

Neural fiber prediction with deep learning

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Abstract—Neurosurgery is a highly demanding field of medicine. Its subject is the central nervous system, which governs all critical functions of the human body. In recent years, artificial intelligence has assisted neurosurgeons' work through decision support systems that help better plan and perform safe surgeries. This paper introduces a novel method for analyzing diffusion data from Magnetic Resonance Imaging. It uses a deep learning to produce maps of white matter bundles. This information is suitable for multiple applications, including the computation of whole-brain maps of fiber crossing points. Neurosurgeons and radiologists can use such knowledge for pre-operative planning and intra-operative navigation.

Index Terms—neurosurgery, fiber bundles, deep learning, magnetic resonance imaging, decision support system

I. INTRODUCTION

Neurosurgery is a necessary treatment for many disorders of the central nervous system. Even though this medical speciality emerged around brain tumor surgery, its applications are vast. Among many diseases, neurosurgeries help to treat meningitis, hydrocephalus, head trauma or movement disorders. Even though such interventions are necessary, they impose certain risks given the delicate nature of the brain tissue and its role in controlling bodily functions. The brain's cortex consists of neural cell bodies attributed to information processing and cognition. The axons of these cells constitute the white matter underneath, connecting various areas of the cortex and transmitting nerve impulses between them. Together they are organized into complex neural circuits, providing a basis for all vital body functions, such as cognition, movement, sight, or speech production and comprehension [1]. Knowledge of the location of the functional regions of the cerebral cortex, as well as the topology of the bands of white matter, is crucial for a successful and safe surgery. This information allows planning the surgery in such a way as to reduce the risk of complications associated with damage to essential, highly specialized structures.

Over the years, many decision support systems have been proposed to support neurosurgeons. Deep learning techniques have been used to detect and classify brain tumors to help radiologists make diagnoses and surgeons prepare for surgeries. Tumor detection, segmentation and classification

are difficult given the wide variety of shape and size. For successful resection of a tumor mass, it is critically important to remove as much as possible to limit tumor re-growth [2], [3]. Another important aspect of preoperative planning is precisely identifying the eloquent regions of the cerebral cortex and the nerve pathways that connect them to other areas of the brain and body. Many algorithms have been proposed that, by analyzing functional data (functional MRI, fMRI), can pinpoint the regions responsible for the specific functions (e.g. hand movement or speech) [4], [5]. Another class of algorithms analyzes diffusion-weighted MRI data and can thus indicate the likely topology of neural pathways near the site of intervention [6]–[9]. All of this information is valuable to the surgeon, who is trying to plan the procedure to minimize the risk of damage to these structures, which could lead to patient impairments.

Neural signal analysis is also a fascinating emerging field, with an example of a decision support system used for Deep Brain Stimulation surgery to treat Parkinson's disease [10], [11]. The target of such surgery is the Subthalamic Nucleus (STN), a structure poorly visible on Computed Tomography (CT) or MRI images. During the surgery, a set of micro recording electrodes is inserted into the brain, and recordings obtained in such way are analyzed to help the neurosurgeon correctly locate the STN structure in stereotactic 3D space.

Machine learning techniques are also used to predict treatment outcomes in patients. That includes treatment of arteriovenous malformations [12], prediction of cerebral vasospasm [13], [14] or the outcome of aneurysmal sub-arachnoid haemorrhage [15]. Data obtained from electroencephalography, and intraoperative electrode recordings were used to train models for predicting signal patterns for language, seizure and face recognition [16], including studies aimed at predicting the outcomes of epilepsy surgeries [17]–[19].

In this paper, we propose a novel approach comprising an artificial neural network to build graphs of neural connections within the brain, which can give valuable insight to neurosurgeons.

II. RELATED WORKS

Information about neural connections within the brain can be obtained through tractography [20]. This approach uses data from diffusion MRI experiments to assess the topology of nerve fibers. Many methods have been proposed to tackle this problem, including simple mathematical models like linear forced vector differential equation [21] or tensor deflection [22]. With the development of artificial intelligence, classical machine learning models and neural networks were used. The first was a random forest classifier proposed by Neher et al. [6]. Further methods include feedforward neural network (FFNN) [7], recurrent neural network (RNN) [8], [9]. Methods of this kind are well suited to utilize raw diffusion data without requiring lengthy preprocessing.

The performance of tractography methods has been studied in benchmarking experiments. Although many methods correctly predict neural fibers, the rate of false positive results is high. Unfortunately, due to the low accuracy level, the clinical applicability is limited [23], [24]. Therefore there is a need for further work on solutions in this area of research.

III. PROBLEM FORMULATION AND ARCHITECTURE OVERVIEW

In this paper, we propose an approach comprising a neural network employed to analyze raw MRI diffusion data (Fig. 1). Matrix produced by this network can be used for different further studies regarding white matter characteristics in the brain, e.g., connectome related works or envisioning the topology of the nerve fibers near the surgical field or connectivity studies between associated functional regions of the cortex.

We developed several artificial neural network architectures, including networks containing one and three-dimensional convolution layers. Next, we conducted a series of experiments for real data. The goal was to learn these networks. Unfortunately, most did not train as the loss, and ROC AUC metrics did not change over 50 epochs. Based on our research, we found that complex network architectures do not work in this case. We investigated simpler structures. Finally, we achieved the best results and performance for a simple feedforward network.

The proposed neural network is depicted in Fig. 2. It consists of two stages. In the first stage, two separate dense layers, activated by the ReLU function [25], process input data in parallel. One of the layers processes four-dimensional diffusion measurements, and the second layer processes gradient table entries (Fig. 2) corresponding to the diffusion data. Data is sampled from an experiment to include measurements of the water diffusion in the main available directions. After this stage, gradient table is represented by a tensor of 1000 values, while diffusion data by a tensor of 5000 values. Both outputs from the two parallel layers are combined. The next stage uses two dense layers, activated by the ReLU function or followed by the sigmoid function, learning to predict the final output from provided data. This network is suited to operate on small portions of the input data, e.g., a series of three-dimensional cubes of a shape $5 \times 5 \times 5$. In

such a cube, a central voxel is assumed to contain neural fiber under investigation, and the neural network result gives the extension of this fiber. Output is a three-dimensional array of probabilities calculated for each voxel on the surface of the cube, describing their likelihood of containing the same neural fiber as the central one. Probability is depicted with colors from white (low probability) to dark blue (high probability).

Voxels with high probability located on the cube's surface become a seed point for the next cube drawn from the diffusion data. Stacking them together allows the construction of a graph of neural connections within the white matter. The process of detecting fiber crossing points based on the results obtained from a neural network is presented in Fig. 3. Vertices marked with red have more than two edges and represent voxels with possible fiber crossings. Such a graph can serve multiple purposes, e.g. detecting splitting, joining and crossing fibers. It can be useful in any future research involving the human connectome.

IV. NUMERICAL EXPERIMENTS

The performance of our approach was evaluated on publicly available datasets.

A. Dataset creation

We used data from the Human Connectome Project (HCP) database (<https://ida.loni.usc.edu/login.jsp>). HCP is the result of efforts of co-investigators from the University of Southern California, Martinos Center for Biomedical Imaging at Massachusetts General Hospital (MGH), Washington University, and the University of Minnesota [26]–[30]. For each of the five randomly selected subjects, we have prepared tractograms for fibers originating on the gray and white matter interface of the Broca's area. A mask derived from an anatomical scan limited the considered area to the brain's white matter. We used the Constant Solid Angle (CSA) reconstruction method to estimate Orientation Distribution Function (ODF) in the diffusion scans [31]. We used ODF peaks to track neural fibers and prepared labels based on computed streamlines. A streamline can be depicted as a series of connected points in a three-dimensional space. A voxel is marked with a positive value in the label if it contains a continuation of the considered streamline. Streamlines generated for each subject are divided into train and evaluation subsets with a ratio of 8:2.

B. Neural network training

Obtained white matter bundles were used to train a neural network. Each subject's white matter topography was split into training and evaluation subsets of streamlines. Data loader iterates over each streamline and coordinates of the current point become coordinates for the central point of a sample. It is sampled from the scan data as a small cube, usually of a shape of $5 \times 5 \times 5$ voxels. Variety of sizes were tested. However, cubes with the shape $5 \times 5 \times 5$ gave the best results. Input to the network comprises two vectors. First represents a part of diffusion measurement done in 14 directions

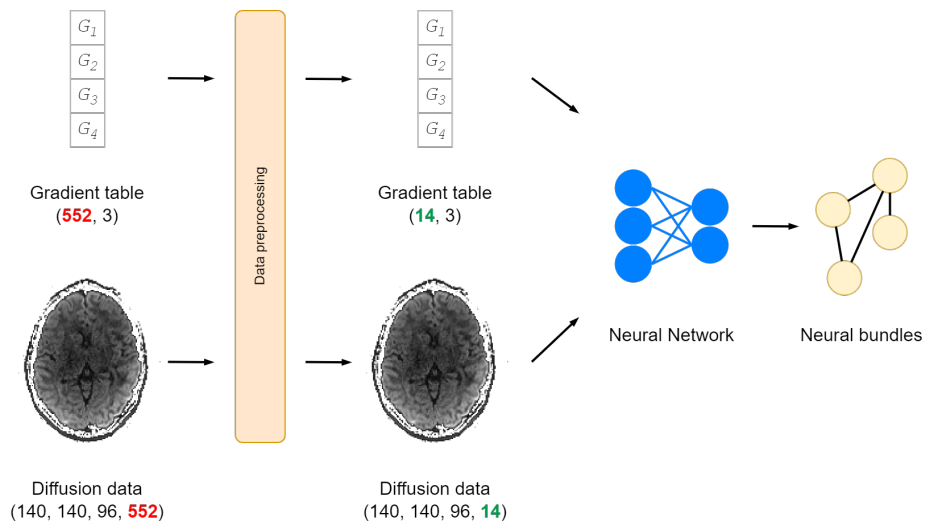


Fig. 1. Outline of the proposed approach.

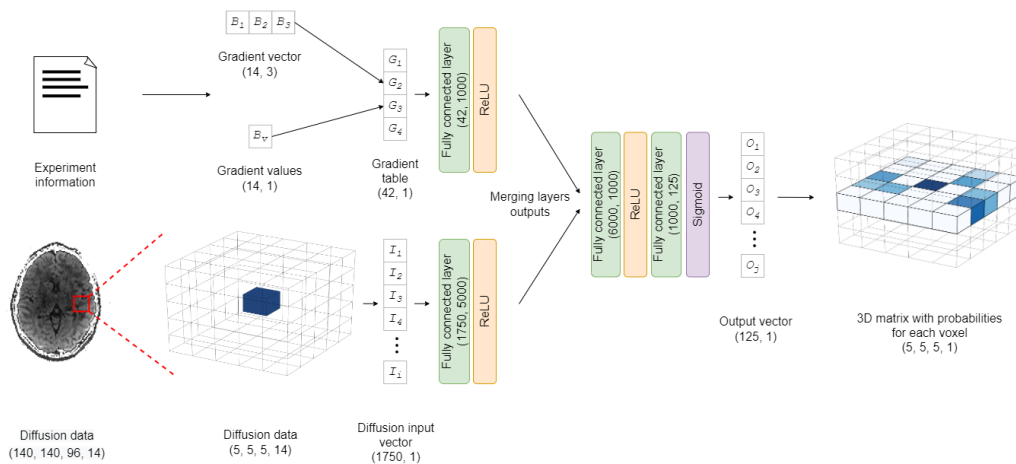


Fig. 2. Architecture of the neural network.

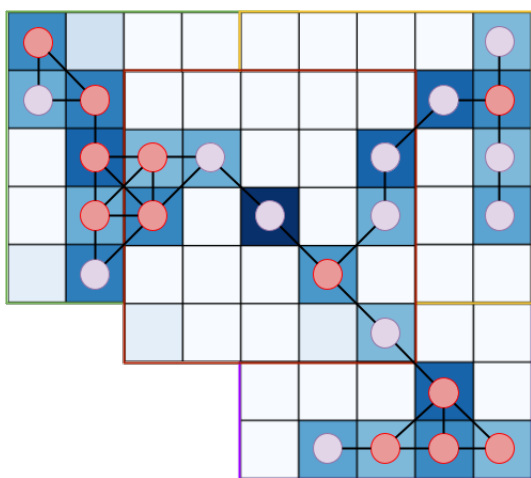


Fig. 3. Fiber crossing points determined based on the results obtained from a neural network.

and is described by a vector of size (5,5,5,14). Second is a gradient table corresponding to the measurements, describing the strength and direction of the gradient, represented by a vector of size (14,3). We trained a neural network for 300 epochs with Adam optimizer [32] with a learning rate varying from $1e-3$ to $1e-7$ and a batch size of 32. We did not foresee weight decay in this approach as it did not yield better results. As a scoring function, we used binary cross-entropy loss (1). During the training, the loss decreased steadily for both training and validation datasets up to epoch 100. After that, we saw a steady increase in the validation set, indicating network over-training (Fig. 4). Similarly, we were calculating ROC AUC [33] value for each epoch, which started to decrease during the validation phase at the exact moment the validation loss started to grow (Fig. 5). This trend holds up to epoch 300. Hence we did not see a reason to keep training the network for longer.

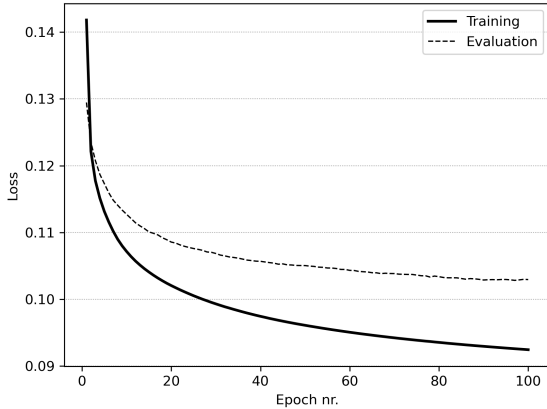


Fig. 4. Values of loss; training and evaluation phases.

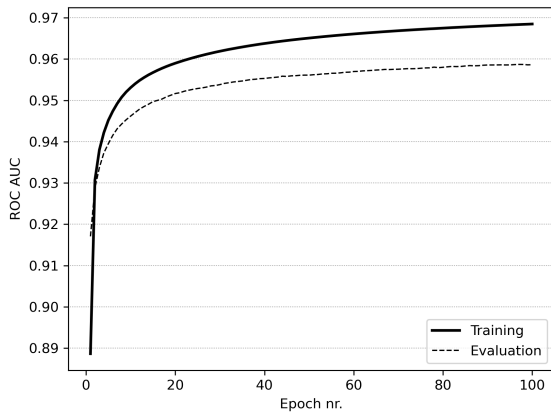


Fig. 5. Values of ROC AUC; training and evaluation phases.

$$H_p(q) = -\frac{1}{N} \sum_{i=1}^N y_i \times \log(p(y_i)) + (1 - y_i) \times \log(1 - p(y_i)) \quad (1)$$

C. Results and discussion

A neural network was trained with various learning rates for 100 epochs. The results for train and evaluation datasets are collected in Table I. It can be seen that the best results were obtained using a learning rate of $1e-4$. We use the ROC curve to show the final model performance. Area under

TABLE I
EXPERIMENTS WITH VARIOUS LEARNING RATES.

Learning rate	Loss		ROC AUC	
	Train	Evaluation	Train	Evaluation
$1e-3$	0.1046	0.1106	0.9562	0.9493
$1e-4$	0.0925	0.103	0.9685	0.9587
$1e-5$	0.1046	0.1068	0.9562	0.9536
$1e-6$	0.1242	0.1242	0.9272	0.9272
$1e-7$	0.1588	0.1586	0.8373	0.8377

the curve equals to 0.9586, showing excellent efficiency of the model (Fig. 6). Analyzing such a curve is much more informative than simply calculating accuracy for predictions above a certain threshold. In binary classification for medical applications, choosing a threshold where the number of true positives is high, even with the cost of a higher false-positive rate, is desirable. A sub-optimal number of false-positive results is acceptable to avoid damaging important brain structures.

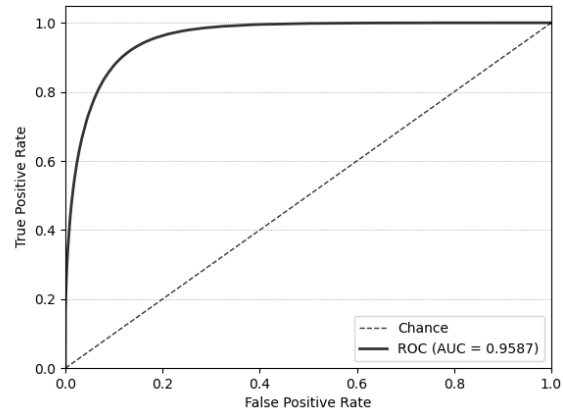


Fig. 6. ROC curve for the trained neural network.

V. SUMMARY AND CONCLUSIONS

A presented neural network produces data that can be easily used to create maps of white matter bundles within the brain, which can be used in multiple applications. One particularly interesting is the creation of the whole-brain map of crossing points. Such a crossing point indicates the location where neural fiber bundles split, merge or cross. Cases of this type involve the most essential fibers, damage to which can cause severe impairments. Areas, where multiple bands of white matter cross or converge, must be if possible avoided during neurosurgical interventions. Damage to them would, unfortunately, affect multiple connections and would adversely affect many brain regions. That is a clear suggestion for a surgeon that the surgical intervention path shall, if possible, spare such regions, and the scope of the intervention itself shall be limited to the area which does not contain such locations. Given the high rate of false positives in tractography analyses, visualizing only crossing points allows the neurosurgeon to focus on these locations with special attention.

Described approach is a working proof of concept, basic research that can be used in future work regarding brain connectome or neurosurgical planning. It can be applied both for the detection of brain regions containing multiple neural pathways as well as mapping bundles leading from and to cortex eloquent regions. Finally described method, together with additional machine learning algorithms, can be used for the construction of full brain pictographs. Applying different thresholds to results given by a neural network it would be

possible to obtain tractograms with different sensitivity as to the existence of neural connections.

We are constantly consulting our research outcome with neurosurgeons and radiologists to apply this in practice. The presented approach is a proof of concept. The final model will be trained on the dataset curated by a trained radiologist. It will help to improve the anatomical significance of the results further. In addition to determining the intersection points of nerve fibers, we also plan to use this neural network to calculate tractograms. Our preliminary work indicates that this will be possible without significant modifications to the architecture of the presented solution.

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