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Modified block-matching 3-D filter in Laplacian pyramid domain for speckle reduction

Donghai Wen [a,*], Yuesong Jiang [a], Yanzhong Zhang [a], Yuntao He [a], Houqiang Hua [a], Rong Yu [a], Xiaofang Wu [a], Qian Gao [b]

[a] BeiHang University, XueYuan Road No.37, HaiDian District, Beijing, China
[b] Dalian Communication Sergeant School of Air Force, Dalian, China

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ABSTRACT

The Laplacian pyramid-based block-matching 3-D filtering (BM3D) is proposed (LPBM3D) for despeckling the speckle image. For BM3D in each pyramid layer, the criterion used to collect blocks in the 3-D groups to the actual data statistics is devised. An adaptive wavelet thresholding operator that depends on both noise level and signal characteristics is proposed. The performance of the proposed LPBM3D method has been compared with the state-of-the-art methods, including the recently proposed nonlocal mean (NLM) and BM3D method. Experimental results show that the visual quality and evaluation indexes outperform the other methods with no edge preservation. The proposed algorithm effectively realizes both despeckling and edge preservation.

1. Introduction

The laser images are corrupted by speckles, which make images hard to interpret valuable information. So the speckle reduction is meaningful preprocessing for advance application such as segmentation and feature extraction.

Indeed, image despeckling has been an active field of research for almost 30 years, and many algorithms are proposed each year. A few reviews on speckle reduction approaches have been done [12]. Some of the classical methods have been proposed to reduce speckle noise. These filters use local pixel intensity statistics to adjust the amount of smoothing and noise removal in certain areas. In areas with large variance of pixel intensities, such as areas with high levels of detail or edges, the filter applies less smoothing in order to preserve those details. In homogeneous areas with little detail, a smoothing kernel is applied to remove the noise.

In the last decade, the Anisotropic Diffusion filter (AD) [10] and the Total Variation minimization scheme (TV) [13] have been developed for speckle reduction. These approaches are iterative and produce smooth images while preserving edges. Nevertheless, meaningful structural details are unfortunately removed during iterations.

Recently, speckle reduction approaches using wavelets [7], texture models [5], adaptive stack filters [2], Markov random field models [6], blind deconvolution methods [8] have been introduced for the speckle reduction.

These despeckling algorithms cannot perform well in both despeckling and preserving edges of speckle images simultaneously. Given these premises, the nonlocal approach [1], recently proposed for the additive white Gaussian noise (AWGN) denoising, looks like a potential breakthrough. The nonlocal approach principle has inspired several extensions, and the BM3D method [4] is one of them. The NLM and BM3D algorithms have been readily extended to speckle reduction [11] with suitable modifications aimed at taking into account the problem peculiarities.

Based on the conceptual path described earlier, and the related experimental evidence, in this work, we go one step further and propose a image-oriented version of BM3D. A speckle reduction method based on BM3D in the Laplacian pyramid domain is proposed to more effectively suppress speckle while preserving edges. A Canny operator is first utilized to detect and remove edges from the speckle image. Then, the pyramid transform and BM3D are used to decompose and despeckle the edge-removed image, respectively. For BM3D in each pyramid layer, a suitable threshold is automatically determined by an adaptive data-driven exponential operator. Finally, the removed edges are added to the reconstructed image.

This paper is organized as follows. The BM3D algorithm and its speckle image-oriented version is proposed in Section 2. In Section 3, the LPBM3D method is proposed. In Section 4, the experimental results demonstrating the effectiveness of the proposed method are given. Some concluding remarks are drawn in Section 5.

* Corresponding author. Tel.: +86 1082339195.
E-mail address: dh_w10@163.com (D. Wen).

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2. BM3D algorithm and its polarization image-oriented version

In this paper, the application of BM3D is extended to image despeckling. To this end, we introduce two major modifications.

First of all, we adapt the criterion used to collect blocks in the 3-D groups to the actual data statistics. The Euclidean distance is devised for AWGN. Once the noise statistics change, the Euclidean distance loses its significance. So the new block similarity measure is devised.

Second modification is an adaptive wavelet thresholding operator that depends on both noise level and signal characteristics is devised. Generally, in the BM3D method, the wavelet coefficients are passed through a threshold testing that requires replacing noisy coefficients below a fixed value with zeros, and keeping the others because they have most of the information. Then, the resulting coefficients are used to reconstruct the signal. The method depends on the choice of threshold value. Thresholding methods have the following two main drawbacks: (1) The choice of the threshold is made in an *ad hoc* manner. (2) the specific distribution of the signal and noise may not be well matched at different scales. So an adaptive wavelet thresholding operator is proposed.

2.1. New block similarity measure

Mathematically, given two values, it results in

$$P[x(k),x(l)|y(k)=y(l)] = \int_R P[x(k)|y(k)=\delta]P[x(l)|y(l)=\delta]P(\delta)\,d\delta \tag{1}$$

where $x(k)$, $x(l)$ are the noisy signal, $y(k)$, $y(l)$ are the corresponding values of the noise-free signal defined over the domain R, and $P(\cdot)$ indicates a probability density function. $x(k)$ and $x(l)$ are assumed to be conditionally independent given y. This expression further simplifies to

$$P[x(k),x(l)|y(k)=y(l)] \propto \int_R P[x(k)|y(k)=\delta]P[x(l)|y(l)=\delta]\,d\delta \tag{2}$$

if we assume, lacking any prior knowledge, $P(\cdot)$ to be uniform over R, then (2) reads as

$$P[x(k),x(l)|y(k)=y(l)] \propto \int_0^\infty \frac{1}{\Gamma^2(\mu)}\left(\frac{\mu}{\delta}\right)^{2\mu} e^{(\mu-1)[x(k)+x(l)]}\exp\left\{-\frac{\mu[e^{x(k)}+e^{x(l)}]}{\delta}\right\}d\delta \tag{3}$$

with the integral equal to

$$\frac{\mu\Gamma(2\mu-1)e^{(\mu-1)[x(k)+x(l)]}}{\Gamma^2(\mu)[e^{x(k)}+e^{x(l)}]^{2\mu-1}} \tag{4}$$

To rewrite this result into a manageable block similarity measure, we must rewrite (5) with vectors drawn from the blocks A_k and A_l in place of scalars and assume again the conditional independence of the observed values given the noise-free signal. Then, we define the block similarity measure as

$$\begin{aligned} d[x(A_k),x(A_l)] &= -\log\left\{\prod_q P[x(k+q),x(l+q)|y(k+q)=y(l+q)]\right\} \\ &= -\log\left\{\prod_q \frac{\mu\Gamma(2\mu-1)e^{(\mu-1)[x(k+q)+x(l+q)]}}{\Gamma^2(\mu)[e^{x(k+q)}+e^{x(l+q)}]^{2\mu-1}}\right\} \end{aligned} \tag{5}$$

discarding the constant term

$$d_1[x(A_k),x(A_l)] = \sum_q\{(2\mu-1)\log[e^{(k+q)}+e^{(l+q)}]-(\mu-1)[x(k+q)+x(l+q)]\} \tag{6}$$

where the subscript 1 indicates that this measure is used in the first step. In the second step, in fact, the similarity measure must take into account the additional information provided by the first step, which is a coarse estimate of the noiseless signal. The similarity measure in the second step is defined as

$$\begin{aligned} d_2[x(A_k),x(A_l)] = \sum_q\Big\{&(2\mu-1)\log[e^{(k+q)}+e^{(l+q)}]-(\mu-1)[x(k+q) \\ &+x(l+q)]+\beta\mu\frac{|\hat{y}(k+q)-\hat{y}(l+q)|^2}{\hat{y}(k+q)\hat{y}(l+q)}\Big\} \end{aligned} \tag{7}$$

where β weighs the relative importance of the data and (loosely speaking) prior terms.

2.2. The adaptive wavelet thresholding operator

To overcome the shortcomings of thresholding methods, an adaptive wavelet thresholding operator is used. The following operator based on exponential function was defined as

$$et(m) = \begin{cases} m\cdot e^{n_l\cdot(|x|-T_{k_l})}, & |x|<T_{k_l} \\ m, & |x|\ge T_{k_l} \end{cases};\ T_{k_l}=k_l\cdot T_{u_l} \tag{8}$$

where n_l is a real parameter identifying the fall degree of exponential function for l decomposition level, while k_l factor provides a modified version of l-level universal threshold. T_{u_l} is the VisuShrink threshold.

The modified BM3D is compared with the original BM3D algorithm. The main procedures of the original BM3D algorithm are illustrated in Fig. 1.

The procedures of the polarization image-oriented BM3D algorithm are illustrated in Fig. 2. The differences with the original BM3D algorithm are the new block similarity measure and the adaptive wavelet thresholding operator.

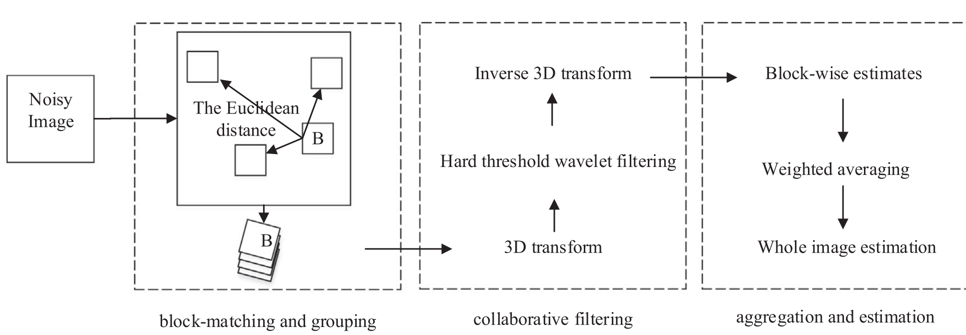

Fig. 1. Flow chart of original BM3D algorithm. The operations surrounded by dashed lines are repeated for each processed block (marked with B). The Euclidean distance is used for block-matching. The hard-thresholding is used for collaborative filtering.