

Segmentation of CT images of fish using Soft Expectation Maximization (EM) algorithm

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Abstract

This work is part of my project to simulate ultrasound backscattering images from fish using CT images. They were used as the scatter maps of the different tissues. So image segmentation is an important step to find the locations of them. In this work, Soft Expectation Maximization (EM) algorithm was applied. The approach searches for a global threshold of gray color level in the image using quadratic potential functions (in this case, it is Gauss function). The advantage of this method is that the convergence is guaranteed. The convergence to local minima is avoided as each point can softly change its group.

Introduction

The procedure for this method is presented in Fig.1. First of all, the gray color image is offset so that the gray level values are greater than 0. Then the image histogram is created. It is a chart that shows the distribution of intensities in an gray scale image. The input parameters are initiated.

Each point is given a probability (weight) to belong to each class.

The E step:

The probabilities of each point are updated according to the distances to the centers.

The M step:

Class centers are computed as a weighted average over all data points.

Final E step: classify each point to the nearest (most probable) center.

Theory

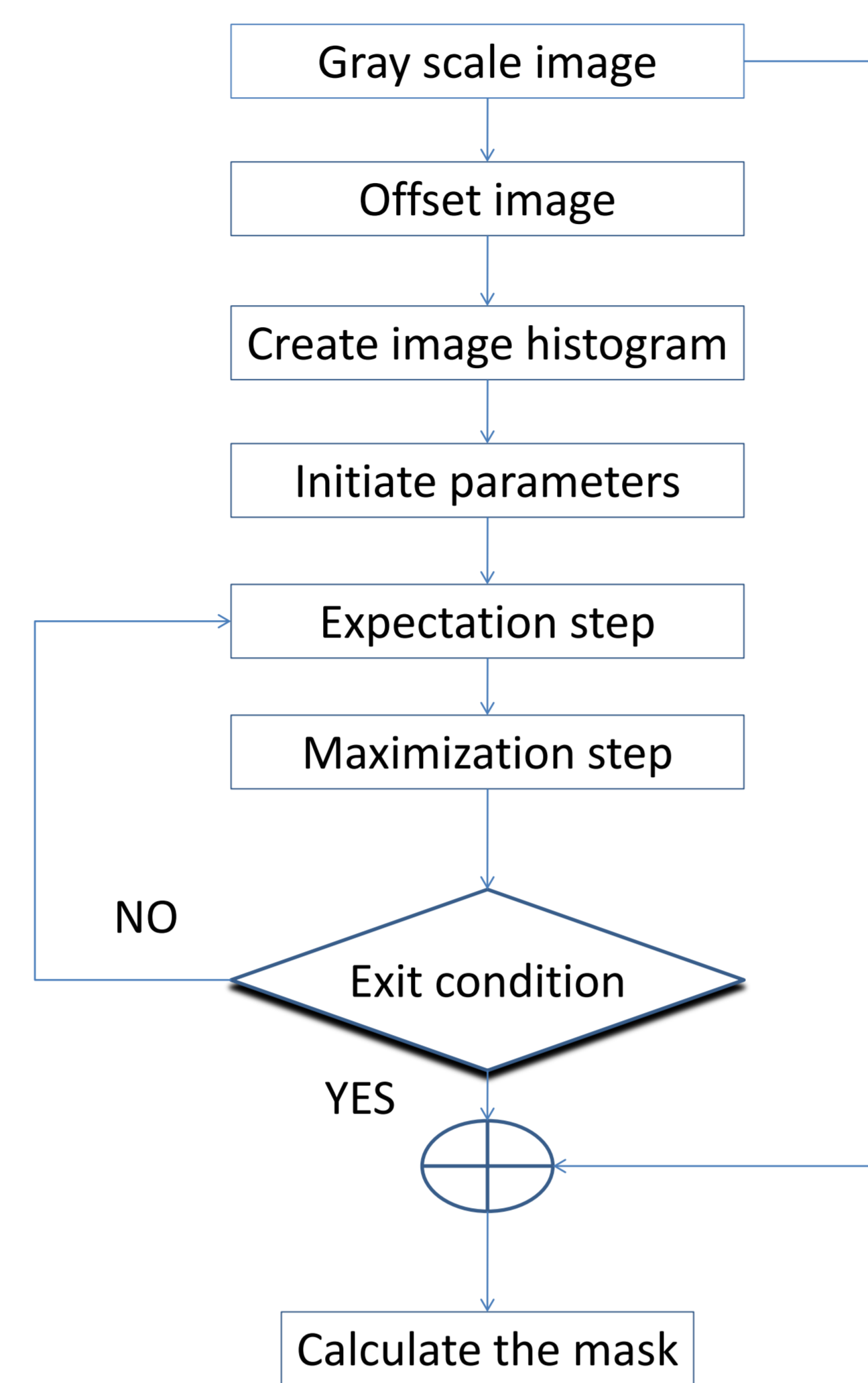


Fig. 1 Flow chart of the EM algorithm

The result:

- . Points near a center of a cluster have high influence on the location of the center.
- . Points near clusters boundaries have small influence on several centers.
- . Convergence to local minima is avoided as each point can softly change its group.

$distribution_i$

$$= p_{class(i)} * \frac{1}{\sqrt{2 * \pi * \sigma}} * e^{-\frac{1(x-offset_i)}{2\sigma}} \quad (1)$$

where

- i class number
- σ standard deviation
- x gray level values

* Expectation

loglikelihood

$$= \sum histogram * \log \left(\sum_{i=1}^n distribution_i \right) \quad (2)$$

where

n number of classes

* Maximization

- . update new threshold for each class
- . update new vector of class variances
- . update new distribution
- . Update new loglikelihood

* Exit condition

$$new_loglikelihood - loglikelihood < stop_value \quad (3)$$

* Calculate mask

- . Make the threshold values for the original image
- . At each point, calculate the distribution. The point belongs to the class that have maximum distribution.

Results

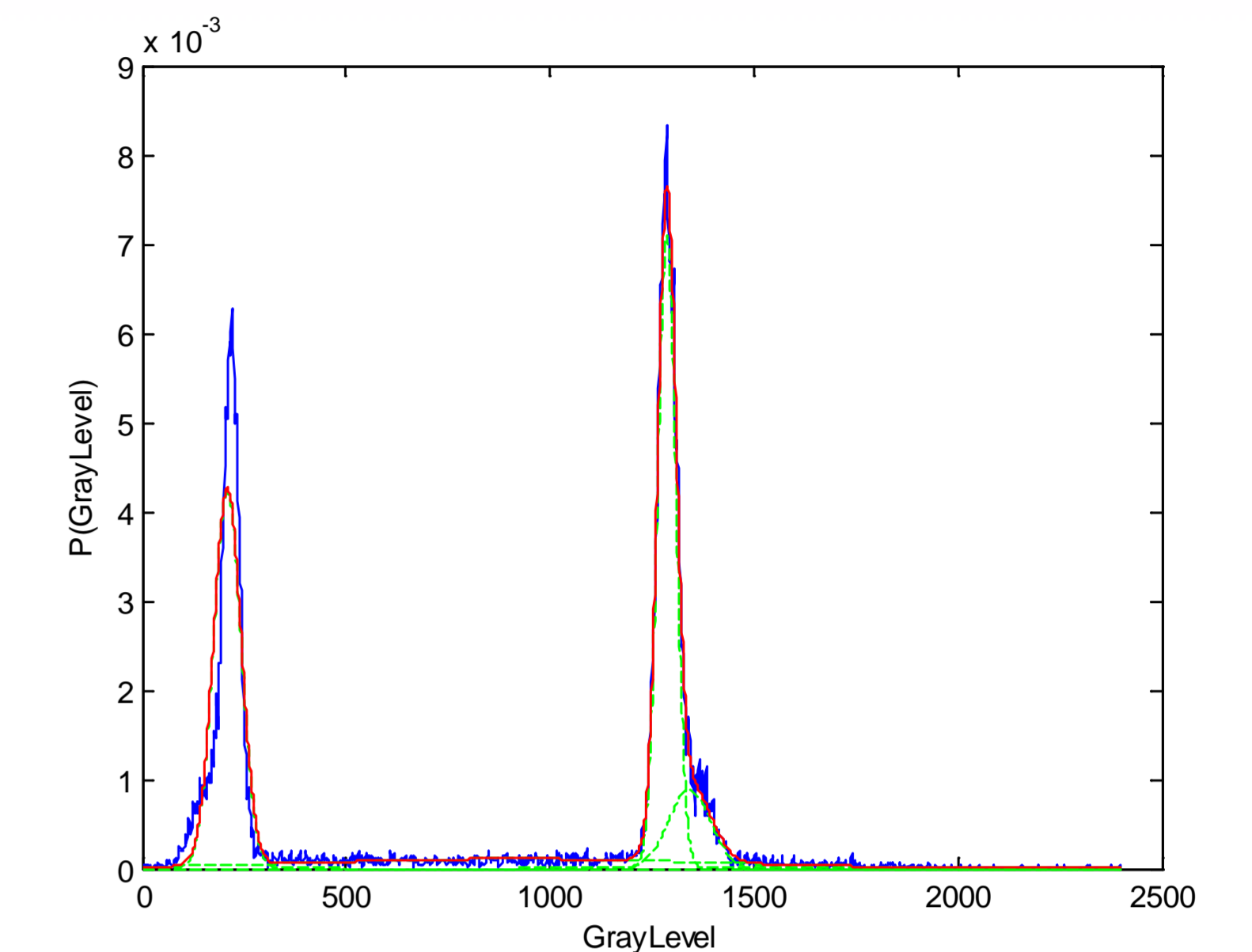


Fig. 2 Final image histogram

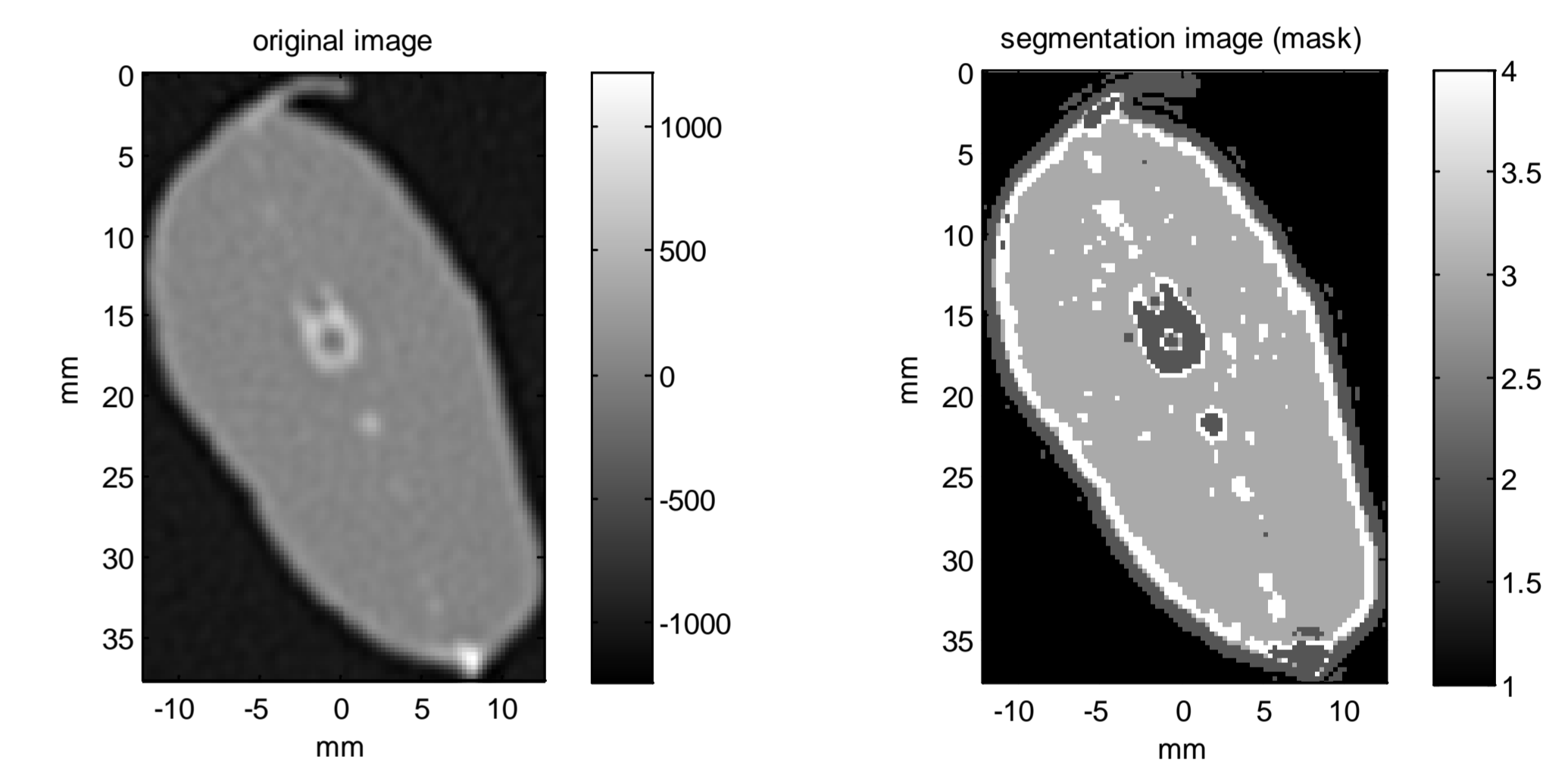


Fig. 3 Original CT image (left) and segmentation image (right)

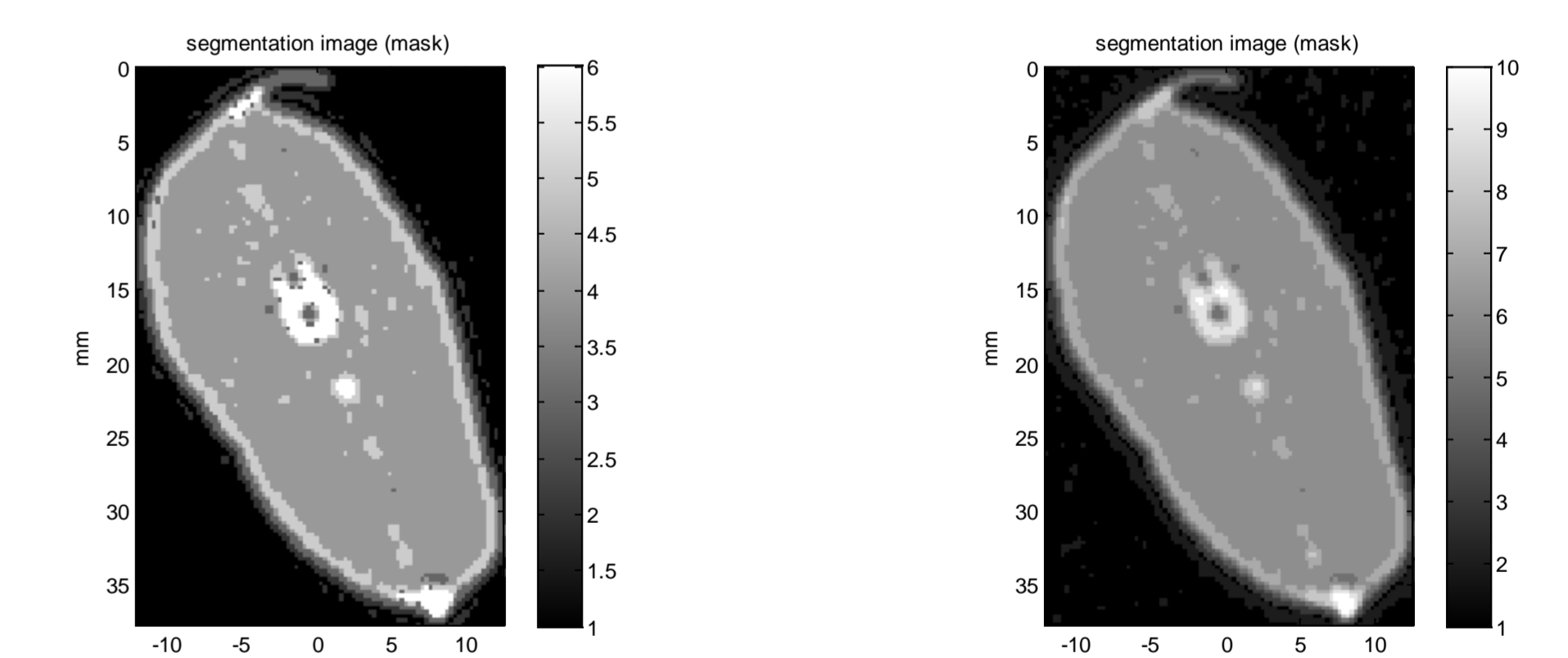


Fig. 4 Segmentation images, with 6 classes (left) and 10 classes (right)

In Fig.3, the result of the segmentation image is fairly good. The image is segmented without using the threshold of Housfield unit. However, this method is still dependent on the initial parameter estimation, the number of classes and the setting of the stop value.