Simultaneous Image Registration, Segmentation and Modeling

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1 Introduction

This work focuses on an algorithm which simultaneously segments and registers a set of medical images in an automatic manner, incrementally constructing a model of the structure and shape deformations of the set. The idea is to exploit a good estimate of any one aspect of image structure (segmentation, registration or model)to achieve a more reliable estimates of the others. The framework explicitly models the construction of each pixel from constituent image segments such as tissue types in brain images, in a reference image frame rather than the expected intensity in each pixel. This effectively decouples the model from the effects of the imaging system (sequence or modality) on image statistics enabling the framework to deal with datasets exhibiting significant variation in intensities and multimodality images. Further, an algorithm based on the Minimum Description Length approach is used to determine the optimal number of image segments and fully automate the approach. When estimating the optimal registration deformation field, each image is compared to a reconstructed image, generated using model segment fractions and current estimate of its intensity distributions for each segment (i.e. an estimate of how the model would appear given the imaging conditions for that image).

2 Method

An overview of the algorithm is illustrated in Figure 2. A set of N images T_i, $i = 1...N$, (the training set), assumed roughly aligned (e.g. MI affine registration). It is further assumed that the structures in the images consist of M distinct tissue types with intensity probability density parameters θ_i and that each pixel contains either a pure tissue or a mixture of at most two different tissues (partial volumes) [1]. Spatial deformation field, $W_i()$ defining correspondence between the reference frame and each training set image T_i is triangulated piecewise affine controlled by a set of control points (vertices). The segmentation, registration and modeling proceeds sequentially through the following steps:

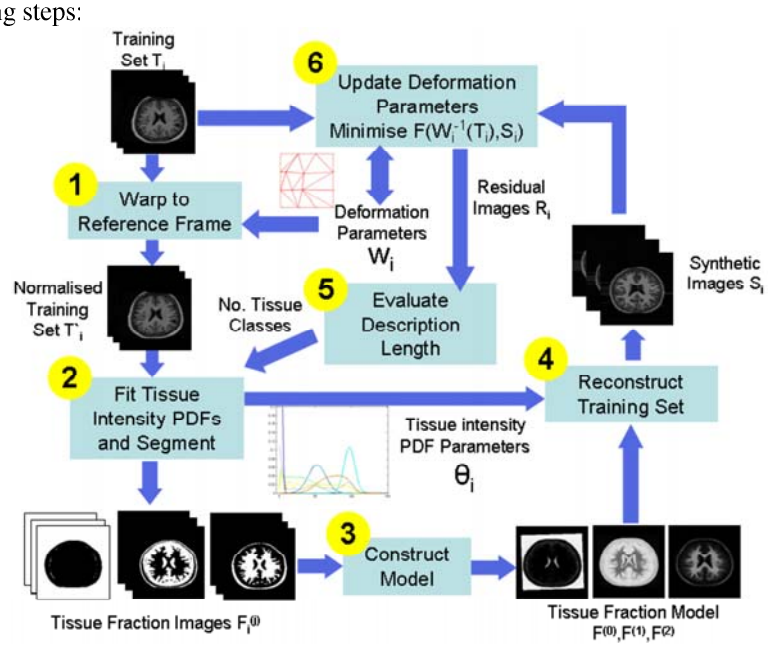

Figure 1. Outline of the algorithm.

1. Warp each training image T_i into the reference frame using the current estimate of the deformation field. $T'_i = W_i^{-1}(T_i)$.
2. Compute the intensity histogram of T'_i, fit a mixture model to estimate the distributions of each pure tissue class and derive by convolution the distribution for each fractional distribution. We use this information in a Bayesian framework to to estimate the most probable fraction of each tissue in each pixel. This information is encoded in a set of tissue fraction images $F_i^{(j)}$, $j = 1...M$ for each training example.

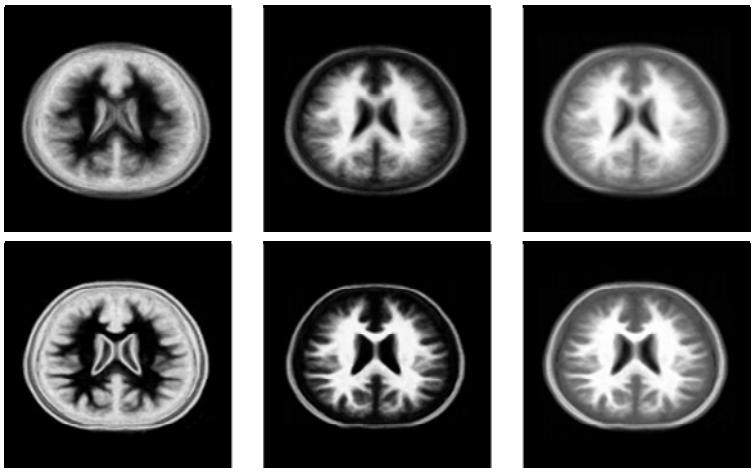

Figure 2. Model tissue fraction estimates and example reconstruction image at beginning and end of registration.

3. Combine the tissue fraction images from all examples using a leave one out trimmed mean approach that uses a fraction of non-current examples to construct a robust model of tissue fractions on the object, $\{\hat{F}^{(1)}...\hat{F}^{(M)}\}$.
4. Synthesize a reconstruction of each training set image using the current estimates of pure tissue class intensity means, μ_{ij}, and the current tissue fraction model, $S_i = \sum_{j=1}^{M} \mu_{ij}\hat{F}^{(j)}$
5. Evaluate the optimal number of different tissues M by evaluating the Description Length of the model (reconstructed) training set representation, as in [2], by evaluating the cost of transmitting the model and the residual images $\mathcal{R}_i$ between each training set and corresponding synthesized example and choosing the one with the minimum DL (MDL).
6. Update the current estimate of W_i to best register S_i onto T_i, by manipulating the control points of the deformation field to minimise a suitable similarity measure, $D_{im}(T_i, W_i(S_i))$.

Initially we apply steps 1 and 2 to all images, then combined them (step 3) into an initial model of the tissue fractions at each pixel in the reference frame. Steps 2 to 5 are then repeated iteratively with an increasing number of image classes until an optimal number of image segments, tissue types is found. This evaluation can be repeated throughout the process with the number of tissue classes changing between iterations of the segmentation-registration. With an optimal number of classes we apply steps 1 to 6 (excluding 5) to each image in turn multiple times, performing coarse registration in the early stages and progressively finer registration as the iterations progresses.The process of shape model building is excluded from the Figure 2 for the sake of clarity, but happens as an integral part of step 3 and can further be used to constrain the deformation field optimisation in step 6.

Results

We applied the method to a set of 2D slices of MR brain images (choosing equivalent slices from affine aligned 3D datasets) using sum of square differences for both the image similarity, $D_{im}()$, and the divergence between intensity distributions, $D_p()$. Figure 2 shows the mean of the model tissue fractions for gray and white matter at the beginning and end of the registration , together with an example of the resulting reconstruction using the means of each pure tissue class. As registration progresses the alignment becomes more accurate, resulting in a crisper and more accurate estimates of the tissue fractions (segments) and thus crisper reconstructions.

References

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2. C. J. Twining, T. F. Cootes, S. Marsland et al. "A unified information-theoretic approach to groupwise non-rigid registration and model building." In *Proceedings of Information Processing in Medical Imaging (IPMI)*, volume 3565 of *Lecture Notes in Computer Science*, pp. 1–14. Springer, 2005.