We create **synthetic resections** on normal brains so that **manual labels are not needed** for training

UCL

Self-supervised transfer learning with synthetic lesions for brain resection cavity segmentation in epilepsy neurosurgery

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Introduction

- Drug-resistant epilepsy can be cured with resective surgery (40-70% success)
- Clinical history, resected structures and surgical outcome must be correlated
- The resection cavity must be segmented on the postoperative MRI
- Little postoperative labelled data is available for deep learning
- We synthesise resections and labels on large publicly-available MRI datasets and use them for self-supervised learning

Results

- Median (interquartile range) Dice score of 0.81 (0.16) when using all synthetic data

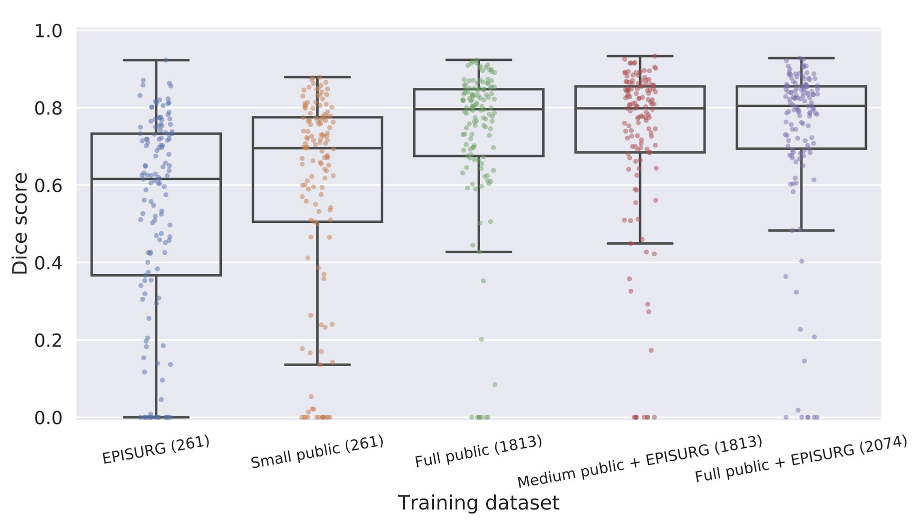
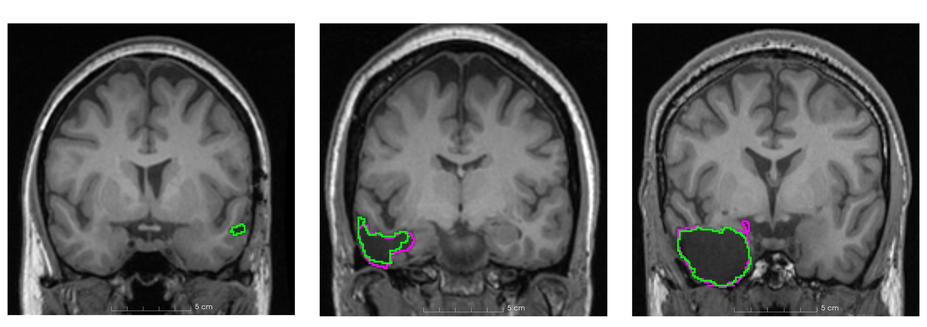


Figure 4: Dice score results training with only synthetic data and testing on the 133 real scans with manual labels. The boxes indicate the first, second and third quartiles. Whiskers represent the first quartile minus 1.5 times the interquartile range and the third quartile plus 1.5 times the interquartile range. The model trained with the smallest datasets performed notably worse.



Worst | Median | Best

Figure 5: Qualitative results of the model trained on synthetic data with the highest median Dice score after testing on the real dataset. Left: worst case (Dice score 0.00); middle: median case (Dice score 0.81); right: best case (Dice score 0.93). Green: manual labels; magenta: model prediction. Note that the model missed the temporal lesionectomy in the worst case.

Experimental design

Data

We curated a dataset called EPISURG with MRI scans from epilepsy patients from the National Hospital for Neurology and Neurosurgery[1].

Table 1: Distribution of the data used for training and testing. The labels of the preoperative data are generated automatically during training.

Source	Num. images	Type	Labelled
Public	1813	Preop	Synthetic
EPISURG	261	Preop	Synthetic
EPISURG	133	Postop	Yes
EPISURG	297	Postop	No

Experiments

- We create synthetic resections[2] on the fly[3] and train a modified 3D U-Net[4] with heavy data augmentation[5]
- We performed five experiments with synthetic datasets of different sizes
- We tested all the models on the postoperative dataset with real labels

1. The dataset will be shared upon publication (DOI: 10.5522/04/9996158)
2. See method on the right side of this poster
3. We open-sourced the code in `https://github.com/fepegar/resector`
4. We open-sourced the implementation in `https://github.com/fepegar/unet`
5. We open-sourced the library in `https://github.com/fepegar/torchio`

Discussion

- Manual labels are not needed to segment the brain cavity if models are trained with synthetic resections and large datasets
- Performance might be improved using the unlabelled real data for weakly-supervised learning
- We will fine-tune our models on real data and investigate inter-rater variability

Synthetic resections

Random non-linear transformation

- Simplex noise creates a smooth n-dimensional random texture
- The displacement of each point on a sphere is proportional to the simplex noise at that point

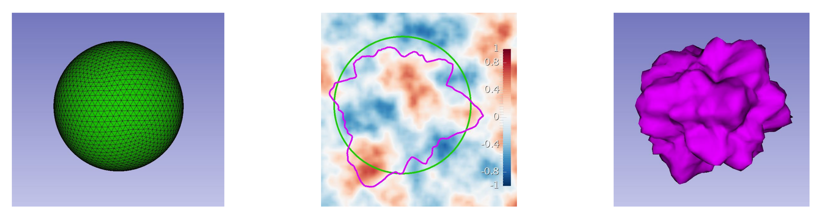


Figure 1: Adding simplex noise to a sphere. Left: a sphere is modelled as a geodesic polyhedron and represented as set of vertices and edges; middle: simplex noise is computed at every vertex (here in the whole volume for visualisation purposes) and they are displaced radially and proportionally to the noise; right: 'noisy sphere' after non-linear transformation.

Random linear transformation

- Random rotation and scaling is applied to the surface mesh
- The mesh is translated to a random grey-matter voxel in a non-lesioned MRI

Resection mask

- The surface mesh is transformed into a binary mask image
- A 'resectable hemisphere mask' is created using a brain parcellation
- The intersection of both is the synthetic resection label y_r

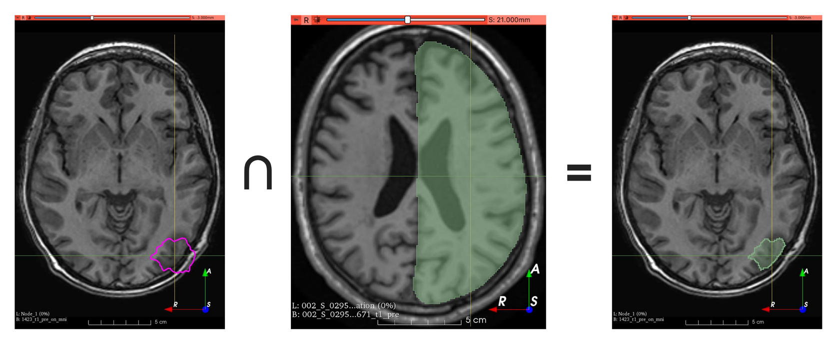


Figure 2: Creating the resection mask. Left: the transformed sphere is translated onto a grey matter voxel; middle: a 'resectable hemisphere' mask is created extracting regions from a brain parcellation and applying binary morphological operations; right: the intersection of the previous masks is the synthetic resection label.

Resected brain image

- A CSF image β is generated with Gaussian noise using values within lateral ventricles
- An alpha channel α is generated by blurring the resection mask y_r
- The synthetic resected image x_r is a convex combination of β and x:

$$x_r = \alpha\,\beta + (1 - \alpha)\,x$$

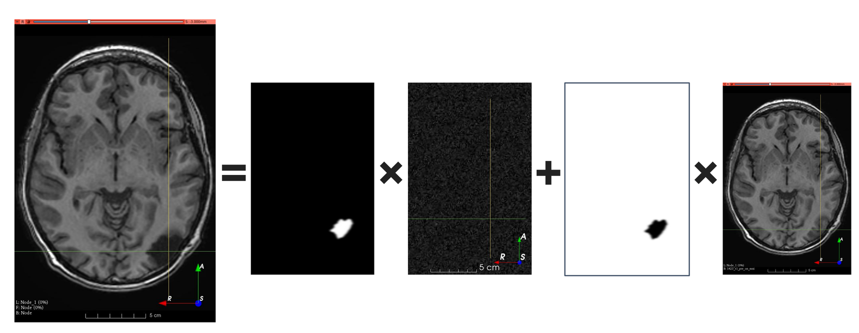


Figure 3: The resected image x_r is an alpha-blending of the preoperative image x and an image β representing CSF values. From left to right: resected image x_r, blurred resection mask α, CSF volume β, inversion of the blurred resection mask $(1 - \alpha)$, and original image x.

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