Automated muscle fat segmentation in DTI data of post-polio patients based on parameter distirbutions

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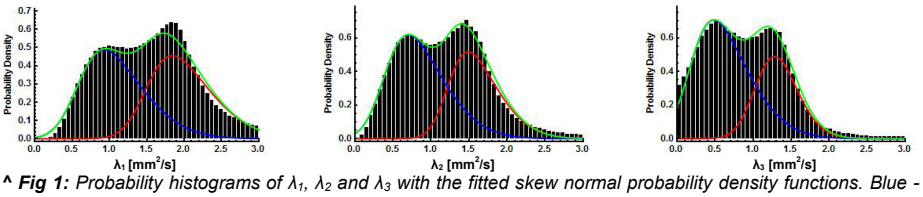
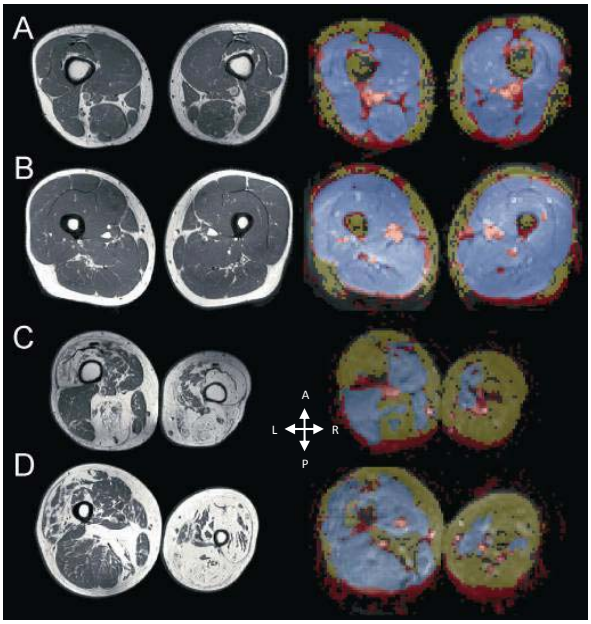
Introduction: Patients with post-polio syndrome have increased or new muscle weakness in addition to their sequelae [1]. There is little known about the precise mechanism of the progression of this disease and its impact on muscle architecture. Similarly there is not much known about the effect of therapeutic interventions on muscle architecture. A technique that could bring more insight into the pathogenesis and the effect of therapy on individual muscles is diffusion tensor imaging [2-3]. A complication is that these patients suffer from severe muscle atrophy and the muscles are partially or completely replaced by fat which hinders the diffusion imaging. One would like to make a distinction between healthy and affected muscles and also investigate if the fat-infiltrated muscles show organized structures and thus differ from the subcutaneous fat. The aim of this work was therefore to develop a fully automated algorithm for segmentation of healthy and fat-infiltrated muscle based on the distribution of the diffusion tensor imaging parameters.



^ ***Fig 1:*** *Probability histograms of λ_1, λ_2 and λ_3 with the fitted skew normal probability density functions. Blue - Fat compartment; Red - Muscle compartment; Green - Combined muscle and fat*

MRI: Both upper legs of a male healthy volunteer and a post-polio patient were measured using a 3T Philips Intera scanner with a 16 channel coil. Three acquisitions were performed: T1 and T2 weighted imaging for assessing muscle damage and anatomical reference and diffusion tensor imaging (DTI). The data was acquired in three 40 slice stacks with a 5 slice overlap and a FOV of 400x400 mm^2 and slice thickness of 4 mm. Total scan time was 45min. Further imaging parameters were; ***T1w:*** TSE, voxel size: 0.8x0.8 mm^2, TR/TE: 760/16 ms, NSA: 2, ***T2w:*** TSE, voxel size: 0.8x0.8 mm^2, TR/TE: 5500/70 ms, NSA: 2, ***DTI:*** SE-EPI, voxel size: 3.125x3.125 mm^2, 15 diffusion gradient directions, TR/TE: 7500/36 ms, NSA: 2, b=400 s/mm^2, fat suppression: SPAIR, SENSE factor: 1.4.

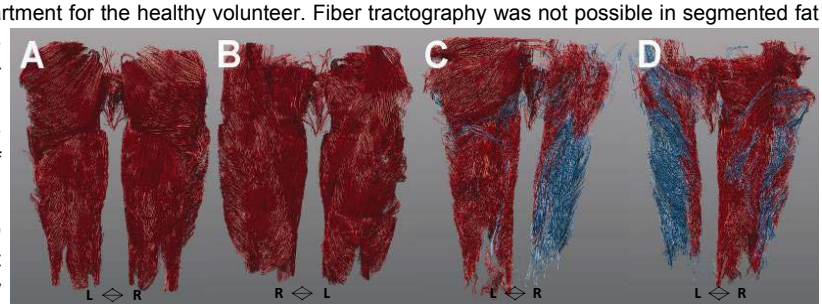


^ ***Fig 2:*** *T1 weighted images (left) together with the segmented compartment masks overlaid on the un-weighted diffusion image (right). A and B are images of the healthy volunteer and C and D are images of the post-polio patient. Blue represents the muscle compartment, yellow the fat compartment and red the residual voxels.*

Methods: From the DTI images the diffusion tensor is computed after which the tensor eigenvalues (λ_1, λ_2 and λ_3), the mean diffusivity (MD) and the fractional anisotropy (FA) were calculated. The proposed algorithm consisted of the following steps. First a probability density histogram of the entire dataset was made for each of the five diffusion parameters. These histograms were used to fit a probability density function which consisted of two skew normal distributions, one to describe the muscle compartment and the second to describe the fat-infiltrated muscle compartment. Next the cumulative probability of each voxel belonging to the muscle compartment was calculated. This probability map was then spatially homogenized by a minimum variance filter that preserves edges. A threshold probability was chosen to segment the muscle compartment. This step is the only user input needed for the algorithm. For resulting voxels the same steps are repeated but then for the probability of them belonging to the fat compartment. These steps result in three segmented compartments: muscle, fat and residual voxels together with an initial guess of the fat fraction and the mean diffusion parameters of the muscle and fat compartment. Whole volume fiber tractography was performed on the segmented compartments. Tracking stopped at an angle change of 15 degrees per 0.2 voxel integration step and tracts had a minimal length of 50mm.

Results and Discussion: Figure 1 show the probability density function fit on the histogram of the entire dataset of the post-polio patient for the three eigenvalues. Figure 2 shows the result of the segmentation for both the healthy volunteer as well as the post-polio patient. Figure 3 A and B shows whole volume fiber tractography of the segmented muscle compartment for the healthy volunteer. Fiber tractography was not possible in segmented fat compartment as expected. In figure 3 C and D whole volume tractography for the post-polio patient is shown. Here fiber tractography in the segmented fat compartment was possible and revealed organized fiber structures in fat infiltrated muscles in the left leg, which on T1 weighted images only showed remnants of skeletal muscle.

Conclusion: With the proposed algorithm it was possible to perform a fully automated fat and muscle compartment segmentation. In the case of the post-polio patient the healthy muscles could be identified. However, fat-infiltrated muscles which have the same diffusion parameters as subcutaneous fat still showed organized structures.



^ ***Fig 3:*** *A and B whole volume fiber tractography of the healthy volunteer (A: posterior view; B: anterior view). C and D whole volume fiber tractography of the post-polio patient (A: posterior view; B: anterior view), fiber tracts in the segmented fat compartment are shown in blue.*

References: **[1]** Nollet F, de Visser M. Arch Neurol 2004;61(7):1142-1144 **[2]** Zaraiskaya et al. J Magn Reson. 2006;24(2):402-408 **[3]** Heemskerk et al. Curr Med Imaging Rev. 2007;3(3):152-160.