Abstract

EEG/fMRI fusion algorithms attempt to construct a spatiotemporal estimate of neuronal activity using data gathered from both MRI and EEG modalities. Recent advances in neuroimaging technologies like multi-fMRI [1] do not reduce the importance of the research attempts to devise plausible methodology to combine different functional brain imaging techniques as fMRI and EEG, which often bear coherent and complementary spatio-temporal information [2].

In the most common framework for positing this problem, which we follow, the research community formulates a set of underlying activities from which the data observed in both modalities can be re-constructed with minimal error using adequate forward models for both modalities. Although squared error (ε²) minimization leads to the best estimator in case of Gaussian data noise, absolute error (|ε|) minimization can lead to a more robust solution in the presence of outliers. This fact lead us to develop two somewhat complementary algorithms to obtain desirable solution for ε² and |ε| error norms. To solve |ε| norm problem we present objective function in a form amendable to be minimized by efficient sparse LP solvers which gives us the unique solution. This method makes a number of simplifying assumptions which convert the EEG/fMRI integration problem into optimization of a correct function. |ε| norm solution is obtained through the steepest gradient-descent method. We present results on both artificial data with realistic parametric structure and preliminary analysis of a difficult challenge benchmark for fusion methods more generally.

Introduction to Fusion

Fusion algorithms are employed in an attempt to construct a spatiotemporal estimate of neuronal activity using data gathered from multiple functional brain imaging modalities. Here, the estimate is built by placing a dipole in each voxel of the modality with highest spatial resolution, and estimating the time course of each dipole without constraining dipoles’ orientation. The solution space thus consists of a matrix S of dimension 3 × N, which actually consists of 3 × N T matrixes. Each such sub-matrix corresponds to the projection of the dipole to the specific axis [3].

Fusion of Functional Brain Imaging Modalities using L-Norms Signal Reconstruction

YAROSLAV O. HALCHENKO1, STEPHEN JOSÉ HANSON2, BARAK A. PEARLMUTTER2

1 Psychology Department, Rutgers-Newark, NJ 07102, USA 2 Hamilton Institute, NUI Maynooth, Ireland

Simulation Data

To check the method artificial data was created. Brain volume is simulated as a half-sphere with 9 voxels in diameter of 32mm along x, y, z axes. Single simple sphere model was used to generate gain matrix for EEG 11 sensors distributed across the half-sphere surface. We’ve generated random activation map S consisting of 5 voxels with 600mm interval along x, y and z from the beginning of the timescans (1 voxel per each 0.9ms, 200ms, 400ms and 20 voxels at 600ms after t=0 with the same amplitude but in different locations and with arbitrary orientation. Using this method we have 1150 EEG and 3MRI were constructed through the forward equations. EEG was sampled at 10ps and ITRM at 1ps, so EEG time resolution in the experiment was 10 times higher than slow fMRI. Another goal was to test EEG and MRI without correlation. Gaussian noise with SNR=5dB which due to sparsity constituted equivalently RMS=23%, where the experimental SNR noise was RIR=100%. Error norms. To analyse both datasets, errors were used to define minimization of the sum of absolute values of [10].

Results

Obtained solutions for fMRI SNR > 3dB returned all original activations as 95% highest obtained activations for duration of the experiment with ~90% of energy spread through the rest of the volume. Lowering SNR down to 1dB lead to a stable detection of ~5 activations.

Real Data

The Finger Sequence Benchmark

Most benchmarks for modality fusion often do not rule out solutions using only one modality. In order to create a true test of any fusion algorithm we propose to receive finger tapping sequence in the M1 hand region around central sulcus. Due to the extent that digit somatopy can be spatially resolved by statistical methods [4] or various classifiers, the problem still poses a severe challenge for modalities such as EEG or fMRI along. Recovering finger tapping sequences in faster time resolutions (we used 12 sec, 4 sec and 1 sec) must require more cross signal fusion exploitation from temporally and spatially rich signals. Solutions to this type of problem are nontrivial for any kind of fusion approach.

Results

We report initial attempts using suggested benchmark where subjects tapped in fixed sequences at different time resolutions between digits. Digits were taken against a REST block and in contrast to all pair wise combinations (10). We preprocessed EEG using ICA and found components that were associated with design frequencies so to eliminate unrelated activity from the fusion process.

To label voxel somatopy we used narrow network classifiers, which are known to generate stable topographic mappings in cases of non-linear decision surfaces.

Discussion and Future Work

In the future we plan to apply proposed methods to the challenge benchmark and to validate the fusion algorithm can produce reliable estimates of the rank order sequence of digits in time.

NN Localization vs GLM: Neuroraming data patterns can often require models that are sensitive to higher complexity then linear frameworks such as GLM can provide. Neural networks can be used to identify voxel function even when progressive decision surfaces are graded and nonlinear [3]. Networks that are overparameterized also provide for simple filtering as well as smoothing of target clustered inputs. Most useful in the present hand somatopy problem is their ability to separate near overlapping non-context regions and to smooth fall off from multiple maxima.

Modality Tradeoff:

The presence of the weight factors δ and β and necessity to scale both modalities to find correspondences between their signal levels make proposed method less attractive while no efficient and robust method for such parameters estimation is suggested. Iterative re-estimation can be used as the one of possible approaches to accommodate useful variance of both modalities during fusion process [6].

fMRI Resolution: Although fMRI spatial resolution is quite high in comparison to localization given by EEG/MEG inverse solutions, exploiting haemodynamic nature of the BOLD signal makes it quite hard to discriminate activations in the neighboring voxels. Increased spatial resolution due to selective slice acquisition should improve the results in case when BOLD is well localized, as in the suggested benchmark experiment.

BOLD Variability: fMRI filters must be estimated for each voxel to account for variability of BOLD dynamics within the brain.

Acknowledgements

We would like to thank the McDonnell Foundation for their generous support of RUMBA through grants awarded in 2000 and 2003. RUMBA was also partially funded by the National Science Foundation under Grant No. 0205178.

No opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the McDonnell Foundation or the National Science Foundation.

References