# A Block-Grouping Method for Image Denoising by Block Matching and 3-D Transform Filtering

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***Abstract*—Image denoising by block matching and three-dimensional transform filtering (BM3D) is a two steps state-of-the-art algorithm that uses the redundancy of similar blocks in noisy image for removing noise. Similar blocks which can have some overlap are found by a block matching method and grouped to make 3-D blocks for 3-D transform filtering. In this paper we propose a new block grouping algorithm in the first step of BM3D that improves the performance of denoising algorithm especially in heavy noise conditions. In heavy noise conditions, BM3D causes some artifacts in the filtered image. These artifacts are reduced by the proposed block grouping algorithm. In the proposed block grouping method, beside of a similarity measure used for block matching, the amount of overlap between blocks is considered. Experimental results show that the proposed block grouping method can improve the performance of BM3D in terms of both peak signal-to-noise ratio (PSNR) and visual quality.**

***Index Terms*—3-D transform, block matching, BM3D, denoising, filtering, image, overlap**

## I. Introduction

DIGITAL images are corrupted by noise during acquisition, compression, and transmission. There are many denoising algorithms, using different methods and tools such as wavelet transform, *Principal Component Analysis* (PCA), *Singular Value Decomposition* (SVD), partial differential equations, and linear or non-linear filtering in spatial domain. The image denoising algorithms attempt to reduce the noise, while preserving the image features with minimum artifacts. Transform domain denoising methods typically assume that a linear compound of basic elements can approximate the noise-free signal, so the signal is sparsely represented in the transform domain. The strategy of the wavelet domain denoising algorithms can be summarized in three stages including: applying wavelet transform, removing noise in transform domain by different rules, and an inverse transform on denoised coefficients. In some algorithms, the noise is removed base on thresholding wavelet coefficients [1]. In this approach, noise can be deleted by changing coefficients which are smaller than a selected threshold to zero. Different shrinkage functions have been used for better denoising [2]-[4]. Some algorithms try to use dependencies of wavelet coefficient in inter/intra-scale [5]-[7]. A group of image denoising methods operate in spatial domain. For example *Non–Local Mean* (NLM) algorithm presented in [8]-[9], takes advantages of the high degree of spatial redundancy in image pixels. Each pixel is estimated by a weighted averaging process over its neighboring pixels (patch). The weights are determined based on the similarity of the pixel with the patch pixels. Larger weights are allocated for more similar pixels and vice versa.

To speed up and increase the performance of NLM algorithm, different techniques are proposed. For example, D.V. De Ville et.al. perform a dimensionality reduction on the NLM algorithm by using PCA and derive *Stein's Unbiased Risk Estimate* (SURE) to find the optimal weights [10]. As another example, SVD and K-means clustering techniques are used for robust block classification in [11]. In another approach, NLM algorithm is speed up by using the Laplacian pyramid [12].

A combination of transform domain and spatial domain image denoising algorithms is presented in BM3D algorithm [13], [14]. BM3D heightened sparse representation in transform domain by collecting similar fragments in spatial domain (grouping). For simplicity fragments are considered as $N_1 \times N_1$ squares which is named block. In this paper we propose a new block grouping algorithm that improves the performance of denoising algorithm, especially in heavy noise conditions. The proposed algorithm tries to make block groups with minimum overlap between blocks in each group. Experimental results show that the proposed method improves the performance of BM3D in terms of both peak signal-to-noise ratio and the visual quality of denoised images.

The paper is organized as follows. The BM3D denoising algorithm is explained in section II. The proposed grouping algorithm is described in section III. Some simulation results and conclusions are represented in Section IV and V respectively.

## II. The BM3D Algorithm

The BM3D image denoising algorithm operates in two steps as explained in the sequel.

### *Step1: Basic Estimate*

For a noisy image $z$, some blocks are considered as reference blocks. They are overlapped blocks which are selected in a sliding manner with a fixed step in horizontal and vertical directions. For finding similar blocks to a reference one, a full-search block-matching is done in a square area around the reference block. If $Z_x$ and $Z_{x_R}$ are the block and the reference block in $z$, located at $x$ and $x_R$ respectively, then the similarity distance is calculated as

$$d^{noisy}(Z_{x_R}, Z_x) = \frac{\| Z_{x_R} - Z_x \|_2^2}{(N_1^{ht})^2} \tag{1}$$

where $x$ is the coordinate of the top-left corner of the block and $N_1^{ht}$ denotes the size of square block in the first step of BM3D that includes hard thresholding. $\|.\|_2$ stands for the $l^2$-norm.

For more corrected grouping, a 2-D transform with a hard threshold is apply on each block to reduce noise before calculating the similarity distance. So (1) is modified to (2) as

$$d^{noisy}(Z_{x_R}, Z_x) = \frac{\| \gamma(\Gamma_{2D}^{ht}(Z_{x_R}) - \gamma(\Gamma_{2D}^{ht}(Z_x) \|_2^2}{(N_1^{ht})^2}, \tag{2}$$

where $\gamma$ is a hard threshold operator and $\Gamma_{2D}^{ht}$ is a 2-D linear unitary transform operator (e.g. DCT, DFT, etc.). Each group is made by stacking together maximum $N_2^{ht}$ similar noisy blocks, with similarity distances less than a predefined threshold ($\tau_{match}^{ht}$), in a 3-D array form, $\boldsymbol{Z}_{x_R}$. A bold-face capital letter denotes the group of blocks. A normalized 3-D transform is applied on each group and noise is removed by a hard threshold filtering. So denoised group $\widehat{\boldsymbol{Y}}_{x_R}^{ht}$ are calculated as

$$\widehat{\boldsymbol{Y}}_{x_R}^{ht} = \Gamma_{3D}^{ht^{-1}}(\gamma(\Gamma_{3D}^{ht}(\boldsymbol{Z}_{x_R}))) \tag{3}$$

where $\Gamma_{3D}^{ht}$ and $\Gamma_{3D}^{ht^{-1}}$ denotes the adopted normalized 3-D linear transform and its inverse transform in the first step, respectively. After denoising all block groups, a denoised image is constructed from the filtered block groups in the basic step. Because of overlap that exists between blocks in a group and between groups, there are several estimates for most of the pixels in the image. Therefore, the pixels of the basic estimate image are obtained by weighted averaging on estimated pixels.

*Step2: Wiener Estimate*

In the second step, a grouping is executed based on the basic image estimated in the first step. The similarity distance is computed as

$$d^{wie}(Y_{x_R}, Y_x) = \frac{\|Y_{x_R} - Y_x\|_2^2}{(N_1^{wie})^2}, \tag{4}$$

where $Y_{x_R}$ and $Y_x$ are two blocks in the basic image. $N_1^{wie}$ denotes the size of blocks in the Wiener step. Corresponding blocks from the noisy image are stacked together base on this grouping to make 3-D blocks ready for filtering. The 3-D noisy blocks are denoised by applying Wiener filter instead of hard thresholding used in the first step. Wiener shrinkage coefficients are calculated as

$$\boldsymbol{W}_{x_R} = \frac{|\Gamma_{3D}^{wie}(\boldsymbol{Y}_{x_R}^{basic})|^2}{|\Gamma_{3D}^{wie}(\boldsymbol{Y}_{x_R}^{basic})|^2 + \sigma^2}, \tag{5}$$

where $\Gamma_{3D}^{wie}$ denotes the adopted normalized 3-D linear transform in the second step on the group $\boldsymbol{Y}_{x_R}^{basic}$. Denoised blocks in each group are estimated as

$$\widehat{\boldsymbol{Y}}_{x_R}^{wie} = \Gamma_{3D}^{wie^{-1}}(\boldsymbol{W}_{x_R}\Gamma_{3D}^{wie}(\boldsymbol{Z}_{x_R})). \tag{6}$$

where $\Gamma_{3D}^{wie^{-1}}$ denotes the inverse adopted normalized 3-D linear transform in the second step on the group $\boldsymbol{Y}_{x_R}^{basic}$.

Because of overlap that exists between blocks in a group and between groups, there are several estimates for most of the pixels in the final image. Therefore, similar to the first step, the pixels of final denoised image are obtained by weighted averaging on estimated pixels by Wiener filter.

Several techniques have been proposed for improving BM3D algorithm [15]-[19]. Shape adaptive fragments are used instead of square blocks in [15]. A separable composition of the 2-D shape adaptive DCT and the 1-D Haar wavelet full-dyadic decomposition are employed as 3-D transform. In another improvement, PCA is used on these fragments to improve sparsity [16]. Presented results show improvement for low level noise conditions ($\sigma \leq 35$) [16]. BM3D is improved by using a soft thresholding instead of hard thresholding in basic estimate step [17]. For heavy noise conditions, the results of BM3D are improved by some modifications in the first step of the algorithm including transform type, group size, and threshold values [18]. Another improvement in the Wiener step for heavy noise conditions is proposed by using a bounded block matching in [19]. A segmenting process is done on basic image for detecting the bounds. Block-matching is limited in the region where the templates of the reference blocks are located.

A new block grouping algorithm is proposed in this paper that is implemented in the first step of BM3D algorithm. The details of proposed algorithm are presented below.

## III. Proposed Method

In the proposed grouping algorithm, the attempt is to make groups of blocks with maximum similarity and minimum overlap between blocks. To simplify the implementation, the algorithm is executed as explained in the sequel. For each reference block, all similar blocks in the search area that have similarity distances less than a predefine threshold $\tau_{match}^{ht}$ are determined and collected in a block set with $N_{All}$ blocks. A block group is made from the block set as explained below.

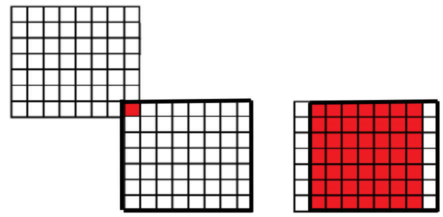
The first member of the group $Z_{x_R}$, is the reference block that has zero distance with itself. The second member is a block from $N_{All}-1$ remained blocks in the block set that has minimum overlapped with the reference block. The third member of group is selected from $N_{All}-2$ remained blocks, such that it has a minimum average overlap with the first and the second member of group. The next group members are selected from the remained blocks if they have minimum average overlap with the previous group members. The amount of overlap is defined as the number of shared pixels between two blocks. Two blocks can have overlap up to maximum $N_1^{ht}\times(N_1^{ht}-1)$ pixels. In Fig.1, two examples of amount of overlap are shown. The amount of overlap between two blocks $Z_{x_i}$ and $Z_{x_j}$ is denoted by $O_{ij}(Z_{x_i},Z_{x_j})$. The average overlap for $Z_{xj}$ is denoted by $\overline{O}_j$ and calculated as

$$\overline{O}_j=\sum_{\substack{i=1\\ i\neq j}}^{M_g}\frac{O_{ij}(Z_{x_i},Z_{x_j})}{N_1^{ht}\times(N_1^{ht}-1)}, \tag{7}$$

Where $M_g$ is the number of previous members in the group. If there are more than one block that have the same minimum average overlap, the most similar block is selected as the next member. The grouping algorithm is continued until the number of group members is equal to $\min(N_2^{ht},N_{All})$. When the group members are determined, they are sorted base on their similarity distance from the reference block. After grouping, the first step of BM3D algorithm is proceeded on provided block groups. Then, the second step of BM3D is executed without any change.

## IV. EXPERIMENTAL RESULTS

To evaluate the effect of proposed block grouping method on the performance of BM3D denoising algorithm, we implemented BM3D algorithm as described in [13] in Matlab software. Moreover, the modified BM3D algorithm by the proposed block grouping method was implemented. A number of 12 images were used for the test. Gaussian noises with standard deviations of 100 and 120 were added to the test images. The noisy images were filtered by both BM3D and the modified BM3D denoising algorithms. Simulation results for two noise levels are presented in Table I and Table II. The quality of filtered images by two algorithms are compared in term of PSNR. The first seven test images mentioned in the tables are available on [20]. Their sizes are 512×512 pixels except for House that is 256×256 pixels. Other test images are available in Matlab software and are shown in Fig.2. 2-D DCT and 1-D Haar transforms are used in both steps of BM3D, such as in [14]. Simulation results show that proposed modified BM3D algorithm provided a higher PSNR for all test images. The average PSNR on all test images has been improved by the proposed algorithm about 0.38 dB for the both noise levels. Moreover, simulation results show a higher degree of visual quality for provided images by the proposed method. Sample visual results are presented in Fig.3 and Fig.4. It is obvious; artifacts are decreased significantly in provided images by the proposed method.



(a) (b)

Fig.1. Demonstration of amount of overlap between two blocks. (a) 1 pixel overlap, (b) 56 pixels overlap

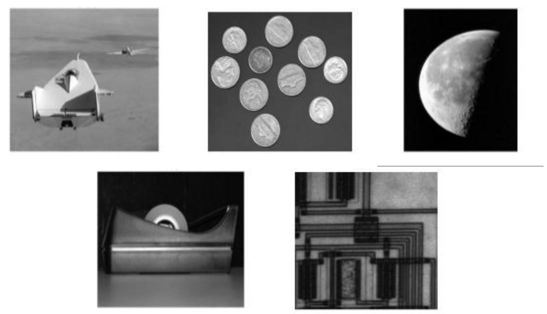


Fig.2. Sample test images. From left to right and up to down: Liftingbody, Coins, Moon, Tape, and Circuit.

TABLE I. Comparing simulation results provided by BM3D and Modified BM3D in term of PSNR for σ = 100

| Image | BM3D | Modified BM3D |
|---|---|---|
| House | 25.59 | 25.91 |
| Lena | 25.67 | 25.96 |
| Barbara | 23.45 | 23.55 |
| Boat | 23.73 | 23.84 |
| Couple | 23.37 | 23.49 |
| Hill | 24.51 | 24.68 |
| F16 | 24.35 | 24.56 |
| Liftingbody | 28.13 | 29.00 |
| Moon | 29.07 | 29.83 |
| Tape | 27.29 | 28.00 |
| Coins | 24.81 | 25.14 |
| Circuit | 25.02 | 25.58 |
| ***Average on all images*** | ***25.42*** | ***25.80*** |

TABLE II. Comparing simulation results provided by BM3D and Modified BM3D in term of PSNR for σ = 120

| Image | BM3D | Modified BM3D |
|---|---|---|
| House | 24.45 | 24.83 |
| Lena | 24.66 | 25.02 |
| Barbara | 22.41 | 22.54 |
| Boat | 22.88 | 23.06 |
| Couple | 22.58 | 22.75 |
| Hill | 23.72 | 23.95 |
| F16 | 23.37 | 23.61 |
| Liftingbody | 26.90 | 27.73 |
| Moon | 28.15 | 28.88 |
| Tape | 26.15 | 26.78 |
| Coins | 23.91 | 24.32 |
| Circuit | 23.89 | 24.18 |
| ***Average on all images*** | ***24.42*** | ***24.80*** |

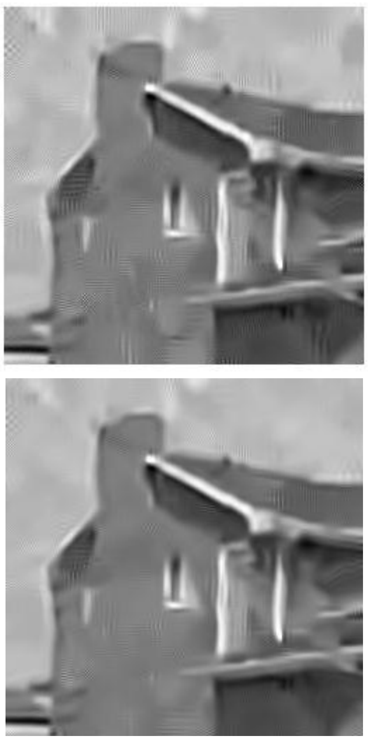


Fig.3. House image denoised by BM3D (up) and modified BM3D (down) for σ=120.

Fig.4. F16 image denoised by BM3D (up) and modified BM3D (down) for σ=120.

## V. CONCLUSIONS

In this paper we proposed a modification on BM3D image denoising algorithm. A new block grouping algorithm was proposed that considers not only the similarity between blocks, but also the amount of overlap between blocks while grouping. Simulation results show that the proposed algorithm can improve the performance of BM3D image denoising algorithm in terms of PSNR and visual quality.

In the proposed grouping algorithm the attempt is to make groups of blocks with maximum similarity and minimum overlap between blocks. This idea was simplified for easy implementation. However, in future research works, a more complicate implementation may provide better results.

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