3D Multimodal spatial fuzzy segmentation of intramuscular connective and adipose tissue from ultralow TE MR images of calf muscle.

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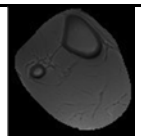
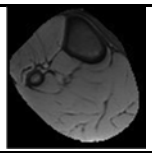
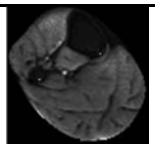
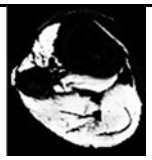
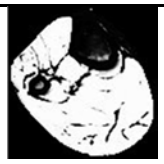
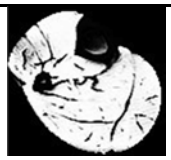
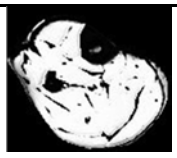
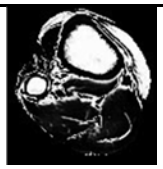
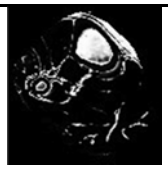
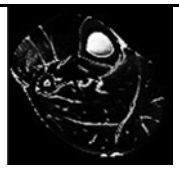
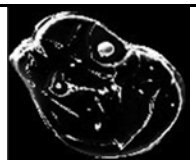
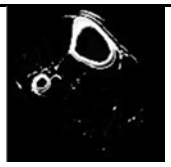
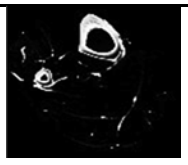
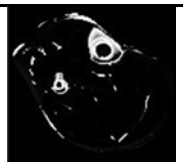
Target Audience: MSK Radiologists, Researchers (Image processing, muscle composition)

Purpose: It is widely accepted that the aging process is accompanied by a progressive loss of muscle mass and strength and an increase in both intramuscular adipose (IMAT) and connective (IMCT) tissues with age. Dual echo Ultrashort TE (UTE) sequences allow imaging of the very short T2 connective tissue. The IMCT and IMAT tissue are present in a distributed 'network' though the muscle volume, making manual segmentation of these tissue near impossible. Our aim is to develop a method to automatically segment the low T2 connective tissue from the UTE image volumes.

Methods: Ten subjects were scanned using a FAST Gradient-echo based, 2D dual echo UTE sequence (8 μs and the other at 3 ms). The sequence includes a short 40 to 80 μs hard RF pulse for excitation followed by dual echo radial ramp sampling. A 3D fuzzy c-means segmentation approach was adopted. In fuzzy c-means, an objective function is minimized: $J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m}\left\|x_i - c_j\right\|^2$ where m is any real number greater than 1; uij is the degree of membership of xi in the cluster j; xi is the ith of d-dimensional measured data ; cj is the d-dimension center of the cluster and ‖*‖ is any norm expressing the similarity between any measured data and the center[1]. The input features used for the voxel classification were the bias corrected intensities of the two imaging volumes, the calculated T2 volume, and indices derived from the 3D structure tensor calculated from each of the dual echo and T2 volumes. The structure tensor, evaluated from the Hessian, was included to isolate voxels that had a specific structure, e.g., the linear/sheet structure of the connective tissue. One of the challenges in the segmentation is the presence of large intensity shading artifacts that confounded the classification. To address this, the fuzzy c-means function was modified to incorporate spatial similarity of voxels; a spatial term was introduced to selectively modify the labeling of voxels in homogeneous regions. The spatial term includes all voxels within a neighborhood(Nx) around central voxel(X) and measures the dissimilarity for each kth cluster centroid(vk) using the dissimilarity index Dk,X: $D_{k,X} = \frac{1}{N_X}\sum_{y\in N_X}\left(d_{k,X}^2\lambda_{X,Y} + d_{k,Y}^2(1-\lambda_{X,Y})\right)$ where λ x,y is the weighting factor controlling the degree of influence of neighboring voxels on the central voxel; d k,X(Y) are the L2 distance between voxels and kth cluster centroid[2]. The algorithm was tested on subject image volumes and evaluated by visual examination by an expert.

Results: One slice of the 6 input volumes (a typical subject) to the fuzzy classifier is shown in Fig. 1a-g. The output of the algorithm for 5 slices is shown in Fig. 2-5. The spatial term was able to classify tissues in the presence of fairly severe shading artifact presented in the input TE1 and TE2 volumes (Fig. 1a and Fig. 1b). Visual examination showed that the proposed segmentation performed well in all slices except the end slices of the volume where shading was severe.

Fig. 1a : TE1 Image	Fig. 1b : TE2 Image	Fig. 1c : T2 Map	Fig. 1d : Hessain TE1 Map	Fig. 1e: Hessain TE2 Map	Fig. 1f : Hessain T2 Map
					
	Fig. 2 : Slice 15	Fig. 3 : Slice 20	Fig. 4: Slice 25	Fig. 5: Slice 36	Average % of Volume:
Muscular Tissue:					55.0883%
Adipose and Connective Tissue:					29.2479%
Cortical Bone:					14.9233%

Discussion and Conclusions: The proposed method provides accurate segmentation of the intramuscular connective tissue in a completely automated fashion. Manual segmentation is impossible since the structures are filament like and distributed in the entire volume of muscle. Simple thresholding, region growing or even level set based algorithms do not provide accurate results due to partial volume effects, severe shading artifacts, and the many small, disjoint regions. The multimodal input included a set of robust features that incorporates intensity, T2 and 3D shape that provided accurate clustering. The routine spatial term included with *fcm* did not produce desired results since it (mis)classified pixels belonging to the IMCT as muscle. The modified spatial term used here allowed selective weights to be assigned that distinguished homogeneous regions with shading artifacts as opposed to true edges (e.g., IMCT) in the volume. The ability to automatically and accurately segment will enable clinical studies to map the connective tissue in muscle.

References: [1] Lei Jiang and Wenhui Yang, in Proc. VIIth Digital Image Computing: Techniques and Applications, 10-12 Dec. 2003, Sydney. [2] Alan Wee-Chung Liew and Hong Yan, IEEE Transactions On Medical Imaging, Vol. 22, No. 9, September 2003.