Fat Segmentation in Abdominal MR-Scans

Thomas Hammershaimb Mosbech (tm@imm.dtu.dk)
DTU Informatics, Technical University of Denmark

Introduction

Obesity, particularly abdominal obesity, is associated with an increased risk of insulin resistance and type 2 diabetes. In the context of measuring fat percentages, Kelley et al. [1] have shown the relevance of distinguishing between visceral, deep subcutaneous and superficial subcutaneous fat. This poster presents an automatic method for such a segmentation performed on 3D T1-weighted MRI of both male and female humans. The work was done in collaboration with Steno Diabetes Center, Copenhagen.

Methods

Preprocessing MRI is often corrupted by a non-anatomic variability within same-tissue intensity over the image domain. This *bias field* must be estimated and removed prior to segmentation. The effect is observed as the variation in intensities of two classes of voxels sampled across the abdomen (Figure 1). By fitting a 3D *Thin Plate Spline* [2] to the observations, the effect can be estimated and removed for each individual patient (Figures 2 and 3).

Fat Tissue Identification Voxels are labeled with respect to intensity, adopting unsupervised classification. *Fuzzy C-Means Clustering* [3] is applied to derive membership values (Figure 4) subject to tissue labeling by thresholding.

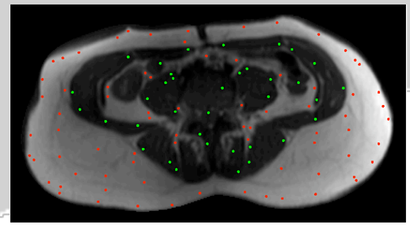

Figure 1: A slice of 3D MRI. Red and green points mark voxels sampled from the two classes (fat tissue and high water content).

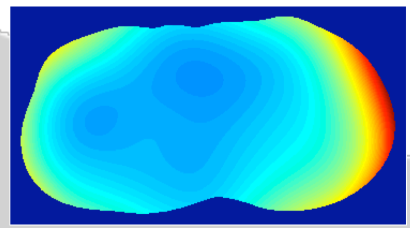

Figure 2: The bias field effect estimated by fitting the 3D Thin Plate Spline to the intensities.

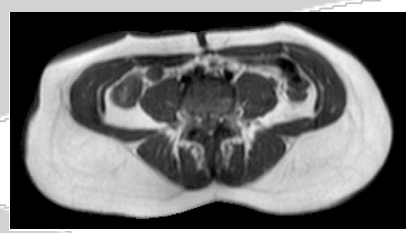

Figure 3: Preprocessed image after removing bias field. Fat tissue voxel intensities are now more homogeneous.

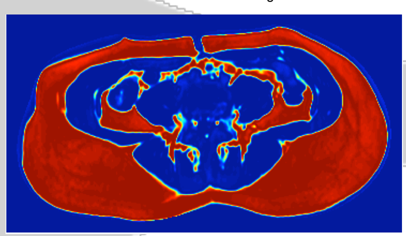

Figure 4: Membership values derived using Fuzzy C-Means Clustering. Dark red indicates high membership of fat tissue class.

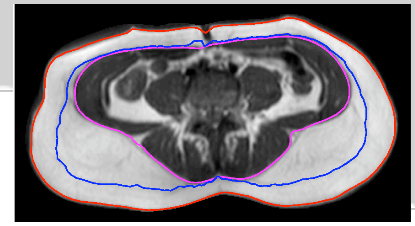

Figure 5: Red and magenta lines mark borders of the subcutaneous fat layer, identified with Active Contours. Blue line shows Scarpa's fascia, found using Dynamic Programming (Figure 6).

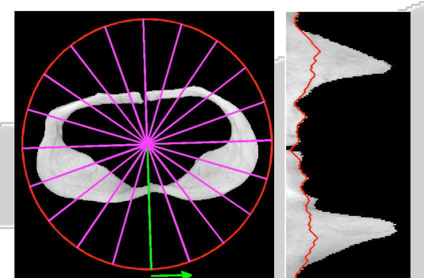

Figure 6: Locating Scarpa's fascia. Left: Spatial image transformation – the fat layer is unfolded by sampling *spokes* anticlockwise outwards from the center. Right: Red line shows resulting fat layer partition on the transformed image.

Figure 7: Resulting segmentation. Red; visceral fat. Yellow and light blue; deep and superficial subcutaneous fat. Dark blue; air and non-fat tissue.

Region Identification The internal and external border of the subcutaneous fat layer are identified using *Active Contours* [4]. This deformable model uses a formulation exploiting the intensity homogeneities of fat tissue voxels present after the preprocessing (Figure 5).

The subcutaneous fat layer is anatomically partitioned by Scarpa's fascia. The fascia is located by applying *Dynamic Programming* on a spatial transformation of the image (Figure 6).

Results

Labels and regions are combined (Figure 7) and the fat percentages can be computed. The segmentations were subject to visual inspection.

References

[1] D.E. Kelley et al.. Subdivisions of subcutaneous abdominal adipose tissue and insulin resistance. *The American Journal of Physiology - Endocrinology and Metabolism*, 278:E941–E948, May 2000.
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[3] B.M. Dawant and A.P. Zijdenbos. *Handbook of Medical Imaging. Volume 2. Medical Image Processing and Analysis, chapter 2*. SPIE Press, 2000.
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