

DL_Track_US: a python package to analyse muscle ultrasonography images

Paul Ritsche ^{1¶}, Olivier Seynnes ², and Neil Cronin ^{3,4}

1 Department of Sport, Exercise and Health, University of Basel, Switzerland 2 Department for Physical Performance, Norwegian School of Sport Sciences, Oslo, Norway 3 University of Jyvaskyla, Faculty of Sport and Health Sciences, Jyvaskyla, Finland 4 School of Sport & Exercise, University of Gloucestershire, United Kingdom ¶ Corresponding author

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Software

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Summary

Ultrasonography can be used to assess muscle architectural parameters during static and dynamic conditions. Nevertheless, the analysis of the acquired ultrasonography images presents a major difficulty. Muscle architectural parameters such as muscle thickness, fascicle length and pennation angle are mainly segmented manually. Manual analysis is time expensive, subjective and requires thorough expertise. Within recent years, several algorithms were developed to solve these issues. Yet, these are only partly automated, are not openly available, or lack in user friendliness. The DL_Track_US python package is designed to allow fully automated and rapid analysis of muscle architectural parameters in lower limb ultrasonography images.

Statement of need

DL Track US is a python package to automatically segment and analyse muscle architectural parameters in longitudinal ultrasonography images and videos of human lower limb muscles. The use of ultrasonography to assess muscle morphological and architectural parameters is increasing in different scientific fields (Naruse et al., 2022). This is due to the high portability, cost-effectiveness and patient-friendlyness compared to other imaging modalities such as MRI. Muscle architectural parameters such as muscle thickness, fascicle length and pennation angle are used to assess muscular adaptations to training, disuse and ageing, especially in the lower limbs (Sarto et al., 2021). Albeit many disadvantages such as subjectivity, time expensiveness and required expertise, muscle architectural parameters in ultrasonography images are most often analyzed manually. A potential reason is the lack of versatile, accessible and easy to use analysis tools. Several algorithms to analyze muscle architectural parameters have been developed within the last years (Cronin et al., 2011; Drazan et al., 2019; Farris & Lichtwark, 2016; Marzilger et al., 2018; Rana et al., 2009; Seynnes & Cronin, 2020). Nonetheless, most algorithms only partly automate the analysis, introducing some subjectivity in the analysis process. Moreover, many analyse only single architectural parameters and can be exclusively used for image or video analysis. Most existing methods further rely on hardcoded image filtering processes developed on few example images. Given that image parameters do no suit the designed filters of the if the filters are improperly adjusted, these filtering processes likely fail. On top of that, most previously proposed algorithms lack in user friendliness as the provided code and usage documentation is limited.

DL_Track_US incorporates analysis modalities for fully automated analysis of ultrasonography images. DL_Track_US employs convolutional neural networks (CNNs) for the semantic segmentation of muscle fascicle fragments and aponeuroses. The employed CNNs consist of a VGG16 encoder path pre-trained on ImageNet (Deng et al., 2009; Simonyan & Zisserman, 2015) and a U-net decoder (Ronneberger et al., 2015). Based on the semantic segmentation,



muscle thickness, fascicle length and pennation angle are calculated as the distance between the detected aponeuroses, the intersection between extrapolated fascicle trajectories and aponeuroses and the intersection angle between extrapolated fascicle trajectories and detected deep aponeuroses, respectively. An example of the analysis process of two muscles included in our dataset (vastus lateralis and gastrocnemius medialis) is demonstrated in Figure 1.



Figure 1: Process from original input image to output result for images of two muscles, gastrocnemius medialis (GM) and vastus lateralis (VL). Subsequent to inputting the original images into the models, predictions are generated by the models for the aponeuroses (apo) and fascicles as displayed in the binary images. Based on the binary image, the output result is calculated by post-processing operations, fascicles and aponeuroses are drawn and the values for fascicle length, pennation angle and muscle thickness are displayed.

All DL_Track_US functionalities are embedded in a graphical user interface (GUI) to allow easy and intuitive usage. Apart from automated analysis, a manual analysis option is included in the GUI as well. This is provided in case the pre-trained CNNs perform badly on input images or videos and subsequently to avoid switching between software. The start window of the GUI is presented in Figure 2 and more information on usage can be found in our repository.



Figure 2: Start window of the DL_Track_US graphical user interface. Here, the input and model directories can be specified, the analysis type (image, video, image manual, video manual) selected and the analysis parameters specified. Moreover, users can choose to train their own models based on their own input images using the "Train Model" button to open a separate window.



Although we included images of the human gastrocnemius medialis, tibialis anterior, soleus and vastus lateralis from four different devices, it is likely the provided pre-trained CNNs fail when images from different muscles or devices are analyzed. However, an option to train CNNs bases on user data is also included in the GUI. Users are thereby enabled to train own CNNs based on own image or video data. The training ultrasonography image data, the pre-trained CNNs, example usage files as well as usage and testing instructions are provided. DL_Track_US was developed to automatically segment muscle architectural parameters in longitudinal ultrasonography images or videos. Nevertheless, ultrasonography can be used to assess muscle anatomical cross-sectional area (ACSA) as well. We recently published DeepACSA (Ritsche et al., 2022), the counterpart of DL_Track_US. DeepACSA was developed for automatic segmentation of muscle ACSA in transversal, panoramic ultrasonography images of the human rectus femoris, vastus lateralis and gastrocnemius muscles.

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