DOI: 10.3217/978-3-99161-050-2-012

Autoregressive model for artifact detection in finger motor imagery decoding for EEG BCI

L. M. Damm*, D. Jiang, A. Demosthenous
UCL, London, UK;
*UCL Department of Electronic & Electrical Engineering Torrington Place London WC1E 7JE
E-mail: laura.damm.23@ucl.ac.uk

Introduction: Invasive recording mechanisms such as electrocorticography (ECoG) achieve high classification accuracy of motor imagery tasks, even for highly correlated signals as elicited by finger movement. The focus of regaining control over fingers, i.e. post-stroke, is on rehabilitation, not substitution, which makes electroencephalography (EEG) the preferred choice. However, EEG suffers from a low signal-to-noise ratio (SNR), which causes significantly lower classification performance. When considering the low-amplitude neural signal of finger motor imagery in EEG, it is crucial to distinguish between event-related neural activity and event-related noise activity. Channels are referred to as bad channels, where erratic waveforms indicate an artifact-heavy recording. SNR can be increased when those bad channels are interpolated to retain their information. The automatic detection of bad channels has been based on a variety of statistical methods, such as standard deviation. Autoregressive model (AR) assesses a given time series considering probable future values, where significant deviations from these values are treated as artifacts [1].

Material, Methods and Results: The dataset was taken from [2] where 256 EEG channels were applied contralateral to the handedness of each subject, where the left-handed subject (S1) was left out for simplicity. Prior to bad channel detection, a bandpass filter (1-40 Hz) was applied. For a z-score greater than 6, as in [2], channels were determined as bad; for AR a threshold of 3 was applied. Bad channels were interpolated, before common average referencing (CAR) and epoch creation. Features were extracted with five component frequency band common spatial patterns (FBCSP), where one subject (S5) had to be regularised at 0.01 post AR.

Conclusion: The findings in table 1 indicate that AR outperforms z-score in bad channel detection where low SNR is precedent. As subjects 2 and 3 performed similar across AR and z-score, subjects with higher variance and lower average with the z-score methodology improved significantly when applying AR. These findings are congruent with previous research on AR for artifact detection and relevant to the current focus on increasing classification accuracy.

Table 1: Classification parametrics of S2-5 comparing z-score and AR model for artifact detection.

Subject	Method	Acc.(%)	A. Dev.(%)	Prec.(%)	P. Dev.(%)
2	Z-Score	92.4	8.8	94.1	6.9
2	AR	93.5	7.4	94.7	6.1
3	Z-Score	93.7	9.5	94.8	8.2
3	AR	93.3	8.4	95.3	5.6
4	Z-Score	66.1	16.5	75	15.7
4	AR	85.4	12.1	88.9	10.1
5	Z-Score	71.2	16.8	76.3	23.1
5	AR	77.4	16.9	81	16.3

Acknowledgments and Disclosures:
No conflicts of interest occurred. This research was supported by the Engineering and Physical Science Research Council (EPSC), grant EP/ S022139/1 - the Centre for Doctoral Training in Connected Electronic and Photonic Systems.

References:
[1] V. Lawhern, W. D. Hairston, K. McDowell, M. Westerfield, and K. Robbins, “Detection and classification of subject-generated artifacts in EEG signals using autoregressive models,” *Journal of Neuroscience Methods*, vol. 208, no. 2, pp. 181–189, May 2012, doi: 10.1016/j.jneumeth.2012.05.017.

[2] H. S. Lee et al., “Individual finger movement decoding using a novel ultra-high-density electroencephalography-based brain-computer interface system,” Frontiers in Neuroscience, vol. 16, Oct. 2022, doi: 10.3389/fnins.2022.1009878. 1007/s42979-024-02773-w.

Published by Verlag der Technischen Universität Graz