Automatic skeletal muscle segmentation through Random Walks with shape prior information

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Introduction. In our research activities, we need to identify precisely the different skeletal muscle groups in order to be able to determine their NMR properties, and to study their evolution through time. Manual segmentation by an expert is extremely long and tedious task and user dependent. Hence, developing a tool performing automatic or semi-automatic segmentation (with minimum user intervention) is of paramount importance to facilitate muscle studies, but little attention has so far been devoted to the NMRI skeletal muscle segmentation. Segmentation of skeletal muscles in 3D MRI poses some very specific issues: simultaneous multi-object segmentation, non-discriminative appearance of the muscles, partial contours between them, large inter-subject variations, spurious contours due to fat infiltrations. For these reasons, it is necessary to impose knowledge-based shape priors into segmentation methods. In this work, we propose a fully automated segmentation method based on the Random Walks (RW) algorithm [1,2] to which we add a prior shape model based on learning from an annotated data set. We use the strength of the RW algorithm on images with weak contours and, at the same time, constrain the segmentation to observe the topology of the expected solution.

Materials and Method. All examinations were performed on a 3T whole-body Siemens Trio Tim scanner, with the body transmitter coil and two phased-array receiver coils covering the entire lower limb. Thirteen subjects of various ages, sexes and morphologies, had their thigh analyzed. Data acquisition. The anatomical volumes passed to the segmentation algorithm were the out-of-phase component of a 3D 3-point Dixon sequence (TR:10ms, TE1:2.75 ms, TE2:3.95 ms, TE3: 5.15 ms, flip angle:3°). Annotations. The muscles of the right thigh were manually segmented in all data for training and testing the algorithm. Registration. The water-fraction map volumes were non-rigidly coo-registered [3], and the deformations were applied to the out-of-phase volumes and annotations. After the registration process, all volumes had the size: 191 × 178 × 63. Random Walks. A segmentation is formulated as a labeling problem of an undirected weighted graph with one node per pixel and one edge per pair of adjacent pixels. The Random Walks method amounts to determining the probability of assignment of each pixel to each muscle. This is achieved by minimizing the Random Walks cost functionnal, which yields a unique solution providing some pixels have been pre-segmented by a user; pre-segmented pixels are refered to as seeds. Our method. Instead of relying on user-provided annotation (*seeds*), we add a shape prior term to the Random Walks *cost functional*. This term has the effect of keeping the probabilistic segmentation similar to a reference segmentation (cf. figure 1). This reference segmentation is obtained by computing the average of the segmentations in the training set. The tradeoff between the prior knowledge and the information between the image can be achieved by setting a weight for each term and they can be weighted differently for each pixel; we chose to make this weight a function of the assignment probability variance estimated from the training set, so that pixels which are usually assigned to one muscle consistently (hence with a small variance) are determined rather by the prior information than by the tested image itself. This approach can be combined with a function of the tested image contour strength, referred to as *confidence map*, so that pixels in regions with strong contours depend more on the image information than on the prior model.

Results. Computing the segmentation takes around 5 min on a 2.8 GHz Intel® processor with 4 GB of RAM. Segmentation results are evaluated using Dice coefficients on muscles labels (cf. figures 2&3). Dice coefficients measure the overlap between the result and a ground truth segmentation. We adopted a leave-one-out cross-validation protocol each volume is used as the test volume, while the other volumes serve as training data. We observe that segmentation errors tend to affect primarily small muscles (e.g. Gracilis) and muscles located on the extreme upper part of the volumes (e.g Tensor Fasciae Latae) which reveals the limitations of the mean model. These errors are due to mis-registration of these muscles. We compared the segmentations obtained with and without using the confidence map. We observe that adding the confidence map consistently improves the segmentation results. Using our method, we achieved significant improvements over segmentation via multi-atlas registration with majority label voting, which is a simple and typical atlas-registration segmentation method.

$$
\begin{aligned}
x(i,s) &= Pr(\text{"pixel i is assigned to label s"}) \\
E_{RW} &= x^{sT} L x^s \\
E_{RW+prior} &= x^{sT} L x^s + \left\| x^s - x^s_{ref} \right\|_W^2
\end{aligned}
$$

$$
\begin{aligned}
W_i &= 1/\sigma_i^2 \text{ ("variance" weighting)} \\
W_i &= cmap_i/\sigma_i^2 \text{ ("variance +c. map" weighting)}
\end{aligned}
$$

Figure1: (top) pixel assignment probability notation; (middle) traditional cost functional for the RW method; (bottom) the proposed cost functional with an added shaped prior term constraining the probabilistic segmentation to remain close to a reference segmentation. L is the combinatorial Laplacian of the segmented image. A per-pixel weight W can be set to modulate the effect of the prior term. We set W either as a function of the assignment probability variance, or of a combination of the variance and of a *confidence map* of the segmented image; this confidence map has values close to 1 in homogeneous regions, and close to zero in regions with strong contours.

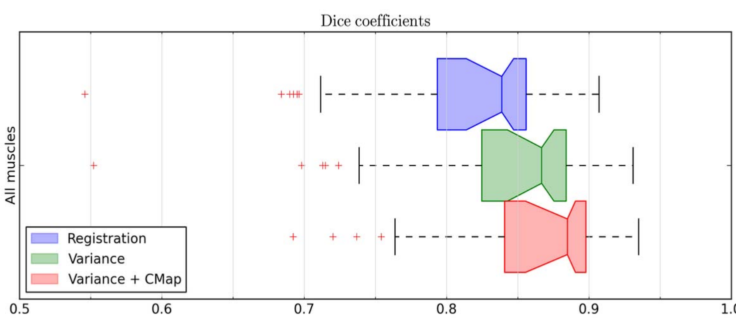

Figure2: Box-plots of Dice coefficients of segmentation using difference technique. “Variance” and “Variance + Cmap” are two versions of our method and “Registration” corresponds to segmenting the image with the average segmentation. Dice coefficients: a value of 1 corresponds to exact overlap with ground truth segmentation; a value of 0 corresponds to no overlapping.

Conclusion. Conclusion. In this work, we presented and validated a segmentation tool that are based on the random walk framework. Our contribution was the addition of a prior knowledge about the muscle shape which made this algorithm fully automatic. We believe to have achieved promising results which demonstrate the potential of our automatic approach.

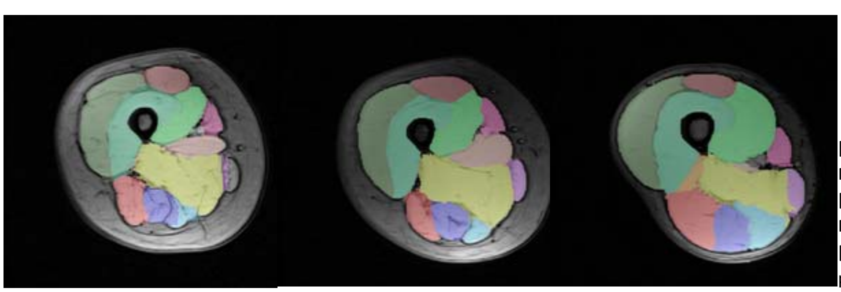

Figure3: Segmentation results obtained with our method (with CMap).

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