Automated Personalization of Muscle-Tendon Paths from Magnetic Resonance Images

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Summary

An automated method to personalize muscle origin, insertion and via points from Magnetic Resonance Images was developed using an nnU-Net model. The model shows high accuracy, with Euclidean Errors between predicted and annotated muscle points that are similar to inter- and intra-rater variability. Future research will focus on the effect of these errors in muscle points on muscle moment arm lengths and estimated muscle and joint forces during movement.

Introduction

Estimations of muscle and joint forces in a biomechanical model are sensitive to individual variation in muscle-tendon paths [1]. However, personalizing muscle-tendon paths is time-consuming and requires expert knowledge**.** Therefore, this study automatically determined personalized muscle points from lower limb Magnetic Resonance (MR) scans using an nnU-Net model [2], and the accuracy of predicted points was evaluated against expert annotation.

Methods

MR scans of 12 bilateral lower limbs (from pelvis to feet) of healthy controls (n = 7) and hip osteoarthritic patients (n = 5) [1, 3, 4] were used to train 3D nnU-net models [2]. The MR scans were cropped to remove empty slices and resampled to the voxel size of the pelvis scan (0.93mm x 1.00mm x 0.93mm or 0.88mm x 1.00mm x 0.88mm). Next, the scans from pelvis, thigh, knee, and feet region were merged into one image and split into left and right. Intensities of the thigh scan of one control case were rescaled to the maximum value found in the other scans of this participant before preprocessing, because the distribution of intensities far exceeded the other scans. Since nnU-Net is a segmentation model and point prediction is desired, cubes of 35 voxels were defined around the muscle points (figure 1) [5]. A subset of 18 relevant muscles during gait (with 61 muscle points) was selected. These points were divided over seven datasets, and thereby models, to avoid label overlap. A custom randomized 80-20 train-test split was implemented and the 3D nnU-Net model was trained for 500 epochs for each dataset (NVIDIA A100 Tensor Core GPU, 80 GB of VRAM). After inference, the centroid of the segmentation was calculated, to obtain a point. One case of the test set was excluded from further analysis due to poor image quality.

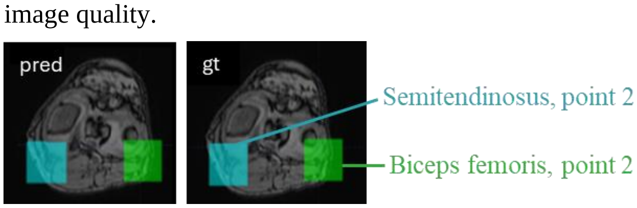

Figure 1: Example of predictions (pred) and ground truths (gt) on an axial slice for a sample of the test set.

The model was validated by comparing the results of the test set against the ground truth of the annotations provided by an experienced muscle point annotator. Additionally, for an independent dataset of one left leg, the predicted muscle points were also compared to the ground truth. The Euclidean Error (EE) and the absolute distance error along each anatomical axis were calculated.

Results and Discussion

The median and interquartile range EE for the test set (table 1) was slightly smaller compared to the inter- and intra-rater operator variability of attachment points reported in previous research (5.6 (10.7) and 6.9 (7.7) mm, respectively [6]). The EE for the independent sample was slightly higher, i.e., 6.8 (5.8) mm, but remains similar to the intra-rater variability. Assuming the operator variability would be the same for the dataset in this paper, this suggests that the 3D point model is similar to human expertise. The median EE difference between via and attachment points is small in both configurations (table 1). However, in two instances, via points were not predicted (via points of the tensor fasciae latae and vastus lateralis).

Table 1: Median (interquartile range) of model errors (in mm) for the attachment (att.), via, and over all muscle points (overall) in the test set. Euclidean error (EE) as well as errors in the three anatomical axes are reported. AP: anterior-posterior, SI: superior-inferior, ML: medial-lateral.

	EE	ML	AP	SI
att. (38)	4.9 (3.8)	1.9 (2.0)	2.8 (2.8)	2.1 (3.7)
via (23)	5.1 (4.3)	1.9 (2.0)	2.8 (2.8)	2.1 (4.4)
overall (61)	5.1 (4.3)	1.9 (2.0)	2.8 (2.8)	2.1 (4.4)

Conclusions

The muscle point model shows high accuracy, similar to previously reported inter- and intra-operator variability of attachment points annotation. The cube-segmentation approach used is accessible and requires limited deep learning expertise. With more and coherent data, this approach could attain higher accuracy. Future research will focus on the effect of reported differences in muscle points on muscle moment arm lengths and estimated muscle and joint forces during movement.

References

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