PHYSICS-INFORMED NEURAL NETWORKS FOR EFFICIENT ELECTRIC FIELD MODELLING IN DEEP BRAIN STIMULATION

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Introduction. Deep brain stimulation (DBS) treats neurological disorders such as Parkinson's disease by delivering electrical stimulation through implanted electrodes. Accurate modelling of the resulting potential distribution supports therapy planning, but conventional finite element method (FEM)-based models can be computationally expensive and limit clinical applicability. We train a physics-informed neural network (PINN) [1] to approximate the electric potential distribution during DBS, aiming to reduce computation time in volume conductor models.

Methods. We solve the quasistatic approximation of Maxwell's equations using a PINN. Dirichlet conditions are imposed on active contacts, and homogeneous Neumann conditions on insulating surfaces. Training points are sampled inside the three-dimensional volume-conductor domain, extracted from a human brain atlas, and on its boundary surfaces. Optimisation follows a loss-attention framework balancing PDE-residual and boundary-condition terms [2].

Results. The PINN reproduces the potential with low mean absolute error compared to the FEM solution in a homogeneous brain model. Impedance differences remain below $0.6\,\%$ relative to the established OSS-DBSv2 software. Although the training process is computationally demanding, evaluation for specific stimulation settings is fast. In a heterogeneous brain domain, larger deviations occur. Further work should focus on improving accuracy in anatomically realistic geometries with heterogeneous tissue properties.

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