Forward modelling of M/EEG: Towards a new automatic head and brain tissue segmentation system

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FORWARD MODELLING OF M/EEG: TOWARDS A NEW AUTOMATIC HEAD AND BRAIN TISSUE SEGMENTATION SYSTEM

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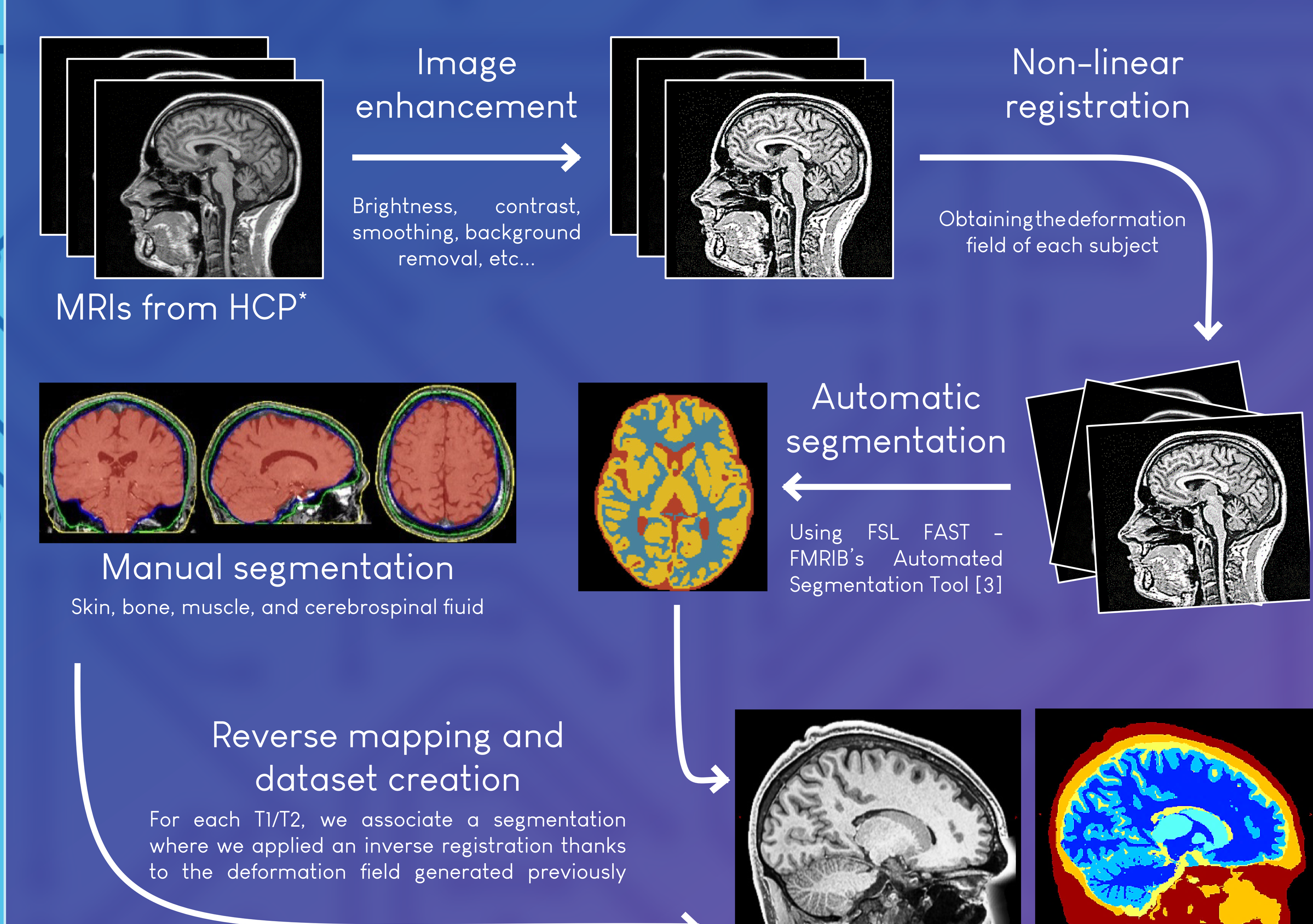
ABSTRACT

Magnetoencephalography and electroencephalography (together M/EEG) are imaging modalities that allow the non-invasive measurement of the magnetic field and the electric potential generated by cortical activity. Inferring which brain areas generated the observed M/EEG measurements is not a trivial task and is referred to as the inverse problem. A common way to solve the problem is to assume than brain sources act like current dipoles in a volume conductor, in this case the head whose geometry can be obtained from magnetic resonance imaging (MRI). The relationship between brain sources and M/EEG measurements can therefore be modeled, a process called the solving forward problem. This process can be seen as injecting anatomical priors into the inverse problem [1]. However, extracting the anatomical information from MRI needed to solve the forward problem is lengthy and tedious with existing tools. In this work, we present the first step in the creation of an automated pipeline to generate a volume conductor model from T1 and T2 images.

OBJECTIVES

- Obtain a **7-tissue segmentation of the MRI** of each individual, consisting of skin, bone, muscle, white matter, gray matter, cerebrospinal fluid and background.
  → Note that existing segmentation systems do not consider the skin, bone, and muscle layers, instead focus only on the brain [2].
- Given this segmentation, a 3D model can be built where a specific electrical conductivity is assigned to each label.

DATASET



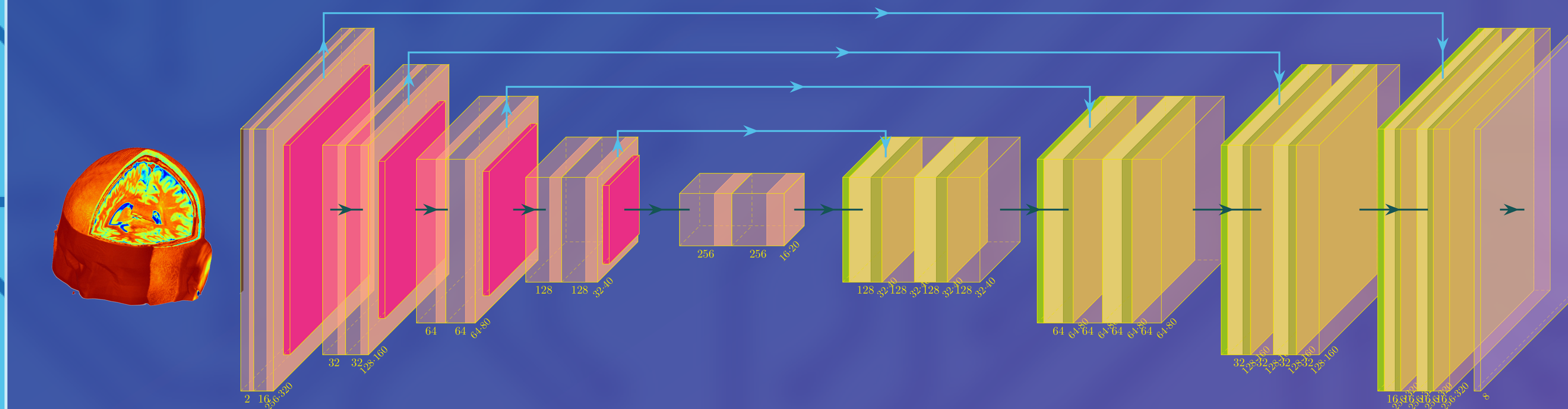
*HCP - Human Connectome Project : project to construct a map of the complete structural and functional neural connections in vivo within and across individuals.

Data distribution for the dataset creation

	Train	Test	Validation
T1	780	222	111
T2	780	222	111
Mask	780	222	111

TRAINING

To segment the MRI volumes, we trained our own deep learning architecture, which is an adaptation of the U-NET model, under Tensorflow. Our 3D U-NET architecture will process dense volumetric data whose methods are inspired by the work of Çiçek et al. [4]

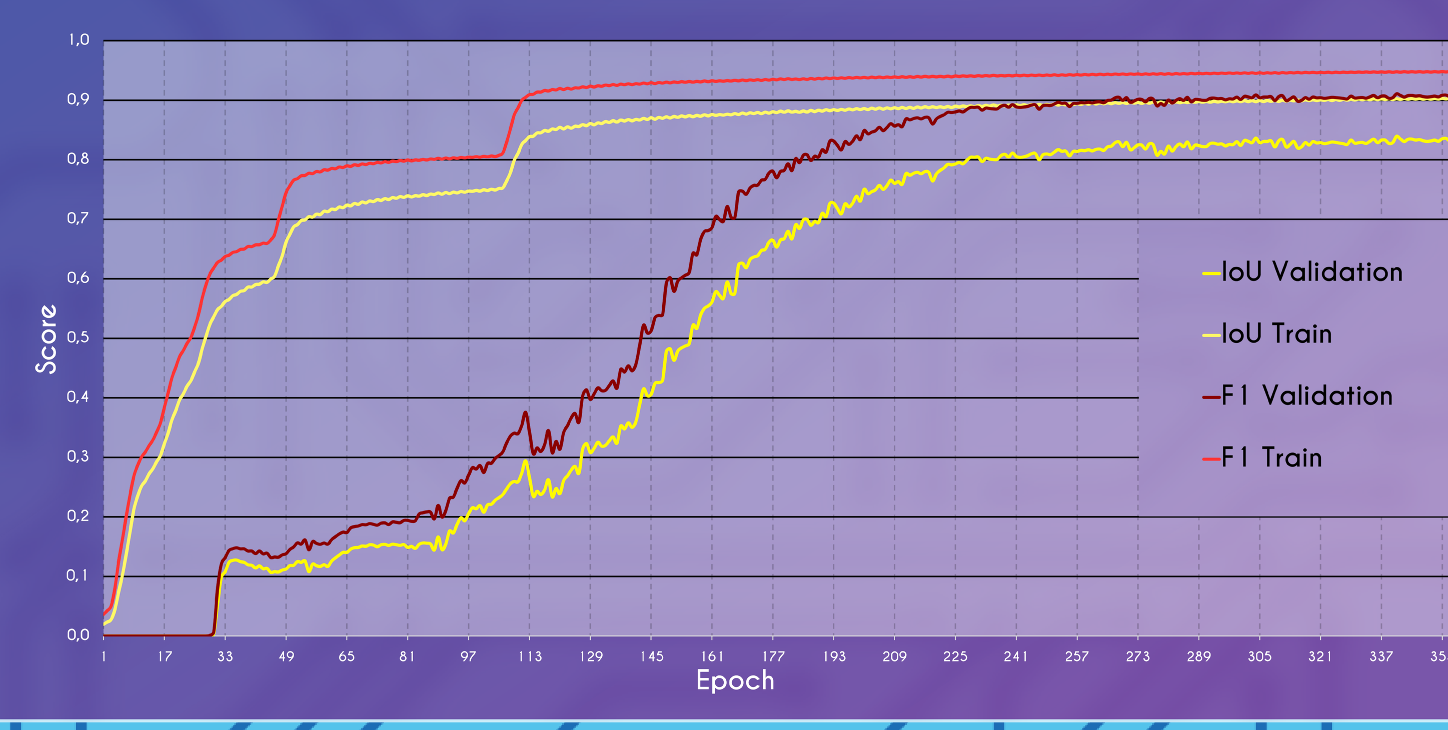


The cost of the error is modelized by the following loss function:

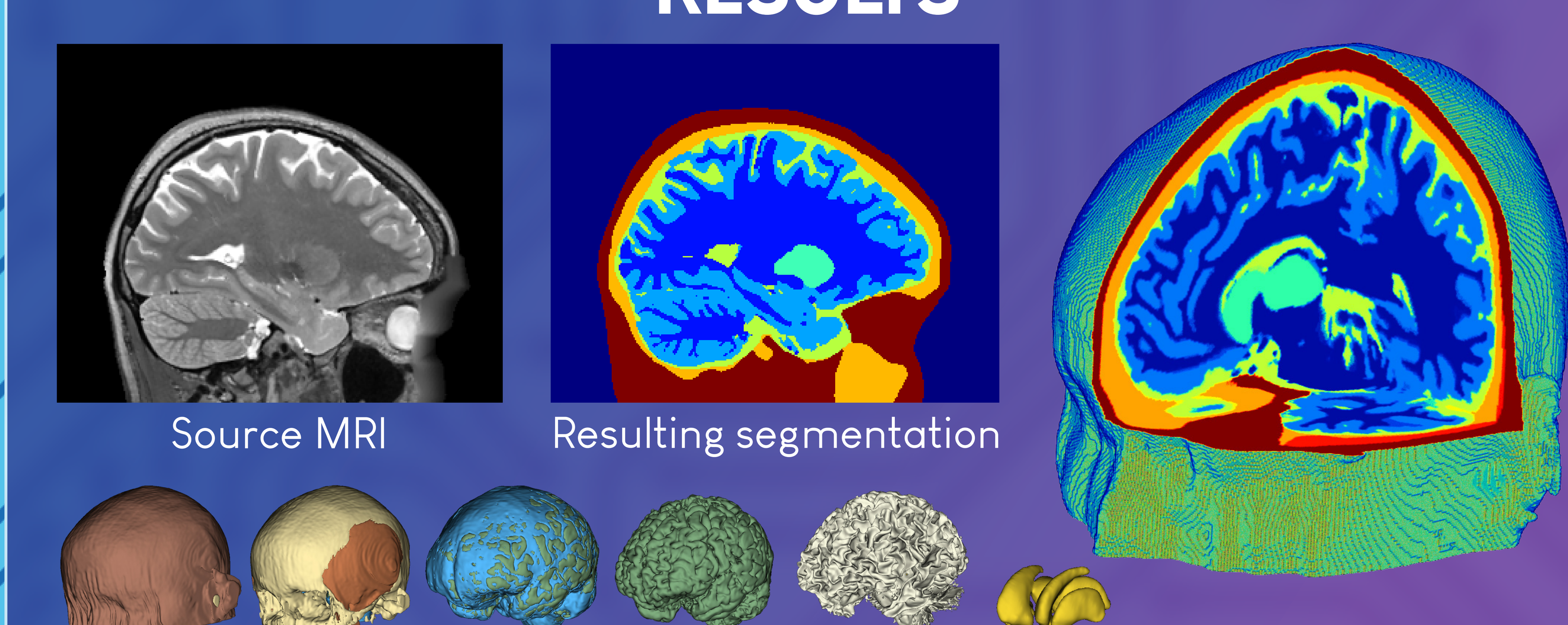
$$\underbrace{\frac{2|X \cap Y|}{|X| + |Y|}}_{\text{Sørensen-Dice score}} + \underbrace{\sum_{i=1}^{n} (i - p_i)^{\gamma} log_b(p_i)}_{\text{Categorial Focal Loss}}$$

To follow how the learning process is going we calculate some metrics:

$$F1_{score} = 2 \times \frac{Pre \times Rec}{Pre + Rec} \qquad IoU = \frac{X_t \cap X_f}{X_t \cup X_f}$$



RESULTS



CONCLUSION

In this work, we presented an automated system to segment tissues which will be assigned specific conduction values for the construction of the volume conductor. This is an important first step in the creation of an automated pipeline to solve the forward problem in M/EEG.

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