3D Non-Linear Model-Driven Registration for Motion Corrupted DCE-MRI Data

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Introduction: Dynamic contrast enhanced MR imaging is now well established in the field of oncology as a means of describing and monitoring tumours, and thus assessing antivascular and antiangiogenic therapies and their efficacy in clinical trials [1]. This is done via the calculation of summary statistics based on the signal changes over time in voxels of interest. These changes reflect contrast agent (CA) uptake, which provides vital information about the microvascular characteristics of tissues at each voxel location. For example a tracer-kinetic model can be fitted to the time course of a single voxel to estimate various parameters at that point. Inevitably, this time signal is distorted by noise and motion, especially breathing effects in the chest and abdomen. This in turn affects the precision of any assessment. However, there will be some underlying structure to the time series data and we can capitalise on this by assuming that a model fit on the corrupted data will be an approximation of the true model fit, at least in a large number of voxels. By fitting a model over a tumour volume of interest (VOI), an uncorrupted approximation to the true time series is generated for that area. Using this approximation as a target, the original data can be brought closer into alignment by transforming each image in the time series to match its counterpart in the target series. By repeating this process the series is gradually brought closer into alignment in an iterative fashion. This model-driven approach has been found to generate targets for registration superior to other methods such as a single or mean image as target [2, 3]. Previous studies using this approach have confined themselves to 2D images [2, 4] or translation only in 3D [3]. In this work we extend the method to 3D non-linear transformations and introduce a new alignment measure. Plus, we present an independent motion assessment which illustrates the success of the registration.

Data: 10 patients were scanned using a volumetric fast field echo (FFE; spoiled gradient echo) on a 1.5T Philips Intera scanner (Best, Netherlands). Each abdominal series had 75 time points at approx 5s intervals. 3 subjects had 2 lesions and all patients had 2 baseline scans – 26 lesions in all.

Method: ***VOI:*** The registration is based on a VOI and each lesion is considered independently. The VOIs were drawn by an experienced radiographer to encompass a single abdominal tumour. ***Transformations:*** Each data series was registered iteratively for 9 transformations, as described in the *Introduction*. Four different matrix transformations were considered: translation; affine (adds rotation, scale, shear); projective (adds tapering); and trilinear (adds pin-cushion and barrelling). In all cases the extended Tofts model [5] was fitted to each voxel in the VOI to generate the target series. The transformation was calculated using a downhill simplex [6] and the sum of squared differences was used as the similarity measure, within the VOI only. No restrictions were placed on the transformations. ***Alignment Measure:*** An alignment measure was devised to monitor the success of the registration. Since, for the most part, the CA uptake has a gradual effect on signal intensity, it was expected that the correlation between consecutive images, $r_{i,\,i+1}$, would be close to 1 for most of the time series when correctly aligned. Therefore, the average correlation coefficient (ACC), taken from all comparisons, in the VOI only, was expected to be close to 1 for good alignment. ***Motion Assessment:*** After the 9th iteration, a final set of images was generated using the last transformation estimate and sinc interpolation for sub-voxel intensity estimation. The images from translation and trilinear transformations were used in a motion assessment to examine the success of the registrations. The average intensity was calculated over each slice of the VOI for each image in the time series. This created an intensity curve over time for any slice (slice curve). An experienced assessor used 3 slice curves (the central and 2 extreme slices from the VOI) for each time series to assign a motion score, ranging from 2: Slight motion, defined as low amplitude noise throughout; to 6: Severe motion, defined as high amplitude noise with one or more severe motion spikes. Figure 1 shows some example curves, before and after registration.

$$ACC = \frac{\sum_{i=1}^{N-1} r_{i,i+1}}{N-1}$$

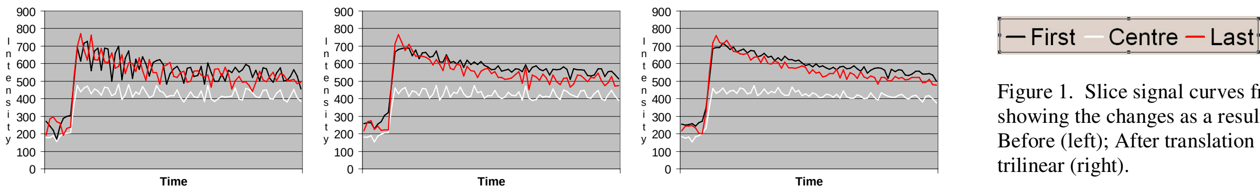

Figure 1. Slice signal curves from a single example showing the changes as a result of registration. Before (left); After translation (middle); and after trilinear (right).

Results: No restrictions were placed on the transformations and visual inspection showed that 4 trilinear registrations failed to align a large number of time points. These severe failures have been excluded from the analysis. Eight translations and 9 trilinear registrations had a small number of time point failures, but these have not been excluded since a small number of poorly registered time points should not greatly affect the ACC or motion assessment. Figure 2 (left) shows that during registration the ACC rises quickly on the 1st iteration and then shows smaller variations after that point. In no case was the final value worse that the starting measurement, but the best value was not always from the last iteration. As the more complex transformations were added ACC generally improved but only by a relatively small amount at each level of complexity. Figure 2 (right) shows the improvement in ACC when the most complex non-linear transform (trilinear) was applied. In only 1 case was this *not* the best measurement. Figure 3 shows the motion scores before and after registration.

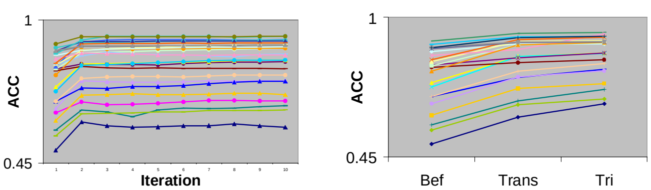

Figure 2. The changes in ACC over registration using translation (left) and after translation and trilinear transform (right).

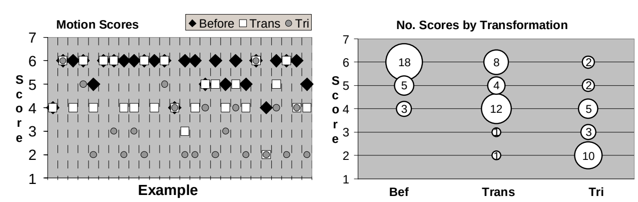

Figure 3. Motion assessment. The score increases with severity of motion. Results show before; after translation; and after trilinear. Left: The change for each example. Right: The number of examples obtaining each score.

Conclusions: It is clear from the figures that the alignment of the time series has been improved in the VOI for all transformations used in the registration. The increase in ACC due to the complexity of the transformations was generally smaller compared to the initial benefit obtained from using just translation, which implies that, in abdominal tumours, a large proportion of the motion corruption is due to displacement rather than deformation or rotation. There is clearly some benefit to introducing non-linear transformations but it is likely that little could be gained by further increasing the complexity. The failure rate could be improved further by imposing biologically plausible restrictions on the transformations, and this is the subject of current work.

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Acknowledgements: Gio Buonaccorsi is funded by Cancer Research UK Grant No. C237/A6295. We would like to thank Yvonne Watson and Sue Cheung for their valuable contributions