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Letter to the Editor

Comment on 'Rapid acquisition of auditory subcortical steady state responses using multichannel recordings'

There is considerable and increasing interest in obtaining accurate and efficient measures of auditory subcortical steady-state responses (SSSR) via EEG. Bharadwaj and Shinn-Cunningham (2014) proposed in this journal a method to achieve this goal by applying a frequency-domain version of principal component analysis (PCA), termed complex PCA (cPCA; Brillinger, 2001), to multichannel EEG data. They reported that their method reduced the variance of the noise floor when estimating phase locking value (PLV) for the target frequency, relative to both traditional multichannel time-domain PCA and single-channel analysis. This method, along with the code provided by the authors (https://github.com/SNAPsoftware/ANLffr/blob/master/anlffr/spectral.py), has enjoyed widespread use. However, we recently discovered that the implementation produces results that do not correspond with the description provided in the paper. Instead, the published code is functionally equivalent to the more traditional method of calculating the average of the squared single-channel PLVs across all channels. This letter outlines the discrepancies in the original paper and accompanying code that lead to this outcome.

It is generally agreed that the SSSR may have multiple neural generators and that the phases of recorded SSSR are different across channels. The proposed method invoked the use of cPCA to capture and correct for these phase differences by applying eigendecomposition on the normalized cross-spectral density matrix (their Equations 6 and 7) and taking the first eigenvalue as the multi-channel PLV. It is true that previous applications of cPCA (e.g., Venne, 1985) have used the first eigenvalue of the cross-spectral density matrix as the power of the first principal component series. Because the principal component series is a weighted sum of all channels in the spectral domain, and the phases of the complex weights estimated by the eigenvectors compensate for the phase differences across channels, the principal component series estimates the dominant underlying source activation after aligning channel phase. However, the first eigenvalue of the normalized cross-spectral density matrix defined through the PLV or inter-trial coherence (ITC; Delorme and Makeig, 2004) does not represent the PLV or the ITC of the first principal component series. One obvious reason is that the eigenvalues of the normalized cross-spectral density matrix are not bound between 0 and 1. If the eigenvalues are instead divided by the sum of all eigenvalues, the normalized eigenvalues represent the ratio of the power of principal component series and total power, which is not related to the PLV or ITC.

The reason for the apparently improved PLV estimates reported in the original paper is due to a flaw in the code. The function "mtcpca" takes a 3-dimensional array (channel by trial by time) as input and returns a one-dimensional multichannel PLV with frequency labels as output. The Fourier transforms of each trial are averaged to obtain the single-channel PLV stored in vector **C[;,f$_i$]** (line 434 and 437), then the **Csd** matrix is calculated as the outer product of the vector **C[;,f$_i$]** and itself (line 440). Therefore, the rank of **Csd** must be 1. In a typical estimated cross-spectral density matrix, the centered data are first multiplied before averaging, so the matrix rank generally will be the number of variables when the sample size is greater than the number of variables. In contrast, the eigendecomposition of the rank-one matrix **Csd** will give exactly one non-zero pair of an eigenvalue and eigenvector. The eigenvalue will be the sum of the squared magnitudes of all complex elements in the **C[:,f$_i$]** vector, which is simply the sum of squared single-channel PLVs. At line 442, this eigenvalue is divided by the number of channels, making it equal to the mean squared single-channel PLV (Delorme and Makeig, 2004). A proof and demonstration that the output of mtcpca (equivalent to mtcplv in the toolbox) is equal to the average of the squared PLVs across channels is provided at https://github.com/HaoLu-a/cPCA-erratum.

The conclusion that the multichannel PLV proposed by Bharadwaj and Shinn-Cunningham (2014) is the mean squared single-channel PLV, rather than the result of cPCA, is supported by the results shown in their paper. In Panel B of their Fig. 2, only one non-zero eigenvalue was extracted in the spectral domain PCA. This is the expected result of applying PCA to a rank-one matrix, and implies that all variables were perfectly correlated, but would be essentially impossible to achieve otherwise, even with the simulated data used in the paper. In Fig. 3, the phase shift was estimated because the first eigenvector is the average phase across trials for each channel. Similarly, the improvements using real EEG data, shown in Fig. 4 and Fig. 5, represent a reduction in the variance of the estimated PLV noise floor rather than a reduction of the mean level of the noise floor itself, and so are consistent with the expected effect of averaging the squared single-channel PLVs across all 32 channels, although the values shown in the figures seem to represent the root of the mean squared PLV.

Although the procedure proposed by Bharadwaj and Shinn-Cunningham (2014) does not function as desired, there may still be potential gain in solving the problem arising from the different phases of the signal at different EEG channels. One such approach would be to apply eigendecomposition to the regular cross-spectral density and to then convert trials of multichannel EEG into trials of principal component series. The principal component series are weighted sums of multi-channel data in the spectral domain, with phase differences aligned by complex weights, so the principal component series carry most of the power in the raw data. The PLVs calculated from trials of principal component series derived from multichannel SSSR may thus achieve a higher signal-to-noise ratio than simple multichannel averaging. Another approach would be via canonical correlation analysis (CCA), which naturally

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handles the different phases across channels by including both sine and cosine functions in the reference signal (e.g., Nakanishi et al., 2015). Any such approach will require further investigation to determine whether it provides consistent benefits over simple PLV averaging. Given the widespread use of multichannel EEG to obtain auditory SSSR data, the development of tools for signal extraction remains an important goal.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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