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Abstract: Electroencephalography (EEG) is widely used in clinical applications and basic research. Dry EEG opened the application area to new fields like self-application during gaming and neurofeedback. While recording, the signals are always affected by artefacts. Manual detection of bad channels is the gold standard in both gel-based and dry EEG but is time-consuming. We propose a simple and robust method for automatic bad channel detection in EEG. Our method is based on the iterative calculation of standard deviations for each channel. Statistical measures of these standard deviations serve as indications for bad channel detection. We compare the new method to the results obtained from the manually identified bad channels for EEG recordings. We analysed EEG signals during resting state with eyes closed and datasets with head movement. The results showed an accuracy of 99.69 % for both gel-based and dry EEG for resting state EEG. The accuracy of our new method is 99.38 % for datasets with the head movement for both setups. There was no significant difference between the manual gold standard of bad channel identification and our iterative standard deviation method. Therefore, the proposed iterative standard deviation method can be used for bad channel detection in resting state and movement EEG recordings.

Keywords: Electroencephalography, dry electrode, artefacts, head movements, brain-computer interfaces

1 Introduction

Electroencephalography (EEG) is a non-invasive technique for recording neural electrical activity with the help of electrodes placed on the scalp. This method is widely used in clinical applications and basic research. Moreover, EEG can be used in brain-computer interfaces or rehabilitation. The latest development of electronics for EEG recordings and dry electrodes enabled self-application and thus usage in out-of-the-lab scenarios [1].

The EEG signal has low amplitude and as such is prone to artefacts and unwanted noise. The reconstruction of the brain activity from bad channels is sometimes not possible. Therefore, it is very important to remove non-reliable channels before applying any type of EEG signal analysis or source reconstruction. The most common procedure for bad channel detection still is manual inspection. This procedure is often time-consuming and subjective, which can lead to different results depending on the experts evaluating the EEG [2–4]. Dry EEG is more prone to movement artefacts compared to gel-based EEG. Due to the lower channel reliability in dry EEG, the manual identification of bad channels is even more time-consuming.

Various semi- or fully automated approaches for bad channel detection have been proposed for gel-based EEG including a combination of different statistical, temporal, and frequency features [5,6]. Our aim is the development of a simple and robust method for automatic bad channel detection in dry EEG recordings [7], which is at the same time also suitable for gel-based EEG.

2 Methods

2.1 Measurements

In the study participated 5 healthy volunteers, 3 females and 2 males, with a mean age of 27 ± 10. We analysed EEG data from two different segments: one segment of resting EEG with closed eyes for 3 minutes and one segment while volunteers were performing head movements. Head movements were not executed rapidly, but rather slowly. The participants were instructed to move their heads downwards to the chest and back to a straight position when they hear a tone. The movement was repeated every 4 seconds. In sum, 45 movement epochs for each participant are recorded.

We used 64-channel gel-based and dry EEG caps with an equidistant layout (waveguard, ANT B.V., Hengelo, The

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Netherlands). The reference electrode was placed on the right mastoid. The sampling rate was 1024 samples/second.

2.2 Data Processing

The data were processed using MATLAB (The MathWorks, Inc., Natick, United States). Each of the 15 datasets was analysed separately. Data were pre-processed using a finite impulse response (FIR) bandpass filter implemented in EEGLAB [8] with a low cut-off frequency of 1 Hz and a high cut-off frequency of 40 Hz, as one of the standard frequency ranges for EEG analysis [9]. After filtering, the newly proposed iterative method for automatic bad channel detection was performed. For comparison, the data were manually inspected and bad channels were identified as well.

The proposed method is applied and tested on two different window lengths for the resting state EEG. The first studied case is a window length of 60 s after skipping the first 10 s of the signal to avoid filter artefacts. For the second studied case, a 30 s window is chosen as commonly used in the standard EEG signal analyses [9]. These windows have the same lengths for all the datasets. However, for the datasets with the head movement, the analysis windows were starting 2.3 s after the movement and had a length of 0.5 s. Thus, transient movement artefacts were not considered for identifying bad channels.

The signal quality of each channel is manually evaluated for the chosen windows [1,10]. The same signal windows were used for the automatic bad channel detection. All datasets were visually inspected by one annotator and the bad channels were annotated similar to the criteria described in [11]. Predefined bad channel characteristics are: exhibiting either a saturated signal, an isoelectric line, or a predominantly artefactual EEG recording.

2.3 Automatic ISD Method

We propose an Iterative Standard Deviation (ISD) method for automatic bad channel detection in both dry and gel-based EEG recordings. The standard deviation is calculated for each of the 64 channels over the whole analysed data window.

First, the standard deviation of the signal for the j-th sensor over the whole analysis window of length N is calculated (see eq 1).

$$\boldsymbol{SD_j} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N-1}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{N}}\left|\boldsymbol{V}_{(i,j)} - \boldsymbol{\bar{V}_j}\right|^2} \tag{1}$$

V_i is the i-th out of N samples for the j-th electrode and $\bar{V}_j$ is mean voltage for the j-th electrode. The result are 64 values of standard deviations. They are observed further as one population from which outliers have to be identified. Four criteria are established to detect the bad channels (see eq 2-5). The criteria used to eliminate the outliers from the population of SDs are the median and the 75th percentile range, the standard deviation of channels lower than 10^{-4} µV and higher than 100 µV.

$$\left|\boldsymbol{SD}_{(j,k)} - \boldsymbol{M_k}\right| > \boldsymbol{75th\ percentile} \tag{2}$$

$$\boldsymbol{SD}_{(j,k)} < \mathbf{10^{-4}}\ \mu\mathbf{V} \tag{3}$$

$$\boldsymbol{SD}_{(j,k)} > \mathbf{100}\ \mu\mathbf{V} \tag{4}$$

An additional criterion for ending the iterations is:

$$\boldsymbol{SD}_{\boldsymbol{p(k)}} > \mathbf{5} \tag{5}$$

$SD_{(j,k)}$ is standard deviation of the j-th channel at the k-th iteration. M is the median of the population of standard deviations in the k-th iteration. SD_p is the standard deviation of all individual channel standard deviations in the k-th iteration.

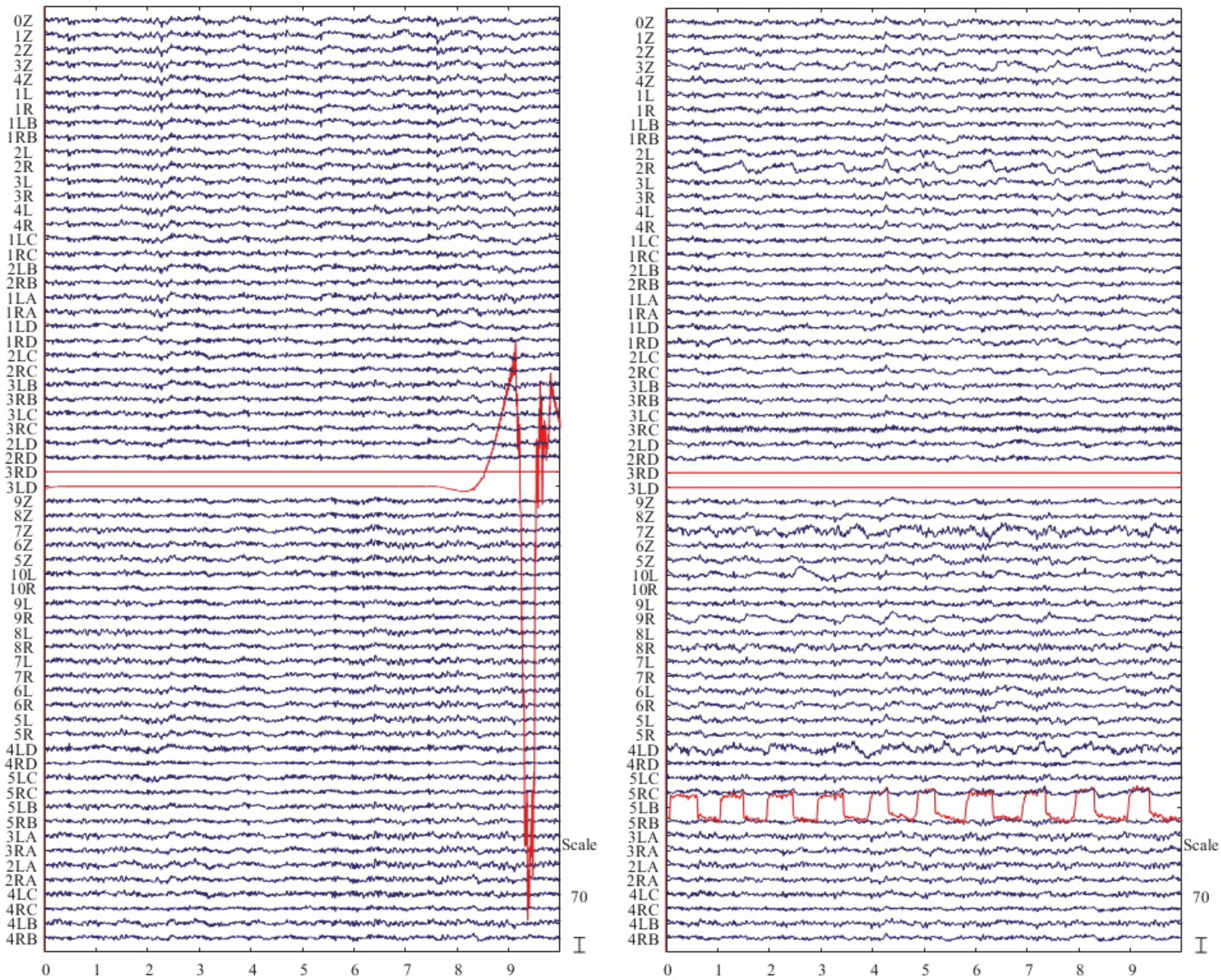
2.4 Statistical Analysis

Statistical analysis was performed in MATLAB R2021a. The aim was to compare the identification of bad channels between the two methods. The manual selection of bad channels is taken as ground truth. The performance of the proposed ISD method is evaluated with the confusion matrix, sensitivity, specificity, and accuracy calculation. In addition, Fisher's exact test at an alpha level of 0.05 is used to check if the two methods are providing significantly different outputs.

3 Results

The main results of the analysis are shown in Table 1 for all 320 analysed channels from all 5 participants. For the 30 s long analysis window and gel-based electrodes, the number of bad channels manually identified is 11 while the ISD method identified 10 bad channels. In the dry dataset 25 channels are manually selected as bad, while the ISD method identified 24 of them. For the datasets with the head movements, the manually identified number of bad channels is 12 and 30 for gel-based and dry recordings, respectively. In this case, the ISD method identified 10 and 32 bad channels in gel-based and dry recordings, respectively. The accuracy of the ISD method for the gel-based and dry alpha EEG recordings with the chosen 30 s window is 99.69 %. The accuracy of the ISD method is 99.38 % for both types of recordings and the 0.5 s fixed window in the head movement datasets.

Figure 1 shows the method's performance for the 10 s exemplary alpha EEG dataset. In both cases (gel-based and dry), both methods (manual and ISD) identified the same channels as bad (colored red in Figure 1). For the gel-based electrodes these are 3RD and 3LD and for the dry ones 3RD, 3LD, and 5LB. All bad channels in the datasets were detected in the first iteration.



a) b)

Figure 1: Alpha EEG dataset for all 64 channels and 10 seconds a) gel-based and b) dry. The red color indicates bad channels that are detected by the manual and ISD methods.

4 Conclusion

We found no significant differences in the channels labelled as bad for the manual and ISD detection of bad channels for both resting state and head movement EEG. The ISD method is simple and robust and can be applied for bad channel identification in both dry and gel-based recordings, replacing manual evaluation. The detection criteria of the ISD method can be adapted to other datasets. As this method is working iteratively and does neither depend on pre-defined hard thresholds nor standardized values, it has the potential to automatize the process of bad channel detection. After the application of the ISD method, processing steps can be applied to further clean the data. However, the ISD method can be also used to detect artefacts, such as e.g. movement artefacts.

We can notice a higher overall number of bad channels detected in the datasets with the head movement for dry recordings. As Debnath et al. reported, existing bad channel detection methods may not perform well if the recordings have a high number of bad channels as e.g. in EEG recordings with movements [3]. The advantage of our proposed ISD method is to overcome this limitation. The next phase of method testing would consider a broader frequency range of the EEG signals.

Future work will address the main limitation of this study which is the low number of subjects.

Table 1: Statistical results of the ISD method for gel-based and dry EEG. Number of channels identified as bad from a total of 320 channels for all 5 volunteers. P-values of Fisher's exact test. The difference between identified bad channels from manual and ISD methods was compared at a significance level of alpha = 0.05.

Dataset		**Alpha**		**Head movement**
	Performance parameter	**30 s window**	**60 s window**	**0.5 s window**
Gel-based	Sensitivity	90.91	84.62	83.33
	Specificity	100	100	100
	Accuracy	99.69	99.38	99.38
	Manual	11	13	12
	ISD	10	11	10
	p-value	$0.04*10^{-16}$	$0.01*10^{-17}$	$0.02*10^{-17}$
Dry	Sensitivity	96.00	100	100
	Specificity	100	100	99.31
	Accuracy	99.69	100	99.38
	Manual	25	24	30
	ISD	24	24	32
	p-value	$0.03*10^{-33}$	$0.01*10^{-34}$	$0.04*10^{-38}$

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Conflict of interest: Authors state no conflict of interest. Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: The research related to human use complies with all the relevant national regulations, institutional policies and was performed in accordance with the tenets of the Helsinki Declaration, and has been approved by the authors' institutional review board or equivalent committee.

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