Abstract

Computational neuroanatomy utilizes various non-invasive medical imaging modalities such as magnetic resonance imaging (MRI) and diffusion tensor imaging (DTI) in quantifying the spatiotemporal dynamics of neuroanatomical structures and functions. Major challenges are caused by the massive amount of nonstandard, high-dimensional, non-Euclidean imaging data that are difficult to analyze using standard techniques. This requires differential geometric solutions in addressing complex neuroscientific hypotheses. However, many of the existing differential geometric approaches assume topological invariance between shapes and deformations. Such approaches are not applicable for objects with changing or different topology. To address the limitation of existing geometric approaches, we propose a novel topological framework, where topological invariance is not assumed. Our approach embeds imaging data into higher dimension and exploits the hidden topological structures in efficiently solving computationally intractable problems. Although the notion of increasing the dimension of data is totally against the widely popular dimension reduction paradigm in sciences, our topological frameworks will show to increase computational speed, representation efficiency and discrimination power.