Reversed Correlation-Based Pairwised EEG Channel Selection in Emotional State Recognition

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Abstract. Emotions play an important role in everyday life and contribute to physical and emotional well-being. They can be identified by verbal or non-verbal signs. Emotional states can be also detected by electroencephalography (EEG signals). However, efficient information retrieval from the EEG sensors is a difficult and complex task due to noise from the internal and external artifacts and overlapping signals from different electrodes. Therefore, the appropriate electrode selection and discovering the brain parts and electrode locations that are most or least correlated with different emotional states is of great importance. We propose using reversed correlation-based algorithm for intra-user electrode selection, and the inter-subject subset analysis to establish electrodes least correlated with emotions for all users. Moreover, we identified subsets of electrodes most correlated with emotional states. The proposed method has been verified by experiments done on the DEAP dataset. The obtained results have been evaluated regarding the recognition of two emotions: valence and arousal. The experiments showed that the appropriate reduction of electrodes has no negative influence on emotion recognition. The differences between errors for recognition based on all electrodes and the selected subsets were not statistically significant. Therefore, where appropriate, reducing the number of electrodes may be beneficial in terms of collecting less data, simplifying the EEG analysis, and improving interaction problems without recognition loss.

Keywords: Emotion recognition · Feature selection · EEG analysis · Data analysis · Machine learning · EEG electrodes selection.

1 Introduction

In everyday life and interpersonal communication, emotions play an essential role. Positive emotions promote well-being, while negative emotions can lead to

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the worsening of health problems. Neurobiological and psychological research confirms that emotions are a vital factor that influences rational behavior. Besides, patients with emotional disorders have trouble conducting daily activities [1].

Emotions can be recognized by verbal (e.g., emotional vocabulary) or non-verbal signs such as intonation, expressions, and gestures. Moreover, emotional states can also be detected by infrared thermal images or EEG signals [2–4]. EEG examination is non-invasive and inexpensive when compared to other types of signal acquisition. However, the accuracy of semantic EEG signal analysis in mental activity classification is still a significant problem. Hence, research on identifying emotions is of great importance in the EEG signal analysis [5, 6].

During EEG examination, the electrical patterns of the brain are recorded. Sensors (electrodes and wires) placed on the patient's scalp monitor the potentials of the synchronous work of groups of cerebral cortical neurons. Therefore, the correct positions of measuring electrodes are one of the positive key factors that influence the analysis of EEG recordings. On the other hand, the noise from internal (physiological) and external (hardware-related) artifacts and overlapping signals from different electrodes may have a negative impact on the EEG analysis [7].

The optimal selection of measuring electrodes is the first and a key stage of works related to the automatic selection of EEG signals [8]. It also leads to improved brain activity analysis. However, due to the complexity of the emotion recognition process, the attempts made so far have not clearly indicated the number and the locations of the best-suited electrodes. For example, Nakisa et al. in [9] suggest using nine electrodes. In contrast, the authors of the paper [10] indicate 3 to 8 electrodes depending on the experiment. An additional difficulty is that the smaller sets of electrodes do not constitute subsets of the covering sets of electrodes in the cited papers.

We propose to reverse the problem of electrode selection and discover the electrodes and their locations that are least correlated with one another. Consequently, our research can contribute to classification advancement due to redundancy reduction and better recognition of brain regions responsible for emotional state conditions. These regions, in turn, may be stimulated to improve human health state and well-being [11]. As recognizing cross-subject emotions based on brain EEG data has always been perceived as difficult due to the poor generalizability of features across subjects [12], we propose a two-phased approach. First an intra-subject electrode selection is performed. Then, the inter-subject subset analysis is proceeded to sum individual subsets and establish parts of brain and electrode locations least correlated with emotions for all users, which makes our solution suitable for unseen subjects as well. We used a reversed correlation-based algorithm (RCA) to select electrodes in conjunction with bands of frequencies automatically. The RCA was described in [13]. The method has already been used in emotion recognition and yielded promising results [14]. The experimental research was carried out on the reference DEAP set [5], which is the primary data source in research on emotions' classification. We applied inter-subject anal-

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ysis to identify band-channel combinations most correlated with emotional states and intra-subject analysis to make the results universal. This two-phases procedure revealed that keeping only 12.5% of the initial number of electrodes does not negatively influence the process of emotion recognition, which contributes to EEG signal analysis in terms of emotional state recognition.

The remainder of the paper is organized as follows. In the next section, the emotion classification problem in terms of human well-being and the EEG test is introduced, and the whole methodology is described. Next, the experiments carried out are presented, and the obtained results are discussed. The final section presents the study's conclusions and delineates future research.

2 Materials and Methods

2.1 EEG Analysis in Emotional State Recognition and Brain Stimulation for Improved Health and Well-Being

Many psychological studies undertake the problem of emotion classification, as emotions play a vital role in human communication and interactions. Various scales of emotion categorization were proposed [15–17]. One of the widely used scales is Russell's valence-arousal scale [18] which is often applied in the automated interpretation of emotions [5]. In this scale, each psychological state is placed on a two-dimensional plane with arousal and valence as the vertical and horizontal axes (Fig. 1).

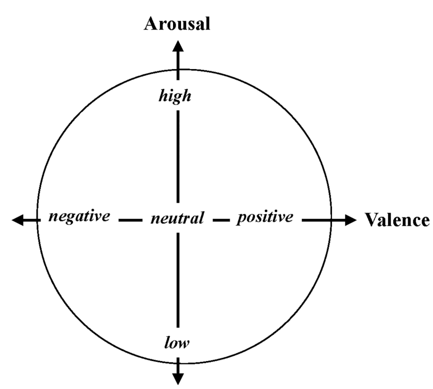

Fig. 1. Russell's circumplex model of affect.

Positive emotions and feelings are fundamentals in cultivating resilience, vitality, happiness, and life satisfaction, which contribute to physical and emotional well-being [19]. Advancing knowledge on how the nervous system implements positive emotions and feelings is critical in developing strategies that enhance the experience of healthy positive emotions and associated well-being outcomes.

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According to neurophysiological and clinical research, electroencephalogram (EEG) reflects the electric activity of the brain and the functional condition of mind. The electrodes gather signals from the four lobes of the cerebral cortex and each of them is perceived as responsible for different activities [20]:

1. the frontal lobe, responsible for thinking, memory, evaluation of emotions and situations,
2. the parietal lobe, located behind the frontal lobe and responsible for movement, recognition, a sensation of temperature, touch, and pain,
3. the occipital lobe, causative for seeing and analyzing colors and shapes, and
4. the temporal lobe, located in the lateral parts, and responsible for speech and recognition of objects.

As the human brain activity also reflects the emotional state, in the last several years EEG analysis have been slowly introduced to emotion recognition [21]. However, as the process usually involves gathering EEG signals and comparing them with expert classification or self-assessment, it is a challenging task due to its subjectivity. Moreover, recent EEG research has also tended to show that during the performance of cognitive tasks many different parts of the brain are activated and communicate with one another, thus making it difficult to isolate one or two regions where the activity will take place [22].

There is no doubt the successful analysis of the user's state can contribute to medical and psychology-related applications, either to identify possible pathology or to assist in developing well-being tools and healthcare-related solutions. Such solutions would provide treatments to improve cognitive performance, enhance mental focus attention, and promote a feeling of well-being and relaxation. Therefore, a considerable amount of research focused on the neural correlations of positive or negative emotions and brain stimulation contributing to good health [23–26]. The EEG analysis can also be beneficial in reflecting the real emotional state of people with neuropsychiatric disorders and deficits in processing emotions, e.g. Parkinson's disease (PD) [27].

EEG signals are gathered from many locations across the brain and frequently entail more than 100 electrodes. However, the huge number of electrodes negatively influence the computational complexity while assessing EEG signals. It also increases the risk of overlapping signals and causes interactions problems. Hence, the efficient channel selection is of great importance. The literature describes that similar or even the same performance could be accomplished using a more compact group of channels. Furthermore, electrode selection may be crucial for overcoming problems of complex and high-intrusive devices [28]. However, researchers argue about the definite number and locations of the EEG electrodes [10, 9].

Therefore, we propose an approach that reverses the problem of EEG channel classification and indicates the electrodes least correlated with emotional states. In addition, we also identify subsequent, inclusive subsets of the electrodes most correlated with emotions.

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2.2 The Method Overview

The considered method for reducing the number of EEG electrodes by excluding least correlated with emotional state recognition can be presented in the following steps:

1. Selecting bands of frequencies based on calculating average frequencies for each second of a trial.
2. Selecting band-electrode combinations based on a statistical analysis of correlation coefficients using intra-subject approach.
3. Building an inter-subject subset of electrodes by eliminating all the electrodes that did not appear in any user's subset and summing up the occurrences.
4. Evaluation of emotions' classification results in terms of valence and arousal.

The description of EEG data, as well as the main steps of the methodology, are presented in Subsections 2.3–2.6.

2.3 EEG Dataset

The experimental study was carried out on the reference DEAP dataset [5], created by researchers at Queen Mary University of London. It is among the most frequently used open-source datasets in research studies on emotional state classification. It contains multiple physiological signals with the psychological evaluation. The data comes from 32 subjects. For every subject, 32 electrodes were placed on the scalp, and 13 physiological electrodes were put on the examined person's fingers and face and recorded bioelectrical signals while the subject was watching 40 trials of music movies with different psychological tendencies.

The distribution of channels is shown in Figure 2. In our research we consider only 32 EEG electrodes placed on the scalp, marked as gray in Figure 2.

Four psychophysical states were assessed (valence, arousal, dominance, liking) while viewing 1-minute movies in the DEAP dataset. Each video lasted 60 seconds, and 3 seconds were reserved for preparing the person for the next trial. Each movie has been ranked on a scale of 1 - 9. The smallest values indicate negative and higher – positive "polarity" of a given emotional quality.

Our research focused on the two most objective feelings: valence and arousal. The valence reflects what the person feels while viewing the film (happy or sad), while arousal demonstrates the degree of the impression the film makes (calm, enthusiastic).

The data was preprocessed by downsampling to 128 Hz and the eye movement (EOG) artifacts removal.

2.4 Band Selection

There are five widely recognized frequency bands in the EEG signal:

– delta (δ) with frequencies in a range of 0.5–4 Hz, specific for deep sleep,

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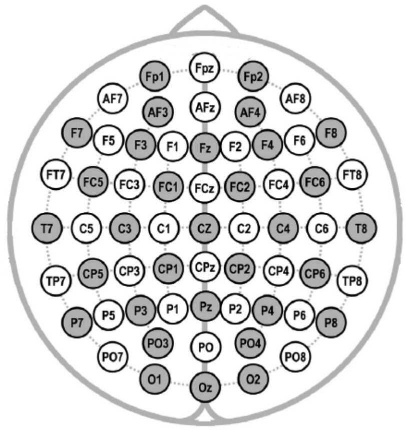

Fig. 2. Names of channels.

– theta (θ) with 4–8 Hz frequency range typical for mental relaxation,
– alpha (α) of 8–14 Hz frequencies characteristic for clear-headed and passive attention,
– beta (β), with frequencies ranged in 14–30 Hz typical for brain awakening alertness, and active, external attention, and
– gamma (γ) in a range of 30–60 Hz, specific for high concentration.

For valence and arousal classification, the delta band can be excluded from analysis. As a result, after preprocessing our data, we have obtained 128 band-channel combinations: 32 electrodes x 4 bands.

In our approach we proposed choosing the mean statistics of frequencies for every second of the recordings.

2.5 Automated Selection of Band-Electrode Combinations

Feature selection algorithms enhance computation time and classification accuracy and identify the most appropriate channels for a specific application or task. As it had been introduced in Section 2.1, the process of channel selection might be of great importance. Hence, the researchers develop new techniques for selecting the optimal number and location of electrodes.

We propose using the Reversed Correlation Algorithm (RCA). The algorithm belongs to unsupervised methods of machine learning and uses reversed correlation coefficients between all the parameters. It means that the RCA suggests features that are the least connected with all their predecessors. For that reason, the RCA might be beneficial in reduction of overlapping EEG signals.

The algorithm was proposed by Wosiak and Zakrzewska in [13] and has already been successfully applied in EEG signal analysis [14]. First, we start building a subset of selected elements with the band-channel combination that is the least correlated with the others. Then, correlation coefficients between the

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chosen element and the rest of the combinations are calculated. The element with the lowest correlation value is indicated as the second component. The obtained subset of two elements is further extended by adding the band-channel combination of the correlation coefficient with the lowest value between the subset and the rest of the items. The process of appending the components of the lowest correlation values is repeated unless the number of elements in the subset R is equal to the initially determined number N. The whole procedure is presented in Algorithm 1.

Algorithm 1 Reversed Correlation Algorithm

```
function RCA(N)                                ▷ N is a desired number of elements from R subset
    //Ch = ch_1, ch_2, ..., ch_128                                        ▷ set of all elements
    R_1 ← take the first element with the min correlation
    while i < N do
        while j < length of Ch do
            while k < length of R do
                value ← compute correlation between elements
                sum ← sum + value
                k ← k + 1
            end while
            R_i ← sum/len(R)
            sum ← 0
            j ← j + 1
        end while
        R_i ← choose element with the lowest sum of value
        k ← k + 1
    end while
    return R_i                                                    ▷ selected subset of elements
end function
```

We propose using RCA approach for building individual subsets of electrodes adapted to each user [12, 29] and as a result we get an intra-subject (within-subject) subsets of electrodes.

However, such an approach cannot be used for unseen subjects as it only uses data related to the particular individual. Therefore, we propose the inter-subject generalization step. First, we summed up occurrences of every channel. Then, we built subsets of electrodes, starting from the most frequent channels

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and adding subsequent electrodes with fewer and fewer occurrences until at least one appeared.

2.6 Evaluation Criteria

Limiting the number of EEG channels and selecting an optimum subset of electrodes requires criteria of evaluation. Concerning emotion recognition, classifier-based measures are usually used. However, considering the fact, that emotional state in the DEAP dataset is self-assessed by real values ranging in 1–9, linear regression was applied. The regression analysis estimates relationships between a dependent variable (in our case users rating) and independent variables (values for selected subset of channels) using linear predictor functions. For regression evaluation we calculated two measures: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Both measures express average model prediction error. However, the RMSE gives a relatively high weight to large errors, since the errors are squared before they are averaged. As a result, the RMSE would be observed as large if our predictions were significantly different from the target participant's rating value.

3 Results and Discussion

The purpose of the experiments was to indicate a subset of EEG channels, which reduces the complexity of the analysis and signal noise and positively influences classifying emotions.

The experiments were conducted according to the methods introduced in Section 2 on the dataset described in Section 2.3. Only valence and arousal were analyzed. The procedures were repeated ten times and the mean values were calculated. The experimental environment was based on Python programming language and its libraries.

The proposed steps of the experiments can be presented as follows:

1. The RCA analysis performed for every user to choose intra-subject electrode-band combinations, including validation of results.
2. The analysis of occurrences of channels and building the most frequent subsets of channels - the inter-subject generalization step.
3. Applying the subsets from the previous step on randomly picked users for final evaluation.

According to the description in Section 2.4, first, every channel was divided into four main frequencies: theta, alpha, beta, gamma. Therefore, as an input, we have 128 features (32 channels x 4 frequencies), which represent Ch subset. Then, the RCA algorithm was applied to every user. We set the number of channels selected to three, according to other studies and data limitations [14]. Every selection was validated according to the evaluation criteria introduced in Section 2.6 to make sure that the selection does not worsen the valence and arousal

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classification. The aggregated preferences are illustrated in Figure 3 as a heat-map. The horizontal axis of the map represents the electrode index (as defined in the original DEAP dataset) and the vertical axis of the map - the frequency subbands. The color intensity highlights the oftenness of a given combination indicated by the RCA algorithm, and varies from 0 to 4 (the occurrence range).

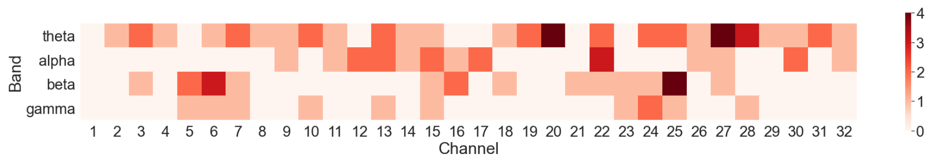

Fig. 3. .The heat-map for channel-subband frequency selections

In the second step of the experiments, we summarized the occurrences of the channels and built the most frequent subsets of channels. Moreover, we identified four channels not selected by the RCA algorithm for any user and built a subset for all channels selected at least once. The results of occurrence frequencies are highlighted in Figure 4 and presented in Table 1. Table 2 depicts the most frequent subsets of channels and their elements.

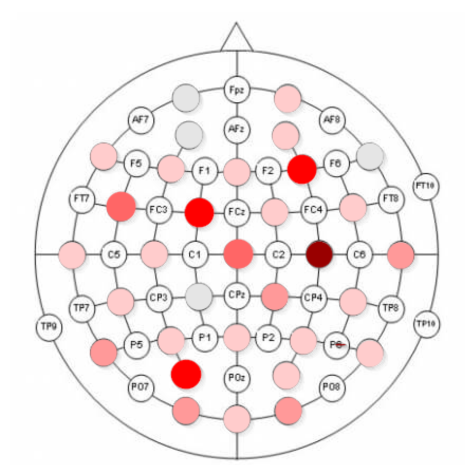

Fig. 4. The channel occurrence frequency illustration

We can observe in Figure 4 that the central and right areas of the brain are favored. It can be justified by the psychological factor showing that negative emotions are generally believed to elicit more reactivity, and they are reflected by higher right-brain activity [31].

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The authors of [30] carried out the research considering temporal channels with features from eye movements. In that way, the researchers achieved accuracy 72%. Our research shows that temporal channels are less important than other lobes in terms of emotional state recognition. Higher accuracy results could be gained by additional EOG signal analysis.

Medical research [32] confirms that neurotransmitter serotonin, also known as the happiness hormone, which is responsible for depression detection [33], is produced in the frontal lobe. Therefore, it might explain that positive emotions are correlated with channels in the front of the scalp. However, our research shows that these channels have a small impact on emotion recognition, which confirms that temporary feelings are not related to happiness hormone.

Table 1. The summarized channels' occurrences

Channel identifiers	No. of occurrences
C4	6
FC1, PO3, F4	4
FC5, Cz	3
P7, O1, T8, CP2, O2	2

Table 2. The most frequent subsets of channels

Subset ID	Channel identifiers
A	C4, FC1, PO3, F4
B	C4, FC1, PO3, F4, FC5, Cz
C	C4, FC1, PO3, F4, FC5, Cz, P7, O1, T8, CP2, O2
D	28 channels (FP1, AF3, CP1 and F8 were excluded from the initial set)

In the final step, we applied the selected subsets of electrodes on six randomly picked users to verify if our approach, aiming at the reduction of the number of electrodes and - as a consequence - simplification of data gathering, does not worsen the valence and the arousal classification. The evaluation was performed according to the methodology described in Section 2.6. The values of RMSE and MAE are presented in Figure 5. Each chart refers to one of the randomly picked users, whereas each group of bars presents emotion-error combination types, and each series represents a subset of electrodes. The first series illustrates errors for all 32 channels.

One can notice that the error values slightly differ between subjects. It can be justified by the fact that experiencing emotions by people has a different impact on the brain. Moreover, we may assume that emotion evaluation by the users

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can be unstable. A similar feeling can be overestimated or underestimated by different subjects.

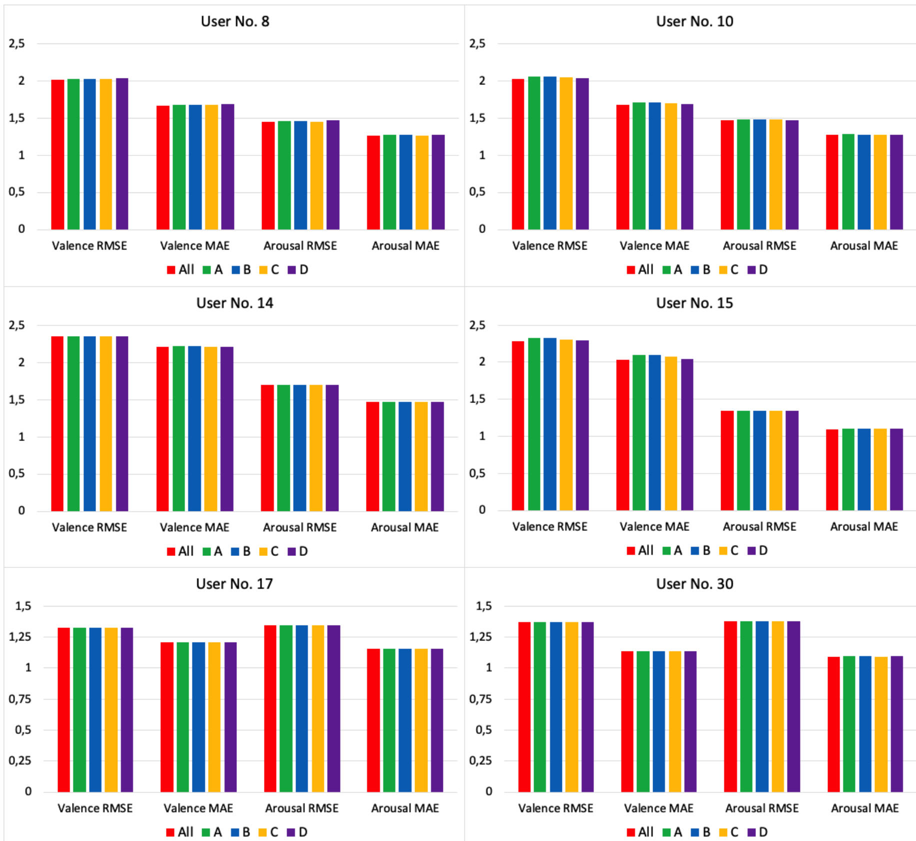

Fig. 5. The values of RMSE and MAE for valence and arousal recognition and random subjects

One can notice that our proposed reduction of electrodes has no negative influence on emotion recognition correctness. Even the most radical reduction, resulting in limiting the number of electrodes to four most often selected, enabled recognition of a similar level. The differences between errors for recognition based on all electrodes and the selected subsets were not statistically significant (p-value ≥ 0.68). Therefore, where appropriate, reducing the number of electrodes may be beneficial in terms of collecting less data, simplifying the EEG analysis, and improving interaction problems without recognition loss.

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4 Conclusions

The research presented in the paper addresses the problem of building reduced and, therefore, more optimal EEG channel set for human emotion recognition. Optimal EEG channel selection and location is a challenging task due to the interconnections between individual channels.

The proposed method incorporating the RCA algorithm finds combinations of electrodes and their frequency bands, which are least correlated with one another. It, therefore, enables noise reduction and classification advancement in the intra-subject approach. The generalization inter-subject step makes our conclusions more universal.

Our method is simple in use. At the same time, it may significantly reduce the number of data needed for the analysis when appropriate. The experiments revealed that we can reduce number of electrodes from 32 channels to 4 channels. It means that keeping only 12.5% of the initial number of electrodes does not negatively influence the process of emotion recognition.

Nonetheless, there is still a need for additional investigations. Therefore, further research is planned to investigate multiple datasets. Moreover, deeper insight into denoising methods is planned. Future research may also explore neural networks and deep learning approaches to find unknown attribute correlations.

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