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ScienceDirect
Signal Processing 88 (2008) 1615–1619
SIGNAL PROCESSING
www.elsevier.com/locate/sigpro

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Adaptive bilateral filtering of image signals using local phase characteristics

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Received 15 October 2007; received in revised form 18 December 2007; accepted 7 January 2008
Available online 11 January 2008

Abstract

This paper presents a novel perceptually based method for noise reduction of image signals characterized by low signal to noise ratios. The proposed method exploits the local phase characteristics of an image signal to perform bilateral filtering in an adaptive manner. The proposed method takes advantage of the human perception system to preserve perceptually significant signal detail while suppressing perceptually significant noise in the image signal. Experimental results show that the proposed method is effective at removing signal noise while enhancing perceptual quality both quantitatively and qualitatively.

Keywords: Denoising; Local phase; Adaptive; Bilateral filtering

One of the most fundamental problems encountered when dealing with signal acquisition and processing is the presence of signal noise. Signal noise may be caused by various intrinsic and extrinsic conditions that are difficult to avoid. As such, the first step to processing a signal is often to suppress noise and extract the desired signal from the noisy signal. Of particular interest over recent years is the denoising of image signals, due largely to the incredible rise in popularity of digital images and movies. A large number of different image signal denoising methods have been proposed and can be generalized into two main groups: (i) spatial domain filtering and (ii) transform domain filtering.

Spatial domain filtering methods have long been the mainstay of signal denoising and manipulate the noisy signal in a direct fashion. Traditional linear spatial filters such as Gaussian filters attempt to suppress noise by smoothing the signal. While this works well in situations where signal variation is low, such spatial filters result in undesirable blurring of the signal in situations where signal variation is high. To alleviate this problem, a number of newer spatial filtering methods have been proposed to suppress noise while preserving signal characteristics in regions of high signal variation. These techniques include anisotropic filtering techniques [1], total variation techniques [2], and bilateral filtering techniques [3,4]. Bilateral filtering is a non-iterative and non-linear filtering technique which utilizing both spatial and amplitudinal distances to better preserve signal detail. In contrast to spatial filtering methods, frequency domain filtering methods transform the noisy signal into the frequency domain and manipulate the frequency

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doi:10.1016/j.sigpro.2008.01.002

coefficients to suppress signal noise before transforming the signal back into the spatial domain. These techniques include Wiener filtering [5] and wavelet-based techniques [6,7].

While effort has been made in the design of image signal denoising techniques to better preserve signal detail, little consideration has been given to the characteristics of the human perception system in such techniques. This is particularly important in the context of image signals, where the goal of signal denoising is often to improve the perceptual quality of the image signal. Furthermore, many of the aforementioned denoising techniques, including bilateral filtering, utilize fixed parameters that may not be well suited for noise suppression and detail preservation for all regions within an image signal. Therefore, a method for adapting the denoising process based on the human perception system is desired.

In this paper, we propose a novel approach to image signal denoising that performs perceptually adaptive bilateral filtering based on local phase characteristics. The proposed method is robust in situations where the image signal is characterized by low signal to noise ratios and provides improved noise suppression and signal detail preservation. This paper is organized as follows. The mathematical background behind the proposed method is presented in Section 1. Experimental results are presented and discussed in Section 2. Finally, conclusions are drawn in Section 3.

1. Mathematical background

Consider a 2-D signal f that has been degraded by a white Gaussian noise n. The contaminated signal g can be expressed as follows:

$$g(\underline{x}) = f(\underline{x}) + n(\underline{x}), \tag{1}$$

where $\underline{x} = (x, y)$. The goal of signal denoising is to suppress n and extract f from g. In spatial filtering techniques, an estimate of f is obtained by applying a local filter h to g:

$$f(\underline{x}) = h(\underline{x}, \varsigma) \times g(\underline{x}). \tag{2}$$

In a traditional linear spatial filtering technique, the local filter is defined based on spatial distances between a particular point in the signal at (x, y) and its neighboring points. In the case of Gaussian filtering, the local filter is defined as follows:

$$h(\underline{x}, \varsigma) = \mathrm{e}^{-(1/2)(\|\underline{x}-\varsigma\|/\sigma)^2}, \tag{3}$$

where ς represents a neighboring point. Such filters operate under the assumption that the amplitudinal variation within a neighborhood is small and that the noise signal consists of large amplitudinal variations. By smoothing the signal over a local neighborhood, the noise signal should be suppressed under this assumption. The problem with this assumption is that significant signal detail is also characterized by large amplitudinal variations. Therefore, such filters result in undesirable blurring of signal detail. A simple and effective solution to this problem is the use of bilateral filtering, first introduced by Tomasi et al. [3] and shown to emerge from the Bayesian approach by Elad [4].

In bilateral filtering, a local filter is defined based on a combination of the spatial distances and the amplitudinal distances between a point in the signal at (x, y) and its neighboring points. This can be formulated as a product of two local filters, one enforcing spatial locality and the other enforcing amplitudinal locality. In the Gaussian case, a bilateral filter can be defined as follows:

$$f(\underline{x}) = \frac{(h_\mathrm{a}(\underline{x}, \varsigma)h_\mathrm{s}(\underline{x}, \varsigma)) \times g(\underline{x})}{h_\mathrm{a}(\underline{x}, \varsigma)h_\mathrm{s}(\underline{x}, \varsigma)}, \tag{4}$$

where

$$h_\mathrm{s}(\underline{x}, \varsigma) = \mathrm{e}^{-(1/2)(\|\underline{x}-\varsigma\|/\sigma_\mathrm{s})^2}, \tag{5}$$

$$h_\mathrm{a}(\underline{x}, \varsigma) = \mathrm{e}^{-(1/2)(\|g(\underline{x})-g(\varsigma)\|/\sigma_\mathrm{a})^2}. \tag{6}$$

The main advantage of defining the filter in this manner is that it allows for non-linear filtering that enforces both spatial and amplitudinal locality at the same time. The estimated amplitude at a particular point is influenced by neighboring points with similar amplitudes more than by those with distant different amplitudes. This results in reduced smoothing across signal regions characterized by large but consistent amplitudinal variations, thus better preserving such signal detail. Furthermore, the normalization term in the above formulation allows the bilateral filter to smooth away small amplitudinal differences associated with noise in smooth regions.

The main issue with bilateral filtering is that while the shape of the filter can change depending on the underlying signal, the way in which the shape can change is constrained by a fixed set of parameters for the entire image signal. While constraining the shape variations of the bilateral filter using a fixed set of parameters is sufficient for contaminated signals characterized by high signal to noise ratios, it may produce undesirable results in situations where the signal to noise ratio is low. This can be rationalized in the following manner. In situations where the signal to noise ratio is low, amplitudinal differences between neighboring points are often large even in the smoother regions of the signal. To achieve noise suppression in smooth regions in such a situation, the spatial spread σ_s and amplitudinal spread σ_a must be made sufficiently large to accommodate for the increased variation. However, such a large spread can have the adverse effect of oversmoothing the signal in regions of significant signal detail. To alleviate this problem, we propose the adaptation of these constraint parameters based on the perceptual sensitivity of the human perception system to the underlying signal characteristics.

To adapt the bilateral filtering process based on the human perception system, it is necessary to determine a quantifiable measure for perceptual sensitivity to signal characteristics. An effective method for measuring human perceptual sensitivity that has been proposed in recent years is the use of local phase coherence [8–10]. Local phase coherence approaches are based on the theory that local phase coherence increases as the perceptual significance of signal characteristics increases. This has been supported by physiological evidence that showed high human perception response to signal characteristics with high local phase coherence [8]. Another advantage to the use of local phase coherence is the fact that it is insensitive magnitude variations caused by illumination conditions in image signals.

The proposed technique measures local phase coherence based on the method proposed by Kovesi [9]. Localized frequency information is extracted using a Log-Gabor filter bank. Local phase coherence at orientation θ is formulated as follows:

$$P(\underline{x},\theta) = \frac{\sum_n W(\underline{x},\theta)\lfloor A_n(\underline{x},\theta)\Delta\Phi(\underline{x},\theta) - T\rfloor}{\sum_n A_n(\underline{x},\theta) + \varepsilon}, \quad (7)$$

$$\Delta\Phi_n(\underline{x},\theta) = \cos(\phi_n(\underline{x},\theta) - \bar{\phi}(\underline{x},\theta)) - |\sin(\phi_n(\underline{x},\theta) - \bar{\phi}(\underline{x},\theta))|, \quad (8)$$

where W represents the frequency spread weighting factor, A_n and ϕ_n represent the amplitude and phase at wavelet scale n, respectively, $\bar{\phi}$ represents the weighted mean phase, T represents the noise threshold and ε is a small constant used to avoid division by zero. One of the advantages to this measure is that it is highly robust to noise and so does not require pre-filtering.

Based on the local phase coherence at different orientations, the perceptual significance of the signal at a particular point can be determined as the maximum moment of phase coherence:

$$\kappa(\underline{x}) = \frac{1}{2}\left(\begin{array}{l}\sum_\theta [(P(\underline{x},\theta)\sin(\theta))^2 + (P(\underline{x},\theta)\cos(\theta))^2] \\ +\sqrt{4\left(\sum_\theta (P(\underline{x},\theta)\sin(\theta))(P(\underline{x},\theta)\cos(\theta))\right)^2 + \left(\sum_\theta [(P(\underline{x},\theta)\cos(\theta))^2 - (P(\underline{x},\theta)\sin(\theta))^2]\right)^2}\end{array}\right), \quad (9)$$

where $P(\underline{x},\theta)$ is the local phase coherence at orientation θ. The maximum moment of phase coherence at a particular point in the signal is proportional to the sensitivity of the human perception system at that point.

Given this measure of perceptual sensitivity, the constraint parameters of the bilateral filter applied to each point in the image signal can be adaptively tuned for improved perceptual quality. As discussed earlier, the amplitudinal differences between neighboring points are large even in smoother regions in contaminated signals characterized by low signal to noise ratios. It is important to suppress noise in smooth regions to improve perceptual quality. As such, the spatial and amplitudinal spreads σ_s and σ_a must be sufficiently large to suppress signal noise in smooth regions. Points that reside within smooth regions in a signal can be characterized by low phase coherence. It is also important to preserve signal detail in regions of high perceptual significance. As such, σ_s and σ_a must be sufficiently small to avoid blurring perceptually significant detail in such regions. Points that reside within perceptually important regions in a signal can be characterized by high phase coherence. Based on the aforementioned conditions, the proposed perceptually adaptive bilateral filter can be defined as follows:

$$f(\underline{x}) = \frac{(h_a(\underline{x},\varsigma,\kappa(\underline{x}))h_s(\underline{x},\varsigma,\kappa(\underline{x}))) \times g(\underline{x})}{h_a(\underline{x},\varsigma,\kappa(\underline{x}))h_s(\underline{x},\varsigma,\kappa(\underline{x}))}, \quad (10)$$

Table 1
PSNR for test signals

Test	PSNR (dB)		
	Portilla method	Bilateral filtering	Proposed method
LENA	29.0231	28.3847	30.9595
CAMERAMAN	28.9678	28.9231	31.3875
BARBARA	29.3890	27.8501	30.3768
MANDRILL	28.8837	27.3137	29.6751
HOUSE	28.3493	30.4947	32.8597

Fig. 1. CAMERAMAN test (from left to right): (a) noisy image, (b) Portilla method, (c) proposed method, and (d) bilateral filtering.

where

$$h_s(\underline{x}, \varsigma, \kappa(\underline{x})) = e^{-(1/2)(\|\underline{x}-\varsigma\|/\sigma_s(\kappa(\underline{x})))^2}, \tag{11}$$

$$h_a(\underline{x}, \varsigma, \kappa(\underline{x})) = e^{-(1/2)(\|g(\underline{x})-g(\varsigma)\|/\sigma_a(\kappa(\underline{x})))^2}, \tag{12}$$

$$\sigma_s(\kappa(\underline{x})) = \sigma_{s,\min} + (1-\kappa(\underline{x}))^2(\sigma_{s,\max} - \sigma_{s,\min}),$$
$$\sigma_{s,\min} \leqslant \sigma_s \leqslant \sigma_{s,\max},$$

$$\sigma_a(\kappa(\underline{x})) = \sigma_{a,\min} + (1-\kappa(\underline{x}))^2(\sigma_{a,\max} - \sigma_{a,\min}),$$
$$\sigma_{a,\min} \leqslant \sigma_a \leqslant \sigma_{a,\max}. \tag{13}$$

It can be observed from the above formulation that the shape of the filter is independently tuned for each individual point in the signal based on its perceptual significance. This fine-grained filter tuning allows for improved noise suppression and perceptual detail preservation even in situations characterized by low signal to noise ratio.

2. Experimental results

The proposed method was applied to five test signals with different characteristics. Each test signal is contaminated by white Gaussian noise with standard deviation of 20. The PSNR of the restored signal was measured for the proposed method as well as the original bilateral filtering method and the state-of-the-art image denoising method using Gaussian scale mixtures proposed by Portilla et al. [6] for comparison. A summary of the results is shown in Table 1. The proposed method achieves noticeable PSNR gains over the original bilateral filtering method for all of the test signals. Furthermore, the proposed method achieves noticeable PSNR gains over the Portilla method in the LENA, CAMERAMAN, and HOUSE tests and comparable PSNR in the BARBARA and MANDRILL tests. The restored signals for the CAMERAMAN test are shown in Fig. 1. It can be observed that the proposed method produced a restored image signal with noticeably improved perceptual quality compared to the Portilla method and the original bilateral filtering method.

3. Conclusions

In this paper, we introduced a novel approach to image signal denoising using adaptive bilateral filtering based on local phase characteristics. By adapting the constraint parameters of the bilateral filter based on local phase coherence, the restored image signal can be tuned based on the human perception system. Results show improved perceptual quality can be achieved in the restored image signal using the proposed method.

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