BLOCK MATCHING AND 3D COLLABORATIVE FILTERING ADAPTED TO ADDITIVE SPATIALLY CORRELATED NOISE

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ABSTRACT 
Visual quality of images is crucial for image processing. Noise is one of the most destructive factors that reduces a visual quality of original images and efficiency of their subsequent treatment. In addition, noise can be not white and might appear more noticeably in images. Additive spatially correlated noise is considered as one of such cases. To improve a visual quality of corrupted images, some denoising technique has to be applied. BM3D (block matching and 3D filtering) is known to be state-of-the-art for additive white Gaussian noise (AWGN) removal. In this paper, we present two mechanisms to adapt the BM3D filter to the case of spatially correlated noise. One is employed for block matching and the second one is used in denoising based on discrete cosine transform (DCT). New similarity measures are considered and applied instead of the standard Euclidean distance. It is shown that both adaptation mechanisms contribute to sufficient improvement of visual quality characterized by the standard metric PSNR and the specialized metric PSNR-HVS-M. Two levels of spatial correlation for noise modelling are used in our studies.

1. INTRODUCTION 
Noise that occurs due to non-ideality of practical image acquisition systems can significantly reduce visual quality of images and prevent their efficient post-processing [1]. A commonly used noise model in optical imagery is an additive white Gaussian noise (AWGN) [2]. Currently, less attention is paid to models of non-white noise, i.e. additive spatially correlated noise that has low-frequency spectrum and distorts fine image details more significantly than AWGN [3]. This deals with the fact that human visual system (HVS) is more sensitive to distortions of low frequency data than to distortions in high-frequency part of data spectrum [4]. Thus, image filtering in such cases should be oriented on removing the distortions in low-frequency part of image spectrum. Recently, a wide variety of denoising techniques for AWGN removal has been proposed. Several of them are based on discrete cosine transform (DCT) due to its good energy compactness and sparseness properties [5, 6]. BM3D filter [6] is known as the state-of-the-art technique for AWGN removal. It consists of two basic procedures: block matching and collaborative 3D filtering. The first procedure searches for blocks similar with respect to a reference one in a certain search region. Size of blocks is 8x8 pixels. As a similarity measure, Euclidean distance is used in the search. Before searching, 2D DCT is performed for each analyzed block. These blocks, if there are any similar blocks, are collected together with the reference block into 3D arrays of size 8x8x2³. Along the third dimension, 1D Haar transform is used whilst DCT is applied for spatial coordinates. The second basic procedure is a hard-threshold denoising mechanism applied in each such an array.

The presence of white noise leads to its uniform (equal) influence on all DCT coefficients. That means equal influence on resulting similarity (distance) value from each noisy spectrum component in a searching procedure. The hard-threshold denoising procedure sets one fixed threshold value for each component. 

On the contrary, for spatially correlated noise case, the noise spectrum is not uniform (in Fourier or DCT spatial domain). Thus, certain adaptation is needed for both basic procedures. In [7], an estimate of spatially correlated noise spectrum was further used for DCT-based filtering and it has been shown that a denoising efficiency is increased. The first steps of adapting the BM3D denoising mechanism by applying other than Euclidian similarity metrics were proposed in [8]. It has been demonstrated that such adaptation provides an improvement of visual quality of images in terms of a standard metric peak signal-to-noise ratio (PSNR) and a specialized metric PSNR-HVS-M [9]. In [10], there is an attempt to adapt both basic BM3D procedures using weighted Euclidean distance and a threshold adjustment.

The goal of this paper is to study a full adaptation of the BM3D for an additive spatially correlated noise applied for two basic procedures. The structure of the paper is the following. Section 2 describes the denoising and searching mechanisms in more details. The proposed full adaptation
mechanism is considered. Section 3 presents test images and noise modelling. Section 4 deals with results of denoising for the standard and adapted versions of the BM3D. Finally, conclusions are given.

2. PROPOSED FULL ADAPTATION

The first basic procedure (block matching) is essential, because spatially correlated noise affects low-frequency DCT components that distort a reference block and other blocks related to it. As a result, a similarity search might find blocks similar to each other not in the content but in realizations of spatially correlated noise. Then, it is worth using some weighting operation in similarity estimation to take into account 2D spectrum of the noise.

In our study, several similarity measures shown to be good in [8] have been considered. For a spatially correlated noise, standard Bray-Curtis and Canberra distances [11, 12] applied to BM3D provided higher efficiency than the BM3D version with the Euclidean distance [8]. Presenting image blocks transformed by DCT as vectors, the weighted Euclidian, Bray-Curtis and Canberra distances in DCT domain can be expressed as:

\[ d_{BM} = \sum_{i=1}^{n} \left( w_i \cdot (x_i - y_i) \right)^2, \]  \hspace{1cm} (1)

\[ d_{BC} = \sum_{i=1}^{n} w_i \cdot |x_i - y_i| / \sum_{i=1}^{n} w_i \cdot |x_i + y_i|, \]  \hspace{1cm} (2)

\[ d_{c} = \sum_{i=1}^{n} w_i \cdot |x_i - y_i| / \sum_{i=1}^{n} w_i \cdot (|x_i| + |y_i|) = \]  \hspace{1cm} (3)

\[ = \sum_{i=1}^{n} |x_i - y_i| / |x_i| + |y_i|, \]

where \( x \) and \( y \) are blocks (vectors) of data in DCT domain, \( i \) denotes an index of vector element, \( n \) defines sample size (equals to 64), \( w \) denotes a weighting function that is calculated as:

\[ w_i = n^* W / \sum_{i=1}^{n} W, \]  \hspace{1cm} (4)

where \( W_i \) is a value of \( i \)-th component of the DCT spectrum of noise [7] which is supposed to be a priori known or pre-estimated with an appropriate accuracy. Later on, we describe in detail the process of noise generation and its spectrum estimation. Note that the weighting function used for Canberra distance is, in fact, ignored due to the structure of numerator and denominator in (3). This means practically the invariance of this similarity metric to a noise spectrum.

The second basic procedure (collaborative denoising) works with the groups of similar blocks. Thus, setting fixed (frequency independent) threshold can lead to an inefficient denoising. The modified procedure with the frequency-dependent thresholds is the following:

\[ B_{out} = \begin{cases} B_{in} & \beta \cdot \sigma_i \\ B_{in} & B_{in} \leq \beta \cdot \sigma_i \end{cases} \hspace{1cm} (5) \]

where \( \sigma_i = \sigma \sqrt{W_i} \). Here \( \sigma \) is a standard deviation (SD) of the noise, \( \sigma_i \) denotes a frequency-dependent SD for a spatially correlated noise, \( B_{in} \) is an input 3D transformed group of blocks (applying the separable 2D DCT in spatial coordinates and the 1D Haar transform in the similarity direction) and expressed as a 2D array (because of vector presentation of each block), \( B_{out} \) is the output filtered data, \( \beta \) is an adjusting parameter set to 2.7, \( W_i \) denotes the \( i \)-th value of the normalized spectrum. This modification of the denoising procedure and new similarity metrics (without weighting function) has been already applied in [8]. No other modifications or changes have been done to the standard BM3D algorithm.

3. NOISE MODELING AND TEST IMAGES

Additive spatially correlated noise appears itself as a more distinctive distortion than AWGN. Note that many real-life image acquisition systems produce images corrupted by just spatially correlated noise [3]. Such spatial correlation of noise pixels is usually essential only for neighboring pixels. Additive spatially correlated noise can be easily modelled from AWGN. Spatial correlation in AWGN realization can be, e.g., provided using sliding window linear filter with 3*3 or 5*5 pixels and weights.

The weights of used linear filter determine a degree of the spatial correlation. In this paper, we consider two degrees of correlation and call them as the middle degree and the strong degree. Noise models with such spatial correlation degrees will be further called as AMSCN and ASSCN, respectively. Weights of the filters for these noise models are presented in Table 1. It is well seen that the weights for both noise models well reallocate an influence of the neighboring pixels.

<table>
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<th>Table 1. Weights of linear filters for noise modelling</th>
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<td>TID2013 image database [13] which contains color images mainly from Kodak dataset has been used for testing. Images used in experiments below are grayscale (they are intensity images obtained using the corresponding reference color images from TID2013). These images have distinctive content like homogenous or textured regions, fine details or object boundaries. The size of all images is fixed and equal to 512*384 pixels.</td>
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4. RESULTS AND ANALYSIS

We have considered seven versions of the BM3D filter that can be applied for removal of non-white noise. The first one is the standard version of the filter. Six others use frequency-dependent thresholds (FDT) and the following similarity metrics: standard and weighted Euclidian distance (BM3D-FDT&E and BM3D-FDT&wE); standard and weighted Bray-Curtis distance (BM3D-FDT&BC and BM3D-FDT&wBC); standard and weighted Canberra distance (BM3D-FDT&C and BM3D-FDT&wC).

To control the denoising efficiency, we have used two criteria: improvement of PSNR (IPSNR) and improvement of PSNR-HVS-M (IPSNR-HVS-M) determined as differences of these metrics for output (filtered) and original (noisy) images. Both improvements are expressed in dB where improvement over 2...3 dB corresponds to noticeable increase in quality.

We have analyzed three values of noise SD: 5, 10, and 15. The SD=5 corresponds to already visible noise in typical real life optical images. The noise with SD=15 is intensive and very annoying. The case of SD=10 is an intermediate situation.

Let us start from considering an example. Fig. 1 represents fragments of two test images (# 5 and # 23 from TID2013, ASSCN with SD=15). As it is seen in Fig. 1.b, noise is annoying and it considerably distorts images. Both proposed modifications of the BM3D filter (their outputs are depicted in Fig. 1.d and 1.e that use the weighted Bray-Curtis and Canberra distances) suppress noise sufficiently and preserve fine details whilst the standard BM3D proposed for AWGN noise removal (see output images in Fig. 1.c) is obviously less efficient.

The obtained plots (dependences of the improvements for seven considered versions on image index in the database) are shown in Fig. 2 for both ASCCN and AMCCN. Analysis of IPSNR shows the following:

1) IPSNR depends upon image content and is the smallest for complex structure images such as the test images ## 1, 5, 13, 14, 18 irrespectively of the used modification of the BM3D filter;

2) The standard BM3D designed for AWGN removal practically always produces the worst results;

3) The use of both versions of Canberra distance and the weighted Bray-Curtis distance results in the best performance; the use of other distances produce intermediate results;

4) The benefit due to exploiting the best distances and frequency-dependent thresholds can reach 4 dB (compared to the standard BM3D filter) for simple structure images and intensive noise;

5) The benefit slightly depends upon noise properties (degree of spatial correlation).

Fig. 1. Zoomed 60*60 pixels fragments of test images ##5 and 23 from TID2013: original fragments (a), noisy fragments distorted by ASSCN with noise SD=15 (b), filtered fragments by standard BM3D (c), by BM3D-FDT&wBC (d), by BM3D-FDT&C (e)
It is worth noting that the results for both modifications of the Canberra distance practically coincide. This is an obvious advantage of this distance since it allows to simplify block similarity search and to make it less sensitive to errors in noise spectrum estimation. Analysis of IPSNR-HVS-M shows the following:

1) This criterion also depends upon image content and its values are the smallest for the aforementioned complex structure test images irrespectively to the used modification of the BM3D filter; for small noise SD, there can be images for which denoising does not lead to noticeable improvement of visual quality;

2) The standard BM3D designed for AWGN removal practically always produces the worst results for spatially correlated noise removal;

3) The use of both versions of Canberra distance leads to the best performance; the use of other distances produce intermediate results;

4) The benefit due to exploiting the Canberra distances and frequency-dependent thresholds can attain about 4 dB (comparing to the standard BM3D filter), this takes place for simple structure images and intensive noise;

5) The benefit slightly depends upon noise properties (degree of spatial correlation).

5. CONCLUSIONS AND FUTURE WORK

Several modifications of the BM3D filter are proposed. Modifications are introduced into the stage of similar block search and DCT-based filtering. These modifications take into account 2D spectrum of spatially correlated noise assumed to be a priori known or pre-estimated. Special kind of weighting is exploited in distance calculation and frequency dependent threshold setting. Both types of modifications contribute to improvement of the filter performance. This improvement can be sufficient and reach a few dB in terms of standard quality metrics (IPSNR) as well as visual quality metrics (IPSNR-HVS-M). The largest improvement takes place for simple structure images whilst for complex-structure images improvement can be negligible, especially for low level of the noise. The latter deals with principle problems in texture image denoising [14].

The use of Canberra metric (even if weighting is not used) is expedient since the versions of BM3D filter with these distances produce the best or nearly the best results for both considered types of spatially correlated noise. We expect that the use of the standard version of Canberra distance offers invariance of similarity search with respect to DCT spectrum estimation. Meanwhile, in future, we plan to analyze the influence of errors in estimation of the noise spectrum in DCT domain on efficiency of denoising by adapted versions of BM3D and attempt to decrease it.

6. REFERENCES

Fig. 2. Improvement of PSNR (a-d) and PSNR-HVS-M (e-i) for TID2013 test images corrupted by AMSCN (a, c, e, h) and ASSCN (b, d, f, i) with noise SD = 25 (a, b, c, f) and SD = 225 (c, d, h, i)