Improving Visibility of Tissue Heterogeneity in Diffusion Kurtosis Imaging Using Vector-Based Non-Local Means Filter

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Introduction:

Diffusion kurtosis imaging (DKI) is a multiple-b-value diffusion model characterizing non-Gaussian diffusion property of water molecules in living tissues [1], and provides additional information to the conventional mono-exponential diffusion model. The DKI model needs to acquire diffusion-weighted (DW) images at high b-values from 2000 to 2500 s/mm^2, which will suffer from low SNR. This situation becomes even more challenging in body application, such as oncology studies of prostate and breast. To guarantee the robust parameter estimation, a common DKI dataset should acquire DW images with more than 3 b-values, and more averages are needed for high b-values to achieve satisfactory SNR. However, high average number may lead to long scanning time and introduce motion artifacts. Alternatively, image denoising technique provides an efficient way to enhance the data quality with no additional hardware and scan time penalty, thus may provide a potential solution to this problem. Conventionally, Gaussian filtering is commonly applied to DW images as a preprocessing step to reduce noise, but it significantly smoothes the image details. Non-local means (NLM) filter shows good performance for noise reduction in nature images, and is also applied for DW image denoising [2]. To further exploit the joint information of DWI data with multiple b-values, a vector–based NLM (VNLM) filter was considered here.

Methods:

NLM filter is a spatial-domain filter, which denoises each image pixel by a weighted average of pixels in its neighborhood region. The weight of pixel j is defined as $w_{ij} = 1/Z{\cdot}exp(-d(i,j)/h^2)$ to denoise pixel i, where h is a parameter controlling the denoising level, Z is a normalization factor. The term $d(i,j)$ measures the euclidean distance between pixel i and j, and the essential idea of NLM is that it defines the distance between pixel i and j not only by the their own intensity difference, but also by the difference in their neighboring window. Therefore, $d(i,j) = G\| N_f(i) - N_f(j)\|^2$, where N is a f x f square neighbor window, G is a Gaussian kernel.

VNLM filter redefines the pixel distance in NLM. It consideres a series of images as a vector and Euclidean distance between two pixels is redefined as $d'(i,j) = G\| N_f(\mathbf{v}(i)) - N_f(\mathbf{v}(j))\|^2$, where v is a vector of pixel intensity including all images in the series at the corresponding pixel. Thus, for DKI data, the multi-b-value DW images are naturely considered as vector in the VNLM filter, and the similarity between pixels is actually based on the whole diffusion decay curve, but not a single pixel in the curve.

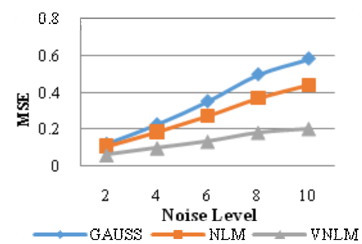

Fig. 1. The Gaussian, NLM and VNLM filters were applied to synthetic DKI data with 5-level rician noise. The MSE of resulting kurtosis map using the three filters was calculated.

Experiments and Results:

We compared denoising methods using both synthetic and real DKI datasets. (1) Synthetic data: We first created a 150 × 150 squared kurtosis map with values slowly varing from 0.2 to 3 (0.2 a step) horizontally, and the corresponding map of diffusion coefficient is calculated by $3/(2b_{max}{\cdot}kurtosis)$, where b_{max} = 2500 s/mm^2. Then the multi-b-value DW images are calculated by these two maps with baseline at 200, and 5-level rician noise (std = 2~10) was added. (2) A real DKI dataset of prostate cancer patient was collected on a 3T Magnetom Trio (Siemens AG, Erlangen, Germany). The dataset was acquired at 12 b-values, 0 ~ 2400 s/mm^2 (TR = 6600 ms, TE = 89 ms , NEX = 2, matrix = 128 × 86, FOV = 250 × 207 mm^2, 40 slices of 5 mm).

We then applied Gaussian (std=1, full-width-at-half-maximum=3mm), 3D NLM and VNLM filter (neighbor region 5 × 5 × 5 , f = 3, h = 1.2σ, σ means noise std) to the synthetic and real data. For synthetic data, we calculated the mean square error (MSE) of the resulting diffusion coefficient (DC) and kurtosis coefficient (KC) maps. The VNLM filter outperformed the other filters in each noise level (see Fig. 1). For real data, the MK maps showed high tissue heterogeneity in tumor region where MD and DWI showed homogeneous distribution. MK generated by the VNLM filter was in high accordance to that by Gaussian filter or without filtering, but with sharper structure or less noisy background (see Fig. 2). The NLM filter showed a few abnormal structures in the MK map which are not clearly visible with the other filters (see red arrow in Fig. 2).

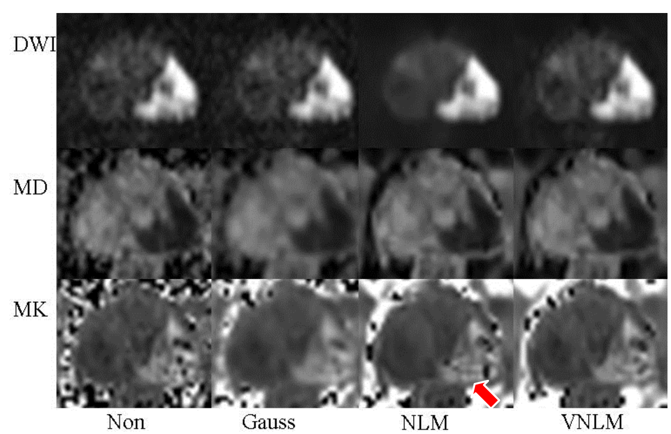

Fig. 2. Mean kurtosis map estimated from DKI dataset denoised by Gaussian, non-local means (NLM) and vector-based NLM filter.

Discussion and Conclusion: We applied VNLM filter to denoise DKI dataset with multiple b-values, and results showed that the VNLM filter successfully solved the low-SNR problem of the DKI model and provided better visibility of tissue heterogeneity in tumor regions, which was potentially valuable in benign-vs-maglinant tumor differentiation and maglinant tumor grading. Histology validation will be considered in our future work.

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References: [1]Jensen et al., MRM,2005. [2] Wiest-Daessle et al, MICCAI, 2008.