DeeptDCS: Real-Time Estimation of Currents Induced During Transcranial Direct Current Stimulation via Deep Learning

Xiaofan Jia, Sadeed Bin Sayed, Guang-Bin Huang, Abdulkadir C. Yucel
School of Electrical and Electronic Engineering
Nanyang Technological University, 639798, Singapore
xiaofan002@e.ntu.edu.sg,
{sadeed.sayed, egbhuang, acyucel}@ntu.edu.sg

Luis J. Gomez
Department of Electrical and Computer Engineering
Purdue University
West Lafayette, IN 47907, USA
ljgomez@purdue.edu

***Abstract*—This paper proposes DeeptDCS, a deep learning-based real-time emulator to estimate the currents induced during the transcranial direct current stimulation (tDCS). The DeeptDCS takes the volume conductor model of a human head and the excitation parameters as inputs and provides the tDCS-induced three-dimensional current density across the whole head as output. The DeeptDCS obtains the current density more than 112x faster than the finite element-based open-source SimNIBS simulator while achieving a mean absolute error less than 0.1%.**

***Keywords*—Current density estimation, convolutional neural networks, deep learning, emulator, transcranial direct current stimulation (tDCS).**

I. Introduction

Transcranial direct current stimulation (tDCS) is a non-invasive brain stimulation technique that alters the excitability of brain regions by inducing a small current in the human head using electrodes attached to the scalp. tDCS has been shown to have therapeutic effects for depression and chronic pain and enhance the working memory of healthy individuals [1].

Currently, the practitioners face two critical issues in optimizing tDCS for clinical and experimental protocols. First, intra- and inter-subject variations in head anatomy greatly influence the current distribution induced during tDCS. Due to these variations, common electrode positions will often fail to generate significant currents in the targetted brain regions. Ideally, the practitioner would be able to visualize and monitor the current distribution induced in the brain and modify the electrode position as necessary to achieve ideal therapeutic effects. However, obtaining in-vivo measurements of tDCS is challenging, and physics-based simulators [2, 3] appear to be the only viable option to determine the induced currents and E-fields inside the brain during stimulation. Second, the closed-loop neuronavigated tDCS protocols, in principle, could be planned to on-the-fly reconfigure electrode positions based on behavioral measurements to target the distinct regions. However, such reconfiguration of the electrodes would require the computation of E-field and current distributions for an ensemble of electrode positions. This is currently not practical because the physics-based simulators do not provide the current distributions (near-) real time and their repetitive execution requires excessive computational resources.

Similar issues persist in the clinical applications of transcranial magnetic stimulation (TMS) [4]. To tackle with these issues, a deep learning algorithm was recently proposed to estimate the strength of E-fields induced in selected regions of the brain during the TMS [4]. However, many TMS and tDCS applications require much rich information, such as the components of E-fields or currents and their distributions on the whole head. Furthermore, no deep learning-based scheme has been proposed for tDCS so far.

In this study, we propose a deep learning-based real-time emulator to estimate the currents induced during tDCS. The proposed emulator, called DeeptDCS, utilizes a 3D U-net that takes the volume conductor model (VCM) and electrode positions as input [Fig. 1]. The emulator outputs the components of the three-dimensional currents distributed on the whole head during the tDCS procedure. The proposed emulator requires 0.465 s on a GPU and 1 s on a CPU for one emulation. On the other hand, the finite-element based open-source SimNIBS requires 112 s on the same CPU for one simulation. Note that the SimNIBS can not be executed on a GPU. Therefore, the proposed emulator is at least 112x faster than SimNIBS while achieving a mean absolute error of only 0.06566 % of the maximum value of the ground truth.

DeeptDCS

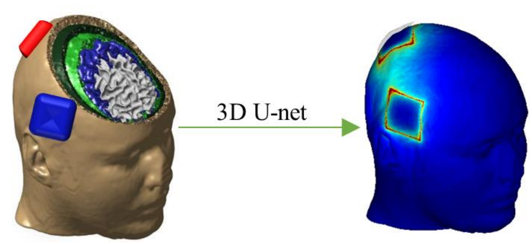

Fig. 1. The workflow of the proposed DeeptDCS, which uses VCM with excitation configurations to emulate tDCS-induced three-dimensional current flow across the whole head.

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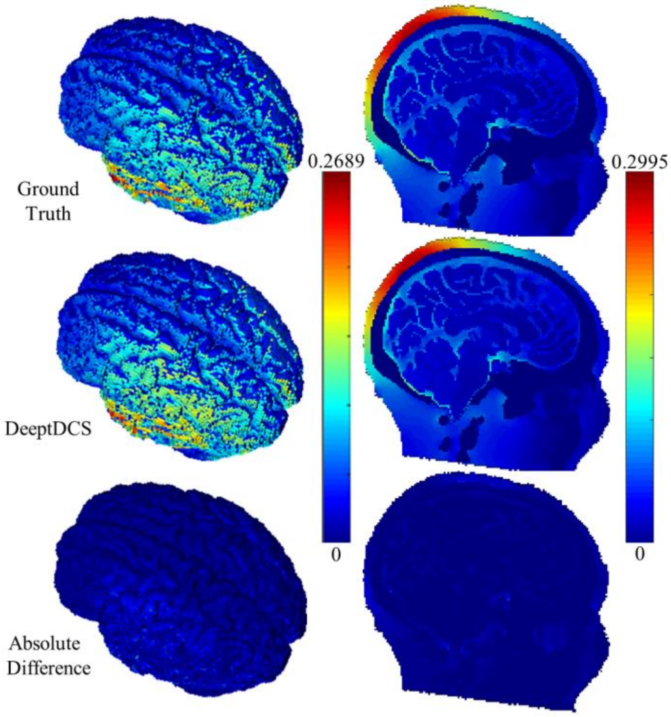

Fig. 2. Visual comparison of magnitude of current density distribution across the brain (the first column) and the sagittal slice (the second column), where the three rows represent the ground truth from SimNIBS, the emulation from proposed DeeptDCS, and the corresponding absolute difference, respectively.

II. DeeptDCS

The proposed DeeptDCS scheme is schematically depicted in Fig. 1, which reads the VCM of head tissues with electrode configurations and predicts the components of current density across the subject's head during tDCS. To learn the relationship between input and output in DeeptDCS, a deep convolutional neural network, 3D U-net [5], is adopted, which is an encoder-decoder framework with skip connections. In the encoding stage, a series of convolutional blocks and max-pooling operators extract local features in various resolutions from the input. Afterwards, transposed convolutional blocks in the decoding path merge information skipped from the encoding path to recover the volume size and predict the three-dimensional current flow.

Apart from the anatomy of the human head, the current distribution during tDCS is affected by the shape, size, and positions of the electrodes. Feeding the electrode information as an additional input channel can increase the computational cost of the emulator. However, in DeeptDCS, the electrode parameters are appended to the VCM by assigning conductivity values larger than those of the head tissues for the corresponding voxels. Compared to methods taking excitation features as an additional input channel, this one-channel input scheme avoids the curse of dimensionality.

III. Data generation

To train and test DeeptDCS, data pairs of VCMs and current distributions are generated for commonly used tDCS excitation patterns. First, 21 subjects' magnetic resonance images are adopted to construct VCMs. Then, the head tissue conductivities are randomly assigned based on the reference ranges [6]. Next, for each excitation pattern of a single subject, VCM is inputted to SimNIBS for acquiring the ground truth current distribution. Finally, the input VCM and output current distribution of SimNIBS, all defined on tetrahedral elements, are voxelized to be applicable to the convolutional operator in 3D U-net and used for training and evaluation of DeeptDCS.

IV. Numerical Results

Samples constructed are split into three subsets: training, validation, and testing. 3D U-net is trained by minimizing mean squared error loss and then applied to predict the three-dimensional current density flow from a new VCM not used in the training. Fig. 2 illustrates the current density of one testing sample, which compares the ground truth obtained from SimNIBS and the estimation from DeeptDCS. As shown in the first column of Fig. 2, the agreement in current density distribution on the brain surface enables DeeptDCS in the clinical application where accurate localization of the target region is critical. Meanwhile, pixel-level consistency between the ground truth and the prediction in the sagittal slice allows research related to deep brain stimulation via tDCS. Furthermore, the mean absolute error of predictions via DeeptDCS is 0.001835 mA/m^2 , which is 0.06566 % of the maximum value in the ground truth. Each emulation via DeeptDCS costs 1 s on a CPU and 0.465 s on a single GPU, over 112 and 240 times faster than one simulation by SimNIBS, which requires 112 s execution time on the same CPU. Therefore, the DeeptDCS is a promising tool for settings requiring real-time tDCS current visualization.

V. Conclusion

DeeptDCS, a deep learning-based real-time tDCS emulator is proposed. DeeptDCS leverages the ultra-short testing time of 3D U-net to visualize the tDCS-induced three-dimensional current density across the whole head. In the talk, the details and performance of DeeptDCS will be presented.

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