MRI-based classification of human abdominal fat phenotypes

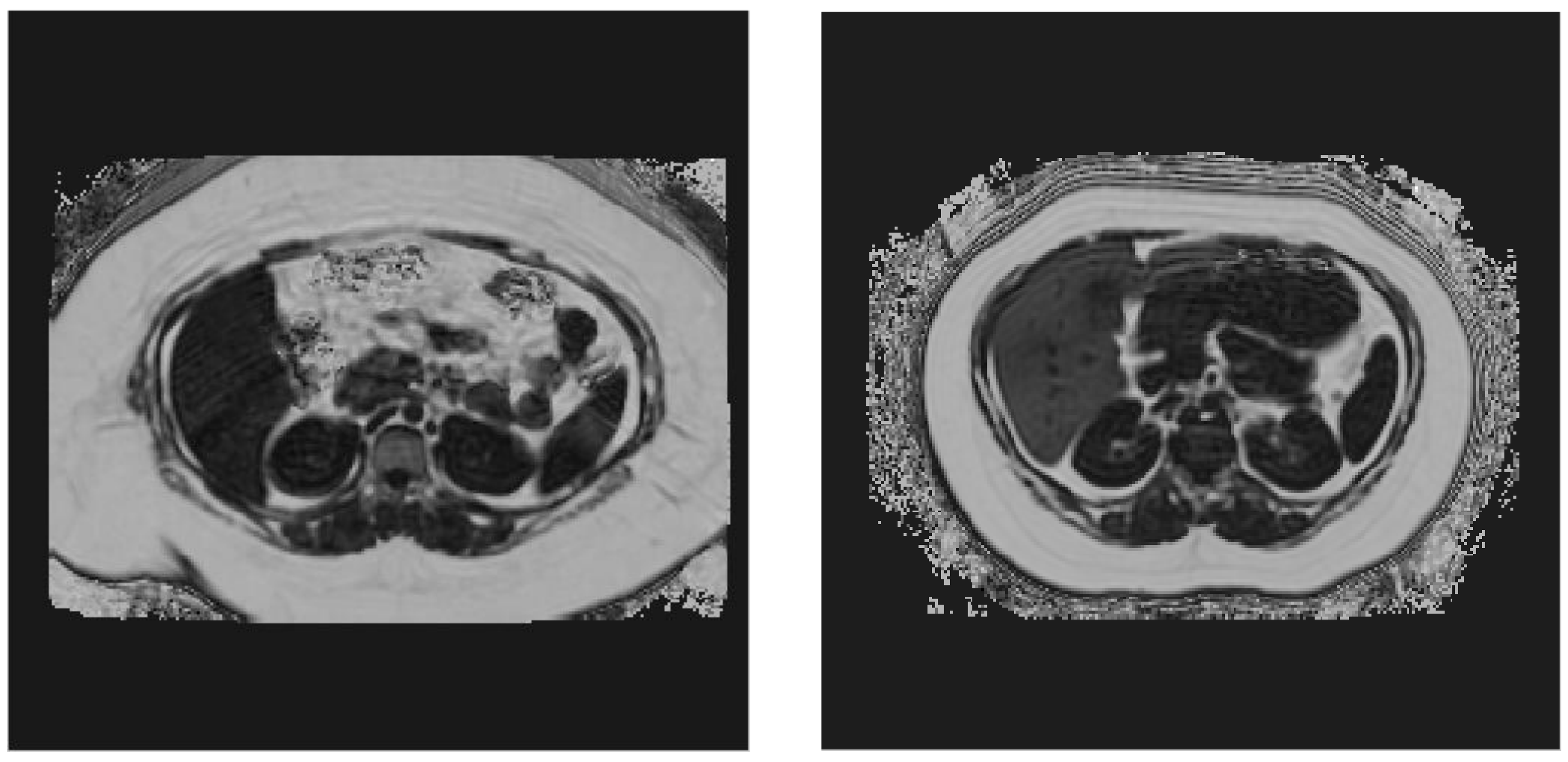
Davi M. Lyra-Leite, Anand Joshi, H. Harry Hu, Michael I. Goran, Krishna S. Nayak
Magnetic Resonance Engineering Laboratory

Introduction

According to the CDC, obesity affects 35.7% of the American population, which justifies its title as one of the big challenges in modern medicine. Obesity-related conditions include, but are not limited to, stroke, heart diseases, type 2 diabetes and certain kinds of cancer [1]. Understanding how the fat is distributed in one's body enables the physician to prescribe a more precise treatment for each specific case, a kind of treatment similar to precision medicine [2] approach.
Using image registration, it is possible to compare datasets and identify the differences distributions in fat based on distances computed from the deformation fields [3].

Experiments

Imaging: 24 obese children were imaged using MRI. Data were acquired using IDEAL sequence on a GE Signa 3T EXCITE HD system (40 mT/m, 150 T/m/s), using a 8-channel torso coil. Field-of-view and number of slices varied depending on the patient size, yielding datasets of size 256x256x60 or 256x256x72.
Evaluation: Using manual segmentation tool, we obtained the a bias map from the proton density weighted in-phase image series. This bias map is used to mask the air signal outside the body, that is due to receiver coil sensitivities [3]. After excluding the background air for each slice, the registration of the 24 fat-fraction datasets is performed using a demon registration algorithm [4]. Finally, we compute the distance between target and baseline volumes using the deformation field.
Figure 2 shows a flowchart summarizing our registration based classification algorithm.



(a) (b)

Fig.1: Fat-fraction axial images for two subjects. It is possible to see the difference in fat distribution: (a) presents subcutaneous and visceral fat in great quantity; (b) proportion of visceral fat is reduced compared to (a). Also, it is possible to identify the background air outside the body, which is removed using the bias maps.

References

[1] http://www.cdc.gov/obesity/data/adult.html
[2] http://precisionformedicine.com/define/
[3] Joshi et al. JMRI 37:423.
[4] http://www.sas.el.utwente.nl/open/research/medical_imaging/registration

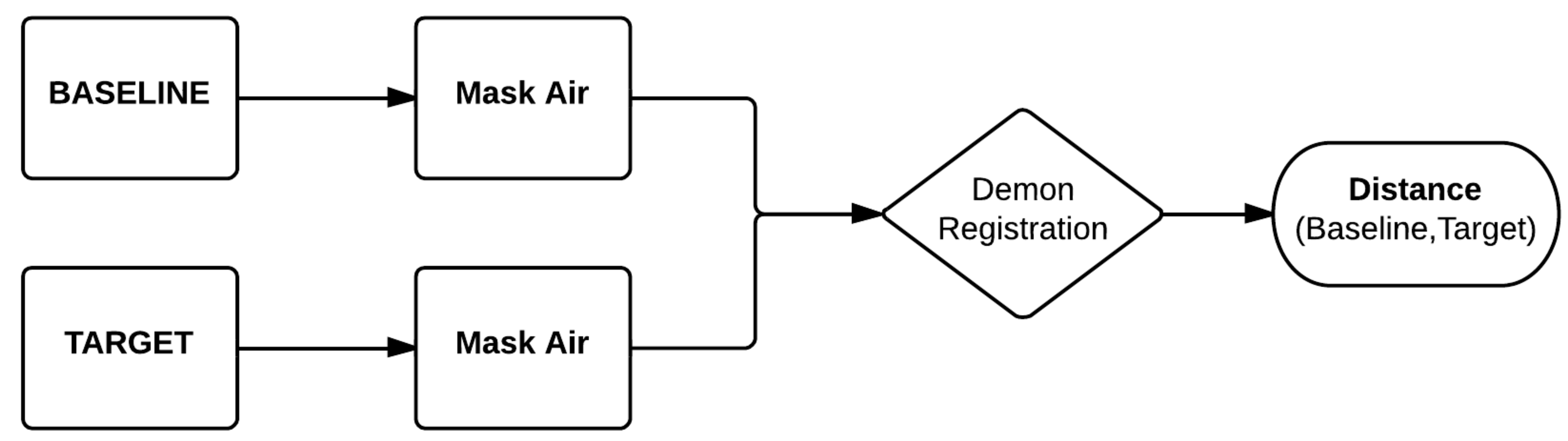


Fig.2: Flow chart of the automated classification system. The strong line indicates the anatomical position of the reconstructed slice. The baseline and target datasets consist of a 3D volumes representing the fat-fraction signal. The deformation field, which is the output of the registration, is used to compute the distance between the baseline and target volumes.

Results

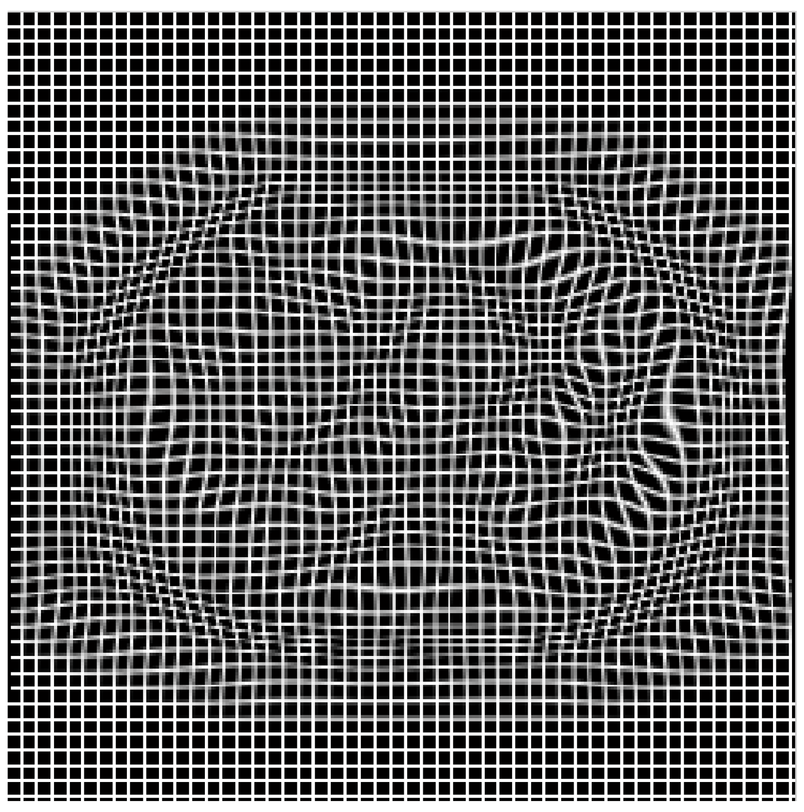


Fig.3: Warped mesh (in the x-y plane), after applying the deformation field obtaining using the registration process with Fig. 1(a) as target and Fig. 1(b) as baseline. It is possible to identify the deformations due to different spatial locations of structures in the baseline and target images.

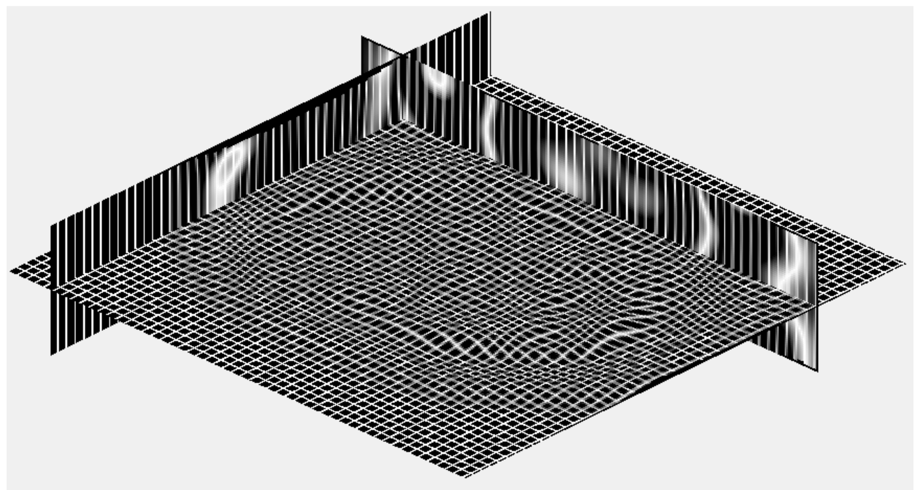


Fig.4: Warped mesh in three plane visualization, for the same registration. In this view, it is possible to identify the deformation, due to registration, in the three planes.

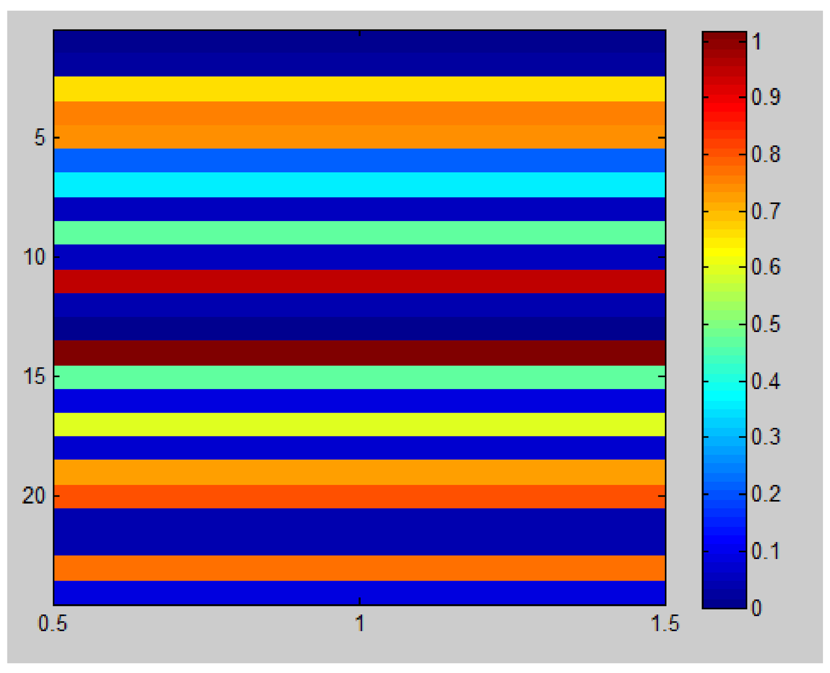


Fig.5: Average vector value of the deformation field computed for the registrations using the dataset presented in Fig.1 (a) as target. Cold colors represent small average value, meaning high similarity among the datasets. Hot colors mean high average value therefore significant deformations between the two images, as the one we can see in Figures 3 and 4.

Discussion & Future Work

Using this registration based approach, it is possible to correlate two different fat-distribution datasets, and analyze their differences in an objective way. Also, it is one can estimate the distance between two volumes in a meta-space using some specific metric (in this case, we used the average vector value of deformation fields, which may not be the most appropriate metric). Future work: (a) identify the right metric to compute the distance among these types of datasets; (b) apply the proposed method to larger datasets, and different time-points of the same subject (similar to the work done by Joshi et al. [3]).

Contact: ***leite@usc.edu*** ***http://www-scf.usc.edu/~leite***