Combined Automated Hippocampal Segmentation and Focus Lateralization in Temporal Lobe Epilepsy

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RATIONALE

Personalized diagnostics in temporal lobe epilepsy (TLE) motivate accurate automated segmentation of the hippocampus, the hallmark site of pathology. We combined a volume-based subfield segmentation method, DeepPatch, relying on convolutional neural networks (CNN) with a linear discriminant analysis classifier (LDA) to lateralize the seizure focus, both in patients with obvious hippocampal sclerosis (HS) and those considered to have MRI-negative HS based on visual evaluation.

METHODS

Training. We trained our algorithm (*DeepPatch*) on freely-available hippocampal subfield labels segmented manually on 0.6 mm isotropic T1-weighted MRI of 25 healthy subjects (31±7 yrs, 13 females) [1]. For cross-validation, the dataset was partitioned to allocate 37.5% hippocampi for training, 37.5% for the atlas (to sample similar patches), and 25% for testing. A similarity function [2] matched the intensity of randomly selected patches of the training set to the atlas. All patches were used to train a CNN to model multiscale intensity features and implicitly learn between-subfields boundaries.

Testing. For each hippocampus, we extracted a patch around each voxel, matched it to the most similar atlas patches, and fed them to the CNN. Resulting probabilistic labels were aggregated through majority voting to produce the final segmentation.

Validation. A clinical dataset of 76 TLE patients with histologically confirmed HS (35±10 yrs, 47 females; 39/76 MRI-negative) were used for validation. Performance. Dice index and Bland-Altman plots evaluated overlap and compared automated to manual labels, respectively. The LDA classifier using volumes and intensity derived from T2-weighted and FLAIR/T1 contrasts was used to lateralize the focus [3].

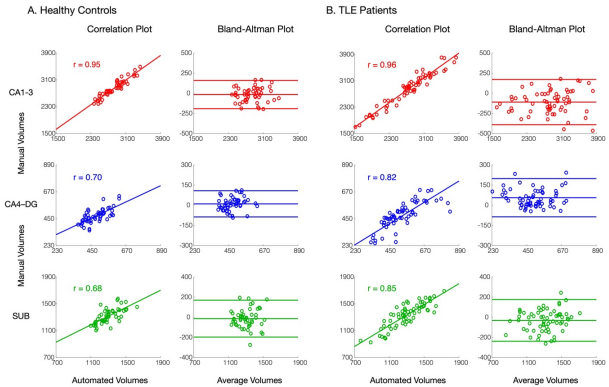

Figure 1. High correlations and small differences between automated and manual volumes (in mm^3) as shown by the Bland-Altman plots in both **controls** (A) and **patients** (B) support the robustness of *DeepPatch*.

RESULTS

SUBFIELD SEGMENTATION

Similar performance was observed in healthy controls and TLE (**Table 1**). High correlations and small differences between in volume between automated and manual segmentations further supported robustness (**Fig 1**); examples are shown in **Fig 2**.

SEIZURE FOCUS LATERALIZATION

Higher accuracy for seizure focus lateralization was obtained using T2 compared to FLAIR/T1 (90.8±2.2% *vs.* **85.7**±2.1%; $p<0.05$); both contrasts were superior to volumetry (**69.7**±3.2%).

The combination of T2 and FLAIR/T1 yielded the best performance, with **91.4**±2.7% in MRI-negative and **99.5**±1.1% in MRI-positive patients.

	CA1-3	CA4-DG	SUB
Controls	91.9% (±1.2)	87.9% (±2.2)	88.9% (±2.0)
TLE	90.6% (±2.3)	86.6% (±4.5)	87.8% (±2.5)

Table 1. Dice overlap indices (mean ± standard deviation) for hippocampal subfields (CA1-3, CA4-DG, and Subiculum) segmentation in healthy controls and TLE patients.

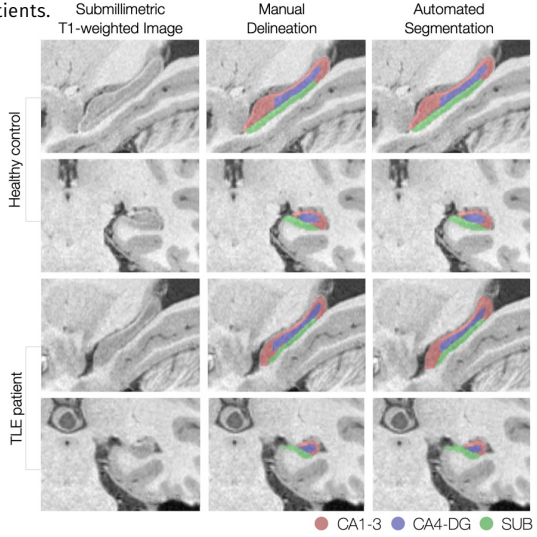

Figure 2. Manual delineation and DeepPatch automated segmentation relying on submillimetric T1-weighted MRI for a representative healthy control (CA1-3: **92.9**%, CA4-DG: **89.7**%, SUB: **91.2**%) and a TLE patient (**89.2**%, **86.3**%, **90.0**%).

CONCLUSIONS

Hippocampal subfield labels obtained using deep learning create the basis for efficient modelling of complex shape and intensity characteristics of the HS spectrum needed for accurate focus lateralization.

REFERENCES

[1] Kulaga-Yoskovitz J, et al. Scientific Data 2015

[2] Fang L, et al. Med Im Ana 2019

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