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Abstract	
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The effect of miniaturization and galvanic separation of EEG sensor devices in an auditory attention detection task

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***Abstract*— Recent technological advances in the design of concealable miniature electroencephalography (mini-EEG) devices are paving the way towards 24/7 neuromonitoring applications in daily life. However, such mini-EEG devices only cover a small area and record EEG over much shorter inter-electrode distances than in traditional EEG headsets. These drawbacks can potentially be compensated for by deploying a multitude of such mini-EEG devices and then jointly processing their recorded EEG signals. In this study, we simulate and investigate the effect of using such multi-node EEG recordings in which the nodes are galvanically separated from each other, and only use their internal electrodes to make short-distance EEG recordings. We focus on a use-case in auditory attention detection (AAD), and we demonstrate that the AAD performance using galvanically separated short-distance EEG measurements is comparable to using an equal number of long-distance EEG measurements if in both cases the electrodes are optimally placed on the scalp. To this end, we use a channel selection method based on a modified version of the least absolute shrinkage and selection operator (LASSO) technique, viz. the group-LASSO, in order to find these optimal locations.**

I. Introduction

Electroencephalography (EEG) is a widely used modality for monitoring neural activity and is currently viewed as one of the most promising non-invasive techniques for future chronic neuromonitoring applications. Chronic EEG devices that can be worn 24/7 would facilitate the promotion and protection of brain health, a better diagnoses of brain disorders, the development of new neural prostheses, etc. However, existing wireless EEG headsets are generally too bulky, too heavy, or too obtrusive to wear in everyday life. A recent surge in the design of novel miniature EEG (mini-EEG) devices with local embedded electrodes paves the way to more wearable alternatives [1]–[4]. Such mini-EEG devices can be concealed, e.g., behind the ear [3], in the ear [1] or even under the skin [4]. However, this miniaturization comes with the drawback that only few EEG channels can be recorded within a single local area. Therefore, to increase spatial information, one could use a multitude of such devices and wirelessly connect them in a sensor network-like architecture, referred to as a wireless EEG sensor network (WESN) [5], [6].

The EEG measured in a WESN will consist of local short-distance measurements made by multiple galvanically separated mini-EEG sensor nodes, i.e. without a wire between them. This is unlike EEG recordings made by traditional headsets where electrodes are usually referenced to a common reference electrode or an average reference signal. To understand the consequences of using a WESN-like architecture, the effect of short-distance measurements and galvanic isolation between the devices should be investigated in various neuromonitoring applications. In this paper, we investigate their impact on one such application, viz. auditory attention detection (AAD).

In the fields of neuroscience and audiology, there has been extensive research to understand and replicate the ability of the human auditory system to attend to one speaker in a cocktail party scenario with multiple simultaneous speakers. Several studies have successfully demonstrated that it is possible to estimate the attended speech envelope from EEG [7]–[11], thereby detecting to which speaker a subject is attending to. It is believed that one day these AAD systems can be used for the cognitive control of auditory prostheses (APs), such as hearing aids and cochlear implants [9]. Therefore, AAD is an application that could benefit hugely from chronic neuromonitoring using a WESN.

In [7], O'Sullivan et al. showed that the envelope of the attended speaker can be reconstructed from multi-channel EEG data using a spatio-temporal decoder trained using a least-squares (LS) error objective function. By computing the correlation between the envelope and the envelopes of the speech signals of all the speakers, it is possible to detect which speaker is being attended to. Attention decoding accuracies of more than 90% have been reported in various studies based on this method [7]–[10]. A similar AAD approach has been used in a binaural hearing aid setting to steer a beamformer to the attended speaker [10], [12]. However, all these studies used high-density EEG caps for recording neural activity. Recently also mini-EEG devices, e.g., around-the-ear EEG [13] or in-ear-EEG [14], have been used to perform AAD. Although, when compared to the use of traditional EEG headsets, using individual mini-EEG devices results in poorer AAD accuracies due to the low channel count and the limited or absent spatial information. Therefore, there is potential for improvement using a multitude of such devices in a WESN to increase spatial information.

In this study, we investigate the AAD problem for the case where EEG measurements are made with short inter-electrode distances obtained from simulated galvanically separated mini-EEG sensor nodes in a WESN setting. To this end, we start from a 64-channel AAD data set, and re-

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reference the electrodes to simulate a WESN with single-channel mini-EEG nodes with short inter-electrode distances. We then select the N best galvanically separated single-channel nodes using a method based on a modified version of the least absolute shrinkage and selection operator (LASSO) optimization technique, viz. the group-LASSO optimization [15]. We applied the same group-LASSO method to two different long-distance electrode configurations for comparison.

We demonstrate that the AAD performance obtained using EEG measured from the N best galvanically separated single-channel mini-EEG nodes, is comparable to the performance obtained when using an equal number of long-distance EEG measurements.

The paper is organized as follows. In section II, the LS AAD algorithm is explained followed by details on the WESN simulation and the group-LASSO based node selection method. In section III, we show results on the AAD performance in a WESN setting and benchmark it against other recording settings with far-distance reference electrodes. Discussions and conclusion are given in section IV.

II. Methods

A. Auditory Attention Detection (AAD)

In this subsection, we briefly review the LS-based method for AAD as originally proposed in [7] with some minor methodological changes as proposed in [9]. First, a spatio-temporal linear decoder $\hat{\mathbf{w}}$ that estimates the attended speech envelope from C-channel EEG data is obtained by solving the following LS optimization problem:

$$\hat{\mathbf{w}} = arg\min_{\mathbf{w}} \frac{1}{2}||\mathbf{A}\mathbf{w} - \mathbf{s}_a||_2^2 \tag{1}$$

where $||\cdot||_2$ represents the l_2-norm, $\mathbf{s}_a$ is a vector containing the samples of the attended speech envelope and $\mathbf{A}$ is a matrix containing m copies of the C EEG channels in its columns, in which a sample delay of $j-1$ is added to the j-th copy of each channel (i.e., $m \cdot C$ columns in total).

The EEG data of each subject is split into trials of equal length (the experiments in this paper were based on trials of 60s). To avoid overfitting, a subject-specific leave-one-out cross-validation is used. This means that, to construct the decoder $\hat{\mathbf{w}}_k$ to decode trial k, data from all the trials[1] except trial k is included in the matrix $\mathbf{A}$ and the vector $\mathbf{s}_a$ [9]. Once the decoder is obtained, an estimate of the attended speech envelope in trial k is constructed using:

$$\hat{\mathbf{s}}_a = \mathbf{A}_k\hat{\mathbf{w}}_k \tag{2}$$

where $\mathbf{A}_k$ now contains the data from trial k only. To perform AAD, the reconstructed envelope is correlated to the envelopes of the different speakers, where the one with the highest correlation is assumed to be the attended speaker. In this paper, we consider a 2-speaker scenario, such that a trial is correctly decoded if $r_a > r_u$, where r_a and r_u are the Pearson correlation coefficients between the reconstructed speech envelope $\hat{\mathbf{s}}_a$ and the attended and unattended speaker, respectively. The percentage of trials successfully decoded is used as the AAD performance parameter.

[1]Note that this procedure is slightly different than [7], where eq. (1) is computed over the data of individual trials, after which the resulting per-trial decoders are averaged across trials (except the test trial k). The single-shot LS optimization used here reduces or eliminates the need for regularization if sufficient data is available in the training set [9].

B. EEG Data Collection

In this experiment, we use the data set described in [9]. The data set contains 16 subjects who listened to two simultaneous speakers at two distinct spatial locations, and were asked to attend to only one of them while ignoring the other. The speech stimuli were presented to the subjects using head-related transfer functions to simulate a realistic acoustic scenario, and the side of attention (left or right) was evenly split over the different trials to avoid decoder bias [16]. During the entire experiment, 64-channel EEG was recorded using a BioSemi ActiveTwo system. The electrodes were placed on the head according to international 10-20 standards and data was recorded with a common reference montage, with the Cz electrode used as the reference.

C. WESN Simulation

To investigate the effect of using short-distance, locally referenced sensor electrodes on AAD, we simulated a WESN consisting of galvanically separated single-channel nodes, i.e., each containing a single short-distance electrode pair. To this end, we first created a set of potential electrode pairs by pairing each electrode with nearby electrodes that are at a distance of at most 5 cm. Using this criteria, a redundant set of $P = 209$ potential single-channel node locations and orientations were generated from the original 64 channels with an average inter-electrode distance of 3.7 cm. Once the redundant set of 209 single-channel nodes was generated, the WESN was simulated by selecting the N best galvanically separated nodes from the $P = 209$ nodes, as explained in the next section.

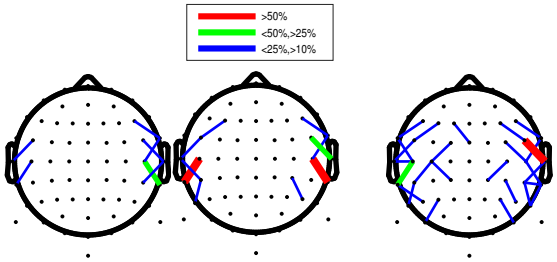
D. Group-LASSO based node selection

Our goal is to select the N best galvanically separated nodes from P potential single-channel nodes. For achieving this goal, we replace $\mathbf{A}$ in eq. (1), which contained 64 EEG channels and their m delayed versions, with $\mathbf{A}_P$ which was constructed out of the EEG data from P single-channel nodes and their m delayed versions. This gives:

$$\hat{\mathbf{w}}_P = arg\min_{\mathbf{w}} \frac{1}{2}||\mathbf{A}_P\mathbf{w} - \mathbf{s}_a||_2^2. \tag{3}$$

It is noted that the matrix $\mathbf{A}_P$ is rank deficient, which means that there are infinitely many solutions for eq. (3). In [8] and [17], an iterative channel selection heuristic was used for EEG based AAD, in which the channel with the lowest corresponding entry in $\hat{\mathbf{w}}$ was removed in each iteration. However, in general the weights in a LS or a linear minimum mean squared error (MMSE) decoder do not necessarily reflect the importance of the corresponding channels [18].

In this paper, we tackle the channel selection problem using LASSO [19] instead, which is one of the most popular methods for variable selection in regression problems.



(a) $N = 2$ (b) $N = 4$ (c) $N = 8$

Fig. 1: Configurations of the selected N nodes across subjects color-coded according to % of subjects that selected a node.

LASSO adds an l_1 norm penalty term to an LS regression problem like eq. (3) to obtain a sparse solution for $\hat{\mathbf{w}}_P$, i.e. a $\hat{\mathbf{w}}_P$ with few non-zero entries [19]. However, it should be noted that in our case, when a particular channel is selected, its delayed versions should also be selected. Hence, our objective is to select groups of variables in $\hat{\mathbf{w}}_P$ that correspond to a particular set of channels and their delayed versions. Yuan and Lin [15] proposed the group-LASSO criterion to solve this problem. Group-LASSO is a modification of LASSO for linear regression which introduces a sparse selection of pre-defined groups of variables without imposing sparsity *within* the individual groups. Applying the group-LASSO criterion, eq. (3) is modified as:

$$\hat{\mathbf{w}}_P = arg\min_{\mathbf{w}} \frac{1}{2}||\mathbf{A}_P\mathbf{w} - \mathbf{s}_a||_2^2 + \lambda \sum_{p=1}^{P} ||\mathbf{w}_p||_2 \quad (4)$$

where $\mathbf{w} = [\mathbf{w}_1^T\ \mathbf{w}_2^T\ ..\mathbf{w}_P^T]^T$, with $\mathbf{w}_p$ the sub-vector of length m of the decoder which contains the weights corresponding to channel p and its m delayed versions and λ is a tuning parameter which controls the sparsity of $\hat{\mathbf{w}}_P$. Note that eq. (4) has an l_1-norm penalization across groups (represented by the summation sign), whereas each group is represented by the l_2-norm over its coefficients.

For each subject, we selected the N (out of P) best nodes using eq. (4) by sweeping the parameter λ until N nodes are selected. To ensure that the selected nodes are galvanically separated, if a galvanic connection is observed between any two (out of N) selected nodes, the data from one of those nodes is removed and the group-LASSO method is applied again. This process is repeated until a galvanically separated set of N single-channel two-electrode nodes are obtained. Once the N best electrode pairs are selected using group-LASSO, these N channels are used in eq. (3) to train an LS decoder, which is then tested in a cross-validation procedure as explained in section II-A.

For investigating the effect of short-distance measurements in a WESN consisting of a galvanically separated set of N single-channel (i.e. two-electrode) nodes, we need to create a corresponding long-distance electrode-reference configuration that can be used as a benchmark. To this end, we first apply the group-LASSO method to the original Cz-referenced EEG data, to select the N best channels for each subject. This yields the best-N long-distance counterpart to the set with the best-N short-distance galvanically separated channels. We refer to this benchmark set with the code 'Long'.

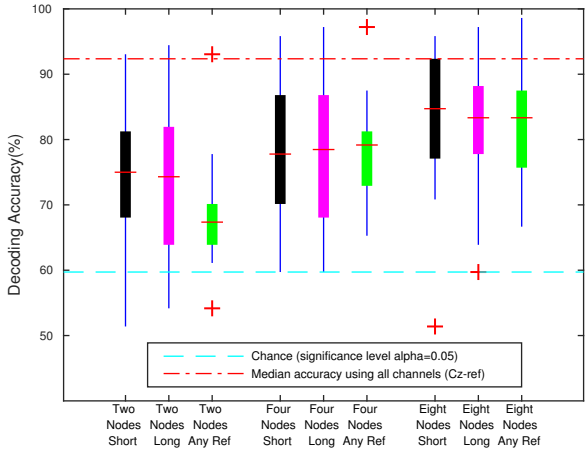


Fig. 2: AAD accuracy using short-distance (*Short*) vs long-distance common-reference (*Long*) vs any-reference (*Any-Ref*) EEG measurements.

It is noted that all 64 channels in this 'Long' benchmark set use the same reference electrode, which may be viewed as a reduction in degrees of freedom compared to the set of 209 short-distance pairs. Therefore, to make a fairer comparison, we created a second benchmark set based on all possible electrode-pairs from the original 64-channel EEG data (i.e. 2016 pairs in total) and applied group-LASSO to select the best N single-channel two-electrode nodes from this set. In this case, the degrees of freedom are maximized, since there is full freedom to choose any electrode-reference pair. We refer to this benchmark set with the code 'Any-Ref'.

III. Results

For all results mentioned in this section, a leave-one-trial-out cross validation was applied for each subject, using subject-dependent decoders. We used the group-LASSO method to select the $N = 2$, 4 and 8 best single-channel nodes for each subject from the set of 209 nodes. The electrode-pair configurations of the selected nodes across subjects is shown in fig. 1 which illustrates the percentage of subjects that selected a particular node. We can observe that for a high percentage of subjects, nodes were selected with electrode-pair configurations corresponding to the auditory cortex. The regions corresponding to the temporal lobe are known to generate neural signals that are relevant for AAD.

To investigate whether a collection of galvanically isolated short-distance mini-EEG nodes causes a performance decrease in comparison to long-distance measurements, the AAD performance is also computed using EEG data from the $N = 2$, 4, 8 best channels selected from the two different benchmark sets 'Long' and 'Any-Ref' as described in section II-D. The comparison with both is depicted in fig. 2. We can observe that, when sensor nodes are placed at ideal locations, the AAD performance with short-distance EEG measurements (along with galvanic separation) is similar to the performance with both benchmarks with long-distance

EEG measurements. For each value of N, the three cases 'Short', 'Long', and 'Any-Ref' were compared to each other using both a paired t-test and a Wilcoxon signed rank test. In all cases, the differences were not significant, meaning that the null hypothesis could not be rejected (all p-values lie between 0.4 and 1, except for the two comparisons with the 'Any-Ref' case for $N = 2$, where $0.09 < p < 0.1$). It is noted that the 'Any-Ref' benchmark (green box plots) by definition includes all 209 electrode pairs from the 'Short' set (black box plot) as well. Therefore, it may seem contradictory that the 'Any-Ref' cases do not have a better performance than the 'Short' cases. This could be due to an overfitting effect, as more channel pairs are available to select from in the 'Any-Ref' case, which may translate in a better optimization of eq. (4), but in a poorer cross-validated AAD accuracy.

IV. Discussion and Conclusions

In this paper, we have simulated a WESN setting in which a multitude of mini-EEG devices are combined to perform an AAD task. We have proposed the group-LASSO procedure to identify the optimal locations to place a pre-defined number of mini-EEG devices on the scalp. We have shown that, when the simulated mini-EEG devices are placed at well-chosen scalp positions, a similar AAD performance can be achieved compared to using an equal number of optimally selected long-distance electrode pairs from a standard EEG cap. This implies that the short electrode distances and the lack of wires across mini-EEG devices, which are often viewed as limitations of WESNs, do not necessarily evoke a performance decrease, i.e., in an AAD setting. This is good news for the use of WESN-like unobtrusive EEG recording platforms for performing AAD in future, e.g., neuro-steered hearing prostheses.

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