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Label fusion for segmentation via patch based on local weighted voting

Key words: Label fusion; Local weighted voting; Patch-based，Background analysis

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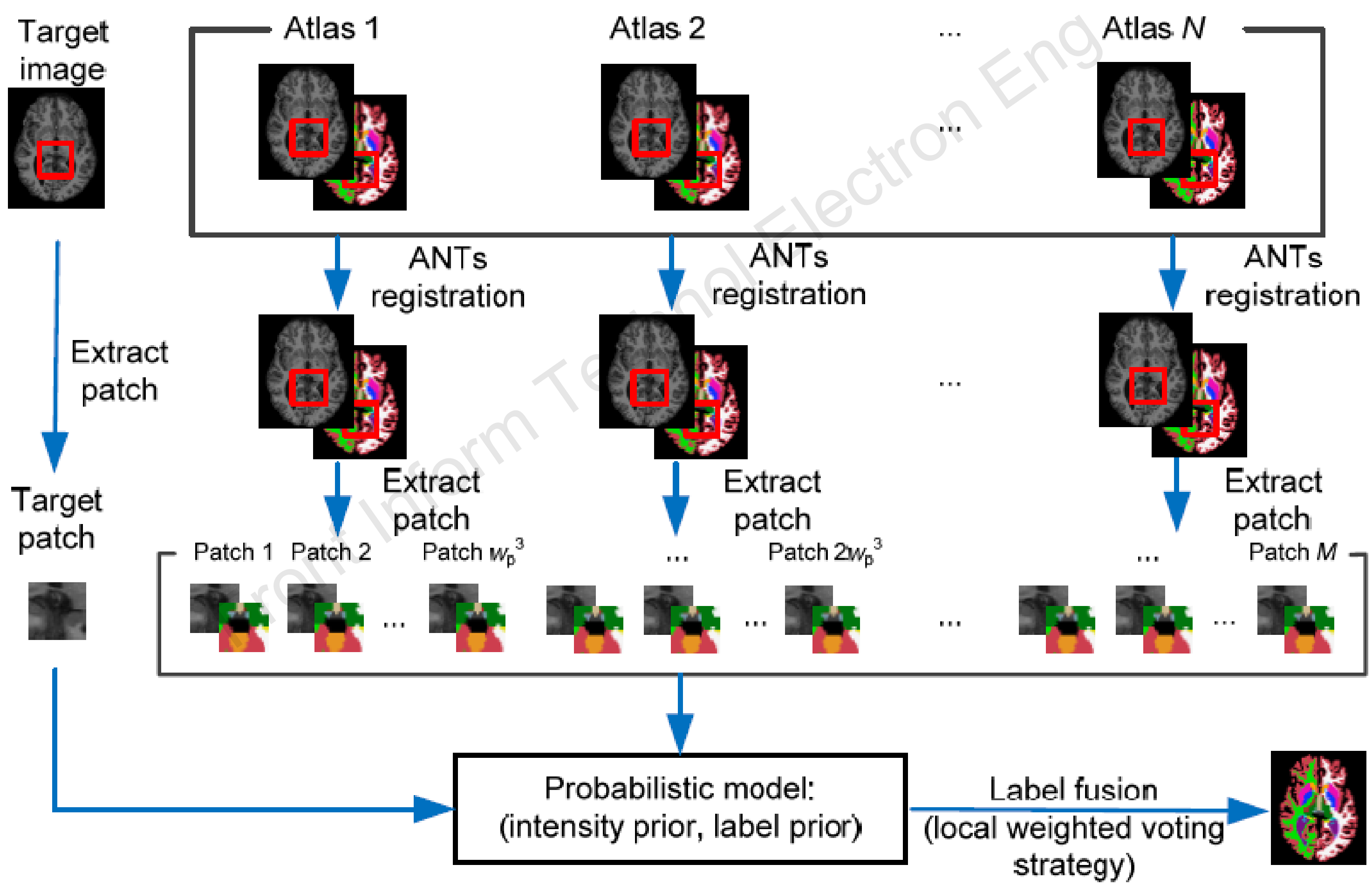
Motivation

- The great challenge of accurate, robust, and reliable segmentation in quantitative magnetic resonance imaging (MRI) analysis.
- The image background is not regarded as a label when the label prior is estimated by the logarithm of odds model based on the SDM (Sabuncu *et al.,* 2010).
- The patch-based methods are less dependent on the accuracy of registration, thus even the low-accuracy rigid registration can also be applied.

Main idea

- Extract patches from the target image and training scans.
- Establish the probability model between the target patch and the training atlases patches.
- Analyze the label fusion procedure concerning the image background and take the background as an isolated label when the label prior was established by the Kronecker delta function in the patch level.

1. The process of the label fusion algorithm via patch based on a probabilistic model and local weighted voting



2. Build the probabilistic model for intensity prior and label prior and label fusion by Bayesian inference

(1). Intensity prior

$$p_m(I(x);I_m) = \frac{1}{\sqrt{2\pi\sigma^2}}\exp\left[-\frac{1}{2\sigma^2}(I(x)-I_m(x))^2\right]$$

(2). Label prior

$$P_m(S(x)=l;L_m(x)) = \frac{1}{Z_m(x)}(\delta(S(x)=l))$$

Where, $$\delta(S(x),l) = \begin{cases} 0, & S(x) \neq l, \\ 1, & S(x) = l. \end{cases}$$

The image background is taken into account as an isolated label. Its value is set at 0 so that the background has the same privilege as the other labels.

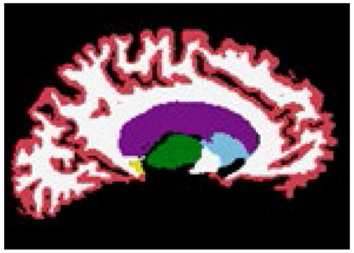
Label fusion:

$$\hat{S}(x) = \underset{S(x)}{\arg\max}\, p_m(S(x)\,|\,I(x);\{L_m, I_m\})$$

$$= \underset{l\in\{0,\text{ labels of target}\}}{\arg\max} \sum_{m=1}^{M} p_m(I(x)\,|\,I_m)\,p_m(S(x)=l;L_m)$$

Bayesian inference

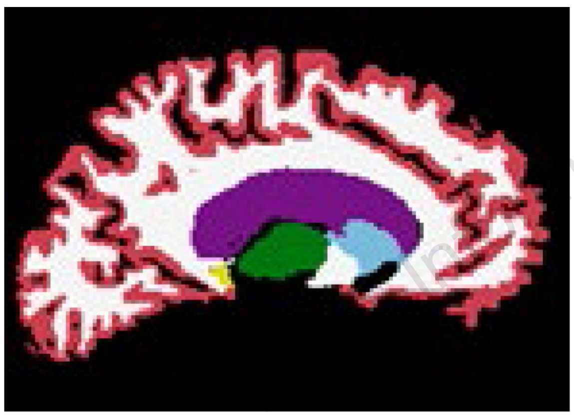
$$\hat{S}(x) = \underset{l\in\{0,\text{ labels of target}\}}{\arg\max} \sum_{m=1}^{M} p_m(I(x);I_m)\,p_m(S(x)=l;L_m)$$



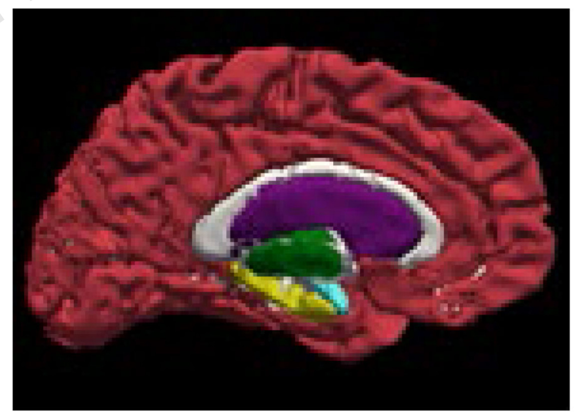
Segmentation result

Major results

- The automated segmentation of a scan on the nine ROIs in the left hemisphere using hemisphere using the proposed algorithm (LWVP)



(a) Sagittal slice of a segmentation



(b) 3D rendering of the segmentation

Major results (Cont'd)

- Compared with other algorithms, LWVP, our proposed method, can produce more accurate and robust results.

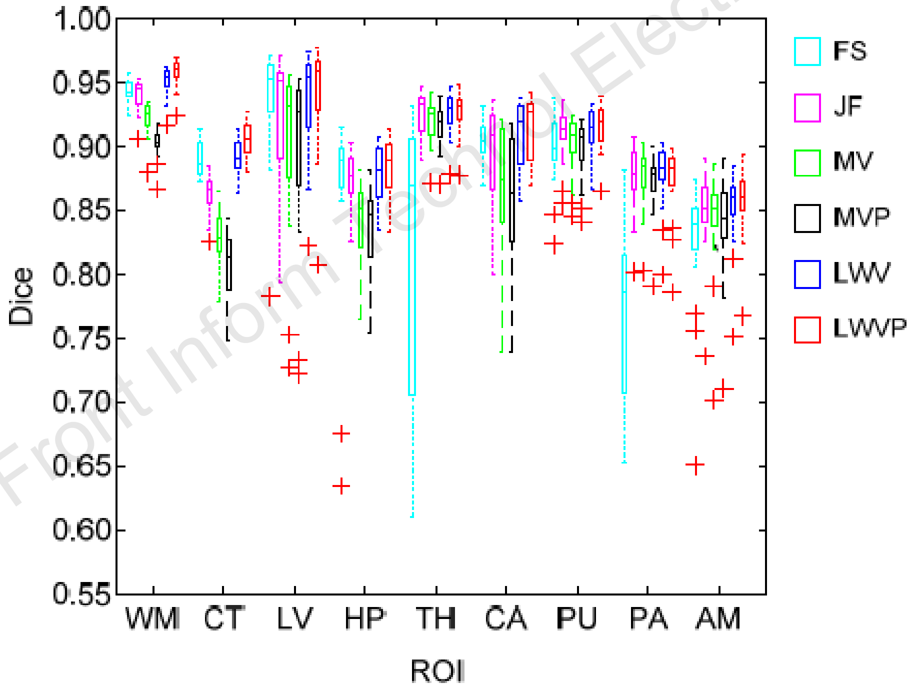


Fig. 7 Dice scores corresponding to the mentioned methods: FreeSurfer (dark green), JF (purple), MV (light green), MVP (black), LWV (blue), LWVP (red)

Conclusions

- A patch-driven level set method for label fusion by taking advantage of the probabilistic model and local weighted voting scheme.
- The label prior was established by the Kronecker delta function in the patch level.
- The running time could be relatively reduced and the segmentation performance could be much better by the application of Kronecker delta function in label prior term rather than the LogOdds model based on the SDM.