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Image Denoising by Scaled Bilateral Filtering

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Abstract—**A nonlinear weighted averaging filter called bilateral filter depends mainly on two parameters. The spatial distance indicates the size, and the intensity distance indicates the contrast of the features to be preserved, with respect to a center pixel. Its simplicity in behavior and implementation makes it easily adaptable to many applications with minor variations. This paper brings out one such variation by using different scales of the image for computing the parametric functions of the filter. Experimental results demonstrate the efficacy of the proposed technique.**

Keywords- bilateral filter; Gaussian smoothing; image denoising; image fusion; image scaling

I. Introduction

Bilateral filtering is a method, generally used for noise suppression, wherein the image smoothing is performed while giving respect to edges. Though this method is evident in the works of Aurich and Weule [1] and Smith and Brady [2], it was Tomasi and Manduchi [3] who named the filter as "bilateral filter". Bilateral filter is a nonlinear weighted averaging filter. The weights depend merely on two parameters, the spatial distance indicating size and the intensity distance indicating contrast of the features to be preserved, with respect to a center pixel. This filter's simplicity in behavior and implementation makes it easily adaptable to many applications with minor variations. One such variation is using different scales of the image for computing the weights, as described in this paper.

The flow of the paper is as follows. Section II describes the bilateral filter with a brief overview of its functioning. Section III explains the proposed variation and the related algorithm. Section IV presents some experimental results. The paper is concluded by Section V.

II. Brief Overview of Bilateral Filter

A. Formalization of Bilateral Filter

Bilateral filtering is very similar to Gaussian smoothing of the image, except for considering the variations in the intensity levels of neighboring pixel values and the current pixel value for the smoothing process. So, any pixel influencing another pixel must meet two criteria: 1. They should occupy nearby locations. 2. They should have similar intensity values. Mathematically, for x and y being pixel locations and $I(x)$ and $I(y)$ denoting the corresponding pixel values, bilateral filter as implemented in [4], is given by

$$G_F(x)=\frac{\sum_{y\in K} G_s(\|y-x\|)\,G_r(|I(y)-I(x)|)\,I(y)}{\sum_{y\in K} G_s(\|y-x\|)\,G_r(|I(y)-I(x)|)} \tag{1}$$

where,

$G_F(x)$ is the bilaterally filtered value at location x;

$G_s(\cdot)$ is a function that spatially controls the influence of other pixels over current value;

$G_r(\cdot)$ is a function that controls the influence of other pixels ranging within specified variance.

Both G_s and G_r are Gaussian weighting functions.

K is a neighborhood of current pixel location.

Spatially varying Gaussian function, G_s, and Gaussian Range function, G_r, are defined as follows [4]:

$$G_s(\|y-x\|)=\exp\left(\frac{-\|y-x\|^2}{2\,\sigma_s^2}\right) \tag{2}$$

$$G_r(|I(y)-I(x)|)=\exp\left(\frac{-|I(y)-I(x)|^2}{2\,\sigma_r^2}\right) \tag{3}$$

where,

σ_s is the spatial parameter and σ_r is the range parameter.

Both σ_s and σ_r together determine the extent of filtering in the image. They are the controlling parameters of the filter. The spatial parameter, σ_s, determines the spatial size of blur. Larger features are blurred by increasing σ_s. The range parameter, σ_r, determines the depth of smoothing. Smaller the value of σ_r, better the preservation of edges. A large value of σ_r approximates the filter very close to mere Gaussian blurring, since the range function remains constant over a large interval of intensity values [5].

B. Characteristics and Applications of Bilateral Filter

An essential characteristic of bilateral filter is the multiplication of weights. Weight at a pixel location is the product of spatial function and range function at that location. Thus, either of the functional values, being close to zero, limits the image smoothing process. The Gaussian spatial weight limits the size of blur and the Gaussian range weight is strictly bound to the contour preservation.

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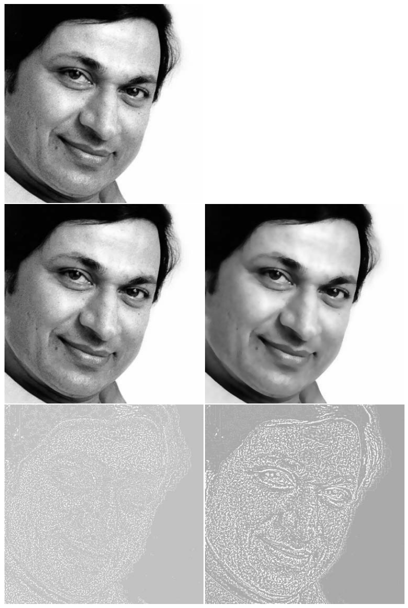

Figure 1. Original Image of Dr. Rajkumar, before filtering (top) . Bilaterally filtered image with σ_s=2, σ_r=4 (middle left) and its corresponding residual Image (bottom left). Bilaterally filtered with σ_s=10, σ_r=20 (middle right) and its corresponding residual image (bottom right).

Image denoising from bilateral filtering is evident from the ability of the filter to retain strong discontinuities in the image and suppress the local variations by smoothing it off. As an immediate consequence, the background noise or texture of different scales can be obtained by splitting the original image into filtered image and residual image, the latter being a difference of original image and filtered image. Different parameter sets of the filter produce different extents of smoothing. Thereby, different scales of background noise or texture can be observed in the residual image, as shown in Fig. 1.

Obviously, image denoising is one immediate application of bilateral filter due to its ability of image smoothing with edges preserved. Under multiresolution framework [6], wavelet decomposition can be used to eliminate different noise components at different resolutions, at the cost of computational complexity, to obtain better results.

Another application of specific interest is image fusion [9]. Images of different illuminations can be merged to give a better and visually plausible composite image. A low-illuminated image invites noise to disturb the scene. An image with flash light would not give a pleasant appearance. But, their fusion may provide the appearance of former image and details of latter one.

Other major applications include mesh smoothing [5], tone mapping and compression artifact reduction [6], separation of illumination and texture [7], and depth mapping [8]. As mentioned earlier, many variants of bilateral filter exist for each of its application requirements. The following section describes a new variant by using an image at different scales to compute the spatial and range parametric Gaussian functions.

III. Scaled Bilateral Filtering

In bilateral filtering, the Gaussian weights are computed from the given image without any prior scaling. In scaled bilateral filtering, the weights are computed by scaling the image prior to weight computation. The Gaussian spatial weight, with spatial parameter σ_s, is computed on the given noisy image as in conventional bilateral filter. The Gaussian range weight, with range parameter σ_r, is computed on scaled version of the noisy image with a scaling parameter σ_G. As in standard convention, scaling is performed by Gaussian convolution. The scaling parameter, σ_G, is the deviation of the Gaussian function.

A. Formalization

The scaled bilateral filter, represented as $G_{FG}(x)$, can be formalized as

$$G_{FG}(x)=\frac{\sum_{y\in K} G_s(\|y-x\|)\,G_R((|I_G(y)-I(x)|))\,I(y)}{\sum_{y\in K} G_s(\|y-x\|)\,G_R((|I_G(y)-I(x)|))} \tag{4}$$

where,

$G_s(\cdot)$ is the spatial function given in (2);

$G_R(\cdot)$ is the scaled range function given by (5);

K is the neighborhood of current pixel; and

$$G_R(|I_G(y)-I(x)|)=\exp\left(\frac{-|I_G(y)-I(x)|^2}{2\sigma_r^2}\right) \tag{5}$$

Here, $I_G(y)$ is the pixel value of scaled image, which is essentially Gaussian-convolved original image. The Gaussian convolution, at location x, is given by

$$I_G(x)=\sum_{y\in K} G_G(\|x-y\|)\,I(y) \tag{6}$$

In (6), $G_G(\cdot)$ is a two-dimensional Gaussian kernel whose neighborhood is defined by the parameter σ_G as follows:

$$G_G(x)=\frac{1}{2\pi\sigma_G^2}\exp\left(\frac{-x^2}{2\sigma_G^2}\right) \tag{7}$$

The Gaussian convolution is a low-pass filtering process, which eliminates the high-frequency components in the image. Therefore, noise in the image, essentially present in portions with high frequency, gets eliminated along with other high-frequency components of the image. Thus, the scaled image is left with coarse structures of the image. This defines the coarse template of the filtered image. The range computation takes the difference of a pixel value in the given image and the corresponding pixel value in the scaled image. Since the fine details are suppressed in the scaled image, the filtered pixel value is evaluated with its coarser form in the scaled image and the current pixel value.

Here, the word 'scaled' refers to the method used in computing the spatial and range functions, which are obtained from the same image at different scales. Following bilateral filter [3], the scaled bilateral filter also belongs to a broad category of nonlinear filters.

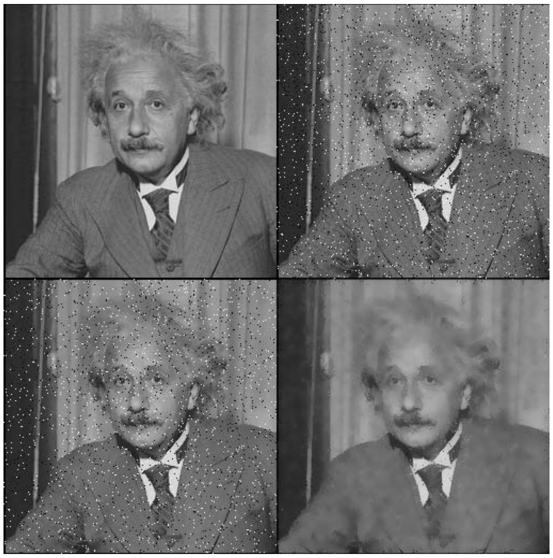

Figure 2. Original image of Einstein (top left). In top right image, 10% salt-and-pepper noise is added. Bottom left image is bilaterally filtered image with σ_s=4 and σ_r=12. Bottom right image shows the scaled bilateral filter output with σ_s=4, σ_r=12, and σ_G=3.

Effectively, this is a process of filling in the finer details of the original image into the coarser structure of the scaled image. The range parameter is the linking function between structure and details. The product of spatial and range functions give the filter coefficients. The extent of smoothness, required for the details being filled into the Gaussian blurred image, is controlled by the spatial parameter. By keeping the scale parameter a constant, same effects continue to exist as in mere bilateral filter, with the variations in spatial and range parameters.

B. Scaled Bilateral Filtering Algorithm

Input: Noisy image

Output: Noise-suppressed image

Steps:

i. Compute the Gaussian spatial function from a spatial parameter σ_s
ii. Scale the image by a scale factor σ_G
iii. Compute the Gaussian scaled range function on scaled image with a range parameter σ_r
iv. Obtain the filter coefficients as the product of spatial and scaled range functions
v. Perform filtering operation on the image with the obtained set of filter coefficients

IV. Results

The scaled bilateral filter performs better than mere bilateral filter for lower values of spatial and range parameters. For much larger values of these parameters, the performance of scaled bilateral filter is much similar to that of the former one. This is due to the blurring effect of a large range parameter value, which fails to preserve the edges efficiently in either of the filters.

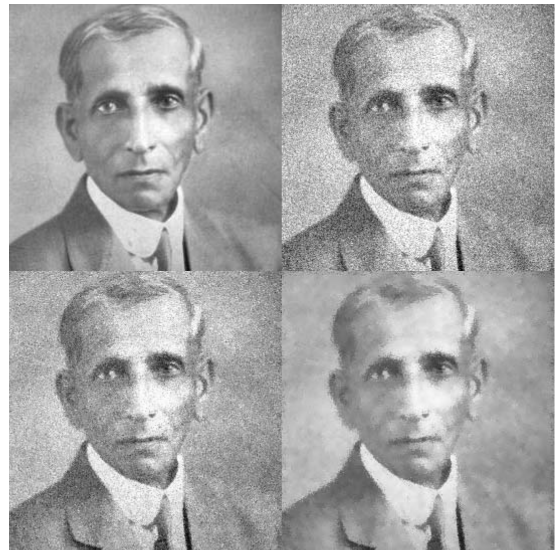

Figure 3. Top left is original image of Sir M. Vishveshwaraiah. A Gaussian noise of variance 0.02 is added in top right image. Bottom left image shows the bilaterally filtered image with σ_s=4 and σ_r=16. Output of the scaled bilateral filter is shown in bottom right image with σ_s=4, σ_r=16, and σ_G=2.

Though bilateral filter performs fairly well in restoring images with a small amount of Gaussian noise, it fails to bring any noticeable effect in images that are corrupted by salt-and-pepper noise or strong Gaussian noise. The scaled bilateral filter is more efficient in suppressing such noise components. The variation of the output with changes in spatial parameter, σ_s and range parameter, σ_r, remains same as in the bilateral filter for a given value of scale parameter, σ_G. Figures 2 - 5 show some of the results.

As shown in Fig. 2, an image of Einstein is added with 10% of salt-and-pepper noise. Scaled bilateral filter has removed the salt-and-pepper noise satisfactorily. But bilateral filter fails to do that. Fig. 3 shows an image of Sir M. Vishveshwaraiah, added with a Gaussian noise of variance of 0.02. The bilaterally filtered image and scaled bilateral filter output are also shown. With the original image as reference, the peak signal-to-noise ratio, PSNR [10], of bilaterally filtered image in Fig. 3 is 30.6 dB. The PSNR of the scaled bilateral filter output is 37.8 dB. For same values of spatial and range parameters in both bilateral and scaled bilateral filters, the latter gives a better result than the former. An image of Zelda in Fig. 4 is added with a Gaussian noise of variance 0.01. The PSNR of bilaterally filtered image of Zelda is 30.12 dB. For the scaled bilateral filtered image, the PSNR is 34.55 dB.

Bilateral filter under multiresolution framework [6] also suppresses noise by considering an image at distinct resolutions. In multiresolution bilateral filter, an image is bilaterally filtered at different resolutions with different parameters, whereas the scaled bilateral filter is applied over the image at a single stage and fixed parameters. The former method can be visualized as mere filtering of images, bilaterally, at different resolutions for corresponding components of noise. The latter is visualized as nonlinear fusion by filtering of two images, one with coarser structures as a scaled image, and the other with finer details in original form.

Figure 4. Image of Zelda (top left). A Gaussian noise of variance 0.01 is added as shown in the image (top right). Bottom left image is the bilaterally filtered image with σ_s=6 and σ_r=24. Bottom right image shows output of the scaled bilateral filter with σ_s=6, σ_r=24, and σ_G=2.

The above results clearly show the efficiency of scaled bilateral filter in noise suppression. In the application-specific framework, the scaled bilateral filtering can be visualized as nonlinear image fusion of a noisy image with its scaled version. By doing so, advantages of both the images can be exploited. The smoothness and cues of the Gaussian blurred image are obtained. At the same time, the details of the original image can be retained to required extent. So, by scaled bilateral filtering, the noise is suppressed and smoothness is imbibed in the image along with retention of cues and necessary details. This is a very important characteristic expected of a filter for restoring images that are highly corrupted by noise.

A comparison between bilateral filter and scaled bilateral filter is shown in Table I, by considering their PSNR values with original images. A standard set of image data is considered with an addition of Gaussian noise of variance 0.01.

As an application of denoising, scaled bilateral filter can be applied to restore paintings. The effect of speckles and glitches can be softened off by the application of this filter. The scaling parameter controls the amount of softness in the image. A large value of the scale parameter causes the halo effect to be predominant over the edges, which appears as blur. An example is shown in Fig. 5.

V. Conclusion

The simplicity of bilateral filter in its behavior and implementation has made a number of variations to evolve depending on specific applications of interest. One of the variations of bilateral filter is presented in the paper which is particularly efficient in denoising of images. An analysis under application-specific framework is also made. The parameter selection for denoising depends on intended applications and extent of noise. An arbitrary consideration of parameters is made in illustrated examples accounting for the generality of the technique. Future work will extend selection of parameters with multiscaling techniques.

Figure 5. Original image (left). Scaled bilateral Filter output with σ_s=5, σ_r=20, and σ_G=1.5 (middle). Right image is filtered with σ_s=5, σ_r=20, and σ_G=3.

TABLE I. Comparison with Bilateral Filter

Image	PSNR value with original image	
	Output of Bilateral Filter (σ_s=4, σ_r=16)	***Output of Scaled Bilateral Filter (σ_s=4, σ_r=16 & σ_G=2)***
Lena	29.36 dB	33.13 dB
Boats	29.34 dB	32.46 dB
Cap	29.39 dB	33.85 dB
F16	29.34 dB	32.94 dB
Watch	29.70 dB	32.36 dB

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