Evaluation on Similarity Measures of a Surface-to-Image Registration Technique for Ultrasound Images

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Abstract. Ultrasound is a universal guidance tool for many medical procedures, whereas it is of poor image quality and resolution. Merging high-contrast image information from other image modalities enhances the guidance capability of ultrasound. However, few registration methods work well for it. In this paper we present a surface-to-image registration technique for mono- or multimodal medical data concerning ultrasound. This approach is able to automatically register the object surface to its counterpart in image volume. Three similarity measurements are investigated in the rigid registration experiments of the pubic arch in transrectal ultrasound images. It is shown that the selection of the similarity function is related to the ultrasound characteristics of the object to be registered.

Keywords: Image registration, similarity measure, ultrasound, pubic arch.

1 Introduction

Ultrasound (US) is widely used as an intra-operative guidance tool in many medical procedures, due to its safety, low-cost and simplicity of use. However, the major shortcoming of US imaging is its poor image quality, compared to Magnetic Resonance Imaging (MRI) and Computer Tomography (CT). Therefore, mapping the pre-operative information obtained from MRI or CT would be a great enhancement to the guidance ability of US, when a high-contrast image modality is infeasible for intra-operative uses.

A number of techniques have been reported on the registration for ultrasound images. These include the fiducial-based method [1], the surface-based method [2-3] and the intensity-based method [4-7]. The fiducial-based approach usually needs to implant markers onto the human body, accurate but invasive. The surface-to-surface means is simple and universal for all modalities, but it requires the extraction of corresponding surfaces or landmark points. The image-to-image method is superior in flexibility and automation because no tissue segmentation is needed. However, registration of ultrasound against other modalities has remained as a challenging task.

For example, the intensity-based approach is not a good choice for MRI-US registration although a few similarity measures, such as correlation ratio [8], mutual information [9], have been tried in some occasions. This is because the key to the intensity-based techniques is that there must be a comparable percentage of mutual information existing in both of the images; otherwise, the information present in MRI image but missing in ultrasound would deteriorate the similarity measure as outlier.

Different from the traditional surface-to-surface and image-to-image registration patterns, the surface-to-image registration technique would be a good compromise between simplicity and flexibility. It extracts the organ surface from pre-operative images and directly utilizes the raw image information obtained intra-operatively. This approach would be especially helpful to the intra-operative ultrasound guided medical procedure when the time concern is critical.

In this paper, we discussed the surface-to-image registration technique used for the pubic arch detection in transrectal ultrasound (TRUS) using the *a priori* information from MRI. Based on the acoustic property of the bone structure in ultrasound, we formulated three candidate similarity measures and made a primary evaluation using three sets of patient data.

2 Methods

Pubic arch registration between the MRI and TRUS image spaces determines a rigid transformation, so six parameters are involved: the triplet translation vector (t_x, t_y, t_z) and the three rotation angles ($\alpha_x, \alpha_y, \alpha_z$) against x, y, and z axes respectively. The pair of data to be matched is the physical coordinate (x, y, z) of the surface extracted from MRI images and the volume content ($x', y', z', I(x', y', z')$) from TRUS, where $I(x', y', z')$ denotes the ultrasound image intensity value at voxel (x', y', z'). Therefore the registration problem is formulated as an optimisation procedure that searches for a transformation T that maximizes the similarity measurement f , a function of T :

$$T = \arg \max f(T(x, y, z), (x', y', z', I(x', y', z')))) \quad (1)$$

The similarity between the geometric surface and the volumetric image was evaluated as a measure of the intensity values at the image voxels where the surface falls in or correlate. Three forms of similarity measure for the surface-to-image registration, were formulated based on different interpretation of the intensity features of pubic arch in ultrasound. The genetic algorithm (GA) [10] was employed as the search engine to maximize the formulated similarity measure, which is calculated as the fitness function in the optimization procedure, as the genetic optimization doesn't require a proper initial guess for the transformation and the searching won't be easily trapped by local maximums.

2.1 Similarity Between Surface Point and Voxel of High Intensity

Similarity between the geometric surface and the image content is calculated based on the fact that the image voxels on the surface should have high intensity. It is formulated as the average intensity on the surface. We refer it as "Aligned Intensity" (AI) measure in this paper.

$$f_{AI}(T) = \frac{1}{N} \sum_{i=1}^N I([T(x_i, y_i, z_i)]) \quad (2)$$

where N is the number of points uniformly sampled on the surface. (x_i, y_i, z_i) is the i -th point and $[x_i, y_i, z_i]$ is the correspondent voxel coordinate in the image at which the intensity value is $I([x_i, y_i, z_i])$. The nearest-neighbor operator $[\cdot]$ is used to transform point coordinate to the image voxel grid. For any point falling outside the 3D image region, its contribution to the fitness function would be zero.

2.2 Similarity Between Surface Normal and Image Gradient

Similarity between the surface normal and the image gradient is derived from the fact that there is high image gradient at the boundary of the pubic arch as its intensity is much higher than its neighborhood. So the metric is formulated as the averaged image gradients along the normals of the surface [11]. We refer it as “Projective Gradient” (PG).

$$f_{PG}(T) = \frac{1}{N} \sum_{i=1}^N \langle \vec{G}([T(x_i, y_i, z_i)]) \cdot T(\vec{n}(x_i, y_i, z_i)) \rangle \quad (3)$$

where $\vec{G}$ is the intensity gradient calculated from the original ultrasound image I . $\vec{n}(x_i, y_i, z_i)$ is the normal vector at the i -th surface point (x_i, y_i, z_i) . $\langle \cdot \rangle$ is the inner product operator. Similarly, the nearest-neighbor operator $[\cdot]$ is used to calculate the intensity value at any surface point in ultrasound image.

2.3 Similarity Between Surface/Shadow and Image Intensity

This similarity measure was formulated from the fact that the ultrasound can hardly penetrate the bone structure therefore the pubic arch appears as a high-intensity echogenic surface with homogenous dark in anterior shadow. So it was evaluated as averaged radial “gradient” between the voxels fallen at the surface against those at the rear, referred as “Intensity Shadow” (IS) measure in this paper.

$$f_{IS}(T) = \frac{1}{N} \sum_{i=1}^N \left(I([T(x_i, y_i, z_i)]) - \frac{1}{M} \sum_{k=1}^M I([T((x_i, y_i, z_i) + k \cdot \vec{c}(x_i, y_i, z_i))]) \right) \quad (4)$$

where M is the user-defined depth of the posterior region (counted in voxels). $\vec{c}(x_i, y_i, z_i)$ denotes the unit vector of the radial echo emitted from the ultrasound probe to the point (x_i, y_i, z_i) on surface at depth of z_i . Since the 3D TRUS image was constructed by a series of transrectal images (in x - y plane) scanned at even intervals (in z direction), the gray value at any voxel was only determined by the reflected echo energy emit and received at the same z depth of the voxel. According to this rule, the intensity “gradient” is calculated radially, along the ultrasound propagation direction, from the transducer center to the surface point, and within the 2D image slice at this depth. The radial vector $\vec{c}(x_i, y_i, z_i)$ at point (x_i, y_i, z_i) is represented as

$$\vec{c}(x_i, y_i, z_i) = \frac{(x_i, y_i, z_i) - (x_p, y_p, z_i)}{\|(x_i, y_i, z_i) - (x_p, y_p, z_i)\|_2} \quad (5)$$

where (x_p, y_p, z_i) is the coordinate of the transrectal ultrasound probe center at depth of z_i . So the z component of vector $\vec{c}(x_i, y_i, z_i)$ is 0 because of the coplanarity. It is noticeable that the IS measure is not strictly the same image “gradient” as the conventional concept since it is computed between the voxel at the surface and the mass of center of its posterior along the ultrasound propagation direction.

3 Experiments and Results

3.1 Data

The experiments were conducted using three sets of patient data, each with a pair of 3D MRI and TRUS images of the prostate and pubic. The MRI scans were performed in a 1.5 Tesla whole body GE MR systems (GE Inc, USA). Patients were kept in a supine position during the scan. T2-weighted fast spine-echo scanning was performed under TR/TE of ~6400.0/85.6ms, slice thickness of 3mm, and slice spacing of 0.5 mm. Imaging resolution was 256×256 pixels in field of view (FOV) of 12.0×12.0 mm². During the intra-operative ultrasound imaging, patients were kept in a lithotomy position for the convenience of delivering biopsy or brachytherapy. The Aloka SSD-1700 system (Medison Inc, USA) was used with a stepping unit to pull the endorectal probe. The transrectal images were acquired at 1.0 mm steps. The image resolution was 0.18×0.18 mm².

3.2 Experimental Design

To evaluate the algorithm’s performance, we first conducted a self-registration test, i.e., registering the pubic arch surface segmented from TRUS image to the image itself. Intuitively, this surface was used not only as the input from other modalities, but also as the “ground truth” of the output. This manner established a so-called “bronze truth” [12] of the transformation, i.e., an identity transformation, for the validation purpose. The accuracy and consistency was assessed using the averaged values and standard deviations of the three translations and three rotation angles (rotation) solved by optimization in multiple rounds. In the other side, since no “ground truth” is easily available in the experiments between the MRI and TRUS image modalities, we computed the statistical deviation to evaluate the algorithm consistency, but sought the expert opinion to judge the acceptability (i.e., accuracy) of the result.

For both of the experiments, a number of 450 Points ($N=450$) were sampled uniformly on the pubic surface according to their parametric coordinates on surface. The GA parameters in the registration algorithm was set to use crowding algorithm, linear scaling, tournament selection, 300 populations and 100 generations, 95% crossover rate and 1% mutation rate. The six transformation parameters, calculated in the local coordinate system of the pubic surface, were coded in the chromosomes. The

search range of the translation was confined to the central half of the entire TRUS image volume, and the variation of angles were within -10 to 10 degree, according to the fact that the scanning orientation and manner was similar between the two modalities (both of them are transverse scan from the superior to the inferior). The rear width M was set to be 40 , which means a thickness of around $7.2\sim 10.2\text{mm}$. The number of repeated experiments performed on each set of patient data is 15 .

3.3 Results

The delineation of the pubic arch surface in the 3D MRI images, and its registration to the corresponding 3D TRUS image was demonstrated in Fig. 1.

Fig. 1. (a) Construction of pubic arch surface in MRI image stack by parallel contouring. (b) The relationship of the pubic arch surface with respect to the 3D TRUS image before the registration. (c) The pubic arch surface after the registration.

Table 1 illustrated the quantitative evaluation of the self-registration test. Statistics in forms of mean and standard deviation was calculated over the 15 repeated experiments of the three sets of patient data. Accuracy of the registration was indicated by the mean value of the translation and rotation vectors, while the algorithm consistency was revealed by the averaged standard deviation of those parameters. The data in Table 1 shown that the “Intensity Shadow” (IS) measure had the best performance among the three similarity matrices. To have a better understanding of the absolute error magnitude, we summarized the errors in separate components to a normalized form, the absolute displacement $\|t\|$ and the rotation angle $\|\alpha\|$ against an arbitrary rotation axis. The averaged $\|t\|$ was found to be $2.04\pm 0.68\text{mm}$, $3.31\pm 1.15\text{mm}$ and $1.87\pm 0.54\text{mm}$ for the AI, PG and IS measure, respectively. Correspondingly, the averaged $\|\alpha\|$ was $3.22\pm 1.63^\circ$, $4.85\pm 1.92^\circ$ and $2.55\pm 1.13^\circ$, respectively. It is obviously that the IS measure obtained the best result among the three measures for it has the highest accuracy and good consistency in average. Comparatively, the “Projective Gradient” (PG) measure yielded the worse accuracy and consistency. The “Aligned Intensity” (AI) measure delivered the intermediate accuracy, but it possessed a consistency comparable to that of the IS measure.

For the cross-modal image registration, due to the limitation of our image collection protocols, we were unable to implant fiducial markers in the patients to establish a “golden standard”. Neither do we have a convenient image navigation system that

allows us to do an accurate manual matching at current stage, nor the “bronze standard” used for self-registration test is feasible because the surface segmented from different image sources varies dramatically. So the expert was invited to assess the failure rate, which is regarded as a qualitative evaluation of the registration accuracy, of the 45 experiments conducted for each similarity measure. Table 2 shown the failure rate of each measure, as well as a quantitative evaluation of the corresponding consistency, the deviation. We can see that a same conclusion can be draw that the proposed IS measure outperformed the other two candidates.

Table 1. Comparison of the averaged self-registration error with “aligned intensity” (AI), “projective gradient” (PG) and “intensity shadow” (IS) using the three sets of TRUS data of patient

f	Translation (mm)			Rotation ($^{\circ}$)		
	$t_x \pm \delta t_x$	$t_y \pm \delta t_y$	$t_z \pm \delta t_z$	$\alpha_x \pm \delta \alpha_x$	$\alpha_y \pm \delta \alpha_y$	$\alpha_z \pm \delta \alpha_z$
AI	-0.47 $\pm$ 0.74	0.64 $\pm$ 0.42	-1.41 $\pm$ 0.70	-0.24 $\pm$ 1.07	-1.30 $\pm$ 1.93	0.04 $\pm$ 1.46
PG	0.15 $\pm$ 1.26	1.22 $\pm$ 1.00	-1.26 $\pm$ 1.55	2.18 $\pm$ 2.05	-0.86 $\pm$ 2.58	0.73 $\pm$ 2.90
IS	0.02 $\pm$ 0.59	0.36 $\pm$ 0.54	-0.37 $\pm$ 0.88	-0.11 $\pm$ 0.97	-0.58 $\pm$ 1.41	-0.75 $\pm$ 1.17

Table 2. Comparison of the averaged cross-registration error with “aligned intensity” (AI), “projective gradient” (PG) and “intensity shadow” (IS) using the three set of TRUS data

f	Failure rate	Consistency in translation (mm)			Consistency in rotation ($^{\circ}$)		
		$\pm \delta t_x$	$\pm \delta t_y$	$\pm \delta t_z$	$\pm \delta \alpha_x$	$\pm \delta \alpha_y$	$\pm \delta \alpha_z$
AI	57.8%	± 0.84	± 0.95	± 0.97	± 0.72	± 1.19	± 1.93
PG	84.4%	± 2.19	± 3.33	± 3.63	± 3.53	± 3.02	± 4.43
IS	0%	± 0.48	± 0.65	± 1.12	± 0.70	± 1.66	± 1.24

4 Discussion

In the cross-modal registration test, we observed that the registration results using PG measure may lead to a complete mismatch and so does sometimes for the AI measure, while IS measure nearly can always locate the pubic arch around the true location (judge by human eyes). However, in [11] we have verified that the PG measure was quite successful for the surface-to-image registration of the prostate. This gave us an idea that the similarity measure behaves differently when it applied to different organs.

To investigate the behaviors of the three similarity measures for pubic arch registration, we demonstrated the solution space of the three measures as a fitness map of the transformation parameters with the self-registration as the basis. Accordingly, a range of variations to the standard identity transformation were applied. Fig. 2 (a)-(c) demonstrated the fitness map over the transformation parameter t_x - t_y , t_x - t_z , t_y - t_z , α_x - α_y , α_x - α_z , and α_y - α_z , with other parameters confined to 0. The fitness maps of f_{IS} shown as a sharp unimodal distribution: higher fitness values concentrated around the ideal solution (the image center), indicating even if the genetic optimization may converge to a local optimum other than the global one, the

result won't be far from the truth. f_{AI} is fairly smooth but the unimodality is not sharp enough to guarantee the accuracy. f_{PG} is far from unimodality because a lot of local maxima present all over the space. Obviously the function with sharp unimodal tendency is the best choice for the global optimum searching. Hence we can conclude that the GA-optimized registration using the IS measure as the fitness function, will be more reliable to find the transformation solution close to the truth.

Fig. 2. Comparison of the solution space of AI, PG and IS measure. The fitness map was calculated over t_x - t_y , t_x - t_z , t_y - t_z , α_x - α_y , α_x - α_z , α_y - α_z with other parameters to be 0. From left to right: $f(t_x, t_y, 0, 0, 0, 0)$, $f(t_x, 0, t_z, 0, 0, 0)$, $f(0, t_y, t_z, 0, 0, 0)$, $f(0, 0, 0, \alpha_x, \alpha_y, 0)$, $f(0, 0, 0, \alpha_x, 0, \alpha_z)$, $f(0, 0, 0, 0, \alpha_y, \alpha_z)$. (a) Solution space of f_{AI} . (b) Solution space of f_{PG} . (c) Solution space of f_{IS} .

5 Conclusion

In this paper, we have presented a surface-to-image registration framework for ultrasound image registration. The use of the pre-operative surface and the intra-operative image is a good balance between human intervention and automation, ensuring not only accuracy but also real-time speed. Three kinds of similarity measures were investigated for the pubic arch registration in transrectal ultrasound image. Our experimental results shown that the “Intensity Shadow” (IS) measure is the best candidate for the pubic arch registration in TRUS image, as this measure best revealed the bone property in echo images. So we can conclude that it is important to choose a proper similarity measure according to the ultrasound characteristics of the object to be registered for the success of the registration.

This technique would be helpful to determine the pubic arch interference (PAI) [13] for the prostate biopsy and brachytherapy application. And we believe it is also extendable to other bony structure registration if they manifest the same acoustic properties.

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