Fast non-local means with size-adaptive search window

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Abstract: In this study, the authors present a fast non-local means (NLM) image denoising algorithm with size-adaptive search window. On the basis of the edge gradient and direction of the noisy image, the proposed fast scheme divides all the pixels into significant edge, moderate edge or non-edge region, and the size of the search window for most pixels which belong to non-edge region can be reduced. The proposed fast scheme also adopts different strategies to pre-select similar patches in the search window for efficient NLM denoising. Experimental results show that compared with the standard NLM method, the proposed fast scheme achieves a substantial reduction in computational cost and improvement in the denoising performance, both in terms of visual quality and numerical results.

1 Introduction

Image denoising is a fundamental yet challenging problem that has been studied for decades. Non-local means (NLM) [1] has proven to be effective and robust in many image denoising tasks. Variations of the NLM method have been proposed to improve the denoising performance [2, 3]. Stein’s unbiased risk estimate is a way to optimise the parameters of the NLM [2]. Shape-adaptive patches (SAPs) [3] can take advantage of the local geometry of the image in the NLM. However, the superior performances of these NLM methods are achieved at the cost of higher computational complexity. Other methods [4, 5] were proposed to accelerate the NLM, but with affecting the denoising performance.

This study contributes two techniques to reduce the computational cost and improve the denoising performance of the NLM method. First, all the pixels of the noisy image are divided into significant edge, moderate edge or non-edge region, and the size of the search window for most pixels which belong to non-edge region can be reduced. Second, the proposed scheme adopts different strategies in different region, by which the similar patches can be pre-selected very efficiently.

2 Size-adaptive search window

To search the self-similarity of the noisy image, the neighbourhood of NLM is defined by the grey-level distance of the patch. A significant amount of computation in NLM is dedicated to calculate each distance between patches in a large size search window. The motivation to search the self-similarity is conserving the image features which are mainly in the edge regions, so the size of the search window for most pixels which belong to non-edge region can be reduced.

Edge detection is one of the most commonly used techniques in the digital image processing. To reduce its sensitivity to noise, the noisy image is blurred with a Gaussian smoothing filter. Then two high-pass filter are used to detect horizontal edge ($G_x$) and vertical edges ($G_y$) of the blurred image. Moreover, the edge gradient and direction can be determined

$$ G = \sqrt{G_x^2 + G_y^2} \quad \varphi = \arctan 2(G_x, G_y) $$

(1)

On the basis of the edge gradient, all the pixels are divided into significant edge, moderate edge or non-edge region

$$ \begin{aligned} &\text{significant edge pixel}, \quad G_{i,j} > \beta_1 \cdot G_{\max} \\
&\text{moderate edge pixel}, \quad \beta_1 \cdot G_{\max} \geq G_{i,j} \geq 0.5\beta_1 \cdot G_{\max} \\
&\text{non-edge pixel}, \quad G_{i,j} < 0.5\beta_1 \cdot G_{\max} \end{aligned} \quad (2) $$

where the $G_{\max}$ denotes the maximum gradient.

The size of the search window is adapted to the type of the central pixel. If the central pixel belongs to non-edge region, small size search window is enough, as the green pixel and its green neighbour in Fig. 1a. On the contrary, if the central pixel in the significant edge region as the purple pixel shown in Fig. 1b, large size window is used to search the self-similarity of the noisy image.

3 Pre-selection similar patches

The proposed fast scheme adopts different strategies to pre-select similar patches. For the pixels which belong to non-edge region, considering zero-mean additive noise, similar neighbourhoods should have similar average grey values. The pixels of above blurred image are as the measure to pre-select similar patches

$$ |B_{k,l} - B_{i,j}| < T_B \quad \forall (k, l) \in \Omega_{i,j}^N $$

(3)

where $\Omega_{i,j}^N$ denotes the $(2N_x+1) \times (2N_y+1)$ search window centred at $(i, j)$ and $B_{k,l}$ denotes the candidate pixel of blurred image location at point $(k, l)$ in the search window.

In the edge region, the patches which central pixel has similar gradient and direction with the central patch are considered be selected as similar patches

$$ \begin{aligned} &\beta_2 G_{i,j} < G_{k,l} < B_{i,j}/\beta_2 \\
&|\varphi_{k,l} - \varphi_{i,j}| < \Delta \varphi \quad \forall (k, l) \in \Omega_{i,j}^N \end{aligned} \quad (4) $$

These different strategies are used to pre-select similar patches of two pixels which belong to different regions in Fig. 1b. The pre-selected results of these two pixels are marked with highlight in their search window as shown in Fig. 1c.

4 Our NLM algorithm

The proposed NLM algorithm with size-adaptive search window (NLM-SAS) is summarised as follows:
(a) Input a noisy image \( u \), estimate the standard deviation of the noise \( \sigma_n \).
(b) On the basis of the edge gradient of the noisy image, select the suitable research window for each pixel according to size-adaptive search window.
(c) For each pixel, pre-selection similar patches according to pre-selection similar patches in its research window.
(d) Restore each pixel by a weighted average of the intensities of its pre-selected similar neighbourhoods.

The weight of the pre-selected similar neighbourhood is calculated by two thresholds \( T_1 \) and \( T_2 \):

\[
\begin{align*}
    w_{k,l} & = 1, \quad d_{k,l}^2 \leq T_1 \\
    w_{k,l} & = \frac{(T_2 - d_{k,l}^2)}{(T_2 - T_1)}, \quad T_1 < d_{k,l}^2 \leq T_2 \\
    w_{k,l} & = 0, \quad d_{k,l}^2 > T_2
\end{align*}
\] (5)

where \( d_{k,l}^2 \) denotes the squared Euclidean distance between the central patch \( u_{c,k,l}^N \) and the pre-selected similar patch \( u_{k,l}^N \):

\[
d_{k,l}^2 = \left\| u_{c,k,l}^N - u_{k,l}^N \right\|^2, \quad \forall k, l \in \Omega_{N_p}
\] (6)

where \( N_p \) denotes the radius of the patch. Moreover, the thresholds \( T_1 \) and \( T_2 \) are defined as

\[
\begin{align*}
    T_1 & = \lambda \sigma_n^2 \\
    T_2 & = 2 T_1
\end{align*}
\] (7)

Table 1 lists the parameters in the proposed NLM algorithm. It can be seen that the size of the patch and research window depends on standard deviation of the noise, the values of \( \beta_1 \) and \( \lambda \) also depend on it. If \( \sigma_n \leq 30, N_p = 1 \) and \( N_S = 5, 10, 15 \) denote that if the standard deviation of the noise <30, the proposed NLM algorithm uses \( 3 \times 3 \) patch and the \( 11 \times 11, 21 \times 21 \) and \( 31 \times 31 \) research window for non-edge edge, moderate edge and significant region, respectively.

To realise a fast algorithm, we reduce the number of processed pixel: rather than sliding by one pixel to every next, use a step of \( N_{step} \) in both horizontal and vertical directions. In the fast NLM algorithm with size-adaptive search window (NLM-FAW), we choose \( N_{step} = N_p \).

5 Experiment

The proposed patchwise NLM-AW and its fast version NLM-FAW are evaluated, and compared with standard patchwise NLM [6] and NLM with SAPs algorithm (NLM-SAP) [3]. Extensive experiments are conducted on four standard test images with distinctly different features, corrupted by additive Gaussian white noise at different power levels. From Table 2, it is clear that our methods provide improvement over other NLM algorithms in peak signal-to-noise ratio (PSNR), especially when image corrupted by high noise level. To compare the results visually, the fragments of noisy Peppers and its recovery results are given in Fig. 2. Figs. 2b–d are the image restored by Standard NLM, NLM-SAP and the proposed NLM-AW, respectively. It is clear that Fig. 2d yields superior visual quality with respect to noise suppression and image detail preservation.

In Table 3, we first compare the proposed NLM-AW with standard NLM in number of distance calculations, which is represented as the percentage of the total amount of calculations required by the standard NLM. It can be seen that the number of distance calculations of NLM-AW is about 10–20% of the standard NLM. Moreover, then we compare the proposed NLM-AW, NLM-FAW with standard NLM in the computing time of \( 512 \times 512 \) noisy image on an Intel Pentium 64 bit, 2.6 GHz personal computer. The computing time of the proposed NLM-FAW is about 6–10 times faster than standard NLM, which is consistent with the number of distance calculations.

Table 1 Parameters of the proposed NLM algorithm

| \( \sigma_n \) | \( N_p \) | \( N_S \) | \( \beta_1 \) | \( T_0 \) | \( \beta_2 \) | \( \Delta w \) | \( \lambda \) |
|---|---|---|---|---|---|---|---|
| \( \sigma_n \leq 30 \) | 2 | 5, 10, 15 | 0.24 | \( \sigma_n \) | 1.35 | \( \frac{\pi}{4} \) | 1.75 |
| \( 30 < \sigma_n \leq 45 \) | 3 | 6, 10, 18 | 0.4 | | | | 1.6 |

Table 2 Comparison of some NLM methods in PSNR (decibels)

| \( \sigma_n \) | 10 | 20 | 40 | 10 | 20 | 40 |
|---|---|---|---|---|---|---|
| Lena (512\(^2\)) | NLM | 34.51 | 31.58 | 28.17 | 33.11 | 29.79 | 26.23 |
| | NLM-SAP | 35.03 | 31.91 | 28.21 | 32.97 | 29.60 | 26.04 |
| | NLM-AW | 35.40 | 32.44 | 29.31 | 33.25 | 30.44 | 27.19 |
| | NLM-FAW | 35.13 | 32.28 | 29.10 | 33.04 | 30.26 | 27.00 |
| Boat (512\(^2\)) | NLM | 33.02 | 29.54 | 25.73 | 33.71 | 30.23 | 26.07 |
| | NLM-SAP | 33.08 | 29.31 | 25.39 | 34.19 | 30.77 | 26.62 |
| | NLM-AW | 33.37 | 30.10 | 26.69 | 34.40 | 31.07 | 27.31 |
| | NLM-FAW | 33.14 | 29.90 | 26.47 | 34.05 | 30.70 | 27.02 |

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The proposed NLM-FAW achieves a substantial reduction in computational cost; it gets a balance between speed and performance for practical application. Furthermore, a parallel implementation on GPU implementation could bring NLM-FAW to real-time image denoising.

### 6 Conclusion

In this study, two techniques to speed-up and improve the standard NLM algorithm are proposed. Experimental results indicate that compared with the standard NLM method, the proposed fast scheme achieves a substantial reduction in computational cost and improvement in the denoising performance.

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