

PROJECT SUMMARY

BOLUS DETECTION IN COLON MRI

BY

CHRISTIAN HARRER

NOVEMBER 9, 2007

SUPERVISORS:

ANDREAS KEIL

DR. SONJA BUHMANN

TUM

CHAIR FOR COMPUTER AIDED MEDICAL PROCEDURES

INSTITUTE OF COMPUTER SCIENCE

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## 1 Introduction

### 1.1 Medical Background

Functional gastrointestinal disorders result in a significant number of consultations in primary care facilities. Chronic constipation as well as diarrhoea are regarded as one of the most common diseases, affecting between 2 and 27 percent of the population in western countries. Defecatory disorders are most commonly due to dysfunction of the pelvic floor or the anal sphincter. Although an exact differentiation of these pathologies is essential for adequate therapy, diagnosis is still only based on clinical evaluation. Regarding quantification of constipation only the ingestion of radio-opaque markers or radioactive isotopes and the consecutive assessment of colonic transit time using conventional X-ray and scintigraphy respectively has been feasible in clinical settings. However, these approaches have several drawbacks such as presenting rather inconvenient, time-consuming examination and exposing the patient to ionizing radiation. Therefore, conventional assessment of colonic transit time has not been widely used.

Most recently, a new technique for the assessment of colonic transit time using MR-contrast media filled capsules has been introduced. However, due to numerous examination dates and corresponding datasets with many images/examination time points to be taken into consideration, the evaluation of image data per patient is relatively time-consuming.

### 1.2 Objectives/Goals

The main objective of this project was to develop a software tool to facilitate the finding of the contrast media filled capsules in each MR-image dataset and thus to shorten the evaluation time of the colonic transit.

### 1.3 Experiments

Several test patients ingested a certain number of (usually five) capsules. After certain periods of time MR-volumes were acquired, in which the capsules had to be located in order to reconstruct their trajectory and transit time through the bowel. This was realized in an interactive Matlab environment where different classification criteria were applied for the segmentation.

Since the visibility of the capsules in T2-weighted datasets was rather poor, the main effort was placed in capsule detection in T1-weighted datasets where contrast and visibility was much better. (For an example, see Figure 1.)

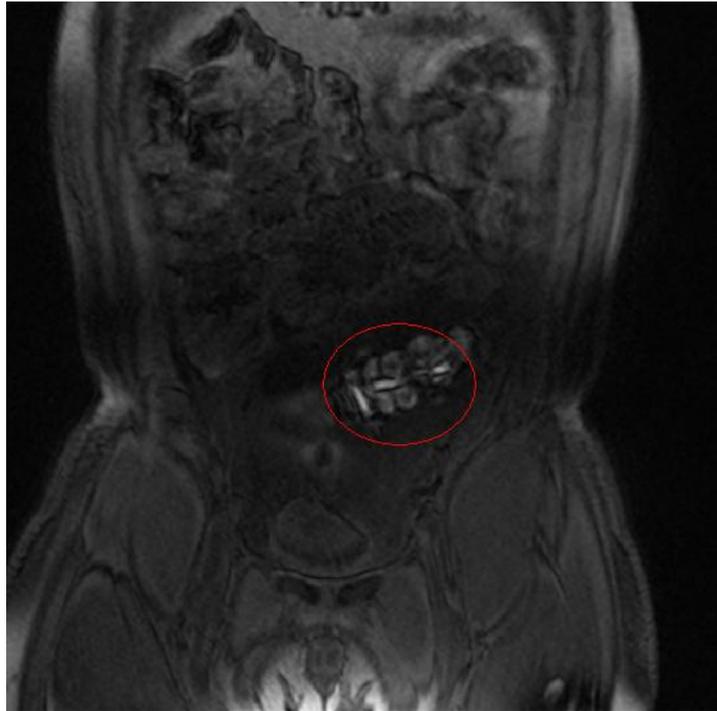


Figure 1: typical MR-slice with capsules

## 2 Classification Criteria

In order to provide doctors with a software tool to help them detecting capsules in the MR volumes, a combination of different classification criteria had to be applied to achieve reliable results.

The following techniques were employed in order to detect the capsules by taking into account their image intensity, their volume, and their shape.

### 2.1 Intensity Thresholding

Since the capsules were filled with MR-contrast media, they turned out to mostly have a very high intensity in the image datasets. Therefore, a simple intensity thresholding was applied in order to find the capsules in the images.

However, since the doctors experimented with different concentrations of contrast medium, the range of intensities of the images of the capsules appeared to be rather wide. Thus, in order to avoid discarding positive matchings already in the first step, the intensity threshold was selected manually by looking at different representative datasets. Its value was chosen rather low, because more sophisticated criteria to separate the capsules from objects with similar intensity will be incorporated, too.(Figure 2)

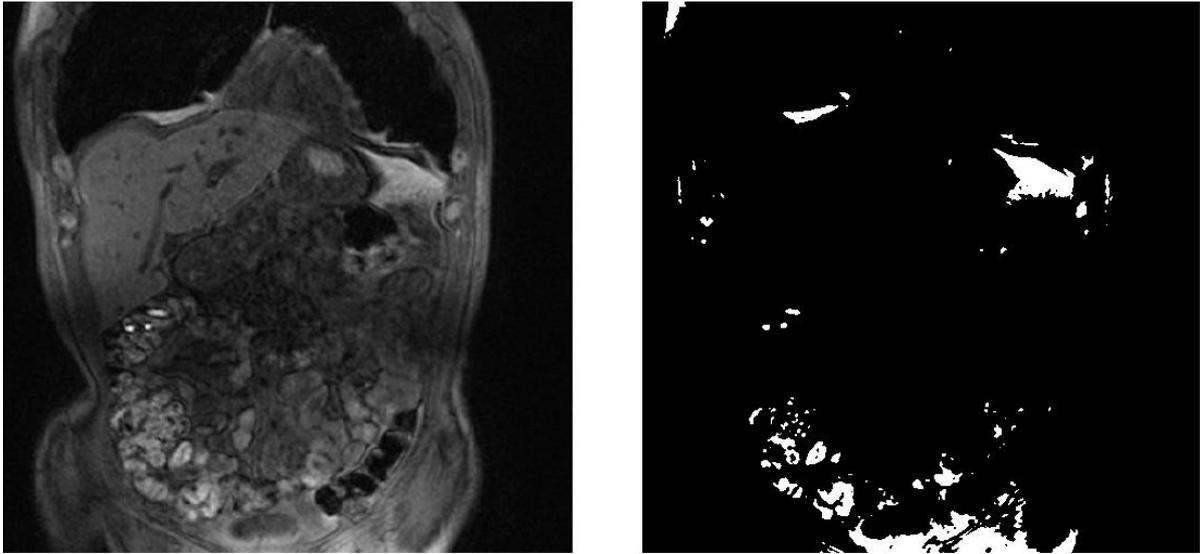


Figure 2: left: original image right: thresholded image

## 2.2 Object Volume (CCA)

After the first intensity-based segmentation, more complex classification methods had to be applied to achieve acceptable results.

Since the measurements of the capsules (see Figure 3) applied in this study were exactly known, basic geometrical calculations were used in order to compute their reference volume. This was done by dividing the object into basic geometrical primitives such as half spheres, cylinders and cones, leading to a volume of roughly  $520 \text{ mm}^3$  per capsule. Comparison of this value and the reconstructed volume of possible capsule candidates in the datasets was performed in order to provide a criterium for discarding false positives.

At first, all disjunct objects with the right intensity (in the thresholded datasets) were labeled using the connected-components-analysis-algorithm (CCA)(Figure 4: 2D objects and their labels generated by CCA). The resolution ( $0.78 \text{ mm} * 0.78 * \text{mm} * 2 \text{ mm}$ ) of the images lead to a volume of  $\sim 1.2 \text{ mm}^3$  per voxel in reality, which means that e.g. an object consisting of 40 voxels in the dataset should have a volume of  $\sim 48 \text{ mm}^3$  in reality.

For the capsules used in the medical study this meant that they should occupy  $\sim 425$  voxels in the dataset, which was then taken into account when deciding whether a segmented object was such a capsule or not.

However, the inhomogeneous resolution and the intensity differences due to different concentrations of contrast medium inside the capsules only made it possible to define a certain range in which the number of the voxels of a capsule-image should lie. Especially the inhomogeneous resolution lead to different results, depending on the capsules' location and orientation with respect to the MR slices inside the patient. (Figure 5: different positions cause different

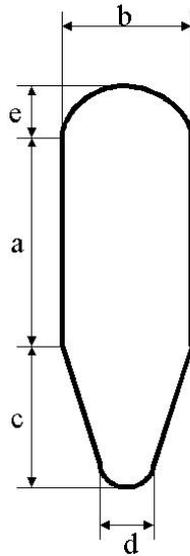


Figure 3: colon capsule

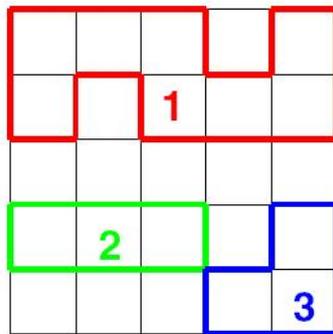


Figure 4: CCA example

'volumes', one capsule consists of only 2 voxels while the other one consists of 5)

Manual evaluation showed that even in the same dataset, the image of some capsules consisted of  $\sim 400$  voxels while others only counted  $\sim 180$  voxels. This leads to the assumption that datasets with homogeneous (e.g.  $1\text{ mm} * 1\text{ mm} * 1\text{ mm}$ ) resolution would yield much better results (while occupying roughly the same amount of computer memory and taking the same acquisition time per patient).

### 2.3 Object Shape (PCA)

The third criterium in the classification process was the shape of the objects. As a simplification, the capsules were assumed to be of roughly ellipsoid shape with main axes  $a$ ,  $b$ ,  $c$  (Figure 6).

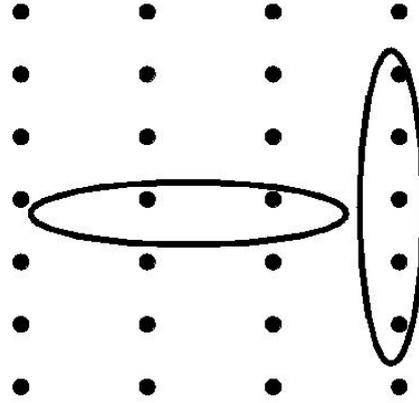


Figure 5: problems due to resolution

If a segmented object was a capsule, this would mean that the length of two of its main axes should be equal and their relation to the third main axis should be similar for each detected capsule, too.

In order to compute the main axes of the labeled objects, the Principal Components Analysis (PCA) algorithm was applied. This algorithm is usually used for statistical data analysis, but it can be used for image processing and image registration as well.

### 2.3.1 Outline of the PCA algorithm

Let  $X$  be a pointset;

$$\mathbf{X} = \begin{pmatrix} x_1 & x_2 & x_3 \dots \\ y_1 & y_2 & y_3 \dots \\ z_1 & z_2 & z_3 \dots \end{pmatrix}$$

First, the pointset is demeaned:

$$X \rightarrow X' : \forall i : x_i' := x_i - \bar{x}; y_i' := y_i - \bar{y}; z_i' := z_i - \bar{z}$$

where  $\bar{x}$ ,  $\bar{y}$  and  $\bar{z}$  are the mean values of the x-, y-, and z-coordinates.

Then the covariance matrix  $C := X' \cdot (X')^T$  is computed.

The singular value decomposition (SVD) of  $C$  yields matrices  $U, D, V$  with

$$C = U \cdot D \cdot V^T,$$

$D$  being a diagonal matrix with the diagonal elements being the principal components of the pointset (in our case the lengths of the main axes). When decomposing a symmetric matrix (like the covariance matrix  $C$  in our case) the matrices  $U$  and  $V$  are identical so that we have:

$$C = U \cdot D \cdot U^T$$

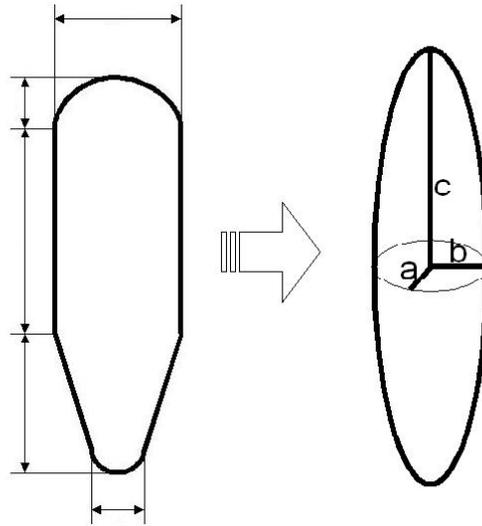


Figure 6: simplification: capsule equals ellipsoid

### 2.3.2 Application of the PCA algorithm

The pointset where the PCA is applied to is approximated as an of ellipsoid shape, the algorithm then provides a Matrix  $D$  of the Type

$$\mathbf{D} = \begin{pmatrix} c & & \\ & a & \\ & & b \end{pmatrix}$$

where  $a$ ,  $b$ ,  $c$  are the lengths of the main axes and  $a = b$ . Since the capsules in this study were  $\sim 24 \text{ mm}$  long with a diameter of  $\sim 6 \text{ mm}$ , the error measure

$$E = \left| \frac{a}{b} - 1 \right| + \left| \frac{c}{a} - \frac{24}{6} \right|$$

was introduced and evaluated for each object candidate. The object was rejected if the value of this error was bigger than a selected threshold. This criterium turned out to be quite accurate, however results were probably also impaired by the inhomogeneous resolution of the datasets.

## 3 Implementation

The methods described above were implemented in an interactive MATLAB environment. A graphical user-interface was developed in order to provide the doctors with a simple and intuitive way of evaluating image-datasets. The typical workflow when using the software can be described as follows:

Image data can be processed either as .MHD metafiles or in the scanner's native DICOM format (where the program is able to scan whole DICOM-directories automatically and show the user a list of datasets and dataset-descriptions to choose from). When a certain dataset is chosen and loaded, the user has the opportunity to browse through the slices manually and choose a region of interest (ROI) in which to search for the capsules.

After the segmentation process the first detected object is shown and the user can post-process the results. This is normally done by switching between the detected candidates in order to decide whether they are really capsules or just areas with similar intensity and shape. These false positives can then be deleted from the results-list by a simple mouseclick. On the other hand, false negatives which were initially segmented by thresholding but were rejected later on due to their shape can be easily re-added to the search results (if they turned out to be capsules anyway), too, see (Figure 7)

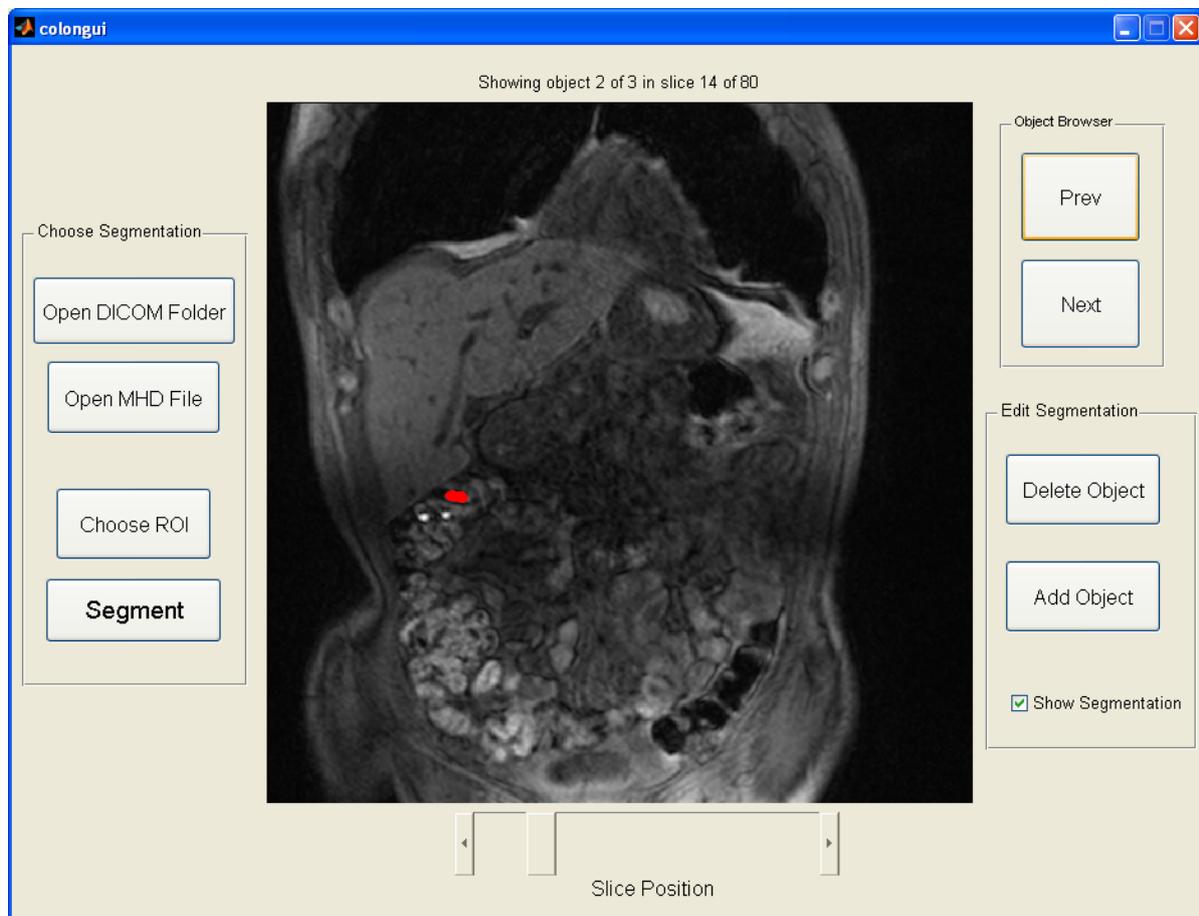


Figure 7: Screenshot of the GUI

## 4 Results

Detection of the capsules proved to be quite a challenging task for several reasons:

First, the image data of the bowel is highly inhomogeneous, making it hard to tell whether a segmented object is a capsule even for the radiologists themselves. Experiments with several image filters (e.g. median filtering) as a pre-processing step showed no significant improvement while slowing down the segmentation process.

Second, as described before, the fact that the image resolution in z-direction in all datasets was less than half of the resolution in x- and y-dimension caused characteristic data like volume and shape of the capsule-images to be highly dependent on the capsule's orientation with respect to the slices, making it hard to give precise thresholds for when to accept and when to reject a possible candidate.

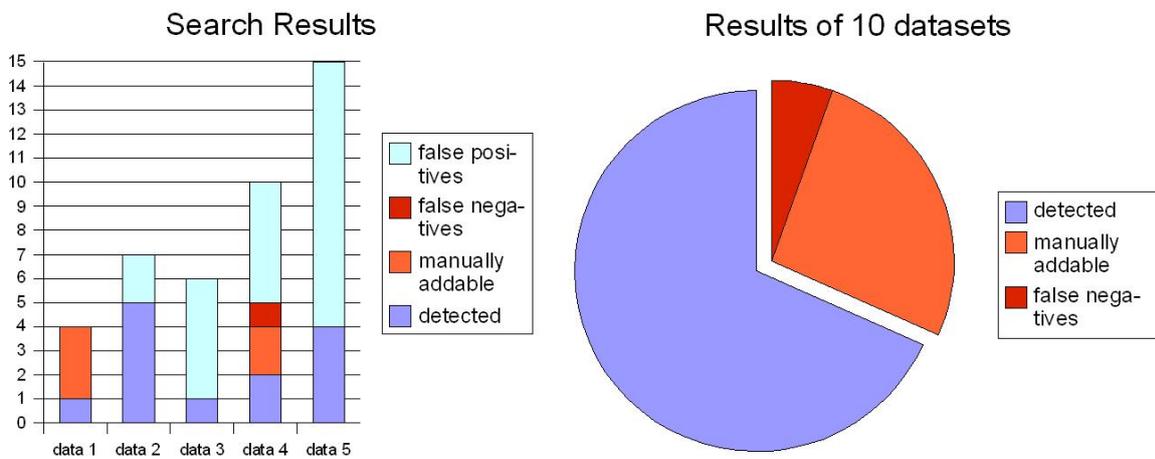


Figure 8: Search results

Figure 8 shows detection results for a selection of test datasets. The settings and thresholds were chosen in order to minimize the number of false positives. The category labeled 'manually addable' corresponds to the capsules which were initially rejected but could be marked manually with the 'Add Object' function of the software. If the ranges of the thresholds of the shape and size measures could be set more precisely, these capsules would be automatically detected. However, given the current datasets, this would have led to a too high number of false positives. Although these could be deleted very easily with the 'Delete Object' function, an extremely high percentage of false positives in order to minimize false negatives was not acceptable. (In the right diagram the false positives are not listed)

Computation time was  $\sim 2$  min per dataset, depending mainly on the size of the selected ROI.

## 5 Conclusion

The software developed for this study provides a very easy and comfortable tool for evaluating MRI data for colon examination. Given the fact that the task of detecting the capsules was performed completely manually up to now, the application of the software tool presented in this work is a big step towards improving and speeding up the workflow in every-day clinical situations. Especially when there are a lot of datasets to evaluate, the semi-automatic detection tool is a very effective help.

Although the detection results of the software are already quite good, they would probably improve significantly when selecting a homogeneous resolution in all three dimensions when acquiring the image data.