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Systematic Literature Review for emotion recognition from EEG signals

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Abstract. Researchers have recently become increasingly interested in recognizing emotions from electroencephalogram (EEG) signals and many studies utilizing different approaches have been conducted in this field. For the purposes of this work, we performed a systematic literature review including over 40 articles in order to identify the best set of methods for the emotion recognition problem. Our work collects information about the most commonly used datasets, electrodes, algorithms and EEG features, as well as methods of their extraction and selection. The number of recognized emotions was also extracted from each paper. In the analyzed articles, the SEED dataset turned out to be the most frequently used. The two most prevalent groups of electrodes were frontal and parietal. Evaluated papers suggest that alpha wavelets are the most beneficial band for feature extraction in emotion recognition. FFT, STFT, and DE appear to be the most popular feature extraction methods. The most prominent algorithms for feature selection among analyzed studies were classifier-dependent wrappers, such as the GA or SVM wrapper. In terms of predicted emotions, developed models in more than half of the papers were designed to predict three emotions. The predictive algorithms that were mostly used by researchers are neural networks or vector machine-based models.

Keywords: emotion recognition, Electroencephalogram (EEG), affect, signal processing, emotion classification, machine learning.

1 Introduction

Emotions have been investigated in various fields providing the foundation of Affective Neuroscience [2]. To better comprehend particular emotions, researchers began to link them to physiological responses such as facial expressions, heart rate, skin conductance response, blood pressure, and respiration rate. According to many neuroscience sources, human emotions are closely tied to activity in a number of brain subregions. [5]

Given these assumptions, one of the most common physiological signals used to recognize emotions is an electroencephalogram (EEG). These signals have been shown to obtain high classification accuracy for emotion recognition in laboratory settings, and have emerged as a viable tool for describing how cognition and emotional behavior are associated on a physiological level [6]. The goal of this paper is to perform the systematic literature review to discover different approaches to the subject of emotion recognition using electroencephalogram (EEG) signals.

2 Literature review process design and execution

We put together the 4 research questions that compactly presented our interests and directed our further steps during the review.

Table 1. Selected research questions.

ID	Question
RQ1	Which emotions are recognizable from EEG in adults?
RQ2	Which methods are used in emotion recognition from EEG signals?
RQ3	Which methods are used in processing EEG signals?
RQ4	Which of the gathered EEG signals are most significant in emotion recognition?

We established criteria (only English articles published within 10 years, focusing on emotion recognition from EEG, necessarily with DOI, abstract and full text available) and searched only by title through the IEEE Xplore, Web of Science, Scopus and Pubmed databases. After removing the duplicates, we had 519 articles (out of 875 found) that were qualified for the next step, i.e. tagging by title, to narrow the range of papers to those most related to our needs.

Seeing the results of title tagging and a large number (122) of articles that received the maximum score from all 3 annotators, we decided to qualify only these for the next step - tagging by abstract. During the title tagging process, we managed to isolate 7 articles, which seemed to be valuable reviews that could contribute a lot to our research. Hence our decision to directly qualify these articles for reading and analysis.

Reading 3 out of 7 papers marked as a review provided us with vital information concerning the use of music for emotion stimulation while acquiring EEG signals for datasets. In the review [12] author noticed that in a study regarding music video excerpts, it was observed that higher frequency bands such as gamma were detected more prominently when subjects were listening to unfamiliar songs. Therefore, for further analysis, we decided to classify only those articles that used a dataset not based on a musical stimulus (i.e. exclude mainly the DEAP dataset). After this exclusion, we obtained 66 papers for further analysis. After combining the two reviews: [3] and [4] that were to form the basis of our analysis, we obtained 34 papers published between 2004 and 2019. We chose 9 other articles published between 2020 and 2021 to have a complete set including also the latest papers on the subject. After analyzing them fully on our own, we ended up with a sum of 43 articles. Our key findings included information about: the most popular EEG signals datasets and stimuli used to evoke emotion, analyzed electrodes, used EEG features, methods of their extraction and selection, recognized emotions, and utilized classifiers.

3 Results

3.1 Datasets

The information about the dataset was found in 20 out of 43 articles. The most commonly used dataset in the articles was SJTU Emotion EEG Dataset (SEED). This dataset was used in twelve out of 20 articles. Other common types of datasets were those created by the authors (8 articles). Only in 1 article, the MAHNOB-HCI database was used, and only in 1 paper, the AMIGOS database was utilized.

3.2 Electrodes

28 out of 43 articles included information about which electrodes were measured and/or used in the model. The largest set of electrodes included in a single study was 62 electrodes in articles [5], [9], [10], and [11] and all of them used the SEED dataset. Figure X shows that the most frequently used electrode was F4 (21 articles), followed closely by F3 (20 articles).

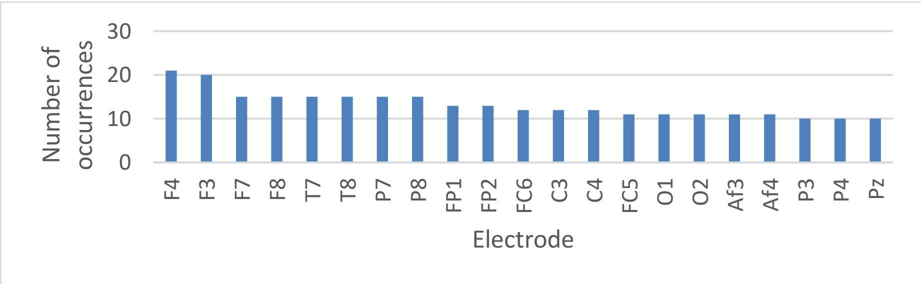

Fig. 1. The total number of times the given electrode was mentioned in articles. Only electrodes used 10 or more times are shown.

Different electrodes can be grouped based on the international 10-20 system and regions of the brain. For the sake of aggregation, we have distinguished 5 groups – Frontal (F), Central (C), Parietal (P), Temporal (T), and Occipital (O). Electrodes are named based on their placement, some electrodes are placed over the border of 2 regions of the brain, which results in electrodes named with two capital letters e.g. FP1, PO3, etc. In the case of these electrodes, we decided to include them in both groups i.e. FP1 belongs to groups Frontal and Parietal. Some electrodes have been labeled differently i.e. CMS and DRL. These two electrodes belong to the Temporal group.
In total there were 522 mentions of different electrodes in 28 papers. From Figure 2.3 one can clearly see that most frequently used electrodes were these placed over the frontal lobe (219 mentions). Other quite popular groups were Parietal and Central, 171 and 153 mentions respectively. The least often used groups: Temporal and Occipital were mentioned 66 and 65 times. This disproportion, however, could be possibly caused by the disproportion of area size. There are 24 different electrodes belonging to the Frontal group, 25 electrodes belonging to Parietal group, 23 electrodes in Central group, Temporal group consisting of 12 electrodes, and Occipital of 10 electrodes.

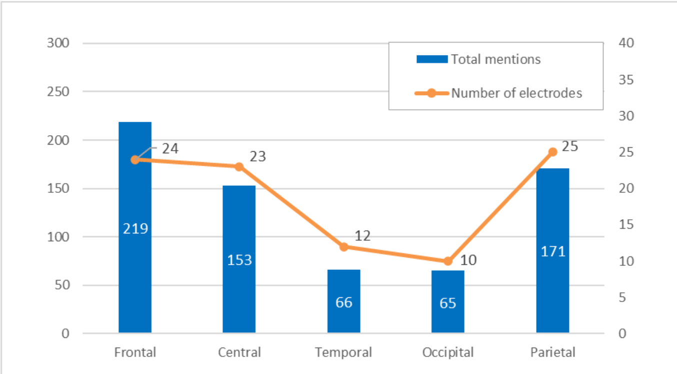

Fig. 2. Number of mentions of particular electrode groups in articles in relation to total number of electrodes per group.

3.3 EEG Features and features extraction methods.

Mostly used EEG features are individual waves that can be distinguished from the signal. The dominant waves are alpha (used in 19/43 papers) beta (18 articles) and theta waves (17). Researchers are less likely to focus on gamma waves (14) and delta waves (13) which may mean that they provide slightly less information that is valuable in recognizing emotions. The number of articles in which waves of a given frequency have been distinguished and utilized are presented in Table 2.

Table 2. EEG wavelets - number of their usages in articles.

Waves	Number of occurrences
Alpha	19
Beta	18
Theta	17
Gamma	14
Delta	13

The most frequently used feature extraction algorithms were FFT (Fast Fourier Transform) or STFT (Short-Time Fourier Transform) - analysis methods in the frequency domain which were utilized in 15 out of 43 articles. In 25% of the analyzed works (11/44 articles) DE (Differential Entropy) was used for feature extraction. Another method was the calculation of statistical measures which enable extraction of signal statistics such as standard deviation (9 papers), mean (7 papers), etc. which were used a bit less frequently. Other algorithms used by the researchers were: PSD (Power Spectral Density) - 7 articles, FD (Fractal Dimension) - 7 articles, PSD Welch's method - 5 articles, DASM (Differential Asymmetry) - 5 articles, Hjorth features - 5 articles, DWT (Discrete Wavelet Transform) - 4 articles, RASM (Rational Asymmetry) - 4 articles, WT (Wavelet Transform) - 4 articles.

In the analyzed works, other features and features extraction algorithms were also used, but due to their appearance in less than 4 articles and the clarity of our analysis, we decided to omit them in this report.

Table 3. Identified feature extraction methods and number of their occurrences in articles.

Feature Extraction Method	Number of occurrences
FFT or STFT	15
DE	11
Statistical measures - std	9
Statistical measures - mean	7
PSD	7
FD	7
PSD (Welch’s method)	5
DASM	5
Hjorth Features	5
DWT	5
RASM	4
WT	4

3.4 Feature selection methods.

The most frequently used method for feature selection was classifier-dependent wrapper. In addition, researchers willingly used methods such as mRMR (min-Redundancy Max-Relevance), PCA (Principal Component Analysis), and Correlation coefficient analysis - each of them was used in 3 articles. Max Pooling algorithm was used in 2 articles and other methods that were used only in individual articles and were therefore omitted in this report.

3.5 Emotions.

21 out of 43 articles included information about which emotions were recognized in a model. There were 16 different types of emotions identified. The maximal number of emotions recognized in a model was 8 (neutral, disgust, anger, joy, amusement, tenderness, fear, sadness) in the article [7]. The minimal found number of emotions recognized was 1 - disgust in the article [8]. Mode and median amount of emotions recognized are equal to 3 and mean amount of emotions recognized equals 3.28.
The most frequently included emotion was neutral emotion (in 13 articles out of 21), followed by positive and negative emotions (each 11 out of 21 articles). Three out of 21 articles used models which recognized emotions based on valence-arousal planes. One article differentiated 2 classes per valence and arousal - high and low valence, high and low arousal. Figure 3 contains a chart showing the number of articles recognizing particular emotion in the model.

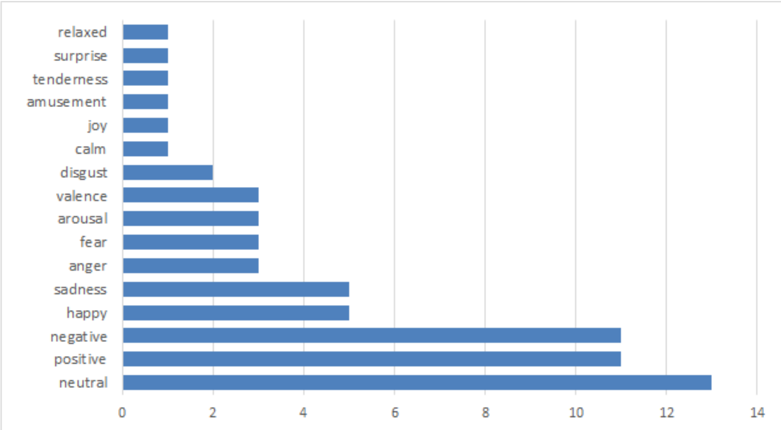

Fig. 3. Number of articles recognizing particular emotion in the model.

3.6 Algorithms.

21 of the 43 articles mentioned 18 types of prediction algorithms used to recognize emotions. The most frequently used algorithm was Support Vector Machine (SVM), applied in 11 articles. Other types of algorithms that were mentioned multiple times were k Nearest Neighbors (kNN) (2 articles), Library for Support Vector Machines (LIBSVM) (2 articles), Linear Discriminant Analysis (LDA) (2 articles), Convolutional Neural Network (CNN) (3 articles), Artificial Neural Network (ANN) (3 articles). The rest of the algorithms (Linear Regression (LR), Relevance Vector Machine (RVM), Deep Belief Network (DBN), Extreme Machine Learning (ELM), Own Neural Network, Bi-hemispheres Domain Adversarial Neural Network (BiDANN), Regularized Graph Neural Network (RGNN), Deep Neural Network (DNN), Graph regularized Extreme Learning Machine (GELM), Graph Regularized Sparse Linear Regression (GRSLR), Naive Bayes, Takagi–Sugeno fuzzy model) were mentioned only in one paper each.

Given this disproportion of usages between SVM and other algorithms, we have decided to divide all of them into five groups based on how they work. The identified groups are Clustering, Regression, Vector Machine, Neural Network, and Other.

Table 4. Categorization of predictive algorithms based on their behavior.

Group	Algorithms
Clustering	Knn
Regression	LR, GRSLR
Vector Machine	SVM, RVM, LIBSVM
Neural Network	DBN, ELM, Own NN, BiDANN, RGNN, CNN, DNN, GELM, ANN
Other	LDA, Naive Bayes, Takagi–Sugeno fuzzy model

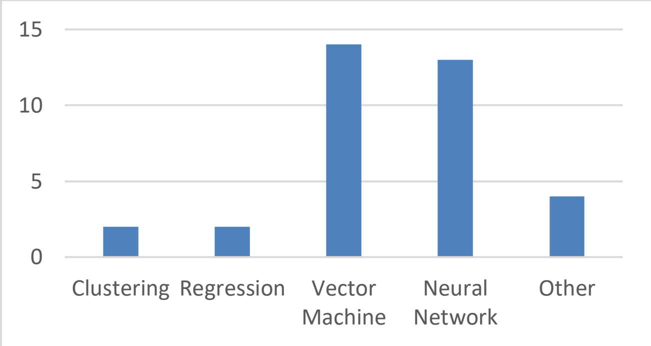

Fig. 4. Number of mentions of particular groups of algorithms in articles.

Two most often used types of algorithms were Vector Machines and Neural Network algorithms (13 articles each). In the Other group, individual algorithms were placed that could not be classified to any of previously mentioned groups (5 articles). The least mentioned groups were Clustering and Regression (2 articles each).

4 Summary

When considering datasets, there were found only 4 datasets that were using visual stimuli. The most commonly used dataset was the SEED dataset, followed by datasets developed by the authors of the articles. Other datasets were used only 1 time each.
Two most prevalent groups of electrodes were Frontal and Parietal. Our findings support the widely held assumption that the frontal lobe stores more emotional activation than other areas of the brain [12]. Considering filtering electrodes to those from the Frontal group could possibly have positive influence on the accuracy of the model.
Evaluated papers suggest that alpha wavelets are the most beneficial band for emotion recognition. In terms of the number of mentions, beta and theta waves were only marginally behind alpha. As we found out in one of the reviews, high-frequency bands such as alpha, beta, and gamma are more effective at distinguishing emotions [12]. FFT, STFT, and DE appear to be the most popular methods of feature extraction. Many researchers were also using simple statistical measures as extracted features.
The most prominent feature selection algorithms were classifier-dependent wrappers, such as the GA or SVM wrapper, which were used to successfully limit the number of features without losing the signal properties that best describe the EEG, boost accuracy and lower the likelihood of overfitting.
In more than half of the papers, developed models predicted three emotions, which is consistent with the finding that more than half of the articles predicted positive, neutral, and negative emotions. These findings are useful in terms of model quality, because model accuracy often decreases as the number of classes predicted increases.
Finally, after conducting an analysis of predictive algorithms, we discovered that most researchers used either a neural network or a vector machine-based models. The Neural Network group included a variety of neural network derivatives, each of which was

only mentioned a few times. The Vector Machine group, on the other hand, contained only three elements, the most prominent of which was the SVM algorithm.

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