Single Trial Multicomponent ERP Estimation via Nonparametric Entropy Minimization

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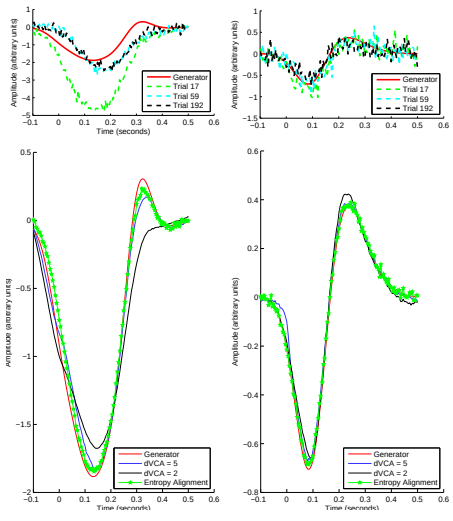
Analysis of Event-Related Potentials (ERPs) recorded during repeated presentations of a sensory stimulus or task performance is critical in domains such as neurophysiology. The measurements are generally modeled as a dynamical interaction between signals that are relatively phase-locked to a specific event onset and signals that are not phase-locked to the event, such as measurement noise or ongoing brain activity. The phase-locked signal may have trial-to-trial variability in amplitude and latency and may in fact be the superposition of multiple components with differential variability in their single trial amplitude scaling factors and latency shifts. Many ignore this fact and resort to extracting the event-related signal as an average across the ensemble of trials (AERP). Recently, models such as differentially Variable Component Analysis (dVCA) [4] have shown promise at accurately determining this phase-locked signal. While dVCA is more realistic than AERP, it sufffers from two shortcomings. First, it requires an *a priori* knowledge of either the number of components within the phase-locked signal or of the ratio between the phase-locked and ongoing process signals. Second, it assumes that the trial-to-trial variability in amplitude and latency is Gaussian.



We propose an unsupervised learning algorithm to extract the phase-locked component as a MAP estimate of the phase-locked component given the set of observed signals[2,3]. The resulting optimization proceeds by minimizing the penalized summed joint entropy across the ensemble of signals in the space of latency and scaling parameters which effect each observation. A software implementation of the proposed algorithm can be found for free at: http://www.eecs.berkeley.edu/˜ramv/EAtoolbox.html [1]. We show the results of the algorithm when compared to dVCA in two instances in the accompanying figure. The underlying signal generator is drawn in red on all plots. Several example sample trials are illustrated in the top two plots, and the results of both alignment procedures are illustrated in the bottom two plots. In the left plots, the signal is generated by five Gaussian components that have variable latencies and scalings that are drawn from a Gaussian distribution. Note, that it looks as if there are only two components. The root mean square error (RMSE) of dVCA with two components is 2.51%, the RMSE of dVCA with five components is 12.1%, and the RMSE of our algorithm is 1.51%. In the right plots, the signal is generated by two Gaussian components that have variable latencies and scalings that are drawn from a uniform distribution. Note that the RMSE of dVCA with two components is 10.63%, the RMSE of dVCA with five components is 7.58%, and the RMSE of our algorithm is 0.63%. Our results show that improved estimates of the phase-locked component can be achieved in a completely unsupervised fashion, without making any parametric assumptions about the underlying signal.

References

[1] Software implementation of algorithm: http://www.eecs.berkeley.edu/˜ramv/EAtoolbox.html

[2] Ahammad et al., Joint Nonparametric Alignment for Analyzing Spatial Gene Expression Patterns of Drosophila Imaginal Discs, CVPR-2005

[3] Ahammad et al., A Framework for Characterization and Comparison of Event Related Neuronal Activity, Technical Report No. UCB/EECS-2006-128

[4] K.H. Knuth et al. Differentially Variable Component Analysis: Identifying Multiple Evoked Components Using Trial-to-Trial Variability, 2006.