

Multi-set Data Analysis and Fusion: Application to SSVEP Detection and Target Identification

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OVERVIEW

The availability of multi-set data, *i.e.*, multiple datasets originating from one or more sensors at different conditions and/or from multiple subjects, enables the exploitation of complimentary information across datasets. However, popular methods to analyze such data suffer from poor performance due to unrealistic assumptions and constrained solution spaces, in addition they ignore potentially informative signal properties, forms of diversity, such as higher order statistics and associations across datasets. We propose to overcome these issues using data-driven techniques including multi-set singular value decomposition (MSVD) [1] and independent vector analysis (IVA) [2] to leverage associations across datasets and, in the case of IVA, leverage diversity using second as well as higher-order statistics [3]. We propose to leverage MSVD and IVA to enhance the detection of steady state visually evoked potentials signals in electroencephalography data using a hybrid approach.

CURRENT RESULTS

SSVEP Detection Using IVA, see references [4] and [5]

The detection of state visually evoked potentials (SSVEPs), a visually evoked signal within electroencephalograph (EEG) data, is of particular interest for brain computer interface systems, as well as many applications in cognitive and clinical neuroscience [6]–[10]. Although SSVEPs have a stable spectrum, their detection is complicated by their low amplitude relative to the recorded EEG, contamination from artifacts arising from muscular activities, movement, as well as the presence of electrodermal, electrovascular, and respiratory signals. Popular methods for the detection of SSVEP are based upon second-order statistical methods, which include power spectral density (PSD) analysis (PSDA), which suffers under low signal to noise ratios [8], and more recently, multi-set canonical correlation analysis based methods [11] which require additional complexity to overcome naturally occurring variations in latency and phase of the induced SSVEP. Since the SSVEP signal is distributed across multiple EEG electrodes, the detection of SSVEPs can be cast in a multi-set framework thus allowing the application of independent vector analysis (IVA) enabling the exploitation of multiple types of diversity—statistical property—such as, second and

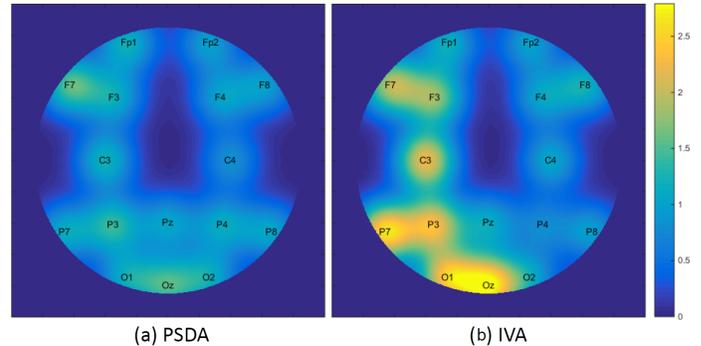


Fig. 1: Topographic maps for an example subject showing unilateral activation in the left hemisphere. The PSDA analysis (a) weakly shows left hemisphere dominance, whereas, the IVA analysis (b) shows significantly stronger left hemisphere activation associated with attention.

higher order statistics as well as dependence across datasets [3]. In this work, we

- Developed a novel framework leveraging the stationarity of SSVEP to re-frame the data as a multi-set problem enabling the use of IVA;
- Showed significant improvement in SSVEP detection with IVA compared to PSDA;
- Demonstrated the applicability of this framework across the range of target frequencies covering the Theta (4–7 Hz), Alpha (8–15 Hz), Beta (16–31 Hz), and Gamma (> 32 Hz) bands;
- Extended the multi-set framework to 16 electrodes across the entire scalp, showing propagation of SSVEP into frontal regions and the presence of hemispheric dominance, indicative of active concentration [12], not found using PSDA, see Figure 1;
- Reformulated temporally constrained IVA (C-IVA) [13] into the PSD domain, thus introducing constrained PSD IVA (CP-IVA);
- Demonstrated that CP-IVA outperforms PSDA, IVA, and C-IVA for SSVEP detection, see Figure 2.

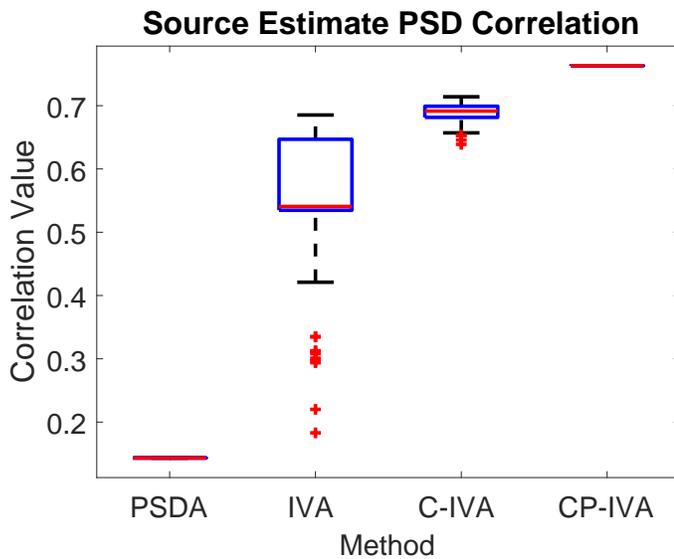


Fig. 2: The average correlation between the true simulated sources and the estimated components for each method is shown in a box-and-whisker plot, where the red-line is the median value. CP-IVA clearly shows superior performance and minimal variance, 10^{-5} , showing improved performance and stability.

FUTURE WORK AND EXPECTED RESULTS

Multi-set Data Analysis Using Second-Order Statistics

Second-order methods, such as principal component analysis, are commonly used on individual datasets to pre-process data for dimension reduction and feature selection prior the application of more advanced techniques. A natural extension for multi-set data is the application of MSVD [1], which simultaneously examines all multi-set data based on second-order statistics, however, currently *ad hoc* methods are used for order and feature selection [14]. Casting MSVD decompositions into an information theoretic (IMSVD) framework is expected to improve mathematical rigor and applicability. In this work, we expect to

- Link the ratio of singular values to Weiner entropy and indirectly to Renyi's entropy;
- Demonstrate the use of entropy measures for de-noising and dimension reduction;
- Study the selection of individual projection directions and their relationship to sources of interest.

Hybrid Approach to Multi-set Data Analysis

In general, IVA suffers from stability issues requiring multiple applications to the same data and methods to determine a "best" run for future analysis, as well as, manual identification of the desired source. These issues do not lend IVA to real world applications. By exploiting the known frequency content of the SSVEPs we can improve the stability and performance of IVA, using CP-IVA. In this work, we expect to show that

- The application of constrained CP-IVA can alleviate issues with convergence and reduce computation time;
- The use of subject specific constraints, as determined by IMSVD, improves performance;
- The use of multiple constraints will alleviate the permutation ambiguity further facilitating the extraction of sources of interest.

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