A semi-automatic method to segment visceral, subcutaneous and total fat in the abdomen from MRI data.

Caroline L. Hoad[1], Kathryn Murray[1], Jill Garratt[2], Jan Smith[2], David J. Humes[2], Susan T. Francis[1], Luca Marciani[2], Robin C. Spiller[2], and Penny A. Gowland[1]

[1]*Sir Peter Mansfield Magnetic Resonance Centre, University of Nottingham, Nottingham, Nottinghamshire, United Kingdom,* [2]*Nottingham Digestive Diseases Centre, NIHR Biomedical Research Unit in GI and Liver Diseases, University Hospitals NHS Trust and the University of Nottingham, Nottingham, Nottinghamshire, United Kingdom*

Target Audience: Image processing scientists working on segmentation of abdominal MRI; physicians working in obesity and metabolic syndrome.

Purpose: There is considerable interest in using MRI to determine the amount and distribution of abdominal adipose tissue, since the relative amounts of visceral adipose tissue (VAT), subcutaneous adipose tissue (SAT) and total adipose tissue (TAT) are thought to be important risk factors for the development of metabolic syndrome[1]. However manual segmentation is very time consuming and so many studies only measure the ratios of VAT/SAT in a restricted region of the abdomen, which may not be representative of the whole abdomen[2]. Several automatic and semi-automatic methods have been proposed which allow larger volumes of data to be processed quickly[3-5], but these often need manually-segmented training data as inputs. Aim to construct a semi-automatic algorithm that uses prior positional knowledge to segment VAT, SAT and TAT in MRI data, without the need for training data, and which performs as well as manual segmentation.

Methods: 10 subjects (6 male) with a wide range of BMIs (23-38 kg m^{-2}) were scanned as part of a study of diverticular disease; all subjects gave written informed consent (Ethics 10/H0405/80). Subjects were scanned on a 1.5 T Philips Achieva Scanner and 16 Element SENSE torso coil. A 3D T1w mDIXON protocol[6] was used to generate the MRI data in the transverse plane (FOV 400–480mm x370-447mm x150mm, acquired resolution 1.5x1.95x6mm^3, reconstructed resolution 1.25x1.25mm^2, 3 mm slice thickness, 150 slices acquired in 3 stacks, FA=15^o, SENSE=2.0, TE_1=1.8ms, TE_2=4.0ms, TR=5.4 ms. Each stack of 50 slices was acquired during a 13s breathhold. This was reconstructed to produce water only (WO), fat only (FO), water and fat in-phase (IP), water and fat out-of-phase (OP) images.

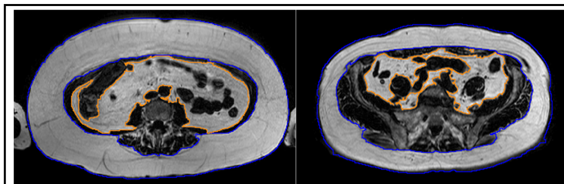

Figure 1. *Example fat only images with boundaries of VAT (orange) and SAT (blue) from the semi-automatic algorithm.*

Semi-automatic Segmentation Algorithm*:* This was written using standard image processing tools in IDL® 6.4 (Research Systems, Boulder Co, USA). First the L4/L5 inter-vertebral disc was manually identified as the centre of a 51 slice sub-region for analysis. The abdomen was separated from the arms using thresholded region growing on all image types (WO, FO, IP, OP), to give a total body mask. A fat mask (FM) was generated by histogram-based thresholding of the FO image data within the total body mask [3]. The inner boundary of the subcutaneous fat was found from the signal variations in multiple vertical and horizontal profiles cast through the FM for each slice. If the subsequent boundary was not complete, a live wire edge[7] was automatically calculated to join the end points using a cost function based on both the FM and OP data. To find the visceral fat region the intra-muscular and spinal fat had to be excluded. First morphological filtering, region growing and some positional information were used to remove small fat deposits which were generally (but not always) associated with spine and muscle. The resulting VAT and SAT boundaries were displayed on the images. The observer selected 3-8 slices that showed the correct separation of SAT and VAT excluding slices that included spinal fat or missed visceral fat. Finally the VAT and SAT regions were grown between these 'good' slices within the original FM, using some positional information. The algorithm then output the VAT, SAT and TAT fat volumes and ratios of VAT/SAT and VAT/TAT within the central 30 slices, as edge slices were more susceptible to errors but 51 slices gave more stable region growing. Figure 1 shows some examples of segmented regions on the FO images.

Validation of Semi-automatic Segmentation: FO images were manually segmented into subcutaneous, spinal and visceral fat regions, by a single observer using the 'smart edge' tool in Analyze9™ (Mayo Foundation, Rochester, MN, USA). These were used in combination with the FO images to generate masks of VAT, SAT and TAT using the same threshold as for the semi-automatic method. Volumes measured by both methods were plotted against each other and compared using Bland-Altman (B-A) analysis; segmented regions were compared using the Dice similarity coefficient. Inter-observer variability for the semi-automatic segmentation was assessed from the volume and ratio results of 2 observers using Intra-class correlation coefficients.

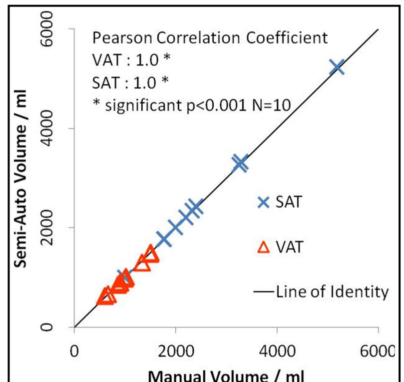

Figure 2. *Graph comparing manual and semi-automatic SAT and VAT volumes.*

Results: The operator time taken for semiautomatic segmentation was 3-4 minutes, though the processing time varied from 10-30 minutes depending on how much live-wire intervention was required. Manual segmentation took from 2-2.5 hours. Results are summarised in table 1 and figure 2. There was excellent agreement between the semi-automatic algorithm and manual segmentation for VAT, SAT and TAT regions across a wide range of volumes. The semi-automatic algorithm slightly overestimated the SAT volume; but this did not translate into a significant bias in the VAT/SAT ratio as the absolute differences were small. The Dice similarity coefficients showed again the excellent agreement between regions drawn and mean differences represented less than 2% of the entire volumes measured across all regions. The ICC showed good agreement between observers suggesting that the algorithm is not particularly sensitive to the observer dependent components.

Conclusions: This semi-automatic algorithm provides a quicker way to quantify visceral and subcutaneous abdominal adipose tissue compared to laborious manual segmentation. It works across many slices, without the need for training data sets and with similar accuracy to manual segmentation.

	VAT vol (ml)	SAT vol (ml)	TAT vol (ml)	VAT/SAT ratio	VAT/TAT ratio
Mean Manual Volume	1018	2508	3661	0.46	0.29
Range Manual Volume	599-1497	987-5172	2035-6887	0.20-0.86	0.16-0.42
B-A Bias (MAN-AUTO)	-0.2	-27.8	0.0	0.004	-0.001
B-A 95%CI	-25.2 to 24.8	-62.4 to 6.8	-0.2to 0.2	-0.008to 0.016	-0.009 to 0.007
Dice Coeff: Mean ± stdv	0.983±0.009	0.994±0.002	1.000±0.000	N/A	N/A
ICC(95% CI) * p<0.001, N=10	0.999* (0.996-1.0)	1.0* (1.0-1.0)	1.0* (1.0-1.0)	0.999* (0.995-1.0)	0.999* (0.996-1.0)

Table 1. *Results from manual and inter-observer validation experiments.*

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