

# TractSpLearn: Robust Individualized Detection of Subtle White Matter Lesions in Traumatic Brain Injury

Jiqing HUANG<sup>1</sup>, Yi CHEN<sup>2,3</sup>, Laurent LAMALLE<sup>1</sup>, Christophe PHILLIPS<sup>1</sup>, Evgenios N. KORNAROPOULOS<sup>1,4,5</sup>

<sup>1</sup>GIGA-CRC Human Imaging, University of Liège, Liège, Belgium, <sup>2</sup>AMIIC-Lab, College of Computer Science and Technology, Guizhou University, <sup>3</sup>The D-Lab, Department of Precision Medicine, Maastricht University, <sup>4</sup>Department of Clinical Sciences Lund, Diagnostic Radiology, Medical Faculty, Lund University, Sweden, <sup>5</sup>Aix-Marseille Univ, CNRS, CRMBM, Marseille, France

c.phillips@uliege.be  
jiqing.huang@uliege.be  
ekornaropoulos@uliege.be

GIGA  
NeuroDay 2026

## Introduction



Traumatic brain injury (TBI) is brain damage resulting from an outside mechanical force. Patients may experience persistent cognitive, emotional, sensory, and motor deficits; in severe cases this leads to long-term disability.

**Objective:** To develop personalized lesion detection, a tract-wise manifold learning framework that:

- 1) leverages 7T DKI to capture subtle microstructural changes;
- 2) jointly models inter-group differences (HC vs. TBI) and within-group variability.

## Methods

### Data & Cohort:

- **Participants:** 21 healthy controls [HC], 17 athletes with repeated head injuries [RHI], 18 former athletes with persistent post-concussive syndrome [PPCS]
- **MRI acquisition:** 7T Philips Achieva, 3D T1 MPRAGE (TR = 8ms, TE = 1.97ms); DWI: FOV 224×224×110 mm<sup>3</sup>, TR = 9200 ms, TE = 65 ms (b = 0, 100, 500 1000, 2000 s/mm<sup>2</sup>).

### Data processing:

- **Preprocessing<sup>[1]</sup>:** Marchenko–Pastur PCA-based denoising; non-iterative Gibbs-ringing correction; brain mask from T1 (ANTs extraction); rigid alignment of DWI to T1 (ANTs registration) to ensure image quality and consistency across participants.
- **DKI parameters estimation:** DKI parameters (FA, MD, AD, RD, MK, AK, RK) were estimated by linear least-squares fit in DIPY (DiffusionKurtosisModel)
- **TractSpLearn:**

- 1) Tract segmentation<sup>[2]</sup>: White matter tracts segmented using TractSeg in subject space;
- 2) features extraction: Manifold learning via UMAP to obtain low-dimensional embeddings in latent space.
- 3) Two-step projection and back-projection: Similar to original Tract Learn framework<sup>[3]</sup>, for each subject  $i$  and DKI parameter  $j$  with group label  $y$  (HC, Patient: RHI or PPCS)  $S_{i,j}^{(y)}$  are first fitted to estimate  $x_{i,j}$ , then back-project to subject space. The mapping consists of three components (baseline, HC/patient-specific).

#### projection:

$$x_{i,j}^{(y)} = \Psi_{\text{base}}(S_{i,j}) + \Psi_{\text{HC}}(S_{i,j})[y_i = \text{HC}] + \Psi_{\text{PAT}}(S_{i,j})[y_i = \text{Pat}]$$

#### Back-projection:

$$S_{i,j}^{(y)} = \Phi_{\text{base}}(x_{i,j}) + \Phi_{\text{HC}}(x_{i,j})[y_i = \text{HC}] + \Phi_{\text{PAT}}(x_{i,j})[y_i = \text{Pat}]$$

- 4) Z-score computation

$$Z_{i,j} = \frac{\Phi_{\text{PAT}}(x_{i,j}^{(y)}) - \Phi_{\text{HC}}(x_{i,j}^{(y)})}{\sigma_j}$$

where  $\sigma_j$  is the standard deviation for DKI metric  $j$ .

## Results

TractSpLearn detected clear white-matter alterations in both patient groups. The RHI group exhibited more frequent and more extensive abnormalities than PPCS, indicating a higher overall lesion burden. Representative tract-wise RD lesion maps for one RHI and one PPCS patient are shown in Figs. 1–2.

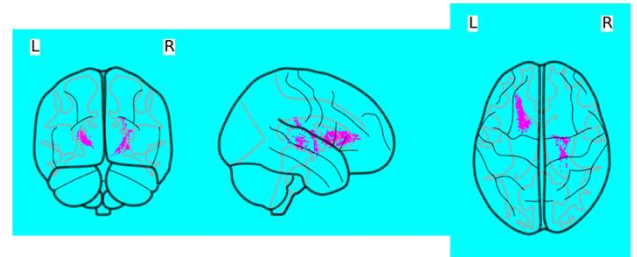


Fig.1 TractSpLearn RD lesion map in an RHI patient

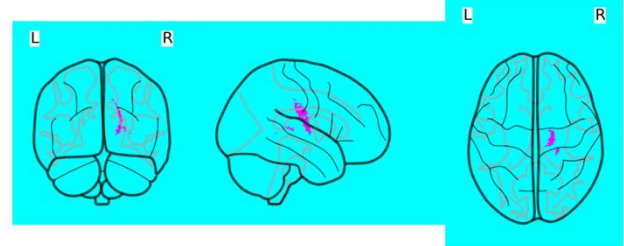


Fig.2 TractSpLearn RD lesion map in a PPCS patient

## Discussion & Conclusion

### Principal findings:

Our primary results suggest that TractSpLearn can provide individualized maps of subtle white-matter damage in sports-related TBI, however its robustness and clinical implications still need to be evaluated.

### Limitation:

The sample size is relatively small, and some tracts—especially large, heterogeneous bundles—show unstable results, suggesting that larger datasets and/or a finer tract parcellation will be needed to obtain more reliable estimates.

### Future works:

- Cross-validate and quantitatively compare with the original method.
- Link TractSpLearn findings to clinical outcomes

## Acknowledgments

We thank Ali Al-Husseini, Anna Gard, Niklas Marklund, and Markus Nilsson for their contributions to data acquisition.

References: [1] Anna Gard, et al., J Neurotrauma, 2024; [2] Jakob Wasserthal, et al., NeuroImage, 2018; [3] Arnaud Attyé, et al., NeuroImage, 2021

