

# Riemannian Nonlinear Mixed Effects Models: Analyzing Longitudinal Deformations in Neuroimaging

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<http://pages.cs.wisc.edu/~hwkim/projects/riem-mem>

## Abstract

*Statistical machine learning models that operate on manifold-valued data are being extensively studied in vision, motivated by applications in activity recognition, feature tracking and medical imaging. While non-parametric methods have been relatively well studied in the literature, efficient formulations for parametric models (which may offer benefits in small sample size regimes) have only emerged recently. So far, manifold-valued regression models (such as geodesic regression) are restricted to the analysis of cross-sectional data, i.e., the so-called “fixed effects” in statistics. But in most “longitudinal analysis” (e.g., when a participant provides multiple measurements, over time) the application of fixed effects models is problematic. In an effort to answer this need, this paper generalizes non-linear mixed effects model to the regime where the response variable is manifold-valued, i.e.,  $f : \mathbf{R}^d \rightarrow \mathcal{M}$ . We derive the underlying model and estimation schemes and demonstrate the immediate benefits such a model can provide — both for group level and individual level analysis — on longitudinal brain imaging data. The direct consequence of our results is that longitudinal analysis of manifold-valued measurements (especially, the symmetric positive definite manifold) can be conducted in a computationally tractable manner.*

## 1. Introduction

A multitude of applications across computer vision and statistical machine learning involve operations on objects that are “structured”; for instance, probability densities, special classes of matrices/tensors, trees and graphs. It is generally accepted in the literature that treating these objects in their vectorized forms within off the shelf machine learning models may, more often than not, lead to unsatisfactory results, since the basic conditions of Euclidean geometry including distances and angles may not be satisfied. Defining machine learning models on such data requires

care because it involves performing calculations while respecting the constraints inherent to the space where our samples come from [1]. This is challenging when the geometry of the space is not very well understood.

Fortunately, in certain cases, the canonical representations of the structured objects of interest lead to spaces that are relatively better characterized. For instance, when the space is a Riemannian manifold, the differential geometry provides a suitable Riemannian metric which serves as a building block for inference models. Within the last ten or so years, numerous authors have reported how respecting the geometry/structure of the data in tasks as simple as summarizing the observed variability in the empirical distribution [2] yields good empirical performance. There is a rapidly increasing body of work showing how manifold-based formulations yield powerful algorithms for problems including affine motion tracking [3, 4], human detection [5], modeling spatial distribution of earthquakes [6], classification tasks [7], robot localization [8], registration [9], and numerous settings in medical imaging [10, 11, 12].

Symmetric positive definite matrices (SPD) are a good representative example of structured data that lie on a Riemannian manifold. In computer vision, SPD matrices are often encountered due to covariance matrices which serve as feature descriptors in tracking [4] as well as for texture analysis and classification [5]. Diffusion tensor magnetic resonance imaging, a type of neuroimaging modality, yields an SPD matrix *at each image voxel* as the local diffusion tensor. But even aside from the SPD manifold, probability densities, shape spaces, and certain warping functions are other examples of Riemannian manifolds which commonly manifest themselves in vision applications [12, 13, 14, 15]. The need for metrics, estimators, hypothesis tests and other tools for inference tasks has led to much interest in Riemannian analogs of classical vision and machine learning methods. Consequently, we now have manifold versions of nearest neighbor queries, dimensionality reduction, dictionary learning, sparse coding, kernel methods, boosting, averaging and regression. These developments were recently

compiled within a handbook [16] which offers an overview of what has been accomplished so far as well as the yet unresolved technical issues.

A majority of the technical contributions in manifold-based algorithms within computer vision have focused on non-parametric formulations of the underlying problems. The parametric versions are recently receiving attention, motivated by applications in the life sciences where *sample sizes are smaller*. For instance, consider the simple parametric model that seeks to identify associations between a predictor (feature)  $x$  and a response  $y$  which is manifold-valued,  $f : x \rightarrow y$ . Efficient parametric algorithms for this problem were developed as recently as a few years back [17] where the model was used to identify the relationship between a “shape-based” manifold variable (e.g., shape of a segmented brain region) and a subject specific variable  $x$  (e.g., age). Only several months back, the generalization of this model for multi-dimensional predictors was obtained — to fit the response  $y$  by a linear combination of multiple predictors (or features),  $x \in R^d$  or even when the predictor variable is manifold-valued. Such a construction also serves to identify associations between a set of covariates while controlling for a set of “nuisance” variables [18, 19].

**Manifold-valued regression.** In a longitudinal neuroimaging study of disease progression, the statistical models need to capture morphometric changes *over time* while controlling for the dependency of *repeated* measurements from the same subject. Consider the following analysis: we have two groups of subjects, “controls” and “disease” which correspond to healthy controls and individuals with a high risk of a disease. We want to identify the group-differences with respect to time (or disease progression). It is known that anatomical changes at a voxel  $X$  can be captured by spatial derivatives, i.e., the Jacobian matrix  $J(X)$ , of deformation maps of a subject (e.g., the changes between the first and the second time points, two years apart). The most widely used “deformation” feature is the log determinant of the Jacobian matrices,  $\log(\det(J(X)))$  — a scalar voxel-wise value which captures the volumetric/anatomical changes. The so-called Cauchy deformation tensor (CDT) [20] represented as  $\sqrt{J(X)^T J(X)}$  is a richer representation of  $J(X)$ , an object on the SPD(3) manifold, see Fig. 1. To understand how each specific voxel in the image is associated with a predictor variable (say, age or disease status), a regression between the predictor and CDT at each voxel will identify brain regions that are most affected by age or disease. This can be accomplished by recently proposed algorithms for geodesic regression [17, 19, 18] or kernel regression on manifolds [21].

**Random effects in longitudinal analysis.** Now, let us consider a slightly more involved setting where each subject provides data over multiple time points, a few years apart. In such a *longitudinal* setting, we obtain *one* CDT

image between each consecutive time point (i.e., pairs). A standard linear regression (or its manifold-valued analog) is *agnostic to dependency of temporal samples*. Since subjects are examined multiple times within the study, the repeated measurements from the same subject as the subject specific “*random effect*”. This dependency violates the i.i.d. assumptions of *fixed effects* models (e.g., generalized linear models), including the manifold versions [17, 18]. The fixed effects model assumes that all data are i.i.d. samples from the same underlying generating function with random noise on the response variable  $Y$ . As Fig. 2 shows, each subject may have a different trend. For example, subject A has an early disease onset (intercept). Subject B shows faster disease progression (slope). Also, based on the age-range of participants, there may be larger variability *between* subjects than the variability *within* a subject. So, a fixed effects linear model for the data in Fig. 2, is *prone to fit population level variability (black) than the trajectory of each subject (red)*. Indeed, such subject specific *random effects* can be modeled via the more general *mixed effects models*. The overarching **goal and contribution** of this work is to derive formulations/algorithms for the regime where the set of longitudinal responses  $Y$  is a manifold valued variable and the objective is to fit linear (or non-linear) mixed effects models.

**Related work.** As briefly described above, there is a growing body of work in vision that incorporates the specific geometry/structure of the data directly within the estimation problem. Various statistical constructs have been generalized to Riemannian manifolds: these include regression [22, 23], margin-based and boosting classifiers [7], classification [24], kernel methods [25], filtering [10] and dictionary learning [26, 27]. The literature also includes ideas related to projective dimensionality reduction methods. For instance, the generalization of Principal Components analysis (PCA) via the so-called PGA [28], Geodesic PCA [29], Exact PGA [30], CCA on manifolds [31], Horizontal Dimension Reduction [32] with frame bundles, and an extension of PGA to the product space of Riemannian manifolds, namely, tensor fields [24]. We should note that an important earlier work dealing with a univariate linear model on manifolds (related to geodesic regression) was studied for the group of diffeomorphisms using metrics which were not strictly Riemannian [33, 34]. Despite these developments, the first results on successful generalization of parametric regression models to Riemannian manifolds is relatively recent: geodesic regression [17, 35], polynomial regression [36] and multi-variate linear regression with manifold-valued responses [18]. Finally, we point out that a recent independent result on mixed effects models in [37] deals with univariate manifolds  $[0, 1]$ , which is the unit interval in a real line  $\mathbf{R}$  with a specifically designed metric to capture sigmoid function like patterns. This work does not deal

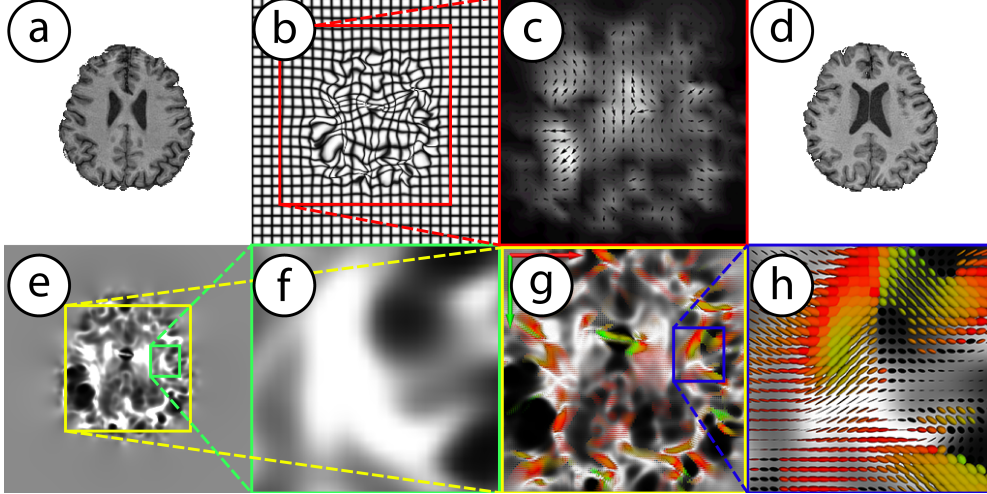


Figure 1. An example panel of data generated in morphometric studies. (a, d) The moving and fixed brain image respectively. (b) Warped spatial grid to move (a) to (d). (c) Vector field of local deformations. (e, f) A map of the  $\det(J)$  of the deformation field. (g, h) The Cauchy deformation tensor field (CDTs) ( $\sqrt{J^T J}$ ). Among the different features of brain morphology that can be analyzed, CDTs are the focus of this paper.

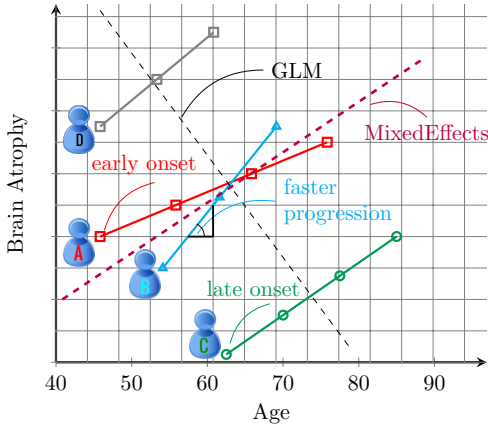


Figure 2. This figure demonstrates the key effects we are interested in capturing. Each subject has a different progression rate of the brain atrophy (acceleration effect) and has a different onset for the change (time shift). A regular general linear model (GLM) with fixed effects is insufficient to capture these effects while including random effects (subject-specific slope and intercept) in mixed effects models can capture these effects. with actual manifold-valued variables (e.g., SPD); further it is computationally impractical for more than hundreds of voxels. In contrast, 3D CDT images we will analyze exceed 1M+ voxels.

## 2. Preliminary concepts and notations

We first briefly review *linear mixed effects models* and their estimation methods. Then, we summarize some basic *differential geometry* notations that we will use. The extended version of this paper and [38, 39] describe more details. Also, we introduce CDT and Jacobian matrices to capture longitudinal morphometric brain changes.

### 2.1. Linear mixed effects model

In general, the estimation of regression models (such as linear/polynomial) assumes that the data come from an un-

derlying model with i.i.d. noise; so effects of the covariates/features are pertinent to the entire sample. These models are called *fixed effects*. For example, a linear regression model is also a fixed effects model given as

$$y = \beta^0 + \beta^1 x^1 + \dots + \beta^p x^p + \epsilon, \quad (1)$$

where  $y \in \mathbf{R}$ ,  $x \in \mathbf{R}^p$ ,  $\beta = [\beta^0, \dots, \beta^p]^T \in \mathbf{R}^{p+1}$ . We see that the coefficients are ‘fixed’ and the same over entire population. However, in longitudinal studies (see Fig. 2), the repeated measurements from the same subject are *no longer independent*. We need a more flexible specification – often covariates/features have different effects on individual subjects (or groups), which is called *random effects*. For example, the rate of brain atrophy and disease progression can vary over subjects given by

$$y_i = u_i^1 z^1 + \dots + u_i^q z^q + \epsilon_i, \quad (2)$$

where  $\mathbf{z}$  is a known vector specifying which subject (or group) a sample belongs to, and  $u_i^q$  is the  $q^{\text{th}}$  random effect for the  $i^{\text{th}}$  subject (or group) denoted by  $\mathbf{u}_i$ . This combination of *fixed* and *random* effects yields *mixed effects models* [40]. When the model is linear, we get linear mixed effects models, which we introduce next. We then work with its *nonlinear* analog. The nonlinear mixed effects models are an intermediate (but necessary) step in deriving our final models for manifold-valued data, introduced in Sec. 3.2.

**Specifying the model.** Let  $\mathbf{y}_i = [y_{[i,j]}]_{j=1}^{n_i}$  be a set of  $n_i$  repeated observations of a response variable for subject  $i$ . Here  $\mathbf{y}_i$  is a  $n_i$  dimensional vector, vertically stacked with  $y_{[i,j]}$  responses for subject  $i$ . The notation  $[i, j]$  simply recovers the specific observation  $j$  for subject  $i$ . Similarly, let the subject-specific matrix  $X_i$  of size  $n_i \times p$  be setup as  $[x_{[i,j]}^1 \ x_{[i,j]}^2 \ \dots \ x_{[i,j]}^p]_{j=1}^{n_i}$  where we collect for

subject  $i$ , all  $p$  measurements for all  $n_i$  visits as rows. The matrix  $Z_i$  will provide information on the number of longitudinal measurements for each subject (design matrix). Similar to  $X_i$ , we define  $Z_i$  by specifying rows as  $Z_i = \begin{bmatrix} z_{[ij]}^1 & z_{[ij]}^2 & \dots & z_{[ij]}^q \end{bmatrix}_{j=1}^{n_i}$ . These correspond to sets of  $p$  and  $q$  variables (features) for the  $i^{\text{th}}$  subject where one is interested in estimating fixed effects for the set  $X_i$  and random effects for the set  $Z_i$  on  $\mathbf{y}_i$ . In the classical setting, a linear mixed effects model ([40]) is given by

$$y_{[ij]} = \beta^0 + \beta^1 x_{[ij]}^1 + \dots + \beta^p x_{[ij]}^p + u_i^1 z_{[ij]}^1 + \dots + u_i^q z_{[ij]}^q + \epsilon_{[ij]},$$

where  $\beta^1, \dots, \beta^p$  are the fixed effects shared over the entire population and  $u_i^1, \dots, u_i^q$  are the (subject-specific) random effects for the  $i^{\text{th}}$  subject. The random effects  $\mathbf{u}_i = [u_i^1 \ u_i^2 \ \dots \ u_i^q]^T$  are assumed to follow a multivariate normal distribution. The “unexplained” random error  $\epsilon_{[ij]}$  comes from a normal distribution  $\mathcal{N}(0, \Sigma_\epsilon^2)$ . We can compactly write the model using matrix notation as

$$\mathbf{y}_i = X_i \boldsymbol{\beta} + Z_i \mathbf{u}_i + \epsilon_i. \quad (3)$$

Let ‘vstack( $\cdot$ )’ be the vertical stack of parameters. By denoting  $\mathbf{y} = \text{vstack}(\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_N)$ , and similarly  $X, Z, \mathbf{u}$ , the final model for all  $N$  subjects can be expressed as,

$$\mathbf{y} = X \boldsymbol{\beta} + Z \mathbf{u} + \sigma_\epsilon^2 I,$$

where  $\mathbf{u} \sim \mathcal{N}(0, \tilde{\Sigma})$  and  $\tilde{\Sigma} = \text{diag}(\Sigma_1, \Sigma_2, \dots, \Sigma_N) = \Sigma \otimes I$  (when  $\Sigma_i = \Sigma \forall i$ ), and  $Z = \text{diag}(Z_1, Z_2, \dots, Z_N)$ . In general, estimation of linear mixed effects models does not have an analytic solution unless  $\tilde{\Sigma}$  and  $\sigma_\epsilon^2$  are known.

## 2.2. Basic differential geometry notations

Let  $\mathcal{M}$  be a *differentiable (smooth) manifold* in arbitrary dimensions. A differentiable manifold  $\mathcal{M}$  is a topological space that is locally similar to Euclidean space and has a globally defined differential structure. A *Riemannian manifold*  $(\mathcal{M}, g)$  is a differentiable manifold  $\mathcal{M}$  equipped with a smoothly varying inner product  $g$ . The family of inner products on all tangent spaces is known as the *Riemannian metric*, which defines various geometric notions on curved manifolds such as the length of a curve etc. A *geodesic curve* is a locally shortest path, which is analogous to straight lines in  $\mathbf{R}^d$  — such a geodesic curve will be the object that defines the trajectory of our covariance matrices in the space of SPD matrices. Unlike the Euclidean space, note that there may exist multiple geodesic curves between two points on a curved manifold. So the *geodesic distance* between two points on  $\mathcal{M}$  is defined as the length of the *shortest* geodesic curve connecting two points (i.e., SPD matrices). The geodesic distance helps in measuring the error of our trajectory estimation (analogous to a Frobenius or

$\ell_2$  norm based loss in the Euclidean setting). The geodesic curve from  $y_i$  to  $y_j$  is parameterized by a tangent vector in the tangent space anchored at  $y_i$  with an exponential map  $\text{Exp}(y_i, \cdot) : T_{y_i} \mathcal{M} \rightarrow \mathcal{M}$ . The inverse of the exponential map is the logarithm map,  $\text{Log}(y_i, \cdot) : \mathcal{M} \rightarrow T_{y_i} \mathcal{M}$ . These two operations move us back and forth between the manifold and the tangent space. Separate from the above notation, matrix exponential (and logarithm) are simply  $\exp(\cdot)$  (and  $\log(\cdot)$ ). Finally, *parallel transport* is a generalized parallel translation on manifolds. Given a differentiable curve  $\gamma : \mathcal{I} \rightarrow \mathcal{M}$ , where  $\mathcal{I}$  is an open interval, the parallel transport of  $v_0 \in T_{\gamma(t_0)} \mathcal{M}$  along curve  $\gamma$  can be interpreted as the parallel translation of  $v_0$  on the manifold preserving the angle between  $v(t)$  and  $\gamma$ . The parallel transport of  $v$  from  $y$  to  $y'$  is  $\Gamma_{y \rightarrow y'} v$  (more details in the extended version).

## 3. Longitudinal analysis of CDT images

Let  $\mathcal{I}_{i,j}$  denote the image acquired from subject  $i$  at time point  $j$ . Given images  $\mathcal{I}_{i,j}$  and  $\mathcal{I}_{i,j+1}$  for successive visits  $(j, j+1)$ , we can compute a deformation that aligns the two images [41, 42]. Let  $\mathcal{I}_{i,1}$  give the subject-specific coordinate system denoted as  $\Omega_i$ . This will provide the (intermediate) common coordinate system to represent the deformations undergone by subject  $i$  over time,  $j = 1, 2, \dots, n_i$ . The global template where all  $(n_i - 1)$  temporal deformations (i.e., CDT images) for each subject  $i$  will be represented is denoted as  $\Omega$ . Then, a nonlinear deformation  $\Phi(\text{vox})$  for voxels (spatial locations)  $\text{vox} \in \Omega$  for each image (rather, for each  $(\mathcal{I}_{i,j+1}, \mathcal{I}_{i,j})$  pair) is given as

$$\begin{aligned} \Phi : \mathcal{I}_{i,j+1} &\rightarrow \mathcal{I}_{i,j} \\ \Phi(\text{vox} + d\text{vox}) &= \Phi(\text{vox}) + J(\text{vox}) d\text{vox} + \mathcal{O}(d\text{vox}^2), \end{aligned} \quad (4)$$

where  $J(\text{vox})$  denotes the Jacobian of the deformations at position  $\text{vox}$ . A nice property of CDTs is that it preserves the determinant of  $J(\text{vox})$ , since  $\det(J(\text{vox})) > 0$ . So, a CDT representation introduced in Sec. 1, nicely symmetrizes  $J(\text{vox})$  without affecting the volumetric change information, i.e.,  $\det(J) = \det(\sqrt{J^T J})$  (proof in the extended version). The CDT “image” comprised of voxel locations  $\text{vox}$  is an object of the same size as  $\mathcal{I}_{1,1}$  and derived from a black-box diffeomorphism solver given as a  $3 \times 3$  SPD matrix  $\sqrt{J^T J}$  at each voxel. It provides the deformation field between two longitudinal images of a subject. Various results have described the benefits of CDT images for analysis; an example from our experiments is in Sec. 6.

Recall that for a pair of real numbers  $a$  and  $b$ , the prediction of a linear model “ $y = ax + b$ ” is always a real number. But if  $a$  and  $b$  are SPD matrices (i.e., CDTs), this property no longer holds: “ $y = ax + b$ ” may not be a valid SPD matrix (e.g., consider when  $x < 0$ ). In addition to the validity of predictions, while in classical linear regression, the residual of a fit,  $(y - (Ax + b))$ , can be estimated directly,

the error (residual) on a SPD manifold must be measured via the *geodesic distance* on a manifold between the prediction  $\hat{y}$  and the true response  $y$ . So, any machine learning model that needs to be extended for manifold-valued data must give particular attention to these issues, and often specialized optimization methods for parameter estimation are needed [17, 18, 21]. With these issues in mind, we first describe a linear mixed effects models with subject-specific intercepts and then transition to nonlinear mixed effects models for manifold valued data.

### 3.1. A model with subject specific intercepts

We know that in any longitudinal dataset, the errors/noise of repeated measurements are dependent. To consider this aspect, a common approach is to express the random effects as nuisance parameters. If the set  $\{i = 1, i = 2, \dots, i = N\}$  indexes the columns, we may write the design matrix  $Z$  as  $\text{diag}(\mathbb{1}_{n_1}, \mathbb{1}_{n_2}, \dots, \mathbb{1}_{n_N})$ , where  $\mathbb{1}_{n_i} = [1 \dots 1]^T \in \mathbb{R}^{n_i}$ . Then, the model in (3) becomes

$$y_{[ij]} = \beta^0 + \beta^T \mathbf{x}_{[ij]} + u_i, \quad (5)$$

where  $y_{[ij]}, \beta^0, u_i \in \mathbf{R}$ , and  $\beta, \mathbf{x}_{[ij]} \in \mathbf{R}^p$ . Note that  $\mathbf{z}_{[ij]} \in \mathbf{R}^N$  recovers a specific row corresponding to subject  $i$ 's visit  $j$  from matrix  $Z$  taking dot product with  $\mathbf{u}$  gives us the subject specific random effects,  $u_i = \mathbf{z}_{[ij]} \mathbf{u}$ .

This model poses two problems. **1)** It has the same slope  $\beta$  for the entire population, whereas subjects in the study may have different rate of disease progression; **2)** Another issue is the interpretation of  $u_i$ , which is viewed as subject-specific shift in the  $y$  space or  $x$  space, i.e., depending on whether we move it to the left or right of the equality in (5). In medical applications, readability of models is important to understand the disease. Our solution involves explicitly adding a subject-specific shift for  $x$  as well as a shift in  $y$ .

### 3.2. Nonlinear mixed effects models with $\psi_i(x)$

Based on the foregoing motivation, we can extend the linear mixed effects models with a subject-specific random function  $\psi_i(\cdot)$  as

$$y_{[ij]} = \beta_0 + \mathbf{z}_{[ij]} u_i + \beta \cdot \psi_i(\mathbf{x}_{[ij]}) \quad (6)$$

Depending on the form of  $\psi_i(\cdot)$ , (6) can be a nonlinear mixed effects model (NLMM). When  $\psi_i$  is the Identity, we simply get a linear mixed effects model. In our analysis, we use  $\psi_i(\mathbf{x}) := \alpha_i(\mathbf{x} - \tau_i - t_0) + t_0$  motivated by [43] where each subject can have their own speed of disease progression ( $\alpha_i$ ) and different onset time  $\tau_i$ , but  $(\beta_0, \beta, t_0)$  are common for the population. Then we have

$$y_{[ij]} = \beta_0 + \mathbf{z}_{[ij]} u_i + \beta(\alpha_i(\mathbf{x}_{[ij]} - \tau_i - t_0) + t_0). \quad (7)$$

Note that this extension is different from the *generalized linear mixed effects models* [44], e.g.,  $y_{[ij]} = h^{-1}(\mathbf{x}_{[ij]}\beta +$

$\mathbf{z}_{[ij]} u_i), u_i \sim \mathcal{N}(0, \Sigma_i)$ . Next, we extend the mixed effects models in (5) and (7) to manifold-valued data.

## 4. Mixed effects models on manifolds

The Linear Mixed Effects Model (LMM) can be extended in many ways to the manifold setting depending on the order of addition and interpretation. For instance, recall that the associativity of addition,  $(a+b)+c = a+(b+c)$ , in the Euclidean space is not directly translated to manifolds, i.e.,  $\text{Exp}(\text{Exp}(a, b), c) \neq \text{Exp}(\text{Exp}(a, c'), b')$ , where  $b'$  and  $c'$  are parallelly transported tangent vectors of  $b$  and  $c$  respectively, so that they are in the right tangent spaces. A natural extension of LMM in (3) can be written as

$$y_{[ij]} = \text{Exp}(\text{Exp}(\text{Exp}(B, V \mathbf{x}_{[ij]}), U_i \mathbf{z}_{[ij]}), \epsilon_{[ij]}), \quad (8)$$

where  $y_{[ij]}, B, B_i \in \mathcal{M}$ ,  $V \in T_B \mathcal{M}^p$ ,  $U_i \in T_{h_{[ij]}} \mathcal{M}^q$ ,  $h_{[ij]} = \text{Exp}(B, V \mathbf{x}_{[ij]})$ ,  $\mathbf{x}_{[ij]} \in \mathbf{R}^p$  and  $\mathbf{z}_{[ij]} \in \mathbf{R}^q$ . Recall that the base point  $B$  on the manifold  $\mathcal{M}$  is the analog to the intercept  $\beta^0$  in (5) whereas  $V$  (and  $U_i$ ) corresponds to the slope  $\beta$  (and the random effects  $u_i$ ) respectively. Unfortunately, the model above has an issue related to  $U_i$ . Note that  $U_i$  is used in different tangent spaces at  $h_{[ij]}$ . Also, especially on  $\text{SPD}(n)$  manifolds with the GL-invariant metric, the norm of the tangent vectors varies as a function of the base point  $B$  of the respective tangent spaces, i.e.,  $\|U\|_B^2 = \langle U, U \rangle_B = \text{tr}(UB^{-1}UB^{-1})$ . So the corresponding scales might be different. As a result, the prior for  $U_i$  needs to be carefully designed [45] to have consistency over all tangent spaces. To address this problem, we change the order of the exponential maps and propose a mixed effects model with subject specific intercepts (shift in  $y$ ) on manifolds. Also, unlike the Euclidean space, in general, there is no equivalence between the shift in  $x$  and the shift in  $y$ . So, we can explicitly add in the shift in  $x$ , denoted as  $\tau_i$ . Then, our formulation on manifolds is given as

$$y_{[ij]} = \text{Exp}(\text{Exp}(B_i, \Gamma_{B \rightarrow B_i}(V)(\mathbf{x}_{[ij]} - \tau_i)), \epsilon_{ij}), \quad (9)$$

$$B_i = \text{Exp}(B, U_i \mathbf{z}_{[ij]}), \quad (10)$$

where  $\tau_i \in \mathbf{R}^p$ ,  $B_i \in \mathcal{M}$ ,  $V \in T_B \mathcal{M}^p$ ,  $U_i \in T_B \mathcal{M}^q$ , and the remaining variables are the same as before. As in the standard mixed effects models,  $U_i$  is assumed to follow a normal distribution. With this construction in hand, we may now include a subject-specific time shift in the onset time (similar to (7)) and assume that the progression of disease has the same overall pattern but only its speed/rate and onset time vary between subjects. The model is given by

$$y_{[ij]} = \text{Exp}(\text{Exp}(B_i, \Gamma_{B \rightarrow B_i}(V)\alpha_i(\mathbf{x}_{[ij]} - \tau_i - t_0), \epsilon_{ij}))) \\ B_i = \text{Exp}(B, U_i), \quad (11)$$

where  $\alpha_i$  is the subject-specific acceleration,  $\alpha_i < 1$  (and  $\alpha_i > 1$  resp.) means slower (and faster resp.) than the population. Further,  $\tau_i$  is the subject-specific shift in onset

time:  $\tau_i > 0$  means a late onset time whereas  $t_0$  is the global shift in onset time. Finally,  $U_i$  (or  $B_i$ ) are the tangent vectors (or base points) that characterize the subject-specific shift in the response variable space (see the Euclidean case in Fig. 2). As in the classical setting, we may assume that the random effects are normally distributed, i.e.,  $\Gamma_{B \rightarrow I} U_i \sim \mathcal{N}_{SYM}(0, \sigma_U^2)$ ,  $\alpha_i \sim \mathcal{N}(1, \sigma_\alpha^2)$ ,  $\tau_i \sim \mathcal{N}(0, \sigma_\tau^2)$ .

## 5. Parameter estimation procedure

The estimation of the mixed effects models on manifolds is challenging; provably accurate estimation methods are almost infeasible to run over the entire brain image. Even for Euclidean response variables, efficient estimation methods for *nonlinear* mixed effects models are still being actively studied in literature, e.g., Alternating algorithms [44], Laplacian and adaptive Gaussian quadrature algorithms [46], as well as generalized EM algorithms with MCMC [47]. Unfortunately, this issue only gets worse in the manifold setting. Fitting a nonlinear mixed effects model exactly, even for *univariate manifolds on the real line* takes about a day [37]. In our data set, the number of voxels is 1M+, it is impractical to perform exact analysis for the full brain. So, we present approximate algorithms based on a certain geometrical interpretation of the models.

### 5.1. Estimation of RNLMM

We observe that the main building block of our models, Riemannian nonlinear mixed effects models (RNLMMs), is a manifold-valued multivariate general linear model (MMGLM). This module has an efficient parameter estimation called the Log-Euclidean framework. It is known [19] that in practice the estimation can be well approximated in the tangent space at the Fréchet mean of the response variables  $Y$  with a centered  $X$ , i.e.,  $B \approx \bar{Y}$ ,  $\tau \approx \bar{X}$ . As in a global manifold-valued linear model [19], the parameter  $V$  will correspond to the full data set; however, we allow subject-specific variability for the base point  $B$  and  $\tau$  via  $B_i(r)$  and  $\tau_i(r)$ , where  $r \in \mathbf{R}$  can be viewed as the mixing rate between the local models that share a global  $V$ . This is given by

$$y_{[ij]} = \text{Exp}(\text{Exp}(B_i(r), \Gamma_{B \rightarrow B_i(r)}(V)(\mathbf{x}_{[ij]} - \tau_i(r))), \epsilon). \quad (12)$$

In other words,  $r \in \mathbf{R}$  is a weight to globally average the population subject specific base points  $B_i(r)$  and time shifts  $\tau_i(r)$  — all subjects share the fixed effects  $V$  but each subject corresponds to its own shifts  $\tau_i(r)$  and  $B_i(r)$  in  $x$  and  $y$  spaces. When  $r = 0$ , the model reduces to the model in [18] with only global intercepts (see the extended version).

Our estimation for (12) is summarized in Alg. 1, where  $\mathbf{y}_{[ij]}^\dagger$  is a tangent vector obtained by: taking the response  $y_{[ij]}$  and mapping it to the tangent space at  $B_i(r)$  and parallel transporting that mapping to  $T_B \mathcal{M}$ . We now briefly de-

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### Algorithm 1 Riemannian mixed effects models

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- 1: Calculate the mean for each subject,  $\bar{y}_i$ ,

$$\bar{y}_i = \underset{\mathbf{y} \in \mathcal{M}}{\text{argmin}} \sum_{j=1}^{n_i} d(\mathbf{y}, \mathbf{y}_{[ij]})^2. \quad (13)$$

Similarly calculate  $\bar{\mathbf{y}}$  for the entire population.

- 2: Given  $r$ , solve for  $B_i(r)$  (interpolation of  $\bar{y}_i$  and  $\bar{\mathbf{y}}$ ) by

$$B_i(r) = \bar{\mathbf{y}}(\bar{\mathbf{y}}^{-1} \bar{y}_i)^r = \bar{y}_i(\bar{y}_i^{-1} \bar{\mathbf{y}})^{1-r}, 0 \leq r \leq 1.$$

- 3:  $\mathbf{y}_{[ij]}^\dagger = \Gamma_{\bar{B}_i(r) \rightarrow B} \text{Log}(\bar{B}_i(r), \mathbf{y}_{[ij]})$ .

- 4: Transport  $\mathbf{y}_{[ij]}^\dagger$  to  $I$  by group action.

- 5: Center  $\mathbf{x}$  by  $\mathbf{x}_{[ij]}(r) = (1-r)(\mathbf{x}_{[ij]} - \bar{\mathbf{x}}) + r(\mathbf{x}_{[ij]} - \bar{\mathbf{x}}_i)$ .

- 6: Calculate  $V^*$  using MMGLM [19] on transported  $\mathbf{y}_{[ij]}^\dagger$  and  $\mathbf{x}_{[ij]}(r)$ .

- 7: Prediction is given by

$$\hat{\mathbf{y}}_{ij} = \text{Exp}(B_i(r), \Gamma_{B \rightarrow \bar{B}_i(r)}(V^*)\mathbf{x}_{ij}(r)). \quad (14)$$


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scribe how we can perform the estimation efficiently. First, in Step 2, we solve for the linear interpolation of two SPD matrices w.r.t the geodesic distance on the SPD manifold using the analytical form of the solution in [48] (note that when the number of samples is large, recursive schemes exist [49]). In Step 4, we transport the tangent vectors from  $B$  to  $I$  and vice versa using group action, which is known to be more efficient than parallel transport but equivalent [50].

### 5.2. Estimation of RNLMM with $\psi_i(\mathbf{x})$

The estimation of the model in (11) with the subject-specific random function  $\psi_i(\cdot)$  involves few additional technical challenges. To reduce the problem complexity, we first find the main longitudinal change direction  $\boldsymbol{\eta}$  controlling for the subject-specific random effects  $\bar{Y}_i$  and  $\bar{X}_i$  (since  $U_i$  and  $\tau_i$  are random effects). This scheme is described in Alg. 2.

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### Algorithm 2 Calculate longitudinal change direction

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- 1: Calculate the population Fréchet mean  $\bar{\mathbf{y}}$  of response.

- 2: Calculate the Fréchet mean for each subject  $\bar{y}_i$ .

- 3: Solve  $\mathbf{y}_{[ij]}^\dagger = \Gamma_{\bar{y}_i \rightarrow I} \text{Log}(\bar{y}_i, \mathbf{y}_{[ij]})$ .

- 4: Solve  $\mathbf{x}_{[ij]}^\dagger = \mathbf{x}_{[ij]} - \bar{\mathbf{x}}_i$ , where  $\bar{\mathbf{x}}_i = \mathbb{E}_j[\mathbf{x}_{[ij]}]$ .

- 5: Collect  $X^\dagger = [\mathbf{x}_1^\dagger; \dots; \mathbf{x}_N^\dagger]$ , and  $Y^\dagger = [\mathbf{y}_1^\dagger; \dots; \mathbf{y}_N^\dagger]$ .

- 6: Calculate longitudinal change direction  $\boldsymbol{\eta}$  by least squares estimation,  $\boldsymbol{\eta} = ((X^\dagger)^T X^\dagger)^{-1} ((X^\dagger)^T Y^\dagger) \in T_I \mathcal{M}$ .
- 

Once the longitudinal change direction  $\boldsymbol{\eta}$  (fixed effects for the entire population) is estimated, we solve for a subset of parameters at a time. This procedure is described in Alg. 3, where we solve for all parameters given the estimate of  $\boldsymbol{\eta}$ . Note that for our downstream analysis, the bias induced by priors on parameters may reduce the statistical power. So, we simply used noninformative priors for all parameters. While Alg. 3 utilizes noninformative priors, with minor changes, we can easily incorporate normal distribution priors, see the extended version.

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**Algorithm 3** Riemannian mixed effects models with  $\psi_i(x)$ 


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- 1: Calculate the Fréchet mean  $\bar{y} \in \mathcal{M}$  of population.
- 2: Calculate the Fréchet mean for each subject  $\bar{y}_i \in \mathcal{M}$ .
- 3: Main longitudinal change direction  $\eta$  by algorithm (2).
- 4: Calculate subject-specific base points (random effects)  $B_i = \text{Exp}(B, U_i^*)$ , where  $U_i^* = \text{argmin}_{U_i} d(\bar{y}_i, \text{Exp}(B, U_i))^2 + \lambda_{U_i} \|U_i\|_B^2$ .
- 5:  $y_{ij}^\lambda = \Gamma_{B_i \rightarrow I} \text{Log}(B_i, y_{ij})$ .
- 6: **while** until convergence **do**
- 7: Calculate the common speed of change  $V = c\eta$  and common time intercept  $t_0 = b/c$  with fixed all other variables by

$$\begin{bmatrix} \sum_{ij} q_i^T q_i & \sum_{ij} p_{ij}^T q_i \\ \sum_{ij} p_{ij}^T q_i & \sum_{ij} p_{ij}^T p_{ij} \end{bmatrix} \begin{bmatrix} b \\ c \end{bmatrix} = \begin{bmatrix} \sum_{ij} q_i^T y_{ij}^\lambda \\ \sum_{ij} p_{ij}^T y_{ij}^\lambda \end{bmatrix},$$

where  $b := t_0 c$ ,  $q_i := \eta(1 - \alpha_i)$ ,  $p_{ij} := \eta(\alpha_i x_{ij} - \alpha_i \tau_i)$ .

- 8: Given  $V$ ,  $t_0$ , calculate the subject-specific acceleration  $\alpha_i$ , and time-shift  $\tau_i$  by generalized least square estimation with the priors for  $\alpha_i$  and  $\tau_i = d_i/\alpha_i$

$$\begin{bmatrix} \sum_j W_{ij}^T W_{ij} & -\sum_j W_{ij}^T V \\ \sum_j W_{ij}^T V & -\sum_j V^T V \end{bmatrix} \begin{bmatrix} \alpha_i \\ d_i \end{bmatrix} = \begin{bmatrix} \sum_j \Upsilon_{ij}^T W_{ij} \\ \sum_j \Upsilon_{ij}^T V \end{bmatrix},$$

where  $\Upsilon_{ij} := y_{ij}^\lambda - V t_0$ ,  $W_{ij} := V(X_{ij} - t_0)$  and  $d_i = \alpha_i \tau_i$ .

- 9: **end while**
- 

Alg. 3 contains many steps in common with Alg. 1. In Step 7, we estimate the fixed effects  $V$  and  $t_0$  by fixing all other variables ( $c$  is a dummy variable). In Step 8, we estimate the subject-specific random effects  $\alpha_i$  and  $\tau_i$  by fixing  $V$  and  $t_0$  ( $d_i$  are dummy variables). Additional details including derivation are available in the extended version.

## 6. Experiments

**Goals.** The overarching goal of our experiments is to evaluate whether the proposed formulations can serve as core modules that drive longitudinal analysis of image datasets in neuroimaging. To this end, when conducting analysis of longitudinal data acquired in the context of a specific disease, the procedure should yield meaningful results for group analysis — for instance, when the population is split with a stratification variable (e.g., gender or disease risk factor), the “maps” of statistically significant group-wise differences in subject/voxel-specific “random” effects (especially, acceleration and spatial shift) should be scientifically interpretable, yet generally consistent with a baseline. Our experiments below show the extent to which the models satisfy this requirement.

**Data.** The CDT images (denoting subject-specific warps) were derived from a longitudinal neuroimaging study of pre-clinical Alzheimer’s disease (AD). The longitudinal warps (or transformations) were obtained using *with-in* subject registration of  $T_1$ -weighted images between two consecutive visits i.e.,  $\Phi_{i,j} : \mathcal{I}_{i,j} \rightarrow \mathcal{I}_{i,j+1}$ . Voxelwise CDTs were derived from the spatial derivatives  $\nabla \Phi_{i,j}(\text{vox})$

of the deformation field. The details of minimizing spatio-temporal biases in the CDT estimation are presented in the extended version due to space constraints.

**CDT versus  $\det(J)$ .** We first present a motivating experiment to demonstrate the rationale behind using CDTs instead of the determinants  $\det(J)$  of Jacobian of the deformations, i.e., do CDTs actually carry more information? We test for group differences in longitudinal changes of the brain between groups of middle versus old aged individuals using CDTs and compare these results to those obtained via determinants. In order to avoid confounding factors in this comparison, we use the Cramér’s test, a nonparametric test for univariate as well as manifold-valued data since it does not require any specification of the null distribution [51]. Fig. 3 clearly shows the improvements in statistical differences across the groups (higher sensitivity) when using CDTs (instead of  $\det(J)$  maps).

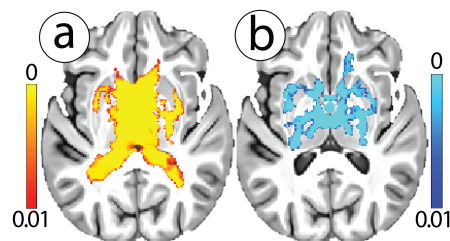


Figure 3. Results of Cramér’s test showing voxels that are different between middle and old age groups ( $p < 0.01$ ) from (a) CDTs and (b)  $\det(J)$ .

**RNLMMs on longitudinal CDTs.** We now present results using our Riemannian nonlinear mixed effects models (RNLMM) using subject specific transformation functions  $\psi_i(x_{[ij]})$  (6). Here,  $x_{[ij]} \in \mathbf{R}$  is used to represent the age of each subject at the previous visit and  $y_{[ij]} \in \mathcal{M}$ , (the CDT image calculated from scans at two points). For these results, we used data from subjects who had at least three visits. We estimated our model at each voxel in the brain ( $1.3M+$ ) using a total of  $N = 228$  participants that had at least two CDT images. The maps for acceleration ( $\alpha_i$ ), spatial shift ( $U_i$ ) and time shift ( $\tau_i$ ) for each of the subjects offer unique advantages. For instance, these maps are *not offered* by standard linear mixed effects models where only a subject specific slope or intercept is used as the random-effects (independently noted in [37]). Fig. 4 shows four representative subject-specific acceleration maps. The regions where *this specific individual* has a faster (slower) aging (or disease progression) compared to the population average rate are colored in yellow (and blue) color-scales respectively. These RNLMM maps can be used to perform additional “downstream” statistical tests using parametric tests. Here, we cover two specific examples. In Fig. 4, we show the kind of results our model can offer at the **individual level**. Fig. 4(a)-(d) shows four results, each pertaining to a different participant in the study. Fig. 4(a)-(b) show maps for

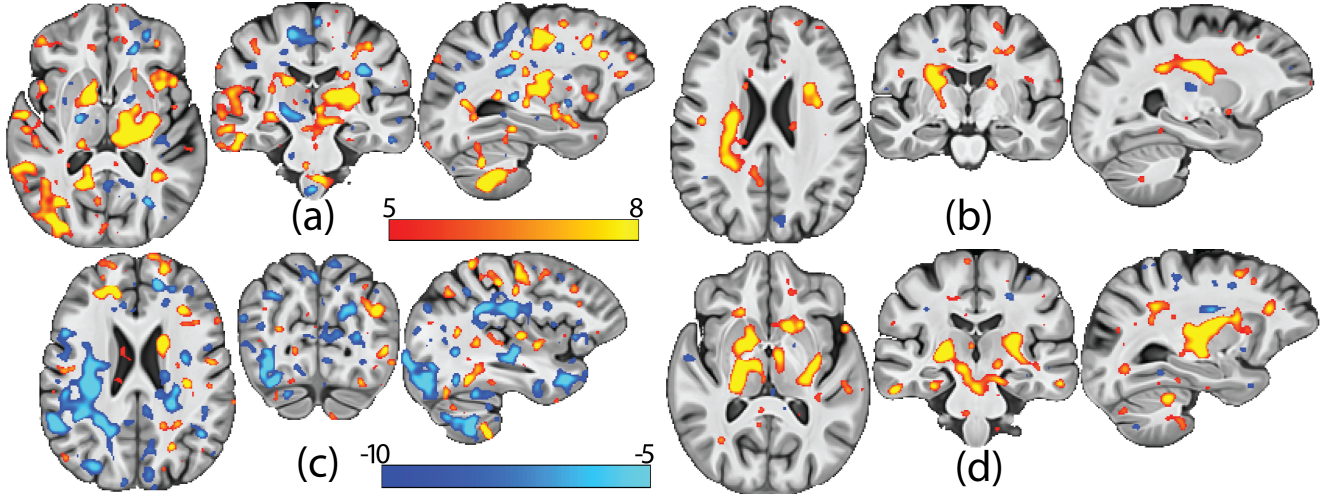


Figure 4. Representative acceleration ( $\alpha_i$ ) maps derived from our RNLMM. (a) Female, APOE-. (b) Female, APOE+. (c) Male, APOE-. (d) Male, APOE+. The male with no APOE risk shows slower progression (more blue regions) compared to the population average.

two females, whereas Fig. 4(c)-(d) show examples of two males. The color indicates the brain deformation over time (captured via acceleration), for this specific person, relative to the population. We see that a representative male (with no APOE risk) shows a slower acceleration rate (blue regions) compared to the population. Few other models in the literature can provide such *personalized assessment*.

Of course, such acceleration and spatial shift maps can also be used for **group level** analysis. We present results of Hotelling- $T^2$  tests on the group-wise  $U_i$  maps using the following two stratification variables: (a) males and females and (b) individuals with/without AD risk (due to APOE) [52, 53]. This enables us to identify longitudinal spatial shifts (deviations from population base points  $B$ ) between these groups, shown in Fig. 5 for the gender and APOE stratification variables. The extended version provides several more analyses including synthetic experiments to show the behavior of RNLMMs in (10) and (11).

## 7. Conclusion

This paper extends nonlinear mixed effects models to the setting where the responses lie on curved spaces such as the manifold of symmetric positive definite (SPD) matrices. By treating the subject-wise “non-linear warps” between consecutive time points as a field of Cauchy deformation tensors (CDT), we show how our model can facilitate longitudinal analysis that respects the geometry of such data. While the existing body of work dealing with regression models on manifold-valued data is inherently restricted to cross-sectional studies, the proposed mixed effects formulation significantly expands the operating range of the types of analyses we can conduct. For instance, the “random” effects in the construction parameterized by acceleration and spatial and time shifts offer interesting advantages. Not only

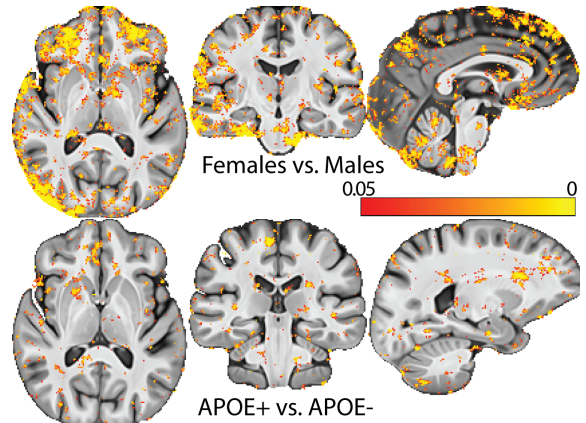


Figure 5. P-value maps of group differences in random effects ( $U_i$ ). Top: Gender differences. Bottom: APOE group {APOE+, APOE-} differences. Gender differences can be effectively captured by our RNLMM.

can these quantities be directly used for downstream models but they also offer interpretability at the *level of individual subjects* — as an example, when conditioned on (or controlled for) race, sex and education, we can ask if a specific person’s onset time of brain atrophy or *rate of atrophy*, at the level of individual voxels, deviates from the group. This capability is not currently available otherwise.

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