CorticalFlow: A Diffeomorphic Mesh Deformation Module for Cortical Surface Reconstruction

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Abstract

In this paper we introduce CorticalFlow, a new geometric deep-learning model that, given a 3-dimensional image, learns to deform a reference template towards a targeted object. To conserve the template mesh’s topological properties, we train our model over a set of diffeomorphic transformations. This new implementation of a flow Ordinary Differential Equation (ODE) framework benefits from a small GPU memory footprint, allowing the generation of surfaces with several hundred thousand vertices. To reduce topological errors introduced by its discrete resolution, we derive numeric conditions which improve the manifoldness of the predicted triangle mesh. To exhibit the utility of CorticalFlow, we demonstrate its performance for the challenging task of brain cortical surface reconstruction. In contrast to current state-of-the-art, CorticalFlow produces superior surfaces while reducing the computation time from nine and a half minutes to one second. More significantly, CorticalFlow enforces the generation of anatomically plausible surfaces; the absence of which has been a major impediment restricting the clinical relevance of such surface reconstruction methods.

1 Introduction

The field of 3D shape reconstruction using deep learning techniques has attracted much attention. Recently, a plethora of methods have been developed for problems such as single-view object reconstruction [22, 53, 81], surface generation [27, 78], and meshing noisy point clouds [32, 43]. At first, these methods solely aimed to retrieve surface meshes as geometrically close as possible to the target shape. However, recent applications require generating regular meshes with a known genus, such as physics simulation, 3D-printing, and clinical analysis of anatomical surfaces [24, 62, 66].

In this direction, three approaches in the literature stand out: DeepCSR [65], Voxel2Mesh [77], and Neural Mesh Flow (NMF) [30]. DeepCSR first predicts implicit surface functions and then employs an iso-surface extraction method along with a topology correction algorithm to obtain genus-zero surfaces without handles or holes. Voxel2Mesh extends the vertex-wise template deformation approach of Wang et al. [75] by optimizing several mesh-smoothing penalty functions. In contrast, NMF builds an invertible mapping that enforces topology conservation upon the resolution of an Ordinary Differential Equation (ODE) through a sequence of residual blocks called Neural Ordinary Differential Equation (NODE) [9]. However, these methods come with several limitations. The topology correction algorithm employed by DeepCSR is computationally expensive and is blind

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Check our project web-page [https://lebrat.github.io/CorticalFlow/]

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towards the anatomical validity of its reconstructions, which can result in implausible corrections
and mesh artifacts. On the other hand, Vox2Mesh and NMF rely on time-demanding and vertex-
dependent building blocks such as graph convolution that do not scale up well as the number of
vertices in the template mesh increases to accommodate complex shapes. In addition, the dynamics
learned by the NODE model in NMF can be very complex and may lead to a non-diffeomorphic
mapping resulting in self-intersections in the reconstructed mesh.

This paper introduces CorticalFlow (CF), a new geometric deep learning model that smoothly
deforms a template mesh towards complex shapes producing high-resolution regular meshes. First,
a simple 3D convolution neural network predicts a dense 3D flow field from a volumetric image
with a modest GPU memory footprint. Second, we formulate a tractable mathematical framework
to compute diffeomorphic mapping for each vertex by solving a flow ODE. We derive sufficient
and comprehensible conditions for meeting the diffeomorphic properties of these transformations.
Finally, a sequence of these diffeomorphic mappings is composed to produce accurate high-resolution
genus-zero regular meshes.

To evaluate our approach and compare it to existing techniques for regular surface reconstruction, we
consider the problem of brain cortical surface reconstruction, which is an essential step for the analysis
of brain morphometry in neurodegenerative diseases [18] and psychological disorders [61]. Given a
3D MRI of the brain, the goal is to describe the inner and outer surfaces of the brain cortex, which are
both homeomorphic to a sphere. Cortical surface reconstruction is challenging given the complexity,
high resolution, and regularity required for the predicted meshes. In our experiments, CorticalFlow is
more accurate than state-of-the-art methods, providing an average reduction of 17.38% in Chamfer
distance across all cortical surfaces compared to DeepCSR (the second-best performing method
in this criteria). In terms of surface regularity, it surpasses NMF or Vox2Mesh with an average
reduction of at least 32.58% of self-intersecting faces while handling template meshes with many
more vertices. It is also faster and more memory-efficient than all of these competitors.

2 Related Works

2.1 Geometric deep learning for surface reconstruction

Supervised surface reconstruction can be broadly categorized according to the 3D shape representation
used to encode the prediction as either volumetric, implicit surfaces representation, novel geometric
primitives, or geometric [22].

Volumetric methods predict shapes encoded as a 3D grid of voxels containing discretized surface
representations such as occupancy [11] and level-sets [48]. From this representation, surfaces are
obtained using iso-surface extraction methods, such as marching cubes [42]. While 3D volumetric
processing is amenable to a convolutional neural network, the memory requirements are often a
limitation to attain high-resolution reconstructions (it grows cubically with the voxel-grid resolution).
To overcome this issue, approaches based on octrees [35, 72, 76] have been proposed to increase the
output resolution from a voxel-grid of $32^3$ to $256^3$. Unfortunately, these approaches sacrifice speed
and necessitate the redefinition of standard network operations such as convolution, pooling, and
unpooling for this hierarchical data structure. Furthermore, as presented in [65], even at this level of
resolution, the precision is too coarse to capture the highly curved regions of the cortical surfaces.

Implicit surface methods alleviate resolution limitations of the volumetric methods by directly predicting
surface representations like occupancy [47], signed distance [57, 79], and 3D Gaussians [26]
for points with continuous coordinates. This formulation allows synthesizing grids at an arbitrary
resolution during inference with an easily implementable local refinement procedure, while training is
performed stochastically over a small subset of sampled points. Following this approach, Santa Cruz
et al. [65] proposed DeepCSR, the first geometric deep learning model for cortical surface reconstruction.
Its main limitation is the difficulty to control the topology and mesh quality of the reconstructed
surfaces, which hampers atrophy estimation used for neurodegenerative disease diagnosis [24, 62, 66].
As a result, DeepCSR resorts to a computationally expensive topology correction algorithm to produce
a final cortical surface almost free of artifacts and with a spherical topology.

Methods based on geometric primitives build a surface representation to approximate complex shapes
as the union of these primitives. In this category, we can highlight the works of Niu et al. [54]
and Groueix et al. [28] which propose to approximate complex object shapes with a collection of
“cuboids” or “surface patches”. Recent works by [10,17] revisit the convex decomposition idea and propose to reconstruct complex object shapes by predicting collections of convex parts. The former predicts a set of localized convex polytopes formed by their hyperplane parameters and a translation vector, while the latter predicts a binary space partitioning tree to reconstruct the target shape. While very promising in terms of information compactness, these approaches are challenged to generate cortical surfaces due to their varied curvatures, which require a large number of convex parts to produce accurate results.

Finally, geometric methods comprise techniques that allow estimating a high-resolution mesh by transforming a known template mesh [55,56,69,75]. Following this approach, Wang et al. [75] propose a graph-convolution network to predict vertex-wise deformations of a spherical mesh while dynamically increasing its resolution with a point pooling process. Wickramasinghe et al. [77] extended this model for the reconstruction of smooth anatomical surfaces such as the liver or hippocampus for different image modalities. Topological errors are reduced using three different penalty functions in the loss function. Recently, Gupta and Chandraker [30] leverage NODE blocks [9] to parameterize regular deformations that allow conserving the two-manifoldness property of the input template.

Indeed, the "manifoldness" measures as non-manifold edges or non-manifold vertices, and defined by Gupta and Chandraker [30], are conserved by a deformable model which is not generating new vertices since those properties are inherited from the template mesh (only the vertices’ positions are affected). However, the normal consistency (non-manifold faces) is only conserved by homeomorphisms which can at most flip globally the faces’ normal orientation.

2.2 Generation of diffeomorphic mappings

The reconstruction of regular surfaces from a deformable model is a subtle trade off between finding the right parameterization or a suitable level of regularization during training. The delicacy of this problem is illustrated in Figure 1. First, one can employ multiple penalty functions as Chamfer normal, normal consistency, Laplacian loss, or edge length loss [75,77]. It is worth mentioning that without such penalizations, a deformable model will learn non-smooth deformations, which leads to irregular meshes (as shown in Figure 1.c). However, those penalizations simply encourage the reconstructed surface to be regular. The second approach consists of parameterizing the set of learned deformations; this approach is favored in our paper since it allows stronger theoretical guarantees and is not subject to hyper-parameter tuning. A natural framework to generate invertible deformations is to consider a flow ODE [20,73]. This framework has been successfully applied in pattern recognition and image registration [2,3,7,19]. The main idea is to consider the mapping as the solution at time $\tau$ of an initial value problem (IVP) of the form,

$$\frac{d\Phi(s; x)}{ds} = v(\Phi(s; x), s), \text{ with } \Phi(0; x) = x,$$

under a regularity hypothesis on $v$ and upon boundedness of its support, and using the Picard-Lidelöf theorem, one can show that a unique solution of this problem exists for $\tau \in \mathbb{R}$. In addition, the mapping $x \mapsto \Phi(s; x)$ defines a family of diffeomorphisms [1,6] for all time $s \in [0, \tau]$ whose inverse can be computed through a backward integration.

When the vector field $v$ is constant over time i.e. $v : \mathbb{R}^3 \to \mathbb{R}^3$, Equation (1) describes the Stationary Velocity Field (SVF) framework [1,3]. If $v$ is a time-varying vector field, the framework described in [1] becomes the LDDMM model [5,8,68,74].
This generic framework has been successfully applied within deep learning methods for diffeomorphic image registration \[15, 50\], point-cloud completion \[52\], single view reconstruction \[30\] and to parameterize set of deformations \[37\].

The SVF formulation has been particularly fecund in medical deep-learning registration \[15, 41, 50, 80\], where the resolution of Equation (1), is performed using the scaling and squaring method \[2, 3\] to predict the displacement of each voxel-center and to compute the registered image. However, this technique is not suitable for points that lie on non-regular coordinates. Naively, one can compute these mappings on a dense grid and then interpolate the deformation at non-regular coordinates. This simple approach is subject to two main limitations. Firstly, Equation (1) has to be solved in our context for millions of grid points where only a few hundred thousand vertices are displaced. Secondly, one cannot guarantee the invertibility of such a mapping with linear interpolation and one cannot compose provably several of those approximated mappings.

In \[30, 52\], the problem is solved using a black-box neural ODE \[9\] and by learning a neural vector field \(v\). Despite allowing learning a time-dependent vector field, this approach has shown its limitations in our targeted application. Cortical surfaces are unique to each individual; indeed, the cortical folding patterns are similar to a fingerprint \[45\] and constitute a distinctive biometric for each individual. Moreover, we observe that the classical approach, which consists of conditioning the neural ODE on a global feature descriptor of the input image, fails to provide satisfactory results for cortical surface reconstruction (see Figure 1.b. and the supplementary material). Instead, one has to equip each moving vertex with a local feature descriptor of the input image, limiting the number of vertices of the resulting mesh.

Our work lies at the intersection of these methods. We propose to extend the SVF framework for points lying in real-coordinates, with particular care given to the numerical affordability of the ODE solver. We define a multi-scale approach, so that the final deformation is the result of the composition of three successive deformations that allow to approach more complex mappings and alleviate the limitations of the one vector field SVF framework \[23, 44\]. This framework is memory efficient, theoretically tractable, and can seamlessly handle large template meshes (\(\approx 450k\) vertices).

### 3 Method

CorticalFlow (CF) is a multi-level deep learning architecture composed of several Diffeomorphic Mesh Deformation (DMD) modules. It takes as input a 3-dimensional Magnetic Resonance Image (MRI) of a patient brain denoted \(I\) (tensor of dimensions \(H \times W \times D\)) and a template \(T_i\) (where \(i\) represents the degree of refinement of the template). CorticalFlow outputs the surface representation of an anatomical substructure by composing stackable diffeomorphic deformations generated by DMD modules. CorticalFlow with \(k\) deformations (CF\(^k\)) can be written using the following recurrence,

\[
\begin{align*}
\text{CF}^{\theta_{i}}_{\theta_{i}}(I, T_{i}) &= \text{DMD}(\text{UNet}_{\theta_{i}}^{1}(I), T_{i}) \\
\text{CF}^{i+1}_{\theta_{i+1}}(I, T_{i+1}) &= \text{DMD}(\text{UNet}_{\theta_{i+1}}^{i+1}(U_{1} \cdots U_{i} \cdots I), \text{CF}_{i}(I, T_{i+1})) \quad \text{for} \ i \geq 1,
\end{align*}
\]

with \(\Lambda \odot B\) the channel-wise concatenation of the tensors \(A\) and \(B\) and where \(U_{k}\) denotes the output of the \(k\)-th UNet\(^{k}\) parameterized by \(\theta_{k}\).

In our paper we describe CF\(^3\), a version of CorticalFlow with three stages where each stage is learned successively. CorticalFlow is trained in a supervised fashion, given a dataset \(D\) composed of pairs of MR-image \(I\) and triangle mesh \(S\) representing a cortical structure and for \(i \in \{1, 2, 3\}\) we optimize the following objective,

\[
\arg \min_{\theta_{i}} \sum_{(I, S) \in D} \mathcal{L}(\text{CF}^{\theta_{i}}_{\theta_{i}}(I, T_{i}), S).
\]

As training loss \(\mathcal{L}(\cdot, \cdot)\), we minimize the mesh edge loss and Chamfer distance computed on point clouds of 150k points sampled from the predicted and ground-truth surfaces using random uniform sampling. The implementation of these losses and sampling algorithm are provided in the PyTorch3D library \[60\].
3.1 DMD Diffeomorphic Mesh Deformation module

The introduction of a Diffeomorphic Mesh Deformation module (DMD) is driven by the following classification of surfaces in 3 dimensions:

**Theorem 3.1.** Suppose that \( B \) is a smooth closed manifold of dimension 2 embedded in \( \mathbb{R}^3 \). Suppose that \( \Phi : [0, \tau] \times \mathbb{R}^3 \rightarrow \mathbb{R}^3 \) is a family of homeomorphisms (continuous map such that for each \( t \), the mapping \( x \mapsto \Phi(t,x) \) is bijective with continuous inverse), with \( \Phi(0; x) = x \). Then, for each \( t \), the homotopy classes of \( B \) and \( \Phi_\star B(t) = \{ \Phi(t,y), y \in B \} \) are the same.

This theorem means that if \( B \) is a sphere, the surface \( \Phi_\star B(t) \) is of genus 0 with no self-intersection.

Existence and uniqueness of a solution to the continuous problem

The DMD generation of diffeomorphic mapping relies on the resolution of a continuous flow ODE. For that purpose, let \( v : x \in \Omega \mapsto v(x) \in \mathbb{R}^3 \) be a constant over time vector field supported on the MRI space \( \Omega \) and obtained by tri-linear interpolation of a feature map \( U \in \mathbb{R}^{H \times W \times D \times 3} \). Suppose that \( v = 0 \) on \( \partial \Omega \). The image origin is denoted by \( O = (o_1, o_2, o_3) \) and denote by \( d_i \) the interpolation spacing in the \( i \)-th direction such that \( \Omega = [o_1, o_1 + d_1(H - 1)] \times [o_2, o_2 + d_2(W - 1)] \times [o_3, o_3 + d_3(D - 1)] \).

**Theorem 3.2.** Existence and uniqueness of the solution. Define \( \Phi \) through the autonomous ODE,

\[
\frac{d\Phi(s; x)}{ds} = v(\Phi(s; x)), \quad \text{with } \Phi(0; x) = x.
\]  

Then \( \Phi \) is uniquely defined on \( \mathbb{R} \times \Omega \) is Lipschitz and for each \( t \), the mapping \( x \mapsto \Phi(t, x) \) is bijective with Lipschitz inverse. The proof of this result can be found in the supplementary material.

Being Lipschitz is more difficult to achieve than being merely continuous. Less formally, Theorem 3.2 ensures that if \( B \) is smooth, then for all \( t \), the surface \( \Phi_\star B(t) \) may, in the worst case, have kinks. If \( \Phi \) is only continuous and not Lipschitz, then the surface \( \Phi_\star B(t) \) might have cusps that are more irregular than kinks. Note as well that the choice of the interpolation technique used to generate \( v \) is pivotal since it drives the regularity of the right-hand side of Equation (5). Indeed, \( v \) Lipschitz’s constant boundedness allows the definition of a solution to the continuous problem. More importantly, and as described in the next section, it rules the step-size to use for obtaining a stable numeric method.

Numerical resolution of ODE

The DMD module solves for each vertices’ position a flow ODE defined in Equation (5), defined by \( \Psi \) the numeric approximation of \( \Phi \) by an explicit forward method, the invertibility of this discretisation is given by the following theorem

**Theorem 3.3.** Let \( v \) be \( L \)-Lipschitz. Define \( \Psi \) as the Forward Euler approximation,

\[
\Psi(h, x) = x + hv(x).
\]  

\( \Psi \) is a Lipschitz homeomorphism for each \( h < L^{-1} \).

As a result, in combination with Theorem 3.2, the surface \( \Psi_\star B(h) \) is smooth as long as \( hL < 1 \). We note that the stability condition \( hL < 1 \) is commonly used in Computational Fluid Dynamics. Less formally, this estimate tells us that the less regular (high gradient) \( v \) is, the smaller the integration step should be chosen.

**Proof.** Let \( h < L^{-1} \) and denote \( f : x \mapsto x + hv(x) \). Then \( f \) is a Lipschitz mapping and it is sufficient to prove the bijectivity of \( f \). The injectivity stems from, for all \( x \neq y \),

\[
\|f(x) - f(y)\| \geq \|x - y\| - h\|v(x) - v(y)\| \geq \|x - y\| (1 - hL) > 0.
\]

The surjectivity comes from the fact that for each \( y \), the mapping \( g : x \mapsto y - hv(x) \) is \( hL \)-Lipschitz with \( hL < 1 \), hence is a contraction. By a fixed point theorem, \( g \) admits a unique \( x^* \) solution to \( g(x^*) = x^* \), or equivalently \( y = f(x^*) \). Hence, \( f \) is surjective. \( \square \)
Following the notations of Equation (2), $\text{UNet}_{\theta_1}^4$ implements a $\text{UNet}$ layer and $\text{UNet}_{\theta_2}^2$, $\text{UNet}_{\theta_3}^3$ implements a $\text{UNet}$ layer. The architecture of $\text{UNet}_4$ and $\text{UNet}_2$ are described in the supplementary materials.

\begin{algorithm}[H]
\caption{DMD module pseudo-code}
\begin{algorithmic}
\State \textbf{Input}: $U \in \mathbb{R}^{H \times W \times D \times 3}$ $\triangleright$ Discrete flow
\State \textbf{Input}: $T$ with vertices $(V_i)_{i \in 1..m}$ $\triangleright$ Triangle mesh
\State \textbf{Input}: $n \in \mathbb{N}^*$ $\triangleright$ Number of integration steps
\State \textbf{Output}: Updated $(V_i)_{i \in 1..m}$
\State $h \leftarrow \frac{1}{n}$
\For{$i \in [1, m]$}
\For{$j \in [1, n]$}
\State $V_i \leftarrow \Psi(h, V_i)$
\EndFor
\EndFor
\end{algorithmic}
\end{algorithm}

Notwithstanding this limitation, we use the rule of thumb $hL \leq 1$, and check that for all considered examples, and we have $hL \leq 1$.

### 3.2 Network architecture

As shown in Figure 2, CorticalFlow consists of a chain of three deformations. Note that more deformation modules could be used, but we focus on three modules to have a fair comparison with existing techniques. The first deformation module receives as input a volumetric image and outputs a flow vector field with the same dimensions using $\text{UNet-3D}$ [63]. This discrete flow vector field is integrated by the DMD module to compute smooth deformations as explained in Section 3.1. The subsequent $\text{UNet-3D}$ receives as input the image and the flow vector fields predicted by the previous deformation modules. The set of resulting mappings are composed to produce the final mesh.

For training CorticalFlow, we adopted a sequential approach where we train one deformation module at a time while freezing the weights of the others. We train the first deformation with a low-resolution template ($T_1$) of 30k vertices and a $\text{UNet-3D}$ architecture with four down/up-sampling levels. To train the second and third deformations, we increase the resolution of the template mesh to 135k and 435k vertices, for $T_2$ and $T_3$ respectively, and reduce the $\text{UNet-3D}$ down/up-sampling levels to two. These networks are respectively labeled as $\text{UNet}_4$ and $\text{UNet}_2$ in Figure 2 while their layer details are described in our supplementary material. The choice of the architecture depth is motivated by the numerical conditions on the integration step-size derived in Section 3.1.

To verify the conditions of Theorem 3.3, it is essential to mention the use of template meshes with different resolutions and different $\text{UNet}$ architectures. Indeed, the first block has to provide a large deformation resulting in a high $\|v\|$. To keep the Lipschitz constant $L$ small, one observes that the use of a low-resolution template with 30k vertices along with a deeper convolutional architecture forces the $\text{UNet}$ to recover only coarse details and thus produces a flow vector field with a small $\nabla v$. During the second and third deformation, more details and higher resolution folds can be learned,
with templates composed of 135k and 435k vertices, respectively (see the ablation study presented in Section 1.1 of our supplementary material). We empirically verify that this hierarchy of deformations was beneficial for producing a flow vector field with a small Lipschitz constant. This multi-step approach allows attaining up to 14.5 times less self-intersection in comparison with Neural Mesh Flow (see Table 1).

To generate the template mesh, we take the convex hull of all surfaces contained in the training dataset and remesh them uniformly using JIGSAW [21]. To achieve a different order of refinement, we use the midpoint subdivision algorithm implemented in MeshLab [12]. Model hyper-parameters and further implementation details are provided in the supplementary material.

4 Experiments

We benchmark CorticalFlow and other existing deep learning techniques on the cortical surface reconstruction problem. The goal is to estimate geometrically accurate and topologically correct triangular meshes for the inner and outer cortical surfaces from a given MRI. Like previous works [14][16][31][33][38][65], these surfaces are further divided into the left and right brain hemispheres. See below a summary of the dataset, evaluated methods, and metrics used in our benchmark, in addition to the detailed discussion of the results summarized in Table 1.

| CorticalFlow | 1.148 sec / 1.071 GB | 0.297 | 0.209 | 0.181 | 0.342 | 0.301 | 0.209 |
| DeepCSR | 1.148 sec / 1.071 GB | 0.523 | 0.415 | 0.346 | 0.521 | 0.473 | 0.346 |
| NMF | 1.148 sec / 1.071 GB | 1.527 | 1.405 | 0.854 | 0.513 | 0.467 | 0.397 |
| QuickNAT | 1.148 sec / 1.071 GB | 2.273 | 2.523 | 0.974 | 0.956 | 0.971 | 0.971 |
| Voxel2Mesh | 1.148 sec / 1.071 GB | 7.188 | 3.801 | 0.721 | 0.837 | 0.809 | 0.870 |

Table 1: Cortical Surface Reconstruction Benchmark. Consider the evaluation metrics: chamfer distance (CH), Hausdorff distance (HD), chamfer normals (CHN), percentage of self-intersecting faces (%SIF), Dice Score (DSC), and Volume Similarity (VS). ↑ indicates smaller metric value is better, while ↓ indicates greater metric value is better. We also report the inference runtime and GPU memory footprint required by the compared algorithms.

Dataset. We used the same MRIs, pseudo-ground-truth surfaces, and data splits as [65]. This dataset consists of 3,876 MRI images extracted from the Alzheimer’s Disease Neuroimaging Initiative (ADNI) [64] and their respective pseudo-ground-truth surfaces generated with the FreeSurfer V6.0 cross-sectional pipeline [23]. We train all methods on the training set (~60%) until their losses plateau on the validation set (~10%) and report their performance on the test set (~30%). We refer the reader to [65] and our supplementary material for full details on the dataset.

Evaluated Methods. We compare CorticalFlow to the following methods: DeepCSR [65], Voxel2Mesh [77], NMF [30], and QuickNAT [64]. As discussed in Section 2, DeepCSR is the state-of-the-art geometric deep learning model for cortical surface reconstruction, while Voxel2Mesh is a deformation-based model proposed to retrieve generic anatomical surfaces from volumetric medical images like MRIs and CT scans. Differently, NMF is a deformation-based model for single-view object reconstruction from 2D images. To adapt this model to our task whose input is a

1 DeepCSR official implementation retrieved from https://bitbucket.csiro.au/projects/CRCPMAX/repos/deepcsr
2 Voxel2Mesh official implementation retrieved from https://github.com/cvlab-epfl/voxel2mesh
3 NMF official implementation retrieved from https://github.com/KunalMGupta/NeuralMeshFlow
4 QuickNAT official implementation retrieved from https://github.com/ai-med/quickNAT_pytorch
3D MRI, we evaluate different 3D convolutional network backbones based on UNet [63], ResNet [33], and Hypercolumn [65]. The Hypercolumn backbone provides the best results thanks to its vertex-dependent features. As such, this is used as the NMF backbone in our benchmark. At the same time, the results for the other backbones are presented in our supplementary material. We also evaluate a baseline composed of a state-of-the-art brain segmentation model QuickNAT [64] followed with the marching cubes to evaluate the surface. All of these methods were trained and evaluated using a NVIDIA P100 GPU and Intel Xeon (E5-2690) CPU, except Voxel2Mesh which required a NVIDIA RTX 3090 GPU due to its GPU memory requirements.

**Evaluation Metrics.** We compare these methods for their geometric accuracy and surface regularity, as well as their time and space complexity. As a measure of geometric accuracy, we report the standard Chamfer distance (CH), Hausdorff distance (HD), and Chamfer normals (CHN). We compute these distances for point clouds of 200k points uniformly sampled from the predicted and target surfaces. As a measure of regularity, we compute the percentage of self-intersecting faces (%SIF) using PyMeshLab [51]. We also report volumetric overlap metrics [71] including Dice Score (DSC) and Volume Similarity (VS) computed on the high-resolution rasterization (4×the input MRI resolution) of the generated and ground-truth surfaces.

For the time and space complexity of the evaluated methods, we report their average inference time (in seconds) and inference GPU memory footprint (in GB) to reconstruct the four cortical surfaces, respectively.

![Figure 3: Predicted outer cortical surfaces color-coded with the distance to the pseudo-ground-truth surfaces. Here we present the results for the three best-performing methods in terms of geometric accuracy: CorticalFlow, DeepCSR, and NMF. See our supplementary materials for more examples.](image)

**Results & Discussion.** In our experiments, we noticed that CorticalFlow produces more geometrically accurate surfaces than the other methods. On average, it presents better geometric metrics across all the cortical surfaces. In addition, as shown in Figure 3, CorticalFlow errors are smaller (≤0.2 mm) and evenly spread across the surface compared to the other methods. In contrast, NMF and DeepCSR can present substantial errors (≥1 mm). The former has its error spread across the entire surface, while the latter can produce large errors at specific regions.

CorticalFlow is also more robust than the competitors presenting lower error variation across individuals as suggested by the smaller standard deviation of the geometric metrics computed. Interestingly, CorticalFlow is also more robust to MRI artifacts even when the pseudo-ground-truth surface has poor quality. For instance, in Figure 4, CorticalFlow predictions are still plausible for a blurry input MRI while FreeSurfer fails significantly to generate appropriate surfaces for the same input. These examples support our claim that a regular parametrization allows us to reduce non-plausible and non-diffeomorphic predictions that our model cannot learn by construction.

CorticalFlow also generates triangular meshes with better properties than the evaluated methods. Compared to the deformation-based methods NMF and Voxel2Mesh, CorticalFlow predicted meshes are genus-zero surfaces and present a lower percentage of self-intersecting faces (mainly for the inner cortical surfaces). Figure 5a presents examples of self-intersecting faces produced by CorticalFlow, which are contrasted with the NMF predicted mesh for the same input MRI. The implicit-surface-
Figure 4: Slices of a blurry MRI and the outer surface delineation generated by FreeSurfer V6 (yellow contour) and CorticalFlow (blue contour). Orange circles highlight blurry MRI regions, green circles highlight FreeSurfer’s underestimated areas, while red circles highlight non-plausible predictions avoided by CorticalFlow thanks to the diffeomorphism of its predicted deformations.

Figure 5: (a) Predicted cortical surfaces by CorticalFlow and NMF with self-intersecting faces highlighted in red. (b) Significant mistakes generated by the topology correction algorithm used in the DeepCSR method.

Based DeepCSR method does not produce a single self-intersecting face since it employs computationally expensive post-processing routines like topology correction [4] and iso-surface extraction. However, these post-processing routines do not take into account the input MRI which can generate non-plausible corrections on the output mesh as previously observed in Segonne et al. [67] and exemplified in Figure 5b. Similarly, the voxel-wise segmentation baseline (i.e., QuickNAT) is free of self-intersecting faces, but it does not produce genus-zero surfaces. Indeed, QuickNAT’s predicted surfaces are composed of multiple connected components presenting many handles and holes which is not acceptable for the purpose of cortical surface reconstruction. Some examples of QuickNAT reconstructed cortical surfaces are presented in our supplementary material. Therefore, we argue that CorticalFlow is the method of choice to reconstruct regular surfaces from volumetric images.

Due to its elemental construction (three UNet-3D backbones and an interpolation module for the integration), CorticalFlow remains highly efficient. It has a minimal GPU memory footprint and faster inference runtime while handling larger surfaces with more vertices both during training and inference. This feature allows its deployment on low-end computers and embedded devices which is pivotal in many scenarios across public health and for commercialization of affordable AI healthcare solutions [13, 58].

Finally, as a by-product of CorticalFlow’s deformable and diffeomorphic nature, one can seamlessly obtain a sub-voxel resolution segmentation by applying a voxelization engine. This can capture variations below the image resolution while traditional segmentation methods [64] are restrained from working at the image resolution (see Figure 6a). Additionally, an essential component of
computational neuro-anatomy consists of computing local shape descriptors for different individuals and transferring them to the same reference space using conformal mappings \cite{29,70}. For the proposed model, one can efficiently compute the inverse transformation $\Phi^{-1}$ as shown in Figure 6b for the surface curvature descriptor.

5 Conclusion

This paper introduces CorticalFlow - a geometric deep learning model for efficiently reconstructing high-resolution, accurate, and regular triangular meshes from volumetric images. We develop a lightweight neural network to predict a dense 3D flow vector field from a volumetric image. Then, we describe a new Diffeomorphic Mesh Deformation (DMD) module, which is parameterized by a set of diffeomorphic mappings. This includes the derivation of numerical conditions for recasting the continuous flow ODE problem into an efficient discrete solver. Finally, we extensively verify that the proposed model achieves state-of-the-art performance in the challenging brain cortical surface reconstruction problem. This benchmark reveals that CorticalFlow is more accurate and, by construction, more robust to image artifacts providing anatomically plausible surfaces. Thanks also to its low space and time complexity, the proposed method can facilitate large-scale medical studies and support new healthcare applications.

6 Compliance with Ethical Standards

This research was approved by CSIRO ethics 2020 068 LR.

7 Acknowledgements

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Supplementary Material

Implementation details

Ablation study for Cortical Flow: number of deformation blocks

As explained in subsection 3 of our paper, CorticalFlow leverages a chain of 3 deformation blocks to provide a coarse-to-fine approximation of the targeted surface. We evaluate CorticalFlow predictions after each deformation block in our cortical surface reconstruction benchmark to empirically validate this modeling decision. As shown in Table 2, every deformation block added allows a better approximation of the ground-truth surfaces. More specifically, on average across all surfaces, adding a second deformation block reduces the Chamfer distance metric by 36.73%, while adding a third deformation block reduces the same metric by a further 5.06%. Importantly, this error reduction is more evident in the sulci region of the cortical surfaces, as shown by the example depicted in Figure 7.

Cortical Flow Architecture and Training details

As shown in Figure 2 of our paper, CorticalFlow consists of a chain of three deformation blocks. Each of these deformations is implemented by some UNet flow vector field predictor and the Diffeomorphic Mesh Deformation (DMD) module described in subsection 3.1 of our paper. More specifically, the first deformation block uses our UNet4 architecture while the remaining ones use our UNet2 architecture. Both architectures are described in details in Figure 8. As explained in subsection 3.2, the reason for this architectural change is to promote the learning of a coarse-to-fine sequence of deformation blocks.

For training CorticalFlow, we adopted a sequential approach where we train one deformation block at a time while freezing the weights of the previous UNet(s). All deformation blocks are trained according to equation 2 for 70k iterations with a batch size of three image-surface pairs. As training loss $L(\cdot, \cdot)$, we minimize the mesh edge loss and Chamfer distance computed on point clouds of 150k points sampled from the predicted and ground-truth surfaces using random uniform sampling. The implementation of these losses and sampling algorithm are provided in the PyTorch3D library [60]. As an optimizer for each deformation, we use Adam [39] with an initial learning rate of $10^{-4}$. Both predicted and ground-truth surfaces are shrunk to lie in the unit ball to normalize the learning loss.
we tried their proposed Hypercolumns architecture which equips each template vertex with a local
architecture (CH), Hausdorff distance (HD), and chamfer normals (CHN).

Therefore, the NMF with Hypercolumns backbone is the NMF model used in our benchmark, whose results are summarized in Table 1 of our paper.

Figure 8: UNet architectures used in CorticalFlow. See Figure 2 of our paper for a global overview of the model.

Table 2: Evaluation of the proposed CorticalFlow model with different number of deformation blocks in the cortical surface reconstruction benchmark. Consider the evaluation metrics: chamfer distance (CH), Hausdorff distance (HD), and chamfer normals (CHN). ↓ indicates smaller metric value is better, while ↑ indicates greater metric value is better.

Backbone selection for Neural Mesh Flow (NMF)

Neural Mesh Flow (NMF) is a deformation-based geometric deep learning model for retrieving regular surfaces for objects depicted in a single 2D image. This model has two main blocks: an image-level feature encoder and a mesh transformer. The former is composed of a ResNet [33] point-cloud predictor and a PointNet [59] network providing an image-level feature vector representation for an input 2D image. The latter receives this image-level feature vector as input and deforms a prescribed template towards the ground-truth surface using Neural Ordinary Differential Equation (NODE) blocks. To adapt this model to cortical surface reconstruction performing only minimal changes, we swap the architecture of the point-cloud predictor from a 2D ResNet to a 3D ResNet. However, as shown in the first row of Figure 8, the resulting model performs very poorly in the cortical surface reconstruction task. More specifically, we found it very hard to predict point clouds to cortical surfaces since these surfaces present many local dissimilarities (e.g., cortical folding patterns) that are hard to capture by funnel-like architectures like ResNet. Trying to overcome this problem, we replaced the ResNet with a 3D UNet [63] with shortcut connections (i.e., our Unet [4] architecture) to exploit high-resolution feature maps within the computation of the image-level feature vector representation. As shown in the second row of Figure 8, the results were still far from satisfactory. As discussed in subsection 2.2 and also observed by Santa Cruz et al. [65], an image-level feature vector does not hold fine-grained information enough to reconstruct cortical surfaces accurately. Therefore, we tried their proposed Hypercolumns architecture which equips each template vertex with a local feature descriptor of the input image resulting in more accurate cortical surface reconstructions as shown in the last row of Figure 8. Therefore, the NMF with Hypercolumns backbone is the NMF model used in our benchmark, whose results are summarized in Table 1 of our paper.
Figure 9: Outer cortical surface reconstruction for four subjects (columns) using the NMF framework with different backbones. The Hypercolumns backbone is significantly better than the others, and thus it is the NMF’s backbone presented in our benchmark.

QuickNAT Baseline

The QuickNAT baseline consists of a voxel-wise segmentation model, iso-surface extraction method, and a mesh post-processing routine. More specifically, we first predict a segmentation of the input MRI into 28 anatomical regions using the QuickNAT [64] state-of-the-art segmentation model for brain segmentation. Second, we build the four cortical volumes by assembling anatomical structures contained in the four surfaces. Third, we run a marching cubes [42] algorithm to retrieve triangle meshes from the obtained binary segmentations. Since the resulting meshes present a lot of unwanted connected components (due to spurious mistakes in the segmentation), we only isolate the largest connected component using the trimesh.graph.connected_component_labels function. Figure 10 presents some meshes generated with this QuickNAT baseline. Our methodology was to get the best geometrical measure stemming from a segmentation-based approach. We verify that the suppression of small connected components improves all the metrics presented in our paper. Note, however, that those meshes cannot be used for the cortical surface reconstruction problem since they comprise hole and handle (not 0-genus). It is also important to notice that numerous errors are imputable to the limited resolution of this approach.
Dataset Information and Preprocessing

The dataset used in the experiments described in subsection 4 of our paper was introduced in [65]. It consists of MR images extracted from the Alzheimer’s Disease Neuroimaging Initiative (ADNI) [36] and their respective pseudo-ground-truth surfaces generated with the FreeSurfer V6.0 cross-subsectional pipeline [24, 25]. It comprises 3876 MR images from 820 different subjects collected at different time points and their respective cortical surfaces split by brain hemisphere (i.e., left outer surface, left inner surface, right outer surface, and right inner surface). This dataset is split by subjects resulting in 2353 MRI scans from 492 subjects for training (≈ 60%), 375 MRI scans from 82 subjects for validation (≈ 10%), and 1148 MRI scans from 246 subjects for testing (≈ 30%). It is also important to emphasize that these splits do not have MRIs or subjects in common for an unbiased evaluation.

As preprocessing, the original ADNI images are conformed and normalized according to the first steps in the FreeSurfer V6 pipeline. These images are saved at <subject_id>/mri/orig.mgz on the FreeSurfer output directory. Then, they are affine registered to the MNI105 brain template [46] using the NiftyReg toolbox [49]. Their respective pseudo-ground-truth surfaces are also transformed using the computed transformation. Finally, for memory efficiency, these images are split by hemisphere since we learn a model for each surface resulting in $1\text{mm}^2$ isotropic T1-weighted images with $96 \times 192 \times 160$ dimensions. Detailed instructions for downloading and preprocessing this data will be provided along with our source code.

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3Data used in preparation of this article were obtained from the Alzheimer’s Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). As such, the investigators within the ADNI contributed to the design and implementation of ADNI and/or provided data but did not participate in analysis or writing of this report. A complete listing of ADNI investigators can be found at: [http://adni.loni.usc.edu/wp-content/uploads/how_to_apply/ADNI_Acknowledgement_List.pdf](http://adni.loni.usc.edu/wp-content/uploads/how_to_apply/ADNI_Acknowledgement_List.pdf)
Proof and discussion

Proof of Theorem 3.2.

**Theorem 3.2.** Existence and uniqueness of the solution. Define $\Phi$ through the autonomous ODE,
\[
\frac{d\Phi(s; x)}{ds} = v(\Phi(s; x)), \text{ with } \Phi(0; x) = x.
\] (6)

Then $\Phi$ is uniquely defined on $\mathbb{R} \times \Omega$, is Lipschitz and for each $t$, the mapping $x \mapsto \Phi(t, x)$ is bijective with Lipschitz inverse.

**Proof.** This is a standard result in flow theory; see Theorem 1.2.6 Berger and Gostiaux [6].

1. First, notice that the vector field $v$ is $L$-Lipschitz with $L > 0$ defined as
\[
L = \text{Lip}(v) = \max_{i \in \{1, 2, 3\}} \frac{\|\nabla_i U\|_{2,\infty}}{d_i}
\]
with $\nabla_d U$ the forward first order finite difference operator in the $d$-th direction with zero padding
\[
\nabla_1 U_{i,j,k} = \begin{cases} 
\text{if } i \in [1, n - 1], & U_{i+1,j,k} - U_{i,j,k} \\
\text{if } i \in \{0, n\}, & U_{i,j,k}
\end{cases}
\]

2. Then verify that vector field $v$ is bounded by $M$ with $M = \|v\|_{2,\infty} = \max_{i,j,k} \|U_{ijk}\|_2$

With these two constants one can use the result of Berger and Gostiaux [6] (Theorem 1.2.6) to define a unique local solution for $t \in [-b, b]$ with $b < \inf(\frac{\text{diam}(\Omega)}{M}, \frac{1}{L})$ where $\text{diam}(\Omega)$ is the diameter of the set $\Omega$.

To extend this result for all $t \in \mathbb{R}$, one has to notice that the solution is defined for every $t$ since the integral solutions are contained in $\Omega$ since $v = 0$ on $\partial \Omega$. To construct the inverse, one uses the same proof method but integrates $v$ from $t$ to zero.

**Caveat: Discrete approximation of continuous surfaces**

![Figure 11: Deformation of a template mesh. From left to right: The original triangle mesh, a prescribed vector-field $v$, deformed triangulation where the map $\Psi$ applied on the mesh’s vertices creating a self-intersection, and continuous deformation of triangle mesh’ surface by $\Psi$.](image)

As explained at the end of Section 3.1, $\Psi$ being a homeomorphism does not guarantee that the discrete problem we are solving is immune to self-intersection, and such a pathological case is described in Figure [11]. Note, however, that one could get rid of the self-intersection up to sufficient remeshing of the self-intersecting faces. This discretization issue has to be kept in mind when using a deformable model that acts on the vertices of a triangle mesh.
Further comparison with pre-existing methods

Comparison with DeepCSR and NMF

| CorticalFlow | DeepCSR | NMF |
|--------------|---------|-----|
| ![Brain Images](image1.png) | ![Brain Images](image2.png) | ![Brain Images](image3.png) |
| ![Brain Images](image4.png) | ![Brain Images](image5.png) | ![Brain Images](image6.png) |
| ![Brain Images](image7.png) | ![Brain Images](image8.png) | ![Brain Images](image9.png) |
| ![Brain Images](image10.png) | ![Brain Images](image11.png) | ![Brain Images](image12.png) |

Figure 12: More examples of predicted outer cortical surfaces color-coded with the distance to the pseudo-ground-truth surfaces as shown in Figure 3 of our paper. Here, each row presents the results for a different input MRI. All the presented anatomies are included between the 40th and 60th percentile for the Chamfer distance.
Figure 13: More examples of predicted inner cortical surfaces color-coded with the distance to the pseudo-ground-truth surfaces as shown in Figure 3 of our paper. Here, each row presents the results for a different input MRI. All the presented anatomies are included between the 40th and 60th percentile for the Chamfer distance.
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