A Novel Method for Registration of US/MR of the Liver Based on the Analysis of US Dynamics

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Abstract. Radiofrequency ablation of liver cancer is a minimally invasive alternative to open surgery. Typically, the preoperative planning is done on an MR (or CT) scan, while the intervention relies on ultrasound (US) guidance. Registration of intra-operative US and preoperative MR (or CT) would assist navigation and increase the confidence of RFA needle positioning. In this paper we present a novel method for registration of US and MR images of the liver. Hepatic vessels are extracted from 2D US by an algorithm that models US dynamics. It generates 2D probability maps representing hepatic vessels which are then combined into probability volumes. A multi-resolution registration framework performs registration of the pre-processed MR with two 3D vessel probability images. The accuracy, robustness and speed of the method were assessed by registering eight US/MR datasets. High robustness (86%) and reasonable accuracy (1.98°, 4.10mm), acceptable for the RFA clinical application, suggest that the method has a good potential for intra-operative use.

1 Introduction

Minimally invasive therapy is an increasingly important alternative to open interventions. Radiofrequency ablation (RFA) of liver cancer is a minimally invasive procedure that can be an alternative to surgery for inoperable tumors or can be combined with surgery in complex cases. An important step of the RFA treatment is insertion of an RF needle into the tumor. Typically, the insertion is performed under ultrasound (US) image guidance. However, US often produces images of poor quality for this task and can fail in depicting small lesions. MR and CT are complementary to US and can often image tumors missed by ultrasound as well as provide high resolution and high contrast image with a large field of view. By registering the preoperative images and the intra-operative US, it would be possible and clinically useful to include the visualization of such lesions to aid with accurate positioning of the needle.

The fusion of abdominal US and MR (or CT) images was a field of active research during the last decade. The problem is particularly complex due to fundamentally different physics involved in these imaging modalities. One strategy

is to model the US from the MR (or CT) and register the real and simulated US images. In [1], Wein et al. developed a technique for simulating US from CT/CTA scans. The method is based on the empirical mapping between CT/CTA and US intensities, and modeling of US-wave propagation. A linear combination of the two was used to achieve the registration by optimizing an NCC-like similarity metric. The results are reported for the freehand 3D US and CTA datasets only. Roche et al. [2] utilized MR intensity and gradient information to simulate US images of the brain. Their Bivariate Correlation Ratio (BCR) similarity metric is based on consecutive optimization of a rigid transformation and simulated US.

To overcome the absence of functional dependency between MR (or CT) and US image intensities, another strategy is to map the datasets to an alternative, typically non-intensity, space - and register images in that space. In [3], Mellor and Brady generated local phase images from intensity US/MR and registered them using Mutual Information [4,5]. The method was only demonstrated on simulated brain US. Blackall et al. [6] produced probabilistic maps from US and MR images of the liver, where each pixel was assigned with a probability of belonging to the hepatic vessel tree. A registration of the two probabilistic representations was achieved by the Cross Correlation metric.

Recently, Milko et al. [7] reported a method for segmentation of liver US. The method differentiates between several anatomical structures, such as liver parenchyma and hepatic vessels. Importantly, the method analyzes not only the static US intensity, but also the dependency of pixel intensity on time. Authors demonstrated that modeling of time-dependent appearance of US has a clear benefit over pure intensity based segmentation approach. A preliminary investigation of method's feasibility for US/MR registration was introduced in [8]. However, only one pair of US/MR images was registered; no quantitative assessment of the registration was reported.

Motivated by the results in [7,8] and focused on the RFA application, we present a novel method for registration of preoperative MR to intra-operative liver US. The method is a significant advance over the ideas presented in [8]. It combines the analysis of US dynamics developed in [7] with a volume reconstruction algorithm and a multi-resolution registration framework. Namely, the information extracted from spatially tracked 2D US images is combined into a 3D volume that is registered with preoperative RFA planning. The accuracy, robustness and speed of the method were assessed on eight US/MR datasets.

2 Methods

2.1 Dynamic Texture Based Analysis of US

An excellent introduction to dynamic texture analysis for general computer vision is given in [9]. Its application to segmentation of liver US is reported in [7]. Here, we give a concise outline of the method from [7] focusing on the image registration problem. Let $\{I(t)|t = 1..\tau\}$, $I(t) \in R^m$ be a sequence of images. We call $\{I(t)\}$ a (*linear*) *dynamic texture* if it can be described by the system of two equations

$$\begin{cases} \bar{x}(t) = \sum_{i=1}^k A_i \bar{x}(t-i) + B\nu(t) \\ I(t) = \phi(\bar{x}(t)) + w(t) . \end{cases} \quad (1)$$

Here, $\bar{x}(t) \in R^n$ is a *state variable*. Its value at time point t linearly depends on previous k values, matrices $A_i \in R^{n \times n}, i = 1..k, B \in R^{n \times l}$ and a known independent and identically distributed (*IID*) sequence $\nu(t) \in R^l$. The equation for $I(t)$ involves a spatial filter $\phi : R^n \rightarrow R^m$ and another known *IID* sequence $w(t) \in R^m$. Following [7], we reduce (1) to a single equation describing the dynamics of individual US pixels. We consider the intensity function at each pixel p as a state variable $x_p(t) \in R^1$. Then $\{x_p(t)|t = 1..\tau\}$ is a time series - a sequence of 1D observations. By setting ϕ to identity transformation and all dimensions l, m, n to 1, the equation (1) can be reduced to

$$x_p(t) = A_1 x_p(t-1) + A_2 x_p(t-2) + \dots + A_k x_p(t-k) + Bu(t) . \quad (2)$$

Equation (2) describes an *Auto Regressive (AR) process* characterized by linear coefficients $\{A_i, i = 1..k\}$ and B , and a residual noise $u(t)$. Respecting different assumptions regarding the type of noise for the US analysis, such as additive Gaussian [7] or multiplicative Rayleigh [10], we model $u(t)$ as a Gaussian with zero mean and unit variance due to its simplicity. Using least squares fitting, one can estimate the order k , coefficients $\{A_i, i = 1..k\}$ and B , that best explain the measurements $\{x_p(t)\}$. This was done by Schneider and Neumaier's **ARfit** algorithm [11].

In [7,8], a maximum a-posteriori (MAP) classifier was used to label each pixel with a tissue class, such as liver parenchyma or hepatic vessel, based on average (over time) pixel intensity and linear coefficients $\{A_i\}$ and B attributed to the pixel. As opposed to such “hard” classification, our method adopts a “soft” labeling where each pixel is assigned a probability of belonging to a certain tissue class. As described in [7], the probabilities were computed by a supervised MAP-classifier for liver parenchyma, hepatic and external (w.r.t. liver) vessels. Note, that hepatic- and external vessels can be separated by the level of “noisiness” (term B in (2)) and average pixel intensity. These two classes of vessels were identified as a basis for registration. To summarize: by analyzing a sequence of 2D US images acquired with a stationary held probe, we computed two probability maps - each reflecting the probability of US pixels to belong to one of the two vessel classes.

2.2 Reconstruction of Probability Volumes

The previous section outlined the analysis of a sequence of 2D images acquired with stationary US transducer. A number of such sequences were recorded, each producing two 2D probability maps for the two identified classes of vessels. Sequence acquisitions were performed at different positions of the probe covering a significant portion of the liver. The imaging planes were largely parallel, 2–3mm apart.

A median position and orientation of each US sequence was calculated based on the recordings of a magnetic tracking sensor attached to the probe. This spatial information was attributed to the 2D probability maps that were then weighted and combined into two probability volumes corresponding to two classes of vessels. Values of the 2D probability maps were weighted according to their geometrical position on the US image. A considerable area around the center of the US image was assigned the weight 1. The weights of pixels located further from the border of this area and towards the US edges gradually decrease to 0. This reflects higher confidence in structures observed in the center of the US image as opposed to boundaries (see Discussions). Probability values were multiplied with their weights and passed to the reconstruction step.

Each reconstruction was done by traversing a set of 2D probability maps twice. On the first traversal, a minimal bounding box containing the entire examined anatomy was determined. It was divided into a uniform grid with isotropic voxels having a resolution of 0.6mm. For all voxels, the probability and hit-counter values were initially assigned to zero. On the second traversal, probabilities were accumulated in a 3D volume. For each pixel p of the weighted 2D probability map a closest voxel v was determined based on the tracking and calibration data. The probability value of the voxel PR_v was updated and a hit-counter HC_v - incremented according to

$$PR_v := \frac{HC_v \times PR_v + PR_p}{HC_v + 1}; \quad HC_v := HC_v + 1$$

where PR_p is the probability value of the pixel p .

To avoid gaps in the reconstructed volume, we assume that 2D probability maps have a non-zero thickness, which grows linearly as we move further from the head of the transducer. Thus, a 2D probability map is considered as a 3D “wedge” in the reconstructed volume and contributes to the intensity of all the voxels it intersects. The wedge thickness was assigned to 1.75mm close to the transducer head and to 3.15mm at the opposite end. These values were derived empirically by visually inspecting the reconstructed volumes. Voxels having zero hit-counter ($HC_v = 0$) were excluded from the registration.

2.3 Registration

A proposed registration method operates with three 3D images: two reconstructed probability volumes corresponding to hepatic- and external vasculature, and a preprocessed MR scan. Note that probability volumes were reconstructed in the same coordinate space and are, therefore, registered. A preprocessing step for MR involves semi-automatic segmentation of major hepatic vessels as well as inferior vena cava and gallbladder. These two anatomical structures are typically visible on intra-operative US and have appearance similar to hepatic vessels. A volume produced on the MR preprocessing step is a binary mask containing ones in voxels belonging to the segmented structures and zeros elsewhere.

To define a formula for the registration metric, we introduce a general registration framework. Given a reference image I and a template image J , we look

for the rigid transformation T , which optimizes some similarity metric S . By x_k we denote the voxels of I . Then $i_k \equiv I(x_k)$ is an intensity value of I at x_k . Similarly, $j_k^\downarrow \equiv J(T(x_k))$, where the arrow $\downarrow$ marks the dependency on T . The position returned by $T(x_k)$ does not generally coincide with the voxel grid of J . Therefore, interpolation between the neighbour voxels of J is necessary. A partial volume (PV) interpolation was used as a tradeoff between speed and accuracy [2].

We chose a preprocessed MR image as a template (J) to respect the clinical context: registration of the pre-operative planning to the intra-operative US scan. Hence, a reference I is a vector image incorporating two probability volumes, and i_k consists of two components $i_k[hep]$ and $i_k[ext]$ representing probabilities of hepatic- and external vessel classes. A similarity metric can be defined as

$$S(T) = \sum_{x_k \in I^\downarrow} (ai_k[hep] + bi_k[ext])j_k^\downarrow, \quad (3)$$

where $a, b \in [0..1]$ are linear coefficients reflecting the importance of two vessel classes for registration. Their values were chosen empirically as $a = 1$, $b = 0.5$ based on the observation explained in Discussions.

The similarity metric was maximized by the Powell optimization method. A multi-resolution registration framework was implemented. First, the images down-sampled to 30% of their original extent were registered. The obtained transformation was used to initialize the registration on the next step, where the registration of images down-sampled to 60% of the original dimension occurred. Finally, the original images were registered starting with the transformation computed on step two. We observed that registration of the original images improved the transformation only marginally, whereas its computational time was intense due to large dimensionality of datasets. Therefore, registrations for the first two resolutions only were used for numerical evaluation of the method.

The accuracy, robustness and speed of the method were assessed by registering eight pairs of 3D US/MR datasets. Each dataset consisted of three images: a preprocessed MR volume and two reconstructed probability volumes for liver US. ‘‘Ground truth’’ transformations were achieved manually by an expert registering the MR and reconstructed 3D US images. For this purpose, US volumes were reconstructed from the tracked 2D images by the algorithm described in the previous section.

We generated 200 perturbations from the ground truth by adding random rotations $\xi_r = (\xi_r^x, \xi_r^y, \xi_r^z)$ and translations $\xi_t = (\xi_t^x, \xi_t^y, \xi_t^z)$. The vectors ξ_r and ξ_t were chosen with random orientation, but constant magnitude: $\|\xi_r\| = 10^\circ$ and $\|\xi_t\| = 10\text{mm}$. A total of $8 \times 200 = 1600$ automatic registrations were performed starting from perturbed initializations.

An automatic registration $R = \{\bar{\theta}, \bar{t}\} = \{\overline{(\theta_x, \theta_y, \theta_z)}, \overline{(t_x, t_y, t_z)}\}$ was considered *successful* if $\|\bar{\theta} - \bar{\theta}^*\| < \Delta\theta$ and $\|\bar{t} - \bar{t}^*\| < \Delta t$, where $R^* = \{\bar{\theta}^*, \bar{t}^*\}$ is a corresponding ground truth registration. The values for $\Delta\theta$ and Δt were chosen as 3° and 6mm respectively to reflect the suitability for the RFA application.

The accuracy was measured on successful registrations achieved for each US/MR pair. Two errors were computed for every successful automatic registration $R = \{\bar{\theta}, \bar{t}\}$ as: $\delta_\theta = \|\bar{\theta} - \bar{\theta}^*\|$ and $\delta_t = \|\bar{t} - \bar{t}^*\|$. The mean $(\delta_\theta^{mean}, \delta_t^{mean})$ and median $(\delta_\theta^{median}, \delta_t^{median})$ rotation and translation errors were then calculated across all successful automatic registrations of each US/MR pair. The robustness was estimated as a percentage of successful registrations achieved by the method.

3 Results

Table 1 shows the robustness, accuracy, and speed of the registration method tested on eight pairs of US/MR images. Recall that 200 registrations were performed for each image pair. Therefore, a success rate of 0.5% refers to a single successful registration. Mean $(\delta_\theta^{mean}, \delta_t^{mean})$ and median $(\delta_\theta^{median}, \delta_t^{median})$ errors were computed on successful registrations only.

Table 1. Accuracy, robustness and speed for registering eight US/MR datasets. Note, that $(\delta_\theta^{mean}, \delta_t^{mean})$ and $(\delta_\theta^{median}, \delta_t^{median})$ errors were computed on successful registrations only. Robustness was measured as a success rate (%). The value 0.5% corresponds to one registration out of two hundred.

Dataset	$\delta_\theta^{mean}, ^\circ$	δ_t^{mean}, mm	$\delta_\theta^{median}, ^\circ$	δ_t^{median}, mm	Time, sec	Success rate, %
1	1.16	5.27	1.16	5.27	569	81.0
2	2.75	5.78	2.75	5.77	473	87.0
3	2.05	3.40	2.05	3.39	425	87.5
4	1.39	3.47	1.37	3.43	467	86.0
5	1.67	5.02	1.66	4.99	508	81.5
6	2.89	4.60	2.89	4.60	592	87.0
7	2.11	3.36	2.11	3.36	536	83.0
8	1.73	2.13	1.73	2.14	346	92.0
Avg. across all	1.98	4.10	2.01	3.47	525	86.0

Fig. 1. Registration of the US/MR datasets: a - original MR; b - reconstructed 3D US; c - probability volume corresponding to hepatic vessels

An example of successfully registered US/MR images of the liver is presented on fig. 1, where cross sections through the original US/MR and a probability volume corresponding to hepatic vessels are shown.

4 Discussion and Conclusion

Table 1 demonstrates that the proposed registration method has a good potential for the RFA clinical application due to its high robustness (86%) and acceptable rotation (1.98°) and translation (4.10mm) errors, averaged across all 1600 registrations. The method is somewhat similar to the algorithm proposed in [6], where manually segmented MR was registered to a sparse set of 2D vessel probability maps computed on the US intensity. We believe that our approach has several advantages. Modeling the dynamics of liver US enables capturing higher number of hepatic vessels and external (w.r.t. liver) vascular structures than the analysis of static US intensity only [7]. This statement is particularly valid for vessels distant from the US probe that have average (over time) intensity similar to the adjacent liver parenchyma. The reconstruction of 3D probability images from a set of 2D probability maps is beneficial as it compensates for re-occurrences of the same anatomy on more than one 2D image. Indeed, since the US acquisition was performed with a hand held probe with relatively small distance between imaging planes (2–3mm), their intersection often occurred. If a sparse set of 2D probability maps was used, re-occurring vessels would influence the registration more than vessels encountered only once.

Multi-resolution registration framework is a popular choice when the similarity metric is not sensitive to down-sampling of the registered images. This holds for the proposed metric computed on US probability volumes and a preprocessed MR. Computational efficiency achieved by the multi-resolution approach makes it attractive for intra-operative use.

The major limitation of our method, as well as the method described in [6], is a necessity for manual preprocessing of the MR. However, it is mitigated by the RFA application - a clinical context of both studies. A preoperative planning for the RFA often includes delineation of critical structures, such as tumors and large adjacent vessels, on the MR. Availability of this information can make the registration method fully automatic. The algorithm does not compensate for non-rigid deformations and is, therefore, sensitive to breathing. The RFA treatment is typically conducted under general anesthesia. It is a common practice to suspend subject's breathing during the needle insertion phase. Therefore, rigid registration is adequate at this stage of the RFA procedure.

We believe that by utilizing probabilities rather than “hard” segmentation as described in [7,8], our method gives better alignment and is more robust to errors in US segmentation. The registration accuracy is, however, limited by the accuracy of the MR segmentation. To address this issue, registration of US probability volumes directly to MR intensities is considered a future work.

A selection of linear coefficients $a = 1$ and $b = 0.5$ in (3) respects the higher importance of hepatic vessels for registration than either external (w.r.t. liver)

vessels or the gallbladder. Due to their larger size, the gallbladder and inferior vena cava can force the registration to drift away from the correct solution unless down-weighted.

A confidence mask applied to the US probability maps reflects higher confidence in structures observed in the center of the US image, as opposed to boundaries. For example, a US region adjacent to the transducer contains compressed and, therefore, distorted structures; a boundary region distant from the probe receives attenuated US signal and is often noisy.

In this paper we proposed a novel method for registration of preoperative MR and intra-operative liver ultrasound based on modeling of US dynamics. Quantitative assessment demonstrated high robustness of the method and accuracy acceptable for the RFA application. Despite the necessity of manual preprocessing step for pre-operative MR, the method benefits from frequent availability of such information for the RFA treatment.

References

1. Wein, W., Röper, B., Navab, N.: Integrating Diagnostic B-mode Ultrasonography into CT-based Radiation Treatment Planning. *IEEE Trans. on Med. Imag.* 26(6), 866–879 (2007)
2. Roche, A., Pennec, X., Malandain, G., Ayache, N.: Rigid Registration of 3D Ultrasound with MR Images: a New Approach Combining Intensity and Gradient Information. *IEEE Trans. on Med. Imag.* 20(10), 1038–1049 (2001)
3. Mellor, M., Brady, M.: Fluid Registration of Ultrasound Using Multi-scale Phase Estimates. In: *Proc. of BMVA 2005* (2005)
4. Maes, F., Collignon, A., Vandermeulen, D., Marchal, G., Suetens, P.: Multimodality Image Registration by Maximization of Mutual Information. *IEEE Trans. on Med. Imag.* 16(2), 187–198 (1997)
5. Viola, P., Wells, W.M.: Alignment by Maximization of Mutual Information. *Int. Journal of Comp. Vision.* 24(2), 137–154 (1997)
6. Blackall, J.M., Penney, G.P., King, A.P., Hawkes, D.J.: Alignment of Sparse Free-hand 3-D Ultrasound with Preoperative Images of the Liver Using Models of Respiratory Motion and Deformation. *IEEE Trans. on Med. Imag.* 24(11), 1405–1416 (2005)
7. Milko, S., Samset, E., Kadir, T.: Segmentation of the Liver in Ultrasound: a Dynamic Texture Approach. *Int. Journal of Comp. Assist. Radiol. and Surgery* 3(1-2), 143–150 (2008)
8. Milko, S., Samset, R., Kadir, T.: A Novel Dynamic Texture Based Approach for Segmentation and Registration of Liver Ultrasound. In: *Proc. of IGSTI 2008* (2008)
9. Doretto, G., Chiuso, A., Wu, Y.N., Soatto, S.: Dynamic Textures. *Int. Journal of Comp. Vision* 51(2), 91–109 (2003)
10. Boukerroui, D.: Velocity Estimation in Ultrasound Images: A Block Matching Approach. In: Taylor, C.J., Noble, J.A. (eds.) *IPMI 2003. LNCS*, vol. 2732, pp. 586–598. Springer, Heidelberg (2003)
11. Schneider, T., Neumaier, A.: Algorithm. ARfit - A Matlab Package for the Estimation of Parameters and Eigenmodes of Multivariate Autoregressive Models. *ACM Trans. on Math. Software* 27, 58–65 (2001)