Multi-class Word Imagery Speech BCI Classification by Machine Learning, Operational Architectonics and Complex Networks

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1. INTRODUCTION

Speech imagery of electroencephalographic (EEG)-based Brain Computer Interface (BCI) is significant for people with motor disabilities, illnesses and speech disorders. However, a reliable and efficient performance of these BCI systems depends strongly on the classification accuracy of speech imagery. Therefore, the development of more robust and consistent classification methods is needed for improving communicating imagined speech BCI systems.

2. METHODS

Imagery pronunciation of 3 words ("*out*", "*in*", "*up*", 100 trials each, lasting for 5 sec) was performed by 5 subjects [1]. EEG data sets (publicly available [1]) of 64 electrodes were recorded (10-20 system) and preprocessed (filtered and downsampled). The filtered EEG data of 60 channels (4 rejected containing EOG artifacts) were analyzed based on a novel classification algorithm comprised of "three pillars": a) Operational Architectonics (OA) concept of brain and mind functioning [2]. b) Complex network measures of brain connectivity [3]. c) Machine Learning for developing multi-class classifiers. In particular, the off-line algorithm utilizes OA framework for a non-parametric segmentation of the filtered EEGs through the identification of abrupt jumps in EEG amplitude, called Rapid Transition Processes (RTPs). Subsequently, the time coordinates of RTPs are used to find the number of common RTPs in a trial with pairwise comparison of each filtered EEG. Then, these numbers are used as weights for the generation of weighted complex networks (60 x 60 adjacency matrix), from which 12 measures of brain connectivity are estimated for feature extraction. In the final step, these network metrics, properly normalized, form the feature vectors which are classified by a Naive Bayes classifier used for the prediction of each class. The results show that the overall mean classification accuracies ranged approximately from 53.67% to 66.17% (10-fold cross validation procedure), significantly above chance level (33.33%) in all tested cases.

Selected References

[1] C H Nguyen, G K Karavas and P Artemiadis, Inferring imagined speech using EEG signals: a new approach using Riemannian manifold features. (2018) J. Neural Eng. 15:016002 (16pp).

[2] A A Fingelkurts and A A Fingelkurts, Operational Architectonics Methodology for EEG Analysis: Theory and Results. (2015) Neuromethods 91: 1–59.

[3] M Rubinov, O Sporns, Complex network measures of brain connectivity: Uses and interpretations. (2010) NeuroImage 52(3):1059-1069.

3. RESULTS

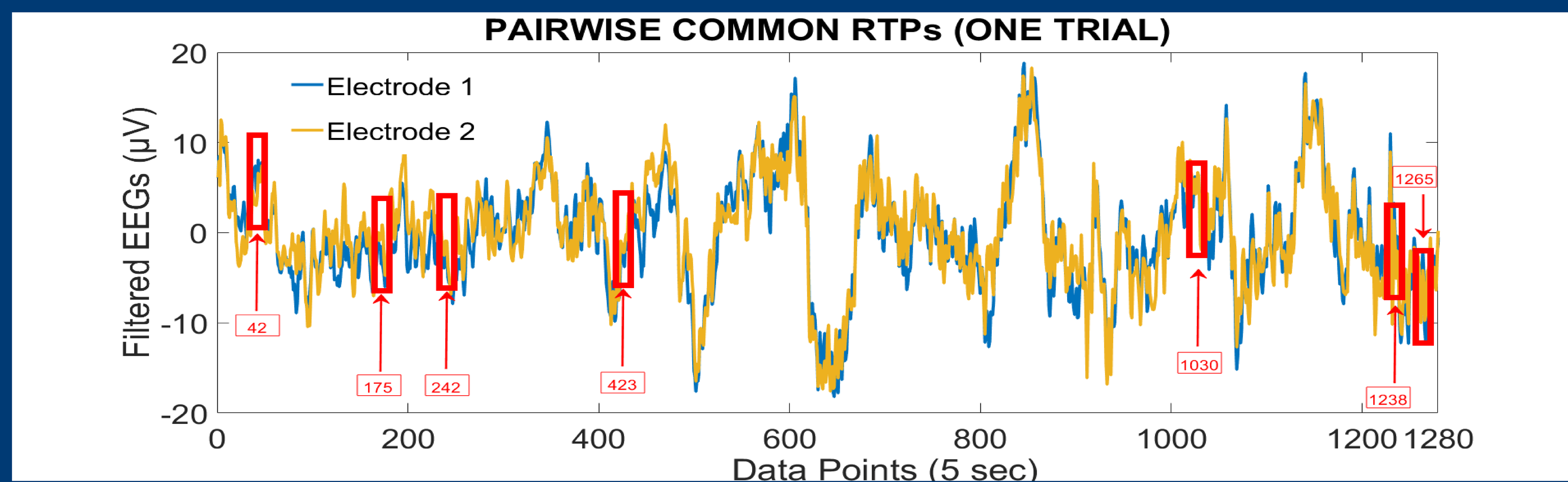

Figure 1. An example of pairwise estimation of common RTPs between 2 electrodes for a trial. In particular, 7 common RTPs were estimated (denoted by red arrows) at times 42, 175, 242, 423, 1030, 1238, 1265.

Table 1 Weighted adjacency matrix estimated for one trial, where the weights denote the common RTPs between the 60 channels.

	C1	C2	C3	C4	…	C60
C1	0	7	4	4	…	5
C2	7	0	6	2	…	3
C3	4	6	0	5	…	6
C4	4	2	5	0	…	7
…	…	…	…	…	…	….
C60	5	3	6	7	…	0

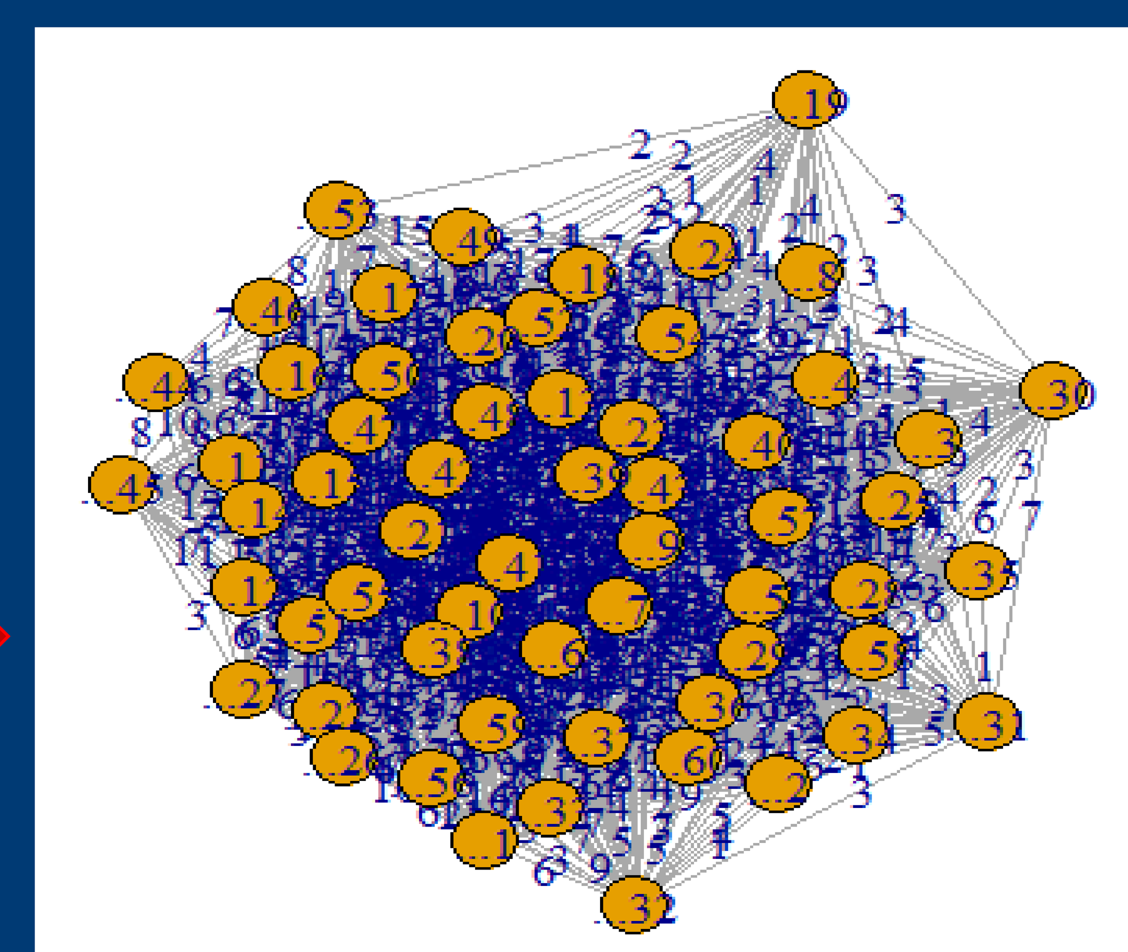

Figure 2. An instance of a weighted complex network generated for one trial. The number on the edges denotes the weights of the adjacency matrix, while the number in the nodes indicate the channels.

Table 2 Five of the 12 Network Features estimated for 3 trials corresponding to different tasks, namely imagery pronunciation of "*out*", "*in*", "*up*".

	Mean Betweeness Centrality	Mean Clustering Coefficient	Mean Degree Centrality	Efficiency	…	Mean Strength
"*out*"	61.0333	4.9495	10.4333	5.09	…	112.8667
"*in*"	80.6861	4.6908	8.5667	4.4490	…	92.1000
"*up*"	42.1278	5.3246	8.6667	3.6418	…	95.2667

Table 3 Overall mean classification accuracies (percentages) for all subjects estimated based on 10-fold cross validation procedure. The maximum accuracy is also shown in parentheses.

SUBJECTS	ACCURACY (%) (Chance Level = 33.33)
1	64.5 ± 7.6 (max = 83.33)
2	53.67 ± 7.7 (max = 66.67)
3	58.167 ± 7.68 (max = 73.33)
4	66.167 ± 9.2 (max = 80)
5	61.5 ± 7.37 (max = 76.67)

4. CONCLUSIONS

This study demonstrates a newly developed classification approach for decoding words during imagined speech production. Classifying imagined speech from EEG data is a difficult task, however, as shown, it is feasible to recognize features which distinguish words from information embedded in the EEG signals, with fairly good accuracies. More applications of the algorithm on new EEG-based BCI data sets are required to verify the aforementioned findings. Notwithstanding, the results are promising and may open a new perspective on the further development of EEG-based BCI systems for communicating imagined speech.