Noise reduction in magnetic resonance images using adaptive non-local means filtering

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Proposed is a noise reduction method for magnetic resonance (MR) images. This method can be considered a new adaptive non-local means filtering technique since different weights based on the edgeness of an image are applied. Unlike conventional noise reduction methods, which typically fail in preserving detailed information, the proposed method preserves fine structures while significantly reducing noise in MR images. For comparing the proposed method with other noise reduction methods, both a simulated ground truth data set and real MR images were used. The experiment shows that the proposed method outperforms conventional methods in terms of both restoration accuracy and quality.

Introduction: Magnetic resonance imaging (MRI) is a diagnostic imaging technique that produces highly detailed information of the interior of the human body. Usually, MR images suffer from noise because of short scan times, weak signal strength, the T1/T2 effect and main/RF field inhomogeneity. To remove this noise, Gaussian smoothing, a weighted average of neighbouring pixels, can typically be applied. However, this method tends to blur structures at high contrast regions containing important information, such as vessels and the boundaries between different organs. To preserve these fine structures while reducing noise, many methods such as total variation, anisotropic diffusion and bilateral filtering have been developed [1–3]. These approaches take an average of neighbouring pixels using weights depending on the detailed information. These approaches, however, do not sufficiently preserve the fine structures, especially in MR images. Recently, non-local means (NLM) filtering has been introduced for reducing noise in MR images [4]. However, the original NLM filtering method also tends to blur detailed information if the weight is not appropriately determined. In this Letter, we propose an adaptive NLM filtering technique that preserves fine structures while reducing noise in MR images.

Non-local means filtering: The NLM filtering method [5] restores a pixel value by taking a weighted average of pixel values over the entire image. This can be described by

$$\bar{I}(\mathbf{x}_i) = \frac{\sum_{xj\in\Omega} \omega(\mathbf{x}_i, \mathbf{x}_j) I(\mathbf{x}_j)}{\sum_{xj\in\Omega} \omega(\mathbf{x}_i, \mathbf{x}_j)} \tag{1}$$

where I and $\bar{I}$ are an input and a restored image, respectively, $\mathbf{x}_i$ denotes the co-ordinates of pixel i, Ω denotes the image, and ω represents the weight of each pixel j. Practically, Ω is limited to a search window rather than the entire image to reduce the computational complexity. The weight is defined as

$$\omega(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{s(\mathbf{x}_i, \mathbf{x}_j)}{\sigma^2}\right) \tag{2}$$

where σ is the decay control parameter. The patch similarity, s, is calculated as

$$s(\mathbf{x}_i, \mathbf{x}_j) = \sum_{\Delta x\in N} h(\Delta\mathbf{x}) \parallel I(\mathbf{x}_i + \Delta\mathbf{x}) - I(\mathbf{x}_j + \Delta\mathbf{x}) \parallel^2 \tag{3}$$

where h denotes a Gaussian kernel, and N denotes the set of pixel offsets in the patch.

Proposed method: The decay control parameter σ [4] adjusts the patch similarity sensitivity. In other words, the structures in the MR image may show various levels of blurring in accordance with the σ value. A fixed σ value may blur the fine structures in the image. An intelligent way of choosing σ is needed in order to keep the fine structures. Thus, we propose the use of an adaptive decay control parameter, σ_i, which varies according to edgeness, representing the amount of detailed information of pixel i. The edgeness, E_i, is calculated by a simple edge detector, and we define σ_i as:

$$\sigma_i = \sigma\left(1 - \frac{E_i - E_{min}}{E_{max} - E_{min}}\right) \tag{4}$$

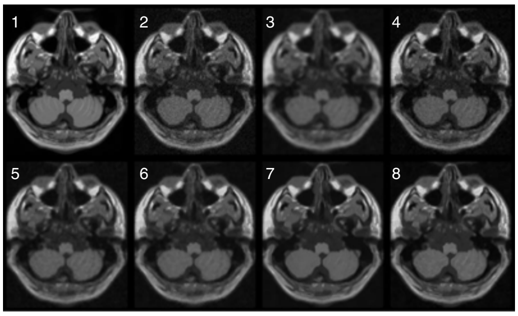
where E_{max} and E_{min} denote the maximum and minimum edgeness values, respectively. The weight ω in (2) is sensitive to patch similarity if σ_i is small due to high edgeness, resulting in preservation of the original structure. On the other hand, the weight becomes similar to those of the original NLM if σ_i is large due to low edgeness. To summarise, the proposed method preserves the detail in high contrast regions and reduces noise in low contrast regions. To increase the denoising performance of our proposed method, we account for adjacent slices in the expansion of search windows, because similar patches may exist in neighbouring slices, and the denoising performance can be improved with more similar patches [6]. The final formula of our proposed method can be expressed as follows:

$$\bar{I}(\mathbf{x}_i^n) = \frac{\sum_{\Delta n}\sum_{xj\in\Omega} \omega(\mathbf{x}_i^n, \mathbf{x}_j^{n+\Delta n}) I(\mathbf{x}_j^{n+\Delta n})}{\sum_{\Delta n}\sum_{xj\in\Omega} \omega(\mathbf{x}_i^n, \mathbf{x}_j^{n+\Delta n})} \tag{5}$$

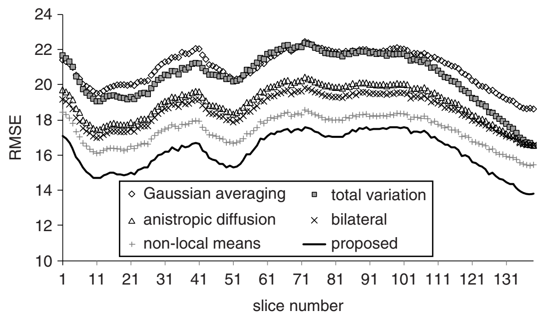
where n denotes the slice number, and Δn denotes the difference between the slice number, n, and its neighbouring slice number.

Experimental results: We compared the proposed method with conventional methods (Gaussian averaging, total variation [1], anisotropic diffusion [2], bilateral filtering [3] and NLM [5]) both quantitatively and qualitatively. For the quantitative evaluation, we used the simulated brain database from BrainWeb [7], which includes noise-free images and images with 9% noise. The parameters used for the experiments were as follows. For σ, we used the optimal values at the relevant noise levels with a 5 × 5 patch and 11 × 11 search window, as suggested in [4]. For the edge detectors, we used the Sobel operator and Δn was set to − 1, 0 or 1.

Fig. 1*a* shows the 20th slice image in the simulated brain database at BrainWeb [7] and the corresponding denoised images (upper: [1]noise free image, [2]noisy image (9%), [3]Gaussian averaging, [4]total variation, lower: [5]anisotropic diffusion, [6]bilateral filtering, [7]NLM, [8]proposed method). Fig. 1*b* shows the root mean square error (RMSE) of the denoised images with respect to the ground truth noise-free image. Table 1 shows the average RMSEs of the methods and indicates that the proposed method more accurately restores the original image than the other methods.



a



b

Fig. 1 *Quantitative evaluation (Fig. 1a) results for (Fig. 1b) RMSE of each method.*

We also evaluated the performance of each method using real MR image data. Fig. 2*a* is the original MR image, and Fig. 2*b* is the image denoised by our proposed method. As indicated by Fig. 2*b*, the overall noise is effectively reduced while fine details are preserved.

Table 1: Average RMSE

Method	3	4	5	6	7	8
RMSE	20.976	20.488	18.959	18.522	17.362	16.209

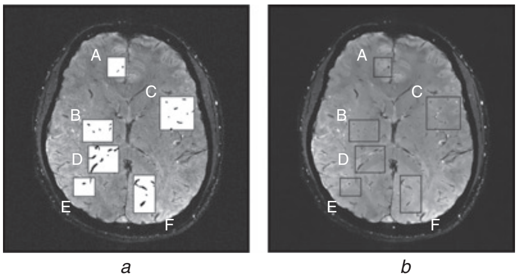


Fig. 2 *ROIs (Fig 2a) in original (real) image (Fig 2b) and denoised image using proposed method*

For the dataset with no ground truth data, the contrast-to-noise ratio (CNR) is utilised. For measuring CNR, we selected six regions of interest (ROIs) with details (see rectangular boxes in Fig. 2*b*).

Fig. 2 shows ROIs (notation from ‘A’ to ‘F’ alphabetically) for the CNR calculation between the foreground (vessel or details) and background (white or grey matter):

$$\mathrm{CNR} = \frac{|\mathrm{A_f} - \mathrm{A_b}|}{\sigma_\mathrm{b}} \tag{6}$$

where A_f and A_b are the averages of the foreground and background pixel values, respectively, and σ_b is the standard deviation of the background pixels in the ROI. If the difference between the foreground and background is high or the foreground is clearly distinguished from the background, the contrast becomes high. The foreground and background pixels were manually set according to their structure in the image. The foreground pixels in the ROIs are indicated in black, and background pixels are white. Fig. 3 contains the comparison results using location B in Fig. 2, showing improved performance of the proposed method. Fig. 4 shows the CNR of each method, and Table 2 shows the average CNRs from the six ROIs. As shown in Fig. 4 and Table 2, the proposed method was the most effective in preserving details while reducing noise.

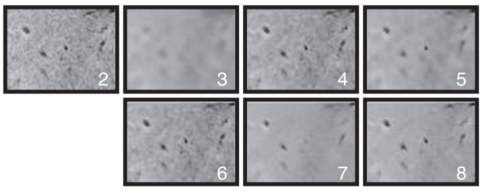


Fig. 3 *Original and denoised images of ROI ‘B’ (2: original image, 3: Gaussian averaging, 4: total variation, 5: anisotropic diffusion, 6: bilateral filtering, 7: NLM, 8: proposed method)*

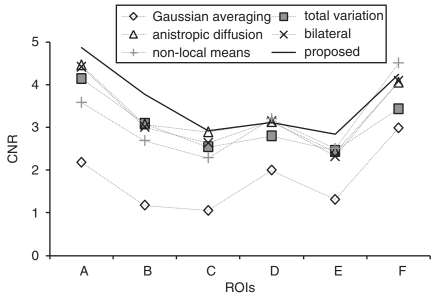


Fig. 4 *CNR of each method*

Table 2: Average CNR

Method	3	4	5	6	7	8
CNR	1.781	3.076	3.339	3.266	3.126	3.630

Conclusion: In this study, we have demonstrated the effectiveness of our proposed adaptive NLM filtering for MR images by overcoming the limitations of conventional NLM filtering that may result in the loss of fine structural information. We first estimated the edgeness of an image and then adaptively applied a non-local means filter based on this edgeness. Experiments show that our proposed method preserves the important structures in MR images, such as vessels, while significantly reducing noise.

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