Image Denoising Algorithm Considering Nonlocal Texture Pattern

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Abstract – Image denoising is indispensable for image processing. In this paper, image denoising algorithm based on Nonlocal Means (NLM) filter is proposed. Recently, abundant enhancements based on NLM filter have been performed. However, the performance of NLM filter is still inferior to that of other image processing approaches such as K-SVD. In this paper, NLM algorithm with weight refinement is utilized for image denoising. Weight refinement is performed to thoroughly take advantage of self-similarity of the image. Experimental results show good performance of the proposed method.

Key words – *image denoising*; *nonlocal means*; *texture pattern*; *weight refinement*; *weight re-ordering*

Manuscript Number: 1674-8042(2011)03-0247-04

doi: 10.3969/j.issn.1674-8042.2011.03.011

1 Introduction

From general CCD and CMOS image sensors to the recently developed Time-of-Flight (TOF) depth sensor for 3D video capture, the denoising problem has been widely studied for the past decades. Purpose of denoising is not only to obtain high quality images, but also to provide enhanced input images for other image processing tasks such as segmentation, feature extraction, texture analysis, pattern matching and auto-focusing systems.

There have been numerous approaches to image denoising for decades. These approaches have been roughly classified into averaging operation based on statistical theory, total variation regularization method and thresholding operation in the spatial and transforming domains. In recent years, denoising method based on NLM filter[1], which is one of the most popular averaging type methods in the spatial domain, has been abundantly studied, because NLM filter performs well and the theoretical idea is intuitive and simple. The NLM filter is considered a variant of the bilateral filter[2]. The primary difference between the bilateral filter and the NLM filter results from the weight value calculated by their similarity. Weight value of the bilateral filter is assigned by the similarity between the denoising center pixel and the neighboring pixels. For the NLM filter, similarity between the patch (a rectangular windowed neighborhood centered on a denoising pixel) and the neighboring patches is regarded in weight evaluation procedure. Improved denoising performance of the NLM filter contributes to this patch based similarity comparison.

Further studies for NLM filter improvement include an in-depth analysis of the variation of the NLM denoising filter that uses Principal Component Analysis (PCA)[3], the formation of the weight function which minimizes estimation errors for multiplicative speckle noise, as well as additive Gaussian noise[4], and the optimization of the parameters of NLM the filter based on Stein's unbiased risk estimator (SURE)[5]. Iterative cost functions were proposed in Ref. [4-6], and convergence of these functions was also discussed in Ref. [4] and Ref. [6]. In order to improve the NLM filter's denoising performance, iteratively denoised supports from other sample dictionary images[7] and support from scaled or down sampled images[8] were used instead of figuring out the weighted average with noisy image support.

In spite of many conventional improvements, the NLM filter shows somewhat inferior performance in terms of numerical and visual quality[6] compared with other recent state-of-the-art denoising methods[7]. It also displays some problems such as false texture pattern in the flat region and blurring artifacts in the edge and pattern regions. In this paper, we propose more improved NLM filter with weight refinement for image denoising. Error noise in the weight image (a group of weights in a sup-

※ **Received**: 2011-03-21
Project supported: This work was supported by the MKE(The Ministry of Knowledge Economy), Korea, under the ITRC(Information Technology Research Center) support program supervised by the NIPA(National IT Industry Promotion Agency) (NIPA-2011-C1090-1111-0003)
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port) is completely refined until the noisy weight image converges to the true weight image. More similar patches with no other sample images can participate in the denoising process through weight refinement and the refined weight image can make the denoised images more definite without artifacts.

2 Image denoising algorithm considering nonlocal texture pattern

In the noise model of this paper, a true pixel value $X(i)$ is measured in the presence of an additive zero-mean white Gaussian noise $N(i)$, with a standard deviation of σ. The measured noisy pixel value $Y(i)$ is

$$Y(i) = X(i) + N(i). \tag{1}$$

Then, the NLM filter equation is

$$\bar{X}(i) = \frac{\sum_{j \in S} w(i,j) Y(j)}{\sum_{j \in S} w(i,j)}, \tag{2}$$

where S represents the index set of a support, which means a rectangular windowed search range centered on a pixel. The corresponding weight $w(i,j)$ can be calculated as

$$w(i,j) = \left\{1 - \frac{\sum_{m \in P} | Y(i+m) - Y(j+m) |^2}{h^2 n(P)}\right\}^2, \tag{3}$$

where h represents a smoothing parameter and P represents the index set of a patch. $n(P)$ is the number of elements in P .

In order to improve the NLM filter's denoising performance, iteratively denoised supports, support from other dictionary sample images[7] and support from scaled or down sampled images[8] were used instead of figuring out a weighted sum with noisy image support. Meanwhile, the NLM filtering concept in a single image NR was directly extended to a video NR in the temporal domain, but the temporal NR structure is also used to motivate improvement of the single image NR in spatial domain. A detailed algorithm for the concept is discussed in a later section. Noisy image pixels and weights have been simultaneously updated in most approaches[4], as shown in Eq. (2). However, weights alone can be refined iteratively, so we concentrate more on the enhancement of the weights.

The problem noted by Buades et al. is that the NLM filter is not able to suppress any noise for non-repetitive neighborhoods[1]. Moreover, as shown in Fig. 1(c), the false texture pattern in the flat region occurs when the smoothing parameter h in Eq. (3) is made small to obtain sharper details and to improve numerical performance, which results from applying partially selected similar patches to the weighted sum in the texture region. The reason is that the number of similar patches necessary for NR is larger in the flat region than in the texture region. As shown in Fig. 2, even the weight image (a group of weights in a support) calculated in the texture region is rugged due to noise. Therefore, we need to smoothen or refine the weights to finally attain a more denoised image. There was a method of gathering more patches in a captured noisy image such as scaled image approach[8]. However our approach focuses on obtaining similar patches from a given noisy image and we need no additional sample images, which is unlike the exemplar approach[7].

Similarity between the patches contributes to not only the weighted sum but also weight refinement. In other words, the initially obtained weight image is reused for weight refinement. As a result, more patches can be utilized for NR, i. e. relatively similar weight images, the central weight value of which are located in the initial support region, are made to participate in weight refinement. The detailed algorithm procedure and the weight refinement are conducted as follows:

1) Weights in a support are calculated through initial NLM filtering by Eq. (3). We called the initially computed weight image $w_0(i,j)$;

2) The calculated weights in the support are similarity-ordered, i. e., re-ordered as

$$\begin{aligned} \bar{A} = \{ & k_1, \cdots, k_n, \cdots, k_N \\ & | \, w(i,k_1) \geqslant \cdots \geqslant w(i,k_n) \geqslant \cdots \geqslant \\ & w(i,k_N), k_n \in A \}, \end{aligned} \tag{4}$$

where the first N elements of $\bar{A}$ are selected. $\bar{A}$ represents the similarity-ordered weight index set, and $n(\bar{A}) = N$;

3) Similarity-ordered weight images are stacked in a sequential array (such as a 3D cube) in the spatio-temporal domain. The weight image to be applied to the refining process, $\Delta w_n(i,j)$ is given by

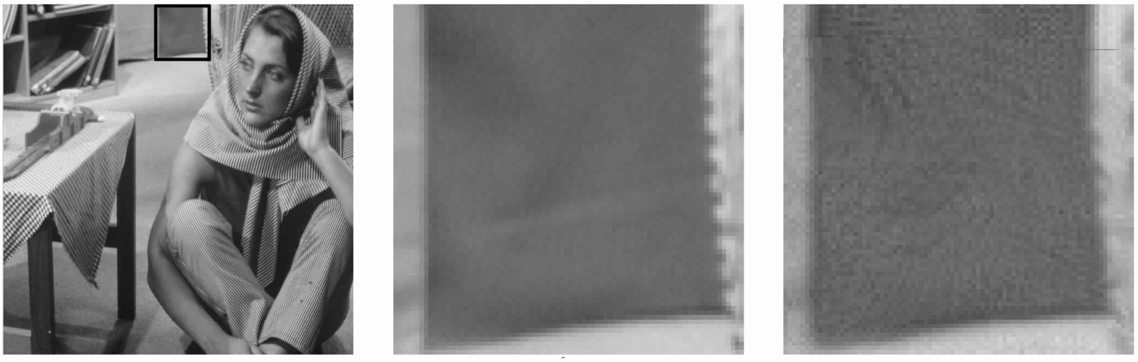
$$D_{Sum} = \frac{\sum_{p \in B} w_0(i+p, j+p) \, | \, Y(i+p+k_n) - Y(j+p+k_n) \, |}{h \sum_{p \in B} w_0(i+p, j+p)}, \tag{5}$$

where the similarities between the patches are considered by adding the term $w_0(i,j)$ to $\Delta w_n(i,j)$ in order to update $w_0(i,j)$ more accurately.

4) Finally, $\Delta w_n(i,j)$ is sequentially blended into the initially computed $w_0(i,j)$ as follows

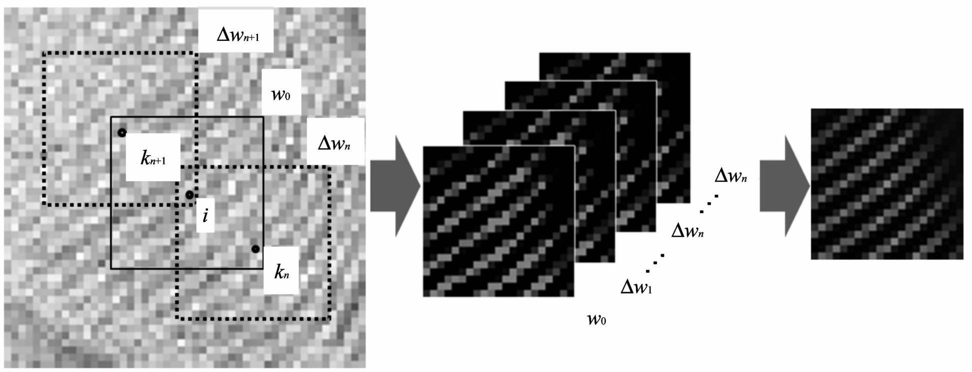
$$w(i,j) = \sum_{n=1}^{N} \{ (1-a) w_0(i,j) + a \Delta w_n(i,j) \}, \tag{6}$$

where a represents an updating ratio, and N determines the number of iterations.



(a) The black box represents the magnified region (b) Paryially magnified original image (c) Partially magnified denoised image by NLM[1] with false texture pattern

Fig. 1 False texture pattern example in the flat region



Similarity-ordering & N selection Stacking in 3D cube Refined weight image

Fig. 2 Weight image refinement process

3 Experimental results

The proposed algorithm was applied to several test images, and the peak signal-to-noise ratio (PSNR) values and visual quality were compared with the proposed method, the NLM method[1] and the exemplar method[7]. Sizes of the patch and support were 7×7 and 21×21 respectively. N and a were 3 and 0.2 respectively. The proposed method outperformed the NLM method by about 1.0 dB (see Tab. 1 and Tab. 2), and equally performed without additional sample images. As shown in Fig. 3(c) and Fig. 3(d), visual quality noticeably improved in the proposed method especially near the texture regions and edges, whereas flat regions showed no false texture pattern.

Tab. 1 Comparison of PSNR values, Barbara 512×512

σ	5	10	15	20	25
Noisy	34.10	28.11	24.62	22.17	20.31
Method[1]	36.58	33.05	30.90	29.52	28.36
Method[7]	36.93	33.82	32.21	30.88	29.77
Proposed	36.97	33.65	31.84	30.70	29.54

Tab. 2 Comparison of PSNR values, house 256×256

σ	5	10	15	20	25
Noisy	34.08	28.10	24.56	22.16	20.21
Method[1]	37.58	34.53	32.99	31.78	30.49
Method[7]	38.89	35.67	34.23	33.24	32.30
Proposed	38.50	35.27	33.86	32.70	31.60

(a) NLM method[1] (b) Proposed method (c) Partial magnification of NLM method[1] (d) Partial magnification of poposed method

Fig. 3 Denoised results for the Barbara image $\sigma = 20$

4 Conclusions

In this paper, NLM weight refinement algorithm for image denoising and super resolution algorithms based on signle frame are proposed. With the weight refinement of the NLM filter, the proposed algorithm improves the performance. Experimental results show that the proposed algorithm improves both visual and numerical quality. We intend to further apply the proposed weight refinement algorithm of the NLM to the video super resolution algorithm.

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