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Editorial

Neuroimaging data including anatomical and functional images have been or are being widely collected from multiple subjects to understand the neural development of neuropsychiatric and neurodegenerative disorders, and normal brains. Based on anatomical images including T1 or T2 magnetic resonance image (MRI), various morphometrical measures are developed to understand the morphology of the cortical and subcortical structures (e.g., hippocampus) for understanding neuroanatomical differences in brain structure across different populations. Based on diffusion tensor images (DTI), various diffusion properties (e.g., fractional anisotropy) and fiber tracts are used for quantitatively assessing the integrity of anatomical connectivity in white matter in a single subject and across different populations. Functional magnetic resonance imaging (fMRI) has been widely used to understand functional segregation and integration of different brain regions in a single subject and across different populations. Since neuroimaging data are extremely high-dimensional and have strong spatial structure, efficiently and optimally modeling neuroimaging data represents both computational and theoretical challenges.

In this special issue, we are very excited to include 10 interesting articles, which represent a wide range of topics within neuroimaging imaging analysis. These papers address problems in fMRI, DTI, positron emission tomography (PET) and MRI and comprehensively cover the wide spectrum of statistical methods in brain imaging research.

We are fortunate to have five papers on functional images including fMRI and PET. Yue, Loh, and Lindquist introduce a novel approach towards spatially smoothing fMRI data based on the use of nonstationary spatial Gaussian Markov random fields. This method can efficiently address the arbitrary choice of smoothing extent in the initial smoothing step and dramatically decrease the numbers of false positives and false negatives in formal statistical analysis. Zhang and Zhang introduce a varying-dimensional model for the Hemodynamic Response Function (HRF), and develop novel regularization methods for estimating the HRF via incorporating the sparsity feature using: the Lasso, the adaptive Lasso and the SCAD. Truong, Bai, Shen, and Huang introduce a novel procedure, called Adaptive Statistical Parametric Mapping, which is capable of adapting itself to any of the existing methods by improving its performance through the application of a penalized smoothing technique. Derado, Bowman, Ely and Kilts propose the use of Moran's I statistic to measure the degree of functional autocorrelation within identified neural processing networks and to evaluate the statistical significance of the observed associations. Ogden and Jiang propose a simple method for assessing the level of heterogeneity within any given ROI along with a procedure for testing a null hypothesis of regional homogeneity that uses a wild bootstrap algorithm. Estimation of outcome measures is accomplished using a mixture modeling approach.

We have two papers on DTI. Chung, Adluru, Lee, Lazar, Lainhart, and Alexander develop a novel cosine series representation for encoding fiber bundles consisting of multiple 3D curves. They also address the issue of registration, averaging and statistical inference on curves in a unified framework. This method is extremely important for carrying out statistical inference on fiber tracts. Clement-Spychala, Couper, Zhu, and Muller systematically examine the statistical properties of two DTI-derived measures including fractional anisotropy and average diffusion coefficient. Of particular interest is that fractional anisotropy (FA) values for given regions of interest are functions of the Geisser-Greenhouse (GG) sphericity estimator. Thus using the approximate distribution eliminates the "curse of dimensionality" for FA values.

We have one paper on MRI. Chi and Muller propose the process of discovering and using scientifically and statistically sufficient statistics to provide a completely successful strategy to overcoming the curse of dimensionality in comparing automatic computer segmentation.

We have two papers on nonparametric methods in neuroimaging analysis. Guo proposes a weighted cluster kernel principal component analysis (PCA) predictive model that addresses the high-dimensional and small sample size challenges in brain imaging data. Hedlin, Caffo, Mahfoud, and Bassett develop a Markov chain Monte Carlo (MCMC) algorithm for conditional permutation testing using propensity scores. It is of great interest and importance to develop advanced data mining methods and nonparametric methods for the analysis of spatially high-dimensional neuroimaging data.

The goal of this special issue is four-fold. First, we hope that this issue will attract more statisticians to develop their strong interest in neuroimaging analysis. Secondly, we hope that this issue will show the importance of using statistical knowledge in developing 'optimal' analytical tools for neuroimaging data. Thirdly, we wish to dedicate this special issue in memory of a great mentor and pioneer, Professor Keith Worsley for his kindness and inspiration to all authors and future statisticians in this great area. Finally, we are sincerely thankful for all authors and reviewers for their hard work.

Hongtu Zhu, Guest Editor
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