3D computational neuroimaging via slab photography and deep learning

https://doi.org/10.1038/
Received: 21 May 2024
Accepted:
Published online:
Check for updates

Sean I. Young[1,2]✉, Juan Eugenio Iglesias[1,2] & Bruce Fischl[1]

Traditional neuroimaging relies on MRI and histological sectioning as a reference for postmortem reconstruction of brain structures, limiting the utility and scalability of studies in which either modality is unavailable. Here, we present a 3D computational neuroimaging modality based entirely on photography of brain slabs. Our approach is based on self-supervised deep learning for 3D volume reconstruction, enabling an accurate spatial map between individual brain slabs and underlying brain without the need for an additional imaging modality, such as MRI. Tested on postmortem brain specimens, this approach leads to a higher level of resolution and accuracy compared to MRI-based methods while maintaining anatomical integrity. This computational imaging modality offers a cost-effective and non-invasive alternative for postmortem brain imaging, with potential applications in neuropathology and neurology, as well as forensic investigations. By eliminating dependence on expensive imaging systems such as MRI scanners, this neuroimaging modality democratizes neuroimaging and enables new avenues of large-scale studies of neuroimaging–pathology correlations through retrospective reconstruction of historical and current slab photographs for neurological conditions of interest, such as Alzheimer's disease.

Neuroimaging plays a key role in correlating the brain's structures and its pathology, with magnetic resonance imaging (MRI) and histological sectioning serving as the "gold-standard" techniques for postmortem brain reconstruction. Although these modalities can provide valuable insights into neurodegenerative diseases, traumatic brain injury, and structural abnormalities, they come with significant limitations. MRI, though widely used, offers limited histological resolution and requires expensive infrastructure, rendering it inaccessible for many research environments. Logistical issues can further complicate both cadeveric and ex vivo MRI of the brain, as tissue degradation due to autolysis and bacteria introduces artifacts in acquired MR images. These constraints significantly restrict the applicability and accessibility of postmortem neuroimaging, particularly if only slab photographs are available, such as in the case of historical brain banks. Several recent works attempt to reconstruct brain models from a combination of slab photographs and MRI (or brain surface scans) using numerical methods[1,2]. However, slab photography as a stand-alone neuroimaging modality on par with MRI has remained elusive due to the computational challenges of piecing together different brain slabs, each of which is subjected to geometric distortions from tissue deformation as well as camera distortion.

Here, we introduce a computational neuroimaging modality that is capable of imaging high-fidelity 3D brain volumes from conventional photographs of postmortem brain slabs, eliminating the need for MRI and other imaging modalities. Our method leverages fully supervised deep learning to learn spatial correspondences between 2D brain slab images and the underlying 3D brain, enabling an accurate volumetric reconstruction without additional imaging modalities. By leveraging deep learning's ability to infer complex spatial structures from limited textural cues, this approach achieves reconstruction accuracies which surpass MRI-based methods while preserving anatomical integrity. We test our approach on postmortem brain specimens, demonstrating its ability to reconstruct 3D brains with high spatial fidelity. Our findings highlight the potential of deep-learning-driven photographic imaging as a cost-effective, standalone computational imaging modality for 3D postmortem neuroimaging. This paradigm shift will enable large-scale studies utilizing existing slab photographs from brain banks to unlock new avenues for neuropathology and neurodegeneration studies, and forensic investigation. By removing reliance on conventional imaging systems, our method democratizes high-resolution neuroimaging for the studies of neurological conditions and diseases, and facilitates new insights into their structural underpinnings.

This approach not only democratizes high-resolution neuroimaging for the fields of neuropathology and forensic science, but also paves the way for a range of future applications. For example, it can enable large-scale retrospective studies of neurodegenerative diseases by transforming archived slab photographs into three-dimensional data, thus unlocking the potential of existing brain banks. In the realm of forensic investigations, this technique offers the ability to create accurate 3D reconstructions of injury patterns from autopsy photos, providing courts and investigators with a new level of spatial detail. Moreover, it allows researchers to revisit historical neurological archives with modern analytical techniques, fostering new insights into the structural underpinnings of neurological conditions. In summary, this innovation extends the reach of 3D neuroimaging into new domains and facilitates a broader understanding of the brain through purely photographic data.

Conventional slab photography

2D slab photographs of the brain are routinely captured at brain banks for postmortem neuroimaging, providing a detailed visual record of a brain's anatomy for neuropathological assessments as well as forensic investigation. Unlike in vivo neuroimaging modalities such as MRI and CT, slab photography can capture high-resolution surface detail of the dissected brain tissue, enabling direct visualization of morphological changes due to neurodegeneration, traumatic injuries, and pathology in the vasculature. However, slab photography is a destructive form of imaging—brain dissection is an irreversible process as slabs undergo a

A list of affiliations appears at the end of the paper.

spatial deformation in addition to the dissection itself. Due to this, the utility of conventional, 2D slab photographs is limited to a qualitative evaluation on the individual slabs rather than on a quantitative one on the whole brain (3D brain morphometry).

Recently, several numerical methods have been proposed to aid 3D reconstruction of the brain from slab photographs in tandem with pre-dissection MRI or surface scan, for example[1,2]. However, the need for a primary, more expensive imaging modality to guide 3D reconstruction can detract significantly from the applicability of slab photography for neuroimaging. For slab photography to be a true imaging modality on par with MRI, it must not only be standalone but also applicable to 3D reconstruction of fresh, non-fixed tissue, a problem that has proved to be elusive to solve using numerical methods[1,2]. Modern, deep learning approaches to imaging—which has already transformed radiology and microscopy[1,2,3]—can guide this problem in a new direction and inform development of a photography-based 3D neuroimaging modality. The relatively low price point of conventional megapixel-resolution digital cameras makes this neuroimaging modality a promising alternative to MRI—especially considering slab photography is the primary imaging modality for image archival at most brain banks[3,4].

Photography-based neuroimaging

The problem of piecing together 2D slab photographs, of varying slab thickness, camera poses, and illumination, is akin to assembling jigsaw puzzles but with two main differences—each puzzle piece or brain slab is malleable (deformable) and its correct location is in 3D space rather than on 2D plane. A general lack of texture and colors also complicates slab assembly. Slab assembly is thus a type of inverse problem[3], where the objective is to recover the spatial correspondence between the 2D coordinates within each slab in a photograph to 3D coordinates inside the underlying undissected whole brain. Tackling this inverse problem using numerical methods[3,4] (that is, solving a regularized optimization problem) has led to poor solutions even when guided using a matching brain MRI or a 3D surface scan, owing to the myriad local minima in the optimization objective used.[3,4] Note that this 3D reconstruction task is different from the structure from motion[3,4] and view-synthesis[3,4] tasks in computer vision, both of which aim to assemble 2D views of a whole 3D scene captured from different vantage points.

Suppose we are given a stack $\mathbf{x} \in \mathbb{R}^{N\times H\times W}$ of N slab photographs with each one measuring $H \times W$ pixels. The 3D reconstruction task at hand is traditionally formulated as the motion (warp) estimation task:

$$\text{minimize} \quad E(\mathbf{u}) = \|\text{warp}(\mathbf{x},\mathbf{u}) - \mathbf{y}\|^2 + \lambda R(\mathbf{u}), \qquad (1)$$

in which $\mathbf{u} \in \mathbb{R}^{N\times H\times W\times 3}$ represents an N-stack of 3D motion fields of the same dimensions as the photos, $\mathbf{y} \in \mathbb{R}^{D\times H\times W}$ a guiding MRI, and $\lambda R(\mathbf{u})$ is a smoothness term with weight λ to regularize this otherwise ill-posed inverse problem. Due to the nonconvexity of warp, minimizing E is not guaranteed to produce the correct solution, and this incorrect warp is a major source of distortion in the resulting reconstruction. Additional bias is introduced from the use of an atlas (MRI scans averaged across a population) instead of subject-specific MRI (**y**) since it is not typically acquired around the time of slab photography.[3]

For some choices of the regularity term, such as $R(\mathbf{u}) = \left\|\nabla_{x,y}\mathbf{u}\right\|^2$, it is possible to solve (1) via non-linear least squares[3,4,5], although this leads to a time-consuming reconstruction procedure, owing to the iterative nature of the solver. Moreover, non-linear least squares formulations are still marred with local minima due to non-leariities in the guiding image **y**, and cannot faithfully reconstruct the underlying brain. While continuation methods[3,4] can ameliorate the degree of non-convexity in the objective, this still does not eradicate the need for a reference MRI or equivalent guide image from the formulation above.

3D reconstruction using deep learning

Deep learning[3,4] serve as the bedrock of modern computational neuroimaging.

Deep learning can similarly nable accurate, reference image-free reconstruction of brains from photographs.