Segmentation of Abdominal Fat in MR Images

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Introduction - The accurate determination of body fat is an important issue in medical image analysis as obesity is related to several chronic diseases, such as non-insulin-dependent diabetes mellitus, dyslipidemia, hypertension, atherosclerosis, and cardiovascular disease in humans. Characterization of the volume and distribution of visceral adipose tissue (VAT) is especially difficult, which is the fat deposited within the abdominal cavity around the internal organs. Yet to date, there is no simple and reliable method to measure VAT. The different proton relaxation properties of fat have been used to develop MRI protocols which allow differentiation of adipose tissue in separate body compartments. Here we propose a method for fat calculation based on modified Fuzzy c-means (FCM) clustering.

Theory- FCM is a soft segmentation method that has been used extensively for segmentation of MR images [1, 2]. The FCM approach is able to make unsupervised classification of data in a number of clusters, by identifying different tissues in an image without the use of an explicit threshold. It performs a classification of image data by computing a measure of membership, called fuzzy membership, at each pixel for a specified number of classes. The fuzzy membership function, constrained between 0 and 1, reflects the degree of similarity between the image pixel at that location and the prototypical data value, or centroid of its class. Thus, a high membership value near unity signifies that the image pixel at that location is close to the centroid of that particular class. FCM is formulated as the minimization of the following objective function with respect to the membership function u and centroid v: $J = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{p} \| x_k - v_i \|^2$

Where N is total number of pixel, p is a parameter greater than 1 that determine the amount of fuzziness of the classification (p=2 in our application), u_{ik} is the membership value at location k for class i, x_k is the intensity value at the k^{th} location, v_i is the centroid of the class i, and c is the number of classes. Standard fuzzy c-means, however can not effectively compensate for intensity inhomogeneities. In order to solve this problem observed objective function is modeled as:

$$J_m = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{p} \| y_k - \beta_k - v_i \|^2 + \frac{\alpha}{N_R}\sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{p} \Big(\sum_{y_r \in N_k} \| y_r - \beta_r - v_i \|^2 \Big)$$

Where y_k and β_k are the observed log-transformed intensities and bias field at the k^{th} pixel, respectively, N_k stands for set of neighbors that exit in window around y_k and N_R is the cardinality of N_k (in our case N_k =3×3 window, N_R = 9). The effect of the neighbors term is controlled by the parameter α (in our case α=0.75). The minimization of J_m is based on suitably selecting u and v by using an iterative process through the following equations:

$$u_{ik} = \left(\sum_{j=1}^{c} \left(\frac{\| y_k - \beta_k - v_i \|^2 + \frac{\alpha}{N_R}\sum_{y_r \in N_k} \| y_r - \beta_r - v_i \|^2}{\| y_k - \beta_k - v_j \|^2 + \frac{\alpha}{N_R}\sum_{y_r \in N_k} \| y_r - \beta_r - v_j \|^2} \right)^{\frac{1}{p-1}} \right)^{-1}, \quad v_i = \frac{\sum_{k=1}^{N} u_{ik}^{p} \left((y_k - \beta_k) + \frac{\alpha}{N_R}\sum_{y_r \in N_k} (y_r - \beta_r) \right)}{(1+\alpha)\sum_{k=1}^{N} u_{ik}^{p}} \quad \text{and} \quad \beta_k = y_k - \frac{\sum_{i=1}^{c} u_{ik}^{p} v_i}{\sum_{i=1}^{c} u_{ik}^{p}}$$

The algorithm stops when the value of v_i converges. In our problem, three tissue classes can be identified: background / air signal, signal related to another tissue like muscle, blood etc, and fat signal. We imposed C = 3 in algorithm; three masks were extracted from every image, each related to a tissue distribution and to a representative value v_i for the extracted tissues. In each mask, white pixel shows high value of membership (i.e. value nearing 1.0). After applying the algorithm followed by dilation and erosion, mask related to fat tissue was taken that gives total adipose tissue (TAT). For visceral adipose tissue (VAT) and subcutaneous adipose tissue (SAT), an ROI was drawn just below the subcutaneous adipose tissue, and all white pixels were set to zero inside this ROI thus giving the SAT. The visceral adipose tissues (VAT) were calculated by the formula: VAT = TAT – SAT. Volume of adipose tissue was computed by multiplying the pixels with pixel size and slice thickness.

The algorithm have been examined on two sets of data **(1)** On 1.5 T GE MRI scanner at the SGPGIMS, Lucknow with a T1-weighted spin- echo pulse sequence (TR = 400 ms, TE = 8ms, flip angle = 90), slice thickness = 20 mm, no gap, FOV = 48cm, image size = 256×256 and **(2)** on 3.0 T SIEMENS MRI scanner with T1-weighted GRE imaging breath holding(TR = 400ms, TE = 20ms), slice thickness = 10 mm ,no gap, FOV = 40-48cm, image size = 320×320.

Results- Figure-1 is obtained form data set (1) which image size was 256×256 and figure-2 is obtained form data set (2) .In Figure-1 (A) is original image, (B) is segmented image obtained by FCM, (C) is segmented image obtained by the algorithm, and (D) is image, obtained by scaling gain field to 0 to 255. In Figure-1(B) some part of subcutaneous as well as visceral adipose tissue were missing, and image obtained by the algorithm will give better result. It has been observed that the results obtained from the algorithm in figure-2 are better than the results obtained from FCM.

Figure-1 (A) (B) (C) (D)

Discussion-Measuring abdominal fat distribution in MR images is not a simple task. Although measuring subcutaneous fat is quite simple, measuring visceral fat is difficult due to the complex structure of the viscera and the presence of artifacts such as volume averaging, and magnetic field inhomogeneities. The proposed methodology is shown to be accurate and robust, and has significant advantage over other methods.

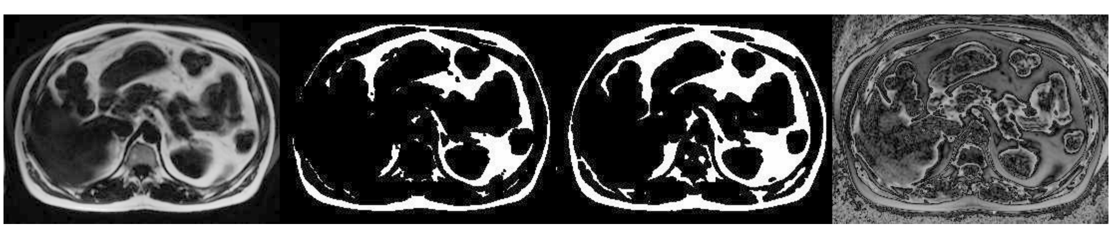

Figure2- (A) (B) (C) (D)

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2. Pham DL, Prince JL. Adaptive fuzzy segmentation of magnetic resonance images. IEEE Trans Med Imaging 1999;18:737-52.