NeuroImage 135 (2016) 152–162

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/ynimg

Multidirectional and Topography-based Dynamic-scale Varifold Representations with Application to Matching Developing Cortical Surfaces

Islem Rekik [a], Gang Li [a], Weili Lin [a], Dinggang Shen [a,b,*]

[a] Department of Radiology and BRIC, University of North Carolina at Chapel Hill, NC 27599, USA
[b] Department of Brain and Cognitive Engineering, Korea University, Seoul 02841, Republic of Korea

ARTICLE INFO

Article history:
Received 19 October 2015
Revised 13 April 2016
Accepted 15 April 2016
Available online 30 April 2016

Keywords:
Multidirectional varifold representation
dynamic scale varifold metric
cortical surface matching
surface topography
surface registration
brain development

ABSTRACT

The human cerebral cortex is marked by great complexity as well as substantial dynamic changes during early postnatal development. To obtain a fairly comprehensive picture of its age-induced and/or disorder-related cortical changes, one needs to match cortical surfaces to one another, while maximizing their *anatomical alignment*. Methods that geodesically shoot surfaces into one another as currents (a distribution of *oriented* normals) and varifolds (a distribution of *non-oriented* normals) provide an elegant Riemannian framework for *generic* surface matching and reliable statistical analysis. However, both conventional current and varifold matching methods have two key limitations. First, they only use the normals of the surface to measure its geometry and guide the warping process, which overlooks the importance of the orientations of the inherently convoluted cortical sulcal and gyral folds. Second, the 'conversion' of a surface into a current or a varifold operates at a *fixed* scale under which geometric surface details will be neglected, which ignores the *dynamic scales* of cortical foldings. To overcome these limitations and improve varifold-based cortical surface registration, we propose two different strategies. The first strategy decomposes each cortical surface into its normal and tangent varifold representations, by integrating principal curvature direction field into the varifold matching framework, thus providing rich information of the orientation of cortical folding and better characterization of the complex cortical geometry. The second strategy explores the informative cortical geometric features to perform a *dynamic-scale* measurement of the cortical surface that depends on the local surface topography (e.g., principal curvature), thereby we introduce the concept of a *topography-based dynamic-scale varifold*. We tested the proposed varifold variants for registering 12 pairs of dynamically developing cortical surfaces from 0 to 6 months of age. Both variants improved the matching accuracy in terms of closeness to the target surface and the goodness of alignment with regional anatomical boundaries, when compared with three state-of-the-art methods: (1) diffeomorphic spectral matching, (2) conventional current-based surface matching, and (3) conventional varifold-based surface matching.

1. Introduction

Studying cerebral cortex development across large-scale imaging datasets stretched the frontiers of our understanding of neurodevelopment and brain disorders (Dubois et al., 2008a,b, 2014; Drobetz et al., 2014; Li et al., 2015; Iyer et al., 2015; Ming et al., 2015; Tremblay & Deschamps, 2015; Shi et al., 2012b; Yan et al., 2015). Notably, these studies require a fundamental step which consists in accurately and meaningfully "linking" these highly convoluted surfaces to one another. This is referred to as *registration* or *matching* in medical image analysis, which founds atlasing, group comparison and statistical analysis of regional growth in a population of subjects. Due to the remarkable convolution and inter-subject variability of cortical foldings, volume-based warping typically produced poorly aligned sulcal and gyral folds (Thompson & Toga, 1996). More sophisticated volume-based cortical registration methods exploited the geometry of the surface and defined local sulcal features to guide the harmonic mapping between cortical hemispheres mapped into a unit square (Joshi et al., 2005, 2007). However, Anticevic *et al.* demonstrated in (Anticevic et al., 2008) the superiority of surface-based registration over volume-based registration for aligning cortical sulci. Indeed, cortical surface-based registration can better align the convoluted and variable cortical folding as it better exploits the topology and topography of the cortex during registration (Essen et al., 2012).

Early leading cortical surface matching tools such as Freesurfer (Fischl et al., 1999) and Spherical Demons (Yeo et al., 2010) were based on geometric features such as cortical curvature and sulcal

* Corresponding author.
E-mail address: dgshen@med.unc.edu (D. Shen).

http://dx.doi.org/10.1016/j.neuroimage.2016.04.037
1053-8119/

depth to drive the warping of spherical surfaces. More recently, a multi-modal surface matching framework was proposed in (Robinson et al., 2014), where they adapt the discrete Markov random field to spherical surface registration, benefitting from multivariate features. However, all these methods (Fischl et al., 1999; Yeo et al., 2010; Robinson et al., 2014) do not directly operate on the cortical surface, as they map each cortical hemisphere onto a sphere and then register them in the spherical space, which inevitably introduces distortion to surface metrics. Recent solutions that target *exact* matching relied on a spectral representation of the geometric properties of the surface, where *smooth* correspondence was generated between spatially smooth low-frequency harmonics (or surface face vibration modes) (Lombaert et al., 2011; Lombaert et al., 2013a). As an extension to this work, Lombaert *et al.* incorporated more local geometric features in an exact surface matching framework, which estimated a *diffeomorphic* correspondence map *via* a simple closest neighbor search in the surface spectral domain (Lombaert et al., 2013b). Its accuracy measured up to the performance of Freesurfer (Fischl et al., 1999) and Spherical Demons (Yeo et al., 2010).

On the other hand, *inexact* surface matching methods based on geodesically shooting one surface into another present a spatially consistent way for both establishing diffeomorphic correspondences between shapes and measuring their dissimilarity. In (Vaillant & Glaunes, 2005; Durrleman et al., 2009), the *current metric* laid groundwork for developing generic diffeomorphic surface registration and regression models without the need to establish the point-to-point surface landmark correspondence on the longitudinal shapes. One of the key strengths of this mathematical model is that it allows to measure the dissimilarity between complex shapes of different dimensions such as distributions of unlabelled points (e.g.,anatomical landmarks), curves (e.g.,fiber tracts) and surfaces (e.g.,cortices); and thereby to *simultaneously and consistently* track local deformations in a set of *multi-dimensional shapes* within the powerful large diffeomorphic deformation metric mapping (LDDMM) framework (Trouvé, 1998; Dupuis & Grenander, 1998). This allows to perform statistics on the surface and its diffeomorphic deformation as diffeomorphisms facilitate further statistical analysis and atlas building (Gori et al., 2013). One drawback of the current-based shape representation model is that it annihilates the sum of two shapes with opposing normals. Recently, Charon *et al.* (Charon & Trouvé, 2013) solved this problem by proposing the use of the *varifold metric* –a variant of the current metric– for matching shapes with inconsistent orientations. Surfaces are encoded as a set of non-oriented normals, which are embedded into a space endowed with the varifold dissimilarity metric. Most importantly, varifold-based shape matching is robustly and easily extendable to multimodal imaging (e.g., white matter fibers (derived from DTI) encoded as 2D varifolds), thus one could effectively embed any shape of any given dimension into a common space of distributions, where they can be deformed, matched and compared (e.g., a set of anatomical shape complexes (Durrleman et al., 2014)). Besides, surface representation as a varifold is robust to mesh imperfections such as holes, spikes, inconsistent orientation or irregular meshing (Durrleman et al., 2014).

However, the conventional varifold matching framework developed in (Charon & Trouvé, 2013; Durrleman et al., 2014) does not consider the principal curvature direction of the deforming surface, whereas this represents a key feature of the convoluted cortical surface as it encodes the local orientation of sulcal and gyral folds that marked previous work on the cortex (Boucher et al., 2009; Li et al., 2010; Boucher et al., 2011). Furthermore, using the conventional varifold metric to measure surfaces and estimate distance between them operates at a *fixed* scale under which geometric surface details (e.g., bumps) will be overlooked, thus ignoring the (spatially-varying) scales of cortical foldings. Indeed, the width of cortical folds and their orientations change during development and diseases as demonstrated in (Boucher et al., 2009; Boucher et al., 2011), hence we refer to the changing cortical scales as 'dynamic' with regard to location in space. Therefore, to better capture the cortical surface geometry, one could integrate the folds *scales* and *orientations* into the measurement metric –which is at the heart of this work. Herein, we propose two different variants to further improve the conventional varifold-based surface matching method introduced in (Charon & Trouvé, 2013; Durrleman et al., 2014). For the first variant, we add a novel *multidirectional* varifold surface representation encoded by its principal curvature direction, which will be combined to its normal varifold representation to solve a variational problem for shape matching. For the second variant, we propose a novel *topography-based dynamic-scale varifold metric* that measures the surface at a *dynamic scale* that spatially varies with the surface topography (e.g.,principal curvature). Finally, we compare the accuracy of the proposed variants for varifold-matching improvement with: (1) diffeomorphic spectral cortical matching (Lombaert et al., 2013b), (2) conventional current-based surface matching (Durrleman et al., 2009), and (3) conventional varifold-based surface matching methods (Charon & Trouvé, 2013; Durrleman et al., 2014) in terms of geometric concordance between target and warped shapes and also the alignment between the boundaries of cortical regions. The proposed varifold variants can also be transferred to current-based matching frameworks. Of note, a preliminary version of this manuscript was presented at MICCAI 2015 (Rekik et al., 2015c). This submission was substantially improved and offers new contributions in the following aspects: (1) introducing the *topography-based dynamic-scale varifold metric*, (2) demonstrating the outperformance of the proposed variants with respect to several state-of-the-art methods, (3) inter-variant performance comparisons, and (4) a more detailed discussion and future directions.

2. Varifold-based surface matching

Geometric measure theory provides powerful tools to build dissimilarity metrics between shapes represented as measures without requiring point-to-point correspondences. More recently, the approach of varifolds was introduced in geometric measure theory and adopted to solve shape matching problems in (Charon & Trouvé, 2013; Durrleman et al., 2014) to overcome orientation issues in current theory (Durrleman et al., 2009). Using measures makes it much more convenient to define metrics without using parametrizations. We first introduce the key ingredients of representing a shape as a varifold and performing pair-wise varifold matching.

2.1. Measuring a surface as a varifold

Measuring a surface S as a varifold is based on embedding the surface space into a Reproducing Kernel Hilbert Space (RKHS) E, where it is encoded using a set of its *nonoriented* unit normals $\overleftrightarrow{n}(x)$ attached at each of its vertices x (Fig. 1). This kernel-based embedding allows to define a proper distance between different embedded surfaces. The nonoriented vectors that encode the surface are defined as elements of the space of non-oriented tangent spaces $G_d(E)$ (Grassman manifold). In the case of surfaces, G_d is defined as the quotient of the unit sphere $\mathbb{S}$ in $\mathbb{R}^3$ by two group elements $\{\pm Id_{\mathbb{R}^3}\}$, where $Id_{\mathbb{R}^3}$ is the space of unit identity 3D vectors. An element $\overleftrightarrow{u}$ in this quotient space G_d(E) belongs to the class of equivalent elements $(u, u/|u|, -u/|u|)$. Any surface is thereby represented as a distribution of non-oriented spaces tangent to each of its vertices and spread out in the embedding space E.

A varifold surface is measured in a similar way that we measure a current surface, except that the reproducing positive Gaussian kernel k_e spanning the space E is *augmented* by a linear continuous a Cauchy-Binet kernel k_t on the Grassman manifold $G_d(E)$, which leads to 'annihilating' the orientation of the normals, thereby producing a nonoriented measurement of the surface (Charon & Trouvé, 2013). In a continuous setting, a varifold is defined as a continuous linear form that integrates