Robust atlas-based brain segmentation using multi-structure confidence-weighted registration

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Automatically generated segmentations can provide a rich feature set to aid image-based registration. However, errors or inconsistencies in the automated segmentations can lead to registration errors. We account for this by learning the accuracy of an automated segmentation method, and incorporating several confidence-weighted segmentations to simultaneously drive image registration.

Segmentation Confidence Maps

Define the segmentation confidence map (SCM) for each anatomical structure, *j*, as the probability of accuracy:

$$\alpha^j(x) = P(f^j_{error}(x) < \epsilon)$$

where $f^j_{error}(x)$ is the distribution of segmentation errors, which we will call the error map.

We estimated the error map using the distance-transform to obtain the nearest boundary distance between the manual and automated contours.

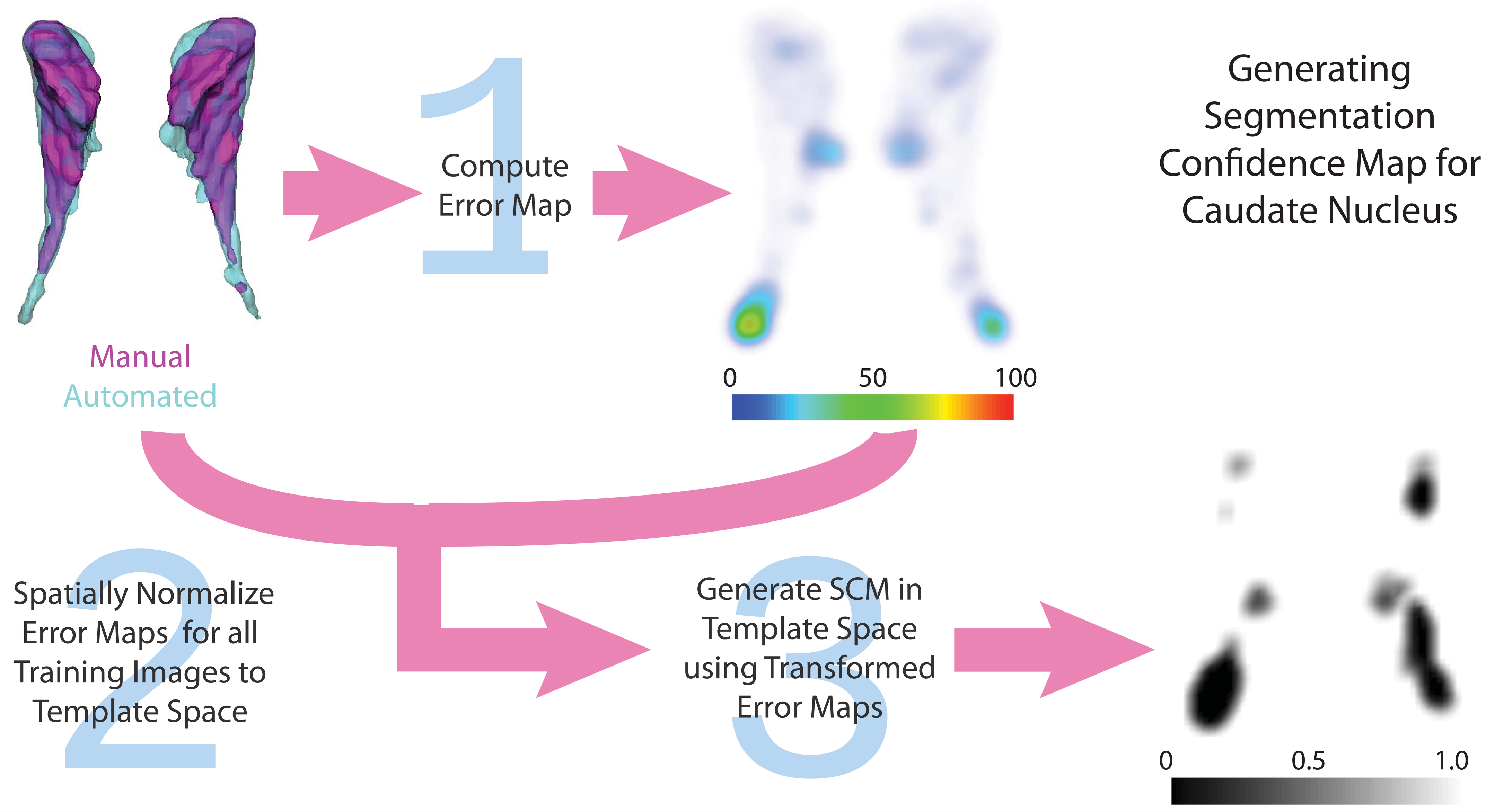
Propagation to Cohort Atlas

If cohorts are structurally similar, such as matched for age and pathological state, then SCMs learned from one cohort can be propagated to the other cohort atlas using registration, alleviating the need for manually-segmented training data.

Supervised Training

To generate the SCMs, we require a training set that is manually and automatically segmented.

1. Compute error maps for each structure in each training image
2. Spatially transform error maps to a template space by registering automated segmentations
3. Generate the SCM in the template space using the transformed error maps

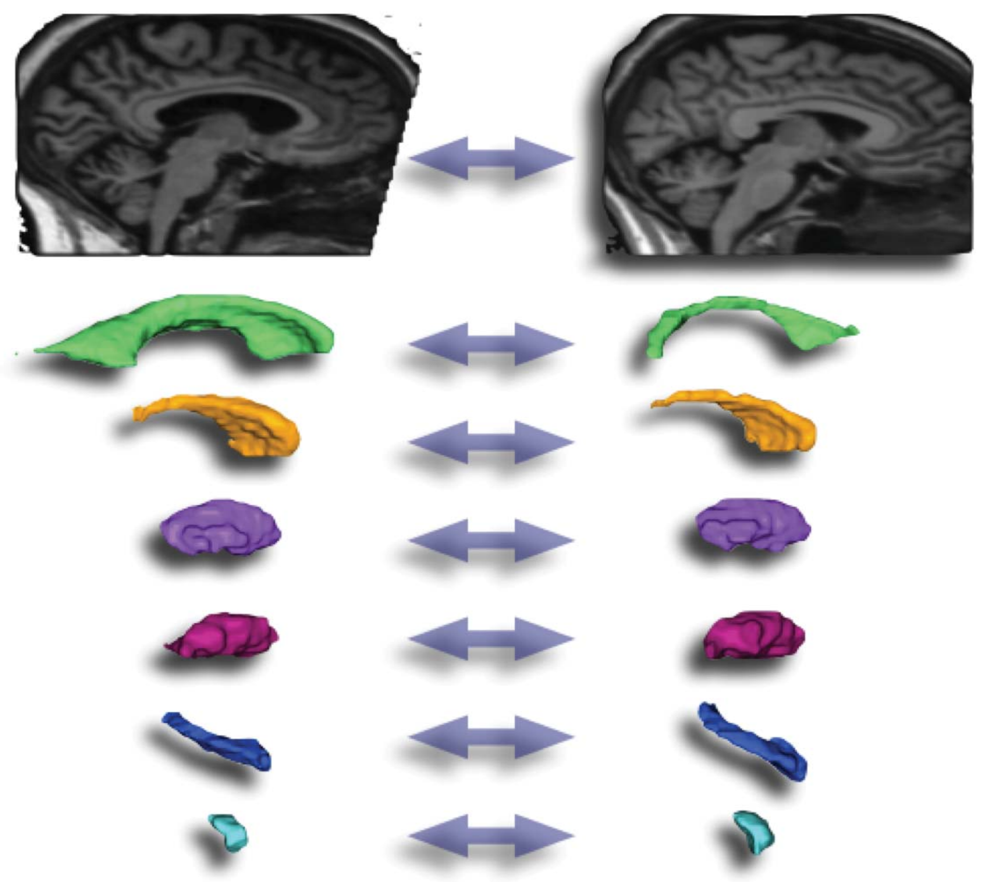


Multi-Structure Registration

We incorporated segmentations into our registration framework by extending it to use multiple data terms, each weighted with a SCM.

For initial segmentations we used the Freesurfer Image Analysis Suite [1], and for registration we used an extension of the Large Deformation Diffeomorphic Metric Mapping (LDDMM) [2]. Registration cost below:

$$\int_0^1 \|v_t\|_V^2 dt + \|A^{MR}(\phi_1^{-1}) - B^{MR}\|_{L^2}^2 + \sum_{j=1}^{N} \|\sqrt{\alpha_B^j}\,(A^j(\phi_1^{-1}) - B^j)\|_{L^2}^2$$



Atlas-based Segmentation

We apply our multi-structure confidence-weighted registration to single atlas-based subcortical brain segmentation.

Supervised Atlas Correction

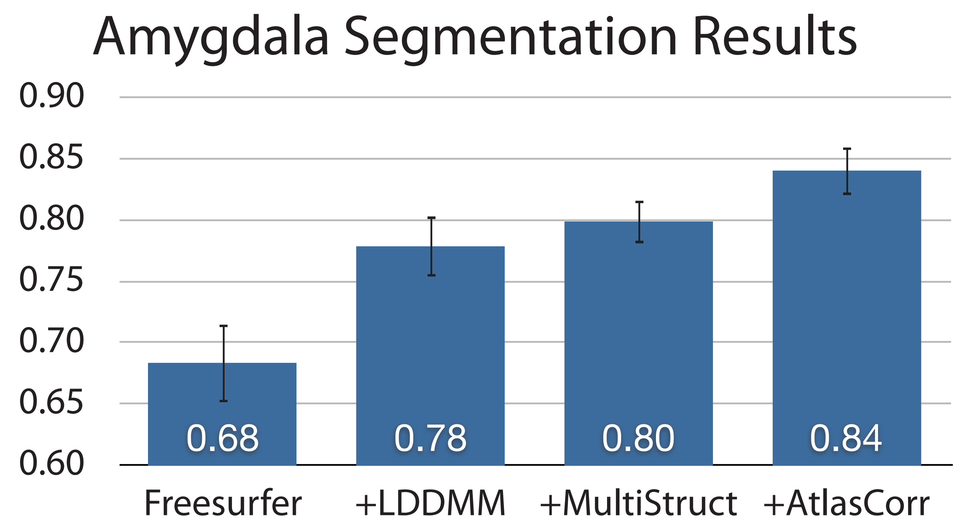
For a multi-atlas approach, we perform single-template segmentation of a manually-labelled training set, then back-propagate and fuse the manual labels in the template space.

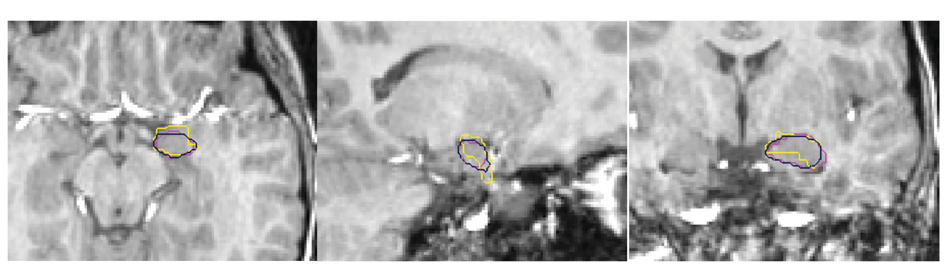
Results

Our segmentation method was applied to a cohort of healthy and autistic subjects for amygdala segmentation (results shown on the right). SCMs were trained on 9 scans from the IBSR dataset, with the SCM propagated to the chosen template from the autism cohort. Results compared to Freesurfer and FS+LDDMM [3].

Segmentation performance evaluated using:

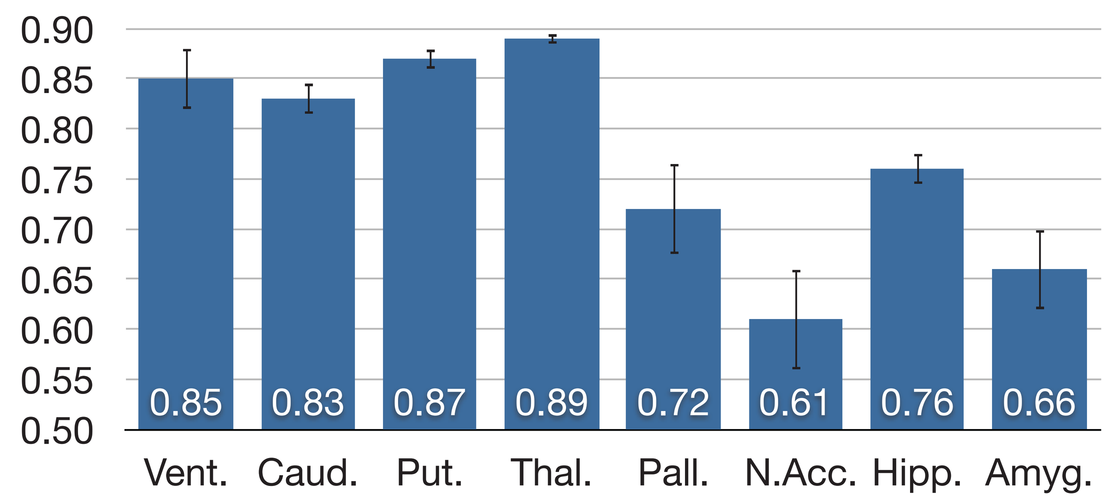
$$DSC = \frac{2V(A \cap B)}{V(A) + V(B)}$$





Legend: Manual Freesurfer Multi-structure Atlas-corrected

We also segmented 8 subcortical structures from the IBSR dataset, testing on the 9 subjects not included in the training set. Results below.



[1] B. Fischl, et al., "Whole brain segmentation ..." Neuron, vol. 33 (3), pp. 341–55, 2002.
[2] M. F. Beg, et al., "Computing large deformation metric mappings ..." IJCV, vol. 61 (2), pp. 139–57, 2005.
[2] A. R. Khan, et al., "Freesurfer-initiated fully-automated subcortical ..." Neuroimage, vol. 41 (3), pp 735-746, 2008.

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