Medical Image Processing for Analysis of Colon Motility

N. Navab, B. Glocker, O. Kutter
S. Kirchhoff MD, and M. Reiser MD

ABSTRACT
A precise analysis and diagnosis of colon motility dysfunctions with current methods is almost unachievable. This makes it extremely difficult for the clinical experts to decide for the right intervention such as colon resection. The use of Cine MRI for visualizing the colon motility is a very promising technique. In addition, if image segmentation and qualitative motion analysis provide the necessary tools, it could provide the appropriate diagnostic solution. In this work we define necessary steps in the image processing chain to obtain clinical relevant measurements for a computer aided diagnosis of colon motility dysfunctions. For each step, we develop methods for an efficient handling of the MRI time sequences. There is need for compensating the breathing motion since no respiratory gating can be used during acquisition. We segment the colon using a graph-cuts approach in 2D over time for further analysis and visualization. The analysis of the large bowel motility is done by tracking the diameter of the colon during the propagation of the peristaltic wave. The main objective of this work is to automatize the assessment of clinical parameters which can be used to define a clinical index for motility pathologies.

1 Introduction

Dysfunctions of large bowel motility presents a common problem in our society that may be attributable to a great variety of possible etiologies resulting most commonly in either constipation or diarrhea. Today's available diagnostic imaging techniques, such as bowel enema and the determination of the bowel transit time by the application of radiopaque markers, provide only snapshots of the dynamic large bowel motility and approximate clues concerning motility dysfunctions. These examination techniques cannot sufficiently demonstrate bowel movement in real-time.

To date, only the pancolonic manometry technique has been used to evaluate colonic motor function over either the entire length or limited segments of the human colon [9, 1, 8]. Manometry as well as the barostat technique present both scientifically established but very complicated methods with several drawbacks such as the invasive examination itself being very time

intensive and inconvenient for the patients and thus, both methods are rarely used in clinical routine. Noninvasive, well-established and examiner-independent methods are Scintigraphic examinations. They allow for determining the colonic transit time. However, a considerable radiation exposure is associated with this method [2]. Thus, classical examination techniques are not suited to monitor large bowel motility. The ideal technique to visualize and quantify large bowel motility would allow for a fast and repeated imaging over larger time frames with a high temporal resolution reducing movement and respiratory artifacts. Additionally, such a technique should allow to include newly available technologies such as biofeedback, electrical stimulation of intestinal pacemakers, or the administration of specific stimulating drugs [6].

Magnetic resonance imaging (MRI) allows noninvasive ultrafast dynamic imaging with a high soft tissue contrast. The potential of functional *Cine MRI* for the visualization of the abdominal organs has been presented previously [12] and makes this technique a very promising tool in our application because it allows for the visualization of morphology and function of the large bowel at the same time, provided that fast image acquisition is used. However, without any stimulation, the activity of the large bowel exhibits a broad range of individual differences, such that an examination within an acceptable time frame of approximately 30 minutes is not feasible [12, 7]. To this end, different prokinetic agents were used in our previous studies [6] in order to achieve a predictable activity of the large bowel which lead to the achievement of the first real-time visualization of the large bowel movement and its peristaltic wave (see Figure 1). A further and detailed analysis of large bowel motility and possible dysfunctions provides an immense progress in diagnosis of the lower gastrointestinal tract also concerning an individual and more suitable therapeutical approach from surgical as well as the internal medical side.

In order to integrate such a novel imaging technique into the daily clinical routine, it is mandatory to develop computer based analysis approaches. The huge amount of data which is acquired per patient needs automatic and semi-automatic methods in order to support the clinical expert in findings and diagnosis. Our main objective in this work is to model and quantify the activity of the large bowel hopefully providing the means to define the clinical significance of a variety of motility disorders in a wide range of patients. Necessary steps in the image processing workflow are defined, and technical approaches towards a computer aided diagnosis tool are proposed.

In the following, we present our preliminary results on a set of experimental data. Volunteer data was acquired and processed using the imaging techniques and algorithms presented in the next Sections.

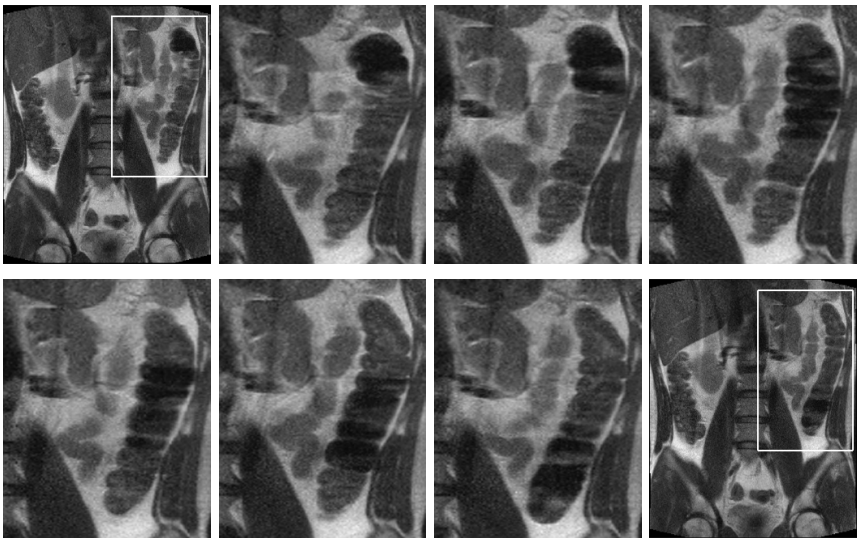


FIGURE 1. Coronal Cine MRI slices visualizing the peristaltic wave in the descending colon.

2 Image Acquisition using Cine MRI

The volunteers undergo functional Cine MRI. The standardized functional Cine MRI examination is performed at 6 AM, after a minimum starving phase of 8 hours, on 1.5-T system (Siemens Avanto). The volunteers are examined in supine position. Neither premedication nor contrast agent is applied. The dynamic part of the examination consists of 2 blocks of repeated measurements covering the entire abdomen, using a T2-weighted HASTE-sequence. Each block contains a stack of approximately 200 slices over time orientated in coronal plane adapted to the anatomic course of the descending colon (see Figure 1). The image resolution is 256×320. Between the 2 dynamic blocks of measurements a prokinetic agent is administered in order to stimulate the colon motility. For the further analysis of the peristaltic motion, the subsequence (usually about 20 slices) showing this motion is manually selected from the image blocks. The pre-scan without stimulation was up to now only used in our previous studies [7, 6].

In order to achieve the fastest possible frame rate for our MRI acquisition, no respiratory gating can be used during the scans. The time between two successive frames could be reduced to approximately 1.4 seconds which is fast enough to visualize the peristaltic wave. Still, the sequences suffer from breathing motion artifacts which makes the identification of corresponding points in the colon quite hard. This was not a problem in our previous studies where manually extracted diameters were measured over time and stimulated and non-stimulated sequences were compared, the identification

FIGURE 2. Our image processing chain within a computer aided diagnosis tool for colon motility dysfunctions.

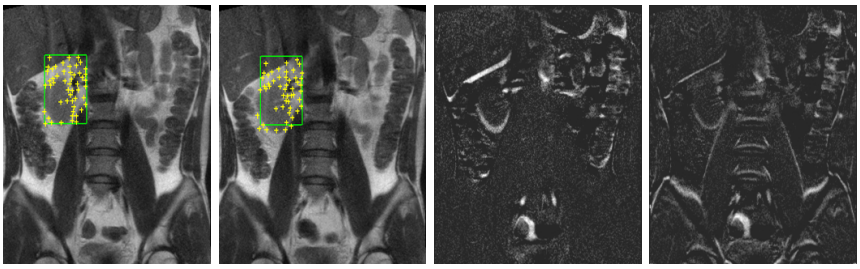
of corresponding points could be achieved manually by the medical expert. In order to automatize such procedures, there is need for an accurate motion compensation in a post-processing step. This leads us to the first step in the image processing chain (see Figure 2).

3 Image Processing

In order to develop a computer aided diagnosis tool for colon motility dysfunctions, we first identify necessary steps within the image processing chain. We already mentioned the problem of breathing motion artifacts in the Cine MRI data sets. Once, these artifacts can be successfully removed, all further steps will benefit from the motion compensation. Our later analysis of the motility is based on the segmentation of the colon in all slices over time. We propose a semi-automatic approach based on interactive graph-cuts. This will be explained in more detail in Section 3.2. The actual analysis and our approach for extracting clinically valuable measurements is then described in Section 4. The full image processing chain is sketched in Figure 2.

3.1 Motion Compensation

As already mentioned, no respiratory gating techniques are used during the image acquisition in order to achieve a high frame rate. The resulting breathing artifacts in the image sequences are visible in a vertical jumping of the abdominal organs effected by breathing motion such as liver, kidney, and of course the colon itself. For our further processing steps, a compensation of this motion is of great interest. In order to make the identification of corresponding points in the colon much easier we try to stabilize the image parts of interest. We propose a semi-automatic motion compensation method. Therefore, the user selects a subregion in one of the slices, which we call the reference frame. The selected region should represent the overall breathing motion but should not include any parts of the colon. So we can avoid to eventually compensate for colon motility. Within the selected region features are extracted which fulfill the Harris [10, 14] assumptions. The robust and fast implementation of the Lucas-Kanade optical flow method [3] is then used to compute the displacements of each single feature in every frame in respect to the reference frame. Afterwards we compute a mean



(a) (b) (c) (d)

FIGURE 3. (a) Selected region and extracted Harris feature points. (b) Tracked features in one of the following frames. (c) Difference image between reference frame and consecutive frame before compensation, (d) and the difference image after compensation. Clearly visible, the motion at the lower boundary of the liver has been reduced.

vertical displacement for every frame which represents the overall breathing motion. By translating each frame by its corresponding mean displacement we can compensate for this motion. In practice, the image part containing the lower liver boundary and right kidney turned out to be a good region for tracking the breathing motion (see also Figure 3). These parts show a very similar breathing motion such as the colon itself. The result of the motion compensation is a clear stabilization of all organs with a similar movement. Naturally, former stable parts (e.g. the spine, see also Figure 3d) are consecutively jumping within the image series, However, this fact does not present a problem for the further processing of the colon.

3.2 Colon Segmentation

The segmentation of the colon is crucial for our further analysis. Shape and appearance have to be well preserved by the segmentation. The individual patient's anatomy is particularly reflected in varying orientation and form of the large bowel. A segmentation method should be highly flexible to handle these variations. To this end, we use the interactive graph-cuts approach proposed by Boykov and Jolly [4]. The segmentation is defined as an energy formulation

$$E(A) = R(A) + \lambda \cdot B(A) \tag{1.1}$$

where A indicates a segmentation of the pixels x of domain Ω of the image series I into two subsets $\mathcal{O}$ (object pixels) and $\mathcal{B}$ (background pixels) with

$$A_{x \in \Omega} = \begin{cases} \text{“}obj\text{”} & \text{if } x \in \mathcal{O} \\ \text{“}bkg\text{”} & \text{if } x \in \mathcal{B} \end{cases} \tag{1.2}$$

Here, the regional term R represents a priori knowledge given through the user interactions. Interactively, the user sets so-called seed brushes for

the object $\mathcal{S}_{obj}$ that is considered to be segmented (i.e. the colon) and additionally, seeds for the background $\mathcal{S}_{bkg}$ (see Figure 4a). The function R is then defined as

$$R(A) = \sum_{x \in \Omega} R_x(A_x) \tag{1.3}$$

where

$$R_x(A_x) = \begin{cases} \infty & \text{if } A_x = \text{“}obj'' \wedge x \in \mathcal{S}_{bkg} \\ \infty & \text{if } A_x = \text{“}bkg'' \wedge x \in \mathcal{S}_{obj} \\ 0 & \text{otherwise} \end{cases} \tag{1.4}$$

Intuitively, the regional term forces the pixels belonging to seed brushes to keep their assignment to the object respectively background segmentation subset. The second part B of the segmentation energy is the so-called boundary term. Here, it represents the interaction energy for pairs of neighboring pixels $x, y \in \mathcal{N}$ to belong to the same segmentation subset and thus provides a certain smoothness on the segmentation result, or

$$B(A) = \sum_{x,y \in \mathcal{N}} B_{x,y} \cdot \delta(A_x, A_y) \tag{1.5}$$

with

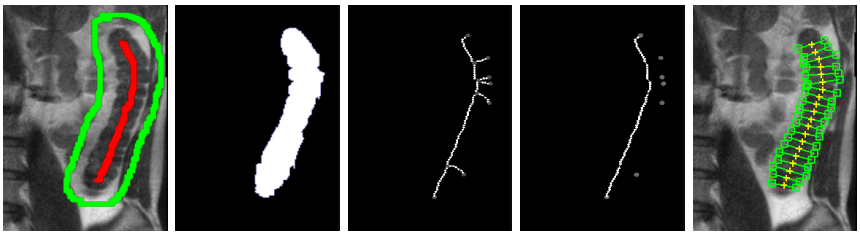
$$\delta(A_x, A_y) = \begin{cases} 1 & \text{if } A_x \neq A_y \\ 0 & \text{otherwise} \end{cases} \tag{1.6}$$

In our experiments, we use a simple boundary term based on intensity differences which is define in terms of a penalty function, or

$$B_{x,y} \propto exp(-\frac{(I_x - I_y)^2}{2\sigma^2}) \cdot \frac{1}{dist(x,y)} \tag{1.7}$$

This function penalizes discontinuities in the segmentation result for neighboring pixels of similar intensities. The weighting λ controls the influence of the boundary term. We set this value to 0.01 which was determined empirically for our kind of image data. The exact global minimum of the energy formulation in 1.1 can be computed by using a max-flow algorithm (*e.g* [5]).

Since we are dealing with MRI time series of 2D slices, each frame is showing a similar image of the patient's abdomen with slightly moved, or in case of motility, extended bowel diameter (see Figure 1). Furthermore, after performing the motion compensation, we can assume that the only large bowel motion left in the images is due to motility. We can make use of this minimal changes within the segmentation method in order to minimize the user interaction. Actually, we can perform a full segmentation of the whole time series very efficiently. The user sets the seed brushes only in one frame. Object seeds have to be set roughly at the centerline of the colon and background seeds are placed around the colon part of interest (see Figure 4a). Thanks to the motion compensation we can benefit from



(a) (b) (c) (d) (e)

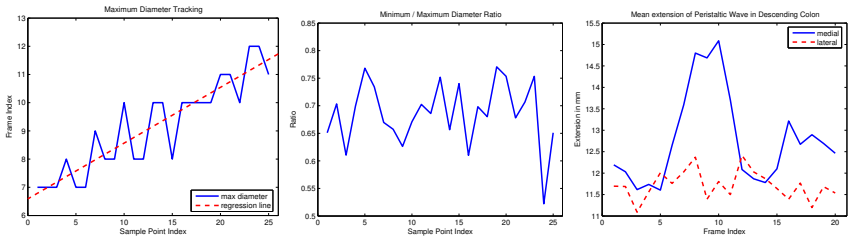
FIGURE 4. (a) Seed brushes in one frame of the image sequence. (b) Resulting segmentation of the descending colon. (c) Skeletonization of the segmentation. (d) Extracted longest path which is used as centerline. (e) Diameter measurement at 20 sample points.

this strategy in two ways: on the one hand, these brushes can be set automatically in all other frames of the time series in a "copy & paste" fashion, on the other hand, the surrounding background seeds can be used as a restriction or bounding box for the computation of the graph-cuts algorithm. The segmentation of the whole series is then done in one single energy formulation. Thus, the boundary term B also acts as a smoothness constraint in the temporal domain. The computation time of one segmentation for a subsequence of about 20 frames showing the peristaltic wave is less than 10 seconds.

One important property of such a segmentation approach is the extreme flexibility. This method can be used for all parts of the large bowel and can deal with extreme shape variations which are likely to occur. This is crucial for our further analysis of the colon motility which is based on the segmentation result.

4 Analysis of Colon Motility

The aim of the colon motility analysis is to obtain as much information as possible about the peristaltic motion visible in the Cine MRI sequences. Our approach is based on the idea of measuring the bowel diameter over time which was previously presented in [7]. In a first clinical trial, this fully manual approach was able to measure significant changes in the motility after administration of stimulating drugs [6]. However, this method was extremely time consuming and tedious in means of reproducibility. A limited number of 5 diameters were measured manually in one frame. Then, the corresponding points were identified manually in the successive frames and again the diameters had to be measured. In order to improve and automatize this approach and increase the number of measurements to a user selected bound, we are making use of the two proposed image processing steps so far, the motion compensation and the segmentation.



(a) (b) (c)

FIGURE 5. (a) The maximum diameter tracked over time at each of the 25 sample points. Such a measure can be used to estimate the speed of the peristaltic wave. (b) Ratio of minimum and maximum diameter at each sample point is used to assess the activity of the colon. (c) The mean extension for the lateral and medial side of the colon during a propagating peristaltic wave over 20 frames.

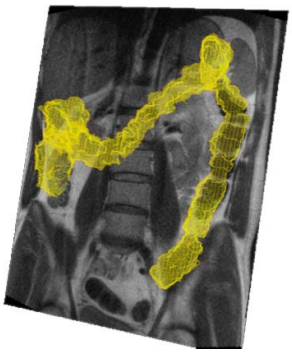
At first, we extract the skeleton of the segmented colon in one frame using a thinning algorithm proposed by Palagyi *et al.* [13]. From this skeletonization we construct a graph using a wave propagation approach presented by Zahlten *et al.* [15]. The result of these two steps is shown exemplary for one image sequence in Figure 4c. We extract the longest path from the resulting graph in order to obtain a good approximation of the real centerline of the colon (see Figure 4d). A B-Spline is fitted to the centerline which then can be subdivided into a user defined number of segments. At each segment we determine the diameter of the colon by measuring the extension of the segmentation perpendicular to the centerline (see Figure 4e). Since the segmentation is already computed for all slices and thanks to the motion compensation, we can easily measure the colon diameter at all these specific positions over time. The user can change the number of measurement points without any recomputation on the segmentation or centerline and gets the new measurements within milliseconds.

In order to analyze the present colon motility, we extract several values with clinical relevance from our measurements. One significant parameter of interest is the propagation speed of the peristaltic wave. This can be measured by tracking the maximum diameter along the measurement points (see Figure 5a). A value also important in assessing pathologies and dysfunctions of the colon motility is the ratio of the average maximum and minimum diameter (see Figure 5b). A ratio close to 1.0 could indicate a local defect on the contraction ability. Besides these values hopefully leading to a clinical index in near future, other phenomena reported in the medical literature could be measured for the first time. We could show that there is a significant difference in the contraction of the large bowel on the lateral and medial side (see Figure 5c). This is what clinical experts actually expected. However, up to now there did not exist any image based method to proof these assumptions.

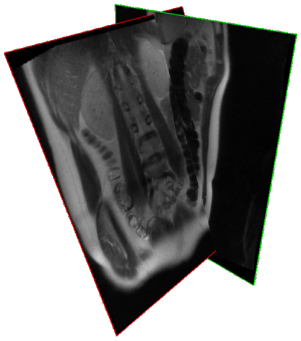
5 Conclusion

Our experiments focused on the descending part of the colon. This part is most relevant for clinical interventions as it is suitable for minimally invasive sugery. We tested our method on volunteer data and compared it to the manual approach of diameter calculation [7]. Our approach significantly reduces user-interaction and is fast in delivering quantitative results on colon motility assessment We increased the number of clinical parameters by for instance the speed of propagation or the min-max ratio.

In future work, we consider fully-automatic methods, *e.g* learning-based template matching approaches may provide a tool to remove user interactions from the motion compensation task. Deformable registration methods will be considered in order to compute dense motion fields. We also would like to propose advanced visualization techniques, *e.g* fused 2D-3D data, which may help during planning and intervention (see Figure 6a). New experiments using manometry are realized allowing a comparison of our non-invasive approach to an invasive but established technique. Our goal is to achieve a higher sensitivity while providing precise spatial information for defects. Recent advances in fast multi-plane imaging allow for capturing motion in three dimensions (see Figure 6b) and thus may further improve the assessment of colon motility [11].



(a)



(b)

FIGURE 6. (a) Fusion of dynamic 2D and static 3D. (b) Multi-plane MRI showing the colon motion in three dimensions.

6 References

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