

An Iterative Framework for Registration and Segmentation of Dynamic Three-Dimensional MR Renography

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Introduction

Dynamic MR renography has broad clinical applications, but suffers from respiratory motion that limits analysis and interpretation. Since each examination yields at least 10-20 serial 3D images of the abdomen, manual registration is prohibitively labor-intensive [1]. An effective framework for registration and segmentation is necessary to analyze these data sets. Our purpose was to develop and validate a computer-aided iterative framework for registration and segmentation of kidney structures on dynamic contrast-enhanced 3D ("4D") MR renography. We hypothesized that an iterative application of registration and segmentation will improve the accuracy of these processes.

Algorithm

Registration and segmentation problems for dynamic MR renography can not be decoupled. Without satisfactory image registration, segmentation algorithms fail. A good registration facilitates tissue segmentation because it allows the algorithm to exploit multidimensional voxel data [2]. On the other hand, a robust segmentation of intrarenal regions (e.g. renal cortex, medulla, and collecting system) for each time series can facilitate accurate image registration. Therefore, a computer-aided iterative method was developed to combine image registration and segmentation of dynamic 3D MR renography. Following a rough registration process, 3D anisotropic diffusion, 3D wavelet edge detection, and 3D Fourier based registration with subvoxel accuracy are used for the registration scheme [3]. This is followed by a rough segmentation procedure, in which an initial shape of cortex, medulla and collecting system are extracted for the following steps. A seed based correlation method is adopted to classify time course features in this step. Based on initial contours, the algorithm adjusts the local contour shapes using an active contour model. The registration scheme is repeated, taking advantage of kidney boundary estimates. Finally, a refined segmentation step is implemented based on a time course correlation method.

Methods

The scheme was evaluated on 3D ("4D") MR renography data sets from four patients, with manual segmentation and registration performed by two experts in body radiology. Furthermore, one of our expert observers manually traced 16 pairs of kidney contours (four subjects, four pairs of volumes) that represented small, medium and large (<1mm, 1-5mm, and >5mm) degree of kidney motions to provide registration ground truth. Coordinates were defined as: x = head to feet, y = left to right, z = anterior to posterior). Conventional rotation angle parameters were expressed in degrees (θ , ϕ , ψ). Manual segmentations for cortex, medulla and collecting system were used as the reference standard for segmentation overlaps and volume evaluations. All translation results were expressed in voxels, the absolute voxel size (1.66, 1.66, 2.5) mm was used throughout this study.

Results

As Fig. 1. shows, the mean value of refined translation errors are small. The mean value of rough translation errors were [0.5344, 0.6390, 0.1508] voxels; the mean value of refined translation errors were [0.2416, 0.5540, 0.1292] voxels. Rotation errors were mainly from the third parameter ψ , which is the rotation angle. Averaged rotation errors were [0.0000, 0.0003, -0.6630] degrees, which represents rotation in sagittal plane. Segmented volumes of intrarenal regions were calculated and compared with expert's results which were showed in Fig. 2. Computer aided segmentation results showed consistent results compared with experts' segmentation shown in Fig. 3. A 3D visualization of registration results based on manually segmented ROIs and computer calculated results are shown in Fig. 4.

Conclusions

An iterative framework for dynamic 3D ("4D") MR renography analysis has been put forward that incorporates iterative computer aided registration and segmentation. Refined average translation errors were almost less than half of a voxel. Averaged rotation error was within one degree.

References

[1] V. S. Lee et al., Radiology, vol. 227, pp. 289-294, 2003. [2] L. M. Fletcher et al., Digital Image Processing Methods, NY, 1994. [3] T. Song et al., vol. 2, pp. 2205-213, MICCAI 2005.

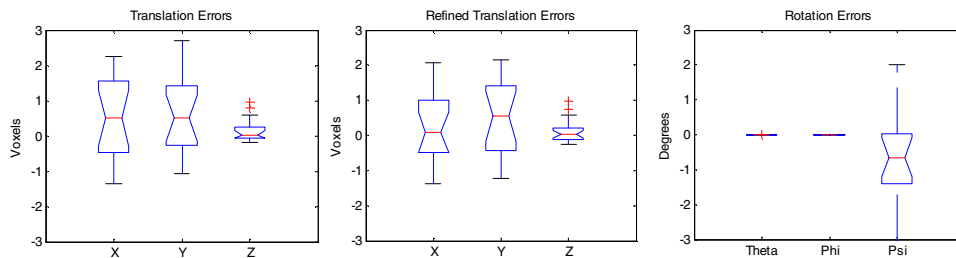


Fig. 1. Distribution of errors in translation and rotation.

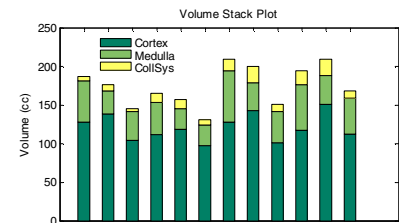


Fig. 2. Volume comparison for cortex, medulla and collecting system on four patient's data from 1 to 4. (a) and (b) are volumes from our two experts, and (c) are volumes from our algorithm.

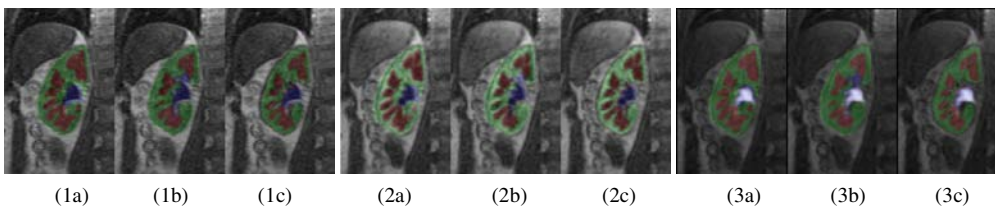


Fig. 3. Segmentation results for three different time points 1~3 on one patient. (a) and (b) are segmentation ROIs from our two experts; (c) is the segmentation ROIs from our algorithm.

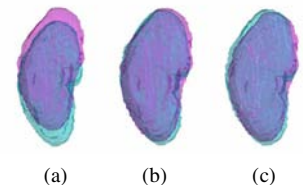


Fig. 4. Registration result in (a) original image, (b) manual roi registered image, and (c) registration from our algorithm.