

RATIONALE

The increasing demand for large-scale data analysis and effective individualized diagnostics in temporal lobe epilepsy (TLE) motivate accurate automated segmentation of the hippocampus, the hallmark site of pathology. We propose *DeepPatch*, a volume-based subfield segmentation method that leverages both patch-based analysis, which optimizes label fusion and image matching by compactly representing anatomy, shape, texture and intensity, and fully deep convolutional neural networks (CNN) that offer hierarchical feature learning ability.

METHODS

Our algorithm (*DeepPatch*) was trained on 50 manually segmented hippocampal subfields (CA1-3, DG-CA4, subiculum) based on submillimetric T1-weighted MRI (0.6 mm³ isotropic resolution) of 25 healthy subjects (mean age: 31±7 yrs, 13 females) [1,2]. Validation was conducted within a 4-fold cross-validation scheme (the dataset was partitioned to allocate 37.5% hippocampi for training, 37.5% for the atlas, and the remaining 25% for testing). The algorithm was further validated on 15 TLE patients (31±9 years, 12 females).

Training. Using a similarity function [3], we matched the intensity of randomly-selected regions of interest (or patches) centered around subfield voxels (size: 32×32×32) from the training dataset to patches extracted from a subset of the dataset (the atlas) with both image intensity and corresponding labels. All training patches and their corresponding atlas patches were used to train a CNN [4] to model multiscale intensity features and implicitly learn transitions along subfield boundaries.

Testing. For each hippocampus in the test set, we extracted a patch around each voxel, matched its most similar atlas patches, combined them and fed them into the CNN. Automatically generated labels were fused through majority voting to produce the final segmentation.

Performance evaluation. We used the Dice index and Bland-Altman plots to evaluate overlap and compare differences between automated and manual labels, respectively.

REFERENCES

- [1] Kulaga-Yoskovitz J, et al. Scientific Data (2015)
 [2] <https://www.nitrc.org/projects/mni-hisub25>
 [3] Fang L, et al. Med Im Ana (2016)
 [4] Ronneberger O, et al. CoRR (2015). abs/1505.04597

RESULTS

In healthy controls, the average (± SD) overlap between manual and automated labels was **92.0% ± 1.0** for CA1-3, **86.8% ± 2.7** for CA4-DG and **88.8% ± 1.6** for the subiculum. Similar high performance was obtained in TLE patients, with an overlap of **90.6% ± 2.3** (CA1-3), **86.8% ± 4.1** (CA4-DG), and **87.7% ± 2.5** (subiculum). High correlations and small differences between automated and manual volumes in both groups further support the robustness of the algorithm (**Figure 1**). **Figure 2** shows segmentation examples.

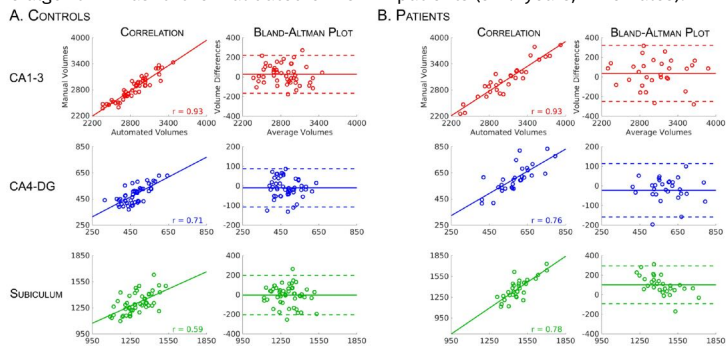


Figure 1. High correlations and small differences between automated and manual volumes (in mm³) as shown by the Bland-Altman plots in both **controls** (A) and **patients** (B) support the robustness of *DeepPatch*.

CONCLUSIONS

DeepPatch, operating on widely available T1-weighted MRI, yields remarkable performance, both in healthy controls and TLE patients. The combination of the patch-based framework with hierarchical feature learning capacity of deep neural networks captures efficiently the complex shape deformations and displacements, which are particularly prevalent in disease.

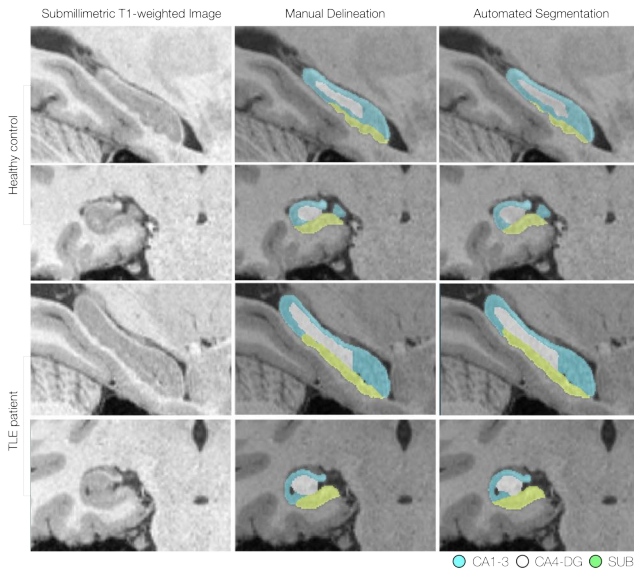


Figure 2. Manual delineation and *DeepPatch* automated segmentation relying on submillimetric T1-weighted MRI in a healthy control (CA1-3: **91.3%** CA4-DG: **85.2%** SUB: **88.4%**) and a patient (**93.6%** **90.7%** **90.5%**). Note that in the patient, despite the presence of hippocampal malrotation, subfields are adequately segmented.