Bayesian Spatio-temporal Brain Source Imaging using Majorization-Minimization Method and Geodesic Convexity

Ali Hashemi

email: hashemi@math.tu-berlin.de

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Having a deep understanding of the neural network structure of the brain (10^{12} neurons with 10^{15} synaptic connections) and the way that brain works (process 10^{12} Giga-bits of information per second), is a challenging field of research, which is highly motivated by observing the outstanding success of deep learning in real-world applications. One of the ways to achieve these goals is to study the brain activities at a millisecond timescale. Electroencephalography (EEG) brain source imaging technique, which is a non-invasive method that allows one to monitor brain activity with high temporal resolution, is a widely used candidate for analyzing brain signals with favorable timescale.

In the first part of this talk, we will study the forward and inverse mathematical modeling of EEG brain source imaging. Then, we will consider the poor spatial resolution drawback of this imaging technique and review the developed regularization approaches proposed so far in order to tackle this shortcoming.

Due to the existing spatiotemporal correlation between brain sources, the full potential of sparse recovery methods in this field is still to achieve. Therefore, the second part of the talk will be dedicated to model and incorporate the whole spatiotemporal correlation of brain sources as a side information into the recovery method, which finally leads to solving a non-convex optimization method. Then, by utilizing majorization-minimization (MM) techniques, we propose an upper bound for convexifying the loss function and use geodesic convexity concept in order to show the global optimality of the solution. Finally, we will show that the obtained updating rules by incorporating temporal correlation act as an adaptive whitening kernel.

In the last part of the talk, we will also explain about using analysis formulation techniques in order to find the most sparsifying transform for brain signals and how to unfold the proposed sparse recovery techniques to recurrent neural network (RNN) structures.