A technical note on the geometric effects of volume to surface mapping of fMRI data

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Abstract

In this technical report we identify and report a problem with the process of volume to surface mapping that has potentially impacted studies that focus upon local neighborhood connectivity. We show that neighborhood correlations vary spatially with anatomical patterns (gyral structure) even when the underlying volumetric data is uncorrelated noise. We explore the effects of this anomaly across varying data resolutions and surface mesh densities. We finally propose an approach to mitigate these unwanted effects.

Keywords: Functional MRI, volume to surface mapping, cortical organization

1. Introduction

Surface based functional MRI has become a popular approach for performing fMRI analysis. An increasing number of large projects provide surface-based data (e.g. Human Connectome Project [HCP] (Van Essen et al., 2012, 2013), Adolescent Brain Cognitive Development [ABCD] study (Bjork et al., 2017)) as well as software packages (e.g. FreeSurfer or Connectome Workbench) to facilitate the surface analysis. Recent fMRI packages have also implemented surface-based analysis in the preprocessing pipelines (e.g. the HCP Pipelines or fmriPrep) (Esteban et al., 2019; Glasser et al., 2013). There are good theoretical (Brodoehl et al., 2020; Glasser et al., 2016) and practical advantages (Coalson et al., 2018) to performing fMRI analysis on a cortical surface mesh. The primary advantages are that smoothing on a two dimensional surface respects the geometry of the brain and reduces signal contamination from geodesically distant areas of cortex (yet close in euclidean distance - such as opposing banks of neighboring sulci) and crosss-subject alignment in 2D on the surface is fundamentally an easier problem than in 3D in the volume. As part of the surface based preprocessing pipeline, the user must first project their volumetric (voxel) data to surface vertices. The process itself, however, has the potential to introduce artefacts that may affect some downstream surface-based analyses.

In this technical note we identify and report a problem with the process of volume to surface mapping in the context of analysing local neighborhood connectivity. The effect has potentially impacted some studies that have not taken it into consideration.

2. The Problem

An anomaly was noted when analysing regional boundaries (or edges) in functional signatures across the cortex (Bajada et al., 2020). Specifically, when aiming to characterize the regional boundaries by calculating the local functional changes between neighborhood vertices along the surface, we observed a clear anatomical

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pattern that follows the gyral boundaries of the brain, even when using stochastic data as an input (Figure 1). This suggests that the local connectivity analysis might be affected, at least partially, by the surface geometry.

A related phenomenon was first noted by (Glasser et al., 2013) where they noted that increasing the resolution of functional MRI data decreases "geometric effects" on surface data. Their primary concern was, however, the effects on correlation between relatively distant (geodesically) cortical areas.

In order to explore the phenomenon as it relates to neighborhood correlations more rigorously, uncorrelated noise (drawn from a standard normal distribution) was used to create synthetic fMRI timeseries at the voxel level. These were then projected to the surface using various volume-to-surface mapping approaches.

To simplify interpretations for this report, we first defined a local region that includes a given vertex and its neighborhood of vertices, one which shares an edge on the cortical mesh. Next, we calculated the pairwise Pearson correlations between any two vertices within the local region. Finally, we performed the Fisher-z transform and used the mean of z-scores as the local connectivity index for the given vertex.

Similar patterns, following the gyrification patterns, that were observed with the real data were found. This prompted a more systematic exploration of the issue with the aim to understand and mitigate the problem.

3. Methodology

The T1-weighted data of a single subject from the minimally preprocessed Human Connectome Project Young Adult data-set were used for this study (Glasser et al., 2013). These data were selected in order to ensure high quality results and ensure state-of-the-art preprocessing up to the point of encountering the discussed issue. Noise timeseries were generated at three isotropic resolutions (0.7 mm, 1.4 mm and 2 mm) in volumetric space and pushed to the surface using five different volume to surface algorithms available within Connectome Workbench. The first two used simple trilinear and cubic interpolation at the level of the midthickness surface. The second two used the advanced ribbon constrained algorithm which uses constructed polyhedra constrained by the pial and white matter surface and uses the volume to weight the underlying voxel contribution (including a variant in which non-overlapping polyhedra are used, designated "thin columns" (TC)). The final approach termed the "enclosing" approach simply uses the voxel beneath the vertex of the midthickness surface. In order to isolate the problem as the interpolation between the voxel data and the surface, random noise was also drawn independently for each vertex in the reconstructed surface, we refer to this in figures as "pure noise".

To ensure a rigorous evaluation of the effect all of the different approaches of volume to surface mapping we carried out the following:

1. Volume to surface mapping of noise timeseries using the five approaches onto the native high-resolution surface (in the MNI standard space as per HCP data). Then down-sampling the maps to the surface resolution of interest (32k and 10k). We term this approach the "native mesh approach";
2. Volume to surface mapping using the five approaches directly onto the resolution of interest (native, 32k and 10k) surfaces. We term this approach the "direct low resolution approach";
3. Volume to surface mapping using the three more basic approaches (trilinear, cubic and enclosing), onto midthickness surface meshes that approximate the resolutions of interest but that have undergone modification to reduced the variance of the inter-vertex distances (Attene, 2010);
4. Scatter plots showing the relationship between mean distance of neighborhood vertices and local correlations were plotted.
5. Histograms of the local correlations were also plotted for all of the different approaches.

For the sake of brevity, only the most pertinent results are discussed in the following section, however, all results and code are made available for further exploration and scrutiny (https://osf.io/dxr6f/) .

4. Results

A clear relationship between volume voxel size and surface resolution was found. As surface resolution (vertex density) is increased, or underlying voxel data resolution decreased, more surface vertices sample the same voxels from the volume. This results in an artefactual local correlation despite the original, volumetric data being uncorrelated noise. We note that this issue should not be unique to brain data or surface-based processing, upsampling any data to a higher sampling density should present a similar issue. Figure 2 shows, in the direct low resolution approach, the neighborhood correlations are approximately zero until the mean neighborhood distance decreases below a certain range (approximately equal to the resolution of the volume data). This pattern is replicated if the native mesh approach is used (see supplementary data and figures).

5. Mitigation

From the results of our investigations two points emerge (in the context of analyzing local correlations):

1. underlying voxel data should be of an equal or higher resolution relative to the surface mesh density. The important point is that the underlying data should not be of lower resolution than the surface mesh density;
2. any variance in intra-vertex distance on the mesh will create systematic "problematic areas." As a result, the uniformisation of surface meshes may mitigate the problem.

We ran the same pipeline on uniform meshes. As can be seen in Figures 4 and 5, the effect on projecting 2 mm data (typical high quality fMRI resolution) onto a 10k uniform surface greatly improves the local connectivity estimation of the data. Figure 5 shows that the noise surface to volume mapping does not show any obvious geometric patterns in local correlations. Further, additional analysis using real fMRI data from resting state and motor conditions show high local correlations in areas that are plausible for the specific task. It is important to note, however, that this approach comes at a cost of 1) decreasing spatial resolution 2) affecting SNR and 3) requires additional steps in order to regain vertex correspondence to a standard template.

6. Conclusion

In this technical report, we note that:

1. the relative difference between the cortical surface vertex density and underlying voxel resolution is important to consider;
2. not considering the variability of oversampling during volume to surface mapping to a relatively dense mesh (in relation to the data resolution) has the potential to affect studies that are interested in local neighborhood connectivity;
3. the artefactual geometric patterns that follow the cortical gyrification pattern can be mitigated (but not necessarily solved) by a) mapping data to a lower resolution mesh and b) ensuring that the mesh has a relatively low intra-vertex distance variance.

Overall, the present study highlights that geometric effects occur in surface based analysis investigating local neighborhood connectivity. As such any researcher that is interested in these investigations should take such effects seriously.

Data are available in a Jupyter notebook that can be used to recreate all of the analysis shown in this report. Additional figures that were not displayed due to limitations of the article format are also available in the supplementary material.

7. Acknowledgements

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8. Figures

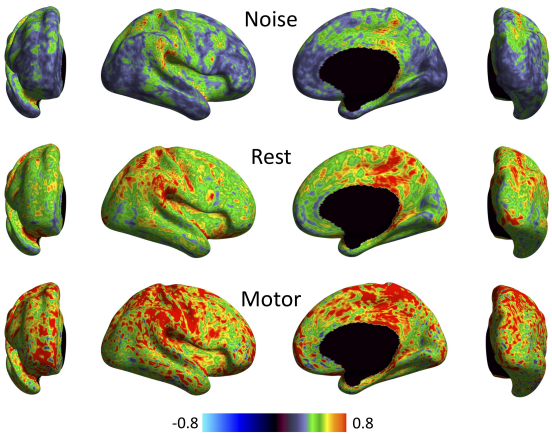

Figure 1: A delineation of the observed anomaly. The maps show, surface based, vertex-wise neighborhood correlation maps on three separate data sets. The top figure shows the map computed on data where the underlying volume was comprised of noise timeseries which was subsequently projected to a surface. The middle map was computed on resting state surface projected data and the bottom image was computed on a motor task dataset. Note that the middle image was rotated to be comparable with figure 5

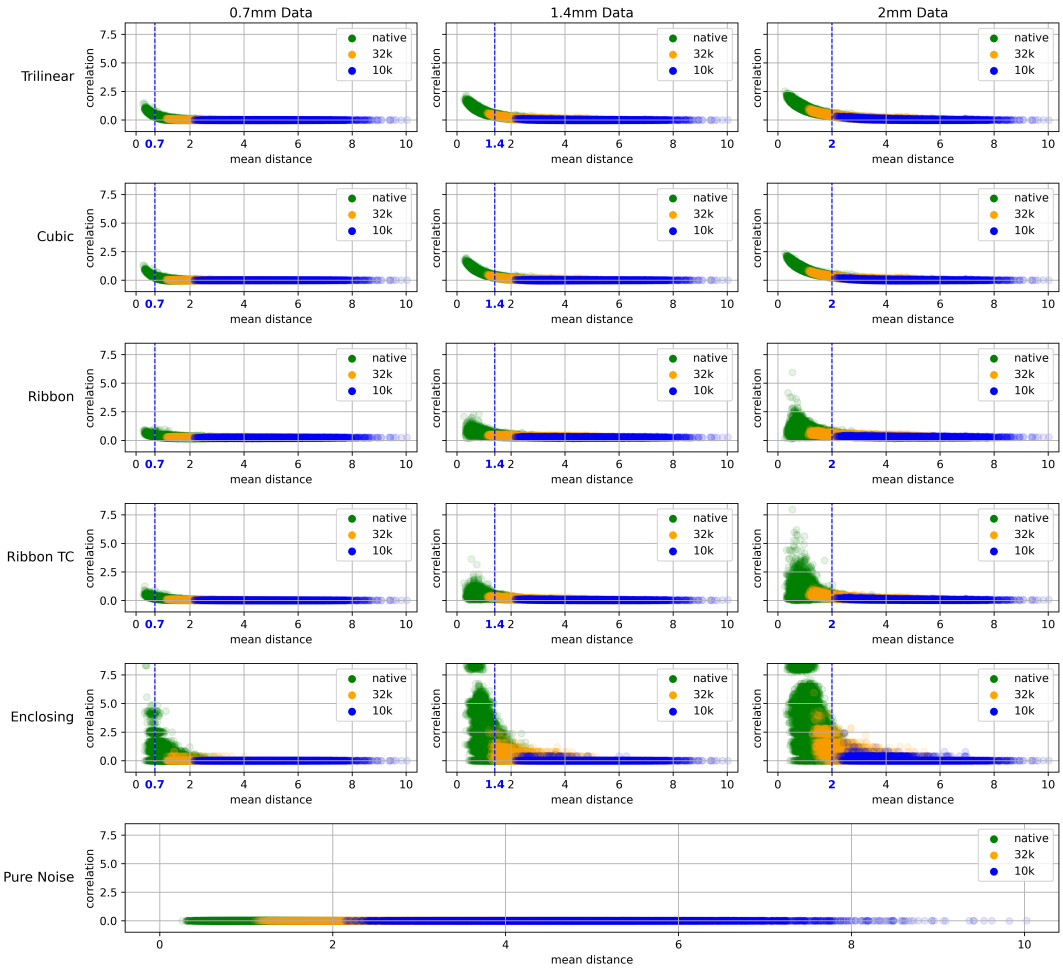

Figure 2: Matrix of various direct low resolution mapping approaches with various underlying voxel resolution. The bottom graph shows what is expected if local correlations are computed on "pure" noise timeseries that were generated directly on a surface mesh (with no volume to surface mapping artefacts. Colours indicate different mesh density, blue = 10k, yellow = 32k and green = native. The colours are consistently applied across all figures in this article and in the supplementary material. Medial wall voxels excluded from plots. The vertical blue line represents the data resolution in a single dimension. Note that more detailed, "individual mesh" level charts are available in the supplementary material.

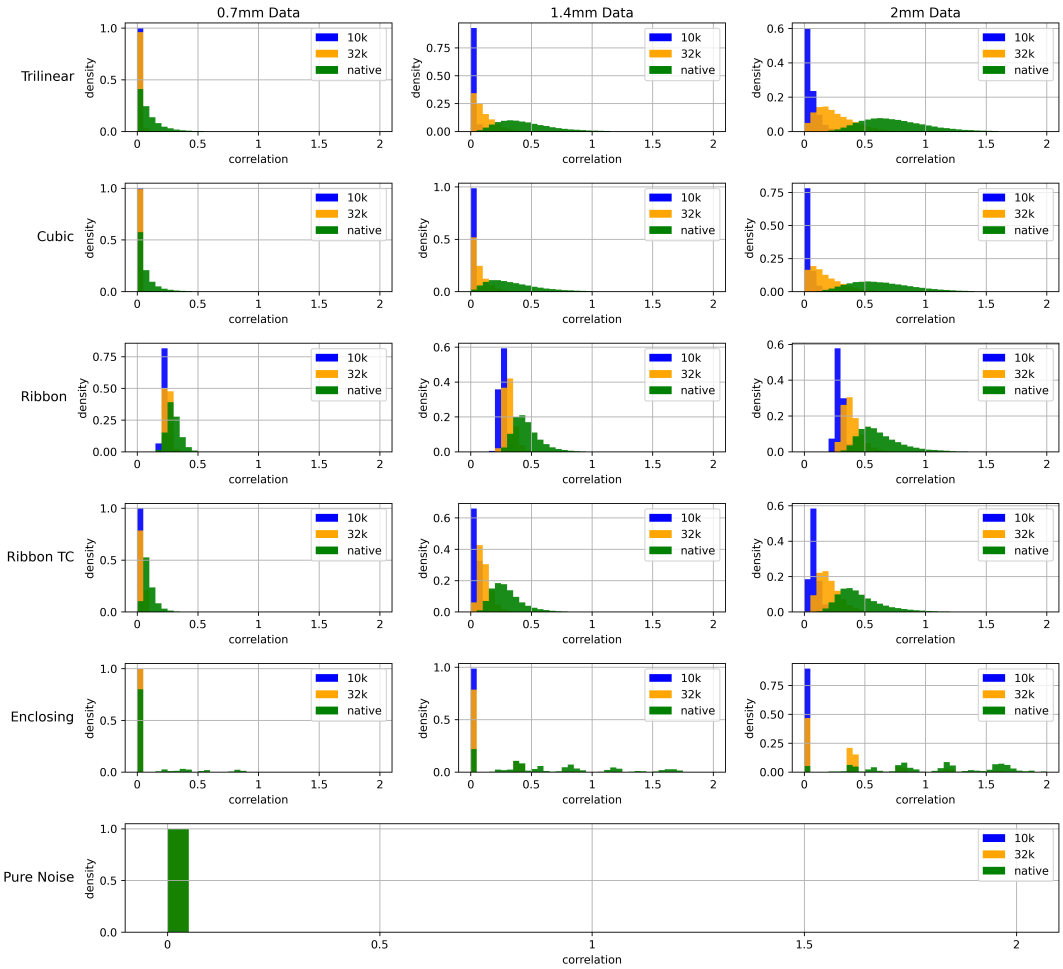

Figure 3: Matrix showing histograms of the various direct low resolution mapping approaches with various underlying voxel resolution. Colours indicate different mesh density, blue = 10k, yellow = 32k and green = native (midline voxels excluded from plots)

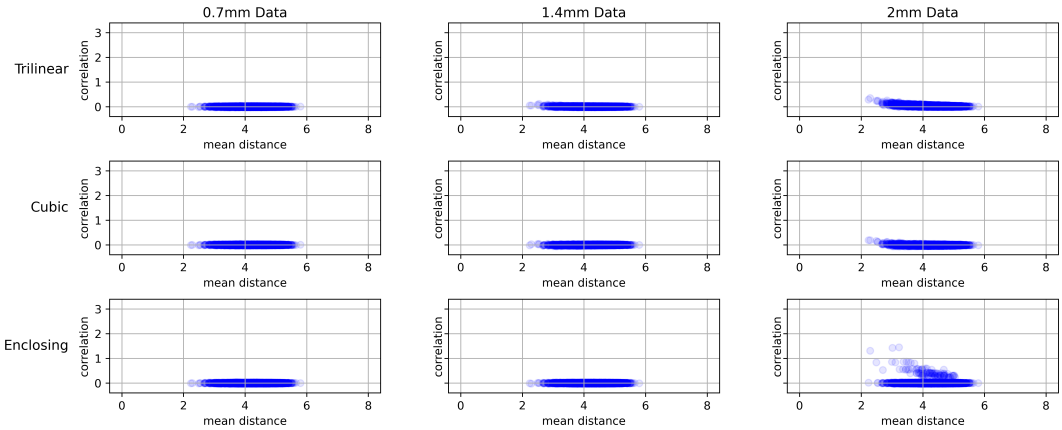

Figure 4: The impact of uniformisation of the mesh. Across all three volume to surface approaches and across all volumetric resolutions at a surface resolution of 10k vertices, the neighborhood correlations remain around zero (except for some neighborhoods in the enclosing approach).

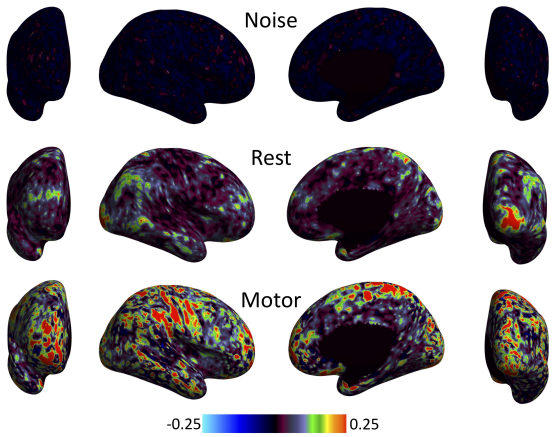

Figure 5: These are the final mitigated results using the direct low resolution approach on uniform 10k meshes and cubic interpolation shown on the brain. Note that the "Rest" image is rotated to demonstrate a clear "activation" in the occipital pole that would otherwise be obscured. One can note the difference as compared to figure 1

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