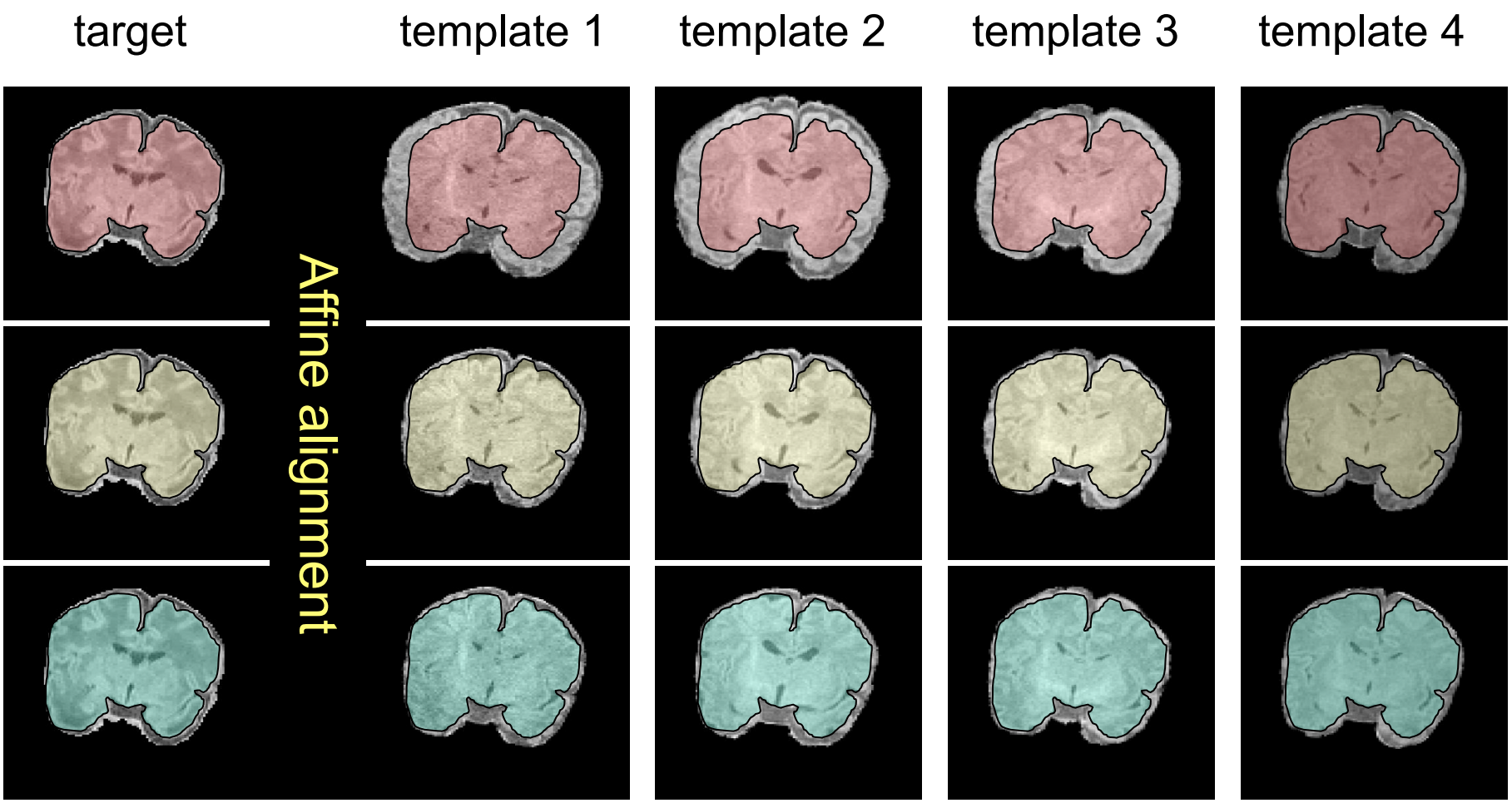
MRI predicts later outcomes

- Quantitative analysis of tissue volume from MRI at term equivalent age has been shown to predict:
  - Impaired visual function in VLBW infants at age 2 (Shah et al. 2006)
  - Object working memory deficits at age 2 (Woodward et al. 2005)
  - PDI and MDI at age 2 (Thompson et al. 2008)

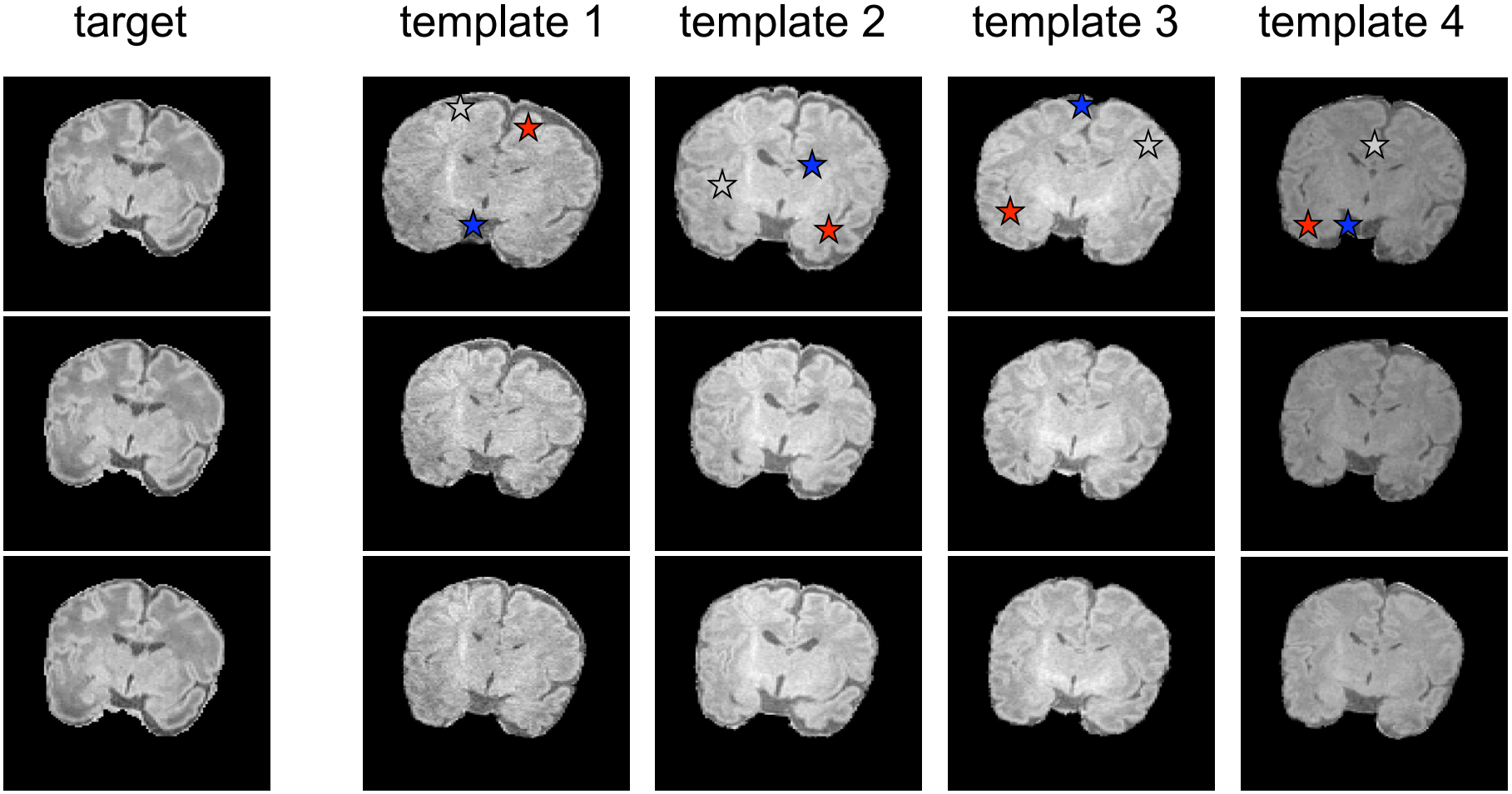
Tissue Class Training Data

- Our previous work has utilized interactive selection of per-subject training data:
  - Time consuming,
  - Subject to intra-rater and inter-rater variability,
  - Enabled identification of subtle contrast between different tissue types.
- We sought to develop an algorithm that avoids per-subject interaction, while maintaining excellent performance.
  - Weisenfeld and Warfield, NeuroImage, 2009.

Template to Target Registration

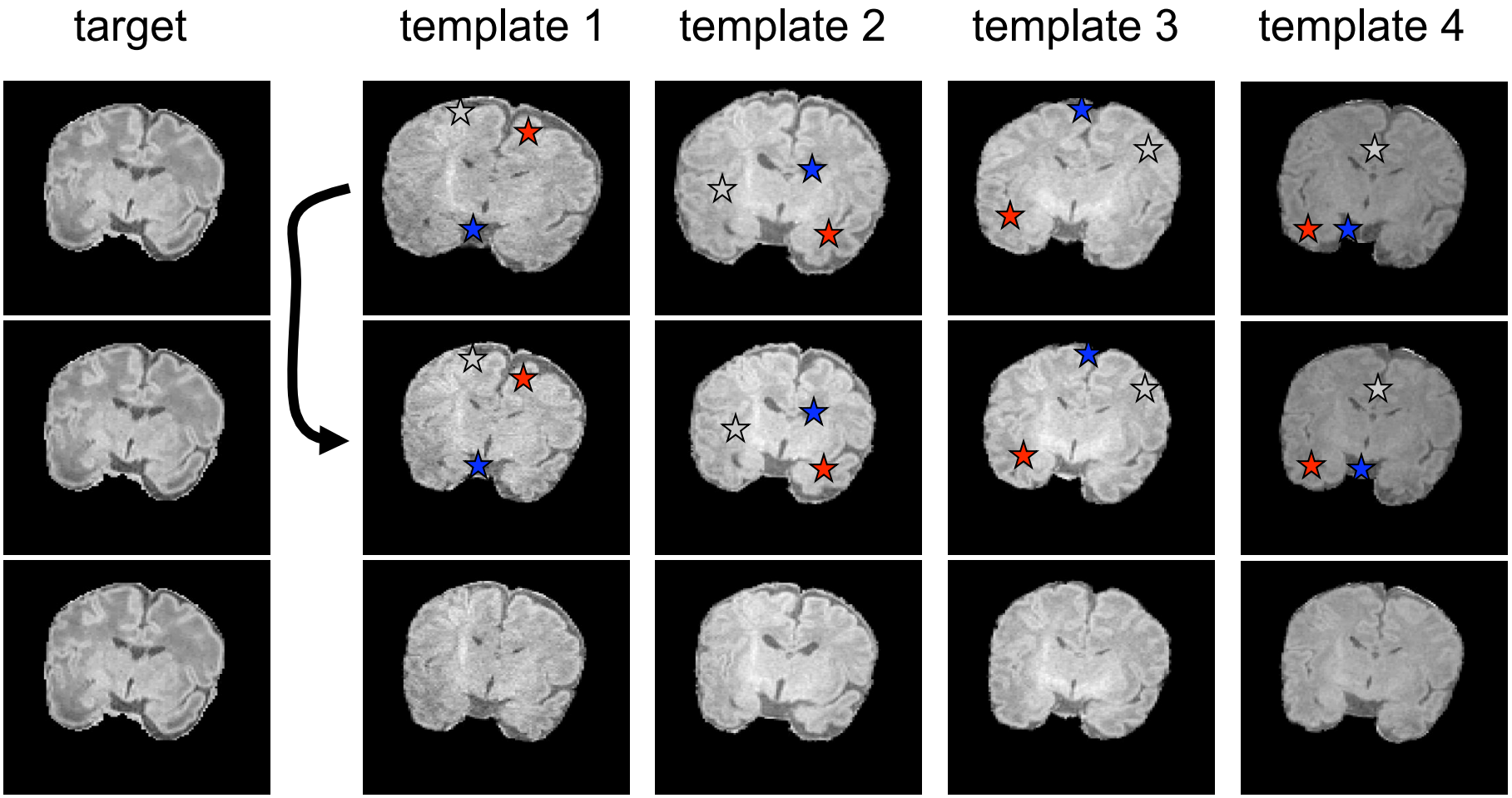


Tissue prototypes manually identified



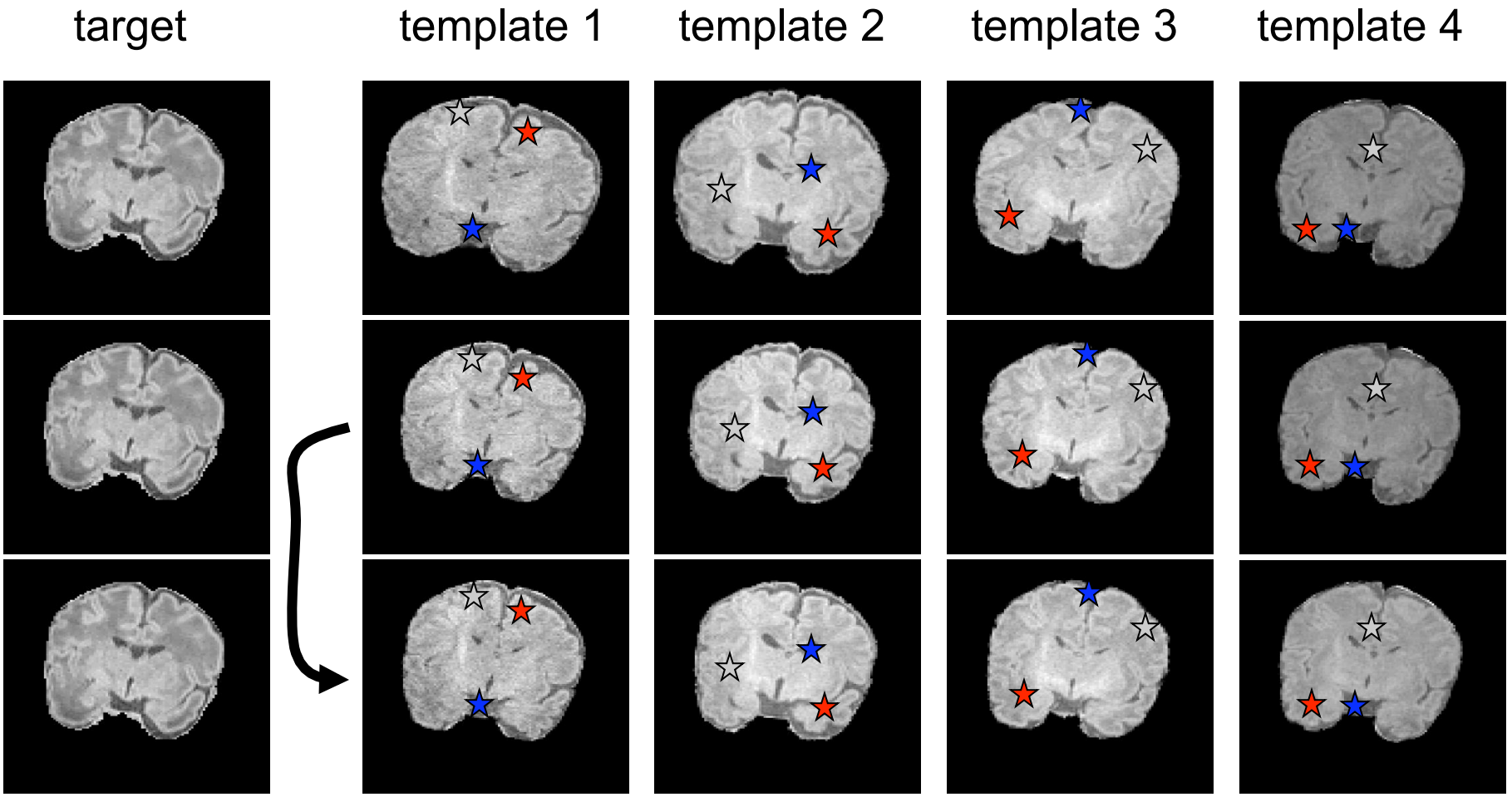
tissue class samples selected once on the original template images.

Tissue prototypes transferred



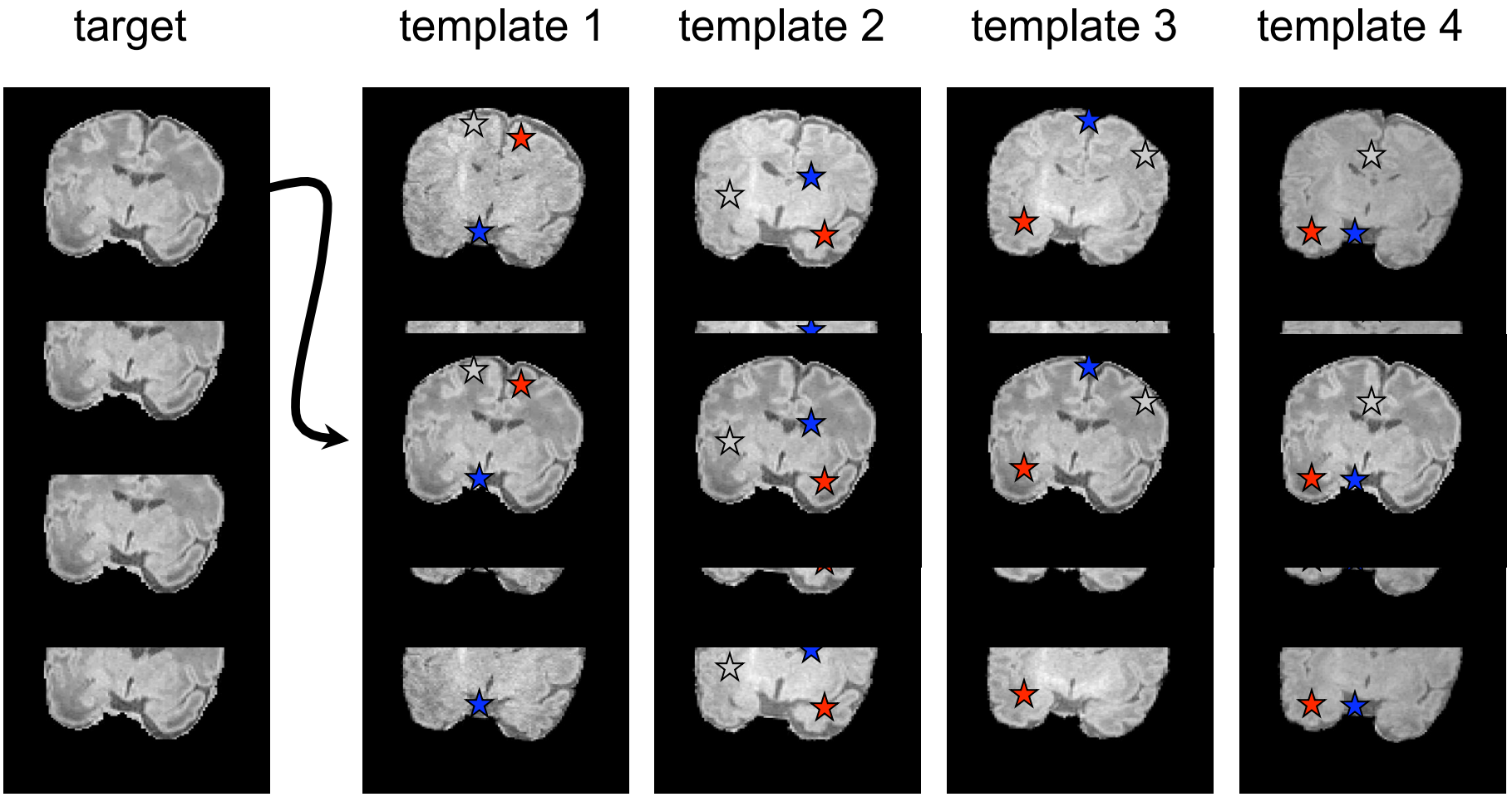
and then projected through the affine transform…

Tissue prototypes transferred



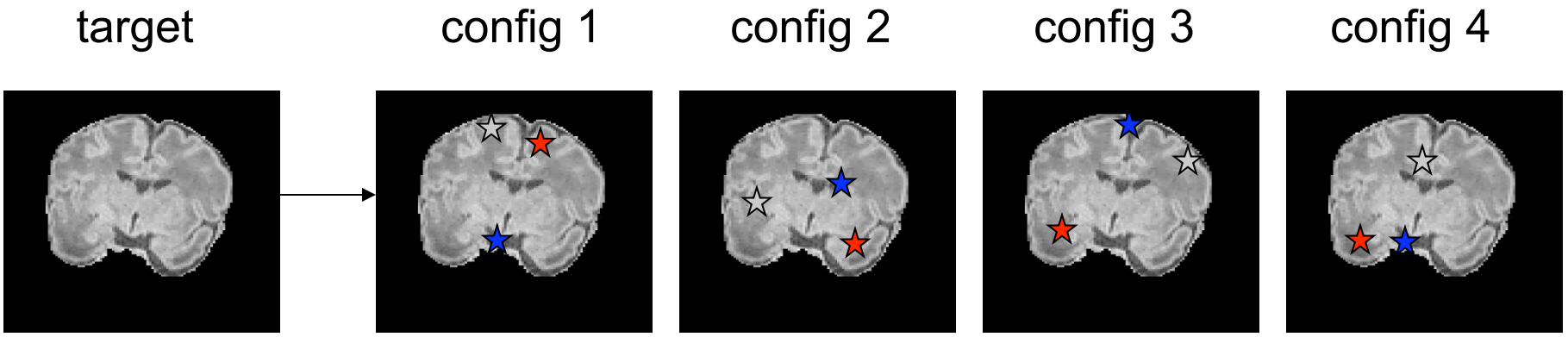
and then projected through the b-spline *non-linear* transform…

Tissue prototypes transferred



Different prototype configurations are projected onto the target subject

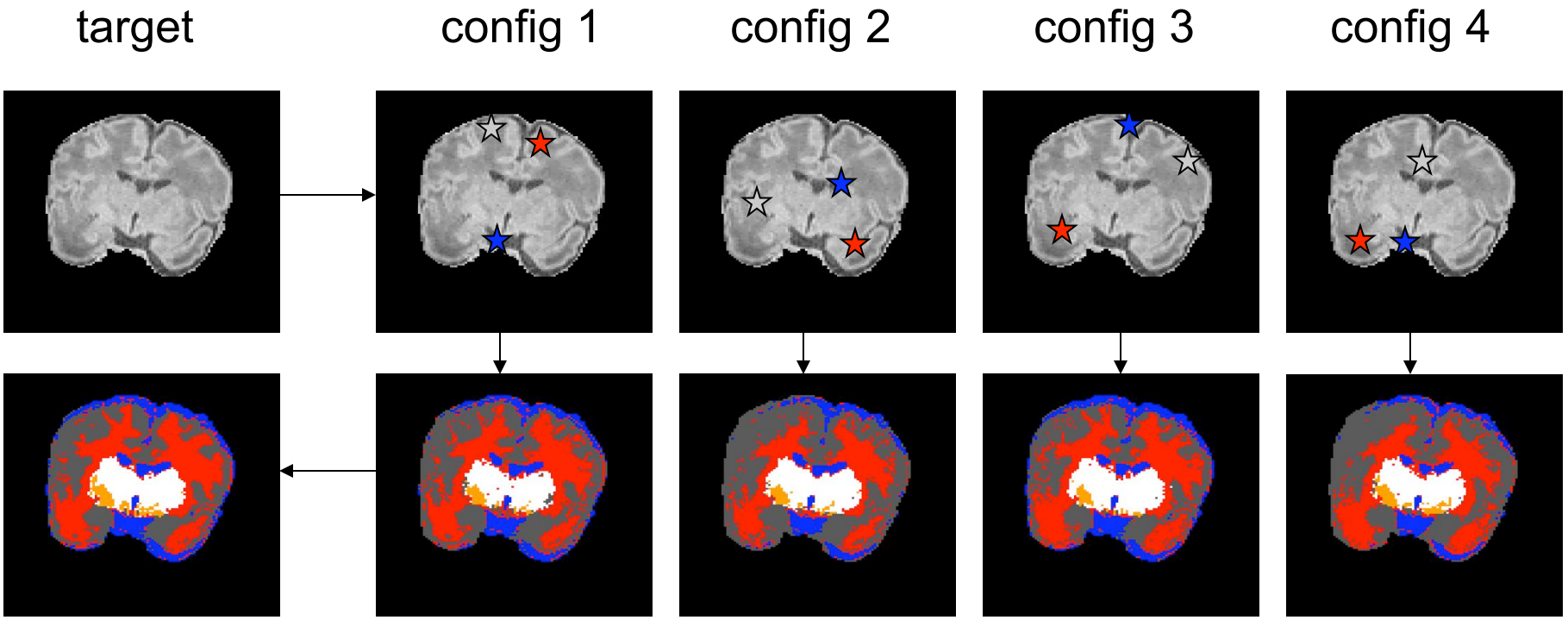
Multiple Configurations on the Target



The different prototype configurations represent the physical variation among the template subjects. By adding template subjects, and choosing prototypes by hand *only once*, a wider range of physical variation can be accommodated. Once a template subject is added, it is re-used without further human intervention.

The image *intensity* data used is *only* from the individual under study (the target).

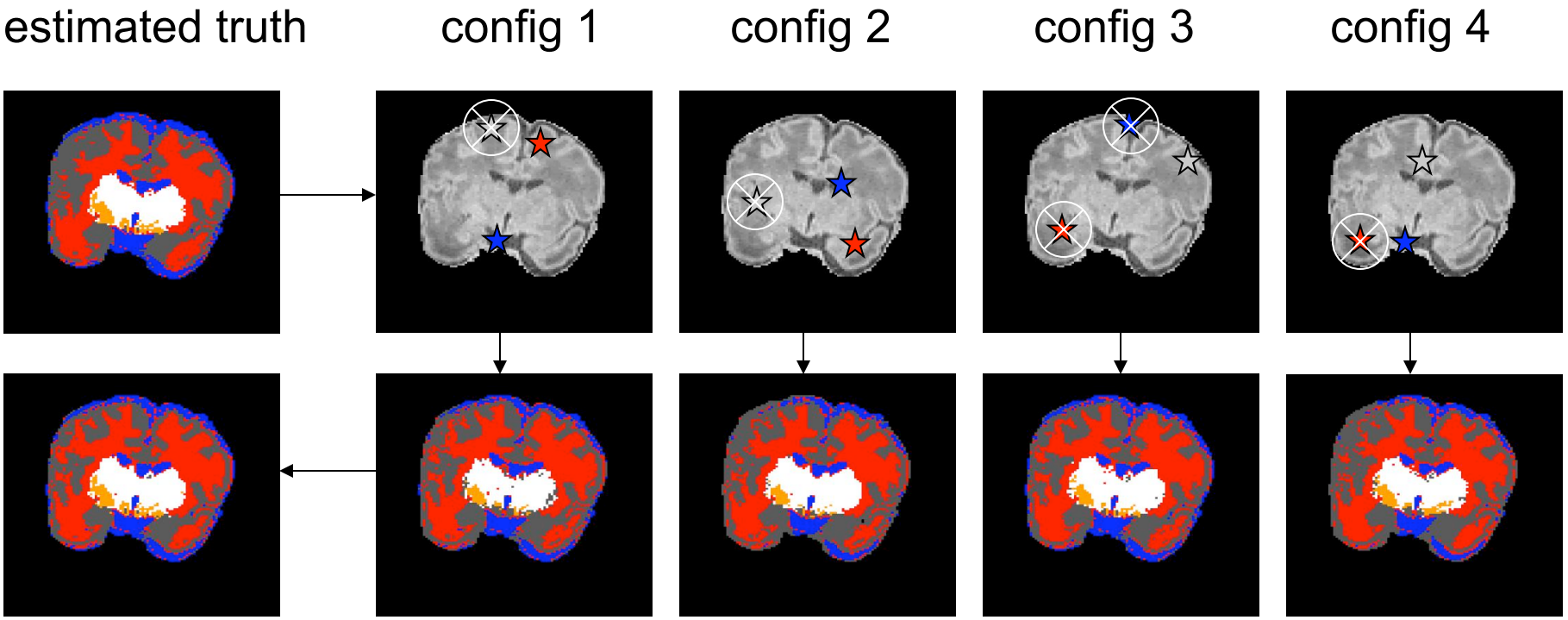
Multiple Configurations on the Target



Each configuration of sample coordinates leads to a different candidate segmentation of the target subject.

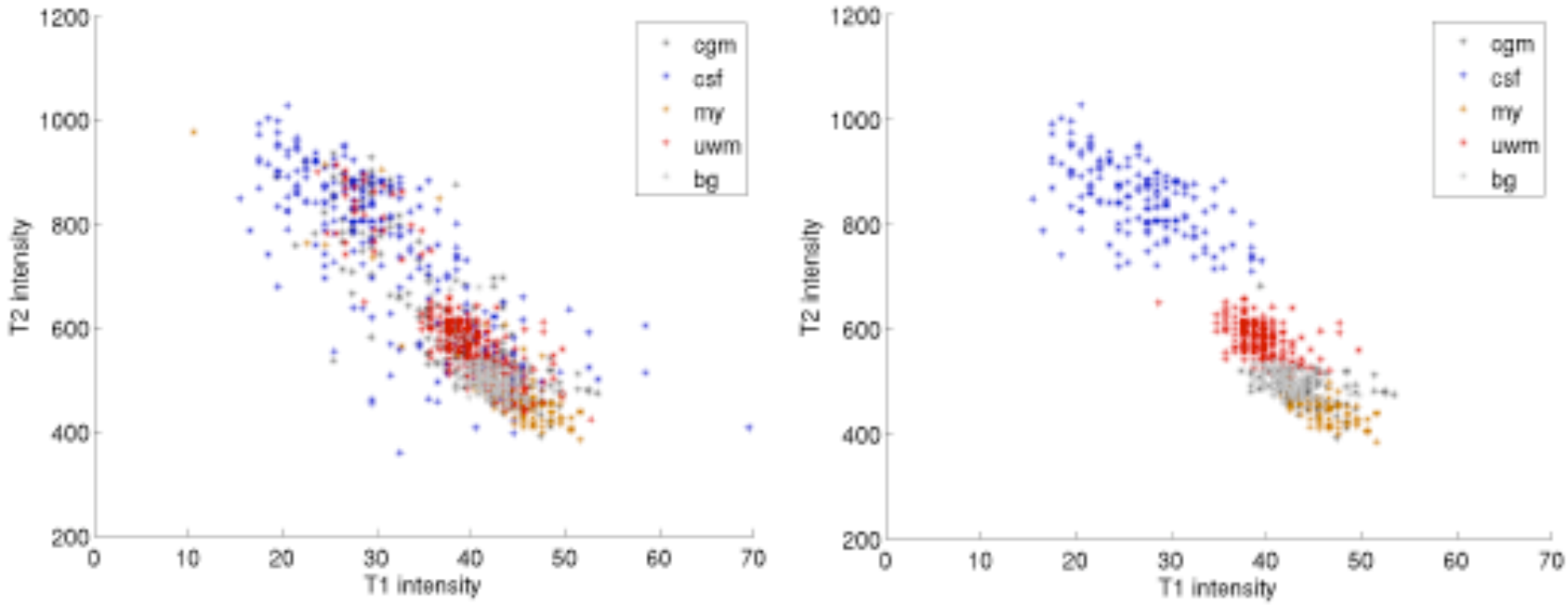
STAPLE is used to combined candidate segmentations.

Configurations are Edited



The previous iteration's STAPLE output (top left) is used to identify and eliminate prototypes which are inconsistent with the data.

Adaptation of training data



Evolution of feature space of training data through the automated projection and editing process.

Tissue class boundaries in feature space are identified.

Evaluation of training data

		train	
		$\mathcal{M}$	$\mathcal{A}$
test	$\mathcal{M}$	0.95 ± 0.02	0.93 ± 0.02
	$\mathcal{A}$	0.95 ± 0.01	0.97 ± 0.01

Posterior probability of correct classification with manually and automatically generated training data.

	test					
Subject	$\mathcal{M}$	$\mathcal{A}^0$	$\mathcal{A}^1$	$\mathcal{A}^2$	$\mathcal{A}^3$	$\mathcal{A}^{\text{FINAL}}$
1	0.98	0.66	0.77	0.86	0.91	0.93
2	0.96	0.65	0.77	0.87	0.92	0.94
3	0.96	0.66	0.79	0.89	0.94	0.95
4	0.96	0.65	0.78	0.87	0.92	0.94
5	0.94	0.66	0.78	0.87	0.93	0.95
6	0.94	0.67	0.80	0.90	0.94	0.95
7	0.94	0.66	0.79	0.89	0.94	0.96
8	0.94	0.70	0.82	0.91	0.96	0.97
9	0.94	0.67	0.79	0.89	0.93	0.95
10	0.96	0.69	0.80	0.89	0.94	0.96
mean±sd	0.95 ± 0.02	0.67 ± 0.02	0.79 ± 0.02	0.88 ± 0.02	0.93 ± 0.01	0.95 ± 0.01

Improved consistency of GM, UWM and CSF over iterations of editing of training data.

Segmentation comparison

Subject	CGM	CSF	myelin	UMWM	SCGM
1	0.95	0.82	0.63	0.95	0.92
2	0.89	0.94	0.80	0.89	0.86
3	0.89	0.93	0.71	0.91	0.89
4	0.84	0.95	0.70	0.85	0.81
5	0.92	0.93	0.77	0.93	0.88
6	0.89	0.98	0.77	0.93	0.85
7	0.93	0.96	0.70	0.96	0.89
8	0.91	0.97	0.79	0.93	0.87
9	0.87	0.94	0.66	0.91	0.80
10	0.94	0.80	0.67	0.95	0.88
mean±sd	0.90 ± 0.03	0.92 ± 0.06	0.72 ± 0.06	0.92 ± 0.03	0.86 ± 0.04

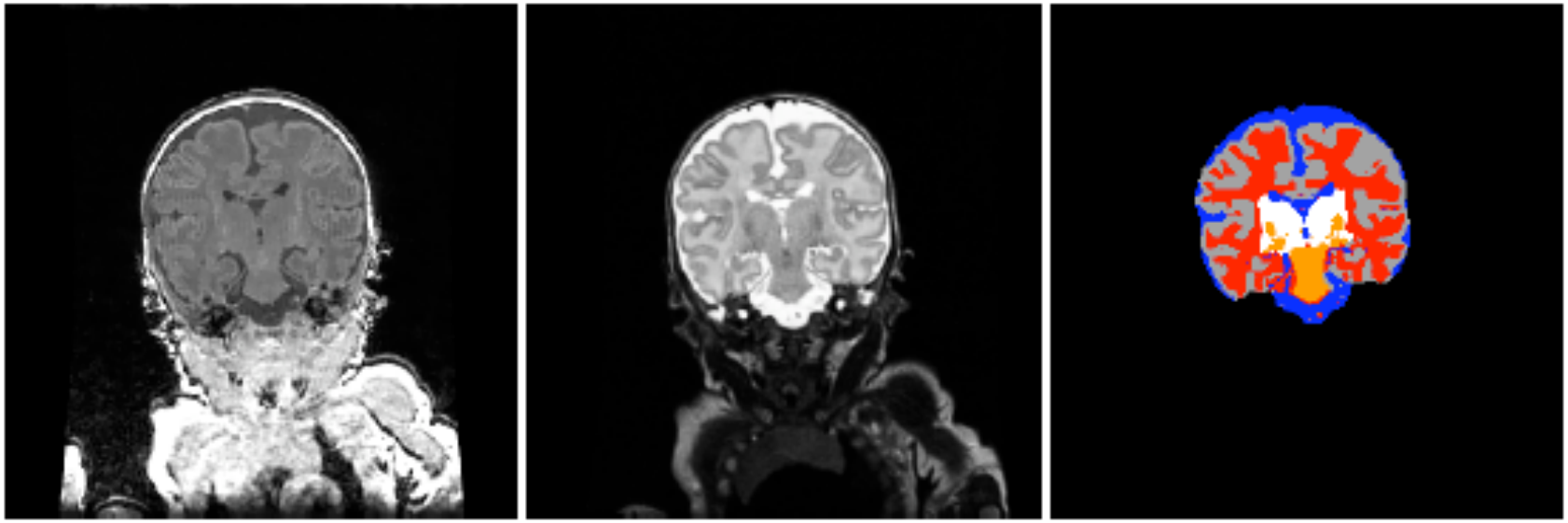
Dice coefficient comparing interactive to automated tissue classification.

Segmentation comparison

Subject		CGM	CSF	myelin	UMWM	SCGM
1	experts	0.86 ± 0.06	0.89 ± 0.05	0.81 ± 0.11	0.85 ± 0.05	0.86 ± 0.08
	automatic	0.75	0.96	0.86	0.79	0.96
2	experts	0.87 ± 0.06	0.93 ± 0.02	0.96 ± 0.05	0.87 ± 0.06	0.90 ± 0.12
	automatic	0.77	0.98	0.96	0.72	0.74
3	experts	0.90 ± 0.04	0.91 ± 0.02	0.77 ± 0.06	0.88 ± 0.03	0.91 ± 0.03
	automatic	0.77	0.97	0.81	0.78	0.95
4	expert	0.87 ± 0.08	0.91 ± 0.02	0.81 ± 0.06	0.87 ± 0.04	0.94 ± 0.04
	automatic	0.84	0.95	0.69	0.70	0.94

Comparison of predictive values of tissue segmentations obtained by interactive drawing and by automated tissue classification.

Newborn brain segmentation



Segmentation Algorithm

- Weisenfeld and Warfield, NeuroImage 2009
- Automatic estimation of training data is comparable to interactive selection by an expert.
- Automated segmentation compares well to hand-drawn segmentations.
- Software for pediatric MRI analysis, CRKit, supported by NIH.

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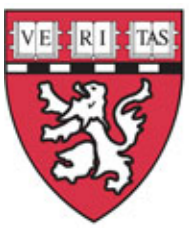

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