Validation and Implementation of an Automated Boundary Finding Algorithm for Muscle Anatomy Studies

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Introduction

Measurements of muscle volume are important in many biomechanical, applied physiology, and pathophysiology studies. While high spatial resolution anatomical MRI methods provide a precise and accurate means for making these measurements, the need to hand-define regions of interest (ROIs) in multiple imaging slices is both subjective and time-consuming. This is further complicated by partial volume artifacts and the resulting lack of clarity in muscle boundaries. In this work, we validate a boundary finding algorithm based on prior models for shape and smoothness, and implement it in anatomical MR images of the leg.

Methods

Boundary Finding Algorithm An ROI containing *N* control points was initially hand-defined in the first imaging slice. Each adjacent pair of points in the ROI was smoothly interpolated into 200 points using a Catmull-Rom spline (1). This ROI was used in the adjacent slice as the input information for an automated boundary finding routine employing a combined model of prior shape and smoothness constraint, as described previously (2). User-selected parameters included the maximum number of iterations (Itr_{MAX}); the maximum number of eigenvectors (ε_{MAX}), specifying the shape complexity; and the half search window (HSW) and region impact factor (RIF), both specifying the relative weighting of nearby and distant control points. Following deformation of the ROI, the user corrected points as necessary.

Validation Using Computer-Generated Phantoms A 128×128 phantom having three muscle ROIs, one fat ROI, and two noise regions was generated (Figure 1A). Realistic T_1 and T_2 values, partial volume effects between muscles, imaging parameters (TR/TE=500/18 ms), and signal-to-noise ratio (SNR=20) values were used. The central muscle ROI was expanded in each of 7 additional slices using 3rd-order polynomial variation of the pixel positions for the muscle boundaries. The algorithm was tested using: *N*=24; Itr_{MAX}=60; ε_{MAX} =5; HSW=5; RIF=1. ROIs were also drawn by hand for each slice. For each set of ROIs, the pixel assignments were characterized as being true positive (TP), true negative (TN), false positive (FP), or false negative (FN). The specificity (Sp), sensitivity (Sn), and positive predictive value (PPV) of pixel assignment were calculated as: Sp=TN/(TN+FP); Sn=TP/(TP+FN); and PPV=TP/(TP+FP). In addition, the number of point corrections required for each slice was recorded. Four independent trials were performed.

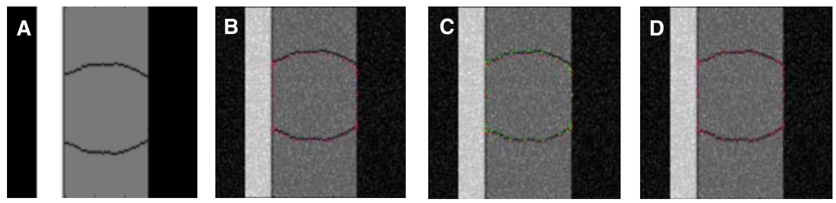

Figure 1. A. The phantom, containing areas of high (fat) and low (muscle) signal (shown in this panel without noise). B. The input ROI. C. The ROI following deformation (green lines and points). D. The user-corrected ROI.

Implementation in Real Images After providing written informed consent, four healthy male subjects were imaged using a 3T Philips Achieva MR imager/spectrometer and an 8-channel SENSE knee coil. A fast spin-echo sequence was used with: TR/TE=500/18 ms, matrix=256×256; FOV=18×18 cm; slice thickness=2.5 mm; and echo train length=3. The slices extended over the entire anterior tibialis (AT) muscle. An ROI was initially drawn by hand around the most inferior position of the AT. In subsequent slices, the ROI from the preceding slice was loaded, deformed, and hand-corrected. A mask was formed from the ROI. The cross-sectional area of the ROI in each slice was measured as the product of the slice pixel count and the in-plane resolution and the total volume was measured as the product of the total pixel count and the voxel size.

Table 1. ROI detection quality parameters for manually specified and semi-automated ROIs.

	Hand- Defined or Corrected Points	Sp	Sn	PPV
Hand-drawn	24	0.998 (SD 0.0)	0.995 (SD 0.001)	0.990 (SD 0.002)
Automated	5.7 (SD 1.0)	0.998 (SD 0.001)	0.990 (SD 0.005)	0.992 (SD 0.005)

Results

Typical ROI placement, deformation, and correction results are shown in Figure 1. Table 1 shows the point selection and ROI quality indices for the hand-drawn and automatically selected ROIs. Figure 2 shows typical results from the human imaging study. The mean maximum CSA was 9.62 (SD 2.4) cm^2 and the mean total muscle volume was 1388 (SD 240) mm^3.

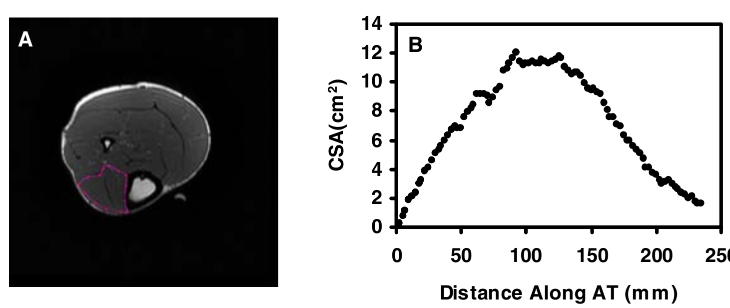

Figure 2. Experimental data. A. ROI selected within the AT muscle. B. The muscle CSA as a function of superior-to-inferior position along the muscle.

Discussion

We have validated and implemented an algorithm for the automated detection of ROI boundaries based on prior shape information and smoothness constraint. The algorithm reduces the amount of user interaction and subjective decision making significantly, and results in ROI selection quality parameters that are both outstanding and comparable to those from hand-drawn ROIs. These data show the utility of the algorithm for muscle boundary finding, as required in muscle physiology and biomechanics studies. Efforts are underway to further reduce the number of hand corrections.

References

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Acknowledgements

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