Impact of Non-local Means filtering on Brain Tissue Segmentation

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Introduction

A wide number of magnetic resonance imaging (MRI) analysis techniques rely on brain tissue segmentation. Automated and reliable tissue classification is a challenging task as the intensity of the data typically does not allow a clear delimitation of the different tissue types because of partial volume effects, image noise and intensity non-uniformities caused by magnetic field inhomogeneities. To solve this problem, classification algorithms traditionally combine data-term (e.g. gray-level intensity or gradient values) with prior spatial information (e.g. local neighborhood and/or atlas information). To be robust to noise, local interactions between voxels are usually taken into account by using Markov random field (MRF) models. In this work, we propose to study the impact of Nonlocal (NL) means denoising (Coupe et al. 2008) on brain tissue segmentation.

Method

NL-means filters have been recently shown very competitive results when compared to other denoising approaches (Buades et al. 2005). This filter is based on the weighted average of all the voxels of the image using a robust similarity measure that takes into account the neighbourhood of the voxels being compared.

In our study, the optimized blockwise NL-means filter proposed by Coupe et al (2008) has been used with the Rician adaption introduced in (Wiest-Daeslle).The amount of Rician noise in the MRI data is ocally estimated using noise in the image background (Aja et al. 2008).

Our segmentation method is based on an adaptive maximum a posteriori (AMAP) approach (Rajapakse et al. 1997) that has been extended by Partial Volume Estimation (Tohka et al. 2004). We start with an initial segmentation of the three pure classes (GM, WM, CSF) and background (BKG) using the segmentation method of SPM8 (Ashburner and Friston 2005) followed by a PVE of two mixed classes (GM-WM and GM-CSF). Subsequently, each intensity value in the resulting image is represented by a weighted sum of random variables, each of which describes a pure tissue type. The AMAP estimation is adaptive in the sense that local variations of the parameters (means and variance) are modeled as slowly varying spatial functions. This does not only account for intensity inhomogeneities, but also for other local variations of intensity. Optionally, we use a spatial prior term based on a MRF model.

In order to validate our method, we used a ground truth image from the brainweb database with varying noise levels of 1-9%. To estimate the segmentation quality after denoising, we calculated the Kappa coefficient of the GM/WM/CSF labels of the brain phantom,. Finally, our proposed approach is compared to algorithms implemented in SPM8 and FSL-FAST4 (with MRF and PVE, no atlas priors).

Results

Figure 1 displays an example of the denoising effect using the T1 brain phantom with 9% noise. In the upper row, the denoising effect of the optimized Rician non-local means (ORNLM) filter is compared to the T1 image without noise (ground truth) and with 9% noise. The filter successfully minimizes noise, while retaining local information of small structures. The two lower rows show the effects of MRF, PVE, and ORNLM on segmentation labels (CSF/GM/WM) of the brain phantom with 9% noise. The combination of PVE and ORNLM achieves the best qualitative results.

Figure 2 illustrates the effect of MRF, PVE, and ORNLM on segmentation accuracy for varying noise levels. The Kappa coefficient is calculated to quantify segmentation accuracy compared to the ground truth brain phantom. A Kappa coefficient of 1 means that there is a perfect overlap between the segmented image and the ground truth. The ORNLM with PVE (solid purple line) clearly outperforms all other approaches, while the additional use of MRF (solid red line) shows no further improvement.

Figure 3 shows the evaluation results for the proposed approach and the FAST4 and SPM8 segmentation algorithms. The FAST4 method (that also uses PVE and MRF) achieves increased segmentation accuracy for all noise levels compared to SPM8 (without PVE and MRF), while the ORNLM approach with PVE achieves the best segmentation accuracy. The improvement is largest for larger noise levels.

Figure 4 displays the effect of the smoothing parameter h on segmentation accuracy for varying noise levels. The estimated smoothing parameter is based on Rician noise estimation, which was demonstrated to be optimal in terms of denoising quality for MRI data. However, this value is always larger than the optimal one in terms of segmentation accuracy, which is based on a maximal Kappa value. The ratio between the optimal for segmentation and denoising is about 0.7.

Conclusion

We have presented a method to improve image partitions using an optimized Rician NL-means filter. This approach permits a reliable segmentation for data affected by noise. We demonstrated that our denoising filter improves the quality of the segmentation mostly for images with higher noise levels (and, for this reason, lower SNR).

The method is based on a computationally efficient blockwise implementation that only requires ~1 min for computation. The estimated Rician noise in the MRI data allows effective denoising over a wide range of varying noise levels and does not need an additional parameter related to the image noise. The estimated Rician noise level might be adjusted with a weighting of 0.7 to better preserve small structures. For segmentation, structure preservation might be more important than additional noise removal.

We suggest this denoising filter as an attractive complement to all available segmentation techniques.

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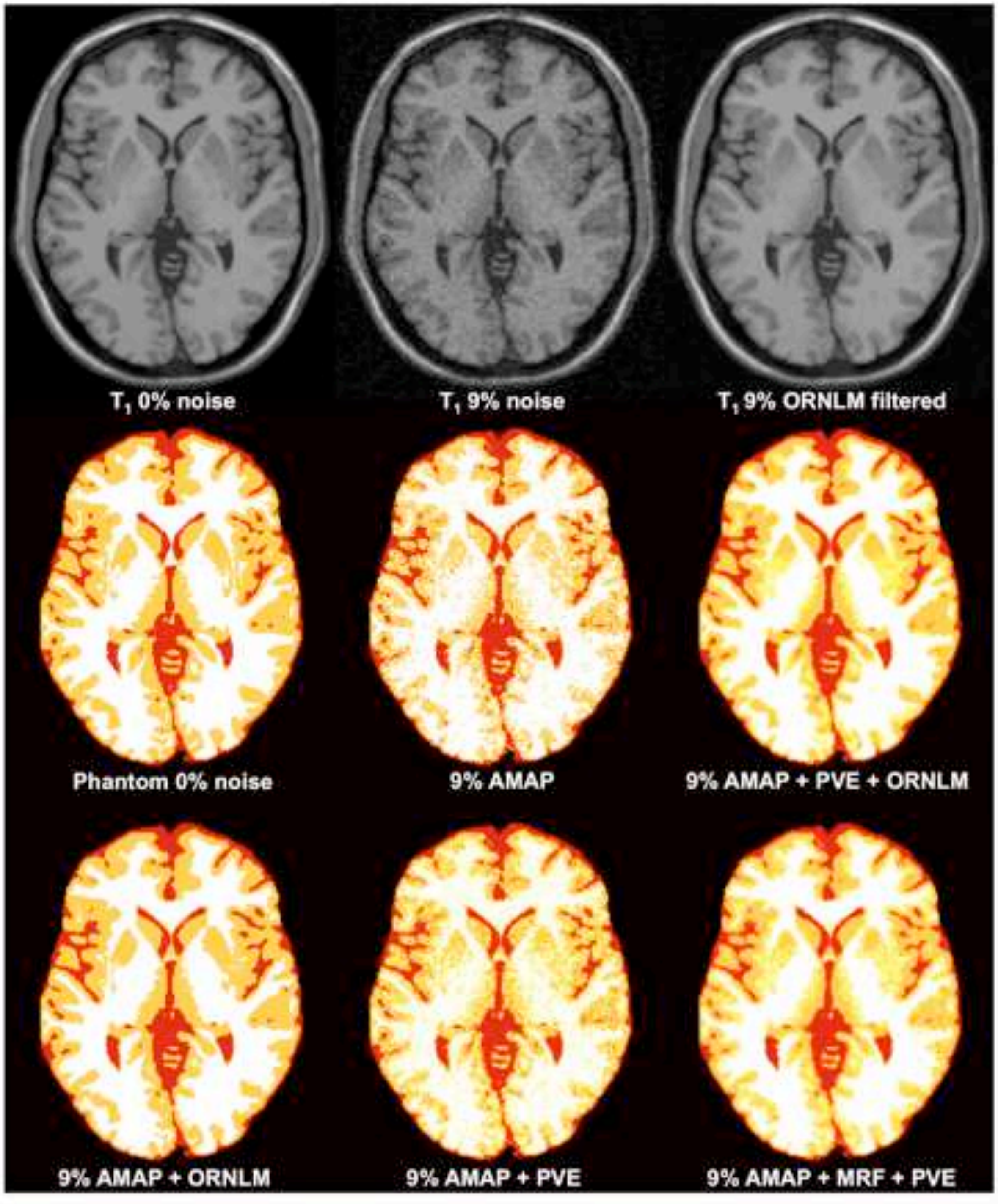

Fig. 1 Effect of Markov Random Fields Model (MRF), Partial Volume Estimation (PVE), and Optimized Rician Non-Local Means Filter (ORNLM) on segmentation using AMAP

In the upper row the T_1 brain phantom with no noise and 9% is displayed and the result after ORNLM filtering. The bottom row shows the labels after segmentation.

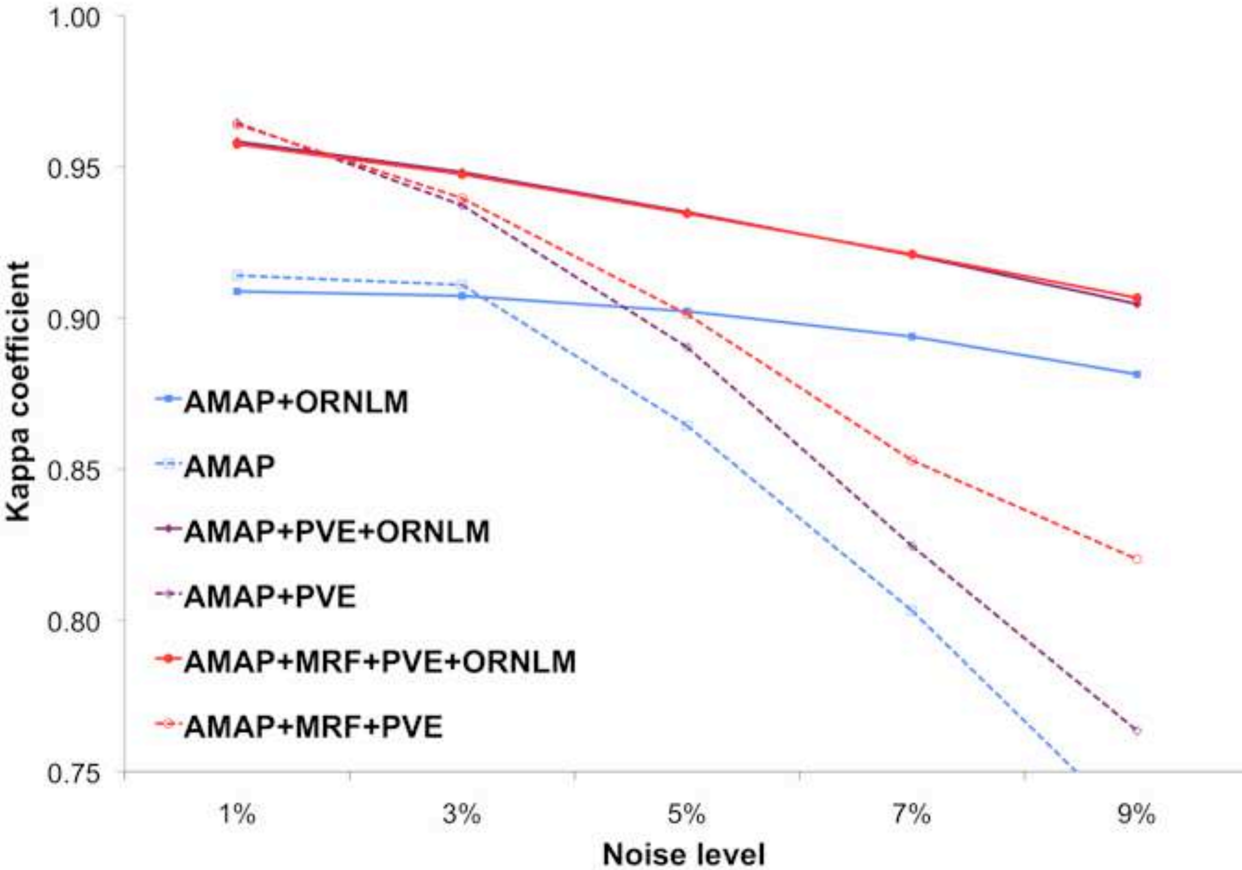

Fig. 2 Effect of Markov Random Fields Model (MRF), Partial Volume Estimation (PVE), and Optimized Rician Non-Local Means Filter (ORNLM) on segmentation using AMAP
Evaluation results with the brain phantom as ground truth are shown for different noise levels from 1 to 9%. Segmentation accuracy for all tissue types is calculated by Kappa coefficient. A Kappa coefficient of 1 means that there is a perfect overlap between the segmented image and the ground truth.

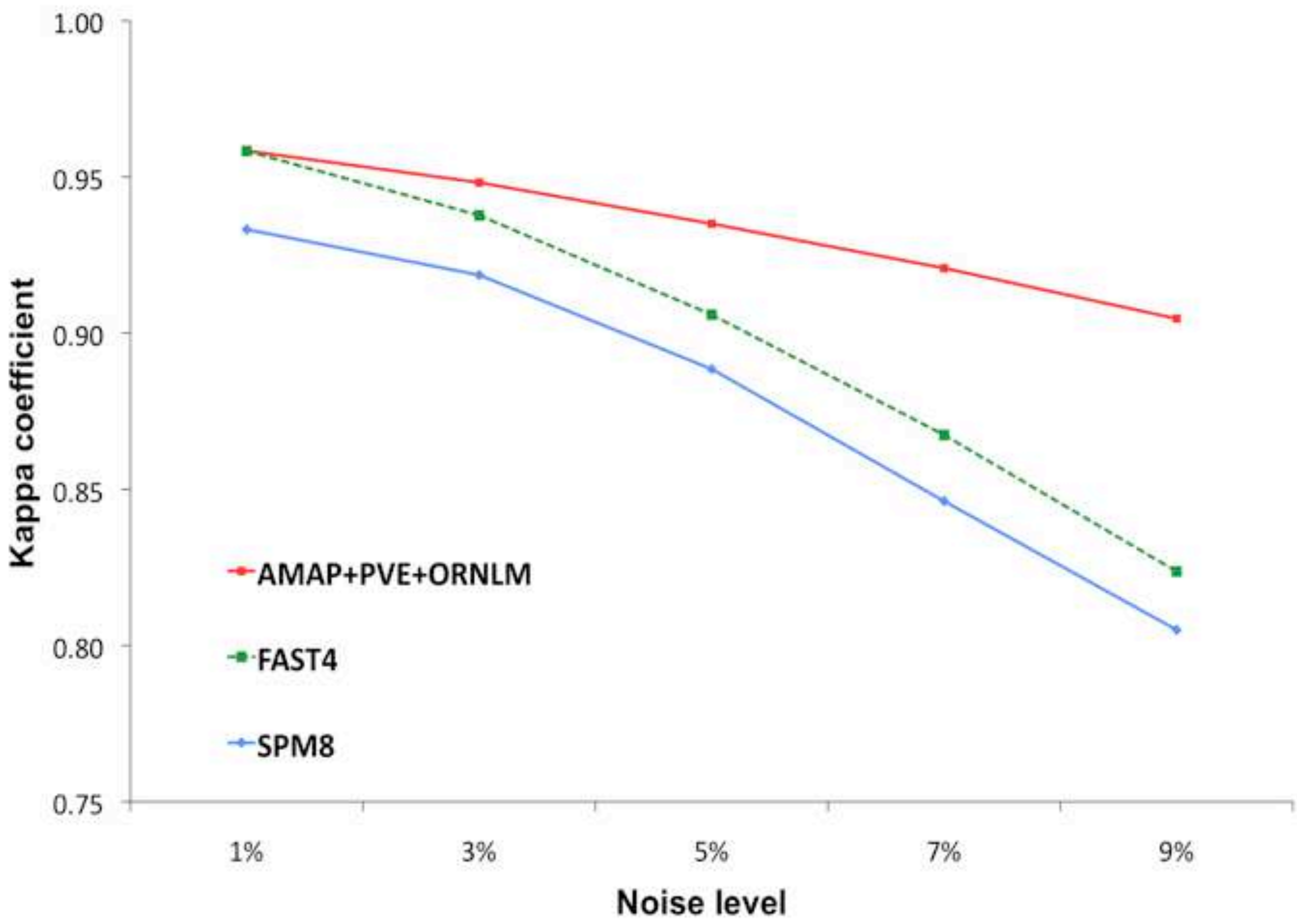

Fig. 3 Comparison between SPM8, FAST4 (FSL), and AMAP using Optimized Rician Non-Local Means Filter (ORNLM) and Partial Volume Estimation (PVE)

Evaluation results with the brain phantom as ground truth are shown for different noise levels from 1 to 9%. Segmentation accuracy for all tissue types is calculated by Kappa coefficient.

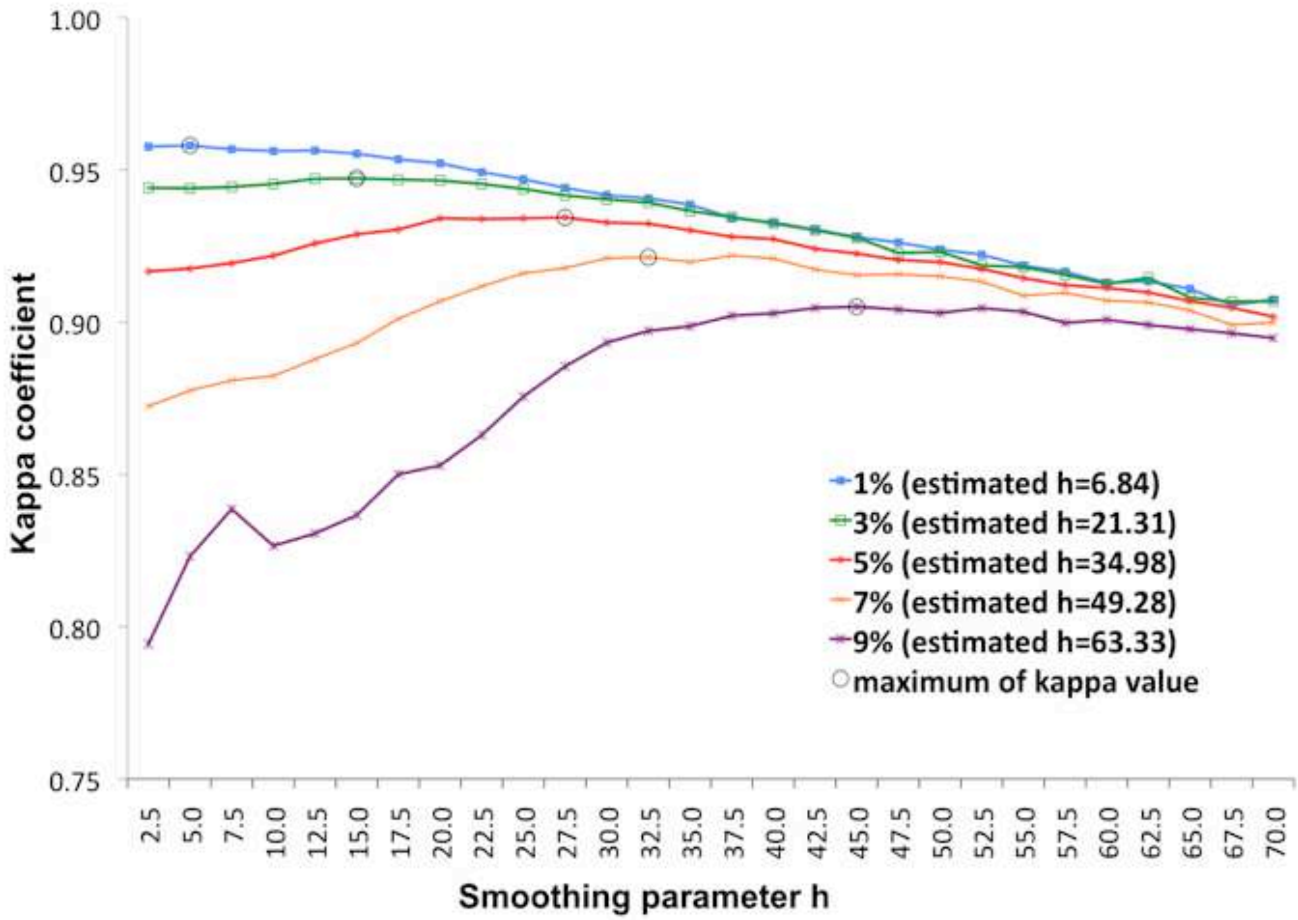

Fig. 4 Effect of smoothing parameter h on segmentation accuracy

Evaluation results with the brain phantom as ground truth are shown for different noise levels from 1 to 9%. The ORNLM filter is applied with varying smoothing parameters h. The estimated parameter h using Rician noise estimation is also displayed in the legend.