Physics-Informed Regularization for MR Image based Segmentation: Enabling Accurate and Fast Segmentation from Scarce Annotations

**Negar Mehrabi[1]** and Geoffrey Gale Handsfield[2,3]
[1] Department of Applied Physical Sciences, University of North Carolina at Chapel Hill, Chapel Hill, NC, United States of America
[2] Department of Orthopedics, School of Medicine, University of North Carolina at Chapel Hill, Chapel Hill, NC, United States of America
[3] Lampe Joint Department of Biomedical Engineering, University of North Carolina at Chapel Hill and NC State University
Disclosures: Authors NM and GGH have no financial or other interests to disclose.

Introduction: Segmentation of muscles from medical image data enables subject-specific muscle analysis in both clinical and research contexts. Manual or semi-automatic segmentation is time-consuming, requires expert input, and is prone to inter- and intra-observer variability. AI-based segmentation using neural networks offers a powerful alternative, delivering high-accuracy results for unseen data in a fraction of the time. However, segmenting abnormal morphologies—such as those present in pathological cases—typically demands large, manually labeled datasets, which is often impractical in clinical settings. A more feasible approach is to develop neural networks trained on healthy datasets, where data is more abundant, and extend their generalization to pathological cases. Achieving this would represent a significant advance in medical image segmentation. In this study, we propose a novel learning framework that combines physics-informed neural network (PINN) regularization with semi-supervised learning. Independent of dense and diverse annotations, our model enabled time-efficient segmentation while enhancing clinical utility for orthopedic diagnosis and treatment, where precise volume-of-interest (VOI) delineation is essential in limited amount of time. **Methods:** Our approach begins with training a 2D residual U-Net on a labeled dataset of healthy medial gastrocnemius (MG) muscle MR images. The network uses five-slice axial stacks to capture rich spatial context and is optimized with a joint Dice and Binary Cross-Entropy (BCE) loss. In the training phase, we applied extensive data augmentation including intensity perturbations, elastic deformations, and random rotations to enhance model generalization. In the fine-tuning phase, the pre-trained healthy model is adapted with the full MRI volume of an adolescent with cerebral palsy (CP) (GMFCS II) patient together with 10 manually segmented slices of that patient's MG muscle. A learned latent vector is spatially concatenated with the input data set to provide vectored anatomical context and create field displacement, upon which the PINN loss is directly applied. A dual-loss strategy is applied including Supervised Loss for the labeled CP slices, a combined Dice + BCE Loss ensures strong voxel-wise prediction and Physics-Informed Loss (PINN Loss) applied to the unlabeled CP slices. This combined loss strategy enables geometrical plausibility and anatomical consistency across the muscle structure. PINN Loss consists of: Divergence Loss which maintains volume consistency by penalizing segmentation divergence, Equilibrium Loss which maintains a balance between internal forces and physiologically realistic shapes, Smoothness Loss which penalizes sharp transitions between slices, enforcing smooth anatomical boundaries. Finally, in prediction phase, the fine-tuned model performs slice-by-slice predictions across the complete CP MRI volume. A post-processing approach was implemented to enable removal of false positives and retain the primary muscle structure. **Results and Conclusion:** Our framework successfully transfers knowledge from a healthy to pathological dataset using minimal annotations. Quantitative evaluation demonstrates high reliability and adoptability to anatomical variation, outperforming purely supervised baselines. Using 3D volumetric evaluation across the entire MRI volume, our model achieved a Dice score of 0.9313, showing excellent consistency with manually segmented ground truth labels. These findings highlight that the proposed model is a clinically robust, time-efficient tool enabling precision in diagnostic and treatment workflows. **Future Work:** We plan to integrate advanced PINN constraints into patient-specific imaging data to rapidly generate biomechanical models, e.g. rigid body modeling or finite element analysis. By advancing the ability to generate subject specific models from imaging data, this framework has the potential to improve the accuracy of biomechanical models and advance early disease characterization through just-in-time clinical modeling, surgical planning, or development of orthopaedic digital twins.
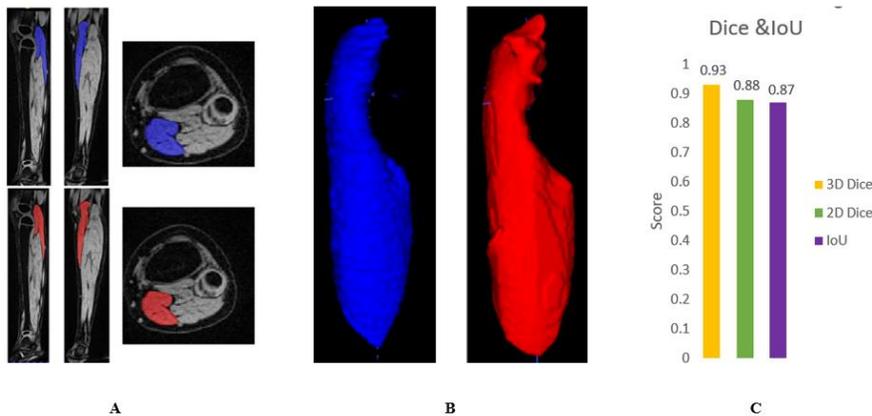
A) Manual segmentations (blue) and model-predicted segmentations (red) of the medial gastrocnemius (MG) muscle. **B)** 3D volume rendering of the segmented medial gastrocnemius (MG) muscle from MRI of an adolescent with cerebral palsy (CP) (GMFCS II) **C)** Segmentation performance metrics quantifying the overlap between predicted and manually segmented masks of the MG.