In the future we plan to increase the robustness and global speed of the method and further automate several tasks to make the process as simple as possible for the final user. Finally, the segmentation and analysis algorithms must be evaluated and validated by clinicians.

Anatomical feature extraction in 3D B-mode ultrasound images for CT-ultrasound image registration

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Keywords Vessel extraction, Diaphragm extraction, CT-US liver image registration

Purpose
In the CT and ultrasound (US) liver image registration, vessels and diaphragm can be considered useful anatomical features. The anatomical feature extraction is essential for the registration accuracy. Unfortunately, 3D B-mode US images of the liver include obstacles to feature extraction such as speckle noise [1], mirroring artifacts, shading artifacts [2], and existence of other organs in the region of interest. In this paper, we suggest to use both vessels and diaphragm for liver image registration and propose a novel vessel and diaphragm extraction method which is robust to those obstacles. After speckle noise filtering, the proposed method performs ROI masking, segmentation, and classification for vessel extraction; and flatness test and refinement for diaphragm extraction, respectively. We prove that the proposed method provides prospective results on the two data sets of 3D B-mode US image. We also demonstrate a pair of 3D CT and US images that the extracted vessels and diaphragm can provide satisfactory affine registration.

Method
Prior to the anatomical feature extraction from a 3D B-mode US image, we first apply the total variation based speckle constraint filtering algorithm combined with an anisotropic diffusion [3], in order to remove the speckle noise and enhance the feature definition. We then initially extract the diaphragm using a Hessian based method. We also extract vessels through vessel segmentation followed by classification. To remove unwanted segments in the diaphragm segmentation, we refine the extracted diaphragm region by using the already extracted vessel information. The proposed segmentation is described in detail in the following.

Diaphragm extraction

Diaphragm in a 3D B-mode US image of the liver can be considered a curved surface. It is easily observed that the intensity variation along the normal direction of the surface is much higher than the one along its tangential direction. Based on this observation, we develop a Hessian based diaphragm extraction method. In the method, we first get a flatness map for all voxels by using the proposed flatness metric, $\mu(v)$. Here, $\mu(v) = \phi_1(v)\phi_2(v)\phi_3(v)/\phi_3(\mu(v))$, $0 \leq \mu(v) \leq 1$, where $\phi_1(v) = (1-\lambda_2(v))/\lambda_3(v)$, $\phi_2(v) = (1-\lambda_2(v))/\lambda_3(v)$, and $\phi_3(v) = \sum_i \lambda_i(v)$, $\lambda_1(v), \lambda_2(v), \text{and } \lambda_3(v)$ denote eigenvalues of the Hessian matrix at voxel $v$. We then select the voxels having a relatively high flatness value, and remove small clutters by morphological opening. Since the diaphragm represents the largest surface in the liver area, the largest surface is selected among the candidates obtained by the intensity-based connected component analysis (CCA), and regarded as the diaphragm. Finally, we smoothen the surface boundaries.

Vessel extraction

For robust and accurate extraction of vessels against the obstacles, the proposed algorithm consists of two steps, vessel segmentation and classification. The former is to obtain vessel candidates and the latter is to classify only true vessels among the vessel candidates by removing non-vessel-type clutters. The vessel segmentation is performed as follows. To avoid the mis-extraction of vessels due to mirroring artifacts, we apply ROI masking method by modelling the diaphragm as a quadratic curved surface and eliminating the region under the surface with a marginal distance. To exclude non-vessel high intensity regions such as diaphragm and vessel walls, we first estimate the low intensity bound of those regions in the ROI masked image and remove voxels with a higher intensity than the bound. The remaining regions are then binarized by applying the adaptive thresholding scheme [4], and the binary segments are labelled as vessel candidates. In the vessel classification step, we first filter out tiny background clutters through the size test. Then, we initially eliminate non-vessel type clutters through the structure-based vesselsness test [5], which evaluates the goodness of fit (GOF) to a cylindrical tube. In this test, threshold $T_{\text{initial}}$ is marginally set so that...
all vessels may be included even if some clutters are not rejected. Clutters among the vessel candidates are then perfectly removed by the proposed gradient magnitude based vesselness test. The proposed test is based on the observation that clutters formed due to shading artifacts have a low gradient magnitude in average. We get an average gradient magnitude map for the initially extracted vessel regions by using the eigen-analysis of the structure matrix, and then remove clutters and remain vessels by thresholding the magnitudes.

**Diaphragm refinement**

In the diaphragm region extracted above, clutters are mainly located near vessel walls. In particular, the vessel wall of inferior vena cava (IVC) is more likely to be connected to the diaphragm and it causes clutters. Since those clutters may degrade the accuracy of feature based registration, we need to refine the obtained diaphragm by removing them. For refinement, we first estimate vessel walls by dilating the initially obtained vessel regions and subtracting the walls removing them. For refinement, we first estimate vessel walls by dilating the initially obtained vessel regions and subtracting the walls.

**Experimental results**

To test the proposed anatomical extraction method, we apply the scheme to two 3D B-mode US data A and B, which are acquired using the Accuvix XQ of Medison. The image dimensions are 200x200x200 for data A and 200x188x168 for data B with the isotropic voxel resolution of 0.8 and 0.6 mm, respectively. Fig. 1 demonstrates that the proposed method successfully extracts the diaphragm and vessels for both datasets. Note that a clutter in a red circle in Fig. 1(a), which is connected to the initially extracted diaphragm region, is successfully removed by the proposed refinement scheme. In vessel extraction, threshold values for the initial and final vesselness test, $\theta_{\text{initial}}$ and $\theta_{\text{final}}$, are set to 0.6 and 0.4, respectively. We can note in Table 1 that clutters remained in the initial vesselness test result are perfectly removed by applying the final vesselness test based on gradient magnitudes. To demonstrate the usefulness of the proposed extraction method, we apply the anatomical features extracted from data A to 3D CT-US affine registration. The adopted registration algorithm is almost the same as the one proposed in [5], except that diaphragm as well as vessels are used. Figure 2 shows that the registration is successful.

**Conclusion**

This paper proposes an anatomical feature extraction method in a 3D B-mode US image of the liver. The proposed method provides robust anatomical feature extraction against obstacles such as speckle noise, mirroring artifacts, shading artifacts, and existence of other organs in the ROI, which are typical in 3D B-mode US images of the liver. Experimental results show that the performance of the proposed feature extraction method is prospective and a result of 3D CT and US affine registration using the extracted features is also satisfactory.

**References**


**Table 1** Vesselness test based on gradient magnitude. Candidates with a bold character are selected as true vessel segment through thresholding

<table>
<thead>
<tr>
<th>Candidates</th>
<th>$C_{\text{initial}}$</th>
<th>$C_{\text{final}}$</th>
<th>Candidates</th>
<th>$C_{\text{initial}}$</th>
<th>$C_{\text{final}}$</th>
<th>Candidates</th>
<th>$C_{\text{initial}}$</th>
<th>$C_{\text{final}}$</th>
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<td>0.98</td>
<td>a</td>
<td>0.79</td>
<td>0.98</td>
<td>f</td>
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<tr>
<td>b</td>
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<td>0.92</td>
<td>b</td>
<td>0.71</td>
<td>0.90</td>
<td>g</td>
<td>0.82</td>
<td>0.27</td>
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<tr>
<td>c</td>
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<td>0.61</td>
<td>c</td>
<td>0.60</td>
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<td>h</td>
<td>0.74</td>
<td>0.27</td>
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<tr>
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<td>d</td>
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<td>0.64</td>
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<tr>
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</tbody>
</table>

**Quantitative evaluation of intensity inhomogeneity correction algorithms for Multiple Sclerosis**

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**Keywords** MRI, Multiple Sclerosis, Inhomogeneity Correction

**Purpose**

Magnetic Resonance Imaging (MRI) is a highly sensitive marker for Multiple Sclerosis (MS) and the potential of its automatic segmentation of normal appearing brain tissues (NABT) and MS lesions is promising for quantitative analysis of large amounts of MRI images. The intensity inhomogeneity (IIH) in MRI is a slow spatial variation of image intensity unrelated to the anatomic information. This variation is due to several factors, most notably the non-uniformity of the magnetic field B0, and can significantly reduce the accuracy, robustness and precision of automated image processing algorithms, and in particular tissue segmentation.

In this work, the objective is to compare different methods of IIH correction in order to build an optimised workflow for NABT and MS lesions automated segmentation that is robust for different protocols or MR scanners.

**Methods**

Many algorithms have been developed for the IIH correction, but only few comparisons among algorithms have been done. The main