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Automatic quantification of fatty infiltration of the supraspinatus from MRI

Hanspeter Hess[1], Michael Herren[1], Nicolas Gerber[1], Olivier Scheidegger[2], Michael Schär[4], Keivan Daneshvar[3], Matthias A. Zumstein[4,5], and Kate Gerber[1]
[1] sitem Center, University of Bern, Switzerland
[2] Department of Neurology, Inselspital, Bern University Hospital, University of Bern, Switzerland
[3] Department of Radiology, Inselspital, Bern University Hospital, University of Bern, Switzerland
[4] Department of Orthopaedics and Traumatology, Inselspital, University of Bern, Switzerland
[5] Orthopaedics Sonnenhof, Bern, Switzerland
hanspeter.hess@sitem.unibe.ch, nicolas.gerber@sitem.unibe.ch, olivier.scheidegger@insel.ch, kate.gerber@sitem.unibe.ch

Abstract

Fat fraction of the rotator cuff muscles has been shown to be a predictor of rotator cuff repair failure. In clinical diagnosis, fat fraction of the affected muscle is typically assessed visually on the oblique 2D Y-view and categorized according to the Goutallier scale on T1 weighted MRI. To enable a quantitative fat fraction measure of the rotator cuff muscles, an automated analysis of the whole muscle and Y-view slice was developed utilizing 2-point Dixon MRI. 3D nn-Unet were trained on water only 2-point Dixon data and corresponding annotations for the automatic segmentation of the supraspinatus, humerus and scapula and the detection of 3 anatomical landmarks for the automatic reconstruction of the Y-view slice. The supraspinatus was segmented with a Dice coefficient of 90% (N=24) and automatic fat fraction measurements with a difference from manual measurements of 1.5 % for whole muscle and 0.6% for Y-view evaluation (N=21) were observed. The presented automatic analysis demonstrates the feasibility of a 3D quantification of fat fraction of the rotator cuff muscles for the investigation of more accurate predictors of rotator cuff repair outcome.

1 Introduction

Stability of the shoulder joint is mainly provided by four rotator cuff muscles, the supraspinatus, infraspinatus, subscapularis, and teres minor. Tears of the rotator cuff tendons, resulting in pain and reduced shoulder function, are common in the population, with a reported incidence of approximately 85 per 100,000 person-years [1]. Arthroscopic repair of the torn tendon has been related to significant short- and long-term improvements in pain, function, and strength, providing a less invasive alternative to complete shoulder replacement [2] [3]. However, not all patients benefit from a repair. A high incidence of complications has been reported including a post-operative re-tear rate of 15 – 20% of all repairs before 24 months [4].

It has previously been shown that rotator cuff tendon failure is associated with progressive degenerative changes of the rotator cuff muscles. Atrophy and fatty muscle degeneration are visible markers on MR images of degeneration of the muscle tissue. Qualitative visual inspection categorisation of fat fraction percentage of the affected muscle, on a an oblique sagittal T1 weighted shoulder MRI slice on a defined anatomical position (Y-view), remains a standard clinical metric of repair suitability. Quantitative chemical shift imaging methods have been shown to provide a more sensitive and objective measure of the fat content of skeletal muscle [5]. Dixon imaging has been used to quantify shoulder muscle volume in clinical studies [6][7], however, application in clinical diagnosis has been limited, at least in part due to the need for segmentation of the affected muscle for extraction of the fat content.

Currently, no system for quantitative analysis of fat fraction of the rotator cuff muscles is available. In this work, we therefore, propose a fully automated end-to-end pipeline to allow user invariant fatty infiltration analysis of the rotator cuff muscles on 2-point Dixon MRI.

2 Methodology

A fully automated end-to-end fat fraction analysis pipeline of the Y-view and whole rotator cuff muscle from 2-point Dixon MRI, was developed. For segmentation of the muscle and the humeral and scapular bones, a 3D nnU-Net [8], a self-configuring state-of-the-art convolutional neural network, was employed. The network was trained on 23, 2-point Dixon MRI image datasets of non-tear patients and corresponding manual annotations. Image data had an isotropic image resolution of 1.1 mm and was acquired from a single center (1.5T 3 cases, 3T 20 cases).

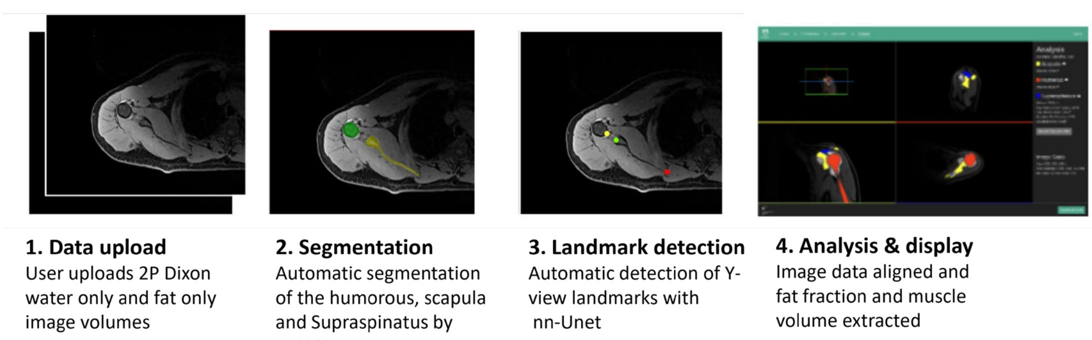

Figure 1 Pipeline of the developed automatic fat fraction analysis software incorporating segmentation of the supraspinatus, humerus and scapula, detection of the Y-view slice and extraction of the whole muscle and Y-view fat fraction.

For automatic identification of the Y-slice along the scapular wing, a landmark detection algorithm based on the nnU-Net was trained on 30, 2-point Dixon image datasets. The superior position on the glenoid face, the center of the fusion of the scapular body and the spinoglenoid notch were used to represent the Y-view in the sagittal axis. Manually selected landmarks were used to generate a pseudo segmentation volume with 6 mm spheres centered around the landmark points. The nnU-Net was trained on the 30 Dixon volumes and the corresponding segmentation masks.

Average fat fraction over the complete volume and the Y-view slice were extracted from the water and fat image datasets. Functionality was integrated into a web application along with a 3D interactive 3D volume viewer to allow inspection of the MRI and results.

3 Results

In a five-fold cross validation versus manual segmentation, the supraspinatus was detected with a Dice coefficient of 90% (N=24) compared to an inter user manual segmentation variability of 86.2 ± 4.4% (2 Users, N=9). A summary of the accuracies of the anatomy segmentation and landmark detection algorithms is provided in Table 1. The average fat fraction, measured over the complete supraspinatus volume differed approximately 1.5% from that measured over the manually segmented muscle (N=21). The difference in fat fraction calculated automatically on the Y-view, as compared to that calculated with manual landmark detection and manual segmentation, was 0.6 ± 2.9% (N=21).

Table 1 (a) Accuracy of the automatic segmentation, compared to manual segmentation in a 5-fold cross validation (DC = Dice coefficient, HD = Hausdorff distance, ASD = average surface distance) (N=23) and (b) mean and standard deviation Euclidean distance error of the automatic landmark detection algorithm, as compared to manual detection in a 5 fold cross validation (N=30)

(a)

	DC[%] (range)	HD[mm] (range)	ASD[mm] (range)
scapula	87.0 ± 5.3 (71.0 - 93.4)	29.0 ± 18.2 (6.4 - 66.8)	1.0 ± 1.0 (0.2 - 4.1)
humerus	93.5 ± 4.1 (83.4 - 98.0)	$25. \pm 21.1$ (4.4 - 96.1)	1.3 ± 1.4 (0.2 - 4.9)
SSP	90.2 ± 4.1 (80.7 - 95.6)	13.4 ± 7.1 (5.0 - 39.1)	0.9 ± 0.4 (0.3 - 2.3)

(b)

	ED [mm]
spino-glenoid notch	2.72 ± 1.5 (0.39 - 6.28)
glenoid face top	5.22 ± 8.97 (0.57 - 51.94)
scapular body fusion	39.05 ± 38.28 (5.21 - 141.78)

4 Discussion

This work demonstrates the feasibility of a fully automated quantitative fat fraction analysis of the supraspinatus on quantitative MRI data. Thereby it builds the basis for further automated quantitative analysis on larger datasets to investigate better predictive metrics for rotator cuff repair outcome from 3D image data. While this analysis was performed on 2-point Dixon due to its isotropic resolution and excellent bone-soft tissue contrast [9], 6-point Dixon has been shown to provide greater accuracy in fat fraction measurement [10]. It would therefore be proposed that, segmentation be performed on 2-point Dixon MRI while the fat fraction metric be analysed from 6-point Dixon data. Accuracy of the presented algorithms have been trained and validated on non-tear data, from a single center with limited ranges of fat fraction content. In the future re-training of the networks and validation on larger datasets including patients with rotator cuff tears are proposed. Correlation between whole muscle fat fraction, Y-view fat fraction and regional fat fraction measurements and the outcome of rotator cuff repair has yet to be studied, but the algorithms described herein could allow standardized and efficient examination of these prognostic values in future studies.

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