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ANALYSIS OF OPPORTUNITIES TO IMPROVE IMAGE DENOISING EFFICIENCY FOR DCT-BASED FILTER

*The **subject matter** of the paper is the process of image filtering. The **goal** is to provide high efficiency of denoising according to metrics that are more adequate to human vision system than traditional criteria as mean square error or peak signal-to-noise ratio. The **tasks** to be solved are the following: to carry out analysis of denoising efficiency using visual quality metric, to determine optimal settings of DCT-based filter depending upon image and noise properties, to propose a method for setting a global threshold adaptively (in quasi-optimal manner) based on preliminary analysis of image and noise properties. The following **results** have been obtained: 1) optimal values of filter parameters depend upon many factors including image complexity and noise intensity, 2) optimal values also depend on optimization criterion (or metric) used to characterize filter performance; 3) optimal values of parameter β that determines the threshold can considerably differ from 2.6 which is traditionally recommended; 4) this opens opportunities for improving image denoising efficiency; 5) one of this opportunities consists in preliminary analysis of image and noise properties with setting the threshold value according to the obtained dependences. **Conclusions**: 1) the filter performance can be sufficiently improved due to the proposed adaptive procedure; 2) this happens if either noise is intensive and image has a simple structure or if noise is not too intensive and image has a complex structure; 3) the proposed adaptive procedure requires a very small amount of additional computations for calculating input parameter and can be realized by 60 or more times faster than filtering itself; 4) the adaptive procedure slightly differs depending upon a metric used as performance criterion.*

Keywords: *image denoising, DCT-based filter, parameter optimization, performance criteria*

Introduction

Images of different origin are widely used nowadays in numerous applications [1]. Quality of original (acquired) images is different. Sometimes it satisfies users and no preliminary processing is needed. Meanwhile, quality of acquired images is unsatisfactory due to noise presence and, thus, image pre-filtering is desired [2, 3].

It is worth noting that there exists an enormous number of image denoising methods where the most advanced ones belong either to orthogonal based group [4, 5] or to non-local filter family [6-8]. Although quite modern and rather efficient principles are put into basis of these methods, there are many situations when achieved results (outcomes) do not satisfy users or researchers. The main reason behind this is that it is difficult to separate signal component and noise especially for cases when their features are close as, e.g., for highly textural images [9, 10]. Then, one needs to look for ways to improve filtering efficiency.

One opportunity (option) to reach this is to set filter parameters “properly”, i.e. so that performance of a considered filter is close to optimal according to a given criterion. It is worth recalling here that most filters have parameters that have to be set empirically by a user or according to some default recommendations. For example, for scanning window filters one has to select, at least, scanning window size and shape. Then other parameters have to be chosen as, e.g., parameter α for standard or modified sigma filters [11]. One has to choose type of thresholds and their values (proportionality factors) for filters based on orthogonal transforms including wavelet and discrete cosine transform (DCT) [4, 5, 12]. Even more parameters that influence denoising performance have to be set for non-local filters including patch (block) size, similarity measure, area of similar block search, thresholds, etc. [6-8]. Thus, filter properties sufficiently depend upon these settings and experience of a user (who sets parameters) or a filter designer who recommends default settings.

Let us put forward a hypothesis that, for a given image and noise intensity, parameters of a used filter can be set properly, in an optimal way according to a quantitative criteria (metric) employed to characterize filter performance. Then, a question arises, what benefit can be gained due to such optimal settings compared to default (recommended) settings. Analysis carried out to answer this question indirectly answers another question – is it worth looking for a way (some adaptation procedure) to set filter parameters optimally.

The goal of this paper is just to carry out such

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analysis for DCT-based filter [4, 12]. The reasons why this filter is chosen for analysis are the following. Firstly, this filter is simple enough and its realization is fast. Secondly, block size does not have too much influence and the block size choice as 8x8 pixels is a good compromise [4]. Thirdly, hard thresholding is the best choice among possible variants [12]. Fourthly, DCT-based filter can be easily adapted to different types of noise [13]. Then, one parameter is left that can be varied and optimized – this is proportionality factor β used in threshold setting as $T_{loc} = \beta\hat{\sigma}_{loc}$ where $\hat{\sigma}_{loc}$ is local estimate of noise standard deviation that can be defined in different manner depending upon noise type.

One peculiarity of this paper is that performance is analyzed not only in terms of standard criteria as output mean square error (MSE) or peak signal-to-noise ratio (PSNR) but also in terms visual quality metrics [14, 15].

Image/noise Model, Considered Filter and Denoising Efficiency Criteria

As it has been mentioned in Introduction, let us consider the simplest image noise model

$$I_{ij}^n = I_{ij}^t + n_{ij}, \quad (1)$$

I_{ij}^n and I_{ij}^t are ij-th pixel values of noisy and true images, respectively, n_i defines the noise in the ij-th pixel. It is supposed that $n_{ij}, i = 1,...,I, j = 1,...,J$ (I and J define the image size) is additive white Gaussian noise with zero mean and variance σ^2 supposed to be known in advance or accurately pre-estimated before denoising.

Recall that DCT-based denoising is usually carried out in blocks of fixed size (mostly often 8x8 pixels). Denoising consists of four main stages. First, in each block, 2D DCT is performed. Second, thresholding is done where the obtained DCT coefficients are compared to thresholds and changed according to certain rules. The simplest case is hard thresholding where DCT coefficients are either assigned zero values (if they do not exceed threshold) or, otherwise, they are kept unchanged. Third, inverse 2D is performed in each block with obtaining filtered values for all pixels that belong to a given block. Since a given image pixel belongs to several blocks (if processing with block overlapping is applied), filtered values for a given pixel coming from different blocks are averaged. This is the fourth (final) stage of DCT-based denoising.

Although DCT-based denoising with full overlapping of blocks take more time than processing without overlapping or with partial overlapping, let us below consider that former variant since it provides the best efficiency with respect to most quantitative criteria. Besides, even in the case of full overlapping of the blocks, the DCT-based denoising is quite fast compared to many other modern methods due to simplicity of the method and availability of hardware and/or software implementations of 2D DCT.

Usually, analysis of filtering performance is carried out using such conventional criteria as output MSE or PSNR [4, 10, 12]. However, in recent years, other metrics including visual quality ones have gained popularity. One problem with them is that nowadays there are already more than one hundred visual quality metrics and design of new ones continues. Visual quality metrics that have shown themselves good for one application or type of distortions occur to be not the best for other applications and vice versa. Currently, there is no visual quality metric accepted by image processing community as the best or the most general one. Because of this, let us use two visual quality metrics, namely, PSNR-HVS-M [14] and FSIM [15]. They have shown themselves quite general in assessment of grayscale image quality in general and for images corrupted by residual noise and artifacts after denoising in particular [10, 13].

The metric PSNR-HVS-M [14] can be treated as extension of PSNR that takes into account two specific features of human vision system (HVS), namely, less sensitivity to distortions in high spatial frequencies and masking effect in texture and edgy areas. Similarly to PSNR, PSNR-HVS-M [14] is expressed in dB and larger values correspond to better visual quality.

The metric FSIM [15] (we consider its grayscale version here) is an extension of famous SSIM that takes into account more emphasis of human vision to edges and small sized objects in assessment of image visual quality. FSIM varies from 0 to 1 where unity corresponds to perfect visual quality.

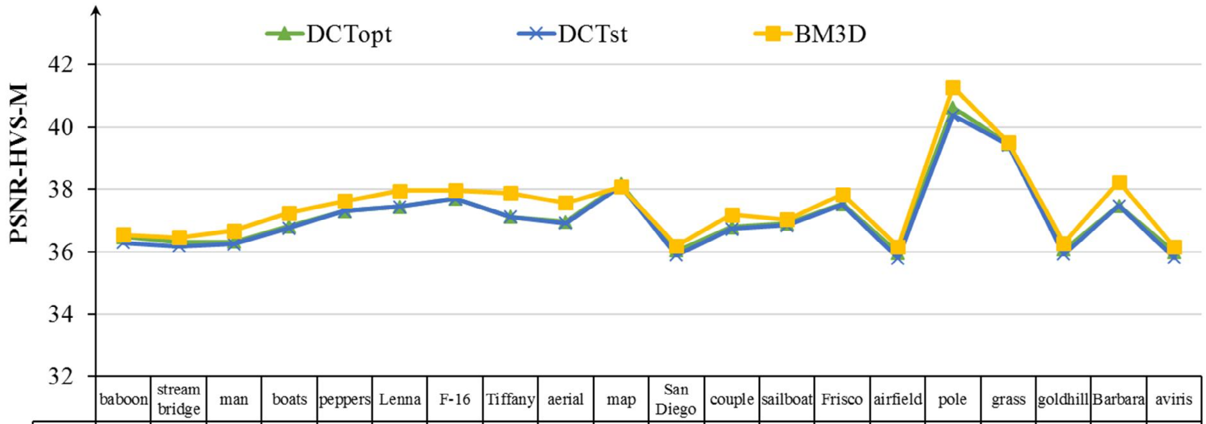
It is also worth noting that the values of PSNR-HVS-M over 41 dB and FSIM over 0.99 relate to invisible or almost invisible distortions [16]. Also note that both visual quality metrics are not perfect, so we have to jointly analyze them both to make adequate conclusions.

Methodology of experiments and their result analysis

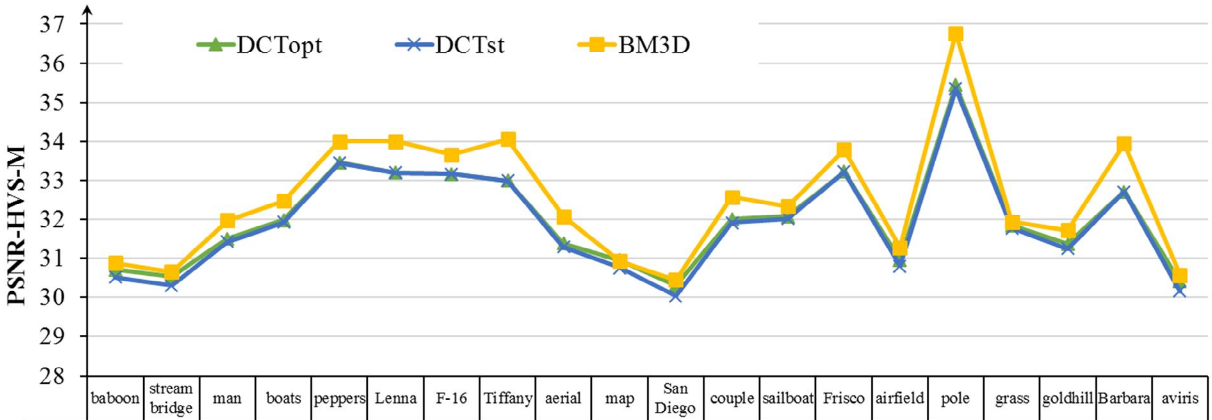
A good tendency now is to use many test images, at least, more than ten [4]. Following this tendency and using experience in [17, 18], we have used twenty test images of different origin and properties including low complexity ones (Peppers, Lenna, F16, Tiffany, Couple, Frisco, Pole), middle complexity images (Man, Boat, Aerial, Sailboat, Airfield, Goldhill, Barbara, AVIRIS) and highly textural ones (Baboon, Stream Bridge, Map, San Diego, Grass).

In analysis, two versions of DCT-based filter have been analyzed – one (called standard and denoted as DCTst) with fixed $\beta = 2.6$ and the optimal one (denoted as DCTopt) that used such β_{opt} that optimum has been provided according to the considered metric (either PSNR-HVS-M or FSIM as explained above. The results for the metric PSNR-HVS-M are presented in Fig. 1. Three values of noise variance have been considered – 65 (middle intensity noise), 200 (intensive noise), and 625 (very intensive noise).

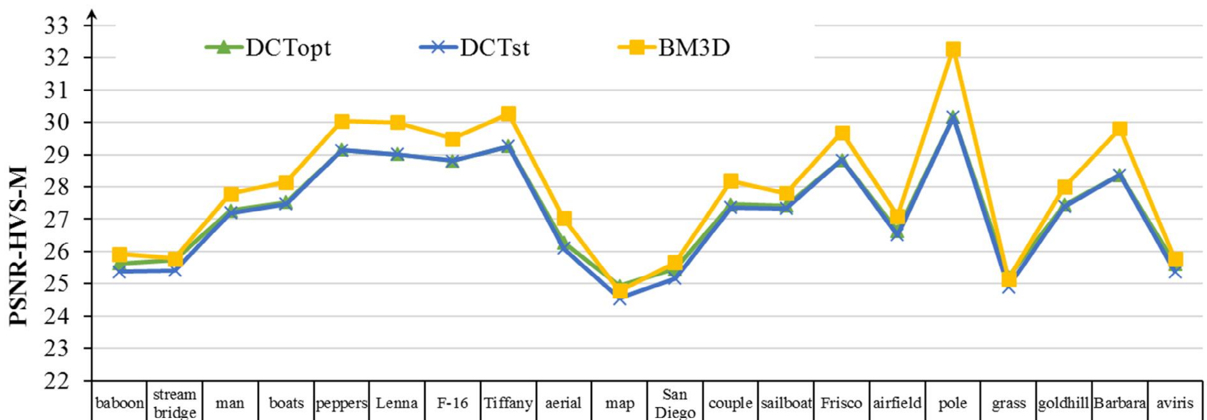
Besides, data are presented for the filter BM3D that is considered currently to be state-of-the-art in AWGN removal.



	baboon	stream bridge	man	boats	peppers	Lenna	F-16	Tiffany	aerial	map	San Diego	couple	sailboat	Frisco	airfield	pole	grass	goldhill	Barbara	aviris
DCTopt	36,48	36,32	36,32	36,81	37,30	37,45	37,70	37,12	36,96	38,17	36,04	36,79	36,91	37,53	35,97	40,62	39,46	36,06	37,46	36,00
DCTst	36,29	36,17	36,25	36,76	37,30	37,45	37,69	37,11	36,91	38,09	35,90	36,73	36,84	37,52	35,79	40,36	39,43	35,93	37,46	35,82
BM3D	36,55	36,46	36,67	37,24	37,62	37,96	37,97	37,88	37,57	38,08	36,20	37,19	37,02	37,84	36,16	41,27	39,51	36,28	38,24	36,14



	baboon	stream bridge	man	boats	peppers	Lenna	F-16	Tiffany	aerial	map	San Diego	couple	sailboat	Frisco	airfield	pole	grass	goldhill	Barbara	aviris
DCTopt	30,71	30,54	31,51	31,99	33,46	33,20	33,16	32,99	31,39	30,96	30,30	32,00	32,07	33,22	30,96	35,44	31,85	31,37	32,71	30,40
DCTst	30,52	30,31	31,42	31,93	33,45	33,20	33,16	32,99	31,29	30,76	30,03	31,91	32,02	33,22	30,81	35,35	31,78	31,25	32,71	30,16
BM3D	30,89	30,66	31,97	32,47	34,00	34,01	33,66	34,06	32,07	30,93	30,45	32,58	32,34	33,78	31,29	36,76	31,94	31,72	33,94	30,58



	baboon	stream bridge	man	boats	peppers	Lenna	F-16	Tiffany	aerial	map	San Diego	couple	sailboat	Frisco	airfield	pole	grass	goldhill	Barbara	aviris
DCTopt	25,63	25,74	27,27	27,53	29,14	29,00	28,81	29,25	26,28	24,94	25,45	27,46	27,41	28,83	26,63	30,16	25,20	27,45	28,36	25,62
DCTst	25,38	25,41	27,20	27,47	29,13	29,00	28,81	29,25	26,10	24,55	25,16	27,36	27,34	28,83	26,51	30,15	24,91	27,38	28,36	25,37
BM3D	25,92	25,79	27,79	28,14	30,03	30,00	29,48	30,28	27,03	24,79	25,65	28,19	27,80	29,68	27,10	32,28	25,15	27,99	29,80	25,77

Fig. 1. PSNR-HVS-M values for twenty test images for noise variances 65, 200, and 625

The data are given only in plots, but also in Tables below each plot. As it is seen, for $\sigma^2 = 65$ (see the uppre plot and Table), PSNR-HVS-M values vary in the limits from 36 to 41 dB. The metric values for the BM3D filter are almost always the best but they are do not differ from the corresponding values for two DCT-based filters too much (less than by 1 dB). The differences between PSNR-HVS-M values for two considered versions of the DCT-based filters are even smaller – they do not exceed 0.3 dB and, thus, visual quality improvement due to setting β_{opt} (under assumption that it is known) compared to denoising with $\beta = 2.6$ can be hardly noticed.

For $\sigma^2 = 200$ (the central plot in Fig. 1), PSNR-HVS-M varies in the wider limits from 30 to 37 dB. Denoising produces rather small values of output PSNR-HVS-M for complex structure images as Baboon or Grass. Meanwhile, they are sufficiently better for simple structure images as Pole, Tiffany or Peppers. Again, BM3D performs the best whilst the standard DCT-based produces the worst results. The DCT-based filter with optimal β provides certain benefit compared to the standard version, but the benefit is not large, it does not exceed 0.25 dB. There are many test images (mainly, simple structure ones) for which β=2.6 is the optimal choice (then data for both DCT-based filters coincide).

Finally, the lower plot in Fig. 1 presents data for very intensive noise. The results for the BM3D filter are the best again. There are some test images (mainly, simple structure ones) for which the BM3D filter outperforms other ones by up to 2 dB. The DCT-based filter with optimal β is usually slightly better than the standard DCT-based filter, but again the benefit is not large.

Results for the metric FSIM are presented in Fig. 2. The upper plot is obtained for σ^2=65. As it is seen, the metric values for each considered test image are close to each other for all three considered filters although for BM3D they are almost always slightly better. The DCT-based filter with optimal β often performs slightly better than the standard DCT-based filter.

The analysis of data obtained for σ^2=200 (central plot) shows that the BM3D filter mostly performs the best. The difference between two versions of DCT filters is not large. The same holds for the last case of σ^2=625 (the lower plot in Fig. 2).

Thus, we can state that BM3D outperforms both DCT-based filters for most test images, especially for simple structure ones and if noise is intensive. For two version of the DCT-based filters, the difference in performance is not large. A question is when it takes place?

To answer this question, the following study has been done. We have obtained scatter-plots of the considered visual quality metrics on statistical parameter $P_{1\sigma}$. This parameter is determined in 8x8 pixel non-overlapping blocks for each image. This is probability that absolute values of alternating current (AC) DCT coefficients are less than σ. Theoretically this parameter varies from 0 to 0.68.

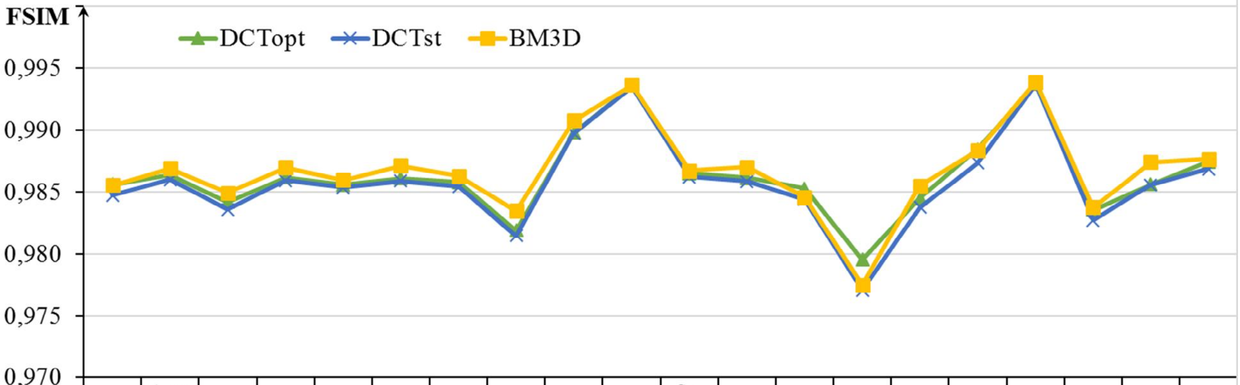
Small values of $P_{1\sigma}$ mainly correspond to small values of noise standard deviation (they are indicated by different colors in Fig. 3) and/or textural images. The values of $P_{1\sigma}$ smaller than 0.13 correspond to images corrupted by AWGN with standard deviation 1 and 2 when filtering is not worth applying at all since noise is invisible [19]. In opposite, large values relate to large values of noise standard deviation and/or simple structure test images.

As it is seen, optimal values of β vary from 1.8 to 3.2 but mostly they concentrate around 2.15 for $P_{1\sigma}<0.5$. This is confirmed by curve fitting (polynomial of the fifth order) in Fig. 4. This conclusion practically coincides with the recommendation earlier given in [13] – to set optimal β approximately equal to 0.9 multiplied by β optimal according to PSNR, i.e. 0.9x2.6=2.34. Meanwhile, for $P_{1\sigma}\geq0.5$, there is an obvious tendency to larger optimal values of β. Then, one can use approximation presented in Fig. 4 (upper part of the plot, *x* should be replaced by $P_{1\sigma}$).

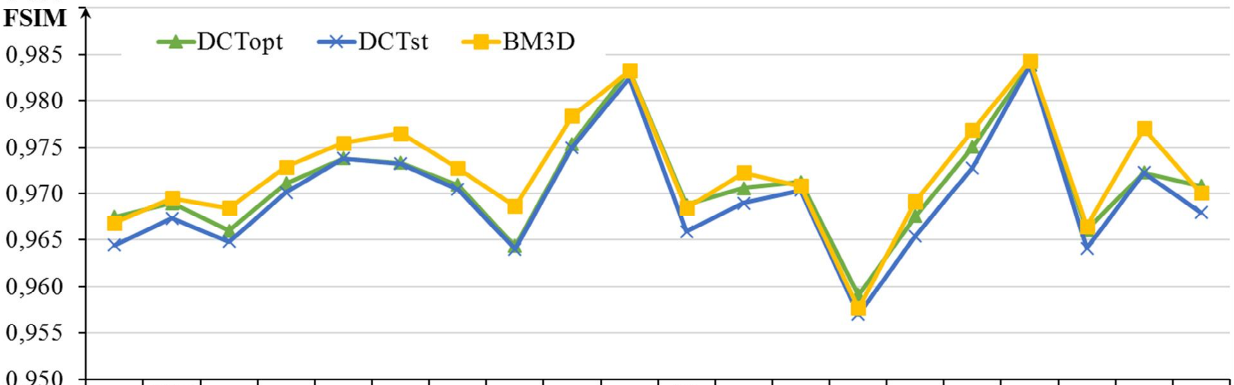
Summarizing the results, the following automatic procedure of predicting β optimal according to PSNR-HVS-M and filtering carrying out can be proposed: calculate $P_{1\sigma}$ and compare it to 0.13; if $P_{1\sigma}<0.13$, skip filtering at all, other wise compare it with 0.5. If $P_{1\sigma}<0.5$, perform filtering with β=2.15, otherwise calculate optimal β according to approximation given in Fig. 4 and carry out denoising using the obtained value of β.

One might think that such operation sufficiently complicates processing. This is not so. Recall that the most time consuming additional task is to calculate $P_{1\sigma}$. This probability is calculated in non-overlapping blocks and their number is about 60 times smaller than the number of DCT blocks for which 2D DCT is calculated at denoising stage if full overlapping of blocks is applied. Moreover, for large size images it is enough to process about 500 non-overlapping randomly placed blocks to calculate $P_{1\sigma}$ with appropriate accuracy.

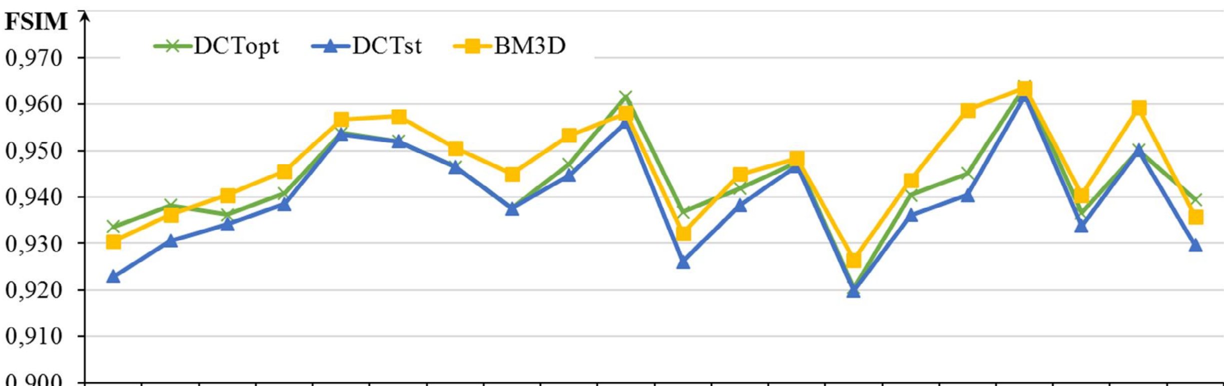
We have carried out similar study for the metric FSIM. The obtained results are presented in Fig. 5. As it is seen, the optimal values of β vary practically in the same limits – from 1.7 to 3.2. Again we have the same tendency – optimal β are about 2.2 for $P_{1\sigma}<0.5$, then they start to grow and can be approximated according to the corresponding expression (polynomial of the fourth order given in the upper part of the plot). Thus, the automatic procedure very similar to that one given above for the metric PSNR- HVS-M can be realized.



	baboon	stream bridge	man	boats	peppers	Lenna	F-16	Tiffany	aerial	map	San Diego	couple	sailboat	Frisco	airfield	pole	grass	goldhill	Barbara	aviris
DCTopt	0,9856	0,9864	0,9842	0,9862	0,9856	0,9861	0,9858	0,9819	0,9898	0,9936	0,9865	0,9861	0,9853	0,9795	0,9845	0,9885	0,9937	0,9835	0,9856	0,9874
DCTst	0,9847	0,986	0,9836	0,9859	0,9853	0,9859	0,9854	0,9815	0,9897	0,9935	0,9862	0,9859	0,9844	0,977	0,9838	0,9873	0,9937	0,9827	0,9856	0,9869
BM3D	0,9855	0,9869	0,9849	0,987	0,986	0,9871	0,9863	0,9835	0,9908	0,9936	0,9867	0,987	0,9846	0,9775	0,9855	0,9883	0,9939	0,9837	0,9874	0,9876



	baboon	stream bridge	man	boats	peppers	Lenna	F-16	Tiffany	aerial	map	San Diego	couple	sailboat	Frisco	airfield	pole	grass	goldhill	Barbara	aviris
DCTopt	0,9675	0,969	0,966	0,9711	0,9738	0,9733	0,9709	0,9643	0,9754	0,9833	0,9688	0,9706	0,9713	0,9591	0,9676	0,975	0,9839	0,9661	0,9723	0,9708
DCTst	0,9644	0,9673	0,9648	0,9701	0,9738	0,9732	0,9705	0,964	0,975	0,9825	0,9659	0,969	0,9703	0,957	0,9654	0,9728	0,9838	0,9641	0,9723	0,9679
BM3D	0,9669	0,9695	0,9685	0,9729	0,9755	0,9765	0,9727	0,9686	0,9784	0,9832	0,9685	0,9723	0,9708	0,9577	0,9691	0,9768	0,9843	0,9665	0,977	0,9701



	baboon	stream bridge	man	boats	peppers	Lenna	F-16	Tiffany	aerial	map	San Diego	couple	sailboat	Frisco	airfield	pole	grass	goldhill	Barbara	aviris
DCTopt	0,9337	0,9383	0,9363	0,9408	0,9538	0,952	0,9465	0,9376	0,9471	0,9616	0,9368	0,9419	0,9475	0,9205	0,9405	0,9451	0,9638	0,9367	0,9501	0,9395
DCTst	0,923	0,9307	0,9342	0,9385	0,9535	0,952	0,9465	0,9376	0,9447	0,9562	0,9261	0,9383	0,9468	0,9198	0,9361	0,9404	0,9619	0,9339	0,95	0,9297
BM3D	0,9305	0,9363	0,9405	0,9456	0,9567	0,9574	0,9505	0,945	0,9533	0,9581	0,9322	0,9449	0,9484	0,9265	0,9437	0,9587	0,9635	0,9405	0,9593	0,9359

Fig. 2. FSIM values for twenty test images for noise variances 65, 200, and 625

Finally, let us give one example of image denoising using the proposed approach. Fig. 6,a presents the test image Stream Bridge corrupted by AWGN with noise variance equal to 200. Noise influence is considerable (PSNR-HVS-M=28.95 dB, FSIM=0.956). The DCT filter output for the used β=2.6 (default setting) is given in Fig. 6,b (PSNR-HVS-M=30.30 dB, FSIM=0.967). Noise is suppressed well but fine details are smeared. The DCT filter output for β=2.15 (determined according to the proposed automatic procedure) is given in Fig. 6,c (PSNR-HVS-M=30.53 dB, FSIM=0.969). Noise suppression is good, fine details and textures are smeared less than in Fig. 6,b.

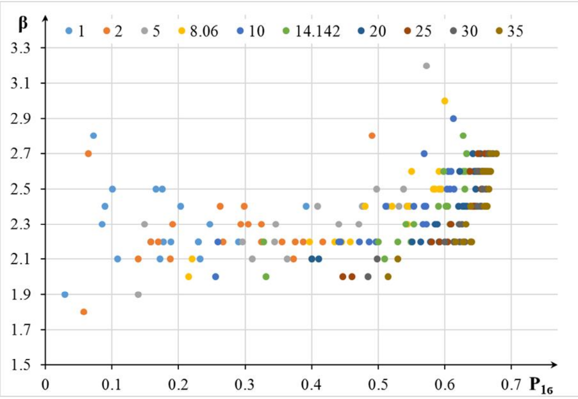


Fig. 3. Scatter-plot of optimal β on $P_{1\sigma}$ for the metric PSNR-HVS-M

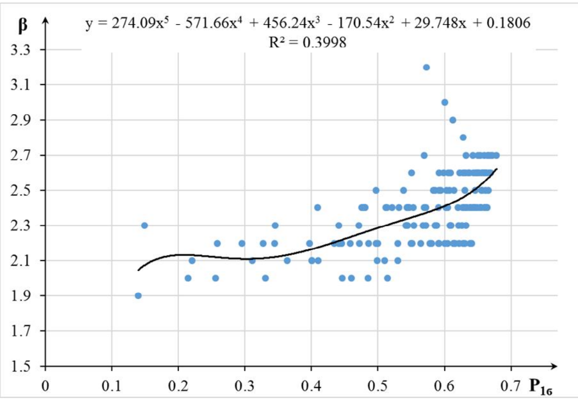


Fig. 4. Scatter-plot of optimal β on $P_{1\sigma}$ for the metric PSNR-HVS-M (σ>4) with fitted curve

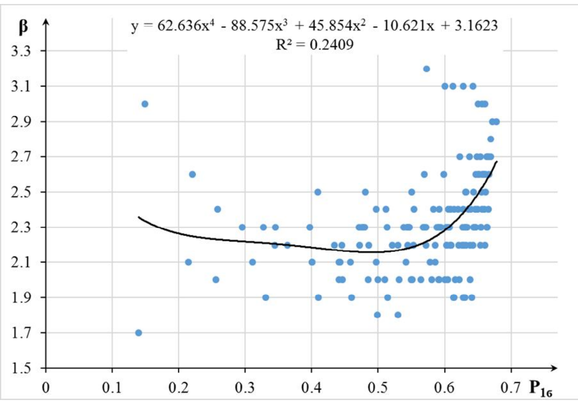


Fig. 5. Scatter-plot of optimal β on $P_{1\sigma}$ for the metric FSIM

a

b

c

Fig. 6. Noisy image (a) and outputs of the DCT based filters for β=2.6 (b) and β=2.15 (c)

Conclusions

The opportunity to improve the DCT-based filter performance is analyzed. It is demonstrated that more careful setting of threshold (compared to the recommended by default) can provide certain improvement of output image visual quality (according to two studied visual quality metrics).

For both metrics, the results are similar and this allows proposing a simple automatic procedure of parameter setting. This provides better visual quality of highly textural images for which denoising with default setting can result in smeared edges and fine details. The proposed procedure needs a very small amount of additional computations and can be realized by 60 or more times faster than filtering itself.

The proposed procedure presumes global adaptation of parameter β. We expect that local adaptation can be done as well, including other DCT-based filters.

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АНАЛІЗ МОЖЛИВОСТІ ПОКРАЩЕННЯ ЕФЕКТИВНОСТІ ФІЛЬТРАЦІЇ ЗОБРАЖЕНЬ ДЛЯ ФІЛЬТРІВ НА ОСНОВІ ДКП

О. М. Земляченко, І. Г. Івахненко, Г. А. Чернова, В. В. Лукін

Предметом статті є процес фільтрації зображень. **Метою** є забезпечення високої ефективності придушення завад у відповідності до метрик, які є більш адекватними до системи бачення людини, ніж традиційні критерії як-то середньоквадратична похибка чи пікове відношення сигнал-шум. **Завдання** є наступними: провести аналіз ефективності обробки з використанням метрик візуальної якості, визначити оптимальні установки ДКП-фільтру в залежності від властивостей зображень та завад, запропонувати метод установки значення глобального порогу адаптивно (квазіоптимальним чином) на основі попереднього аналізу властивостей зображення та завад. були отримані наступні **результати**: 1) оптимальні значення параметрів фільтру залежать від багатьох факторів, включаючи складність зображення та інтенсивність завад, 2) оптимальні значення також залежать від критерію оптимальності (або метрики), що використовується для опису ефективності фільтрації; 3) оптимальні значення параметру β, який визначає поріг, можуть суттєво відрізнятись від 2,6, що зазвичай рекомендується до використання; 4) це відкриває можливості підвищення ефективності фільтрації зображень; 5) одна з можливостей полягає у попередньому аналізі властивостей зображення та завад із наступною установкою значень порогу у відповідності до отриманих залежностей. **Висновки** є такими: 1) робота фільтру може бути значно покращена завдяки запропоновані адаптивній процедурі; 2) це має місце, якщо шум є інтенсивним, а структура зображення не є складною, або якщо шум не є інтенсивним, а зображення має складну структуру; 3) запропонована адаптивна процедура вимагає малого об'єму додаткових обчислень для визначення значення вхідного параметру і може бути реалізована у 60 або більше разів швидше, ніж сама фільтрація; 4) адаптивна процедура дещо відрізняється і залежності від метрики, що використовується в якості критерію ефективності.

Ключові слова: фільтрація зображень, фільтр на основі ДКП, оптимізація параметрів, критерії ефективності

АНАЛИЗ ВОЗМОЖНОСТИ УЛУЧШЕНИЯ ЭФФЕКТИВНОСТИ ФИЛЬТРАЦИИ ИЗОБРАЖЕНИЙ ДЛЯ ФИЛЬТРОВ НА ОСНОВЕ ДКП

А. Н. Земляченко, И. Г. Ивахненко, Г. А. Чернова, В. В. Лукин

Предметом статьи является процесс фильтрации изображений. **Цель** – обеспечит высокую эффективность фильтрации в соответствии с метриками, которые являются более адекватными системе зрения человека, чем такие традиционные критерии, как среднеквадратическая ошибка или пиковое отношение сигнал-шум. Решаются следующие **задачи**: провести анализ эффективности фильтрации, используя метрики визуального качества, определить оптимальные установки ДКП-фильтра в зависимости от свойств изображений и помех, предложить метод адаптивной (квазиоптимальной) установки глобального значения порога на основе предварительного анализа свойств изображения и помех. Были получены следующие **результаты**: 1) оптимальные значения параметров фильтра в зависимости от разных факторов, включая сложность изображения и интенсивность помех, 2) оптимальные значения также зависят от используемого критерия оптимизации (метрики), характеризующего свойства фильтра; 3) оптимальные значения параметра β, который определяет порог, могут существенно отличаться от 2,6, являющегося обычно рекомендуемым значением; 4) это открывает возможности повышения эффективности фильтрации изображений; 5) одна из этих возможностей состоит в предварительном анализе свойств изображений и помех с установкой пороговых значений в соответствии с заранее полученными зависимостями. **Выводы**: 1) работа фильтра может быть существенно улучшена благодаря использованию предложенной адаптивной процедуры; 2) это имеет место либо если шум интенсивный и изображение имеет простую структуру, либо если шум не слишком интенсивный, а изображение имеет сложную структуру; 3) предложенная адаптивная процедура требует очень малого объема дополнительных вычислений для расчета входного параметра и может быть реализована в 60 и более раз быстрее, чем собственно фильтрация; 4) адаптивная процедура немного отличается в зависимости от того, какая метрика используется в качестве критерия эффективности.

Ключевые слова: фильтрация изображений, фильтр на основе ДКП, оптимизация параметров, критерии эффективности

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