DEEP LEARNING-BASED AUTOMATIC SEGMENTATION OF SKELETAL MUSCLES

Zhicheng Lin (1), William H Henson(4), Claudia Mazzà(4,3), Enrico Dall'Ara (2,3), Lingzhong Guo (1,3)

1. Department of Automatic Control and Systems Engineering, The University of Sheffield, UK;
2. Department of Oncology and Metabolism, The University of Sheffield, UK;
3. INSIGNEO Institute for in silico Medicine, The University of Sheffield, UK;
4. Department of Mechanical Engineering, The University of Sheffield, UK

Introduction

Rapid and accurate muscle segmentation from Magnetic Resonance Imaging (MRI) is essential for the diagnosis and monitoring of many musculoskeletal diseases, and for creating personalized biomechanical models. Traditionally, muscle segmentation has relied on manual work by experts, which is very time-consuming and subject to inter-operator reproducibility errors [1]. The high labour cost becomes a bottleneck in muscle segmentation tasks of large cohorts of patients.

With the development of deep learning technology in recent years, there has been a growing trend to apply deep neural network models for classification [3], segmentation [2], and recognition of targets in different scenarios. While a number of models have been already proposed, there is still room for improvement in the accuracy and efficiency of automatic multi-target segmentation of muscles. In this study, we aim to develop and test new deep-learning models for automatic muscle segmentation of human lower limbs.

Materials and Methods

The Unet [2], which is a widely used convolutional neural network (CNN) in medical image segmentation, will be used as a baseline for the purpose of comparison. Unet employs multiple convolution operations combined with up and down sampling to extract the feature information of different dimensions and levels of the image so as to segment and recognize the target image. In this study, two new CNNs (Model1 and Model2) are proposed by introducing attention mechanisms in Unet, to improve muscle segmentation.

The data is composed of the full lower-limb MRI data of 25 muscles of the thigh part from eleven post-menopausal women (mean (standard deviation, SD): 69 (7) y. o., 66.9 (7.7) kg, 159 (3) cm) with no muscle disease, recruited by the Metabolic Bone Centre (Sheffield, UK) as part of larger studies. The study was approved by the East of England—Cambridgeshire and Hertfordshire Research Ethics Committee and the Health Research Authority (October 2000).

Manual segmentations of each muscle were used as a gold standard [1]. The leave-one-out approach was used to evaluate the accuracy of the models in segmenting the muscles. In the evaluation phase, the mean values (11 trials; 16 muscles with high intra-operator reproducibility of the manual segmentations [1]) of three metrics were used to evaluate the accuracy of the models: Dice Score Coefficient (DSC) [4], Relative Volume Error (RVE), and Hausdorff Distance (HD).

Results

On the test set, both newly adjusted models performed better than the Unet (1.5% and 2% mean improvement in DSC and RVE, 20mm in HD, $p<0.05$). The percentage improvements over Unet for DSC, RVE, and HD were 2.2% (±1.54%), 3.2% (±3.1%), 38.1% (±18.1%) for Model1, and 2.0% (±1.4%), 2.6% (±2.2%), 31.7% (±20.1%) for Model2.

	Unet	Model 1	Model 2
DSC	0.81	0.83 *	0.83 *
1-RVE	0.83	0.86 *	0.85 *
HD (mm)	49.9	29.9 *	32.4 *

Table 1: Testing results evaluation for Unet and two modified models. (means p<0.05 in T-test)*

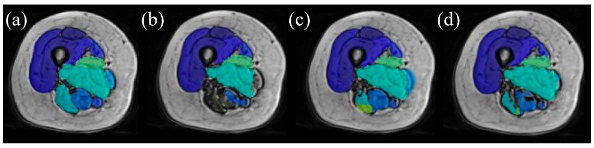

Figure 1: Visualization of (a) manual work, prediction of (b) Unet, (c) Model1, and (d) Model2.

Discussion

This deep learning approach provides the potential for automated segmentation, analysis of human muscles, and inputs for biomechanical models. There is a small average improvement in DSC and RVE but a good improvement in local errors (HD) of our modified models, which include attention mechanisms. In the future, it should be tested on a larger or different cohort to see whether the attention mechanism will improve the Unet output and evaluate the generalization ability of the model.

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