Fuzzy algorithms: Application to adipose tissue quantification on MR images

Vincent Roullier\textsuperscript{a,b,c,\star}, Christine Cavaro-Ménard\textsuperscript{a}, Guillaume Calmon\textsuperscript{b}, Christophe Aubé\textsuperscript{c}

\textsuperscript{a} LISA UPRES-EA 4014, Angers, France
\textsuperscript{b} GE Healthcare, Buc, France
\textsuperscript{c} University Hospital, Department of Radiology, Angers, France

Received 28 February 2007; received in revised form 18 June 2007; accepted 4 July 2007
Available online 4 September 2007

Abstract

Metabolic syndrome, which is related to abdominal obesity, is a fast growing disease in our western countries. Its presence greatly increases the risk of developing cardiovascular diseases. The accumulation of visceral adipose tissue plays a key role in the development of the metabolic syndrome. The increase of waist circumference is one of the five criteria of the metabolic syndrome diagnosis. But this increase can be due to visceral or subcutaneous adipose tissues. And these adipose tissues do not play the same rule in metabolic syndrome. The purpose of this study was to develop software for automatic and reliable quantification of visceral and subcutaneous adipose tissues, to detect patient with high risk to develop metabolic syndrome and to follow the evolution of adipose tissue repartition after treatment. A gradient echo magnetic resonance (MR) technique is used, with a TE such that fat and water are opposed in phase. The developed process is based on two fuzzy algorithms. First, we fuzzy generalized clustering algorithms allow to merge pixels according to their intensities. Then, fuzzy connectedness algorithm allows to merge pixels according to cost function related to distance, gradient distance and intensities. A validation is performed with a comparison between expert results made by manual drawing and purpose-made software results. Our software provides an automatic and reliable method to segment visceral and subcutaneous adipose tissue and additionally avoids in some case the problem of inhomogeneity of signal intensity.

# 2007 Elsevier Ltd. All rights reserved.

PACS : 87.57.Nk; 07.05.Mh; 07.05.Kf

Keywords: Fuzzy methods; FGcM; MRI; Medical image analysis

1. Introduction

Medical image computing has deeply modified the medical practice by providing new methods to extract specific medical informations. Image processing can help radiologists in diagnosis, treatment planning, as well as treatment delivery. Image segmentation is one of the most important step as preprocessing of many image data analysis. The main goal of the segmentation process is to divide an image into regions that have strong correlations with objects or areas of the real world depicted in the image. Medical images are fuzzy by nature and can be regarded as a superposition of signals of various intensities depending on tissue, noise, blurring, partial voluming and acquisition-specific effects (e.g. surface coil intensity falls off in MR imaging).

The metabolic syndrome\textsuperscript{1} is a fast growing disease due to bad nutrition in occidental countries. By example, it is found in more than one quarter of all adults over the age of 40 years in US population [1]. Its presence is associated with a high risk of cardiovascular diseases, with dramatic consequences on renal, cerebral and heart system [2]. The accumulation of visceral adipose tissue plays a key role in the development of the metabolic syndrome. Normally visceral adipose tissue represents 10–15\% of total adipose tissue in lean subject. Metabolic syndrome diagnosis are based on five biological and clinical criteria [3]. Among them the waist circumference can depend

---

\textsuperscript{1} Metabolic syndrome is a cluster of medical disorders that occur together, increasing the risk for heart disease, stroke and diabetes.
on both visceral and subcutaneous adipose tissue surfaces. As
distribution between these both categories of adipose tissue is
one of the main factor of development of the metabolic
syndrome, the measurement of the ratio visceral/subcutaneous
adipose tissue is a useful marker of this disease [4]. We propose
to quantify in the population patient with a high risk to
metabolic syndrome and to follow abdominal adipose tissue
distribution in patient under treatment of this disease.

In clinical practice, this measurement requires a long and
tedious manual segmentation by radiologists and can not be
used in daily routine. Positano et al. [4] proposed a method
based on fuzzy algorithm and active contour models to quantify
the surfaces of visceral and subcutaneous adipose tissue.
Results are good for subcutaneous fat but take into account
some internal organs (as kidney, colon, aorta that do not contain
fat) in the visceral adipose tissue quantification. In fact, active
contour model is not adapted to segment visceral adipose tissue
because internal organs, characterized by complex shape, are
difficult to be outlined. The method described in [5] used a
specific acquisition which suppressed the peak of the water. The
segmentation was obtained by a simple manual threshold. This
method is rapid but requires radiologist intervention to find
threshold and to discriminate visceral fat to subcutaneous fat.
Moreover, this method includes non-fat pixels because of
inhomogeneity of signal intensity.

This paper presents an automatic and reliable method to
quantify adipose tissues on MR images. The rest of the paper is
organized as follows. Section 2 gives the characteristics of
patients selected and MR acquisition. Section 3 describes the
segmentation methods that we have developed which included
fuzzy classification and fuzzy connectedness algorithms. Section 4
details results obtained by expert and by our process.
Conclusion and perspectives are given in Section 5.

2. Materials

2.1. Patients

Thirty seven patients (28 men and 9 women) with a median
age of 59.7 years (range 42–73) were included in this study.
These patients are over weighted since their median weight was
94.13 kg (range 66–126) and their median BMI2 was 33.4 kg/m²
(range 24.3–41.3). All of them have a metabolic syndrome
diagnosed according to the medical definition. They did not have
contra indication to an MRI examination (claustrophobia,
pacemaker, ...).

2.2. Acquisition

A standard MR imaging technique was used for all patients.
In brief, patients were examined using a static 1.5 Tesla
machine and flexible phase array surface coil wrapped around
patient abdomen (Signa Excite and 8-channel flexible body
phase array coil – GE Healthcare – Milwaukee). Axial T1-
weighted out-of-phase gradient echo images were acquired in
axial position at vertebrae L3. All examinations were
performed in breath hold (about 20 s per acquisition) to
avoid motion artefact. The acquisition parameters are the
following: field of view = 42–48 cm, slice thickness = 6.0 mm,
repetition time = 145 ms, echo time = 2.2 ms, flip angle = 75
and image matrix = 512 × 512. One image is presented in
Fig. 1. TE of the gradient echo magnetic resonance (MR)
technique used, is such that fat and water are opposed in phase.
As shown in Fig. 1, out-of-phase image presents an outlined
drawn around organs due to the difference of magnetic
resonance frequency between water and fat components.
Close to organs, proportions of fat and water are equal, and so,
the signal is zero.

In the following section, we present our automatic
segmentation process divided in two steps : fuzzy clustering
and fuzzy connectedness.

![Fig. 1. (a) Image with water signal opposed to fat signal. A slice of abdominal
patient acquires by MR scanner. In this acquisition, water signal is opposed to
fat signal. (b) Detail of original image. A detail of image (a).](image-url)
3. Methods

3.1. Fuzzy Logic

MR images are fuzzy by nature because each pixel in the image is the result of a superposition of signal intensities received from a volume element (voxel) of the patient. Fuzzy logic is a generalization of boolean logic which takes into accounts the concept of partial truth. Using classical logic, a statement can only be expressed in binary terms (0 or 1, black or white, yes or no). Using fuzzy logic, the boolean truth values are replaced by degrees of truth (see Fig. 2). Fig. 2 shows two curves representing a sample of membership function in boolean logic (dashed line) and in fuzzy logic (dot line).

3.2. Fuzzy clustering based on objective function

Segmentation methods based on fuzzy clustering allow to merge pixel intensity together related to intensities population. Results give a prototype of each regrouping pixel intensities.

Fuzzy clustering methods are based on the definition of an objective function. The objective function assigns an error to each cluster arrangement, based on the distance between data and typical attributes of every cluster (i.e. prototypes). The objective function was first developed by Dunn [6] and typical attributes of every cluster (i.e. prototypes). The objective function assigns an error to each cluster arrangement, based on the distance between data and typical attributes of every cluster (i.e. prototypes). The objective function was first developed by Dunn [6] and improved by Bezdek in 1981 [7] with the introduction of the fuzzy factor m. This fuzzy factor defines the amount of fuzziness desired in the fuzzy partition.

3.2.1. Clustering problem

The aim of clustering is to create from an initial dataset a partition that underlines the structure of this dataset. The clustering problem is stated as follows:

- Let $Y = \{y_1, y_2, \ldots, y_n\}$ be the dataset to be partitioned. Each of the $y_i$ is a p-dimensional vector, $y_i = (y_{i1}, \ldots, y_{ip})$.
- Let $c$ be the wished number of classes.
- Let $U = (u_{ik})$ be a $c \times n$ matrix where $u_{ik}$ is the membership of point $y_k$ in class $i$.
- Let $V = \{v_1, v_2, \ldots, v_c\}$ be the $c$ prototypes resulting of clustering algorithm. These cluster prototypes are p-dimensional points.
- Let $m$ be the fuzzy index, $m \in [1, +\infty[$ as defined in [8]).

The fuzzy $c$-means (FcM) algorithm, presented by Bezdek, is based on the minimization of the following objective function $J(U, V; Y)$ (Eq. (1)):

$$J(U, V; Y) = \sum_{k=1}^{n} \sum_{i=1}^{c} u_{ik}^m d^2(y_k, v_i)$$

where $d(., .)$ is the distance between a data point and a prototype (in our algorithm, we used the Euclidean distance, classically used in literature). The smaller this distance is, the more the point is considered as similar to the prototype.

To obtain the solution of this objective function, formula (1) must be minimized by an iterative process presented in Algorithm 1. The membership update function is the following (Eq. (2)):

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} (d(y_k, v_i)/d(y_k, v_j))^{2/(m-1)}}$$

The cluster prototype update function is given by (Eq. (3)):

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m y_j}{\sum_{j=1}^{n} u_{ij}^m}$$

The probabilistic fuzzy partition (Eqs. (1)–(3)), considers that for each point the sum of all the memberships should be equal to 1. A possibilistic $c$-means algorithm was proposed by Krishnapuram [9] to alleviate the influence of outlier by relaxing this constraint.

Algorithm 1. Iterative resolution of the minimization of objective function

Require: $m, U_0, V_0, \varepsilon$

while $|V_{n+1} - V_n| > \varepsilon$ do

$U_{n+1} = f(U_n)$

$f$: membership update function

$V_{n+1} = g(V_n)$

$g$: prototype update function

end while

Different functions (probabilist or possibilist) and some approach have been proposed in literature [7,9,10]. Our approach uses generalized objective functions (FGcM and PGcM) presented by Ménard [8] including Tsallis information [11]. Tsallis information takes into account points that can be far from prototype and spaces out centroids more than the classical objective function, as shown in Fig. 3. In fact, FGcM allows to deal better with inhomogeneity of signal intensity than FcM as shown in Fig. 4. FcM tends to overestimate number of pixels classified as non-fat (Fig. 4(a)), leading to under-detection of adipose tissue. In this case, the expert must manually add the
badly classified region. Moreover, FcM tend to overestimate non-fat in subcutaneous adipose tissue as shown in Fig. 4(b)).

3.2.2. A probabilistic generalized function family

We must minimize the following probabilistic generalized objective function (Eq. (4)):

\[
J(U, V; Y) = \sum_{c} \sum_{i=1}^{n} u_{ik}^{m} d^2(y_k, v_i) + \frac{1}{\lambda (m - 1)} \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^{m} \\
- \frac{1}{\lambda} \sum_{k=1}^{n} y_k \left( \sum_{i=1}^{c} u_{ik} - 1 \right)
\]  

The first term is the mean square term, equivalent to the Bezdek objective function presented in [7]. The second term defines Tsallis entropy when \( \sum_{i=1}^{c} u_{ik} = 1 \).

The minimization of Eq. (4) gives Tsallis normalized distribution (Eq. (5)):

\[
u_{ik} = \frac{1}{Z_m} \left[ 1 + \lambda (m - 1) d^2(y_k, v_i) \right]^{(1/m-1)}
\]

where \( Z_m = \sum_{j=1}^{c} \left[ 1 + \lambda (m - 1) d^2(y_j, v_i) \right]^{(1/m-1)} \). The prototype update equation can be written as (Eq. (6)):

\[
u_i = \frac{\sum_{k=1}^{n} u_{ik}^{m} y_k}{\sum_{k=1}^{n} u_{ik}^{m}}
\]

The probabilistic generalized algorithm is called probabilistic generalized c-means (FGcM).

3.2.3. A possibilistic generalized function family

If the probabilistic constraint \( \sum_{k=1}^{n} y_k (\sum_{i=1}^{c} u_{ik} - 1) \) is replaced by the possibilistic term \( 1/\lambda \sum_{k=1}^{n} u_{ik} \), the functional is the following (Eq. (7)):

\[
J(U, V; Y) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^{m} d^2(y_k, v_i) + \frac{1}{\lambda (m - 1)} \sum_{i=1}^{c} \sum_{k=1}^{n} [u_{ik}^{m} - u_{ik}]
- \frac{1}{\lambda} \sum_{k=1}^{n} y_k \left( \sum_{i=1}^{c} u_{ik} - 1 \right)
\]

The second term is the Tsallis entropy. The last term is the possibilistic constrain.

Fig. 3. (a) Fuzzy c-Means membership function. (b) Fuzzy Generalized membership function. (a) (respectively (b)) presents the graph of the fuzzy c-means membership function (respectively fuzzy generalized c-means) applied to three clusters with values 64, 128, 192.

Fig. 4. (Left column) Zoom of MR image. (Middle column) FcM classification result. (Right column) FGcM classification result. (a) FcM classified more pixels as background (black) in visceral adipose tissue than FGcM. These pixels cannot be connected with the second algorithm and were not considered as adipose tissue in this case. (b) FGcM classified more pixels as fat (white) in the subcutaneous adipose tissue than FcM classification.
The membership update function is then the following (Eq. (8)):

$$\mu_{ik} = \frac{1}{1 + \lambda(m-1)d^2(y_k, v_j)^{(1/m-1)}}$$

(8)

The prototype update function is given by (Eq. (9)):

$$v_j = \frac{\sum_{k=1}^{n} \mu_{ik} y_k}{\sum_{k=1}^{n} \mu_{ik}}$$

(9)

The possibilistic generalized algorithm is called possibilistic generalized c-means (PGcM).

In our algorithm, we use successively FGcM and PGcM algorithms. First, the FGcM algorithm, because of the inhomogeneity of signal intensity and to separate subcutaneous and visceral adipose tissues.

3.3. Fuzzy connectedness problem

Fuzzy connectedness was introduced by Udupa [12] and has been successfully used for segmentation of multi-channel images in several applications. A fuzzy connectedness algorithm is necessary because MR images are inherently inhomogeneous due to field inhomogeneity and acquisition (coil, sequence, movement of patient, ...). Object segmentation is achieved by defining a group of pixels that show a certain level of global hanging togetherness (fuzzy connectedness).

Udupa has defined affinity between two elements in an image (e.g., pixels or voxels) via a degree of adjacency and the similarity of their intensity values. A global fuzzy relation, called fuzzy connectedness, is defined in the image by assigning to every pair of elements a strength measurements of global hanging togetherness. The strength of a path connecting two elements is defined as the “weakest” link, e.g. the lowest affinity value along the path. The strength of the fuzzy connectedness between two pixels is defined as the strongest path among all paths connecting them. A fuzzy scene map representing fuzzy connectedness value between each pixel in the image and a seed pixel is computed using dynamic programming. A user-defined threshold applied to the fuzzy scene map results in a segmented object with the selected level of fuzzy connectedness.

Now, we present the different formulas of affinity and adjacency. As presented in [5], Udupa defined a binary scene over a fuzzy digital space (\(Z^n, \alpha\)) as a pair \(\xi = (C, f)\) where C is a n-dimensional array of pixels (or voxels) and \(f\) a function from C (the scene domain) to a subset of the closed interval [0, 1]. Udupa defined also a reflexive and symmetric fuzzy relation \(k\) in \(C\). The fuzzy affinity \(\mu_k\) is one of this reflexive and symmetric fuzzy relation in \(C\). In other words, we can defined a fuzzy affinity \(\mu_k\) as follows (Eq. (10)):

\[ k = \{(c, d) : \mu_k(c, d) \in [0, 1]\}, \]

\[ \mu_k : C \times C \rightarrow [0, 1], \quad \mu_k(c, c) = 1 \quad \forall c \in C, \]

\[ \mu_k(c, c) = \mu_k(d, c) \quad \forall (c, d) \in C \]

(10)

where \(c\) and \(d\) are two pixels of the images. The general form of \(\mu_k\) can be written as follows (Eq. (11)):

\[ \mu_k(c, d) = h(\mu_a(c, d), \mu_p(c, d), \mu_f(c, d), c, d) \quad \forall (c, d) \in C \]

(11)

where \(c\) and \(d\) are two pixels and \(c\) the seed point of the studied region, \(\mu_a(c, d)\) represents the degree of space adjacency of \(c\) and \(d\), \(\mu_p(c, d)\) represents the degree of intensity adjacency of \(c\) and \(d\), and \(\mu_f(c, d)\) represents the degree of intensity adjacency of \(c\) and \(d\) for the gradient image.

Udupa defined a not empty path \(P_{cd}\) in \(C\) from a pixel \(c \in C\) to a pixel \(d \in C\) as a sequence \(< c^{(1)}, c^{(2)}, \ldots, c^{(m)} >\) of \(m \geq 2\) pixels, all in \(C\), such that \(c^{(1)} = c\) and \(c^{(m)} = d\). The set of all paths (empty or not empty) in \(C\) from \(c\) to \(d\) is denoted \(P_{cd}\).

We use \(P_C\) to denote the set of all paths in \(C\), defined as \(P_C = \bigcup_{(c,d) \in C \times C} P_{cd}\). We note \(N\), the fuzzy k-net of \(C\) as a fuzzy subset of \(P_C\) with its membership function defined as
follows (Eq. (12)):
\[
\mu_K(p) = \min [\mu_k(c^{(1)}, c^{(2)}), \mu_k(c^{(2)}, c^{(3)}), \ldots, \mu_k(c^{(m-1)}, c^{(m)})]
\]
(12)
for all \(p = \{c^{(1)}, c^{(2)}, \ldots, c^{(m)}\} \in P_C\) and \(\mu_K(\{c^{(1)}, c^{(1)}\}) = 0\).

The fuzzy \(k\)-connectedness \(K\) in \(C\) is the strength of the strongest path between \(c\) and \(d\), in other words, the fuzzy \(k\)-connectedness is the cost to connect \(c\) with \(d\). The strength of one path between \(c\) and \(d\) is the smallest affinity (Eq. (10)) along the path. The fuzzy \(k\)-connectedness \(K\) can be written as (Eq. (13)):
\[
\mu_K(c, d) = \max_{p \in P_c} [\mu_K(p)]
\]
(13)
To obtain a binary image and defined a fuzzy connected component, we used a hard binary relationship, noted \(K_\theta\) that can be written as follows (Eq. (14)):
\[
\mu_{K_\theta}(c, d) = \begin{cases} 1 & \text{iff } \mu_k(c, d) \geq \theta \in [0, 1] \\ 0 & \text{otherwise} \end{cases}
\]
(14)
In a generic implementation of a fuzzy connectedness, \(\mu_k(c, d)\) is given by (Eq. (15)):
\[
\mu_k(c, d) = h(\mu_a(c, d), f(c), f(d), c, d)
\]
(15)
where \(c\) and \(d\) are the image locations of the two pixels, \(\mu_a(c, d)\) an adjacency function based on the distance of two pixels, and \(f(c)\) and \(f(d)\) are the intensities of pixels \(c\) and \(d\), respectively.

In this general form, \(\mu_k(c, d)\) is shift-invariant. In other words, it is dependant on the location of pixels \(c\) and \(d\).

A more specific and shift-invariant definition for a fuzzy affinity was introduced by (Eq. (16)):
\[
\mu_k(c, d) = \mu_a(c, d)[w_1 \cdot h_1(f(c), f(d)) + w_2 \cdot h_2(f(c), f(d))], \quad \mu_k(c, c) = 1
\]
(16)
\(\mu_k(c, d)\) is a linear combination of \(h_1(f(c), f(d))\) and \(h_2(f(c), f(d))\), with \(w_1 + w_2 = 1\) (in our application, we used \(w_1 = w_2 = 0.5\)). The three features taken into consideration are: the space adjacency between the pixels \(\mu_a(c, d)\), the intensity of the pixels \(h_1(f(c), f(d))\), and the gradient of the pixels \(h_2(f(c), f(d))\).

The space adjacency function \(\mu_a(c, d)\) is assumed to be a hard adjacency relation, such that:
\[
\mu_a(c, d) = \begin{cases} 1 & \text{if } \sqrt{\sum_i (c_i - d_i)^2} \leq 1 \\ 0 & \text{otherwise} \end{cases}
\]
(17)
where \(c_i\) are the pixel coordinates in \(n\) dimensions.

The functions \(h_1\) and \(h_2\) are Gaussian functions of \(1/2(f(c) + f(d))\) and \(|f(c) - f(d)|\), respectively, such that:
\[
h_1(f(c), f(d)) = \exp\left\{-\frac{1}{2}\left[\frac{(1/2)(f(c) + f(d)) - m_1}{s_1}\right]^2\right\}
\]
\[
h_2(f(c), f(d)) = \exp\left\{-\frac{1}{2}\left[\frac{|f(c) - f(d)| - m_2}{s_2}\right]^2\right\}
\]
(18)
where \(m_1\) and \(s_1\) are the mean intensity and standard deviation of the intensity of the sample region and \(m_2\) and \(s_2\) are the mean and standard deviation of the gradient of the sample region.

The algorithm of fuzzy connectedness is presented in Algorithm 2.

**Algorithm 2. Algorithm of fuzzy connectedness**

**Require:** \(\xi = (C, f)\) a fuzzy scene, \(c \in C\)
\(Q\) set of \(d \in C\) such that \(\mu_k(c, d) > 0\)

while \(Q\) is not empty do

remove \(d\) from \(Q\)

find \(f_{\text{max}} = \max_{d \in C} [f(d), \mu_K(c, d)]\)

if \(f_{\text{max}} > f(c)\) then

\(f(c) = f_{\text{max}}\)

push all \(e\) such that \(\mu_K(c, e) > 0\) to \(Q\)

end if

end while

In our application, we used \(\theta = 0.5\). This value was determined by experience and gives no modification in the segmentation results when we modified the threshold \(\theta\) range from 0.3 to 0.5.

### 3.4. Our algorithm

The general algorithm implemented for this application is presented in Fig. 6. First, we classified the image in three classes (background, adipose tissue, others tissues (organs,
muscles, kidneys, ...). The classified image is processed with the fuzzy connectedness algorithm to correct the badly classified regions, particularly close to organs, due to inhomogeneity signal intensities. Finally, the fuzzy connectedness provides a binary image of the segmented region. Results are presented in Fig. 7.

4. Results

To evaluate the method, we compared the surface of visceral and subcutaneous adipose tissue obtained by different methods. The validation of the segmentation process was divided in two steps. First, two experts outlined manually subcutaneous

![Fig. 7. Example of result. On the left, the out of phase image (a). In the middle, the automatic segmentation of the subcutaneous fat (b), on the right, the automatic segmentation of intra-abdominal fat (c).](image)

![Fig. 8. (a) Correlation for subcutaneous adipose tissue quantification. (b) Correlation for visceral adipose tissue quantification. Comparison between results obtained by expert 1 and by the algorithm. (a) (respectively (b)) present comparison between results obtained by the radiologist and by the software for the subcutaneous fat ($R^2 = 0.94, P < 0.05$) (respectively visceral adipose tissue ($R^2 = 0.84, P < 0.05$)).](image)
and visceral adipose tissue. One of them repeated the measurement two months after the first measurement. Inter and intra observer variabilities were analysed. There was an excellent correlation for subcutaneous adipose tissue quantification (inter: $R^2 = 0.96, P < 0.05$ and intra: $R^2 = 0.96, P < 0.05$). The results for visceral adipose tissue segmentation were few less good (inter: $R^2 = 0.94, P < 0.05$ and intra: $R^2 = 0.95, P < 0.05$) but kept excellent. Second, results obtained by the experts were compared with results obtained by the purpose made software. There was an excellent correlation ($R^2 = 0.94, P < 0.05$) (Fig. 8(a)) for subcutaneous adipose tissue segmentation. Automatic quantification of visceral adipose tissue showed a good correlation ($R^2 = 0.84, P < 0.05$) with manual segmentation (Fig. 8(b)).

As shown in Fig. 9, we have some differences between expert and algorithm results. These differences can be explained by the presence of structures like vessels, small bowel or colon in peritoneum or by inhomogeneity of signal intensity. For subcutaneous adipose tissue, differences are mainly due to an error of coil place providing an image without the entire of patient body (Fig. 9(a)) and to the presence of structures in the subcutaneous under-estimating the subcutaneous adipose tissue surface (Fig. 9(b)). For visceral adipose tissue segmentation, differences are mainly due to inhomogeneities of signal intensity.
geneity of signal intensity near organs providing a miss detection of adipose tissue (Fig. 9(c)) and to some organic matter in colon similar to adipose tissue (Fig. 9(d)) providing fault detection in colon.

We excluded four patients from this study because their breath hold (during the examination) was not controlled (Fig. 10). For the images of these patients, the automatic process gave a classification but this one was absurd.

In all these cases, the knowledge of expert allows to correct the problem. That’s why we developed a specific graphic user interface that permits to expert to correct the classification.

5. Conclusion and perspectives

In this paper, we propose an automatic, reliable and non-invasive method to quantify abdominal fat and to quantify a marker of the metabolic syndrome.

The coefficient of correlation between automatic and manual measurements is comparable to inter- and intra-observer variabilities for the subcutaneous fat, and acceptable for intra-abdominal fat.

This evaluation confirms the choice of fuzzy logic that is adapted to the nature of our images. Moreover the process needs only few seconds whereas active contour models needs long computer time.

Future developments could improve these results by taking into account inhomogeneity of the signal intensity. The inhomogeneity could be reduced by using a new protocol that corrects the intensity with a pre-calibration.

References