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Evaluating Baseline Correction Techniques for EEG Time-Frequency Feature Classification

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ABSTRACT: EEG-based classification is sensitive to preprocessing procedures. Although baseline correction is widely applied in EEG research, its impact on classification performance remains underexplored.
We compared four baseline strategies: (I) amplitude-domain correction, (II) normalized power-domain correction, (III) combined amplitude- and power-domain correction, and (IV) no baseline correction. Analyses were conducted using both an empirical speech imagination dataset and simulated data.
Across both datasets, power-domain baseline correction produced significantly lower classification accuracies than amplitude-domain correction and no baseline correction. The replication of this pattern in simulated data indicates that these differences reflect fundamental signal-processing properties rather than dataset-specific confounds.
These results suggest that baseline correction applied after nonlinear power transformation can distort feature distributions, whereas amplitude-domain correction removes additive offsets prior to nonlinear expansion, thereby preserving more stable variance structures.

INTRODUCTION

Electroencephalogram (EEG) signal processing comprises a multi-stage preprocessing pipeline that can substantially affect downstream machine learning classification performance [1]. Among these stages, baseline correction procedures as well as their concrete positions in the preprocessing sequence received limited attention, despite the potential for nonlinear interactions that may alter feature distributions [1,2]. Different baseline correction procedures have been shown to produce substantially different outcomes [2,3], with some authors even reporting the presence of illusory interactions arising from the usage of inadequate baseline correction techniques [4]. Machine learning algorithms are highly sensitive to preprocessing order and feature normalization, thus, inappropriate sequencing can reduce signal-to-noise ratios and impair model training [5].
One standard feature type commonly used in EEG-BCI research are time-frequency features, which are typically extracted by means of short-time Fourier, Hilbert or wavelet transforms. The resulting estimated band-specific power features are then fed into classifiers (e.g., linear discriminant analysis or support vector machines) to map features to labels [6,7]. Although certain neuroscience subfields, such as event-related potential (ERP) research, commonly adhere to relatively standardized processing pipelines [8], the decision to apply trial-based baseline correction remains a matter of ongoing scientific debate, even within this domain [9,10]. While some authors advocate the usage of baseline correction [1,10] and state that baseline correction can complement high-pass filtering [11], others doubt the usefulness or even warn of adverse results when used in conjunction with high-pass filters [9]. This ambiguity can also be found in the time-frequency feature realm of EEG research, where some authors endorse the application of trial-based baseline correction [2,3,12,13], while others report no usage of baseline correction techniques [14,15]. Variation also exists with respect to the mode of baseline correction: some have adopted the ERP 'standard', performing subtractive pre-stimulus baseline correction in the amplitude-domain [12,13,16,17] followed by power transformation, while others have adopted single-trial spectral baseline correction techniques, which are applied after power transformation of the EEG signal ([2,18–20]). The latter represent techniques for time-frequency feature extraction which were derived from established spectral metrics with integrated baseline correction, such as ERSPs [21] and event-related (de-) synchronization (ERDS) [22]. These measures were originally designed to incorporate baseline correction based on signals averaged across multiple trials but have since been adopted for single-trial application [2,3]. Ultimately, clarifying the optimal arrangement and methods used in the preprocessing pipeline is essential to maximize classification accuracy and to enhance the robustness and generalizability of EEG-based systems across subjects and recording conditions [1–3].
In the current study, we explored the effects that four trial-wise baseline strategies had on classification performance based on EEG-based imagined speech data: I. Subtractive baseline correction based on amplitude signals followed by power transformation. II. Baseline-normalized baseline correction in the power domain [2]. III. A combination of baseline-correction in the amplitude- and the power domain. This version represents a mixture of I and a non-normalized version of II [3]. IV: No baseline correction was applied. One empirical dataset was utilized, made available by Hons and colleagues [12,23]. Secondly, we explored the same

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mechanisms based on simulated data designed to reflect EEG data. We used a normalized approach in II instead of a simple baseline subtraction to keep the number of statistical contrasts to a minimum and thereby not further reduce the power of the analysis.

MATERIALS AND METHODS

Sample The publicly available empirical dataset [23] was collected by the authors and comprised data of 22 participants between the ages of 19 and 37 (M = 25.41, SD = 4.02). All participants were native German speakers, showed no hearing problems and had normal or corrected-to-normal vision.

Experimental design The dataset was recorded during speech imagination: Participants were instructed to imagine speaking one of four different phonemes /a/, /i/, /b/ and /k/. The dataset consisted of 5 second trials, with 1 second baseline intervals. Each block consisted of 20 trials representing only one phoneme. Ultimately, a total of 80 trials were collected for each phoneme.

Data simulation We simulated data of 22 subjects consisting of 10 channels for each frequency band of interest, which were alpha (8-12 Hz), beta (12-30 Hz) and gamma (30-70 Hz). For each of the four classes, 80 trials were created. First, we simulated one sine wave per frequency band by means of the formula in (1). The specific frequency f was drawn for each subject from a uniform distribution limited by the minimal and maximal band frequency.

$$y(t) = A\sin(2\pi ft+\phi) \quad (1)$$

Here, A denotes the amplitude, f denotes frequency, t denotes time points, and ϕ denotes phase. Phase values were randomly drawn from a uniform distribution from 0 to 2π. Subsequently, normalized colored noise was added, such that the power of the noise was proportional to the inverse of the frequency (2), with P denoting power and f denoting frequency.

$$P(f) \propto 1/f \quad (2)$$

To introduce class-specific activity that enables downstream classification of the signals, anchor amplitudes of the produced sine waves systematically differed between classes (Tab. 1). These anchor amplitudes defined the means of a normal distribution with standard deviation of 0.4 from which the actual amplitudes were drawn for each subject independently. The rationale behind this approach was to maintain a level of variation across subjects both in the frequency and amplitude domain.

Table 1: Anchor amplitudes for each frequency band and class

Dataset	Class 1	Class 2	Class 3	Class 4
Alpha	2.2	2.4	2.6	2.8
Beta	1.2	1.4	1.6	1.8
Gamma	0.2	0.4	0.6	0.8

EEG preprocessing The data were processed in Python 3.12 by means of the mne package (version 1.7) [24]. The initial part of the pipeline was only applied to the empirical dataset: the data were re-referenced to the bilateral mastoid averages and were then corrected for ocular artifacts by means of Gratton-Coles regression [25]. Subsequently, the data were visually inspected to mark trials corrupted by motor, technical or residual ocular artifacts for removal. From this point onward, the preprocessing pipeline was applied to the simulated data as well. The data were filtered for the frequency bands of interest, which were alpha (8-12 Hz), beta (12-30 Hz) and gamma (30-70 Hz). Subsequently, the filtered data were epoched. From here, the data were subjected to four different preprocessing subsequences: I. Baseline correction by subtraction of the average baseline value in the amplitude domain $B_{(f)A}$ from all data points t of the trial data $A_{(t,f)}$, and power-transformed (3).

$$P_{(t,f)I} = (A_{(t,f)} - B_{(f)A})^2 \quad (3)$$

II. The power-transformed trial data $P_{(t,f)}$ were baseline corrected by subtraction of the average power value of the baseline interval $B_{(f)P}$ from all data points t, and normalized by the standard deviation of the baseline interval $SD(B_{(f)P})$ [2].

$$P_{(t,f)II} = (P_{(t,f)} - B_{(f)P}) / SD(B_{(f)P}) \quad (4)$$

III. A combination of non-normalized baseline-correction in the amplitude- and the power domain [3]. The initial step is identical to subsequence I. The power-based signal $P_{(t,f)}$ that we derived from employing subsequence I was then baseline corrected again in the power domain by subtracting the mean power-value of the baseline $B_{(f)P}$.

$$P_{(t,f)III} = P_{(t,f)a} - B_{(f)P} \quad (5)$$

IV. The trial data was power transformed without applying baseline correction. Irrespective of the subsequence performed, this resulted in a feature matrix of shape $m*n$, with m being the number of trials and n being the number of channels multiplied by the number of frequency bands.

Table 2: Estimated marginal means of all factorial combinations

Dataset	Baseline correction mode	Estimated marginal mean	*SE*
Empirical	Amplitude	72.01	2.53
Empirical	Power (normalized)	25.60	1.53
Empirical	Combination	28.23	1.31
Empirical	No baseline correction	71.92	2.58
Simulated	Amplitude	72.44	1.22
Simulated	Power (normalized)	23.93	1.21
Simulated	Combination	26.63	1.21
Simulated	No baseline correction	72.51	1.19

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Feature extraction and classification pipeline Final feature matrices consisted of trial-wise averaged band power values. The extracted feature matrices were split into training and test set by a ratio of 80/20 for each subject independently. The data were z-transformed based on a scaler fitted on the training data. For classification a Multilayer Perceptron (MLP) with two hidden layers of sizes 200 and 20 and the corresponding ReLU activation function was employed. The stochastic optimization algorithm 'Adam' [26] was used and the regularization parameter was set to 10^{-4}.

Statistical analysis To test whether the differences between the different baseline correction modes were significant, repeated measures ANOVA was performed for each of the two datasets. Since the sphericity assumption has been violated in both cases, p-values were Greenhouse-Geisser corrected.

Table 3: Statistical results for the contrasts of interest

Dataset	Contrast	*df*	*t-ratio*	*p*
Empirical	Amplitude - Power (normalized)	21	19.12	<0.001
Empirical	Amplitude - Combination	21	16.44	<0.001
Empirical	Amplitude - No baseline correction	21	0.25	0.80
Empirical	Power (normalized) - Combination	21	-1.57	0.26
Empirical	Power (normalized) - No baseline correction	21	-18.47	<0.001
Empirical	Combination - No baseline correction	21	-16.11	<0.001
Simulated	Amplitude - Power (normalized)	21	26.40	<0.001
Simulated	Amplitude - Combination	21	26.95	<0.001
Simulated	Amplitude - No baseline correction	21	-0.33	0.75
Simulated	Power (normalized) - Combination	21	-1.50	0.30
Simulated	Power (normalized) - No baseline correction	21	-26.84	<0.001
Simulated	Combination - No baseline correction	21	-26.64	<0.001

RESULTS

Tab. 2 displays the estimated marginal means of all possible combinations of the tested baseline correction techniques. There was a significant main effect of baseline correction mode for both the empirical ($F_{3, 63}$ = 275.03, p < 0.001; Fig. 1A) and the simulated dataset ($F_{1, 63}$ = 564.42, p < 0.001; Fig. 1B). Regarding both datasets, post-hoc tests (Tab. 3) revealed that amplitude-based baseline correction resulted in significantly higher classification accuracies than normalized power-based baseline correction (Empirical: $t\text{-}ratio_{21}$ = 19.12, p < 0.001, d = 4.08; Simulated: $t\text{-}ratio_{21}$ = 26.40, p < 0.001, d = 5.63) and the combination of amplitude- and power-based baseline correction (Empirical: $t\text{-}ratio_{21}$ = 16.44, p < 0.001, d = 3.51; Simulated: $t\text{-}ratio_{21}$ = 26.95, p < 0.001 d = 5.75). Similarly, applying no baseline correction yielded higher downstream classification accuracy than normalized power-based baseline correction (Empirical: $t\text{-}ratio_{21}$ = 18.47, p < 0.001, d = 3.94; Simulated: $t\text{-}ratio_{21}$ = 26.84, p < 0.001, d = 5.72) and the combination of amplitude- and power-based baseline correction (Empirical: $t\text{-}ratio_{21}$ = 16.11, p < 0.001, d = 3.43; Simulated: $t\text{-}ratio_{21}$ = 26.64, p < 0.001, d = 5.68). All remaining contrasts were insignificant at the significance level α = 0.05.

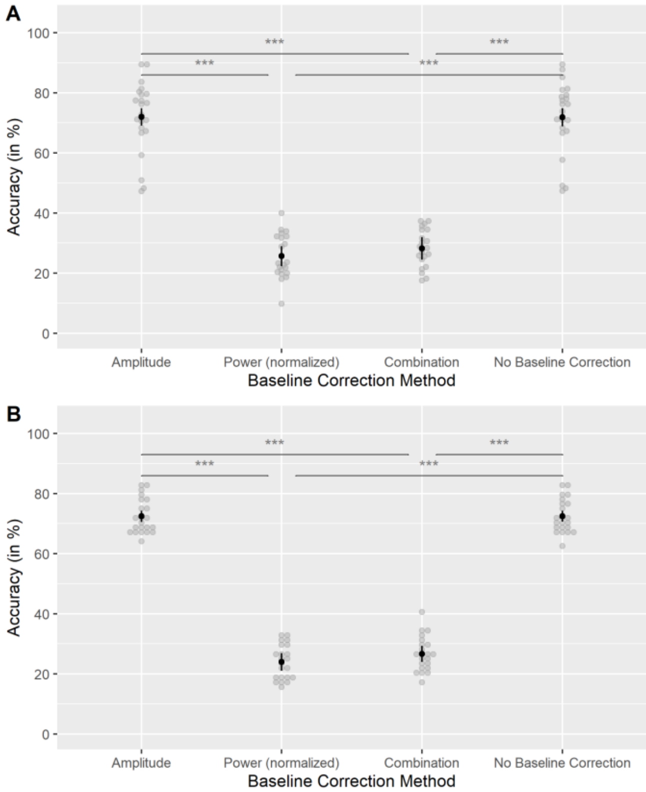

Figure 1: Classification performance of all factorial combinations for **A** the empirical and **B** the simulated dataset. Error margins denote standard errors.

DISCUSSION

The present study examined how different methods of subtractive baseline correction influence classification performance with regards to empirical EEG-based imagined speech data as well as simulated data. Across both datasets, amplitude-based baseline correction yielded higher classification accuracies than alternative approaches in the power-domain. Notably, this superiority extended not only to normalized power-domain baseline correction, but also to the combination amplitude- and power-based correction. When no baseline correction was performed, a similar superiority over baseline corrections in the power domain was

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observed. These findings indicate that the method of baseline normalization constitutes a critical factor of downstream decoding performance.

Nonlinear transformation as a mechanistic explanation A principled explanation for these results lies in the nonlinear transformation of the EEG signal from the amplitude to the power domain. Power is derived from the squared analytic amplitude, thus, any additive offset present at the amplitude level is nonlinearly amplified after squaring. The observation that power-based baseline correction is prone to biases is partially coherent with previous reports: Grandchamp and Delorme [2] found that trial-based normalized subtractive baseline correction in the power-domain led to a positive bias in the averaged ERSP maps compared to alternative procedures, meaning they are disproportionally affected by outliers. Gyurkovics and colleagues [4], on the other hand, showed that divisive baseline correction methods produced illusory interactions in a simulated factorial design, while subtractive baseline correction in the power domain did not. Note that both author groups did not compare their findings to amplitude domain baseline correction.

Baseline correction after power transformation causes residual amplitude-level offsets to be transformed into multiplicative distortions in the power domain. Subtracting a mean baseline from already squared signals does not reverse this nonlinear expansion and potentially culminates in biased feature estimation. In contrast, subtractive correction in the amplitude domain removes additive offsets before nonlinear transformation occurs. As a result, the subsequent squaring operation acts on a signal that is already centred relative to baseline, preserving proportional differences between task-related oscillatory components. The importance of preprocessing order has already been underlined by prior research [1]. The consistently lower performance observed for the combined amplitude–power correction further suggests that baseline correction in the amplitude domain does not stabilize the subsequent power-domain baseline correction. This finding does not cohere with earlier research, in which the application of combined trial-based, subtractive amplitude- and power-domain baseline-correction was shown to be superior to alternative measures, producing no bias in resulting ERD/S maps compared to a trial-based percentage approach [3]. Our results suggest that this reported superiority is not simply transferable to classification tasks.

Non-stationary within session influences EEG recordings are further characterized by slow drifts, 1/f background activity [4], and fluctuations related to vigilance, fatigue [27], and electrode impedance [28]. While slow drifts can be addressed by employing high-pass filters, other signal fluctuations may be more complex and require alternative correction measures, such as baseline correction. When baseline correction is applied exclusively in the power domain, these non-stationary influences may already have been nonlinearly scaled. Consequently, subtractive power-domain correction may insufficiently remove session-specific variation or may alter the variance structure in a way that increases heterogeneity across trials. This is particularly relevant in BCI contexts, where classifiers operate on single-trial data and are sensitive to distributional instability. The simulated dataset provides additional insight into this mechanism. Because the simulated signals consisted of controlled sinusoidal components combined with 1/f noise, the superiority of amplitude-based correction cannot be attributed to unknown cognitive or physiological confounds. Instead, the replication of the empirical pattern in simulated data supports the interpretation that the effect is driven by fundamental signal-processing properties rather than dataset-specific artifacts. Finally, despite the observation that baseline correction in the amplitude-domain did not exhibit better classification performance compared to no baseline correction, the potential influence of non-stationary, within-session confounds, such as changes in mental fatigue and electrode signal quality, may represent a principle-driven argument for the application of baseline correction rather than the omission thereof. Specifically, if intra-session drifts and influences are pronounced and no baseline correction is performed, artificially enhanced classification accuracy might arise [29], impairing model validity and generalizability. This might be especially relevant when data show pronounced levels of noise. Delorme [29], for instance, reported that referencing measures and baseline correction methods decreased the number of significant trials needed for significant results. Furthermore, Xu and colleagues [30], found that mere temporal autocorrelation in the EEG signal sufficed to successfully classify arbitrarily assigned, block-wise class labels in watermelons. Contrary to popular believe that autocorrelations in the EEG are only present in low-frequency components of the signal, the authors demonstrated that artificial decoding performance could be achieved in all frequency bands and despite employing a high-pass filter.

Methodological implications and reporting standards The findings contribute to the ongoing lack of consensus regarding preprocessing standards in time–frequency EEG classification research. While ERP research has converged on relatively standardized amplitude-domain baseline procedures, spectral feature extraction in BCI research remains heterogeneous. The present results suggest that adopting amplitude-domain baseline correction prior to power transformation may represent a principled and empirically supported strategy for oscillatory feature-based decoding.

The issue of reporting transparency is of equal importance. Given that many EEG classification studies do not explicitly describe baseline handling, it is difficult to assess reproducibility or compare results across studies. The large effect sizes observed here demonstrate that baseline strategy alone can substantially influence performance metrics. Therefore, detailed documentation of preprocessing order and baseline correction measures should be considered essential for methodological rigor. If no baseline correction was applied, this should be explicitly stated. The rationale for omitting baseline correction should also be provided, for example, if a sufficiently strong high-pass filter when deliberately used to adequately remove slow drifts and DC offsets.

Limitations and future directions Several limitations should be acknowledged. First, only subtractive baseline correction methods were examined. Alternative approaches—such as divisive normalization [2], decibel conversion [21], regression-based drift removal [11], or adaptive baseline modelling [31]—may interact differently with nonlinear transformations. Second, only one classifier architecture was used. Although multilayer perceptrons are sensitive to distributional properties, future studies should test whether similar effects emerge for linear discriminant analysis, support vector machines, or convolutional neural networks. Third, the paradigm focused on imagined speech; generalization to motor imagery, visual paradigms, or resting-state classification requires further investigation. Future research should additionally examine cross-session transfer performance and online BCI implementations to determine whether amplitude-based baseline correction enhances robustness under realistic deployment conditions.

CONCLUSION

In summary, the present findings show that subtractive baseline correction in the amplitude domain, as well as the omission of baseline correction, resulted in superior downstream classification performance compared to baseline correction applied in the power domain or a combined approach. Under conditions of non-stationary intra-session fluctuations - such as mental fatigue or changes in electrode impedance - amplitude-domain baseline correction may be preferable to omitting baseline correction entirely, as it may enhance model validity and generalizability. Overall, these results emphasize the necessity of accounting for nonlinear signal transformations when designing preprocessing pipelines and demonstrate that preprocessing order is a critical determinant of robustness, validity, and interpretability in EEG-based machine learning applications.

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