ESTIMATING 3D DEFORMABLE MOTION FROM A SERIES OF FAST 2D MRI IMAGES WITH CLARET

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TARGET AUDIENCE:
MR researchers involved in deformable registration and characterizing anatomical motion.

PURPOSE: CLARET is an image registration method that has been used to relate a set of 2D images to a corresponding set of 3D images.[1] Previous applications include the estimation of 3D body position from digitally reconstructed radiographs. We seek to use this method of registration to estimate 3D deformable motion in the abdomen from a series of fast 2D MRI images.

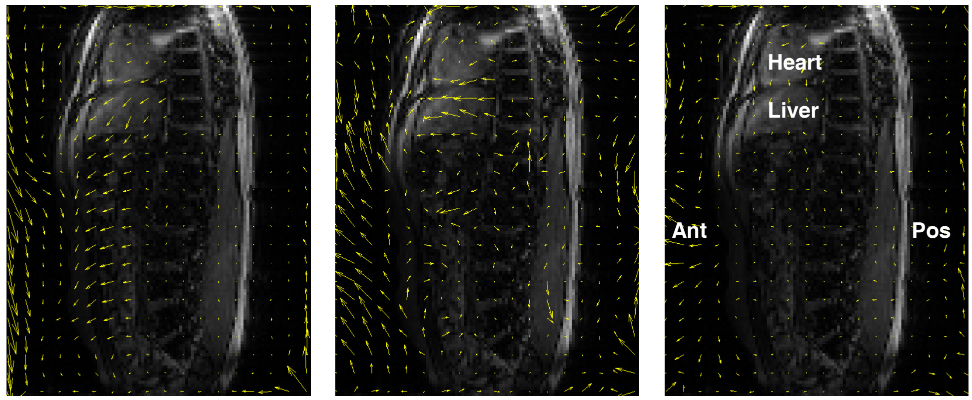

Figure 1: A central sagittal slice showing the direction of deformation vectors in the first three principal modes generated from principal component analysis on the original set of 8 deformation vectors. The most significant

METHODS: CLARET uses a previously-acquired gated 3D dataset from the patient to construct a patient-specific motion model, and then relates the parameters of that model to 2D images that can be acquired quickly, allowing instantaneous body pose to be estimated from the 2D image.

1. A dataset was acquired from a healthy volunteer using a CINE 3D MRI gradient echo sequence with respiratory bellows-gating.
2. Nine 3D CINE image sets were collected. Each of these images corresponded to a different phase of the respiratory cycle.
3. Once the 3D dataset was acquired, all of the 3D images were registered using log demons deformable registration.[2]
4. The resulting deformation vectors were then analyzed using principal component analysis and a patient-specific shape space, representing all respiratory motion as a weighted sum of six "modes" of deformation vector fields.
5. After shape space generation, Claret found a relationship between a 2D image and the weights of the mode. The 2D image is a thick slab projection and can be acquired at a temporal resolution of 300ms. In this case, we were able to acquire 100 free-breathing test images in 30 seconds. Once the 2D images are obtained, a complex summation must be done on the 3D shape space to preserve the characteristics of the 2D slab. Once the complex projection is done on the shape space, the metric learning allowed an estimation of a complete 3D motion vector field from each member of the set of 100 fast 2D images, leading to an estimate of the instantaneous body pose at each of the 100 time points.
6. To evaluate the effectiveness of the CLARET method at predicting patient-specific motion, we compared the estimated 3D images to the 100 acquired 2D test images. This was achieved by doing a complex digital projection of the complex 3D datasets that were estimated using CLARET registration.
7. Once the 3D images were projected to 2D, the estimated images were registered with the actual acquired test images using log demons deformable registration, to evaluate the error in the resulting predicted deformation. The per-pixel average deformation magnitude was computed as an error metric.
8. This was then compared to the deformation error from a static image registered to the measured 2D dataset to quantify the results of this registration.

RESULTS: The first comparisons were done between the estimated 3D dataset and the original 3D images that were acquired using respiratory bellows-gating. In figure 2 below, the first frame (red) represents the CLARET estimation and per pixel error, the other frames (cyan) are the various static images which correspond to the original 9 images collected with bellows gating. The next comparison was between the CLARET method and the mean deformation calculated from the set of deformations registered using log demons deformable registration. In this comparison, the areas that were statistically significantly better in favor of CLARET are highlighted in red, while the areas where the mean deformation was statistically significantly better are in blue.

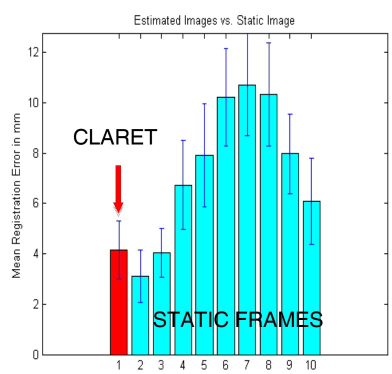

Figure 3: The first bar (red) is the mean error for the CLARET estimated images. The other bars (cyan) are estimates from the static images. Measurements were taken in a 225cm^2 region in the upper abdomen.

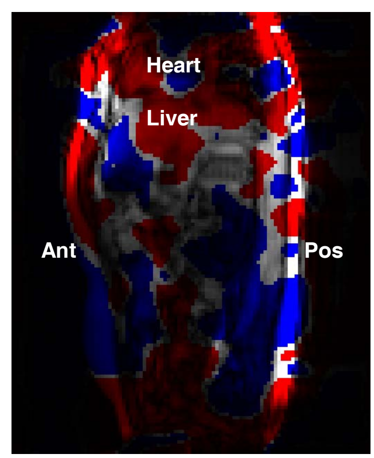

Figure 2: Areas that were statistically significantly better in favor of CLARET are highlighted in red, while the areas where the mean deformation was statistically significantly better are in blue. Gray regions had no significant difference.

DISCUSSION: The CLARET registration is able to quickly estimate a set of 3D images from a set of 2D images. After shape space generation, the estimation of parameters takes 0.019189 seconds for 100 test images. In our testing of the method, the method tends to work best in areas of higher MR intensity, and areas where there is significant motion. Also, the standard deviation of the error is significantly reduced in the CLARET method of motion estimation. In figure 3, the red areas in the upper abdomen show locations where the CLARET method achieves the best results. These red areas in the upper abdomen are also where motion is most prevalent, the liver and diaphragm. The blue areas are typically areas where there is either low signal or little motion. The mean error is smaller in the upper abdomen. Gray is background and has no significant difference.

CONCLUSION: Using CLARET to predict the 3D motion of a subject from a set of 2D projection images has the potential to be used in MRI imaging of dynamic processes. An extension of this method could be to use these quick 2D projection images to estimate the 3D motion during a PET scan and perform motion correction on that dataset.

REFERENCES:
1. Chou, C.R., Pizer, S.M.: Real-time 2d/3d deformable registration using metric learning. In: Medical Computer Vision, Springer (2013) 1–10
2. Wang et al.: Validation of an accelerated 'demons' algorithm for deformable image registration in radiation therapy. Phys. Med. Biol., 50 (12) (2005), pp. 2887–2905