Graph-based surface extraction of the liver using locally adaptive priors for multimodal interventional image registration


Abstract

The 3D fusion of tracked ultrasound with a diagnostic CT image has multiple benefits in a variety of interventional applications for oncology. Still, manual registration is a considerable drawback to the clinical workflow and hinders the widespread clinical adoption of this technique. In this paper, we propose a method to allow for an image-based automated registration, aligning multimodal images of the liver. We adopt a model-based approach that rigidly matches segmented liver shapes from ultrasound (U/S) and diagnostic CT imaging. Towards this end, a novel method which combines a dynamic region-growing method with a graph-based segmentation framework is introduced to address the challenging problem of liver segmentation from U/S. The method is able to extract liver boundary from U/S images after a partial surface is generated near the principal vector from an electromagnetically tracked U/S liver sweep. The liver boundary is subsequently expanded by modeling the problem as a graph-cut minimization scheme, where cost functions used to detect optimal surface topology are determined from adaptive priors of neighboring surface points. This allows including boundaries affected by shadow areas by compensating for varying levels of contrast. The segmentation of the liver surface is performed in 3D space for increased accuracy and robustness. The method was evaluated in a study involving 8 patients undergoing biopsy or radiofrequency ablation of the liver, yielding promising surface segmentation results based on ground-truth comparison. The proposed extended segmentation technique improved the fiducial landmark registration error compared to a point-based registration (7.2mm vs. 10.2mm on average, respectively), while yielding a statistically insignificant differences in tumor target registration error ($p > 0.05$) compared to state-of-the-art methods.

Description of purpose

Needle-based interventional procedures such as biopsy and image-guided ablative techniques are common clinical procedures for diagnosis and treatment of malignant or potentially malignant lesions in the liver or soft-tissues. These are usually guided by ultrasound (U/S), and fused with computed tomography (CT) and/or magnetic resonance (MR) imaging based on the identified tumor location using an electromagnetic (EM) tracking system [1]. The automated registration of these different modalities is an important component to allow for a streamlined clinical workflow [2].

A surface-based approach which relies on segmented liver shapes registered with a weighted iterative closest point (ICP) algorithm is presented in this work. However for the specific case of liver boundary segmentation from U/S images, varying contrast levels between different regions within the liver makes the surface extraction a challenging problem for interventional applications. This can be due to tissue inhomogeneities, rib shadowing artifacts and limited field of view caused by narrow acoustic windows between ribs. The difficulty in boundary segmentation may reduce the accuracy of the procedures, which in turn results in poor therapeutic outcomes. Various methods were proposed for surface detection in volumetric images using for example graph-minimization approaches [3],[4]. Still, inter- and intra-patient variations in the boundaries intensity appearance make the surface detection very difficult when empirically determined feature properties are assigned to cost functions.

The objective of this work is to develop an automated liver registration procedure anchored on a patient-specific liver surface extraction from U/S imaging which is robust towards varying levels of contrast, dropped signal in the image and shadowing effects due to rib occlusion. The proposed method does not rely on a static prior shape model given the high variability in liver shape from patient to patient. The method performs a local analysis of the tissue intensities to segment an initial section of the diaphragm and extracts the internal
surface proximal to the transducer. Based on the obtained surface shape, a graph-cut approach is then used to detect additional surface points. Local neighboring transitions in intensity between internal tissue and diaphragm are used as priors to ultimately determine cost functions assigned to optimal surface boundaries. The use of locally adaptive priors for guidance enables reasonable estimate of the missing liver boundary in shadow areas.

Methods
The workflow for the procedure is illustrated in Fig. 1. The inputs to this method include a diagnostic CT dataset and a sequence of tracked ultrasound images obtained from a liver sweep at a probe position denoted as \( p_{US} \). The output is a rigid transformation enabling fused CT images with ultrasound frames.

Pre-processing of the diagnostic CT image
Prior to the image-guided intervention, the pre-operative or intra-procedural CT image volume is automatically segmented to obtain a 3D shape model of the liver. The process generates a triangulated liver surface model \( S_{CTliver} \), as shown in Fig. 1. The same prior CT image is then processed to extract the skin surface \( S_{CTskin} \) employed by the registration scheme to constrain the search space and enable initialization of the registration matrix.

Graph-based U/S liver surface extraction
From an input 3D U/S volume \( I(x,y,z) \) of the liver, a confidence-based region growing method initialized with an automatically determined seed located inside the diaphragm region is first used to obtain a baseline surface of the liver \( s.t. I(X) \in [\mu-f\sigma,\mu+f\sigma] \) by iteratively adjusting the mean and standard-deviation based on a multiplicative factor \( f \). We automatically compute \( f \) to generate the optimal surface segmentation, which detects the factor of \( f \) causing the segmentation to propagate inside the liver tissue based on a pre-defined surface thickness \( t_{thick} \) while achieving optimal surface coverage. An inner layer surface extraction method was developed as a subsequent step to obtain a thin surface area of the liver capsule \( S_{USliver} \).

By representing the segmented surface \( S_{USliver} \) as a terrain-like structure, a node-weighted directed graph \( G = (V, E) \) is constructed to propagate and expand the surface, where every node \( V(x,y,z) \in V \) represents one and only one voxel in \( I(x,y,z) \) s.t. \( V(x,y,z) \notin S_{USliver} \), each associated with a cost \( c(x,y,z) \). The cost \( c(x,y,z) \) assigned to the image voxel \( I(x,y,z) \) can be constructed by minimizing the difference in intensities inside and outside the boundary based on the local \( a \ priori \) measures adapted to the neighborhood \( N \) of segmented surface points:

\[
c(x,y,z) = \sum_{z \in C} (I(x,y,z') - \eta_1)^2 + \sum_{z \in C} (I(x,y,z') - \eta_2)^2
\]

(1)

where \( \eta_1 \) and \( \eta_2 \) are the mean intensities below and above the liver surface computed in \( N \) such that:

![Flowchart of the system’s inputs and processes.](Image)
\[ \eta_1 = \frac{1}{n_1} \sum_{V(x,y,z) \in N} I(x,y,z) ; \eta_2 = \frac{1}{n_2} \sum_{V(x,y,z) \in \bar{N}} I(x,y,z) \]

with \( n_1 \) and \( n_2 \) being the counted number of segmented surface points in \( N \) surrounding \( V(x,y,z) \) above and below the liver surface respectively. Hence, the graph cut-minimization procedure is achieved by maximizing the similarity of new segmented surface point with intensity-based priors adapted in the local region of a search point.

**Weighted ICP-constrained registration**

A reliable starting point is crucial for avoiding local minima and restricting the search space to anatomically feasible solutions. We propose an approach which uses the tracked U/S probe as a scan plane selector at any location near the midline of the sternum \( (p_{\text{mid}}) \), thus allowing the tracking data to be used to estimate translation and rotation parameters. The minimization term follows an anisotropic weighted ICP objective function in a \( k \)-iterative process, constrained by penalizing potential transformation candidates \( (R \) and \( t) \) which map probe positions further away from skin surface:

\[
E^k = \arg \min_{T \in \text{trans-ct}} \sum_{i \in \text{ptcs}} \left\| W_i^k \left( R p_i^k + t - q_i^k \right) \cdot n_i^k \right\|^2 + \sum_{j \in \text{ct}^k} \Psi \left( R_{CT}^k, R_{US}^k \right) + \phi \left( T, p_{US,init}^k, S_{CTskin} \right)
\]

where the first term minimizes the alignment of both CT \( (q_i) \) and U/S \( (p_i) \) point sets. We account for non-corresponding surface points using the anisotropic distribution \( W_i^k \). We incorporate regional \( (R_{CT,US}) \) salient statistics as a second data-related similarity term \( \Psi \) in Eq.(3). Finally, a cost assigning function \( \Phi \) is linked to the transformation applied to the U/S sweep and midline probe locations \( (p_{US,init}) \). This prevents the EM tracked probe positions acquired on the patient's skin from being mapped further away from surface \( S_{CTskin} \).

**Results**

A study on abdominal data from a cohort of 8 patients was conducted in order to evaluate the performance of the registration algorithm in a clinical context. The clinical trial was approved by the institutional investigational review board at our institution, and all patients gave written informed consent. The mean age of the patient population was of 51.8 years ± 17.4. Patients who had one or more malignant or suspicious lesions which were not previously treated were included. The CT scans (3-mm thick sections, 1.5-mm overlap) were obtained in a supine position with a 256-slice CT scanner (Brilliance iCT, Philips Healthcare, Cleveland, Ohio). IU-22 scanners (Philips Healthcare, Andover, MA) were used for U/S acquisitions.

The U/S surface extraction method was tested with increasing levels of electronic noise added to the data. Comparison to expert determined ground-truth liver surface (with no noise) shows root-mean-square (RMS) surface-to-surface distances as shown in Fig. 2(a), demonstrating the accuracy and robustness of the surface extraction technique with errors under 0.7mm. We also evaluated the amount of additional surface segmentation provided by the graph-based approach using locally adaptive priors. On average, an increase in geometrical extent of the liver surface of 41% was achieved from the patient cases (range 12 – 87%).

![Fig. 2 – (a) Accuracy of the U/S surface extraction compared to ground truth. (b) Sample results from the graph-based liver surface extraction using locally adaptive priors (blue). In green the baseline surface.](image)
The proposed new algorithm correctly registers without any manual interaction in all cases and outperforms a skin marker-based registration approach in 75% of cases [1], with an average landmark registration error (LRE) of 7.2 mm compared to 10.2 mm with the alternative workflow (Table 1). The target registration error (TRE) based on tumor location was of 6.9 ± 4.1 mm and 6.8 ± 5.3 mm with the fiducial-based method. Fig. 3 illustrates the results with side-by-side U/S and corresponding CT slices. In terms of registration accuracy improvement, adding the graph-cut component to the segmentation phase lowered the LRE by 1.5 mm.

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Table 1 – Quantitative results comparing accuracy between fiducial skin marker registration method and the automatic registration. Both anatomical landmark registration errors (LRE) and tumor target registration errors (TRE), identified on U/S and CT images are reported.

Fig. 3 – Qualitative results of the liver registration in 2 patients, with side-by-side U/S and CT images.

**Conclusion**

An automated registration method aligning ultrasound with prior diagnostic images based on surface shape matching is described, thus enabling image fusion in the context of interventional procedures of the liver. Our main contribution lies in developing a robust liver surface extraction technique using dynamic region growing which adapts to varying image contrast, combined with a graph-based segmentation framework with cost functions locally adapted from neighboring priors. Results show an improvement in anatomical fiducial registration error and target registration accuracy based on landmark and tumor locations. Respiratory compensation and deformable registration techniques are crucial factors which may explain the residual errors observed in these experiments, and are issues which will be addressed in future work.

**References**


This work has not been presented elsewhere in form of journal or conference presentation.