Magnetic Resonance Image Segmentation with Thin Plate Spline Thresholding

Xianhong Xie[1,2], Moo K. Chung[1,2,3], Grace Wahba[1,2]

[1]Departments of Statistics, [2]Biostatistics and Medical Informatics, [3]Waisman Lab for Brain Imaging and Behavior

THE UNIVERSITY of WISCONSIN MADISON

Introduction

There are many ways to segment magnetic resonance image (MRI). Among them the SPM method, the neural network based method [1], and the level set method are well known. We propose a novel image segmentation technique called thin plate spline (TPS) thresholding. The goal is to segment the image into 4 types of tissues: gray matter (GM), white matter (WM), cerebrospinal fluid (CSF), and others.

Methods

We fit thin plate splines to overlapping blocks of image slice, find thresholds on each block, and then blend the blocks along with the thresholds smoothly.

Step 1: Partitioning of Slice

The slice is divided into overlapping blocks (Figure 1). The criterion is to have all 4 tissue types (GM, WM, CSF, and others) in each block. To reduce the computing load, we crop the empty space before the partitioning.

Step 2: Finding Optimal fGCV

For each block, we fit thin plate splines with different number of knots to the image intensities. The GCV scores with a fudge factor (fGCV), which inflates the degrees of freedom of the splines by a constant factor [2], are calculated. We search for the configuration that gives the smallest fGCV.

Step 3: Predicting and Thresholding

We fit thin plate splines with the optimal knots configuration and predict on a fine grid. Thresholds are obtained on each block by taking averages of the adjacent centers from the K-means algorithm. Four centers are used with the algorithm.

Step 4: Blending Images Together

We blend the predicted block images and the thresholds together respectively with some smooth weighting function (Figure 1). The output is one smooth image with 3 thresholding fields.

Materials & Evaluation

Image Used

The 20 normal data was downloaded from http://www.cma.mgh.harvard.edu/ibsr/. Five subjects were used out of the 20. We first sorted the subjects based on their id's, and then chose the 2nd, 6th, 10th, 14th, and 18th subjects. Manual segmentations are available with this data set. Three methods (TPS, Manual, and SPM) were compared on segmentation of one slice from each subject.

Evaluation Method

Both the correlation coefficient and the kappa index [3] were used for evaluation. The kappa index is defined as

$$\kappa(S_1, S_2) = \frac{2|S_1 \cap S_2|}{|S_1| + |S_2|}.$$

The subpixel results of TPS were converted to pixel level (Figure 4 lower right) to be compared with other methods. The segmentations by TPS and SPM were thresholded to calculate the kappa index.

Results

The segmentations by human, TPS method, and SPM method are given in Figure 3. The summary table for all the coefficients and indices is given in Table 1, which shows that the performance of TPS is similar to that of SPM by comparing against manual segmentation. Also, the TPS segmentations tend to have smaller variances than the SPM segmentations. The subpixel property of TPS method is shown in Figure 4.

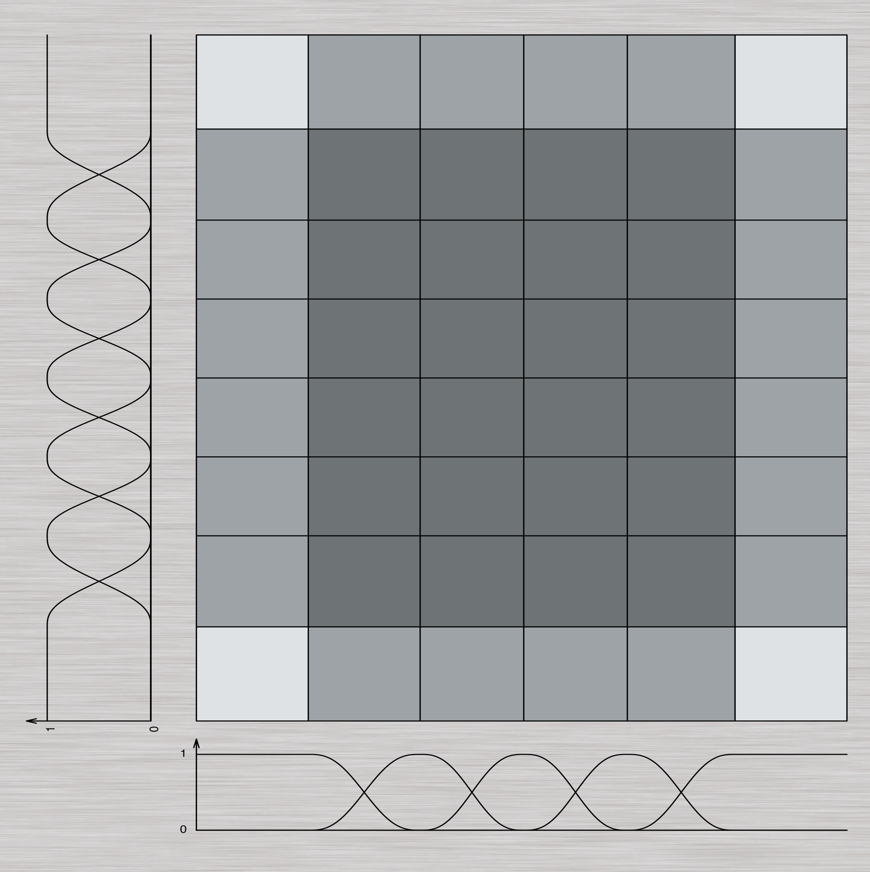

Figure 1: Overlapping scheme and weighting functions for the blocks. Every 4 adjacent rectangles form one block. There are 5 by 7 blocks. Different gray levels represent different times subblocks are being covered.

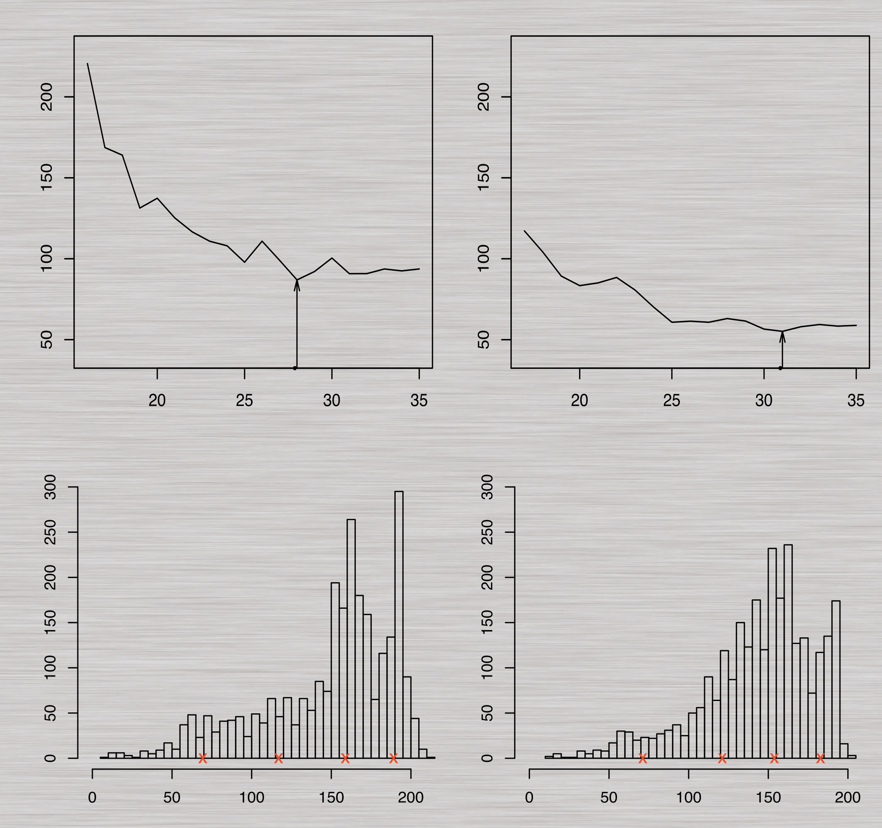

Figure 2: fGCV curves (top) and histograms (bottom) for 2 adjacent blocks. The arrows in the top plots point to the minimum of fGCV scores. The red markers in the bottom plots represent the centers found by K-means.

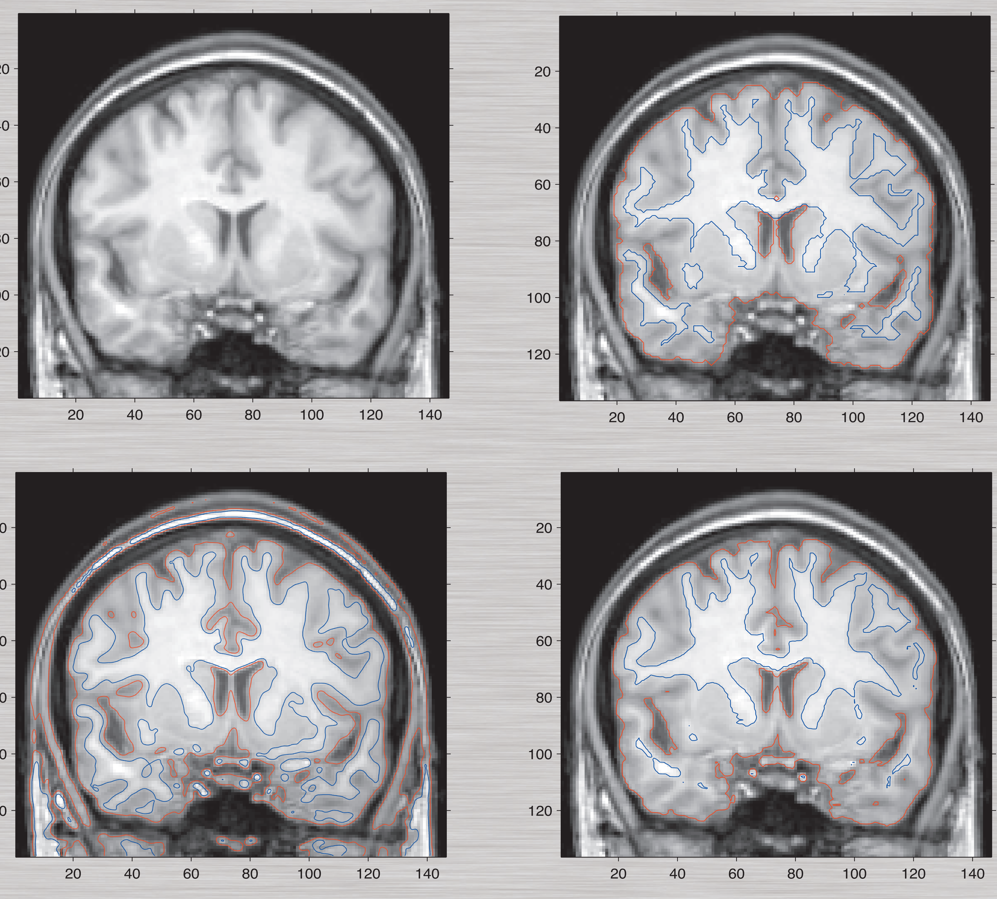

Figure 3: Plots for the original image (upper left), manual segmentation (upper right), TPS segmentation (lower left), and SPM segmentation (lower right).

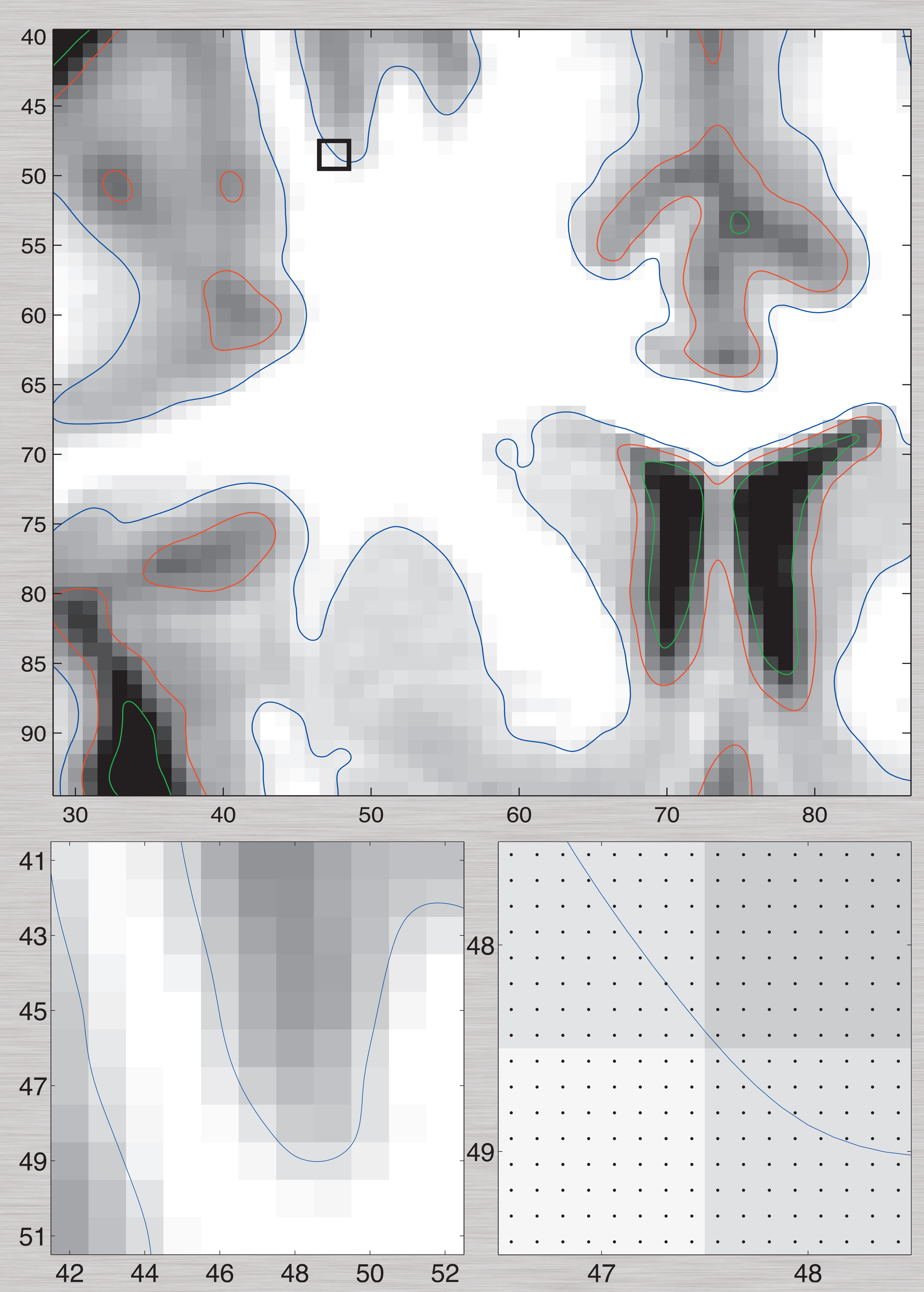

Figure 4: Plots for the subpixel segmentation of TPS. Top plot: TPS result zoomed to a local region; lower left: further zoom of the TPS result; lower right: TPS result zoomed to 2 by 2 pixles with subpixels shown in dots.

Table 1: Coefficients for all the Comparisons with Mean and SD Summary

	subject no.	corr. coef. GM	corr. coef. WM	kappa index GM	kappa index WM
tps vs manual	1	0.660	0.827	0.836	0.872
	2	0.702	0.757	0.841	0.827
	3	0.654	0.787	0.811	0.850
	4	0.410	0.678	0.723	0.770
	5	0.612	0.791	0.776	0.838
mean (sd)		0.608(0.115)	0.768(0.056)	0.798(0.049)	0.831(0.038)
spm vs manual	1	0.675	0.846	0.883	0.866
	2	0.686	0.839	0.887	0.880
	3	0.637	0.810	0.863	0.842
	4	0.091	0.672	0.679	0.753
	5	0.450	0.803	0.825	0.824
mean (sd)		0.518(0.250)	0.794(0.071)	0.827(0.087)	0.833(0.050)
tps vs spm	1	0.806	0.883	0.848	0.900
	2	0.626	0.759	0.794	0.824
	3	0.734	0.822	0.808	0.861
	4	0.426	0.767	0.730	0.793
	5	0.645	0.800	0.785	0.836
mean (sd)		0.647(0.143)	0.806(0.050)	0.793(0.043)	0.843(0.040)

Conclusions

1 A new intensity based segmentation method is being proposed.

2 The method generates subpixel results and smoother boundaries.

3 It handles the partial volume effects and image inhomogeneity through local thresholding and blending.

References

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