ICEEMD based data driven filtering for P300 BCIs

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Introduction: Simple filters can exclude narrow-band higher/lower frequency noises (Urigüen and Garcia-Zapirain, 2015) and remove features of interest in the same frequency band. Empirical Mode Decomposition (EMD) is an adaptive data-driven source decomposition method that separates a source signal into multiple oscillatory modes with instantaneous frequency. EMD has a filter-bank property that decomposes the source signal into intrinsic scales of band-passed signals relevant to numerous applications(Huang et al., 1998; Mandic et al., 2013; Pal et al., 2019). Improved Complete Ensemble Empirical Mode Decomposition (ICEEMD) is suggested to be an enhanced, noise-added method that prevents mode mixing problems present in traditional EMD methods (Colominas et al., 2014; Pal et al., 2019). P300 Event-Related Potentials (ERPs) contain significant contributions from the delta, theta bands, and minor contributions from alpha and lower frequency beta bands (Başar-Eroglu et al., 1992; Labounek et al., 2021). Simple filtering might not capture these contributions, which either omits or obscures the specific oscillatory modes. Therefore, we apply ICEEMD based filtering method for a visual P300 Electroencephalogram (EEG) dataset having healthy and disabled subjects (Hoffmann et al., 2008). We compare the performance improvement of ICEEMD based framework with a Butterworth filter in terms of accuracy and bit rate metrics and provide Matlab scripts for further development. (Link: https://github.com/NeuralLabIITGuwahati/ICEEMD_filter).

Methods and Results: Recorded EEG data at 2048Hz sampling rate was epoched into one-second trials for every subject's four sessions. Single Cz channel was chosen randomly for P300 testing(Sutton et al., 1965; Berlad and Pratt, 1995). Each trial was decomposed into Intrinsic Mode Functions (IMFs) using ICEEMD method (with two hundred iterations of white noise having standard deviation of 0.2). Relevant IMFs in each trial were chosen based on band power with at least 70% in the range of 1-12 Hz. This is similar to the band-power ratio of the Butterworth filter used in (Hoffmann et al., 2008), but with a lower cutoff, to reconstruct the filtered signal. The filtered signal was then down-sampled, windsorized to remove eyeblink artifacts, normalized, and classified using a Bayesian Linear Discrimination Analysis (BLDA) as in (Hoffmann et al., 2008). We present the metrics (accuracy and statistics) for both ICEEMD based framework and a simple filter in Table 1. An increase in performance was observed for healthy subjects, with an average increase in accuracy of 3.3% ($p < 0.01$). Interestingly, the subject with Traumatic Neurological Disorder (TND) showed a better performance of 12% with the ICEEMD algorithm. When tested between two groups without NTND (i.e., healthy subjects and the subject with TND), the one-tailed paired t-test of the comparison between accuracy metrics of simple filtering vs. ICEEMD method showed great significance ($p<0.001$) in this group. The performance of our framework was unsatisfactory for subjects suffering from Non-Traumatic Neurological Disorder (NTND) ($p > 0.5$). These results are further depicted in Figure 1, where the performance metrics of all subjects show a lesser increase in performance than the subjects without NTND for the ICEEMD method. These results seem to indicate that the ICEEMD algorithm performs well when compared to a simple Butterworth filter.

Inference and Conclusion: In this work, we implemented a single channel ICEEMD filter and observed an increase in accuracy and bit rate for all healthy patients. The lower performance in unhealthy subjects may be attributed to the generally low performance of P300 BCIs in neurodegenerative patients (Lazarou et al., 2018) or the intrinsically different nature of ERP related oscillations within ND subjects (Borgheai et al., 2019). The performance increase in healthy subjects seems motivating, while high performance in the TND subject needs to be further confirmed with additional subjects. Hence, we suggest that ICEEMD based filtering can be useful for neuro-ergonomics applications in healthy subjects.

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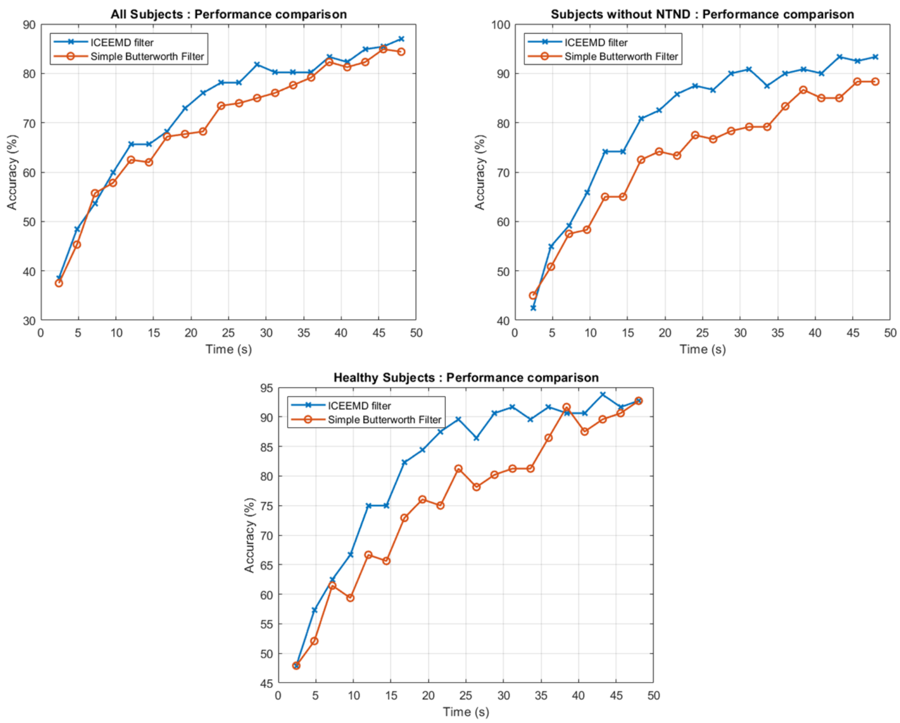

Figure 1. Accuracy vs. time metrics of All subjects (top left), Subjects without NTND (top right) and healthy subjects (bottom)

Subjects	Subject Type	Gender (Age in years)	Correct Predictions using Simple Butterworth filter (Accuracy,%)	Correct predictions using ICEEMD filtering (Accuracy,%)	Paired one tailed t-test of accuracy vectors (p value)
1	Cerebral palsy (NTND)	Male (56)	213 (44%)	215 (44%)	$p > 0.1$ (0.407)
2	Multiple sclerosis (NTND)	Male (51)	317 (66%)	296 (61.6%)	$p > 0.1$ (0.994)
3	Late-stage amyotrophic lateral sclerosis (NTND)	Male (47)	384 (80%)	339 (70.6%)	$p > 0.1$ (1.0)
4	Traumatic brain and spinal-cord injury, C4 level (TND)	Female (33)	306 (64%)	363 (76%)	$p < 0.01$ (5.508×10^{-6})
6	Healthy	Male (30±2.3)	377 (78%)	420 (87%)	$p < 0.01$ (1.337×10^{-5})
7	Healthy	Male (30±2.3)	322 (67%)	329 (68%)	$p < 0.01$ (0.0076)
8	Healthy	Male (30±2.3)	412 (86%)	429 (89%)	$p < 0.01$ (5.431×10^{-4})
9	Healthy	Male (30±2.3)	346 (72%)	376 (78%)	$p < 0.01$ (2.091×10^{-4})
t-test between accuracy vectors of Hoffmans and ICEEMD filtering for subjects without NTND $p = 2.43 \times 10^{-8}$ ($p < 0.0001$)					

Table 1 Accuracies and t-test statistics of the algorithms for the different subjects

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