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Research and Analysis of Emotion Recognition Systems Based on Brain-Computer Interfaces

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Abstract. Electroencephalography (EEG) presents an approach toward practical emotion recognition by being noninvasive, providing a rich source with precise timing, and showing resilience to interference. This paper aims to present recent developments of emotion recognition systems based on brain-computer interfaces (BCI) using EEG, starting with a view into approaches used in modeling emotional states along with the methodologies used in acquiring, collecting, and preprocessing the datasets, then exploring different features or techniques from classical time/spectral representations as well as more modern differential entropy methods including connectivity-based measurement followed by advanced deep learning methodologies such as graph neural networks, transformers, etc., and gives special attention on studies involving the fusion of multistreaming data, mainly combining EEG signals with other streams of input data contributing into the robustness and generalization of current emotion recognition models. A number of reflections are presented from setting up these studies where problems related to the heterogeneity across subjects, noise due to insufficiently defined labels or ground-truths, and low natural context validity of collected datasets occur, and is followed by the discussion and elaborated review of methodologies aiming towards providing an overview that can help building better accurate and efficient methods with ability to process raw brainwave measurements and extract insights leading to characterization of affective state changes.

Keywords: Emotion Recognition; BCI; EEG; Multimodal fusion; Deep Learning.

1. Introduction

Emotion recognition refers to the identification and expression of emotions, it is not only an interesting research topic in science, but also an area of growing interest in neuroscience and artificial intelligence. The former enables us to understand more on how emotions are represented in the brain and processes with this brain network, while the latter makes us better understand affective states that exist or can be induced, thereby building more helpful, practical and adaptive technology for people [1-3].

BCIs are the technologies that offer a new form of human-computer interaction through signals from neural systems, and among different applications of affective interaction technologies, BCI has become one important field in study about emotion recognition because of its capacity to detect and analyze various physiological signals from users' central nervous systems, which allows emotional information to be quantified via EEG through an objective and real-time approach based on machine-based processing [4]. Unlike current emotion assessment tools using questionnaires with self-reported information or assessing individuals' facial expressions, EEG could capture emotion-related neural activities free of individual subjectivity or environmental interference; compared with traditional techniques for emotion evaluation, it is more effective to identify and classify different emotional statuses [5, 6]. Meanwhile, numerous practical functions using affective measurements by detecting features extracted from EEG have been generated. For instance, monitoring the mental health status through these methods can provide the service such as providing smart interactive technology, making individualized and customized learning more efficient, improving work performance and so on, and these are beneficial to improve emotional sensitive and learn machine-based models for entertainment and market needs scenarios and others. These examples explain that accurate modeling's of human affect remain important challenges even when being robust across people and complex contexts.

However, researchers may still encounter many obstacles when implementing this field of study in detail. Some examples include unreliable and invalid reliability, generalization abilities between individuals, real events difficult to be labeled with available feature, high noise, movement and artifact difficulties affecting signal quality are frequently detected, etc., as well as certain constraints caused by the hardware in real-time processing scenarios [7, 8]. Therefore, different approaches will be tried and selected in pursuit of overcoming these hurdles. For example, researchers used continuous discrete dimensional approaches, hybrid multiple approaches to model emotions, frequency domain and time domain approaches, or other methods such as extracting based upon information entropy approach, etc [4]. Many datasets also offer help for analyzing emotions in EEG such as DEAP and SEED and DREAMER and AMIGOS datasets [8]. It provides material for researchers from many domains to take into consideration in developing a large number of models involving with many novel technical frameworks such as deep learning architectures like graph neural network, attention, or transformer structures. Moreover, deep learning has shown success on several issues.

Therefore, it is indeed necessary for us to sum up and analyze models related to emotion recognition according to EEG evaluation technologies with respect to their characteristics and validity within the scope of this discipline and guide studies in new aspects to explore emotional cognition and provide insights for technological designing, thereby helping modeling's more precisely capturing affective patterns via analyzing real and detailed EEG data and optimizing the designs with various models.

2. Theoretical Foundation Analysis

2.1. Emotion Models

Emotion modeling provides the theoretical basis for emotion recognition research. Discrete models, such as the well-known "basic emotion" framework, remain widely used in recent work because they provide clear categorical distinctions and straightforward labeling schemes [9]. These models support efficient experimental design but can be limited in representing emotional intensity and temporal variation. Dimensional frameworks, such as the valence–arousal model, have received increasing attention in recent EEG-based emotion research because they enable a more continuous and fine-grained depiction of affective dynamics [10]. In efforts to better approximate real-life emotional variations, other additional axes—such as dominance, motivational strength, or approach–avoidance tendencies—are also being explored. More dimensions allow richer representation of nuanced variations that may not directly correspond to categorical classes [11]. In parallel, hybrid models that use both categorically labeled sets of predefined options and dimensional ratings are also increasing in popularity [12]. Cross-cultural research shows that although we share many similar feelings and expressions across borders and backgrounds, emotional expression and recognition in human brains vary with cultural background. Thus, models need to be adaptable and generalizable if they are to be implemented into an emotionally intelligent machine.

2.2. BCI Signal Acquisition and Processing

Among the existing approaches, electroencephalography (EEG) is the most commonly used method for implementation of affective BCI due to its high temporal resolution and linking directly with the activity of cortex. The EEG data from different channels were recorded in real-time when participants were shown some emotional images or videos. Some commonly-used benchmark datasets have been published publicly on Internet, where EEGs are collected from participants under standard conditions for emotion analysis, including SEED, DEAP, DREAMER, AMIGOS, and so on which provide the possibility of comparability and reusability in emotion analyses in these studies [13, 14].

As an illustration, Fig.1 depicts a schematic diagram of acquisition and processing of BCI signal processing approach applied to emotion classification tasks. Still, those signals are contaminated by noises introduced by eye blinking, body movements and environment interference, which might lead to reduce signal consistency.

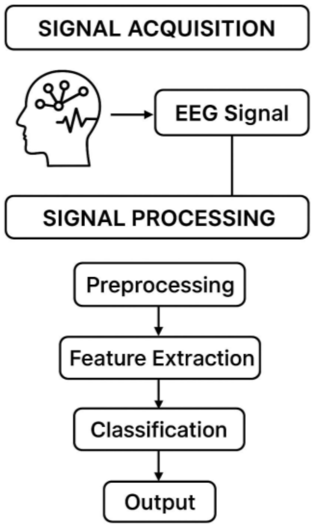

Figure 1. Flowchart of BCI Signal Acquisition and Processing

Therefore, we may apply techniques such as band-pass filtering (BPF), independent component analysis (ICA), noise reduction or suppression through specific algorithms [15].

Then, it’s time to determine the affectively labeled category based upon extraction of features from raw or processed data. There exist various methods, but there are mainly some features extracted. Some typical frequency features were used, including the power spectral density over several bands, such as delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) bands. Among those, the commonly adopted method of extracting features related to emotion in EEG was in power feature across several frequencies [3]. Others may involve some time-based features, such as defining Var, RMS, variance, slope, correlation and Hjorth parameter (Hj). Other types of features also involving entropy and complexity such as permutation entropy (PE), approximate entropy (AE), Lyapunov exponent (LE), correlation dimension, sample entropy (SampEn), Hölder exponent (HL), relative dispersion, detrended fluctuation analysis (DFA), Higuchi fractal dimension and so on. Recent years have witnessed many researches exploring emotional signal using information entropy measures such as differential entropy (DE) showed promising outcomes due to its sensitivity against emotional intensities [8]. Also, other types of spatial features, including common spatial patterns (CSP) as well as multiscale spatiotemporal graphs to model the connectivity patterns. Recently, researchers captured relation between electrodes using adjacency matrix and calculated graph edge weights and learned graph-embedded models, performed model prediction, which would make further analysis to be possible.

Eventually, it's time to label them with corresponding emotional categories to be predicted among all these learned features should be categorized according to labels. Early on, classical machine learning pattern classification methods such as Support Vector Machine (SVM), Nearest Neighbor classifiers (NN) for classification of two or more classes in EEGs, etc., and later with emerging techniques applied as well [8]. Deep neural network has been successfully applied for that purpose as well. Among many deep learning architectures, Convolutional Neural Network (CNN) can get outstanding performances to process and learn features from time-series data due to its efficient capturing of local and spatio-temporal relationship among features. If applied repeatedly with layers, the algorithm can better learn from the same dataset without need to manually define features within time-based characteristics as a matter of fact, it's time to apply the model to new input and compute desired output during inference period after training. Another popular design for RNNs was Recurrent Neural

Network (RNN), recurrent modules helped the network to hold memories from the input and then perform predictions for coming data via sequential processing by itself.

Also, recently attention mechanism gained more interest in BCI area and was proposed to simulate the interaction between different regions of feature inputs in real-time, since such mechanisms were applied and obtained good results in NLP or language field. By introducing these models into signal processing as part or complete replacement of conventional techniques, hybrid CNN–RNN could also model time variation embedded in raw input features or processed results using Principal Component Analysis (PCA) or other technique while simultaneously consider multiple kinds of parameters that potentially helps both intra-subject and inter-subject classification performance enhancement, which makes this hybrid type even more valuable compared to other structures . Another architecture in deep learning family is Transformer recently proposed in NLP as self-attention-based model, followed by some variations were replacing feedforward fully connected networks with the similar structure [16].

3. Case Studies and Analysis

The DEAP dataset has been widely adopted in EEG emotion recognition, providing both EEG and peripheral physiological signals from participants watching music video stimuli. Labels are given along valence, arousal, dominance, and liking dimensions, supporting continuous and multidimensional annotation [7].

The SEED dataset contains EEG recordings of subjects exposed to film clips with positive, negative, or neutral content. Recent work highlights the strong discriminative power of differential entropy (DE) features extracted across multiple frequency bands [8].

The DREAMER dataset is notable for its use of portable EEG and ECG devices alongside subjective emotion ratings. It demonstrates the feasibility of reliable affective data collection with low-cost wearable sensors [13].

The AMIGOS dataset extends emotion recognition to group settings, combining individual EEG with social interaction data, thus enabling research on social and collective affect [14].

Recent attention-based models, such as channel–temporal attention and multi-scale graph frameworks, have substantially improved accuracy. Transformer-based approaches and hybrid attention–graph networks provide state-of-the-art recognition performance and interpretability [17].

4. Challenges and Future Directions

Although many advances have been made in recent years, EEG-based emotion recognition still has its own problems. First, the label quality is a limiting problem because the emotional experience is highly subjective, even with strict experimental conditions. Second, the model performs well for an individual but breaks down significantly upon transfer to another user, indicating poor cross-subject generalization. Third, since the neural signals obtained by EEG are fragile and have many noise and artifact characteristics, they are not conducive to robust classification. The main limitation of current research is the small size of the dataset, which limits the robustness and cross-subject generalization ability of emotion classification models.

To overcome this, building a large-scale, multi-domain, cross-cultural dataset will be a topic for future research. In terms of method, some researchers believe that the problem of lack or errors in labeled data can be effectively solved by introducing novel training paradigms, such as self-supervised representation learning, transfer adaptation, contrastive objectives, etc. to train the emotion classification models. At the same time, models that rely on the spatiotemporal dependency (especially graph-based networks and transformer models) are very appealing for recognizing human affect from raw EEG data.

5. Conclusion

This study provides a comprehensive review on the field of EEG emotion recognition and discusses some important aspects, such as the basic theories, EEG data acquisition and cleaning, feature representing, generating dataset, other deep learning methods. Both discrete and dimensional emotions are two kinds of effective modeling approaches. Furthermore, more studies have paid attention to an integrated model of both models because of its capability for measuring emotions in a more delicate form or interpretation. The model combined with preprocessing of EEG analysis together with frequency-based, time-based, entropy-based, and spatial-based features provides an important basis for subsequent classification for obtaining accurate results of effective emotion recognizing.

In addition, these open datasets (i.e. DEAP, SEED, DREAMER and AMIGOS) play important roles of promoting development within these fields. As a matter of fact, more emphasis is made on deep learning (graph network, attention-based framework and transformer) which achieves high accuracy level for tasks of emotion recognizing using the EEG-based methods with above dataset.

Also, many challenging issues have arisen due to limited quantity of labels' qualities, cross-subject transferring limitations, real-world scenarios, etc., and promising future development direction includes gathering large-scale data sets with richer information types, further self-learning and knowledge-transfer abilities and exploring emotional interpreting in real scenario usage by BCI-based emotion recognition systems to help users overcome mental health problems.

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