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# A Brief Survey of Spleen Segmentation in MRI and CT Images

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## ABSTRACT

The segmentation of the spleen is a challenging problem given the complicity and variability of abdominal anatomy. There are different imaging techniques, which are used in the medical diagnostic of this human organ. One of them is the magnetic resonance imaging (MRI), which gives good contrast between the different soft tissues of the body. This could be an important criterion for good image segmentation. However most of the researched segmentation techniques are applied to other popular type of medical images (Computer tomography - CT), but still could be used also for other image types. This paper gives a short classification of the modern methods for spleen segmentation that can be found in the specialized journals and that could be used with little improvements for most of the spleen medical images.

**Key words:** Spleen MRI, Spleen segmentation

## 1. INTRODUCTION

The human spleen is the largest lymphoid organ in the body, which is in the left upper abdomen. Its anatomy and surface structure is presented in Figure 1[13]. It also plays an important role in the peripheral immune organs. In view of the gray level of the spleen and grayscale similarity of the adjacent abdominal fat, spleen segmentation has always been a problem. At the same time, the shape and position of the spleen of different individuals are not entire same. That is why new medical research is in progress, which needs better, faster and if possible automated methods for diagnostic.
Radiologists used to make many interactions (such as organ segmentation) in the medical images per hand, which is time consuming and not acceptable for large scale of data.

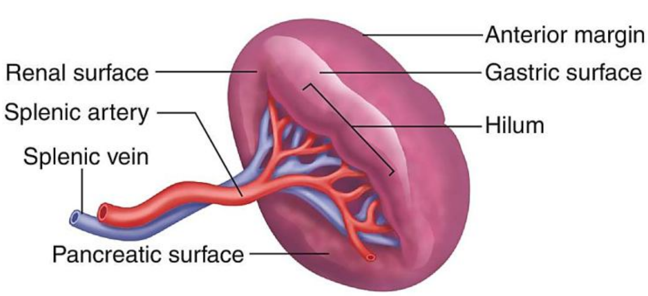


**Figure 1:** Anatomy and surface structure of the spleen

Therefore, designing and developing a computer-aided diagnosis (CAD) tools for spleen MRI is necessary to increase the productivity of radiologists who interpret and diagnose hundreds of MRI images every day [8].
Segmentation is a key preliminary step in many medical applications such as planning and follow-up procedures, here modeling patients' organs is helpful for both visualization and quantitative measurements [5].The measures of the spleen are giving important information for the health of the human. In fact all types of medical imaging techniques for diagnostic of the spleen are used from the doctors. Each of them has its advantages and disadvantages. For example ultrasound imaging (US) gives simultaneously results and is cheaper, but is not fully reliable, because of its average quality, presence of a lot of artifacts and it interpretation depends mostly on the doctors knowledge and competence. The X-ray imaging is also cheap, but brings not very good quality of abdominal images (other structures such as bones are covering the spleen) and as a result the observation and diagnostic is hard. The CT and MRI are the preferred techniques for observation of the abdominal anatomy. They are much more expensive, but the quality of the images is much better. By the CT imaging there is a risk of exposure to unhealthy radiation. That is way this method is more preferred when there is some kind of pathological indications by the patient. For researches and health studies, also for children and pregnant women the doctors are using MRI. Also MR imaging has been shown to enable accurate volumetric assessment of solid organs in humans [1].
Spleen segmentation from abdominal images is a process of subdividing a medical image into organ of interest and other tissues such as organ parts and abdominal fat. Because of the partial volume effect, the gray level of the spleen and grayscale similarity of the adjacent abdominal fat, spleen segmentation has always been a problem [7]. Although there exist many methods for abdominal organ segmentation including region growing, active contour, level set, graph cuts, clustering and threshold based methods, deformable model, statistic shape model; support vector machine (SVM) based, neural network (NN) based, etc.
This paper is organized as below. Section 2 presents the literature review of spleen segmentation. It is structured in four categories including gray level based method, structure based method, texture based method and hybrid methods.
Section 3 describes the importance of the a- priory-knowledge and the image data specification by the process of segmentation. Section 4 discusses performance comparisons among the classes along with the remarks on the problems

existed and possible solutions. Finally, conclusions are made in Section 5.

## 2. CLASIFIKATION OF METHODS FOR SPLEEN SEGMENTATION

Based on thorough study of various spleen and abdominal segmentation methods and systematic summary of the methods, we can categorize a segmentation method according to the image features it works on and offer a classification of methods for such segmentation, which is shown in Figure 2.
In fact we are speaking of segmentation of both spleen and abdominal organs, because most of the researched methods are segmenting a group of organs, one of which is the spleen. Some of those one who are developed only for the spleen could be use with some changes also for other abdominal organs, because of the similar specifications of the stomach anatomy.
Other critical moment is the problem with the variety of image data, which is used for the creation of the segmentation methods. All variations including imaging technique, quality of the aperture, used contrast borrowings, spatial resolution, etc. could bring different image specifications with its difficulties and different solutions that are not universal for all image data.
In this paper we offer a summary of the method of abdominal segmentation that are or could be used for Spleen MRI. All the methods are categorized into four main classes including gray level based method, structure based method, texture based method and hybrid methods.

### 2.1 Gray level based methods

Gray level is the most obvious feature of image [12]. The benefits of gray level based methods are: the feature is easy to extract without using special algorithm; they are stable and robust, can easily be used into similar cases; they often achieve high accuracy result. Their drawbacks are: most of them are semi-automatic methods and need user's operation; when the difference of gray level intensity between target and background is small, the methods will lose their effectiveness. These are the main methods used in clinical practice, especially in tumour segmentation, but they rely heavily on the evaluation of the gray level of targets. There are different ways to determine the gray level range of the organ of interest: use of prior knowledge; utilization of histograms; use of manual work or automatic rough segmentation; use of gradient information.
Figure 3 shows the variety of segmentation methods that are based on gray level determination.
A clustering based algorithm was proposed in [1]. The main idea of clustering based method is that in n-dimensional feature space, the distance between samples is shorter if they belong to the same class and the similarity of samples from same class is higher [12]. There is a dual-space clustering algorithm that is proposed for MRI Spleen segmentation in [1]. This algorithm operates by interrogating each voxel in the data set to determine whether the voxel is contained within both a user predefined quantitative MR imaging space sub volume and a predefined anatomic space volume [1]. One of the advantages of the clustering based algorithm is that they are semi- or fully automated as it is here. However there is a risk of many false positive regions needing post-processing or better predefinition of a-priori-parameters for ROI for example.

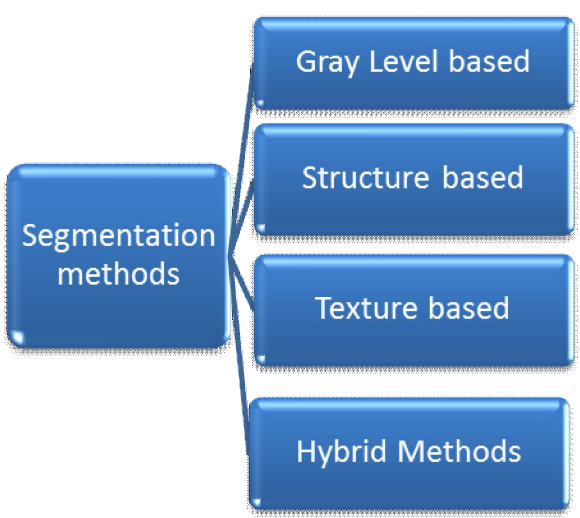


**Figure 2:** New classification of Methods for Segmentation of abdominal organs

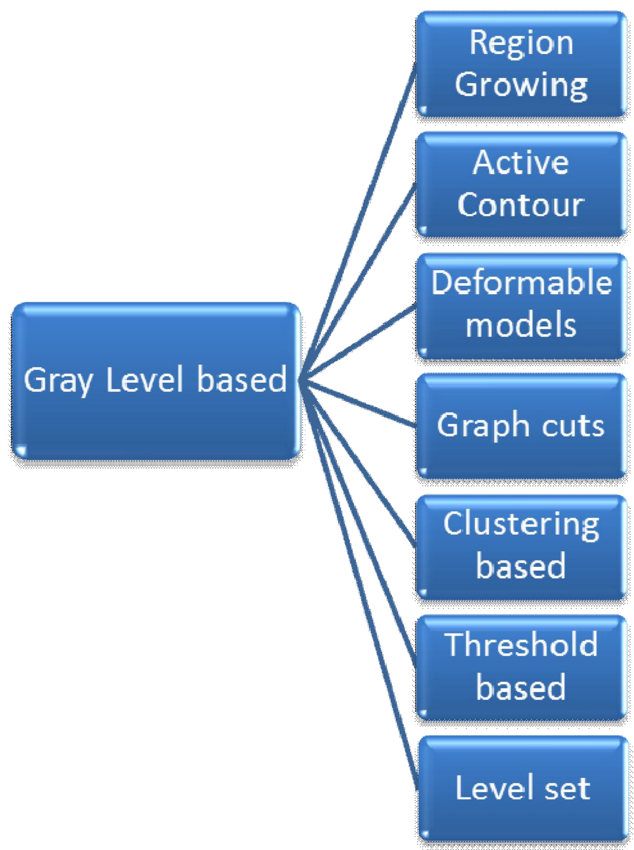


**Figure 3:** Gray level based methods

### 2.2 Structure based methods

These methods are effective and powerful in many medical applications. They are more like Atlas based methods. The central hypothesis of it is that structures of interested objects have a repetitive form of geometry [12]. In the approach, a probabilistic model is created to represent the variation of the shapes of organs, and use this model as prior knowledge to impose constraints in an image for segmentation [12]. It can be found a decision for the unclear boundary of the organ by using prior knowledge, meaning that they can handle some problems which gray level based methods cannot handle. The difficulty of these methods is that they need a large amount of training data to cover all the conditions of the abdominal organ. Reference [5] proposes a fast, automatic and versatile framework for the segmentation of multiple anatomical structures (one of which is the spleen) from 2D and 3D images, where the variational formulation optimizes the non-rigid transformation of a set of templates according to image-driven forces. The method is evaluated on CT volumes (50 for training and 50 for testing). This approach is a wise combination of the robustness of atlas-based methods with the adaptivity of active contour techniques. The method presented in [6] is based on a hierarchical atlas registration and weighting scheme that generates target specific priors from an atlas database by combining aspects from multi-atlas registration and patch-based segmentation, two widely used methods in brain segmentation [6]. This method is evaluated on a database of 150 manually segmented CT images. Reference [9] proposes to integrate a level set shape model into the traditional label fusion framework to create a shape-constrained multi-atlas segmentation framework.

In [4] is proposed a novel method based on a strategic combination of the active appearance model (AAM), live wire (LW), and graph cuts (GCs) for abdominal 3-D organ segmentation. This is a complex combination and improvement of methods, but the results given from the authors seems to be very impressive (see the accuracy level in section 4).

### 2.3 Texture based methods

They are different from other segmentation methods, because they do not focus on the boundary of object. They are interested in the texture features. It is more like using human eyesight to do segmentation. The main procedure of texture based methods is:

1) the texture features of target are extracted;
2) a classifier is employed to classify the features;
3) the target region is refined and smoothed by post-processing;

Texture based methods rely on machine learning and pattern recognition and the description of texture feature is a challenge. The advantages are that more features are considered together, and the result is closer to the results of manual segmentation and they can also achieve better results when the boundaries are not clear.

They could currently produce satisfactory segmentation results, but it is still necessary to find more refined methods.

A spleen segmentation method is based on watershed approach in [2]. There have been used morphological filters such as the geodesic reconstruction to extract the spleen and a pre-processing stage for improving the image gradient consisting of spatial filters followed by the morphological filters.

Neural networks (NNs) are non-linear statistical data modeling or decision making tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data, which makes it suitable for liver segmentation [12]. NN is used in [8] to spleen features extraction, where firstly the abdominal MRI images are partitioned to different regions using combined recursive watershed transform. The features extracted using neural networks are used to monitor the quality of the output of watershed transform and adjusting required parameter automatically [8].

A novel spleen segmentation method based on PCA and ISO is proposed in [7]. PCA (Principal Component Analysis) is a method that is used often in face recognition. This method can be used in spleen segmentation by preserving the spleen region and removing the abdominal muscles adjacent to the spleen. ISO (Isoperimetric) method is a popular method by color image segmentation, because of its robustness. But when the target area and the surrounding environment are very similar in gray level, singly-using ISO method will lead to over segmentation [7].

### 2.4 Hybrid methods

In fact all modern structure and texture based methods are complex methods that are in combination with gray level based methods or other with the purpose of improving the structure modeling stage or recognizing the texture features (e.g. [4], [7], [9] etc.). That is way we can think of them also like Hybrid methods.

### 2.5 Generalization

In general, the gray level based methods are more highly developed. They are often used together to handle the problem of complex segmentation. In most cases, they can achieve better segmentation results. Structure based methods focus on the shape of the object, which makes them more robust. Texture based methods try to simulate the way our brains process information.

## 3. IMPORTANCE OF THE A-PRIORI-KNOWLEDGE AND THE IMAGE DATA SPECIFICATIONS

From all of the researched papers it seems that the specifications of the image data used for each study is very important for the choice of a-priori-knowledge and it is closely linked with the algorithm development. It isn’t 100% sure that any algorithm will work well with new data that was not used by the developing of the new method. That means that the methods could not be universal for all image data. At least they would need new settings for doing this. By different imaging techniques (e.g. CT and MRI) there are different a-priori-parameters that could be used for a-priori-knowledge for the algorithm developing. In reference [1], where MRI is used, in addition to the ROI specifications, there are three adjustable segmentation parameters that allow the operator to tailor the dual-space clustering segmentation and thus improve segmentation fidelity and volumetric assessment: number of standard deviations relative to the mean T1, mean T2, and mean normalized proton density of the pixels; the nominal cluster size in the anatomic space; percentage acceptance cluster size in the anatomic space. T1 and T2 are weightings for a fast four-time-points quantitative MR imaging, which is specific only for MRI.

Image contrast is the goal in all imaging procedures. MRI structural image contrast is natively (i.e. without using contrast enhancing agents) superior than CT and other imaging techniques. In both CT and MRI, image contrast is a function of tissue density. For MRI in which the source of signal are the protons (especially hydrogen protons), the type of density that matters the most is proton density. In addition to tissue density, tissue relaxation properties contribute to image contrast in MRI (but not CT). There are two types of relaxation properties: T1 relaxation and T2 relaxation. During the process of T1 relaxation, protons reorient resulting in recovery of longitudinal magnetization. During the process of T2 relaxation, protons diphase (spin becomes desynchronized) resulting in decay of transverse magnetization [14]. By T1-wieghted images tissues with high fat content (e.g. white matter) appear bright and compartments filled with water (e.g. Cerebrospinal fluid) appear dark. This is good for demonstrating anatomy. By T2-weighted imaging compartments filled with water appear bright and tissues with high fat content (e.g. white matter) appear dark. This is good for demonstrating pathology since most (not all) lesions are associated with an increase in water content.

Even if the image data is from the same imaging technique (e.g. MRI) the MR imaging parameters used to perform the mixed fast spin-echo sequence for example could be different, which could lead to worse segmentations then it was expected from a given algorithm.

There are some studies that have been tested its algorithms on various data and they argue that they will work with the most images made with the same imaging technique, e.g. CT. Data were acquired on a variety of scanners from different manufacturers and at varying resolution [3].

For the image specifics of the CT we can say that there is a good soft tissue differentiation especially with intravenous contrast. Higher imaging resolution and less motion artifact due to fast imaging speed.

We can conclude that there are specific a-priori-parameters by the MRI, such as proton density, T1 and T2 relaxation that are not usual for CT and other techniques. So this a-priori-knowledge can be used only by segmentations in MRI data. The inverse is although possible. The a-priori-knowledge by the CT data, such as gray level of pixels, position with 2D or 3D coordinates, mass of object, tissue type, area and histogram is generally applicable also for MRI data.

## 4. ANALYSIS OF SEGMENTATION TECHNIQUES

All the researched papers argue that their method can significantly improve both segmentation accuracy and robustness and the presented results seem to confirm this. However all are very specific, because they have been done with different data and with different targets. The main problem is that there is no world accepted standard for data, comparison and methodologies. The quantitative comparison of different methods is rather challenging due to the absence of public software, widely accepted standards and publicly available data sets (see Table 1). Choosing a proper technique depends on several factors but generally on image modality and the target at the end.

**Table 1**: Problems contributing to the absence of the world standard for measuring MRI and CT images results

| Problems related to the software part |
|---|
| **Public data not available** |
| **Public software not available** |
| **Widely accepted standards for algorithms, metrics, evaluation and methodologies not available** |

Most of the studies are improving their new methods for spleen segmentation comparing them with segmentations made per hand from a specialist. Based on their percentage results we made two tables for comparison of the accuracy of the segmentation methods by the MRI and CT (see Table 2 and 3).

We should note that these results are calculated not always with the same method. There are authors that are using Dice/Tanimoto methods for calculating the similarity and accuracy (e.g.[3], [5], [6], [10]), other are comparing the volume of the spleen (e.g.[1], [3], [4], [10]) and some of them are using other calculation methods that they found to be appropriate (e.g.[2], [7], [8], [9]). However we decided to use them to make some kind of metric comparison of the methods for spleen segmentation by the different imaging techniques.

**Table 2**: Comparative results for the spleen segmentation by MRI

| Class of methods | Average accuracy [%] |
|---|---|
| **Gray level based** | 99.1 |
| **Structure based** | - |
| **Texture based** | 89,3 |

**Table 3:** Comparative results for the spleen segmentation by CT

| Class of methods | Average accuracy [%] |
|---|---|
| **Gray level based** | - |
| **Structure based** | 91,33 |
| **Texture based** | 88,86 |

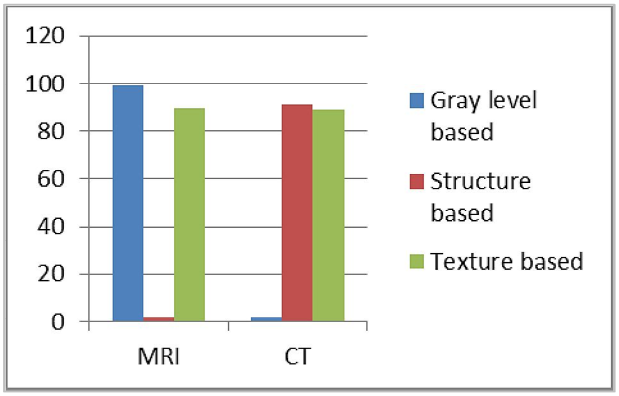


**Figure 4:** Diagram of the accuracy level in % by different classes of methods for spleen segmentation in MRI and CT images

The diagram in Figure 4 shows that globally the gray level based methods are with highest accuracy level, followed by the structure methods and then the texture methods. When we consider the results for MRI and CT separately, there is no find information for one class of methods by each imaging technique. By MRI the most accurate class of methods is the gray level based, followed by the texture based. By CT the accuracy level is highest by the structure based methods, followed again by the texture based. The Texture based methods are with accuracy level under 90% by both imaging techniques.

## 5. CONCLUSION

Spleen segmentation from MRI and CT is still an open issue and the tendency is that multiple methods will be employed together to achieve better Segmentation Performance. In most of the observed approaches it was not accentuated on the pre-processing stage that includes Filtration methods of noise, which should improve the quality of the segmentation. More researches could be done in this direction. The hybrid methods could be also more deeply investigated with the purpose of combining the methods with the best accuracy.

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