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<tr><th>authors</th><td>Hinkle, Jacob</td></tr>
<tr><th>title</th><td>Doctor of Philosophy</td></tr>
<tr><th>publication_date</th><td>2015-12-01 00:00:00</td></tr>
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<tr><th>id</th><td>id-5206450644757267672</td></tr>
<tr><th>abstract</th><td>dissertationThe statistical study of anatomy is one of the primary focuses of medical image analysis. It is well-established that the appropriate mathematical settings for such analyses are Riemannian manifolds and Lie group actions. Statistically defined atlases, in which a mean anatomical image is computed from a collection of static three-dimensional (3D) scans, have become commonplace. Within the past few decades, these efforts, which constitute the field of computational anatomy, have seen great success in enabling quantitative analysis. However, most of the analysis within computational anatomy has focused on collections of static images in population studies. The recent emergence of large-scale longitudinal imaging studies and four-dimensional (4D) imaging technology presents new opportunities for studying dynamic anatomical processes such as motion, growth, and degeneration. In order to make use of this new data, it is imperative that computational anatomy be extended with methods for the statistical analysis of longitudinal and dynamic medical imaging. In this dissertation, the deformable template framework is used for the development of 4D statistical shape analysis, with applications in motion analysis for individualized medicine and the study of growth and disease progression. A new method for estimating organ motion directly from raw imaging data is introduced and tested extensively. Polynomial regression, the staple of curve regression in Euclidean spaces, is extended to the setting of Riemannian manifolds. This polynomial regression framework enables rigorous statistical analysis of longitudinal imaging data. Finally, a new diffeomorphic model of irrotational shape change is presented. This new model presents striking practical advantages over standard diffeomorphic methods, while the study of this new space promises to illuminate aspects of the structure of the diffeomorphism group</td></tr>
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<tr><th>authors</th><td>Singh, Nikhil Pratap</td></tr>
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<tr><th>id</th><td>id-568168145645730241</td></tr>
<tr><th>abstract</th><td>dissertationAn important aspect of medical research is the understanding of anatomy and its relation to function in the human body. For instance, identifying changes in the brain associated with cognitive decline helps in understanding the process of aging and age-related neurological disorders. The field of computational anatomy provides a rich mathematical setting for statistical analysis of complex geometrical structures seen in 3D medical images. At its core, computational anatomy is based on the representation of anatomical shape and its variability as elements of nonflat manifold of diffeomorphisms with an associated Riemannian structure. Although such manifolds effectively represent natural biological variability, intrinsic methods of statistical analysis within these spaces remain deficient at large. This dissertation contributes two critical missing pieces for statistics in diffeomorphisms: (1) multivariate regression models for cross-sectional study of shapes, and (2) generalization of classical Euclidean, mixed-effects models to manifolds for longitudinal studies. These models are based on the principle that statistics on manifold-valued information must respect the intrinsic geometry of that space. The multivariate regression methods provide statistical descriptors of the relationships of anatomy with clinical indicators. The novel theory of hierarchical geodesic models (HGMs) is developed as a natural generalization of hierarchical linear models (HLMs) to describe longitudinal data on curved manifolds. Using a hierarchy of geodesics, the HGMs address the challenge of modeling the shape-data with unbalanced designs typically arising as a result of follow-up medical studies. More generally, this research establishes a mathematical foundation to study dynamics of changes in anatomy and the associated clinical progression with time. This dissertation also provides efficient algorithms that utilize state-of-the-art high performance computing architectures to solve models on large-scale, longitudinal imaging data. These manifold-based methods are applied to predictive modeling of neurological disorders such as Alzheimer's disease. Overall, this dissertation enables clinicians and researchers to better utilize the structural information available in medical images</td></tr>
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