7] J. Deng, X. Xu, Z. Zhang, S. Frühholz, B. Schuller, Semisupervised autoencoders for speech emotion recognition, IEEE-ACM T. Audio, Spe. 26 (1) (2018) 31–43.
[8] S.E. Kahou, et al., Emonets: multimodal deep learning approaches for emotion recognition in video, J. Multimodal User In. 10 (2) (2016) 99–111.
[9] M. El Ayadi, M.S. Kamel, F. Karray, Survey on speech emotion recognition: features, classification schemes, and databases, Pattern Recognit 44 (3) (2011) 572–587.
[10] G.Z. Zhao, J.J. Song, Y. Ge, Y. Liu, T. Wen, Advances in emotion recognition based on physiological big data, J. Comput. Res. Dev. 53 (2016) 80–92.
[11] Y.-.P. Lin, et al., EEG-based emotion recognition in music listening, IEEE Trans. Biomed. Eng. 57 (7) (2010) 1798–1806.
[12] W.L. Zheng, B.L. Lu, Investigating critical frequency bands and channels for eeg-based emotion recognition with deep neural networks, IEEE T. Auton. Ment. De. 7 (3) (2015) 162–175.
[13] G. Zhao, Y. Ge, B. Shen, X. Wei, H. Wang, Emotion analysis for personality inference from EEG signals, IEEE Trans. Affect. Comput. 9 (3) (2018) 362–371.
[14] O. Hilborn, Evaluating classifiers for emotion recognition using EEG, Lecture Notes in Comput. Sci. 8027 (2015) 492–501.

[15] I.B. Mauss, M.D. Robinson, Measures of emotion: a review, Cogn. Emot. 23 (2) (2009) 209–237.
[16] K.X. Cao, The Research of the EEG Frequency Power Feature in Three Basic Emotions, CN: Tianjin Med. Univ., Tianjin, 2019.
[17] M.N. Shiota, J.W. Kalat, Emotional Psychology, China Light Ind. Press, Beijing, CN, 2015.
[18] P. Ekman, An argument for basic emotions, Cogn. Emot. 6 (3–4) (1992) 169–200.
[19] E.L. van den Broek, Ubiquitous emotion-aware computing, Pers. Ubiquit. Comput. 17 (2013) 53–67.
[20] S. Koelstra, et al., DEAP: a database for emotion analysis using physiological signals, IEEE Trans. Affect. Comput. 3 (1) (2012) 18–31.
[21] N. Kumar, K. Khaund, S.M. Hazarika, Bispectral analysis of EEG for emotion recognition, Procedia Comput. Sci. 84 (2016) 31–35.
[22] T.H. Li, W. Liu, W.L. Zheng, B.L. Lu, Classification of five emotions from EEG and eye movement signals: discrimination ability and stability over time, 9th Int. IEEE/EMBS Conf. Neur. Eng, 2019.
[23] T. Song, W. Zheng, P. Song, Z. Cui, EEG emotion recognition using dynamical graph convolutional neural networks, IEEE Trans. Affect. Comput. 11 (3) (2020) 532–541.
[24] R.M. Mehmood, H.J. Lee, A novel feature extraction method based on late positive potential for emotion recognition in human brain signal patterns, Comput. Elect. Eng. 53 (2016) 444–457.
[25] Y. Liu, O. Sourina, EEG databases for emotion recognition, 2013 Int. Conf. Cyberworlds (2013) 302–309.
[26] M. Soleymani, J. Lichtenauer, T. Pun, M. Pantic, A multi-modal database for affect recognition and implicit tagging, IEEE Trans. Affect. Comput. 3 (1) (2012) 42–55.
[27] M. Soleymani, M. Pantic, T. Pun, Multimodal emotion recognition in response to videos, IEEE Trans. Affect. Comput. 3 (2) (2012) 211–223.
[28] Y.-.J. Liu, M. Yu, G. Zhao, J. Song, Y. Ge, Y. Shi, Real-time movie-evoked discrete emotion recognition from EEG signals, IEEE Trans. Affect. Comput. 9 (4) (2018) 550–562.
[29] M. Teplan, Fundamentals of EEG measurement, Meas. Sci. Rev. 2 (Jan. 2002) 1–11.
[30] Z. Liu, Q. Xie, M. Wu, W. Cao, D. Li, S. Li, Electroencephalogram emotion recognition based on empirical mode decomposition and optimal feature selection, IEEE T. Cogn. Dev. Syst. 11 (4) (2019) 517–526.
[31] E.S. Pane, A.D. Wibawa, M.H. Pumomo, Channel selection of EEG emotion recognition using stepwise discriminant analysis, 2018 Int. Con. Comput. Eng. Net. Intel. Multimedia (2018) 14–19.
[32] G.H. Zhang, et al., A review of EEG features for emotion recognition, Sci. Sin. Inform. 49 (9) (2019) 1097–1118.
[33] D.O. Bos, EEG-based emotion recognition the influence of visual and auditory stimuli, Emotion (2012).
[34] J.X. Zhang, H. Bo, Research on EEG emotion recognition based on CNN, Mod. Comput. (8) (2018) 12–16.
[35] P. Li, et al., EEG Based emotion recognition by combining functional connectivity network and local activations, IEEE Trans. Biomed. Eng. 66 (10) (2019) 2869–2881.
[36] A. C. N. Society, “Guideline5: guidelines for standard electrode position nomenclature,” Available at https://www.acns.org/pdf/guidelines/Guideline-5.pdf, 2016.
[37] J.N. Acharya, A. Hani, J. Cheek, P. Thirumala, T.N. Tsuchidak, American clinical neurophysiology society guideline 2: guidelines for standard electrode position nomenclature, Clin. Neurophysiol. 33 (4) (Aug. 2016) 308–311.
[38] L. Piho, T. Tjahjadi, A mutual information based adaptive windowing of informative EEG for emotion recognition, IEEE Trans. Affect. Comput. 11 (4) (2020) 722–735.
[39] S. Liu, X. Wang, L. Zhao, J. Zhao, Q. Xin, S. Wang, Subject-independent emotion recognition of EEG signals based on dynamic empirical convolutional neural network, IEEE ACM T. Computat. Bi. (1) (2020).
[40] C. Wei, L.-.L. Chen, Z.-.Z. Song, X.-.G. Lou, D.-.D. Li, ‘EEG-based emotion recognition using simple recurrent units network and ensemble learning, Biomed. Signal Process. Control 58 (101756) (2020) Art.
[41] H. Li, C. Qing, X. Xu, Z. Tong, A novel DE-PCCM feature for EEG-based emotion recognition, 2017 Int. Conf. Secu. Pattern Anal. Cybern, 2017.
[42] X.F. Liu, Research On Feature Extraction and Channel Selection of EEG for Emotion Recognition, Shandong Norm. Univ., Jinan, CN, 2020.
[43] G.K.P. Veeramallu, Y. Anupalli, S.K. Jilumudi, A. Bhattacharyya, EEG based automatic emotion recognition using EMD and Random forest classifier, 10th Int. Conf. Comput., Comm. Net. Tech., 2019.
[44] N. Zhuang, Z. Ying, Z.Chi L.Tong, H. Zhang, B. Yan, Emotion recognition from EEG signals using multidimensional information in EMD domain, BioMed Res. Int. 2017 (8317357) (2017) Art.
[45] R. Nawaz, K.H. Cheah, H. Nisar, V.V. Yap, Comparison of different feature extraction methods for EEG-based emotion recognition, Biocybern. Biomed. Eng. 40 (3) (2020) 910–926.
[46] T. Chen, S. Ju, F. Ren, M. Fan, Y. Gu, EEG emotion recognition model based on the LIBSVM classifier, Measurement 164 (108047) (2020) Art.
[47] T.B. Alakus, M. Gonen, I. Turkoglu, Database for an emotion recognition system based on EEG signals and various computer games GAMEEMO, Biomed. Signal Process. Control 60 (2020) 101951.
[48] H. Zamanian, H. Farsi, A New feature extraction method to improve emotion detection using EEG signals, Elec. Lett. Comput. Visi. Image Anal. 17 (1) (2018) 1–15.
[49] E.S. Pane, A.D. Wibawa, M.H. Purnomo, Improving the accuracy of EEG emotion recognition by combining valence lateralization and ensemble learning with tuning parameters, Cogn. Process. 20 (2019) 405–417.
[50] H. Dabas, C. Sethi, C. Dua, M. Dalawat, D. Sethia, Emotion classification using EEG Signals,” in*2nd Int*, Conf. (2018).
[51] L. Zhu, et al., EEG-based approach for recognizing human social emotion perception, Adv. Eng. Inform. 46 (101191) (2020) Art.
[52] W.-.L. Zheng, J.-.Y. Zhu, B.-.L. Lu, Identifying stable patterns overtime for emotion recognition from EEG, IEEE Trans. Affect. Comput. 10 (3) (2019) 417–429.
[53] W. Zheng, Multichannel EEG-based emotion recognition via group sparse canonical correlation analysis, IEEE Trans. Cogn. Develop. Syst. 9 (3) (2017) 281–290.
[54] T. Zhang, W. Zheng, Z. Cui, Y. Zong, Y. Li, Spatial–temporal recurrent neural network for emotion recognition, IEEE Trans. Cybern. 49 (3) (2019) 839–847.
[55] S.K. Khare, V. Bajaj, G.R. Sinha, Adaptive tunable Q wavelet transform based emotion identification, IEEE T. Instrum. Meas. 69 (12) (2020) 9609–9617.
[56] Z. Li, et al., Enhancing BCI-based emotion recognition using an improved particle swarm optimization for feature selection, Sensors 20 (11) (2020) Art. no. 3028.
[57] K. Yang, L. Tong, J. Shu, N. Zhuang, B. Yan, Y. Zeng, High gamma band EEG closely related to emotion: evidence from functional network, Front. Hum. Neurosci. 14 (2020).
[58] J. Atkinson, D. Campos, Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers, Expert Syst. Appl. 47 (2016) 35–41.
[59] B. Hjorth, EEG analysis based on time domain properties, Electroencephalogr. Clin. Neurophysiol. 29 (3) (1970) 306–310.
[60] C.P. Panagiotis, J.H. Leontios, Emotion recognition from EEG using higher order crossings, IEEE Trans. Inf. Technol. Biomed. 14 (2) (2010) 186–197.
[61] L.-.C. Shi, Y.-.Y. Jiao, B.-.L. Lu, Differential entropy feature for EEG-based vigilance estimation, in: Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., 2013, pp. 6627–6630.
[62] X.J. Zhu, Hilbert-Huang Transform and its Application in EEG Signals Processing, TaiyuanCN: Taiyuan Univ. Tech., 2012.
[63] M.H. Tang, Emotion Recognition Research Based on EEG Signal, CN: Nanjing Univ. Posts Telecom., Nanjing, 2018.
[64] W.Y. Deng, Research on Emotional Recognition Technology Based on Brain Electrical Signals, Huazhong Univ. Sci. Tech., Wuhan, CN, 2019.
[65] D.-.W. Chen, et al., A feature extraction method based on differential entropy and linear discriminant analysis for emotion recognition, Sensors 19 (7) (2019) 1631 Art.
[66] Y. Zhang, X. Ji, S. Zhang, An approach to EEG-based emotion recognition using combined feature extraction method, Neurosci. Lett. 633 (2016) 152–157.
[67] Q. Gao, C.H. Wang, Z. Wang, X.L. Song, Y. Song, EEG based emotion recognition using fusion feature extraction method, Multimed. Tools Appl. 79 (2020) 27057–27074.
[68] H. Chao, L. Dong, Y. Liu, B. Lu, Improved deep feature learning by synchronization measurements for multi-channel EEG emotion recognition, Complexity 2020 (6816502) (2020) Art.

[69] L.Liu Z.Yin, J.N. Chen, B.X. Zhao, Y.X. Wang, Locally robust EEG feature selection for individual-independent emotion recognition, Expert Syst. Appl. 162 (113768) (2020) Art.
[70] S. Taran, V. Bajaj, Emotion recognition from single-channel EEG signals using a two-stage correlation and instantaneous frequency-based filtering method, Comput. Methods Programs Biomed. 173 (2019) 157–165.
[71] H. Cui, A.P. Liu, X. Zhang, X. Chen, K.Q. Wang, X. Chen, EEG-based emotion recognition using an end-to-end regional-asymmetric convolutional neural network, Knowl. Based Syst. 205 (106243) (2020) Art.
[72] A. Rahman, F. Hossain, M. Hossain, R. Ahmmed, Employing PCA and t-statistical approach for feature extraction and classification of emotion from multichannel EEG signal, Egy. Inform. J. 21 (1) (2020) 23–35.
[73] A. Alnafjan, K. Alharthi, H. Kurdi, Lightweight building of an electroencephalogram-based emotion detection system, Brain Sci 10 (11) (2020) Art. no. 781.
[74] S.K. Khare, V. Bajaj, Time-frequency representation and convolutional neural network-based emotion recognition, IEEE T. Neur. Net. Lear. (2020) 1–9.
[75] M.A. Asghar, M.J. Khan, M. Rizwan, R.M. Mehmood, S.H. Kim, An innovative multi-model neural network approach for feature selection in emotion recognition using deep feature clustering, Sensors 20 (13) (2020) Art. no. 3765.
[76] A.E. Putra, C. Atmaji, F. Ghaleb, EEG-based emotion classification using wavelet decomposition and K-nearest neighbor," in *4th Int*, Conf. Sci. Tech. (2018).
[77] D. Nath, A. Anubhav, M. Singh, D. Sethia, S. Indu, A comparative study of subject-dependent and subject-independent strategies for EEG-based emotion recognition using LSTM network, 4th Int. Conf.Comput. Data Anal., 2020.
[78] Y.Q. Yin, X.W. Zheng, B. Hu, Y. Zhang, X.C. Cui, EEG emotion recognition using fusion model of graph convolutional neural networks and LSTM, Appl. Soft Comput. 100 (106954) (2021) Art.
[79] J. Yang, X. Huang, H. Wu, X. Yang, EEG-based emotion classification based on bidirectional long short-term memory network, Procedia Comput. Sci. 174 (2020) 491–504.
[80] A. Garg, A. Kapoor, A.K. Bedi, R.K. Sunkaria, Merged LSTM Model for emotion classification using EEG signals, 2019 Int. Conf. Data Sci. Eng. (2019).
[81] Y. Huang, K. Tian, A. Wu, G. Zhang, Feature fusion methods research based on deep belief networks for speech emotion recognition under noise condition, J. Ambient. Intell. Human Comput. 10 (2019) 1787–1798.
[82] J. Cheng, M. Chen, C. Li, Y. Liu, X. Chen, Emotion recognition from multi-channel EEG via deep forest, IEEE J. Biomed. Health (2020) 1.
[83] H. Yang, J. Han, K. Min, A multi-column CNN model for emotion recognition from EEG signals, Sensors 19 (21) (2019) Art. no. 4736.
[84] J. Chen, D. Jiang, Y. Zhang, P. Zhang, 'Emotion recognition from spatiotemporal EEG representations with hybrid convolutional recurrent neural networks via wearable multi-channel headset, Comput. Commun. 154 (2020) 58–65.
[85] L. Yang, J. Liu, EEG-based emotion recognition using temporal convolutional network, 2019 IEEE 8th Data Driven Contr. Learn. Sys. Conf., 2019.
[86] Y. Luo, B.-.L. Lu, EEG data augmentation for emotion recognition using a conditional wasserstein GAN, 40th Ann. Int. Conf. IEEE Eng. Med. Bio. Soc (2018) 2535–2538.
[87] C.Y. Liu, W.Q. Li, X.J. Bi, Emotional feature extraction and classification based on EEG signals, J. Trans. Tech. (1) (2019) 82–88.
[88] Z.Q. Li, Study and System Implementation of Automatic Emotion Recognition Based On EEG Time-Space Frequency Multi-Domain Features, South China Uni. Tech, Guangzhou, CN, 2018.
[89] B.H. Kim, S. Jo, Deep physiological affect network for the recognition of human emotions, IEEE Trans. Affect. Comput. 11 (2) (2020) 230–243.
[90] S. Sheykhivand, Z. Mousavi, T.Y. Rezaii, A. Farzamnia, Recognizing emotions evoked by music using CNN-LSTM networks on EEG signals, IEEE Access 8 (2020) 139332–139345.