Reconstructing Cortical Sources by Exploring Sparseness in Multiple Transform Domains

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SPARSE source imaging (SSI) using the L1-norm regularization recently attracts more attentions in solving electroencephalography (EEG) and magnetoencephalography (MEG) inverse problems [1] due to its ability to address the smoothness problem in conventional regularizations using L2-norm [2]. SSI was firstly developed with constraints on the L1-norm of source itself [3, 4] and further extended to transform domains where sparse representation of cortical activities exists [5-7]. In the present study, we developed a novel SSI algorithm by exploring sparseness in multiple transform domains, named as variation and wavelet based sparse source imaging (VW-SSI). The proposed VW-SSI method was evaluated using simulated MEG data and its performance was compared to classic SSI and other SSI methods with single transform, i.e. variation based SSI (V-SSI) [5] and wavelet based SSI (W-SSI) [7]. Given EEG/MEG measurement vector φ and source vector s, VW-SSI method can be mathematically casted as: $\min\|\mathbf{V}s\|_1 + \lambda\|\mathbf{W}_n s\|_1$ *subject to* $\|\varphi - \mathbf{L}s\|_2 < \varepsilon$; where **V** is the variation transform matrix [5] and $\mathbf{W}_n$ is the wavelet transform operator at compression level n [7]. **L** is the lead field. ε is the regularization parameter and λ is a hyper-parameter to balance two L1-norm penalties. Cortical source model and volume conductor model were obtained by segmenting a sample MRI (http://surfer.nmr.mgh.harvard.edu). Monte-Carlo simulations were conducted with 200 randomly located sources and simulated MEG measurements from a 148-channel system. Multiple SSI methods, i.e. classic SSI (in the original source domain), V-SSI, W-SSI as well as VW-SSI, were performed to estimate cortical sources and their performances were assessed using the metric of area under receiver operating characteristic (ROC) curve (AUC). Fig. 1(1) showed that VW-SSI was robust to the selection of hyper-parameters with slightly changes of AUC when $\lambda<0.02$. VW-SSI indicated better performance than W-SSI and less sensitive to compression levels (Fig. 1(2)). Fig. 2 suggested that VW-SSI ($\lambda=0.01$, level 1) had better performance (AUC median>0.8) than the classic SSI (AUC median≈0.5) since it overcame the over-focality problem in the classic SSI using transform sparseness. VW-SSI also showed better performance than W-SSI (level 4) (AUC median≈0.7) due to the combined used of two transforms. It further indicates less variance than V-SSI due to the use of wavelet transform in constraining the global energy in solutions. The simulation study demonstrated advancements of use of multiple transform domains in SSI than the original source domain and single transform domain, making it a promising tool in estimating cortical sources underlying electromagnetic measurements.

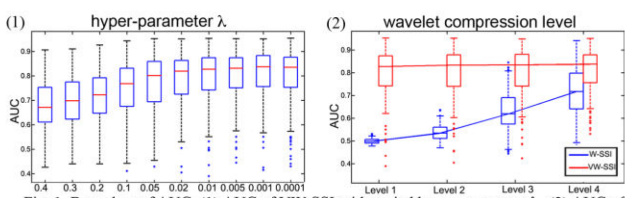

Fig. 1. Box-plots of AUC. (1) AUC of VW-SSI with varied hyper-parameter λ. (2) AUC of W-SSI and VW-SSI with varied wavelet compression levels.

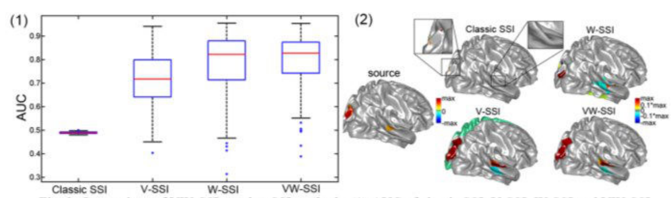

Fig. 2. Comparison of VW-SSI to other SSI methods. (1) AUC of classic SSI, V-SSI, W-SSI and VW-SSI. (2) One example of true and estimated sources.

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This work was supported in part by NSF CAREER ECCS-0955260, OCAST HR09-125S, and DOT-FAA 10-G-008.

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