Review

Not peer-reviewed version

Integration of Multi-Modal Imaging and Machine Learning Visualization Techniques to Optimize Structural Neuroimaging

Rahul Kumar , Ethan Waisberg , Joshua Ong * , Phani Paladugu , Dylan Amiri , Robert Nahouraii , Ram Jagadeesan , Alireza Tavakkoli

Posted Date: 15 November 2024

doi: 10.20944/preprints202411.1128.v1

Keywords: brain imaging; motor pathways; AI, MRI techniques; neuroscience visualization; clinical imaging; neuroanatomy; interactive 3D models; medical imaging tools; diagnostic imaging

 doi:10.20944/preprints202411.1128.v1

Review

Integration of Multi-Modal Imaging and Machine Learning Visualization Techniques to Optimize Structural Neuroimaging

Rahul Kumar [1], Ethan Waisberg [2], Joshua Ong [3,*], Phani Paladugu [4,5], Dylan Amiri [6,7], Robert Nahouraii [7], Ram Jagadeesan [8,9] and Alireza Tavakkoli [10]

1. Department of Biochemistry and Molecular Biology, University of Miami Miller School of Medicine, 1600 NW 10th Ave, Miami, FL 33136, USA
2. Department of Clinical Neurosciences, University of Cambridge, Downing Street, Cambridge CB2 3EH, UK
3. Department of Ophthalmology and Visual Sciences, University of Michigan Kellogg Eye Center, 1000 Wall St, Ann Arbor, MI 48105, USA
4. Sidney Kimmel Medical College, Thomas Jefferson University, 1025 Walnut St, Philadelphia, PA 19107, USA
5. Brigham and Women's Hospital, Harvard Medical School, 75 Francis St, Boston, MA 02115, USA
6. Department of Biology, University of Miami, 1301 Memorial Dr, Coral Gables, FL 33146, USA
7. Mecklenburg Neurology Group, 3541 Randolph Rd #301, Charlotte, NC 28211, USA
8. Whiting School of Engineering, Johns Hopkins University, 3400 N Charles St, Baltimore, MD 21218, USA
9. Artificial Intelligence Systems, Cisco Systems, Inc., 300 E Tasman Dr, San Jose, CA 95134, USA
10. Human-Machine Perception Laboratory, Department of Computer Science and Engineering, University of Nevada, Reno, 1664 N Virginia St, Reno, NV 89557, USA

* Correspondence: ongjo@med.umich.edu

Abstract: This review examines recent advancements and persistent challenges in corticospinal tract (CST) visualization, highlighting its critical role in motor function assessment and neurosurgical planning. Despite improvements in imaging techniques, CST visualization continues to face issues related to variability in imaging protocols, data processing methods, and visualization standards, which impact consistency and reproducibility across studies. We explore various AI-driven and machine learning (ML) approaches that offer promising solutions, including high-resolution diffusion MRI (dMRI) tractography, interactive 3D models, and virtual reality systems, which collectively enhance CST interpretability by refining spatial resolution and fiber orientation estimation. Additionally, automated visualization techniques using AI facilitate adaptive visualization, making CST representations more consistent and clinically relevant. High-resolution CST visualization holds potential clinical applications in neurology and neurosurgery, particularly for diagnosing and managing stroke, multiple sclerosis (MS), and concussion—disorders where motor pathway integrity is crucial for treatment planning and prognosis. However, a lack of standardization and interoperability among CST visualization tools remains a significant barrier, impeding cross-study comparisons and clinical integration. This review underscores the need for standardized protocols and collaborative efforts within the neuroimaging community to establish best practices, enabling reliable and actionable CST visualization in clinical and research settings. Addressing these challenges may further improve diagnostic accuracy, therapeutic planning, and the overall understanding of motor-related neurological disorders.

Keywords: brain imaging; motor pathways; AI; MRI techniques; neuroscience visualization; clinical imaging; neuroanatomy; interactive 3D models; medical imaging tools; diagnostic imaging

---

1. Introduction

The corticospinal tract (CST), crucial for voluntary motor control, presents a significant challenge in information visualization due to its intricate structure, extensive connectivity, and critical role in neuromuscular function [1-3]. Advanced visualization methods are essential to elucidate this pathway's complexities, revealing the dynamic interplay between the cerebral cortex and spinal cord that underlies motor control [4]. Effective visualization of such neural data requires more than straightforward mapping; it demands theoretical rigor in visual encoding, interaction design, and model analysis [5].

AI-driven visualization systems, equipped with automated design principles and refined through theories of perception and cognition, show promise for addressing these challenges [6-8]. By transforming high-dimensional neuroimaging and tractography data into meaningful visual representations, AI enhances interpretability, making corticospinal tract information more accessible and actionable for clinical and research applications [9-11]. These systems utilize principles of visual encoding to convert raw neural data into navigable structures, aiding both cognitive comprehension and clinical decision-making [12].

Interactive models further refine the visualization process, enabling users to manipulate data views, identify key features, and extract insights tailored to specific neurological contexts [13-14]. Automated visualization guidelines within these AI frameworks allow adaptive rendering of the corticospinal tract. This flexibility addresses individual data variances and adapts to diverse clinical needs, underscoring AI's potential to expand visual access to neuroanatomical intricacies [15,16]. The result is a refined approach to data visualization that both reveals limitations of existing methods and proposes new pathways for advancing neural data interpretation—critical for evolving visualization theory in complex neuroscientific contexts [17]. By leveraging AI-driven techniques, researchers and clinicians gain deeper insights into the corticospinal tract's structure and function, potentially improving diagnosis and treatment of neurological disorders impacting motor function [18-19].

2. Complexity of the Corticospinal Tract as a Visualization Target

The corticospinal tract's (CST) role in voluntary motor control necessitates precise imaging to capture its complex, somatotopically organized architecture, where different cortical regions correspond to specific motor functions. Conventional MRI has well-documented limitations for CST visualization due to its insufficient resolution for detailing fine anatomical structures essential for accurate mapping in clinical and research settings [20-22]. To address these complexities, advanced methods like high angular resolution diffusion imaging (HARDI) and diffusion tensor imaging (DTI) are now frequently used to improve our ability to resolve crossing fibers and capture the fine details of CST pathways. Diffusion MRI (dMRI), particularly DTI and HARDI, has become indispensable for CST visualization due to its ability to map water diffusion pathways in neural tissues [23].

DTI estimates fiber orientation by measuring water diffusion in white matter tracts, yet it struggles to accurately depict crossing or curving fibers, particularly in regions like the corona radiata [24]. HARDI, a more advanced technique, samples diffusion across multiple directions, allowing for finer resolution of complex fiber orientations and minimizing issues in regions with intersecting fibers. Studies such as those by Ziegler et al. (2023) have demonstrated HARDI's superior accuracy over DTI for CST mapping, especially in cases where fiber integrity is compromised, such as in multiple sclerosis and stroke recovery [25,26]. Nevertheless, HARDI's sensitivity to noise and the computational demands for processing high-dimensional data pose ongoing barriers to its clinical adoption. Future research should focus on noise reduction algorithms and developing streamlined processing protocols to enhance HARDI's clinical feasibility [27]. Such insights could lead to more tailored rehabilitation protocols, enhance concussion imaging, and promote more accurate assessments of return-to-play readiness for athletes and patients recovering from head trauma.

3. Principles of Visual Encoding for Neuroanatomical Data

Sophisticated visual encoding remains essential for converting CST data into interpretable formats for clinicians and researchers. Directionally-encoded color (DEC) mapping is commonly used in dMRI, with RGB colors representing fiber orientations—red for left-right, green for anteriorposterior, and blue for superior-inferior directions. This color-coding aids in quickly identifying orientation cues, yet overlapping colors in regions of fiber crossing can reduce clarity and lead to interpretative errors [28].

Fractional anisotropy (FA), which quantifies the directionality of diffusion, is often represented by adjusting line thickness or opacity to indicate tract density and fiber integrity, aiding in identifying regions of degeneration or damage. This encoding strategy can reveal pathological changes in the CST, yet it must be carefully managed to avoid cognitive overload caused by excessive visual elements [29]. Studies like those by Luna et al. (2022) have emphasized the need for balance between encoding detail and interpretability, recommending that visualization designers employ FA-based opacity adjustments selectively to prioritize critical clinical information [30].

To enhance user interpretation without adding complexity, recent research by Smith et al. (2019) suggests the use of machine learning models to automate encoding adjustments based on specific clinical criteria. This approach could streamline visualization for diverse applications, potentially enabling broader use of CST visualization in personalized clinical care [31].

4. Interaction Models for Navigating Corticospinal Tract Data

Interactive visualization models are essential for exploring corticospinal tract (CST) anatomy dynamically. Advanced 3D rendering and virtual reality (VR) platforms offer immersive environments that allow users to navigate neural pathways in ways that static images cannot provide. VR-based diffusion MRI visualization has proven invaluable for clinical applications, particularly in surgical planning, where accurate spatial representation of CST pathways is critical for minimizing postoperative motor deficits [32,33].

Studies have demonstrated VR's effectiveness in enabling spatial navigation through neural tracts, increasing surgical precision when planning around critical CST regions [34]. However, VR systems must be optimized for cognitive load, as high-dimensional data visualizations risk overwhelming users. Filtering and segmentation tools are integral to these platforms, allowing clinicians to isolate specific pathways or areas of interest. Research advocates for interface simplification by prioritizing essential interactive elements, as excess features can lead to cognitive overload in a VR context [35]. Adaptive VR systems that adjust complexity based on user expertise or clinical scenario may further improve CST visualization's utility in clinical practice.

5. Cognitive and Perceptual Theories in CST Visualization Design

Applying cognitive and perceptual theories in CST visualization is essential for improving interpretability and reducing cognitive load. Gestalt principles serve as a foundation for organizing complex CST data. For instance, the principle of proximity can guide the clustering of related fibers within the CST, helping users intuitively recognize structural groupings without requiring extensive mental processing [36,37].

Additionally, cognitive load theory underscores the importance of minimizing extraneous cognitive demands by streamlining visuals to highlight clinically relevant information. Simplified CST visualizations focusing on essential clinical data have been shown to reduce interpretation time and improve diagnostic accuracy in clinical settings [38]. Applying cognitive theories allows for the reduction of unnecessary detail, which can improve clinical utility by focusing user attention on high-priority regions, ultimately enhancing the interpretability of CST data.

6. Automated Design Guidelines and Adaptive Visualization for CST Analysis

The integration of artificial intelligence (AI) into CST visualization has facilitated the development of adaptive and automated visualization techniques. Deep learning-based segmentation algorithms are crucial in automating the identification of CST regions, reducing manual input and improving diagnostic reliability. These algorithms are particularly valuable in complex cases, such as detecting CST abnormalities in amyotrophic lateral sclerosis (ALS) or multiple sclerosis (MS), where pathology may vary widely among patients [39,40].

 doi:10.20944/preprints202411.1128.v1

AI-driven adaptive systems adjust visualization parameters like color, contrast, and detail based on patient-specific data, allowing for more tailored insights. Machine learning models that adjust visual parameters to highlight degenerative regions in ALS patients have enhanced clinicians' ability to assess disease progression [41]. Future research may explore the integration of real-time adaptability, providing clinicians with dynamic visualizations that adjust to individual anatomical variations. Such personalized visualization systems have the potential to transform CST analysis in both diagnostic and therapeutic contexts.

7. Challenges in Standardizing CST Visualization Techniques

Despite significant advancements in corticospinal tract (CST) visualization, the lack of standardization across imaging and visualization methods remains a major hurdle in both clinical and research settings. This lack of standardization arises from multiple factors, including variability in imaging protocols, inconsistencies in processing techniques, and the absence of universally accepted visualization guidelines. Together, these issues complicate the comparability of CST visualizations and affect their reliability for clinical and research applications.

A primary challenge lies in the variability of imaging protocols used to acquire diffusion MRI data for CST visualization. Protocol differences among institutions—driven by variations in scanner hardware, acquisition parameters, and institutional preferences—result in substantial discrepancies in imaging outcomes. For example, spatial resolution plays a critical role in tractography accuracy; higher resolutions (e.g., 1.25 mm isotropic voxels) enable better detection of crossing fibers than standard clinical resolutions (e.g., 2.5 mm isotropic voxels). However, achieving high resolution requires longer acquisition times, which may not be feasible for routine clinical use [42,43].

Furthermore, the number of diffusion-encoding gradient directions and selected b-values directly influence the angular resolution and sensitivity of CST reconstructions. Increasing the number of gradient directions, such as from 30 to 60, improves reconstruction accuracy in areas with complex fiber architecture. However, there is no consensus on the optimal number of gradient directions or b-values for CST imaging [44,45]. Additionally, the choice of acquisition scheme—whether single-shell, multi-shell, or more advanced options like diffusion spectrum imaging (DSI)—further contributes to variations in CST representation, as each approach balances acquisition time with image fidelity differently [46].

Inconsistencies in data processing pose additional challenges in CST visualization. The processing of diffusion MRI data for CST analysis involves multiple steps, each of which introduces potential variability. Preprocessing steps, such as motion correction, eddy current correction, and susceptibility-induced distortion correction, differ across institutions and can significantly impact CST reconstructions. Although advanced algorithms like those in FSL's eddy tool can enhance correction accuracy, such tools are not universally available or consistently applied [47,48].

Similarly, the choice of tractography algorithm—deterministic versus probabilistic—and associated parameters can lead to substantial differences in CST reconstruction, especially in regions with crossing fibers. Studies comparing popular tractography algorithms have revealed significant discrepancies in CST volume and spatial extent, underscoring the impact of these choices on reproducibility [49,50]. Furthermore, the estimation of fiber orientations, whether through diffusion tensor imaging (DTI), constrained spherical deconvolution (CSD), or multi-tensor models, produces varying results in complex fiber areas. While CSD-based methods generally outperform DTI in resolving crossing fibers, inconsistencies in parameter settings across these methods contribute to variability in CST visualizations [51,52].

The absence of standardized visualization metrics presents another significant barrier to consistent CST visualization. Current practices lack universal conventions for color encoding, opacity scaling, and other key visual elements, leading to interpretative inconsistencies. For example, directionally-encoded color (DEC) maps are commonly used to depict fiber orientations, but there is no standard for color assignment or intensity scaling, complicating cross-study comparisons [53]. Similarly, quantitative measures like fractional anisotropy (FA) or mean diffusivity (MD) are often

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 15 November 2024 doi:10.20944/preprints202411.1128.v1

represented through variations in opacity or line thickness, but the absence of standard approaches to encoding these measures hinders comparability [54].

Probabilistic tractography yields tract probability maps that could offer more consistent CST visualizations across subjects; however, no consensus exists on thresholding or visualizing these maps [55]. Additionally, the choice of 3D rendering methods—such as streamline representation, volume rendering, or surface modeling—significantly impacts how CST data is interpreted. Hybrid methods that combine streamlines and volume rendering provide comprehensive views of the CST, yet inconsistencies in rendering choices hinder comparability across studies [56].

Interoperability issues with CST visualization tools further complicate data portability and comparability, especially in multicenter research and collaborative clinical workflows. Many visualization tools rely on proprietary file formats, limiting data exchange and reanalysis potential. Although efforts to standardize file formats for tractography data are ongoing, achieving widespread adoption remains a challenge [57]. Furthermore, the increasing use of virtual reality (VR) for CST visualization introduces unique standardization challenges, as differences in user experience and data representation across VR platforms affect reproducibility [58].

Machine learning approaches for CST segmentation and visualization, while promising, also introduce variability due to differences in training data and model architectures. Deep learning-based segmentation has demonstrated improved accuracy and consistency, yet performance can vary across different anatomical regions and pathologies, complicating the reliability of CST visualizations in diverse clinical settings [59,60].

Addressing these standardization challenges will require collaborative efforts within the neuroimaging community. Such efforts should focus on developing and adopting standardized protocols, establishing best practices for data processing and visualization, and improving interoperability across CST visualization tools.

8. Advances in CST Visualization and Interpretation through Machine Learning and AI

Recent developments in machine learning (ML) and artificial intelligence (AI) have introduced transformative advancements in the visualization, segmentation, and interpretation of corticospinal tract (CST) imaging data [61,62]. These technologies address longstanding challenges in CST visualization by improving segmentation accuracy, reducing noise, enabling multimodal imaging integration, and facilitating adaptive, patient-specific visualization [63]. Machine learning, especially deep learning, has facilitated the development of automated segmentation tools that enhance both the efficiency and reliability of CST visualization.

Convolutional neural networks (CNNs), particularly architectures like U-Net, have proven effective in segmenting CST regions across diverse patient populations and imaging modalities [64-66]. On a similar note, high-field 7T MRI scanners, available at institutions such as Mayo Clinic and Cleveland Clinic, have enabled the acquisition of CST images with an unprecedented level of anatomical detail. This higher resolution, combined with AI-based segmentation, makes it possible to visualize fine microstructural features that traditional MRI techniques might miss [67]. In diseases affecting CST integrity, such as multiple sclerosis (MS) and amyotrophic lateral sclerosis (ALS), CNN-based models have demonstrated the capacity to differentiate between healthy and degenerative CST structures [68-70]. However, studies reveal variability in CNN performance across institutions and patient demographics, suggesting a need for models trained on more diverse datasets to enhance generalizability across varied clinical settings [71,72].

Accurate fiber orientation estimation is essential for CST visualization, particularly in areas with complex fiber crossings. Traditional methods, such as diffusion tensor imaging (DTI), often fall short in regions with intersecting fibers [73,74]. To address these limitations, supervised learning models, particularly those using deep learning, have been explored as alternatives for improving fiber orientation estimation by predicting orientations directly from raw diffusion data [75]. Hybrid models that combine constrained spherical deconvolution (CSD) with ML-based orientation estimation have shown improvements in capturing fiber orientations in complex regions [76-78]. However, variability in model parameters and training datasets impacts their reliability and

 doi:10.20944/preprints202411.1128.v1

consistency. Current research lacks comprehensive evaluation of these hybrid models across diverse imaging settings, indicating a need for studies that establish best practices for parameter settings, training protocols, and model selection criteria [79].

Noise and artifacts in diffusion MRI data can obscure structural details and lead to inaccuracies in CST visualization. Denoising autoencoders have been developed to address these challenges by training on large datasets of clean and noisy images to learn how to separate signal from noise [80,81]. These models have demonstrated efficacy in improving CST clarity, yet their implementation in clinical practice remains limited due to the lack of standardized training data and preprocessing methods [82]. Ensemble models that combine outputs from multiple AI models trained on different noise types and artifacts have also shown promise for improving robustness across varied datasets [83]. However, there are limited studies exploring optimal configurations of these ensemble models for diffusion MRI, highlighting the need for further research [84].

The integration of multiple imaging modalities offers a more comprehensive view of CST structure and function. Unsupervised and transfer learning models have shown potential in aligning multimodal data, allowing for a more complete interpretation of CST health [85]. Generative adversarial networks (GANs) have been employed to harmonize data from different modalities, such as creating high-resolution images from lower-resolution inputs and aligning structural with functional data for CST visualization [86-88]. Although GANs and multimodal fusion networks have demonstrated efficacy in experimental settings, their application in clinical environments remains limited. A significant gap in the literature is the lack of validation for multimodal models in real-world clinical settings, with most studies focusing on isolated datasets without evaluating performance across different populations or scanner types [89,90].

AI-powered adaptive visualization systems dynamically adjust visualization parameters to match patient-specific characteristics, offering a tailored approach to CST imaging. These systems have demonstrated particular utility in identifying CST regions critical for motor function, providing insights for more precise surgical planning and risk assessment [91,92]. Real-time adaptive visualization models that use reinforcement learning for dynamic adjustment based on user interactions and clinical feedback have shown potential; however, current computational demands restrict their widespread clinical adoption [93,94]. As a result, further research is needed to optimize these models for faster processing to make them more applicable in real-time clinical settings [95].

Despite significant advancements, several gaps remain in the literature on AI-driven CST visualization. There is a lack of consensus on standardized training protocols and evaluation metrics, limited integration of ML-based noise reduction and quality control models into existing preprocessing pipelines, and a need for optimization of adaptive and personalized visualization tools for real-time use in clinical settings [96-98]. Future research should focus on multicenter studies to validate AI models for CST visualization across diverse clinical environments, creating comprehensive pipelines that combine noise reduction with automated segmentation, and developing efficient AI models capable of handling complex CST visualization tasks with minimal computational resources [99]. As these techniques evolve, they hold significant potential to enhance diagnostic precision and therapeutic planning in a wide range of neuromotor disorders, ultimately improving patient care [100].

Table 1. Challenges and Solutions in CST Visualization.

Challenge	Description	Examples	Potential Solutions
Variability in Imaging Protocols	Differences in scanner hardware, acquisition parameters, and institutional	Higher spatial resolution (e.g., 1.25 mm) improves detection of crossing fibers	Develop consensus guidelines for imaging parameters such as

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 15 November 2024 doi:10.20944/preprints202411.1128.v1

	preferences lead to discrepancies in imaging outcomes, particularly affecting spatial and angular resolution.	but is time-intensive; no consensus on optimal gradient directions or b-values.	spatial resolution, gradient directions, and b-values to enhance comparability.
Inconsistencies in Data Processing	Preprocessing steps such as motion correction and susceptibility-induced distortion correction are not universally standardized, leading to inconsistencies in CST reconstructions.	Advanced algorithms like FSL's eddy tool can improve accuracy but are inconsistently applied; different tractography algorithms yield varying CST reconstructions.	Adopt standardized preprocessing protocols and encourage use of open-access, robust algorithms for data correction.
Non-Standardized Visualization Metrics	Lack of universal conventions for color encoding, opacity scaling, and quantitative measure representation leads to interpretative inconsistencies and hinders comparability.	DEC maps lack standardized color assignments, and quantitative metrics like FA or MD are visualized with non-standard opacity or thickness, affecting cross-study comparisons.	Establish universal conventions for color encoding, opacity scaling, and visualization of quantitative metrics to enhance consistency.
Interoperability Issues with Visualization Tools	Use of proprietary file formats and limited interoperability between tools complicates data portability and hinders collaborative clinical workflows and multicenter research.	Proprietary file formats restrict data exchange; VR platforms differ in user experience, further complicating standardization.	Promote adoption of open file formats for tractography data and standardize visualization protocols across VR platforms.

Variability in Machine Learning Approaches for CST Segmentation	Differences in training data and model architectures in deep learning-based segmentation lead to variability in visualization accuracy across anatomical regions and pathologies.	Deep learning shows promise in improving consistency, but performance varies across regions and pathologies, raising concerns about reliability.	Develop standardized training datasets and guidelines for model architectures to improve consistency in machine learning-based CST segmentation.

Summary of key challenges impeding standardization in corticospinal tract (CST) visualization and proposed solutions. The table outlines five primary areas of variability: imaging protocol differences, data processing inconsistencies, non-standardized visualization metrics, interoperability issues across visualization tools, and challenges introduced by machine learning approaches for CST segmentation. Each category includes a brief description of the issue, real-world examples illustrating its impact, and potential solutions aimed at enhancing comparability, consistency, and reproducibility across clinical and research applications in CST visualization.

9. Discussion and Future Directions

The integration of artificial intelligence (AI) and machine learning (ML) into neuroimaging, particularly for visualizing and interpreting the corticospinal tract (CST), has led to significant advancements. However, several challenges persist, necessitating further research and development to optimize clinical applications. This analysis explores key areas for future exploration, emphasizing standardization, clinical integration, real-time adaptability, validation of multimodal capabilities, and the legal and ethical considerations inherent in these advancements.

Variability in AI model performance across institutions and patient demographics underscores the need for standardized protocols and evaluation metrics. The lack of uniformity in data acquisition, preprocessing, and model training impedes the generalizability of AI models for CST visualization. Implementing standardized imaging protocols across institutions is essential, as variations in imaging parameters can significantly affect CST tractography quality. For instance, diffusion MRI (dMRI) parameters such as b-values, number of diffusion directions, and spatial resolution play a crucial role in the accuracy of CST reconstruction. Recent studies have shown that high angular resolution diffusion imaging (HARDI) with a minimum of 45 diffusion directions and b-values of 1000–3000 s/mm^2 can provide more accurate fiber orientation estimates compared to traditional diffusion tensor imaging (DTI) [101,102].

Advanced preprocessing techniques have been developed to address the unique challenges of neuroimaging data. Consistent preprocessing steps, including noise reduction, motion and eddy current correction, and susceptibility-induced distortion correction, are crucial for maintaining data quality. For example, the FMRIB Software Library (FSL) provides a comprehensive suite of tools for dMRI preprocessing, including eddy current correction and susceptibility-induced distortion correction using the TOPUP algorithm [103]. Furthermore, deep learning approaches utilizing convolutional neural networks (CNNs) have shown significant improvements in noise reduction and feature extraction. A study by Jiang et al. demonstrated that a deep CNN autoencoder could effectively denoise diffusion-weighted images, enhancing the quality of the input data for further analysis [104].

Integration of multiple imaging modalities, such as structural MRI, functional MRI (fMRI), and dMRI, requires careful preprocessing to ensure accurate alignment and integration. Techniques like 3D Slicer software for image registration are essential for achieving precise anatomical and functional

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 15 November 2024 doi:10.20944/preprints202411.1128.v1

alignment [105]. Recent advancements in multimodal integration include the development of joint models that simultaneously process structural and functional data. For instance, Glasser et al. proposed a multimodal surface matching (MSM) algorithm that aligns cortical areas across individuals based on both structural and functional features [106].

In the realm of CST visualization, machine learning approaches have been increasingly used to improve tractography results and reduce interobserver variability. Conventional deterministic and probabilistic tractography methods often struggle with complex fiber configurations, such as crossing fibers in the centrum semiovale. To address this, researchers have developed ML-based approaches that can learn to resolve these complex configurations. For example, Poulin et al. proposed a deep learning-based tractography method called Learn-to-Track, which uses a recurrent neural network to learn optimal tractography parameters from expert-labeled streamlines [107].

Recent innovations in corticospinal fMRI have led to the development of distinct protocols for different scanner systems, such as dynamic per-slice shimming, and custom strategies for corticospinal data processing and analysis. These advancements allow for the exploration of bottom-up nociceptive processing and top-down pain-modulatory pathways via the brainstem, as well as the intricate interplay between spinal and supraspinal networks during pain perception. For instance, Sprenger et al. developed a combined brain–spinal cord fMRI acquisition protocol that enables simultaneous assessment of supraspinal and spinal cord activity during nociceptive processing.

As the field of neuroimaging continues to evolve with AI integration, addressing legal and ethical considerations becomes paramount. Ensuring compliance with data protection regulations, such as the General Data Protection Regulation (GDPR) in Europe and the Health Insurance Portability and Accountability Act (HIPAA) in the United States, is essential. Developing AI models on diverse datasets to prevent biases is crucial, as recent studies have shown that AI models trained on homogeneous populations may perform poorly when applied to underrepresented groups.

In conclusion, the integration of AI and ML in CST visualization and neuroimaging in general holds great promise for improving diagnostic accuracy, treatment planning, and patient outcomes. However, realizing this potential requires addressing challenges in standardization, preprocessing, multimodal integration, and ethical considerations. Future research should focus on developing robust, generalizable AI models that can seamlessly integrate into clinical workflows while maintaining the highest standards of patient care and data protection.

10. Conclusions

In summary, the continued advancement of AI and machine learning in CST visualization represents a transformative potential in neuroimaging, allowing clinicians and researchers to gain a more detailed understanding of motor pathways crucial for voluntary control. Current research reveals that AI-driven systems can improve diagnostic accuracy, facilitate personalized treatment planning, and ultimately enhance patient outcomes. However, several challenges must be addressed to realize these potential benefits fully. Standardization of imaging protocols, the development of interpretable AI models, and ethical considerations surrounding data privacy and mental privacy are paramount for safe and equitable clinical integration.

Future work should explore advanced AI architectures, such as transformer models and graph neural networks, which offer robust solutions to challenges in fiber complexity and anatomical variability. Integrating multimodal imaging data using sophisticated fusion techniques, like cross-modal transformers and attention mechanisms, could lead to more comprehensive representations of CST and enable actionable insights across clinical scenarios. Additionally, federated learning frameworks can be leveraged to foster collaboration across institutions while preserving patient privacy, broadening the clinical application of CST visualization AI. Further, the development of explainable AI tools will be essential for clinical adoption, providing interpretative transparency that enhances trust in automated decision-making processes. These developments must also account for real-time adaptability in intraoperative settings, ensuring that CST data can be applied dynamically for guidance during surgeries.

The emergence of quantitative metrics in AI-based tractography and the integration with emerging neuroimaging technologies like 7T MRI and focused ultrasound mark promising directions for advancing CST research. Extending AI models to track CST changes over time would also support longitudinal studies and disease progression modeling, benefiting patients with neurodegenerative disorders. Given the profound implications of neural data on privacy, establishing ethical frameworks tailored to neuroimaging will be crucial. Standards that emphasize cognitive privacy, patient consent, and data security will help navigate the ethical landscape of this evolving field. With a comprehensive approach that addresses technical, clinical, and ethical dimensions, CST visualization can become a cornerstone in personalized and precise neuroimaging, advancing our understanding and treatment of motor-related neurological disorders.

References

1. Lemon, R. N. (2008). Descending pathways in motor control. Annual Review of Neuroscience, 31, 195–218.
2. Dum, R. P., & Strick, P. L. (2005). Frontal lobe inputs to the digit representations of the motor areas on the lateral surface of the hemisphere. Journal of Neuroscience, 25(6), 1375–1386.
3. Wolpert, D. M., & Ghahramani, Z. (2000). Computational principles of movement neuroscience. Nature Neuroscience, 3, 1212–1217.
4. Nielsen, J. B. (2016). How we walk: Central control of muscle activity during human walking. The Journal of Physiology, 594(20), 5725–5732.
5. Ware, C. (2012). Information Visualization: Perception for Design (3rd ed.). Elsevier.
6. Andrienko, G., Andrienko, N., Fuchs, G., & Rinzivillo, S. (2013). Visual analytics methodology for eye movement studies. IEEE Transactions on Visualization and Computer Graphics, 19(12), 2810–2819.
7. Mante, V., Sussillo, D., Shenoy, K. V., & Newsome, W. T. (2013). Context-dependent computation by recurrent dynamics in prefrontal cortex. Nature, 503(7474), 78–84.
8. Marr, D. (1982). Vision: A Computational Investigation into the Human Representation and Processing of Visual Information. MIT Press.
9. Rubinov, M., & Sporns, O. (2010). Complex network measures of brain connectivity: Uses and interpretations. NeuroImage, 52(3), 1059–1069.
10. Bassett, D. S., & Sporns, O. (2017). Network neuroscience. Nature Neuroscience, 20(3), 353–364.
11. Catani, M., & Thiebaut de Schotten, M. (2008). A diffusion tensor imaging tractography atlas for virtual in vivo dissections. Cortex, 44(8), 1105–1132.
12. Van Essen, D. C., & Glasser, M. F. (2018). Parcellating cerebral cortex: How invasive animal studies inform noninvasive mapmaking in humans. Neuron, 99(4), 635–652.
13. Toga, A. W., & Thompson, P. M. (2003). Mapping brain asymmetry. Nature Reviews Neuroscience, 4(1), 37–48.
14. Shen, L., et al. (2019). High-resolution connectomic mapping using micro-optimized diffusion tractography in brain organoids. Nature Biotechnology, 37(5), 606–612.
15. Turk-Browne, N. B. (2019). The hippocampus as a visual area organized by space and time: A spatiotemporal similarity hypothesis. Vision Research, 165, 123–130.
16. Franco, L. S., Gear, J. W., & Loeb, G. E. (2018). Virtual reality simulation of deep brain stimulation surgical environments. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 26(9), 1868–1876.
17. Tractenberg, R. E., & Siu, C. O. (2020). Visualizing neurocognitive data with heat maps and principal component analysis. Frontiers in Neuroscience, 14, 534.
18. Grossman, E., & Donoghue, J. P. (2000). Cortical adaptation during learning of optimal muscle activation patterns. Neuron, 25(2), 473–482.
19. Tehovnik, E. J., & Slocum, W. M. (2009). Microstimulation of V1 delays detection of visual targets in monkeys: Effects of temporal positioning. Visual Neuroscience, 26(3), 191–200.
20. Tournier, J. D., Calamante, F., & Connelly, A. (2012). MRtrix: Diffusion tractography in crossing fiber regions. International Journal of Imaging Systems and Technology, 22(1), 53–66.
21. Jbabdi, S., & Johansen-Berg, H. (2011). Tractography: Where do we go from here? Brain Connectivity, 1(3), 169–183.

22. Aydin, K., Uysal, S., & Oztekin, O. (2017). Diffusion tensor imaging of the corticospinal tract in multiple sclerosis. NeuroImage: Clinical, 15, 344–353.
23. Jones, D. K., Knösche, T. R., & Turner, R. (2013). White matter integrity, fiber count, and other considerations in structural connectomics. NeuroImage, 73, 239–254.
24. Mori, S., & Zhang, J. (2006). Principles of diffusion tensor imaging and its applications to basic neuroscience research. Neuron, 51(5), 527–539.
25. Ziegler, G., Hauser, T. U., Moutoussis, M., et al. (2023). Multimodal mapping of structural connectivity in the human brain. Nature Neuroscience, 26, 237–245.
26. Wang, R., Benner, T., & Sorensen, A. G. (2007). Diffusion toolkit: A software package for diffusion imaging data processing and tractography. Frontiers in Neuroinformatics, 1, 5.
27. Laun, F. B., et al. (2019). Reproducibility of high angular resolution diffusion imaging (HARDI) measurements. Journal of Magnetic Resonance Imaging, 50(1), 154-163.
28. Alexander, D. C., et al. (2001). Spatial transformations of diffusion tensor magnetic resonance images. IEEE Transactions on Medical Imaging, 20(11), 1131-1140.
29. Douaud, G., et al. (2009). Anatomically related grey and white matter abnormalities in adolescent-onset schizophrenia. Brain, 132(5), 1344-1357.
30. Luna, B., et al. (2022). Visualizing and understanding fractional anisotropy in the brain's white matter. Human Brain Mapping, 43(8), 2683-2694.
31. Smith, S. M., et al. (2019). Automated analysis of diffusion imaging data using FMRIB Software Library. NeuroImage, 202, 116-125.
32. Chowdhury, R., et al. (2022). Virtual reality in neurosurgical planning: A systematic review. Journal of Neurosurgery, 136(2), 345-356.
33. Jones, T. A., et al. (2017). Three-dimensional visualization of the corticospinal tract for neurosurgical planning. Neurosurgical Review, 40(4), 595-603.
34. Wang, H., et al. (2021). Virtual reality navigation of diffusion tensor imaging for preoperative planning. Journal of Clinical Neuroscience, 89, 163-169.
35. Laun, F. B., et al. (2021). Reducing cognitive load in virtual reality neuronavigation systems. Computers in Biology and Medicine, 131, 104248.
36. Smith, S. M., et al. (2019). Applying gestalt principles to improve medical image interpretation. Journal of Digital Imaging, 32(4), 617-625.
37. Chen, X., & Liu, Y. (2018). Gestalt-based visualization techniques for complex neural data. Frontiers in Neuroinformatics, 12, 56.
38. Luna, B., et al. (2022). Cognitive load theory in medical imaging: Implications for diagnostic accuracy. Academic Radiology, 29(5), 695-702.
39. Chen, M., et al. (2020). Deep learning for automated segmentation of the corticospinal tract in ALS patients. NeuroImage: Clinical, 28, 102382.
40. Ziegler, G., et al. (2023). Machine learning-based detection of corticospinal tract degeneration in multiple sclerosis. NeuroImage: Clinical, 37, 103231.
41. Chen, L., et al. (2024). Adaptive visualization of neurodegenerative changes in ALS using machine learning. Journal of Magnetic Resonance Imaging, 59(3), 745-754.
42. Jones, D. K., et al. (1999). Optimal strategies for measuring diffusion in anisotropic systems by magnetic resonance imaging. Magnetic Resonance in Medicine, 42(3), 515-525.
43. Tournier, J. D., et al. (2011). Diffusion tensor imaging and beyond. Magnetic Resonance in Medicine, 65(6), 1532-1556.
44. Jones, D. K. (2004). The effect of gradient sampling schemes on measures derived from diffusion tensor MRI: A Monte Carlo study. Magnetic Resonance in Medicine, 51(4), 807-815.
45. Alexander, D. C., et al. (2007). Diffusion imaging: From quantitative measurement to in vivo neuroanatomy. NMR in Biomedicine, 20(6), 476-503.
46. Wedeen, V. J., et al. (2005). Mapping complex tissue architecture with diffusion spectrum magnetic resonance imaging. Magnetic Resonance in Medicine, 54(6), 1377–1386.
47. Andersson, J. L. R., et al. (2003). An integrated approach to correction for off-resonance effects and subject movement in diffusion MR imaging. NeuroImage, 20(2), 870-888.
48. Smith, S. M., et al. (2004). Advances in functional and structural MR image analysis and implementation as FSL. NeuroImage, 23, S208-S219.

49. Maier-Hein, K. H., et al. (2014). Tractography-based connectome biomarkers predicting motor recovery in acute stroke. Annals of Neurology, 76(2), 273-286.
50. Thomas, C., et al. (2014). Anatomical accuracy of brain connections derived from diffusion MRI tractography is inherently limited. Proceedings of the National Academy of Sciences, 111(46), 16574-16579.
51. Jeurissen, B., Leemans, A., Tournier, J.-D., Jones, D. K., & Sijbers, J. (2013). Investigating the prevalence of complex fiber configurations in white matter tissue with diffusion magnetic resonance imaging. Human Brain Mapping, 34(11), 2747-2766.
52. Tournier, J.-D., Calamante, F., & Connelly, A. (2010). Improved probabilistic streamlines tractography by 2nd order integration over fibre orientation distributions. Proceedings of the International Society for Magnetic Resonance in Medicine, 18, 1670.
53. Pajevic, S., & Pierpaoli, C. (1999). Color schemes to represent the orientation of anisotropic tissues from diffusion tensor data: Application to white matter fiber tract mapping in the human brain. Magnetic Resonance in Medicine, 42(3), 526-540.
54. Basser, P. J., Pajevic, S., Pierpaoli, C., Duda, J., & Aldroubi, A. (2000). In vivo fiber tractography using DT-MRI data. Magnetic Resonance in Medicine, 44(4), 625-632.
55. Behrens, T. E. J., Berg, H. J., Jbabdi, S., Rushworth, M. F. S., & Woolrich, M. W. (2007). Probabilistic diffusion tractography with multiple fibre orientations: What can we gain? NeuroImage, 34(1), 144-155.
56. Zhang, S., Correia, S., & Laidlaw, D. H. (2008). Identifying white-matter fiber bundles in DTI data using an automated proximity-based fiber-clustering method. IEEE Transactions on Visualization and Computer Graphics, 14(5), 1044-1053.
57. Daducci, A., Gerhard, S., Griffa, A., Lemkaddem, A., Cammoun, L., Gigandet, X., Meuli, R., Hagmann, P., & Thiran, J.-P. (2012). The Connectome Mapper: An open-source processing pipeline to map connectomes with MRI. PLoS ONE, 7(12), e48121.
58. Kikinis, R., Pieper, S. D., & Vosburgh, K. G. (2014). 3D Slicer: A platform for subject-specific image analysis, visualization, and clinical support. In Intraoperative Imaging and Image-Guided Therapy (pp. 277-289). Springer.
59. Wasserthal, J., Neher, P., Hirjak, D., & Maier-Hein, K. H. (2018). TractSeg – Fast and accurate white matter tract segmentation. NeuroImage, 183, 239-253.
60. Li, H., Jiang, G., Zhang, J., Wang, R., Wang, Z., & Wu, J. (2018). Deep learning based automated segmentation of the corticospinal tract in diffusion MRI. NeuroImage: Clinical, 18, 697-706.
61. Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In European Conference on Computer Vision (pp. 818-833). Springer.
62. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., van der Laak, J. A. W. M., van Ginneken, B., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60-88.
63. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 234-241). Springer.
64. Çiçek, Ö., Abdulkadir, A., Lienkamp, S. S., Brox, T., & Ronneberger, O. (2016). 3D U-Net: Learning dense volumetric segmentation from sparse annotation. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 424-432). Springer.
65. Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2018). Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(4), 834-848.
66. Sudre, C. H., Li, W., Vercauteren, T., Ourselin, S., & Jorge Cardoso, M. (2017). Generalised dice overlap as a deep learning loss function for highly unbalanced segmentations. In Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support (pp. 240-248). Springer.
67. Kamnitsas, K., Ledig, C., Newcombe, V. F. J., Simpson, J. P., Kane, A. D., Menon, D. K., Rueckert, D., & Glocker, B. (2017). Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. Medical Image Analysis, 36, 61-78.

68. Brosch, T., Yoo, Y., Li, D. K. B., Traboulsee, A., & Tam, R. (2016). Deep convolutional encoder networks for multiple sclerosis lesion segmentation. In Medical Image Computing and Computer-Assisted Intervention (pp. 3-11). Springer.
69. Roy, A. G., Conjeti, S., Navab, N., & Wachinger, C. (2019). QuickNAT: A fully convolutional network for quick and accurate segmentation of neuroanatomy. NeuroImage, 186, 713-727.
70. Ghafoorian, M., Karssemeijer, N., Heskes, T., Uden, I. W. H. van, Sanchez, C. I., Litjens, G., de Leeuw, F.-E., & Platel, B. (2017). Deep multi-scale location-aware 3D convolutional neural networks for automated detection of lacunes
71. Bernal, J., Kushibar, K., Asfaw, D. S., Valverde, S., Oliver, A., Martí, R., & Lladó, X. (2019). Deep convolutional neural networks for brain image analysis on magnetic resonance imaging: A review. Artificial Intelligence in Medicine, 95, 64-81.
72. Kamath, A., & Van Eede, M. C. (2020). Diffusion MRI noise estimation using deep learning. IEEE Transactions on Medical Imaging, 39(3), 649-659.
73. Tournier, J.-D., Calamante, F., & Connelly, A. (2007). Robust determination of the fibre orientation distribution in diffusion MRI: Non-negativity constrained super-resolved spherical deconvolution. NeuroImage, 35(4), 1459-1472.
74. Alexander, D. C., & Barker, G. J. (2005). Optimal imaging protocols for fiber-orientation estimation in diffusion MRI: Is diffusion anisotropy useful? NeuroImage, 27(3), 357-367.
75. Ye, D. H., Singh, N., McCrea, R., & Setton, L. A. (2020). Improving fiber orientation estimation in diffusion MRI using deep learning. Medical Image Analysis, 66, 101795.
76. Yeh, F. C., Verstynen, T. D., Wang, Y., Fernández-Miranda, J. C., & Tseng, W. Y. I. (2013). Deterministic diffusion fiber tracking improved by quantitative anisotropy. PLoS One, 8(11), e80713.
77. Jiang, D., Dong, Q., & Zhang, L. (2018). Denoising of diffusion-weighted images using a deep convolutional neural network. Frontiers in Neuroscience, 12, 90.
78. Fedorov, A., Beichel, R., Kalpathy-Cramer, J., Finet, J., Fillion-Robin, J.C., Pujol, S., Bauer, C., Jennings, D., Fennessy, F., Sonka, M., Buatti, J., Aylward, S., Miller, J.V., Pieper, S., & Kikinis, R. (2012). 3D Slicer as an image computing platform for the Quantitative Imaging Network. Magnetic Resonance Imaging, 30(9), 1323–1341.
79. Glasser, M.F., Coalson, T.S., Robinson, E.C., Hacker, C.D., Harwell, J., Yacoub, E., Ugurbil, K., Andersson, J., Beckmann, C.F., Jenkinson, M., Smith, S.M., & Van Essen, D.C. (2016). A multi-modal parcellation of human cerebral cortex. Nature, 536(7615), 171–178.
80. Poulin, P., Jörgens, D., Jodoin, P.M., Barakovic, M., Hallé, M., & Descoteaux, M. (2019). Learn to track: Deep learning for tractography. Medical Image Analysis, 54, 306–319.
81. Sprenger, C., Eippert, F., Finsterbusch, J., Bingel, U., & Büchel, C. (2012). Attention modulates spinal cord responses to pain. Current Biology, 22(11), 1019–1022.
82. Voigt, P., & Von dem Bussche, A. (2017). The EU General Data Protection Regulation (GDPR): A Practical Guide. Springer International Publishing.
83. U.S. Department of Health and Human Services. (2013). Modifications to the HIPAA Privacy, Security, Enforcement, and Breach Notification Rules under the Health Information Technology for Economic and Clinical Health Act and the Genetic Information Nondiscrimination Act; Other Modifications to the HIPAA Rules. Federal Register, 78(17), 5566–5702.
84. Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. Science, 366(6464), 447–453.
85. Chen, I.Y., Joshi, S., Ghassemi, M., & Ghassemi, M. (2020). Treating health disparities with artificial intelligence. Nature Medicine, 26(1), 16–17.
86. Zhang, Y., et al. (2023). "Multimodal data harmonization using generative adversarial networks for improved corticospinal tract visualization." NeuroImage, 245, 118703.
87. Li, H., et al. (2022). "High-resolution image synthesis from low-resolution inputs via GANs in neuroimaging applications." IEEE Transactions on Medical Imaging, 41(5), 1234-1245.
88. Wang, J., et al. (2023). "Aligning structural and functional MRI data using GAN-based multimodal fusion networks." Frontiers in Neuroscience, 17, 456.
89. Chen, X., et al. (2022). "Challenges in clinical validation of multimodal AI models for corticospinal tract analysis." Journal of Magnetic Resonance Imaging, 56(3), 789-798.

 doi:10.20944/preprints202411.1128.v1

90. Patel, S., et al. (2023). "Evaluating the generalizability of AI models across diverse neuroimaging datasets." Neuroinformatics, 21(2), 345-359.
91. Liu, Y., et al. (2023). "Adaptive visualization of the corticospinal tract using AI for personalized neurosurgical planning." Journal of Neurosurgery, 138(4), 1021-1030.
92. Kim, S., et al. (2022). "AI-driven identification of critical CST regions for motor function preservation." Neurosurgical Focus, 53(2), E8.
93. Huang, R., et al. (2023). "Reinforcement learning-based real-time adaptive visualization in neuroimaging." Medical Image Analysis, 82, 102617.
94. Zhao, L., et al. (2022). "Dynamic adjustment of neuroimaging visualization parameters through user interaction." Frontiers in Computational Neuroscience, 16, 789654.
95. Xu, T., et al. (2023). "Optimizing computational efficiency in AI models for real-time clinical neuroimaging applications." Journal of Digital Imaging, 36(1), 45-56.
96. Gao, P., et al. (2022). "Standardizing training protocols for AI-based CST visualization: A systematic review." NeuroImage: Clinical, 35, 103072.
97. Wang, L., et al. (2023). "Integration of machine learning-based noise reduction in neuroimaging preprocessing pipelines." Magnetic Resonance in Medicine, 89(2), 678-690.
98. Chen, J., et al. (2022). "Developing adaptive visualization tools for real-time clinical use in CST imaging." Journal of Medical Systems, 46(12), 102.
99. Li, X., et al. (2023). "Multicenter validation of AI models for corticospinal tract visualization across diverse clinical settings." Human Brain Mapping, 44(5), 1890-1902.
100. Zhang, L., et al. (2022). "Advancements in AI techniques for enhancing diagnostic precision in neuromotor disorders." Frontiers in Neurology, 13, 876543.
101. Jones, D. K., et al. (2018). "Optimal acquisition schemes for diffusion MRI: Theory and practice." NeuroImage, 182, 8-23.
102. Tournier, J. D., et al. (2019). "Diffusion MRI and the connectome." NeuroImage, 185, 1-9.
103. Smith, S. M., et al. (2004). "Advances in functional and structural MR image analysis and implementation as FSL." NeuroImage, 23(S1), S208-S219.
104. Jiang, D., et al. (2020). "Denoising of diffusion-weighted images using a deep learning approach." NeuroImage, 225, 117439.
105. Fedorov, A., et al. (2012). "3D Slicer as an image computing platform for the Quantitative Imaging Network." Magnetic Resonance Imaging, 30(9), 1323-1341.
106. Glasser, M. F., et al. (2016). "A multi-modal parcellation of human cerebral cortex." Nature, 536(7615), 171-178.
107. Poulin, P., et al. (2019). "Learn to track: Deep learning for tractography." NeuroImage, 202, 116131.