



A Comparison of ERP Data Cleaning Strategies for Neuroergonomic Error Detection

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The decision to employ postprocessing on electroencephalographic (EEG) data, toward the removal of undesirable artifacts, is associated with concerns of inadvertently filtering brain process data of interest to the research question. The rich data provided by multichannel EEGs supports a variety of postprocessing approaches. Brain process characteristics are often already well-studied^{1,2}, and so the approach often impractical terms involves applying a postprocessing technique, and determining if the aggregate signal representing the brain process of interest matches those previously reported in the literature. However, as increased interest in real-time approaches to characterizing brain processes dominates the applied neuroergonomic literature, it is worth considering the absolute merits of various postprocessing techniques.

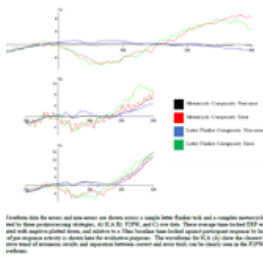
For example, in event related potential/evoked response potential (ERP) work analyzed after collection it is common to utilize independent component analysis (ICA), which relies upon this statistical independence of variance accounted for by artifacts and separates them from variance accounted for by brain activity. ICA techniques, in effect, “clean” the waveform for analysis, preserving epics of interest. This is, however, a relatively computationally “expensive” approach for real-time applications. A relatively simple technique, moving window peak-to-peak amplitude detection (P2PW), uses differences between the highest and lowest voltages within successive epics of time to flag artifacts for removal. P2PW, therefore, does not preserve epics of interest, instead removes them entirely. The present work compares the performance of these two approaches in data collected by Sawyer et al.^{2,3} during an experiment which, for the first time, demonstrated the detection of the error related negativity (ERN) ERP in visual search for complex stimuli. In this work, participants completed tasks during 8 channel EEG recording, which was then analysed using ICA post-processing³. Successfully elicitation and detection of this ERN in visual search of complex images opens the door to applied neuroergonomics ‘in the field’ (as in Fedota & Parasuraman, 2010)^{1,3}. The question of how best to process data “on-the-fly”, however, is relevant specifically because of the context: computation costs power, which is heavy and expensive to carry in the field.

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Figure 1: Waveform data for errors and non-errors are shown across a simple letter flanker task and a complex motorcycle conspicuity task, separated by three postprocessing strategies, A) ICA B) P2PW, and C) raw data. These average time-locked ERP waveforms for are represented with negative plotted down, and relative to a 50ms baseline time-locked against participant response by keypress. A full 100ms of pre response activity is shown here for evaluative purposes. The waveforms for ICA (A) show the clearest ERN pattern, but the negative trend of erroneous results and separation between correct and error trials can be clearly seen in the P2PW (A) and raw data (C) waveforms.



Figure 1



Feedback data for error- and non-error are shown across a single letter flanker task and a complex perceptual and/or time processing strategy. At 0.5 s, ERP, and 0.5 s later. These average time-locked ERP waveforms with negative polarity down, and relative to a 100 ms baseline time-locked average component response to long alpha negative polarity in time from the component. The resolution for 0.5 s (from the original) number of samples (within) and reported between condition and error trials (in the ERP) is

Image 1

Flanker Letter			Motorcycl	
correct	total	error%	correct	inorre
488	6336	7.7%	5942	394
463	5857	7.9%	5427	380
460	5810	7.9%	5349	373
161	3049	5.3%	2946	144
5.1%	7.6%		8.7%	3.6%
5.7%	8.3%		10.0%	5.3%
67%	52%		50%	64%

lata type, by post-processing type.

At times, due to technical failure, EEG data v
v". Data loss percentages are relative to "All"

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Keywords: Electroencephalography, error detection, event related potentials (ERP), Error related negativity (ERN), independent component analysis (ICA), peak to peak amplitude detection

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