Whole Body Muscle Classification using Multiple Prototype Voting

Anette Karlsson[1,2], Johannes Rosander[3], Joakim Tallberg[2], Thobias Romu[1,2], Magnus Borga[1,2], and Olof Dahlqvist Leinhard[2,4]
[1]*Department of Biomedical Engineering (IMT), Linköping University, Linköping, Sweden,* [2]*Center for Medical Image Science and Visualization (CMIV), Linköping University, Linköping, Sweden,* [3]*Advanced MR Analytics (AMRA) AB, Linköping, Sweden,* [4]*Department of Medical and Health Sciences (IMH), Linköping University, Linköping, Sweden*

Purpose:
Fat and water separated magnetic resonance imaging (MRI) enables non-invasive quantification of volume and fat infiltration in muscles. This is of high interest in e.g. rehabilitation medicine, sports medicine and muscle diseases. However, manual segmentation of muscles is extremely time consuming why automatic alternatives are needed. We have developed an infrastructure that enables a robust platform for non-rigid whole body registration[1-4] where manual classifications of an anatomical structure (i.e. muscles) in an image volume (prototype) may be automatically transferred to a new patient volume (target). Due to anatomical variation between humans, using a single prototype and register it onto a target may however fail. By instead registering several prototypes onto one target and only classify a voxel as a muscle if a sufficient number (or threshold value) of the prototypes agree may reduce the risk of failure due the anatomical variation. The purpose of this work was therefore to evaluate if using such a multiple prototype voting procedure provides a robust automatic muscle classification.

Methods:
Muscles consists mainly of water. They are located with low structural variation between different humans, and are generally only altering slightly in size and shape. Fat on the other hand is more variable in both location and volume. To make a robust registration it is therefore of great value to be able to remove the fat contribution.
Ten subjects, seven females and three males with an age range between 21.7 to 29.8 (mean: 24.9 std: 2.4) years) were included in this study. The data were acquired with a ten minute whole body scan on a Philips Achieva 1.5 T (Philips Medical Systems, Best, The Netherlands) with a 3D gradient echo sequence with out-of-phase and in-phase echo times of 2.3 ms and 4.6 ms respectively. The repetition time was 6.58 ms and the flip angle was 10 º with a resolution of (3.5*3.5*3.5) mm^3. The data were reconstructed using novel techniques for fat and water separated images[2-4].
Ten different muscle groups (lower leg, upper back leg, upper front leg, arm, and abdomen for both left and right side) were manually segmented in all ten volumes. All subjects were then cross-registered to each other using non-rigid co-registration[5]. Thus nine prototypes were registered onto each target volume. A voxel was classified as a specific muscle if more than half of the prototypes agreed on that classification. In this study this meant that five or more had to agree.
Similarity Index (SI) was used as an objective quantitative measure to determine the best and worst segmentation results. The SI was calculated by $SI(Muscle_{GT}, Muscle_{AUT}) = \frac{2n\{Muscle_{GT} \cap Muscle_{AUT}\}}{n\{Muscle_{GT}\}+n\{Muscle_{AUT}\}}$ where Muscle_{GT} represent the manual "Ground Truth" segmentation and the Muscle_{AUT} stands for the automatic segmentation, and n stands for the total number of voxels. SI was calculated for every muscle group.

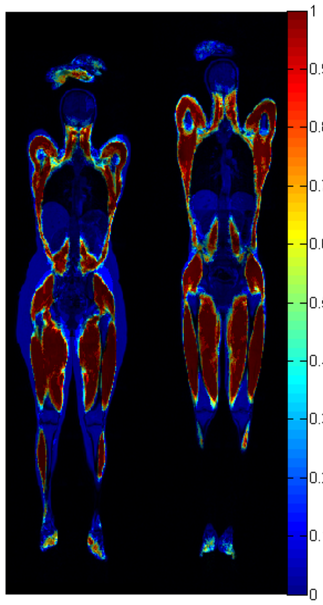

Fig. 1 - Two probability map of the volume with highest SI-value (left) and lowest SI-value (right). A value equal to one corresponds to that all prototypes agrees.

Results:
For every target the mean SI over all the muscle groups were calculated. The mean values ranged from 0.73-0.83. A probability map of a plane in the volume yielding the highest SI is shown in Fig. 1 to the left and the probability map of the volume yielding the lowest SI is shown in Fig. 1 to the right. A value equal to one means that all nine prototypes agreed on classifying that voxel as a muscle. A value of 0.55 means that 5/9 prototypes agreed. In Fig. 2, the probability map is shown for the different muscle groups on the left side of a volume with a typical case SI result (SI = 0.78).

Discussion: The approach of classifying muscles with multiple prototype voting was robust and could handle the anatomical variation between the subjects in the study group. When one or a few of the prototypes leaked into the abdominal area, they did not contribute to the segmentation result. We saw only small differences between the volume with the highest SI and the one with the lowest (Fig.1). One potential problem for the muscle classification is leakage between muscle groups. However, looking at Fig.2 there is very few voxels that were classified as another muscle than the right one. Some problems occurred in the arms due to a non-optimal placing of the subjects. In this work, we chose to use 5 out of 9 prototypes as the threshold value. It is however not clear if this is the optimal value or if the optimal threshold is the same for every muscle group. A too low threshold leads to leakage and overestimation, while a too high will instead lead to an underestimation. Future works therefore includes finding the optimal threshold value for each muscle group combined together with other post processing steps that finds the exact border of the muscle tissue.

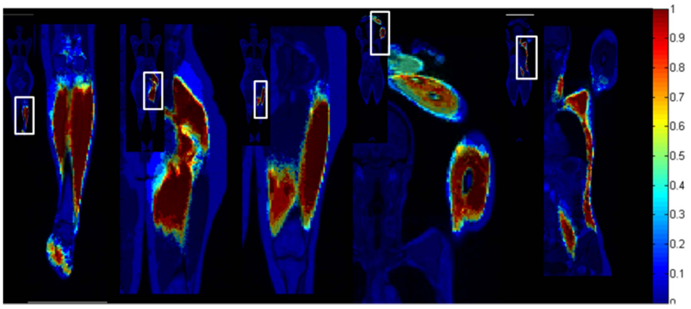

Fig. 2 - Following a typical result (SI = 0.78) muscle by muscle on the left side of the body in order to investigate leakage and performance on a local level. A value equal to one corresponds to that all prototypes agrees.

Conclusion: A very robust result was obtained when using multiple prototype voting where five out of nine prototypes must agree on a voxel in order to classify it as a muscle.

References: [1]Rydell, J. et. al. Phase sensitive reconstruction for water/fat separation in MR imaging using inverse gradient. *MICCAI.* 2007. [2]Rydell, J. et. al. Three dimensional phase sensitive reconstruction for water/fat separation in MR Imaging using Inverse Gradient. *ISMRM,* 2008. [3]Romu, T. et. al. MANA – multi scale adaptive normalized averaging. *ISBI.* 2011 [4]Dahlqvist Leinhard O. et. al. Quantitative abdominal fat estimation using MRI. *ICPR*. 2008. [5]Knutsson, H and Andersson M. Morphons: Segmentation using Elastic Canvas and Paint on Priors. ICIP. 2005.