Targeted coregistration of abdominal DCE MRI

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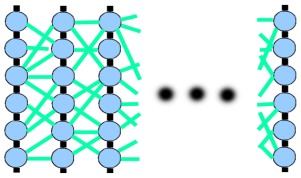
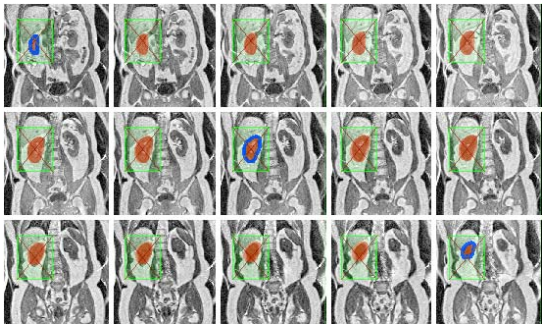
Dynamic contrast enhanced (DCE) MRI has emerged as a reliable and diagnostically useful functional imaging technique. When applied to abdominal regions, DCE MRI data are affected by the motion induced by patient breathing or movement. DCE protocol typically lasts 3-15 mins and it results in a time series of N volumes. For automated analysis it is important that volumes acquired at different times be spatially coregistered. Simple coregistration algorithms that make use of edge alignment, or image correlation do not work well for DCE images because of the change in intensity due to the uptake and washout of contrast agent [1]. Coregistration based on normalized mutual information (NMI) [2-5] can deal with contrast-related intensity variations. However, in clinical practice straightforward application of NMI does not give reliable results. We have implemented several DCE-MRI oriented variants of NMI technique and tested them in the setting of functional exams of the kidney. The variants differ in sequencing of coregistration steps and in the way the organ of interest is specified. To quantify registration accuracy we have introduced a measure that generalizes Dice's similarity coefficient [6].

Methods

Let $i \in [1 \ldots N]$ be the time index and $T_{i,j}$ the transformation that maps the coordinates of source volume i into the target volume j. For the present T was restricted to a rigid body transform defined by its 3 translational and 3 rotational parameters. T is computed to maximize NMI between the target and the transformed source. Optimization is done in two stages: **S1**) an exhaustive search over a discrete grid of translational and rotational parameters distributed in the 6-dimensional parameter space; and **S2**) an iterative search for a local maximum of NMI, initialized at the most promising grid points from stage S1. Coregistration is said to be **serial** if it is computed in the order: $T_{2,1}$, $T_{3,2'}$, $T_{4,3'}$, … , where i' denotes volume i after applying the transformation. Coregistration is done in **radial** mode with target g when we transform all volumes to time point g by computing $T_{1,g}$ $T_{2,g}$, $T_{3,g}$ … We also consider a **full 4D** mode, by reducing the problem to finding the maximum clique in a weighted N-partite graph [7]. In 4D formulation, time points represent graph partitions, graph edges represent discrete transforms considered in S1 stage, and edge weights are the corresponding NMI metrics. A heuristic "greedy" maximum clique method was implemented for this preliminary study. The organ to be registered was specified interactively on a single time point (see figure) using either a "box" or a volume of interest (VOI).



N-partite graph. Horizontal axis: time points. Vertical axis: search space S1. Edges: potential transforms.



Target organ – here the right kidney -- can be specified using a 3D box (green) or by free-hand drawing the contours on three slices (shown in blue). From these contours the program constructs target VOI (shown in red) using interior filling and convex morphing.

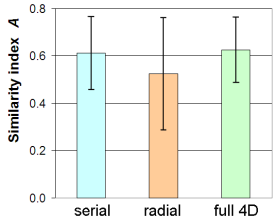
Registration accuracy can be quantified if organ of interest is segmented at each time point. Let R_i be a 3D binary mask (1=on, 0=off) constructed from unregistered volumes at time i. (Masks R_i are not used for coregistration.) Let $T_{i,.}$ denote the optimal transformation constructed using a given variant of coregistration algorithm. We construct transformed binary masks R'_i by voxel subsampling, application of $T_{i,.}$, trilinear interpolation and thresholding the results at the level >0.5. We define similarity index A ($0 \le A \le 1$, with 1 = perfect alignment) as the volume of intersection divided by the volume of the union of transformed masks R'_i.

$$A = \frac{Vol \bigcap_{i=1,\ldots N} R'_i}{Vol \bigcup_{i=1\ldots N} R'_i}$$

Ten cases were selected from a database of ~200 recent (past 2 years) clinical DCE MRI exams. Four of these exams had "large organ/patient motion" noted by the body radiologist. The protocol was based on 3D FLASH, TR/TE/FA=2.8ms/1.0ms/12°, FOV=42.5 x 42.5 x 10 cm, 1.7×1.7×5 mm voxels, 256x256x20 matrix, volume acquisition time 3s. Abdominal aorta and both kidneys were included in the field of view. A 4 ml bolus of Gd-DTPA was injected, followed by 20 ml saline flush, both at 2 ml/s. In each exam ~30 3D volumes were acquired over 8-15 min. The coregistration software (FireVoxel) is written in C++ and uses Microsoft Foundation Class and Intel Threading Building Blocks libraries. The program features multi-core processor parallelism. All tests were done on an inexpensive desktop computer equipped with a low-end quad-core CPU.

Results and Discussion

Before coregistration, the similarity index A ranged 0.194-0.567. Serial and full 4D modes were found to be more accurate than radial mode (p=0.02), with average A= 0.61 for serial, 0.52 for radial, and 0.62 for full 4D. There was no statistically significant advantage of full 4D over serial modes. The execution times ranged 16-25 sec for serial, 14-16 sec for radial, and 61-73 sec for full 4D. Interactive specification of a single kidney as the target organ took on the average 20 sec for both box and VOI method. VOI targeting significantly improved registration accuracy compared to the box method. Execution times were also consistently shorter (by 13-47%) for VOI targeting.



Targeted coregistration of time series data appears to be reliable and ready for clinical use. This task can be accomplished in several minutes on a modern multi-core computer. Inferior accuracy of radial versus serial coregistration is likely due to the need of aligning 3D images with widely disparate contrast. While our current implementation of full 4D approach gives on the average best results, the accuracy improvement is marginal compared with more computationally efficient serial method.

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