A REVIEW OF THE METHOD OF USING THE SCALP ELECTRIC FIELD IN EEG ANALYSIS

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ABSTRACT: This paper reviews a recent method to study electroencephalogram (EEG) data involving a combination of the surface Laplacian and tangential electric field on the scalp. The method was applied to problems in EEG classification, where it was effective in improving results using data from a variety of experiments. The most relevant result was a 13.3% improvement on the average classification rate of a visual perception task involving nine different two-dimensional images. It also improved performance in language-comprehension and mental-imagery tasks.

KEYWORDS: Electroencephalogram; Local filters: Surface Laplacian; Electric field; "EEG regularization

It is a pleasure to contribute to the Foundations of the Mind 2 conference proceedings with a paper presented at the special session in honor of Patrick Suppes (1922-2014). We were both long-term collaborators of Pat, who influenced not only this work, but our own views about nature, science, and the brain. In fact, this work is the continuation of our collaboration, and part of our ongoing research projects with Pat when he passed away. The authors wish to acknowledge his support, mentoring and friendship throughout the years we worked together.

1 INTRODUCTION

The joint use of the electroencephalogram's (EEG) surface Laplacian[1] (SL) and scalp electric fields (SEF) to study brain data was recently introduced by Carvalhaes, de Barros, Perreau-Guimaraes, and Suppes (2014). The basis for this approach is the local relationship between the electric field and current density. According to Ohm's law, the electric field is locally related to the current density, which means that the field's

[1]For a review of the surface Laplacian technique see Carvalhaes and de Barros (2015).

value at a specific position is determined by the current density at that position only, and does not involve values at other locations. The same does not hold for the EEG. In fact, since the electric potential is the negative gradient of the electric field, its value at any position integrates the current density over the entire space (contributing to the ubiquitous blur effect observed on conventional EEG topography). Given that the electric field is also reference free, its analysis carries significant potential for improvement in spatial analysis.

In conventional EEG the scalar potential, obtained from current measurements, is recorded, and not the electric field. Hence, the field components have to be estimated by means of numerical techniques to differentiate the potential distribution along each coordinate axis. However, the field component normal to the scalp surface cannot be obtained this way, because it requires the potential distribution perpendicularly to the scalp surface, which is not available. Based on geometrical and physical observations, Carvalhaes et al. (2014) circumvented this problem by applying the SL derivation to approximate the normal component of the SEF.

Numerical differentiations to estimate the tangential components of the SEF and SL were carried out using spherical splines. One advantage of this procedure is that it provides a regularization mechanism to reduce spatial noise and improve estimates. Additionally, computations can be cast into a linear transformation fashion for efficiency and to facilitate interpretation. The transforming matrix in this case is data-independent and has to be determined only once for each electrode configuration. More details about this procedure and a computer code are available in Carvalhaes et al. (2014)(see also Carvalhaes and Suppes, 2011; Carvalhaes and de Barros, 2015).

The applicability of this technique was evaluated in the context of EEG classification. EEG classification is an important and challenging task in brain computer interface, and can also serve as a tool to infer brain functioning and support theories and models for the brain (Vallabhaneni, Wang, and He, 2005). The main goal in EEG classification is to extract relevant information from labeled trials in EEG and build a model to identify unlabeled trials presented to the same individual. Performance is usually measured in terms of classification rates, which correspond to the percentage of trials that are correctly classified by the model on a test dataset. This work employed a 10-fold cross-validation procedure to compute classification rates, thus generating 10 classification rates that were average to determine the final classification rate of an individual. In the following, it was adopted the abbreviations SL, EF, and SL-EF to stand for surface Laplacian, tangential scalp electric field (only two spatial components), and the combined surface Laplacian and tangential electric field derivation, respectively.

2 EXPERIMENTS AND RESULTS

One of the classification problem on which the SL-EF technique was employed involved the recognition of two-dimensional images exhibited on a computer screen. Seven adults, four males, voluntarily participated in this experiment having the task of recognizing the images while EEG was recorded. The images were a *red circle*, a *green circle*, a *blue circle*, a *red triangle*, a *green triangle*, a *blue triangle*, a *red square*, a *green square*, and a *blue square*. Each image was randomly presented to the participant multiple times. Each presentation lasted 300 milliseconds and was followed by a 700-millisecond period of a blank screen, except for a fixation cross ('+') showed at the center of the screen. The total interval of 1,000 milliseconds locked to image presentation is called a *trial*. Each participant responded to 2700 trials. There was a short break after each block of 20 trials and the participant was able to control the length of the break through a keyboard. EEG data was recorded at 1,000 Hz sampling rate, using a system of 32 electrodes distributed over the back part of the head and referenced to linked ears.

A second experiment involved the recognition of 32 English phonemes, uttered by a male native speaker and presented through a computer speaker. This experiment is explained in detail in Wang, Perreau-Guimaraes, Carvalhaes, and Suppes (2012). Each phoneme consisted of an initial consonant and a following vowel, selected from a group of eight initial consonants and four vowels. The initial consonants were /p/, /t/, /b/, /g/, /f/, /s/, /v/, /z/ and the vowels /a/ (as in c**a**t), /a/ (sp**a**), /i/ (as in m**ee**t), and /u/ (s**oo**n). Pairwise combination of these consonants and vowels formed the 32 phonemes. Four adults, one male, reporting no hearing problem participated in the experiment. The total number of trials changed from a participant to another as follows: 7,168 trials for the first participant, 3,584 for the second, 6,272 for the third, and 4,480 for the forth participant. Each trial lasted 1,000 milliseconds. Due to the large number of trials the experiment was divided into multiple sessions of 896 trials (approximately 15 min). Within each session the experiment was paused after each block of 56 trials and resumed after the participant hit the space key on the computer keyboard. EEG data were recorded at 1,000 Hz sampling rate on a 128-electrode system.

A third application involved a mental imagery task that followed the presentation of visual and auditory stimuli[2]. The visual stimulus was an image of a "stop" sign displayed at the center of a computer screen, whereas the auditory stimulus corresponded to the sound of the English word "go", uttered by a male native speaker of English and presented via computer speaker. Eleven adults voluntarily participated

[2]See Carvalhaes, Perreau-Guimaraes, Grosenick, and Suppes (2009) for more detail.

in this experiment, responding to 600 trials on a single session each, with a regular break after each block of 20 trials. Stimulus presentations were separated by a 2,000-millisecond interval, with the first 1,000 milliseconds been allocated to stimulus presentation and identification. The remaining 1,000 milliseconds were allocated to the mental task that consisted of the participant creating a vivid mental picture of the stimulus that had just been presented or its alternative. That is, if the previous stimulus was the "go" sound, the alternative stimulus was the "stop" sign, and vice versa. The first seven participants were instructed to perform the first task, whereas the other four participants were asked to imagine the alternative stimulus. EEG signals were recorded at 1,000 Hz sampling rate using a 62-electrode system. Only the second half of each trial, corresponding to stimulus imaginations, was analyzed in this study. For convenience, we will refer to this interval as a trial.

The results showed below summarize Tables 1-5 of Carvalhaes et al. (2014). All classifications used temporal features from the waveform, after EEG signal was down sampled at 16:1 ratio. Only the first 500 milliseconds of each trial was used for classification. Classifications were performed using Fisher's linear discriminant analysis (LDA) on individual EEG channels (Perreau Guimaraes, Wong, Uy, Grosenick, and Suppes, 2007). The average classification rate of the best channel across all participants was as follows: 61.9±5.9% (potential), 63.0±10.2% (SL), 70.2±7.1% (EF), and 75.2±6.7% (SL-EF). The rate for correctly classifying trials by chance (*chance level*) of this experiment was 11.1%. Hence, the null hypothesis could be safely rejected for the four waveforms. Clearly, the SL-EF method was the best performing method for this experiment. It also resulted in the highest classification rate for each participant in the experiment.

In the second experiment classifications were carried out in three different ways: (*i*) using the eight initial consonants as labels; (*ii*) using the 32 syllables as labels; and (*iii*) using the four vowels as labels. Chance levels corresponded, respectively, to 12.5%, 3.1%, and 25%. Similar to the first experiment, the method of using the scalar potential resulted in the lowest average classification rates among the four procedures. The rates for the potential were: (*i*) 35.9±7.4%; (*ii*) 10.0±2.5%, and (*iii*) 39.0±1.6%. Therefore, once again the null hypothesis could be rejected at high confidence level. The SL-EF method provided the highest classification rates in all tasks: (*i*) 46.5±12.5%; (*ii*) 14.0±6.7%; and (*iii*) 42.8±3.4%.

The classification rates of the third experiment were also beyond the chance level (50%). Namely, the following average result was obtained across the 11 participants: 82.8±7.3% (potential), 83.7±7.1% (SL), 86.7±6.1% (EF), and 86.4±6.1% (SL-EF). This was, therefore, the only task in which the performance of the SL-EF was not superior to SL and EF methods, although it outperformed the potential.

3 CONCLUSIONS

This work discussed the method of combining the surface Laplacian of EEG and the estimated spatial components of the tangential electric field on the scalp's surface to analyze brain waves. This method was applied in the context of EEG classification, where it demonstrated effectiveness to improve results of five distinct classification tasks, related to visual perception, language comprehension, and mental imagery. This shows that the method can be an effective tool for decomposing interlaced spatial information on the potential waveform, as suggested by theoretical analysis. It is import to remark that the results presented here can be improved significantly, for instance, by increasing electrode density, using magnetic resonance or other technique to reconstruct the scalp surface Babiloni, Babiloni, Carducci, Fattorini, Onorati, and Urbano (1996); Babiloni, Carducci, Babiloni, and Urbano (1998), and applying supplementary technology to determine the realistic electrode locations for accurate estimates of spatial derivatives (He, Lian, and Li, 2001).

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