Segmentation of Fat Tissue in MRI images with Gaussian Models

Vladimir Kanchev[1], Ognian Boumbarov[2]

Abstract – **This paper presents a method for automatic segmentation of Fat tissue in MRI image using Gaussian models. Parameters of the model are adapted to histograms of other MRI images from training set with Maximum-Likelihood estimation, Bayesian estimation, Expectation– Maximization. It is selected adapted model with highest significance value of Kolmogorov Smirnov test in relation to histogram. It is performed segmentation with two intensity thresholds derived from model.**

Keywords – **Segmentation, Gaussian model, Maximum-Likelihood, Bayesian Estimation, Expectation– Maximization**

I. INTRODUCTION

Obesity is an individual clinical condition and is increasingly viewed as a serious public health problem in developed countries. It is considered as a factor of risk in diverse chronic pathologies like diabetes, cardiovascular Type 2 hypertension, arteriosclerosis diseases and etc [1]. The precise and consistent measurement of the volumes of fat can allow quantitative characterization of the obesity.

Methods of measuring body fat includes computed tomography (CT/CAT), magnetic resonance imaging (MRI) and ultrasound. MRI is preferred method because it uses non-ionizing radiation so it is harmless to patient and provides comparable to CT resolution with far better contrast resolution for soft tissue. Its disadvantage is high cost of MRI scanner.

Brightness of MRI images depends on saturation of body tissues with hydrogen atoms and period T1 for recovery of transverse magnetic moment of their nuclei. Therefore, tissues with different magnetic properties and saturation appear with different intensity values in MRI image. In T1 images the Fat tissue has higher brightness than muscles. Unfortunately their intensity thresholds are not constant and depend on the parameters of scanning, size and position of patient, quality and type of magnets of scanner. Inhomogeneity of constant magnetic field leads to difference at intensity values of pixels of tissue located at different part of the human body of the patient.

There are a lot of methods for segmentation of Fat tissue from MRI images [1]. Generally they perform segmentation after calculation of the intensity thresholds to discriminate the Fat, Muscles and other tissues. Groenmeyer proposes to use a single section, taken at the height of the navel, to perform estimation of abdominal Fat tissue [2]. This procedure is fast but not very precise. Goodpaster performs manual measurement of Fat content at 5 inferior extremities [3].

The method of seed growing draws a region from an initial location of interest points and then gradually expands it by contiguous pixels with similar intensity level [4]**.** This technique can generate errors when the interest region is scattered by different disconnected zones from MRI image, as in case of intramuscular fat [5].

Poll proposes Gaussian models for intensity values of the Fat tissue and water with volume of abdominal fat in diabetic subjects from MRI images [6]. The model adjusts to image data and is calculated automatically a threshold that separates two regions. This technique requires intervention of an operator to set external margins of the zone of interest – subcutaneous Fat tissue. The method of Positano combines grouping of similar intensity levels with Gaussian models [1, 7]. It is a simple and completely automatic method but is subjected to errors when the distribution of intensity values of MRI image is not adapted to the assumed Gaussian model.

Finally, several statistical techniques of segmentation that use neural networks, methods and algorithms have been outlined, some of them oriented to cerebral tissue separation [8] and [9]. They have high theoretical and computational complexity and provide a precise segmentation in each section but do not consider global 3 - dimensional information.

II. DESCRIPTION OF THE SUGGESTED METHODS

We perform segmentation by Gaussian models on MRI images of human thigh of obese female patient. Intensity thresholds are calculated from a determined confidential interval applied to normal distribution after adaptation of its parameters on histogram of current MRI image. Because of inhomogeneity of constant magnetic field of MRI scanner, it is necessary to perform learning of model on histograms of all images from MRI set – scanned in axial plane from pelvis to knee of thigh. The algorithms are simulated on Matlab 2008a.

We use one-dimensional Gaussian model Eq. (1) with a random variable intensity value x in a gray-scale MRI image:

$$f(x) = \frac{1}{\sigma.\sqrt{2\pi}}.\ell^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad (1)$$

, where σ is an intensity standard deviation and μ - intensity mean value.

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To compensate the difference in the intensity values of the Fat tissue in MRI images depending on their position in the human thigh, the model is adapted to image histograms in the following three methods:

- Maximum Likelihood estimation (MLE);
- Expectation-Maximization estimation of Gaussian model;
- Bayesian estimation of distribution of mean intensity value μ_1 and its uncertainty σ_1 ;

To verify that the distribution of Fat tissue in histogram can be modeled by normal distribution, we use non-parametric t Kolmogorov–Smirnov test (KS-test) of normality. It is applied for an estimation of the level of significance for the initial Gaussian model and three histogram-adapted models to histogram. The intensity thresholds for segmentation of current i MRI image are obtained from the model with highest level of significance and it serves as an input model for next i+1 MRI image from the learning set. For the first MRI image parameters of the Gaussian models are obtained by applying MLE method of a labeled mask on the segmented region.

The algorithm of the adaptation of model to the histogram of a current i MRI image comprise of the following few steps:

1. The initialization of the parameters of Gaussian model - μ_0^i , σ_0^i and a sample of the intensity levels $\left\{y_j^i\right\}$ j=1...m, corresponding to the Fat tissue region from previous i - 1 MRI image or from its labeled mask in case of first image from set.
2. Loading of the current i - MRI image and calculation of its histogram H_i .
3. Perform of KS-test on part of histogram H_i , which is determined by a confidential interval of the Gaussian model, and find out whether it allows performing adaptation. If it does - we go to step 4, otherwise perform an adaptation on histogram of the next i+1 MRI image from the beginning.
4. The adaptation consists of three separate methods for estimation of the parameters of the Gaussian model:

– perform MLE – passing parameters μ_0^i , σ_0^i , histogram H_i and receive parameters of a sample - μ and σ ;

-apply Bayesian estimation - we pass μ , σ , μ_0^i , σ_0^i and then we obtain posterior distribution of mean intensity value μ_1^i and estimation of its uncertainty σ_1^i ;

-perform Expectation Maximization - the input parameters are μ_0^i ,σ_0^i , sample of intensity values $\left\{y_j^i\right\}$, j=1...m and histogram H_i . Parameters of adapted model are μ_2^i and σ_2^i ;

5. Calculate significance value with KS-test for initial and three adapted Gaussian models and histogram H_i . Select model with highest value with parameters $\mu_0^{(i+1)}$ $\sigma_0^{(i+1)}$ and sample $\left\{y_j^{(i+1)}\right\}$ that consists of a part of histogram of confidence interval of model. The data from this step are passed to the next i+1 MRI image and process of adaptation repeats until reaching final MRI image from the training set.

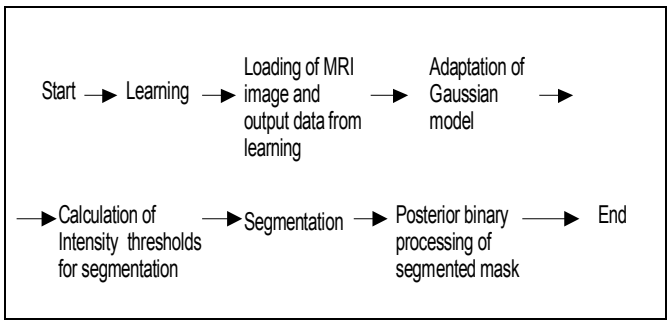

Fig. 1 Segmentation of MRI image

The algorithm of the segmentation of MRI image is shown in Fig. 1. Firstly is applied the Gaussian model whose parameters are obtained after learning and then the model is adapted to the histogram of the current MRI image in the above mentioned method. At next stage are calculated intensity thresholds corresponding to the confidential interval of the selected Gaussian model. Afterwards it is performed a segmentation by thresholds. Finally a binary mask is subjected to a binary filtering for a noise reduction.

In case of MLE, it is assumed that the unknown parameters of model have fixed values and they are fitted to the observed data and thus probability of the Gaussian model to generate the data is maximized. The estimated parameters of the model μ and σ of data sample are given as follows:

$$\hat{\mu} = \frac{1}{n}\sum_{k=1}^{n} x_k \tag{2}$$

$$\hat{\sigma}^2 = \frac{1}{n}\sum_{k=1}^{n} (x_k - \hat{\mu})^2 \tag{3}$$

In case of Bayesian estimation, the unknown parameter of the model is an intensity mean value μ_1 that is a random parameter with a normal distribution Eq. (5). The standard deviation σ_1 estimates uncertainty of μ_1 Eq. (7). The Bayesian estimation will be applied for calculation of posterior probability distribution $p(\mu_1 / D)$ Eq. (5). It is assumed that the data sample D has a normal distribution and the priori intensity mean value of region has a normal distribution Eq. (4), as well:

$$p(\mu) \sim N(\mu_0, \sigma_0^2) \tag{4}$$

, where μ_0 and σ_0^2 are parameters of a priori Gaussian model for current MRI image.

The posterior normal distribution of mean value μ_1 is:

$$p(\mu_1 / D) = \frac{1}{\sqrt{2.\pi}.\sigma_1}.\exp\left[-\frac{1}{2}\left(\frac{\mu - \mu_1}{\sigma_1}\right)^2\right] \tag{5}$$

After a series of mathematic transforms, we get Bayesian estimation of two parameters [10]:

$$\mu_1 = \left(\frac{\sigma_0^2}{\sigma_0^2 + \hat{\sigma}^2} \right) . \hat{\mu} + \frac{\hat{\sigma}^2}{\sigma_0^2 + \hat{\sigma}^2} . \mu_0 \quad (6)$$

, where $\hat{\mu}$ and σ are calculated from Eqs (2) and (3) and an intensity standard deviation σ_1^2 respectively from:

$$\sigma_1^2 = \frac{\sigma_0^2 . \hat{\sigma}^2}{\sigma_0^2 + \hat{\sigma}^2} \quad (7)$$

The Expectation Maximization (EM) is an iterative algorithm for estimation of the parameters in the probabilistic model which depends on unobserved (missing) variables that are independent and identically distributed. Let y_{obs} is a vector with observed data samples - $y_{obs} = (y_1, ..., y_m)^T$.

1. The estimation of the current distribution of missing variables is calculated at E-step during t iteration:

$$s_1^{(t)} = E_{\mu^{(t)}, \sigma^{2(t)}} \left(\sum_{i=1}^{n} y_i \mid y_{obs} \right) = \sum_{i=1}^{m} y_i + (n-m).\mu^{(t)} \quad (8)$$

$$s_2^{(t)} = E_{\mu^{(t)}, \sigma^{2(t)}} \left(\sum_{i=1}^{n} y_i \mid y_{obs} \right) =$$

$$= \sum_{i=1}^{m} y_i^2 + (n-m).\left(\sigma^{(t)^2} + \mu^{(t)^2} \right) \quad (9)$$

, where n is a size of complete vector $n > m$, m - a number of intensity levels $\{y_i\}$ of the segmented Fat tissue region from the previous i-1 MRI image. The parameters μ^t and σ^t of first (t=1) iteration are of chosen model from previous image.

2. The estimation values from the previous step are substituted in equations for $\mu^{(t+1)}$ and $\sigma^{2(t+1)}$ at M step:

$$\mu^{(t+1)} = \frac{s_1^{(t)}}{n} \quad (10)$$

$$\sigma^{2(t+1)} = \frac{s_2^{(t)}}{n} - \mu^{(t+1)^2} \quad (11)$$

The Kolmogorov – Smirnov (KS-test) is used to determine if a sample is obtained from a population with a specific, generally normal distribution. KS statistic quantifies distance between an empirical distribution function of sample S (x) Eq. (12) and a cumulative reference distribution function $F^*(x)$.

$$S(x) = \frac{1}{n} . \sum_{i=1}^{n} I_{\{X_i \le x\}} \quad (12)$$

, where $I_{\{X_i \le x\}}$ is an indicator function with a value 1 for $X_i \le x$.

The non–parametric test of KS calculates maximum vertical distance T between $S(x)$ and $F^*(x)$ (both are normalized to their sample size):

$$T = \sup_x \left| F^*(x) - S(x) \right| \quad (13)$$

The null hypothesis H_0 suggests that the data sample is generated from normal distribution:

$$H_0 : S(x) = F^*(x) \text{ For x } -\infty \ \infty \quad (14)$$

The alternating hypothesis H_1 suggests the opposite:

$$H_1 : S(x) \neq F^*(x) \text{ For at least one value of x} \quad (15)$$

If T Eq. (13) exceeds level α determined by special table, then H_0 is rejected at level of significance α. Generally we choose α according to the size of the data sample and use the nearest value, for which null hypothesis is not rejected.

III. RESULTS

Algorithms of adaptation, learning and segmentation are simulated on Matlab 2008a. It is used a set of 10 MRI images (1 Tesla Siemens scanner) of human thigh from pelvis to knee, in axial plane of an obese female patient whose area of the Fat tissue must be estimated. All MRI images are in DICOM file format. The learning of Gaussian model is applied on other 9 MRI images from the training set. In the first image parameters of the Gaussian model are calculated with the MLE using the labeled mask. After that a model is adapted on the histogram of all images from the set and for every image model with highest significance level value of KS-test is selected and then is passed with set of all intensity values of segmented region to next image.

After the learning, the Gaussian model with already calculated parameters is imposed over the histogram of MRI image that would be segmented. The determined confidential interval is used for calculation of intensity thresholds and then it is performed a segmentation on two MRI images - 4th one from set, scanned from upper part of human thigh and 10th one – from the lowest part – close to knee as shown in Fig 2. It is necessary to perform a morphological filtering on the segmented binary masks to remove inner and outer noisy pixels, segmented zone which corresponds to the bone whose intensity distribution coincides with intensity distribution of the Fat tissue. For a precise presentation of results, the binary segmentation masks are compared with the corresponding labeled masks and are shown the correctly segmented zones (true positive) and the incorrectly ones (false positive and false negative). In Figs 3 and 4 are shown the experimental

results - zones of Bone and Fat tissue before and after segmentation. Their numerical values are given in Table I

TABLE I
Information about segmented region of Fat tissue

Number of MRI image	Before binary filtering		After binary filtering		
	True Positive	False Positive	True Positive	False Positive	Area [%]
4th MRI image	0.9839	0.0062	0.97678	0.00148	47.89
10th MRI image	0.9516	0.0157	0.9525	0.00464	62.67

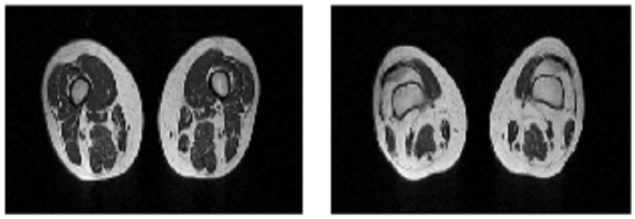

Fig.2. 4th and 10th MRI image of human thigh in axial plane

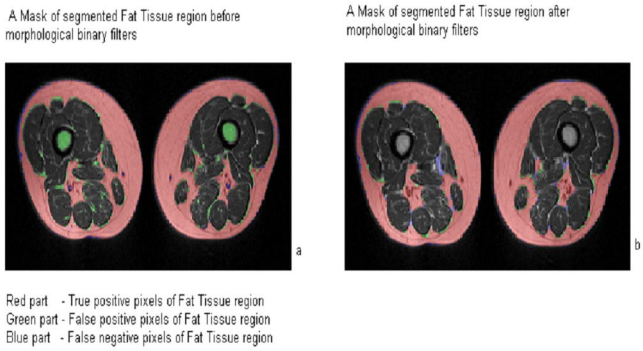

Fig.3. Segmentation of Fat tissue in 4th MRI image

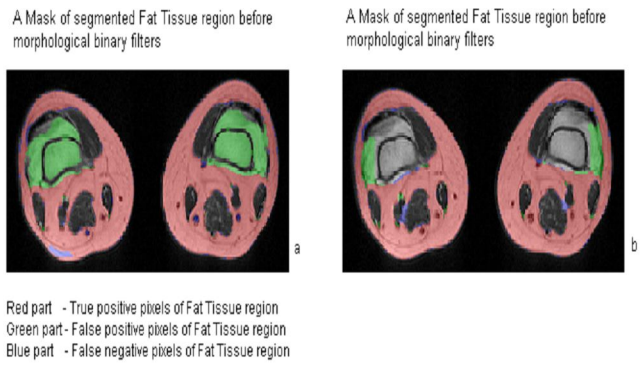

Fig.4. Segmentation of Fat tissue in 10th MRI image

IV. CONCLUSION

In this paper a method for automatic segmentation of Fat tissue in axial MRI images of human thigh using Gaussian models has been presented. During the preliminary process of the learning parameters of the Gaussian model are adapted to the histograms of other images from the learning set of MRI images of the same patient. Three methods of an adaptation are described: Maximum Likelihood estimation, Bayesian estimation and Expectation-Maximization. The main reason for the adaptation of the parameters is the difference in variation and distribution of intensity levels of the tissues from the human body in MRI images because of the inhomogeneity of the constant magnetic field, the different parameters of scanning, the different magnetic properties of human tissues and the characteristics of magnets in the MRI scanner. The advantage of the approach of using these three methods for adaptation is a rapid learning and its automatic nature and disadvantage – necessity of a post processing filtering. It can be applied in complex systems for segmentation of different tissues from MRI medical images obtained from other patients and MRI scanners.

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