Automated Scan Prescription for MR Imaging of Deformed and Normal Livers

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Purpose: We propose an automated scan prescription to assess normal and deformed livers and demonstrate its efficacy in normal volunteers and in simulated deformed livers.

Methods: Our automated scan prescription can be used to identify the upper and lower edges of the liver based on commonly used axial slice positioning. The liver’s upper edge is detected by template matching and finally identified by applying an active shape model to a sagittal projection image. The lower edge is detected using a maximum a posteriori (MAP) probability estimate that utilizes statistical information from a region of interest (ROI) placed in the liver. This places no restraints on liver shape and is therefore effective in assessing a deformed liver.

Following institutional review and approval, we tested our method in 45 healthy volunteers. We also used clinical information to simulate deformed livers and tested our method with those datasets offline.

Results: We could detect the upper edges within an error range of -3 to 6 mm, even without intensity correction for normal volunteers. Similar detection of the lower edges with maximum 21-mm and 7.84-mm standard deviation for normal volunteers confirmed the superior efficacy of our modified approach for deformed livers to that using our previous method. Clinical use required approximately 10 s’ computational time on a Core i5 laptop with 2-GB memory.

Conclusion: We propose a method for automated scan prescription in magnetic resonance (MR) imaging of the liver and demonstrate the efficacy of our algorithm for evaluating deformed livers within a practical computation time. Detection of liver edges of various shapes by applying the MAP estimate combined with statistical information from the ROI demonstrated the potential clinical utility of this technique.

Keywords: active shape model, automated planning, automated scan prescription, MAP estimate, MRI liver imaging

Introduction

Use of an automated scan prescription simplifies the workflow of magnetic resonance (MR) imaging and aids accurate and consistent slice positioning in an operator-independent fashion. Various such prescriptions have been proposed that depend on the target region, such as the brain, spine, knee, or shoulder.

Manual application of an MR imaging scan prescription to the liver is relatively easier than in these other regions but may preclude detection of a few slices in which there is no respiratory motion effect and is dependent on operator skill. One approach has been proposed for automated slice prescription of the liver, but its accuracy and the computational time required for its use were not suitable for practical implementation. We attempted to achieve adequate slice positioning within a practical computational time for the automated scan prescription of the liver. We previously detected both the upper and lower edges of the liver using an active shape model (ASM) in 38 healthy volunteers and in 12 patient datasets offline, even when the dataset was acquired without intensity correction. Such correction is commercially...
available but requires an additional reference scan because we implemented homomorphic filtering for additional intensity correction.\textsuperscript{15,16} Practically speaking, however, hepatic disease or surgical intervention can deform the liver's normal shape. In this study, we propose an automated scan prescription algorithm that can be applied to livers of various shapes, and we test its efficacy in normal volunteers and in simulated deformed livers. We then compare the previous and new methods, discuss the efficacy and robustness of the new method, and propose further improvements.

**Materials and Methods**

*Previous method and problem*

Figure 1 is a flow chart of the previous algorithm used for automated scan prescription for liver scans.\textsuperscript{11,12} Once preprocessing is performed using the median (6 neighbors) and homomorphic filters,\textsuperscript{15,16} the mean shape of the ASM is placed on a coronal projection image by matching a certain landmark of the ASM with an anchor point, which is the peak position in the profile calculated from the projection images. In the next step, the ASM is evolved to the coronal projection image to detect the lower edge of the liver. This procedure worked according to specification and showed good results for 38 healthy volunteer datasets. Although we also tested the algorithm using datasets of 12 patients, most of their livers showed no severe deformation. Our interviews with clinicians indicated that roughly 70 to 80% of patients with deformed livers undergo detailed MR imaging examination following either X-ray, computed tomography (CT), or ultrasound screening. Thus, these patients have some hepatic disease, particularly hepatic cirrhosis (HC) or hepatocellular carcinoma (HCC), known to cause liver deformation\textsuperscript{17} and reduce liver size. Typically, the liver is deformed when the left lobe grows more than the right lobe, and the lower edge of the liver shifts anteriorly from the center beneath the liver dome. Because we used data of 21 volunteers with normally shaped livers to train the ASM, we can suspect that the model may not fit the shape of a deformed liver.

*New algorithm*

To improve our approach, we modified the previous algorithm by eliminating intensity correction (homomorphic filtering) and thresholding, devising a new strategy for detecting an anchor point, and applying a new technique for detecting the lower edge without using the ASM.

Although a homomorphic filter can be used to minimize severe variation in intensity, its use flattens image contrast and unnaturally enhances the edge of the image. These typical drawbacks during intensity correction make it more difficult to detect the peak signal of the projection profile. That is,
the peak value of the profile drops lower, and the derivative of the boundary between the liver and other regions decreases. Because of these problems, we did not use any intensity corrections such as homomorphic filter. Although thresholding has been used to remove intestinal signal, the condition of the patient, such as whether he or she has eaten before examination, can dramatically change the signal, and a simple thresholding method rarely gives accurate results. Alternatively, we adopted a method to detect the anchor point that does not depend on the peak signal of the profile. Furthermore, in patients with deformed livers, acquisition of data from normal volunteers to train the ASM constrains evolution of the ASM shape and precludes the model’s application. Nevertheless, collecting data from patients with deformed livers would have been of little help because of the difficulty in controlling the degree of deformation based on common principle component analysis. Thus, we discarded the ASM and employed a new technique to detect the lower edge of the liver.

Figure 2 is a flow chart of the new algorithm. We acquired datasets from a scout scan (T1-weighted fast spoiled gradient echo with fat suppression) using parameters identical to those used in our previous study: repetition time (TR)/echo time (TE), 3.8/1.8 ms; scan matrix, 256 × 160 × 60; 3-mm slice thickness; 11° flip angle (FA); number of excitations (NEX), one; field of view (FOV), 400 × 320 × 360 mm; and scan time, 17 s during breath-holding. In pre-processing, we applied a 3-dimensional (3D) median filter and noise level detection successively to the scout data to reduce noise and for thresholding to recognize the body area in 2-dimensional (2D) projection images. We then constructed 2D projection images from a limited number of slices. The last 2 steps of the algorithm are new and detailed in the next 2 sections. The new algorithm employs an anchor point for placing a region of interest (ROI) on the coronal projection images.

**Upper edge detection and anchor point identification**

Figure 3 shows the new steps. First, we produced 2D sagittal projection images from half the volume data to decrease blurring and used the row projection profile extracted from that projection to determine body depth. Both Th1 and Th2, calculated from the noise level, limit the number of coronal image slices that generate the 2D coronal projection image (central row in the diagram, Fig. 3). We then used template matching to extract the upper edge from this image. The template data on the vertical line was built in advance using data from 21 volunteers (dotted line in the upper right corner of the graph). We calculated the cross correlation of every vertical line, selected multiple points (cross mark) on each line showing cross correlation (Rg) greater than 0.85, gathered all these points, and selected a median point in their distribution that was nearest the correct upper edge to represent the liver’s upper edge. In Fig. 3, the dotted line passes through the detected upper edge. However, because this line does not always accurately represent the position of the upper edge, the ASM is used to improve detection accuracy. Because the shape of the liver dome varies less (deformation) in the sagittal than coronal view, the ASM can be applied in the sagittal view to detect the most appropriate upper point of the liver. Our ASM consisted of 5 landmarks and was trained using data of 21 volunteers. The most superior landmark in the ASM is matched with the initial detected upper edge position (dotted line in Fig. 3). To observe the evolution of the model’s shape, we traced a strong edge, determined through cross correlation with the template of the gradient profile, on the line crossing the landmark and perpendicular to the direction of the adjacent landmarks. Basically, this ASM was the same as the model of the previous technique. The anterior/posterior (A/P) and superior/interior (S/I) positions of the anchor point were fixed using this step. The new technique searched intensively for the boundary between the lung and liver, whereas the previous technique to detect the liver’s upper edge depended strongly on the strength of the signal aris-
Fig. 3. Upper edge detection and anchor point identification. (a) Half of the 3-dimensional (3D) volume dataset is utilized to make a 2-dimensional (2D) sagittal projection image. (b) Make a row projection of the 2D sagittal projection image and determine threshold values (Th1, Th2). (c) A coronal projection image is constructed from the partial volume restricted by the Th1 and Th2. (d) The upper edge is identified initially by calculating the cross correlation ($R_g$) of sample and template profiles on each vertical line for general template matching and identifying points satisfying $R_g > 0.85$ on each vertical line (cross marks in the diagram). The median of the superior/interior (S/I) position of the cross marks is much nearer the upper position of the liver (horizontal dotted line). (e) Finally, the upper edge is determined using the active shape model (ASM). The S/I position of the upper edge identified in (d) is used as an initial position of the ASM. The solid line in (e) shows the final shape of the ASM fitted to the dome shape of the liver. The cross mark is the detected anchor point located at the peak of the ASM.

Lower edge detection

One difficulty in detecting the lower edge of the liver is its similar signal intensity to that of other tissues and organs. However, the greater variation in signal within these entities can help distinguish them from the liver. We addressed this feature as a prior probability using Gibbs distribution. To collect statistical information for the liver, we placed the scaled-down ROI on the coronal projection image by matching the landmark at the upper left corner of the ASM (scaled-down mean shape of the ASM) with the anchor point. We measured the standard deviation (dotted line) of the ROI. Because this procedure fixes the R/L position based on the statistical information of a chosen area, it is not susceptible to small or rapid signal changes and various kinds of noise.
pixel data within the ROI and used the measurement to calculate the mean ($\mu$) and variance ($\sigma^2$) of all the pixels inside the scaled-down ROI as well as the mean ($\mu_s$) and variance ($\sigma^2_s$) of the adjacent pixels (8 neighbors). Figure 5 shows the relationship among adjacent pixels. This means that if homogeneity inside the tissues or organ is similar to or better than that of the liver, $p(X=x_l)$ increases. In contrast, if homogeneity is worse than that of the liver, $p(X=x_l)$ decreases.

The signal distribution of the liver was expressed using Gauss distribution as:

$$p(Y=y | X=x_l) \propto \frac{1}{\sqrt{2\pi \sigma^2_l}} \exp \left(-\frac{(y-m_l)^2}{2\sigma^2_l}\right),$$  \hspace{1cm} (3)

where, $x_l$ is the label of the liver. Posterior probability was obtained by Bayes' theorem as:

$$p(X=x_l | Y=y) = \frac{p(Y=y | X=x_l) p(X=x_l)}{p(Y=y)},$$  \hspace{1cm} (4)

where

$$p(Y=y) = p(Y=y | X=x_l) p(X=x_l) + p(Y=y | X=x_others) p(X=x_others).$$  \hspace{1cm} (5)

This term can be ignored because it is a constant. Then,

$$p(X=x_l | Y=y) \propto \frac{1}{\sqrt{2\pi \sigma^2_l}} \exp \left(-\frac{(y-m_l)^2}{2\sigma^2_l}\right) \times \exp \left(\sum_{c \in C} \beta \cdot U_c(x_c)\right).$$  \hspace{1cm} (6)

If Eq. (6) is applied to a small region containing $N$ pixels, it becomes a combination of a likelihood function and prior probability, given by:

$$P(X=x_l | Y=y) \propto \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi \sigma^2_i}} \exp \left(-\frac{(y_i-m_i)^2}{2\sigma^2_i}\right) \times \exp \left(\sum_{c \in C} \beta \cdot U_c(x_c)\right).$$  \hspace{1cm} (7)
where
\[ \nu := \{ y_i \}_{i=1}^N. \]

Here, we use a square region (called a kernel) consisting of 5×5 pixels, take a natural log of Eq. (7), and negate the equation.
\[
E(X=x|Y=\nu) = -\log P(X=x|Y=\nu)
\approx \frac{1}{2} \log (2\pi\sigma^2) + \sum_{i=1}^{N} \left\{ \frac{(y_i-m)^2}{2\sigma^2} \right\}
- \sum_{c \in C} \beta \cdot U(s_i, r) \]
Equation (8) denotes that if the kernel belongs to the liver, the likelihood of the liver being expressed by Eq. (8) is lower than that likelihood for the other regions. In other words, \( E \) represents an energy variable, and lower energy indicates a stable state. Such a region more likely belongs to the liver.

The liver region is identified by a maximum a posteriori (MAP) estimate as:
\[
\hat{x}_l = \arg \min_x [E(X=x|Y=\nu)]. \quad (9)
\]
In Eq. (9), \( x \) can be changed by moving the 5×5 region. To detect the lower edge of the liver using Eqs. (8) and (9), we subtracted the 2 regions located on the upper and lower sides across the point of interest. In Fig. 6, one of the 2 regions is \( E_{in} \), and the other is \( E_{out} \). If we compute \( E_{in} - E_{out} \), the point located at the upper edge shows the highest value of \( E_{in} - E_{out} \), and the point at the lower edge shows the lowest value. In other words, the lower edge can be detected as:
\[
Lower \ edge = \arg \min_{p \in L} [E_{in} - E_{out}], \quad (10)
\]
where \( p \) is any image pixel and \( L \) is a subset of the image points existing on the vertical lines as illustrated in Fig. 6. In this method, the computational cost is low because no iterative calculations are involved. In addition, the combination of the intensity term and the homogeneity term in Eq. (8) works effectively for the boundary, which is difficult to distinguish from the real edges of other tissues if there are a lot of edges with pixel intensity resembling that of the liver around its real lower edge. Furthermore, because the ASM is not used for detection, the algorithm works well for detecting the lower edge of the deformed liver without constraining shape.

**Volunteer test**
Following institutional review and approval, we tested our method in 45 healthy volunteers. We also simulated 7 deformed livers based on clinical data of the volunteers and tested the data offline using our proposed method. All data were acquired using a 1.5-tesla MR imaging scanner (Signa HDx; GE Healthcare, Milwaukee, WI, USA).

**Results**

**Upper and lower edge detection**

Table shows results for upper and lower edge detection. Errors were calculated by subtracting the edge position detected using the new algorithm and manually measuring the point with reference to sagittal, coronal, and axial images reformatted from the 3D volume data of the scout scan. Here, the positive sign for numerical value indicates overestimation (detected position outside the liver) of the error and the negative sign, underestimation (detected position inside the liver).

![Fig. 6. Kernel scan to detect the lower edge of the liver](image)

**Table.** Detection errors for lower and upper edges

<table>
<thead>
<tr>
<th>Error [mm]</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper edge</td>
<td>1.87</td>
<td>2.04</td>
<td>6</td>
<td>−3</td>
</tr>
<tr>
<td>Lower edge</td>
<td>−0.90</td>
<td>7.84</td>
<td>21</td>
<td>−15</td>
</tr>
</tbody>
</table>
the cross correlation method is used. The vertical blue line represents the boundary between the red and green crosses and is not used in the actual algorithm at this moment.

Figure 8 is a histogram of the error distribution for the lower edge, showing the peak shifted negatively. Five data showing error greater than 10 mm clearly demonstrate that the algorithm does not work properly. This means the same edges look like the true lower edge still remain even applying to our constraint (prior information).

Simulation of deformed liver

Figure 9 shows the results of applying the proposed algorithm to the simulated livers in the 2D coronal projection images. In Fig. 9(a, b), the larger left lobe than right represents deformation following surgery; in Fig. 9(c), a larger right lobe indicates liver enlargement. The dotted line shows the detected lower edge. Use of the proposed method permitted accurate detection of the lower edge, but the ASM (white line) could not because of the shape constraint on the model imposed by normal liver data.

Computational time was less than 10 s using an E4310 Dell laptop computer with Intel Core i5 2.4 GHz. The algorithm code was written using the Matlab version R2010a. Two-thirds of the computational time was spent on post-processing, applying the 3D median filter, generating projection images, and identifying the anchor point.

Discussion

In this article, we demonstrate the greater efficacy of our new algorithm for detecting the edge of the deformed liver than that of our previous method using the ASM. The new method does not limit liver shape to constrain lower edge detection and so provides superior detection to that using our previous ASM method (Fig. 9). In addition, because our MAP estimate does not require iterative calculations, computational time with the new method was less than 10 s even when the liver was deformed. In detecting the upper edge of the liver, a clear boundary between the lung and the liver yielded a much smaller standard deviation of the positioning error at the upper edge than the lower edge (Table). In Fig. 8, the shift to minus can be corrected by add-
Fig. 9.Detection results for the simulated deformed liver. (a, b) Simulation of a larger left lobe than right. (c) Simulation of a larger right lobe. Red marks are detected anchor points.

ing an offset. Particularly in the new technique for detecting the lower edge, there is a tendency to underestimate the detected position because the size of the small region (kernel) used for energy evaluation dominates the resolution of the detected edge. For instance, in principle, sharp edge detection is more difficult in a larger region, but the presence of outliers in a smaller region often yields incorrect energy estimation. Ideally, an iterative procedure, which reduces the region size by narrowing the scan range of the vertical line, will be appropriate (the outlier detection and exclusion are also necessarily in the small region). In usual 2D axial liver scans, a few slices are added to both the lower and upper edges to prevent the operator from scanning only part of the liver, and 7- to 8-mm thickness and one- to 2-mm spacing are commonly employed as the scan parameters for the axial planes. Therefore, the lower edge error may be acceptable because 2 missing slices are equivalent to 14 to 20 mm. By contrast, a thinner slice thickness in 3D volume scanning than 2D scan may yield less accurate detection. Furthermore, the current error in detecting the lower edge is comparable with respiratory motion length (S/I direction), so acquisition of a scout scan using this method requires breath holding to avoid respiratory motion effect. Consequently, performance of the proposed method is unsatisfactory for clinical use at this time.

A practical clinical algorithm requires implementation of a multi-slab technique, a detection algorithm that distinguishes the side of the liver with larger volume, more accurate detection of the lower edge using a smaller kernel iteratively within the allowed computational time, definition of the final specifications of the detection technique, and complete clinical evaluation to determine possible exemptions.

As mentioned, the coronal projection image, often called the slab, is constructed from a limited number of coronal slices to reduce blurring. The slab center is selected to correspond with the dome peak of the liver in the A/P direction. This single-slab technique may be appropriate for most normal volunteers but will not work for patients in whom the dome peak is shifted anteriorly. In those patients, a multi-slab technique will be required at the expense of greater computational time. Fortunately, because the algorithm for detecting the lower edge of the liver does not take most of parts in current computational time, the multi-slab technique can be applied using our method. The current algorithm works only for patients with greater right lobe volume. For those with a bigger left lobe, a detection algorithm is needed that distinguishes the largest lobe. More accurate detection of the lower
edge requires a smaller kernel for the iterative detection within the allowed computational time, which is less than 20 s in practical use. It is also important to fix the specification of the detection technique through testing a lot of patient scans with identifying which kind of disease will be a problem for our method. For instance, we assume that signal distribution is the same inside the scaled-down ROI as in the liver area outside the ROI. Therefore, in the case of a cyst the same size as the ROI or one that dominates most of the area inside the ROI and has different signal distribution, the assumption is not valid and lower edge detection may not work properly. Complete clinical evaluation is needed to establish optimal ROI setting or possible exemption for our method depending on the kind of hepatic disease.

Application of intensity correction, available commercially on scanners, to the original 3D volume dataset in the sequence can also improve edge detection. However, intensity correction requires the operator to acquire a calibration scan for reference data prior to the scout scan of this algorithm. This method of correction can help reduce artifacts arising from intensity changes without significantly degrading contrast, such as occurs from smoothing when low pass filtering, such as a homomorphic filter, is applied. The pixel value in the measured ROI approaches the true mean value of the entire liver, and there is less variance, a particular advantage of the new method because edge detection accuracy has been observed to depend strongly on anchor point location. Application of such intensity correction can render dependency on the anchor point location insensitive.

Clinical evaluation is needed to assess actual workflow improvement. Our method increases total examination time by 17 s for the scout scan, but the automated prescription feature decreases scanner operator work time. Workflow can also be reduced by reformatting the volume dataset acquired from our scout scan to make 3 plane images equivalent to those of the usual scout scan; in that case, the images in the volume dataset have sufficient spatial resolution and contrast for use as 3-plane images.

Both respiratory and cardiac motion affect the quality of abdominal MR scan images. We assume acquisition of our scout scan under breath holding and acquisition of successive scans. However, during actual acquisition, reproduction of liver position is highly dependent on the patient’s respiration control rather than breath holding. Slice tracking is helpful in reproducing slice alignment independent of patient respiration control, employing navigator echoes to detect the upper edge of the liver at every TR or the last position of the upper edge just before breath holding scan starts and then changing the location of axial slice to obtain identical slice position to previous one. Sagittal and coronal images for setting a navigator tracker can be obtained by reformatting the same 3D scout dataset. Accordingly, combining our method with slice tracking will be more practical for clinical use.

Our method has 2 major limitations. One is the partial volume effect associated with measurement accuracy in detecting both edges. The manual identification of the lower and upper edges of the liver used spatial resolution of \(1.5625 \times 1.5625 \times 3 \text{ mm}^3\) in the 3D dataset, which limited identification by 3 mm in the S/I direction, so some partial volume effect may remain. Thus, the error in detection of the upper edge in Table is not extremely accurate but should still be better than that for the lower edge. Still, the error in detecting the lower edge is more than twice 3 mm and, so, did not reach a level comparable to the partial volume effect and was much worse than detection of the upper edge.

Our study is also limited because we tested our method using only data from volunteers. Its clinical usefulness requires clinical testing. Particularly, actual clinical data of deformed livers will aid understanding of how the approach works properly in these patients. We must also evaluate how our approach contributes to improve work flow in practical use.

Conclusion

We proposed a new algorithm for automated scan prescription in MR imaging of the liver and demonstrated its efficacy for assessing deformed livers within practical computation time. Detection of liver edges of various shapes by combining MAP estimate with statistical information from an ROI indicated the technique’s potential clinical utility. Future work will include modifications to vary the size of the region iteratively for MAP estimate to improve accuracy of our automated scan prescription.

References