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An image driven bilateral filter with adaptive range and spatial parameters for denoising Magnetic Resonance Images☆

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ABSTRACT

Bilateral filter is an edge preserving denoising filter, widely used in medical image processing and raster graphics editors. Its performance greatly depends upon selection of spatial and radiometric parameters. Subjective selection of these parameters through trial and error can be sub-optimal. In this paper, an image driven method to compute the optimum values of spatial and radiometric parameters is proposed. Local optima of the parameters are adaptively estimated from the local grey level dispersion. The proposed method exhibited a Noise Suppression Ratio (NSR), Edge preservation Index (EPI) and Edge Strength Similarity Index Metric (ESSIM) of 0.62 ± 0.15, 0.76 ± 0.04 and 0.9998 ± 0.00005, respectively. It is superior to the method of computing the operational parameters from the standard deviation of noise in which the values of the performance matrices are NSR $= 0.556 \pm 0.223$, EPI $= 0.72 \pm 0.01$ and ESSIM $= 0.9998 \pm 0.0001$. The bilateral filter with locally adaptive spatial and radiometric parameters could selectively denoise homogeneous regions, without degrading the morphological edges.

1. Introduction

Bilateral filter [1] is one of the popular edge preserving spatial filters. It is superior to Non Local Means (NLM) and Anisotropic Diffusion (AD) filters because of its local and non-iterative nature of computation [2]. Many commercial as well as open source raster graphics editor software like Adobe Photoshop, GNU Image Manipulation Program (GIMP) and ImageJ contain the bilateral filter plug-in in their denoising application. Nowadays, it is a frequent choice for denoising images from Ultra Sound (US) [3], Optical Coherence Tomography (OCT) [4] and Echocardiography [5]. Its utility for denoising images from different sequences of Magnetic Resonance Imaging (MRI) like Fluid-Attenuated Inversion Recovery (FLAIR) [6], Diffusion Tensor [7] etc. and functional Magnetic Resonance Imaging (fMRI) [8] is well known.

In the bilateral filter, each pixel intensity in the corrupted image, '$X(i, j)$', is replaced by the weighted sum of the pixels in a square window of arbitrarily defined size, $[2D+1] \times [2D+1]$, centred at (i, j). The intensity, '$Y(i, j)$', which replaces $X(i, j)$ is computed as,

$$Y(i,j) = \sum_{m=-D}^{+D} \sum_{n=-D}^{+D} W[X(i,j), X(i+m, j+n)] X(i+m, j+n), \; i = 1, 2, \ldots M \text{ and } j = 1, 2, \ldots N \tag{1}$$

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The weight between the contextual pixel, $X(i, j)$ and one of the pixels with in the square window, $X(i+m, j+n)$ $\forall$ $-D \le m \le +D$ and $-D \le n \le +D$,

$$W[X(i,j),X(i+m,j+n)] = \frac{\left[e^{-\left(\frac{(X(i,j)\ -\ X(i+m,j+n))^2}{2\sigma_r^2}\right)}\right]\left[e^{-\left(\frac{(i-\ (i+m))^2+\ (j-(j+n))^2}{2\sigma_d^2}\right)}\right]}{\sum_{m=-D}^{+D}\sum_{n=-D}^{+D}\left[e^{-\left(\frac{(X(i,j)\ -\ X(i+m,j+n))^2}{2\sigma_r^2}\right)}\right]\left[e^{-\left(\frac{(i\ -\ (i+m))^2+\ (j-\ (j+n))^2}{2\sigma_d^2}\right)}\right]} \tag{2}$$

where M^*N is the dimension of the image. The terms σ_d and σ_r are spatial and radiometric parameters. The discrete kernel in (1), derived from the Gaussian function of the spatial distance between the contextual pixel $X(i, j)$ and other pixels available in the window is known as spatial weighting kernel, W_d. Similarly, the kernel derived from the Gaussian of the grey level difference between the contextual pixel $X(i, j)$ and other pixels available in the window is known as radiometric weighting kernel, W_r. (2) in its most simplified form is,

$$W[X(i,j),X(i+m,j+n)] = \frac{\left[e^{-\left(\frac{(X(i,j)\ -\ X(i+m,j+n))^2}{2\sigma_r^2}\right)}\right]\left[e^{-\left(\frac{\left(m^2+n^2\right)}{2\sigma_d^2}\right)}\right]}{\sum_{m=-D}^{+D}\sum_{n=-D}^{+D}\left[e^{-\left(\frac{(X(i,j)\ -\ X(i+m,j+n))^2}{2\sigma_r^2}\right)}\right]\left[e^{-\left(\frac{\left(m^2+n^2\right)}{2\sigma_d^2}\right)}\right]} \tag{3}$$

It is apparent from (3) that the spatial weighting kernel depends on the window size and the value of the arbitrary parameter, σ_d. It does not depend on the grey scale values in the image. The overall weight applicable for a particular pixel in the window depends both on the spatial distance and the grey level difference between that pixel and the contextual pixel. The pixels in the window which are close to the contextual pixel, spatially as well as in grey scale space will have higher weights. Consequently, the restored intensity is approximately the mean of the similar pixels in the window. Similarity refers to the closeness in grey scale space and spatial proximity. The spatial weight decays exponentially with respect to the increase in the spatial distance from the contextual pixel. Similarly, the radiometric weight also decays exponentially with respect to the increase in the grey scale difference between the contextual pixel and other pixels available in the window. The slope of decay of the spatial and radiometric weighting kernels depends on the values of σ_d and σ_r, respectively. The extent to which the pixels in the widow which are away from the contextual pixel either 'radiometrically' or spatially are penalized depends on these parameters. In summary, these two parameters control the depth of neighbourhood averaging. Fig. 1 illustrates that both radiometric and spatial parameters have equally significant impact on the degree of smoothening.

The radiometric parameter becomes more influencing at higher values of spatial parameter. At lower values of the spatial parameter the influence of the radiometric parameter on the degree of smoothening is comparatively less. The decay of the grey level variance of the denoised image with respect the increase in radiometric parameter (σ_r) for different values of the spatial parameter (σ_d) is illustrated in Fig. 2. The variance of the grey levels in the denoised image is one which can be used as an objective measure of its homogeneity of the denoised image and the depth of smoothening. It can be observed in Fig. 2 that the rate of decay of the grey level variance in response to the increase in radiometric parameter is more at higher values of the spatial parameter. The depth of smoothening is more at higher values of σ_d. σ_r becomes more influential at higher values of σ_d.

Usually, the spatial and radiometric parameters are selected arbitrarily by evaluating the visual quality of the denoized image. The process of tuning the operational parameters manually is laborious and subjective. Sometimes, the parameter setting can be sub-optimal also. Majority of the modified versions of the bilateral filter available in literature [9–12] are meant for reducing its computational time. Noise adaptive or 'image driven' selection of the operational parameters of the bilateral filter has not received proper attention so far, even if it is more important than reducing the computational time.

The adaptive configuration of bilateral filter suggested by Farzana et al. [13] for denoising panoramic images is a contribution worth mentioning, in which the range and domain parameters were adapted to the level of noise and local phase coherence, respectively. Differentiating noisy pixel intensity transitions from the true morphological edges is more challenging in MR images, than differentiating them from panoramic images captured with high definition CCD cameras. Kaplan and Erer [14] used bilateral filter for the multi-scale decomposition of images. The value Spatial and range parameters were selected such that relative dimensionless global error in synthesis (ERGAS) and spatial ERGAS (SERGAS) are optimized. However, this method is not directly applicable to denoising.

Zhang and Gunturk [15] had put forth few empirically observed recommendations, regarding the selection of the operational parameters of bilateral filter. They observed that the Mean Squared Error (MSE) between the original and restored images is minimum when σ_r is typically 2 to 3 times of the standard deviation of the noise (σ_n), for $\sigma_d = 1.8$ and $D = 5$. The linearity between σ_n and σ_r holds good for other values of σ_d also. But the slope, σ_r/σ_n decreases with the increase in σ_d.

Akar [16] used Genetic Algorithm (GA) to adaptively select the window size, spatial and radiometric parameters of the bilateral filter. The fitness value at which the GA is expected to converge was the maximum Peak Signal to Noise Ratio (PSNR) between the original and restored images. Instead of GA and PSNR, Zhang et al. [17] employed Artificial Bee Colony (ABC) algorithm and the minimum of Steins Unbiased Risk Estimate (SURE) as its fitness function. Kishan and Seelamantula

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