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DECISION MAKING ON EXPEDIENCE OF IMAGE DENOISING

Abstract

The chapter deals with discussing expedience of image denoising. It is shown that this expedience can be considered from different viewpoints including traditional criteria, metrics of visual quality, and quantitative indicators characterizing specific tasks of image processing as classification, object detection, etc. It is also demonstrated that there is no agreement in opinions of people (observers) that assess visual quality of original (noisy) and filtered images. One reason is that all existing filters are not perfect. Another reason is that there are practical situations when it is very difficult to effectively discriminate image and noise. Then, it is desirable to have tools for decision making concerning expedience of image denoising. It is shown that such decisions can be performed based on analysis of parameters that jointly characterize image and noise properties as well as predict potential effectiveness of denoising. Such a methodology of prediction is quite universal and can be employed for different types of the noise, several popular filters and different number of image channels. Prediction is possible for white and spatially correlated noise. Ways to improve prediction accuracy and to minimize computations are considered. Results of experiments with observers are presented. Examples for images of different origin including remote sensing ones are given. Directions of further research are discussed.

Keywords: image denoising, effectiveness prediction, decision undertaking

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INTRODUCTION

Image denoising (also called filtering or smoothing) is a standard operation employed in image processing chain with a general purpose to improve quality of images acquired by different types of systems [1–5]. These can be conventional optical (photo) devices [1], synthetic aperture radars [2], medical diagnostic means [3], remote sensing (e. g., multispectral or hyperspectral) sensors [4], etc. The goals of denoising can be different as well including improving of image visual quality [1, 5, 6], better classification of remote sensing data [2, 4, 7, 8], providing pre-requisites for improved compression [9], better object (phenomenon) detection [2, 3], etc.

However, researchers that have applied some filter or a set of filters are often not satisfied with the produced results. There can be one or a few reasons behind this including the following:

1) a filter introduces undesired smoothing or artifacts;

2) a positive effect of filtering is negligible or there are more negative effects than positive ones; a denoised image looks not natural;

3) an observer (specialist, researcher) is got used to deal with (to analyze, to process by visual inspection) original (noisy, acquired) images and he/she is not got used (has not been trained) to consider filtered images;

4) filtering takes too much time to get processed images (of better quality with guaranteed positive outcome);

5) denoising cannot be done automatically, i. e. without interactive selection of a proper filter, its parameter setting and/or carrying out several trials.

These reasons will be considered more in details in the next Section. But it is already clear that a question arises can one predict in advance is it worth performing denoising or is it better to save time and resources by skipping denoising. The corresponding decision can be done automatically or this can be a part of decision support system that gives a user an advice to denoise or to skip filtering of a given image (possibly, such system can also give advice concerning filter type selection and its parameter setting). The aforementioned reasons and pre-requisites for decision making are the main aspects studied in this chapter.

REASONS AND FACTORS INFLUENCING EXPEDIENCE OF DENOISING

Let us consider reasons that have impact on expedience of image denoising more in detail. First of all, it is worth recalling that there are numerous filtering techniques and thousands of papers are devoted to their analysis (see, e. g., [10–13] and references therein). This is explained by the following main factors:

1) there are many different assumptions and theoretical backgrounds that were put into basis of design of image filtering starting from nonlinear non-adaptive

and adaptive scanning window approaches [1, 2] continued by orthogonal transform based methods [12] and completing by modern non-local and dictionary based techniques [10, 11];

2) there are many types of noise including additive, signal-dependent, multiplicative and mixed noise [1–3] where noise can be white or spatially correlated; no filter is able to perform well enough for aforementioned variety of possible practical situations;

3) there can be different priorities in requirements to filtering techniques [1, 10–14] where the most typical requirements are to effectively suppress noise and to preserve edges/textures/small-sized objects with providing an appropriate computational efficiency; additional requirements could be to remove specific types of noise, to introduce minimal artifacts, to provide favorable preconditions for solving such tasks as object or edge detection, classification, etc.; there can be also requirements concerning implementation of denoising by a specific hardware or concerning power consumption, etc.;

4) images to be denoised can be single or multichannel where in the latter case there are, in general, more opportunities to provide effective denoising [1, 7, 13];

5) denoising performance can be characterized (described) in different ways including the use of standard and less conventional metrics [15], opinions of humans [16], criteria that describe success in solving the final tasks (e. g., probability of correct classification [7]);

6) effectiveness of filtering considerably depends upon image properties [11] where the term „image complexity“ is well understood intuitively but is not yet strictly defined quantitatively.

There are several consequences that follow from observations given above.

First of all, noise properties (characteristics) should be taken into account under assumption that they are either known in advance or preliminarily estimated with appropriate accuracy. Fortunately, for the latter case, there exist approaches to determination of noise type [17] and blind estimation of noise characteristics [18, 19]. A priori information on noise type considerably restricts a set of filters that can be applied to a particular practical situation.

Secondly, there are other factors that restrict (or can restrict) a set of applicable denoising techniques. Many filters are too „slow“ and image processing by them cannot be sufficiently accelerated by hardware or software means [20]. Other filters can introduce undesired artifacts [1, 3]. Some filters perform well for one set of images whilst they fail for others (see data for non-local mean [21] and LPG-PCA filter [22] in [23]). Component-wise filtering is considerably less effective than vector (three-dimensional, 3D) one in processing of multichannel images [1, 8, 13, 24].

Thirdly, there are very interesting preliminary results offering insight on potential denoising efficiency in terms of standard (conventional) criteria as mean square error (MSE) and peak signal-to-noise ratio (PSNR) for particular types of noise. For additive white Gaussian noise (AWGN), it is shown [11] that potential of denoising is practically reached for highly textural (complex structure) grayscale images corrupted by low and middle intensity noise if non-local denoising techniques are applied (recall that modern state-of-the-art denoising techniques mostly belong to this family). The same is confirmed in [25] using simulations for a wide set of test images and one more approach to evaluating potential effectiveness of filtering [26] applicable for the case of additive spatially correlated noise.

It is said that it is better to see one time than to hear (to read) a hundred of times. So, let us present one example. Fig. 1 shows screen-shot of experiments carried out with volunteers. About 70% of them have voted in favor of denoised image (placed in the right part) compared to the noisy one (AWGN with standard deviation equal to 15). Really, noise in the original image is intensive and it is seen well especially in homogeneous regions (texture masks noise and makes it less visible). The used filter (block matching three dimensional (BM3D) technique [27]) has removed noise well but it has also partly smeared edges, fine details and textures (see grass fragment in the lower part of the processed image). The processed image looks slightly unnatural (oversmoothed). These are the reasons why about 30% of observers have preferred the original (noisy) image. Note that output mean square error (MSE) for the filtered image is by about 3 times less than AWGN variance in the noisy image, i. e., in fact, 4.5 dB improvement of peak signal-to-noise ratio (PSNR) is provided by denoising. However, even such a large improvement of PSNR does not guarantee that the processed image quality is confidently perceived as better one compared to visual quality of the noisy image.

The example presented above also shows that many experiments with filters and observers are needed. Such experiments require sufficient time and efforts. Fortunately, some of them have been already carried out in design and verification of visual quality metrics [5, 15] using image databases [28, 29]. Many databases do not contain images distorted by residual noise observed for filtered noisy images [28]. However, the databases TID2008 and TID2013 contain such images and this allows performing analysis of results obtained for them.

Before such an analysis, it is worth recalling how such databases are formed and how data processing for them is done. Usually, the databases contain a set of reference (distortion-free) images and sets of distorted images with several types and levels of distortions. TID2013 is one of the largest databases in the sense of number of types (24 types) and levels (5 levels that correspond to PSNR

Fig. 1. Screen-shot of experiments carried out with volunteers to determine expedience of denoising

equal to 21, 24, 27, 30, and 33 dB) of distortions. A labor-consuming stage is obtaining the mean opinion score (MOS) from observers. There exist different methodologies of MOS obtaining and its representation. In our case of further analysis of MOS values for TID2013 it is important to know that larger MOS values correspond to better visual quality according to averaged opinion of observers. Distorted images for which MOS exceeds 6.05 can be qualified as having excellent quality [31] and distortions for them are either invisible or hardly noticeable. Images that have MOS smaller than 3.94 can be qualified as having bad quality [31].

Keeping this in mind, let us consider the results presented in Fig. 2. Quality of noisy images (shown by red points) vary from excellent (for a few distorted images, PSNR about 33 dB, AWGN variance equal to 32.5) to almost bad (for the highest level of distortions, PSNR about 21 dB, AWGN variance equal to 520).

If PSNR is about 33 dB, visual quality of noisy and filtered images is practically the same and high enough (excellent or good). On the other hand, if PSNR is about 21 dB, noisy images look much better than filtered ones having the same PSNR where denoised images obviously have bad quality (MOS about 2).

The data in Fig. 2 one more time clearly show that PSNR is not an adequate metric to characterize (describe) image visual quality. The same value of PSNR can relate to sufficiently different MOS values (consider point position diversity in Fig. 2 for PSNR about 28 dB). This was the reason why numerous visual quality metrics have been designed in recent 25 years [5, 15, 29]. Meanwhile, it has not been yet determined what visual quality metric is the best for characterizing quality of noisy and denoised images (see the results of recent studies in [32]). Because of this, let us use in our preliminary analysis the visual quality metric PSNR-HVS-M [33]. There are the following reasons for this. This metric is one of the best for such types of distortions as different types of noise, blur, lossy compression and denoising [29, 30]. This metric is expressed in dB and varies in almost the same limits as PSNR. The metric takes into account such important peculiarities of human vision as less sensitivity to distortions in high spatial frequencies and masking effect of textures. PSNR-HVS-M can be calculated quickly. Finally, the author of this chapter has larger experience in using this metric (compared to many others) since it has been designed in our group (see http://ponomarenko.info/psnrhvsm.htm).

To understand peculiarities of image quality analysis carried out using PSNR-HVS-M, recall some of its properties. Metric larger values correspond to better

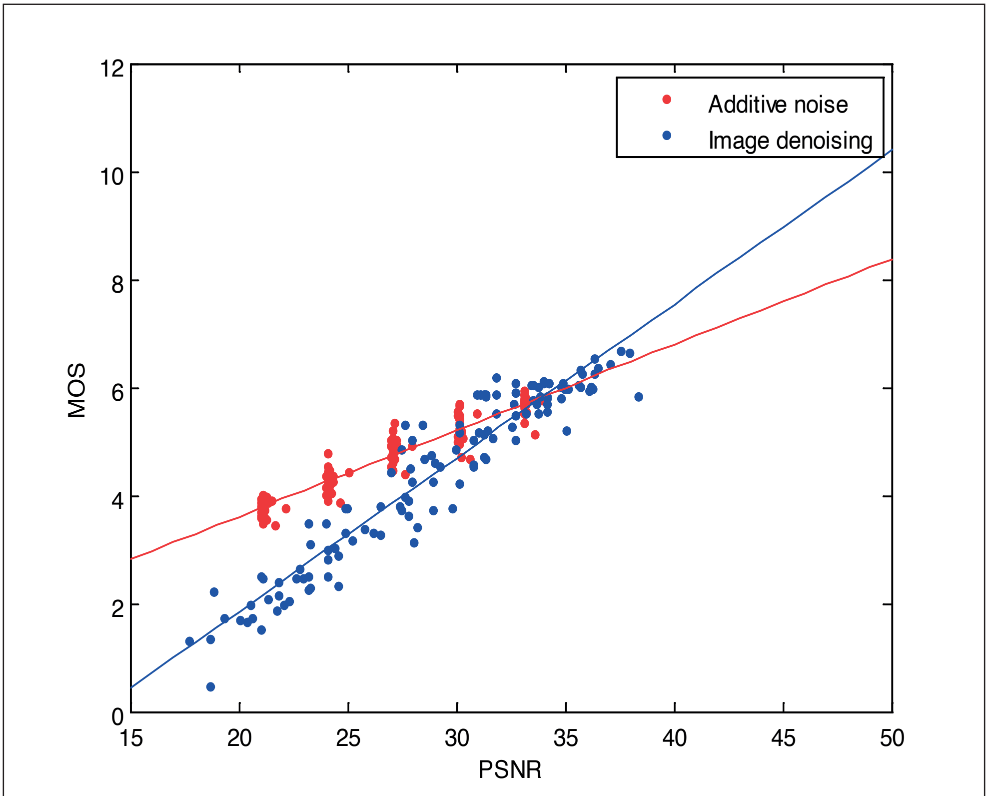


Fig. 2. Scatter-plots of MOS vs PSNR for images with AWGN and denoised images (with residual noise) in the database TID2013, MOS_f=0.286×$PSNR_{inp}$-3.9; MOS_n=0.160×$PSNR_{inp}$ + 0.4 (MOS_f and MOS_n are MOS for filtered and noisy images, respectively)

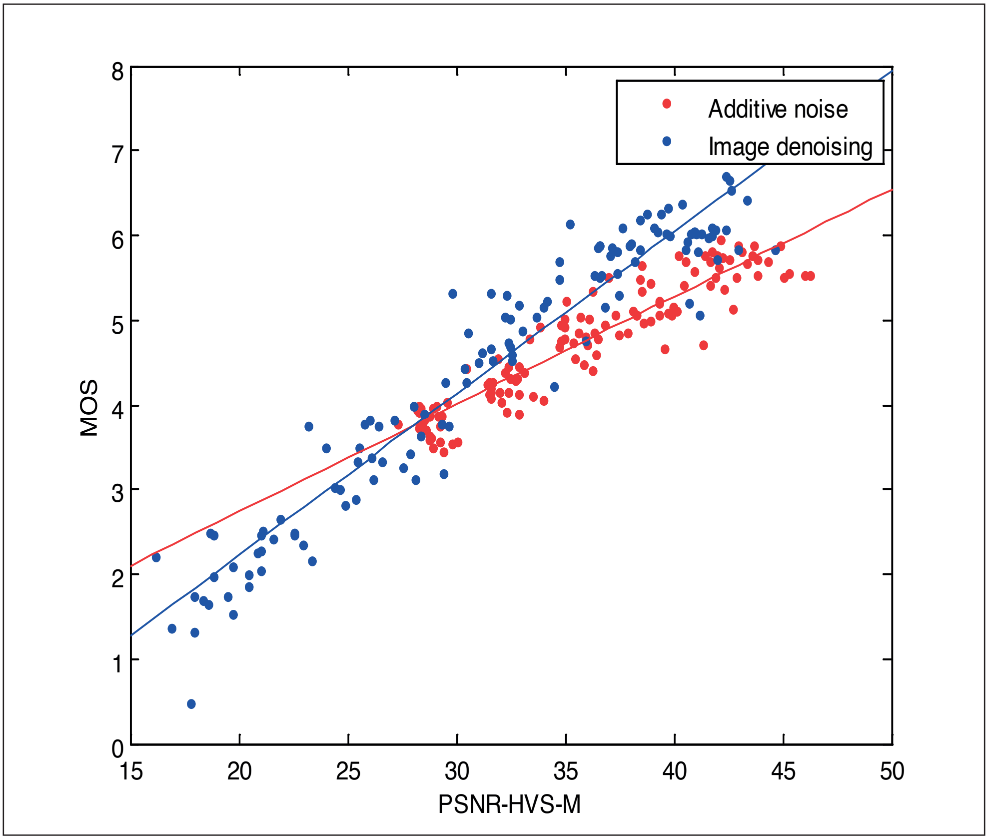


Fig. 3. Scatter-plots of MOS vs PSNR-HVS-M for images with AWGN and denoised images (with residual noise) in the database TID2013; MOS_f=0.193×$PHVSM_{inp}$-1.65; MOS_n=0.128×$PHVSM_{inp}$ + 0.15

visual quality. Metric values over 40…42 dB mainly relate to invisible distortions, metric values about 38 dB basically relate to excellent quality, whilst quality is bad if PSNR-HVS-M is less than 30 dB. Then, it is possible to come to analysis of data presented in Fig. 3.

There are many noisy and denoised images in the database that have excellent quality for which, for a given PSNR-HVS-M (e. g., equal to 42 dB), quality of denoised images is, on the average, even better (according to MOS). However, this relates to cases when original or residual noise are hardly noticeable visually and, thus, necessity in image denoising is not obvious. There are PSNR-HVS-M values in the interval from about 30 to 40 dB where visual quality of denoised images is, on the average, better (according to MOS) than quality of corresponding noisy images. This means that if denoising (for the considered case) improves PSNR-HVS-M, then image filtering is expedient. Finally, there is also an interval of PSNR-HVS-M values (<30 dB) where quality of denoised images is bad. This interval corresponds to images contaminated by very intensive noise and this means that sufficient increase of PSNR-HVS-M should be provided by filtering to guarantee that image visual quality has improved.

An example relating to the last statement is presented in Fig. 4. Original image (left) of urban area in Germany has been acquired by high-resolution single-look synthetic aperture radar TerraSAR-X. It is corrupted by intensive speckle (specific non-Gaussian multiplicative spatially correlated noise-like phenomenon). Output image after denoising is shown in Fig. 4 (right). The filter based on discrete cosine transform (DCT) [33] adapted to speckle properties has been applied. Speckle is suppressed well, edges and details are preserved well enough. Improvement of PSNR (IPSNR) about 4 dB and improvement of PSNR-HVS-M (IPHVSM) about 1 dB have been provided. However, the denoised image does not look better than the original one. The reasons for this are the following. Firstly, edges and details look slightly smeared with decreased spatial resolution. Secondly, there are some artifacts in image homogeneous regions. Thirdly, many specialists of radar image interpreting got used (have been trained) to analyze unprocessed images and this is one more reason to prefer the original SAR image.

Therefore, it is possible to draw the following preliminary conclusions:

1) There are practical situations when denoising is, in fact, not needed; this happens if noise in original image is not intensive (is hardly noticeable) and/or if the image is rather textural and masks noise; then, even if denoising can be effective according to considered criteria (e. g., IPSNR or IPHVSM), it is practically useless since an observer is unable to see (notice) considerable difference in visual quality of original and denoised images;

2) There exist many practical situations when image quality is worth improving since noise is seen well and it is annoying; this usually happens if noise intensity is moderate or high; then a question arises is a given filter (or one of filters best suited for a considered noise model) able to perform so well that quality of denoised image sufficiently (confidently) improves compared to original image according to a used criterion (or employed criteria);

3) The fact that IPSNR or IPHVSM is positive does not guarantee that image quality (at least, visual quality) has really improved; to be sure that a decision to denoise an image is correct one needs to have IPSNR and IPHVSM (or other metrics) sufficiently larger than zero and dependent upon noise intensity.

There are several obstacles that complicate further design of decision undertaking procedure. Firstly, it is not clear what quantitative parameters characterizing effectiveness of image denoising to consider, how accurately they can be predicted and what is the best way of prediction. Secondly, some parameters that can be used in decision undertaking cannot be determined. For example,

Fig. 4. Original (left) and denoised (right) SAR images

it follows from analysis done above that noise variance or input PSNR can be useful in predicting expedience of image filtering. Noise variance (intensity) can be known in advance or pre-estimated, PSNR can be estimated as well but there is uncertainty how to define it. Meanwhile, input PSNR-HVS-M can be useful in prediction of denoising expedience as well but this parameter cannot be determined without having noise-free image (maybe, a way to pre-estimate input PSNR-HVS-M without reference will be found soon). Hence, let us review what kind of prediction can be made for decision undertaking on performing or avoiding image filtering.

PREDICTION OF DENOISING EFFECTIVENESS

Let us demonstrate that many of metrics characterizing image denoising effectiveness can be predicted before performing denoising. First of all, consider requirements to metric prediction [23, 35, 36]. A predicted metric should be informative, i. e. able to characterize filtering effectiveness adequately (this means that only metrics that correlate with filtering effectiveness well should be considered as candidates for practical use). Prediction should be fast, i. e. one has to have an opportunity to carry out prediction sufficiently faster than filtering. Then, prediction has to be accurate enough, i. e. it is desirable to have unbiased estimate of a used (predicted) metric with appropriate variance.

An approach to prediction was first proposed in [35] based on results obtained for DCT-based filters [12, 27] in [12, 37]. The ratio MSE_{out}/σ^2 was considered as a metric characterizing filtering effectiveness where MSE_{out} is output MSE of a studied filter and σ^2 denotes AWGN variance. Note that this ratio is directly connected with the metric IPSNR discussed above (IPSNR=$10\log_{10}(\sigma^2/MSE_{out})$).

Smaller MSE_{out}/σ^2 relates to larger IPSNR and more effective denoising. Both MSE_{out}/σ^2 and IPSNR can be treated as standard (conventional) metrics characterizing denoising effectiveness.

It has been found in [35] that MSE_{out}/σ^2 is strictly connected with simple statistics of DCT coefficients $P_{2\sigma}$ and $P_{2.7\sigma}$ where $P_{2\sigma}$ denotes mean probability that DCT coefficient absolute value does not exceed 2σ; $P_{2.7\sigma}$ is mean probability that DCT coefficient absolute value exceeds 2.7σ; both probabilities are determined for all possible non-overlapping positions of 8x8 pixel blocks in an image to be denoised. Due to possibility to use fast algorithms of DCT calculation in a rather small number of blocks, determination of $P_{2\sigma}$ or $P_{2.7\sigma}$ can be done much (by two orders) faster than standard DCT-based filtering with fully overlapping blocks [12] and by three-four orders faster than denoising by BM3D [27].

It has been supposed in [35] that prediction is done in the following manner. Firstly, an approximating dependence (curve) that links output (predicted) metric and input statistical parameter (e. g., $P_{2\sigma}$ or $P_{2.7\sigma}$) is obtained in advance (off-line) using regression (curve fitting into scatter-plot, see an example taken from [35] presented in Fig. 5, a). It is available to the moment when prediction has to be performed. Then, having an image to be filtered with known variance of AWGN, a used input parameter is calculated and substituted as argument into the obtained dependence. For example, if $P_{2\sigma}$=0.75, the predicted MSE_{out}/σ^2 is about 0.5 and, thus, the predicted IPSNR is about 3 dB.

The initial results presented in [35] have opened a set of partial tasks to be solved:

— how to form a scatter-plot properly;
— what functions to use in regression;
— how to characterize accuracy of regression;
— what input parameters to employ in prediction;

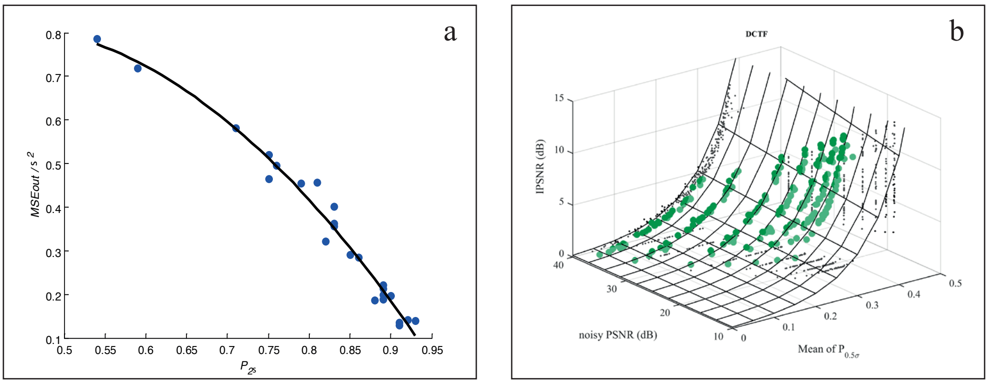


Fig. 5. Illustration of output parameter prediction for the standard DCT-based filter [12] for one (a) and two (b) input parameters

— how accuracy of fitting is connected with accuracy of prediction;

— how to further accelerate prediction and so on.

Let us briefly answer these questions first. A scatter-plot describes dependence of an output (predicted) parameter on an input parameter. Each point corresponds to some test image corrupted by noise of a given intensity (variance) and processed by a considered filter where input parameter(s) and output metric are determined for each particular case. Since then regression has to be done, it is desirable to have argument values placed approximately uniformly for entire interval of possible variation of input parameter(s). In this sense, the scatter-plot in Fig. 5, a is not good since it does not contain points for $P_{2\sigma}$ values from 0 to 0.53 (that are possible) and the observed distribution of argument values is far from uniform. In fact, our experience shows that there is a need for a rather large set of noise-free test images where images should be of considerably different content and complexity. One has also to artificially add noise with intensity varying in very wide limits (that correspond to practice and „even wider“). Then, it is possible to expect that an obtained scatter-plot covers all range of possible situations and a derived approximation does not contain „surprises“ that will be met in practice later. One example of such a surprise is that a predicted value of MSE_{out}/σ^2 can be less than 0 that does not have sense. This means that physical restrictions should be taken into account in regression and choosing candidate functions for fitting.

The example in Fig. 5, a shows that a reasonable assumption is that dependence of output on input parameters is monotonous and rather smooth. The 2D example taken from the paper [23] confirms this and simplifies the choice of candidate functions for fitting. Experience that stems from data in [23, 35, 36, 38–40] shows the following. It is usually enough to use quite simple approximating functions as polynomials of low order (less than 5), sums of two exponentials with weights, power functions. After fitting, one has to visually control behavior of the obtained approximation — is the function monotonic (if its' monotonicity is assumed), is it within reasonable limits? This task is slightly routine, but it is „not really scientific“. Modern Matlab, Excel or other tools allow solving it in reasonable time by finding an acceptable solution. As a rule, there exist several approximations that provide similar and appropriately good results.

Accuracy of regression can be described in different ways [41]. The most common parameters are goodness-of-the-fit R^2 (that should tend to unity if scatter-plot is compact and fitting is good) and root mean square error (RMSE) that should be as small as possible. These parameters are useful in fitting and comparison of approximations. However, one should be careful since properties of R^2 slightly depend on number of points in an analyzed scatter-plot, whilst RMSE depends upon what parameter is predicted (it is impossible to directly compare RMSE values for predicted IPSNR and MSE_{out}/σ^2).

Performance of prediction also depends upon what parameter is used as input one (or what parameters are used as input ones and how)? The paper [39] deals with these aspects. It is shown that, under condition of the same number of test images and noise standard deviations as well as quasi-optimal fitting for each possible input parameter, it is possible to determine the best input parameter among the considered ones according to maximal R2 or minimal RMSE. It is also possible to employ several input parameters under condition that all of them can be easily (quickly) calculated and they are all informative (their joint use improves accuracy compared to the use of each of them separately). Fig. 5, b shows an example of 2D scatter-plot where input parameters are mean $P_{0.5\sigma}$ (probability that DCT coefficient absolute value does not exceed 0.5σ determined for all possible non-overlapping positions of 8x8 pixel blocks) and input PSNR equal to $10\log_{10}(255^2/\sigma^2)$ for AWGN and images represented as 8-bit data 2D arrays. Recall that joint processing of several input parameters can be done in different ways — using an approximating function of several variables of certain type, employing trained neural networks or support vector machines as approximating tools, etc. Thus, there is a wide space for further research in this field.

It is clear that accuracy of fitting sufficiently determines accuracy of prediction. In fact, RMSE of fitting describes potential accuracy since prediction is made using the fitted curve (in some sense, averaged for the used set of test images and noise standard deviations) whilst the considered parameter characterizing denoising effectiveness is individual for each processed image. Meanwhile, regression accuracy is not the only factor that determines accuracy of prediction. There are two other factors. First is accuracy of input parameter estimation. Clearly that for a smaller number of independent blocks (due to, e. g., smaller size of an analyzed image) input parameter is estimated with worse accuracy. Our analysis has shown that usually it is enough to have, at least, 300…500 independent blocks to provide accuracy of input parameter estimation in such a manner that it influences accuracy of prediction considerably less than accuracy of fitting. Second factor is accuracy of estimation of noise parameters [42]. Errors in estimation can lead to biased prediction. Because of this, noise parameter estimation has to be accurate enough and/or input parameter(s) should be quite robust with respect to such errors. This aspect of prediction is not thoroughly studied at the moment.

It has been already shown above that computational efficiency of prediction can be very high if a simple input parameter determined in a limited number of image blocks is used. However, computational efficiency reduces if one employs several input parameters, one or a few of them cannot be calculated easily and quickly, approximation is rather complex and so on. This means that one has to keep this in mind in designing of prediction procedures. Input parameters to be used have to be simple enough, their number should be limited, their calculation has to be done in parallel (if possible), and a reasonably small number of blocks has to be exploited.

One might be interested what accuracy of prediction is reached now. To give some image, let us present some results from [39]. Recall that it is proposed there to predict a used output parameter as $\mu = a \cdot \prod \exp\left(b_f \cdot O_{f\alpha\sigma}\right)$, where a and b_f are function parameters to be optimized, $O_{f\mathrm{as}}^{f}$ is the f-th statistical parameter. Having local estimates of probability $P_{\alpha\sigma}$ in 8x8 pixel blocks, it was proposed to use not only mean M_{as} of these estimates, but also other statistics median Med_{as}, mode Mod_{as}, variance V_{as}, skewness S_{as} and kurtosis K_{as}. Studies [39] have been performed for $P_{2\sigma}$ and $P_{0.5\sigma}$ where the obtained results are slightly better in the latter case. So, let us present fitting results first. They are given in Table 1.

Table 1. Accuracy of multiparameter fitting for $P_{0,5\sigma}$

Filter type	Predicted parameter	Used input parameters	RMSE	R^2
DCT-filter	IPSNR	M	0.29	0.98
		M, V	0.26	0.99
		M, S, K	0.25	0.99
		M, Med, S, K	0.25	0.99
		M, V, Med, Mod, S	0.25	0.99
	IPHVSM	Mod	0.70	0.84
		M, V	0.43	0.94
		M, V, Mod	0.42	0.95
		M, V, Mod, S	0.42	0.95
		M, V, Med, Mod, S	0.41	0.95
BM3D	IPSNR	M	0.40	0.97
		M, V	0.40	0.98
		M, V, S	0.39	0.98
		M, V, Med, S	0.39	0.98
		M, V, Med, Mod, S	0.38	0.99
	IPHVSM	Mod	0.73	0.85
		M, V	0.51	0.94
		M, V, Mod	0.5	0.94
		M, V, Mod, S	0.5	0.94
		M, V, Med, Mod, S	0.49	0.94

Analysis shows many interesting aspects. For the standard DCT-based filter, the results for even one input parameter are very good for the metric IPSNR and prediction accuracy can be further improved using more input parameters. Accuracy for prediction of IPHVSM is considerably worse if one input parameter is used (RMSE values can be compared since both metrics are expressed in dB). But it can be considerably improved using two or more input parameters.

For the BM3D filter, accuracy of denoising effectiveness prediction is worse than for the standard DCT-based filter. However, it is rather high and can be considerably improved using two or more input parameters. It seems that it is enough to employ two input parameters, namely, M and V because of two reasons. The use of three or more input parameters does not produce considerable improvement of accuracy. Besides, the prediction procedure becomes more complicated and slow. Recall that if one uses two aforementioned input parameters, error of prediction does not exceed 0.5 dB and this is a good result. For interested readers, the optimized weights for two-parameter approximation function are presented in Table 2.

Table 2.

Filter type	Metric	a	b_1	b_2
DCT-filter	IPSNR	0.17	10.80	19.28
	IPHVSM	0.01	15.66	144.3
BM3D	IPSNR	0.15	11.33	17.7
	IPHVSM	$4*10^{-3}$	18.25	161.7

UNIVERSALITY OF PREDICTION APPROACH

Only two filters, both based on DCT, have been considered above. Only the case of AWGN has been studied. A limited number of metrics has been analyzed. This might lead to an opinion that the proposed approach to prediction has a limited applicability. However, this is not true.

First of all, different types of noise have been considered [38, 40]. If noise is signal-dependent [38] (multiplicative as a particular case [40]), there are two main approaches to filtering. Firstly, an appropriate direct homomorphic transform can be applied before denoising for converting signal-dependent noise to additive and inverse homomorphic transform is carried out after denoising [2]. Secondly, some denoising techniques, in particular, the DCT-based filter can be adapted to removal of signal-dependent noise by locally adaptive threshold setting in each block.

If the corresponding homomorphic transform is applied, earlier proposed approaches to prediction work well. The only changes are that: 1) noise standard deviation has to be determined taking into account noise characteristics in original image and parameters of the homomorphic transform used; 2) input PSNR (if it is used as input parameter) has to be calculated taking into consideration noise type and parameters. If a denoising method is adapted to noise type and characteristics, then input parameters used in prediction have to be calculated accordingly. For example, local estimates of probabilities $P_{\alpha\sigma}$ have to be calculated for thresholds set individually for each block using known dependence of noise variance on mean. Although scatter-plots for these cases can slightly differ, the behavior of fitted approximating functions is very similar [36, 40].

It might seem intuitively clear and explainable that effectiveness of DCT-based denoising can be predicted using statistics of DCT coefficients for a given image. Moreover, the metric IPHVSM is also based on DCT.

Then one question arises — is it possible to predict effectiveness for filters that are not based on DCT? Another question is can we perform prediction for other metrics. The answers are surprisingly „Yes" for both questions [23]. Fig. 6 presents the example for improvement for the metric MSSIM [43] (IMSSIM calculated as difference between MSSIM values for denoised and original images). Input parameters are $P_{0.5\sigma}$ and variance of this parameter estimates in blocks. The scatter-plot has been obtained for six filters including aforementioned DCT-based filter [12], BM3D [27], SAIF [20] and BLSGSM [44], KLLD [45], and KSVD [46]. Although these denoising techniques are based on different principles, scatter-plot points for them are placed in a compact manner and the same approximation can be applied (see Fig. 6 and some quantitative data concerning accuracy of fitting presented there). One can argue that prediction is possible since these filters have similar performance [23]. But it is shown in [47] that prediction is possible as well when filter performance (e. g., for non-local mean filter [21]) differs from the performance of aforementioned filters [47].

Based on the results in [23, 45], it is impossible to guarantee that denoising effectiveness prediction is possible for any filter. Meanwhile, it is possible to explain why prediction occurred possible for aforementioned filters. Usually, filter performance depends on image complexity (it is more difficult to provide good denoising for complex structure images [10–12]) and noise intensity (improvement of metrics is usually larger for more intensive noise [10–12, 23]). Such parameters as $P_{\alpha\sigma}$ simultaneously characterize image complexity and noise intensity — $P_{\alpha\sigma}$ reduces if image complexity increases and/or noise intensity decreases. Just due to this property the parameters $P_{\alpha\sigma}$ perform well in prediction.

The next step in analysis and proving universality of the proposed approach was to consider multichannel image denoising [48–50]. The cases of identical noise characteristics in component images of multichannel data [48] and different noise characteristics in component images subject to proper variance stabilizing transformations [49] have been analyzed. It has been shown that similar

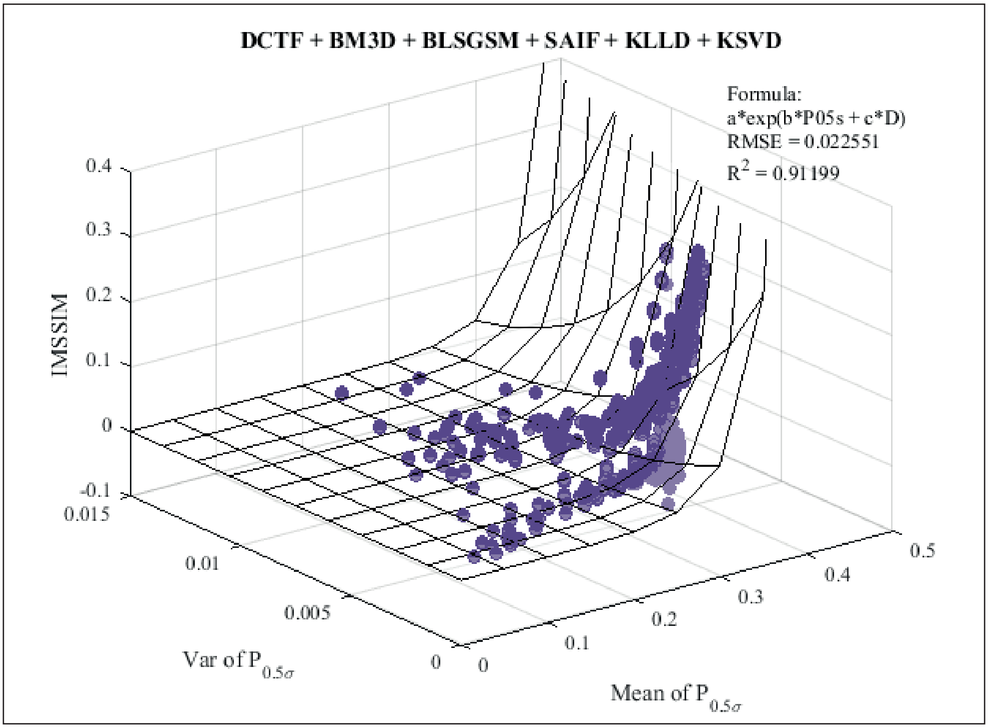
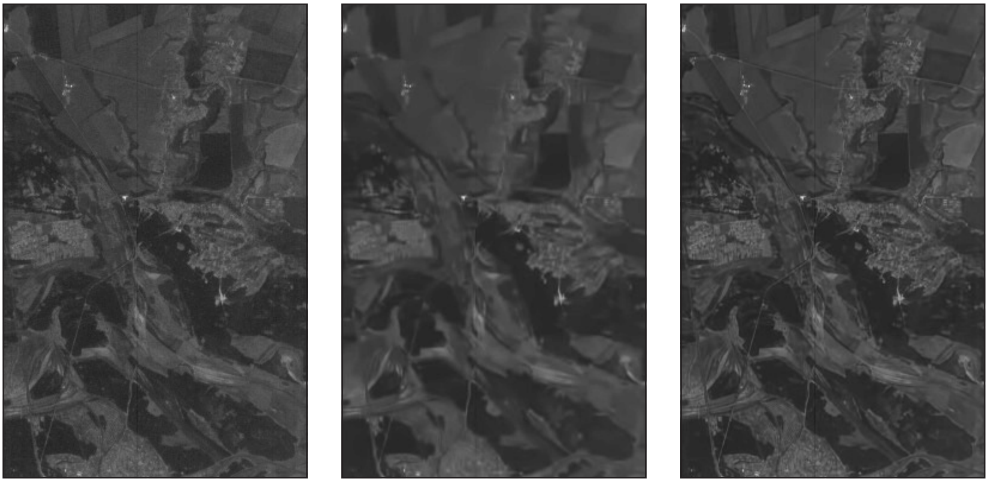


Fig. 6. Scatterplot of IMSSIM vs $P_{0.5\sigma}$ and variance of this parameter and the fitted surface (2D function)

input parameters (probabilities $P_{\alpha\sigma}$ adapted to 3D case) can be used and IPSNR for a group of channels (sub-bands, components) denoised jointly can be predicted. An interesting effect is that if component images have had different input PSNR before denoising, the largest IPSNR is observed for component images that had the smallest input PSNR, i. e. quality of the most noisy component images is improved in the first order. This is a very important practical aspect.

Another valuable practical aspect is that potential and practical effectiveness of 3D filtering in multichannel case is sufficiently higher than in single-channel case (or if denoising of multichannel images is carried out component-wise) [48–50]. Sometimes the use of 3D (vector) denoising is the only possibility to improve the quality of highly textural images, i. e. to exploit inter-channel correlation of information data for this purpose.

An example of denoising (see images in Fig. 7) is taken from [50] for the 13-th band of Hyperion hyperspectral data. Noise is signal-dependent and it is visible in the original image (Fig. 7, a). Component-wise denoising has removed noise but introduced smearing (see the output in Fig. 7, b). 3D DCT-based filtering with preliminary variance stabilizing transform and inverse transform after denoising produced sufficiently better result (see Fig. 7, c) due to better



a b c

Fig. 7. Real-life data: a — Hyperion image in 13-th sub-band, b — output of 2D (component-wise) denoising, c — output of 3D denoising for the 13-th sub-band

preservation of edges, small-sized objects and textures. Note that the images in 13-th, 14-th and 15-th sub-bands have been processed jointly. Component images in 14-th and 15-th sub-bands have higher input PSNR than in 13-th, 12-th and 11-th sub-bands. This shows one possible way to smart processing of multichannel images with large number of components where there are different options what components to process jointly in order to provide maximal positive effect for component images having the lowest input PSNR. Note that output MSE in joint processing does not decrease as 1/N where N is the number of jointly processed components. It reduces slower and then some compromise value of N should be found.

Above, the cases of white noise have been considered. However, there is necessity to study the cases when images are corrupted by spatially correlated noise that can arise in practice due to several factors [2, 51]. The annoying influence of spatially correlated noise is illustrated in Fig. 8 where images corrupted by AWGN and spatially correlated noise with the same variance are represented. Obviously, the necessity to cope with spatially correlated noise is more obvious. Meanwhile, it is a more complicated task due to several factors.

First problem in analysis of denoising effectiveness for the case of spatially correlated noise is that there is an infinite variety of possible characteristics (e. g., spatial spectra) of such a noise. This means that one can simulate one or two or more types of spatially correlated noise but this does not cover all possible variants. A second problem is that there is a considerably less number of filters able to successfully cope with spatially correlated noise. In fact, it is possible to

Fig. 8. Color test image fragments corrupted by AWGN (left) and spatially correlated (right) noise having the same variance equal to 130

apply any filter, but, being not adapted to characteristics of the noise, most filters loose effectiveness compared to the case of AWGN [52]. Because of this, let us present below some results given in [51, 53] for the DCT-based filter that can be easily adapted to suppressing spatially correlated noise under condition that its DCT spectrum is a priori known or properly estimated. The adaptation consists in using frequency dependent thresholds that take into account the noise spectrum [51, 53].

In [51], studies were done for two particular shapes (types) of spatially correlated noise spectrum. Later, in [53], a considerably wider range of spectra shapes (properties) has been considered. Spatially correlated noise has been modeled using function of weights $G(i,j) = \exp\left[-\pi * \frac{(i^2 + j^2)}{2 * \sigma_G^2}\right]$ where the parameter σ_G determines degree of spatial correlation (a larger σ_G corresponds to a larger correlation of the noise in neighbor pixels).

Let us analyze the scatter-plot of IPSNR vs two input parameters — $P_{0.5\sigma}$ and σ_G (Fig. 9, a). As it is seen, the scatter-plot points are placed close to the fitted surface $IPSNR_{pred} = \exp(bP_{0.5\sigma}) \times (c_3\sigma_G^3 + c_2\sigma_G^2 + c_1\sigma_G + c_0)$ (b=9.48, c_0=0.64, c_1= -0.94, c_2= 0.6 and c_3=-0.01). For the fitted surface, R^2 is about 0.91. This means that a quite good prediction accuracy is provided if $P_{0.5\sigma}$ and σ_G are used as input parameters under assumption that σ_G is either known in advance or pre-estimated with an appropriate accuracy.

Fig. 9, b shows cross-sections of the fitted surface for different σ_G, i. e. for different degrees of noise spatial correlation. One more observation is important — maximal value of the predicted IPSNR has the tendency to reduce if σ_G increases, i. e. with greater degree of spatial correlation.

DECISION MAKING AND ADDITIONAL INFORMATION

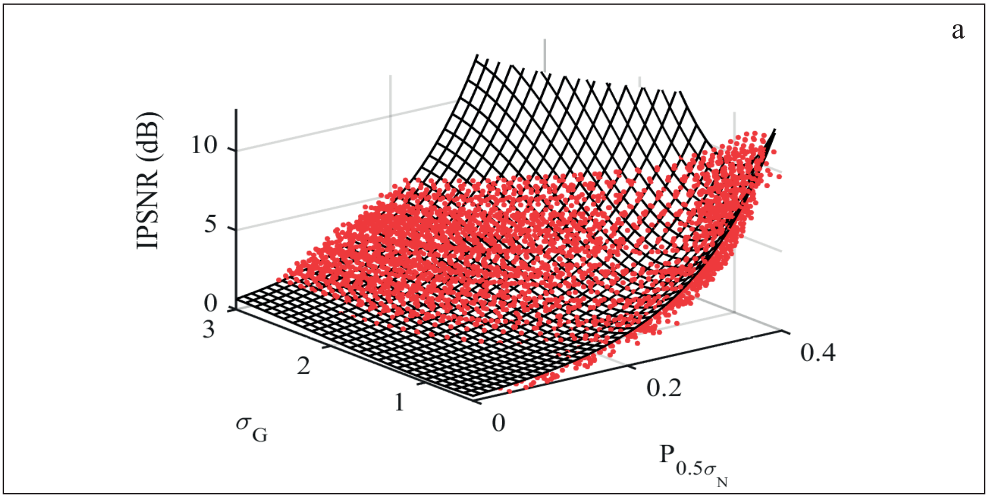
The results of analysis presented above show that it is possible to predict such criteria as IPSNR and IPHVSM that characterize denoised image quality and filtering effectiveness more or less adequately. To increase adequateness, it is possible to take into account data presented in scatter-plots in Figures 2 and 3. Earlier, we have analyzed only positions of points in scatter-plots and general properties of observed dependences. Meanwhile, two linear approximations are presented in Fig. 2 and two more in Fig. 3. The corresponding formulas for them are given below scatter-plots where MOS_f and MOS_n are MOS for filtered and noisy images, respectively, $PSNR_{inp}$ is PSNR for original image assumed to be known in advance or accurately pre-estimated, $PHVSM_{inp}$ is input (noisy) image PSNR-HVS-M that is approximately equal to $PSNR_{inp}$ for intensive noise.

It follows from analysis of the approximations in Fig. 2 that, on the average, to provide improvement of visual quality one has to apply filtering that provides IPSNR larger than 16.17–0.47$PSNR_{inp}$. This means that large improvements of PSNR values do not always lead to better visual quality of processed images compared to original ones. For example, if $PSNR_{inp}$=21 dB, IPSNR should exceed 6 dB to make probability P_{vote} of voting in favor of filtering larger than 0.5. Note that such an improvement is not always provided by denoising [23, 47]. At least, this is true for textural single channel (grayscale) images. In turn, if $PSNR_{inp}$ is about 30 dB, IPSNR should exceed 1 dB to make probability P_{vote} over 0.5 and this is quite realistic.

Consider now the metric IPHVSM. It follows from Fig. 3 and approximating expressions that, on the average, to reach improvement of visual quality one has to provide IPHVSM larger than 9.33–0.337 $PSNR_{inp}$. This means that, for $PSNR_{inp}$=20 dB, IPHVSM has to be larger than 2.6 dB and it is not easy to provide [23, 47]. Meanwhile, if $PSNR_{inp}$=30 dB, IPHVSM should be simply positive. This is quite realistic. Therefore, denoising leads to obvious improvements of image quality for middle level of noise and low/middle complexity images.

Summarizing the presented data, it is possible to state that one can expect improvement of visual quality if IPSNR>16.17–0.47$PSNR_{inp}$ and IPHVSM>9.33–0.337 $PSNR_{inp}$. These can be the basic expressions for decision undertaking.

It might seem that these conditions can be easily satisfied for $PSNR_{inp}$>32 dB (see data in Figures 2 and 3), but the situation then is not so simple and obvious. To analyze it more in detail, consider data presented in recent paper [54]. Experiments have been carried out for 16 grayscale test images corrupted by AWGN with noise standard deviation varying from 3 to 30 for the standard DCT and BM3D filters. Eight test images have been taken from TID2013 (or Kodak database, one with index 7 is presented in Fig. 1) and eight other test images with



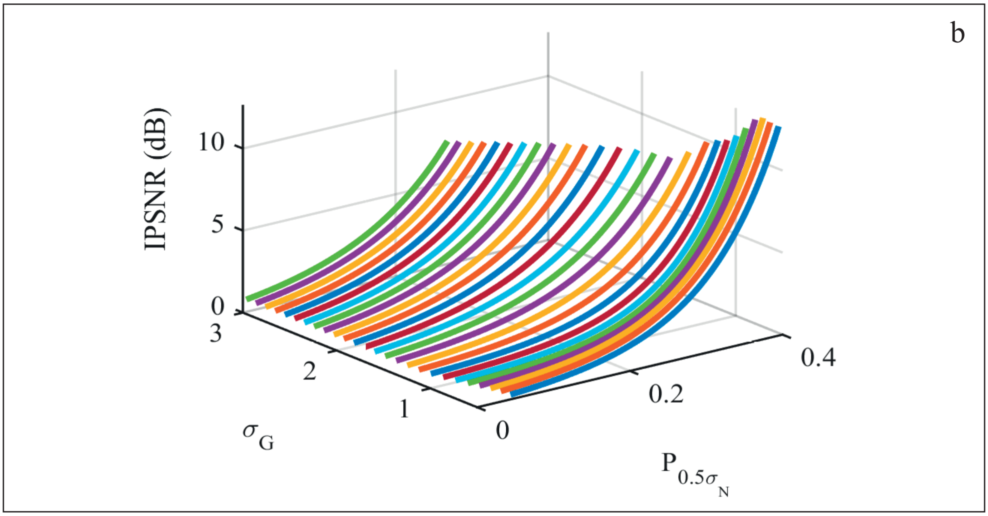


Fig. 9. Scatter-plot of IPSNR vs $P_{0.5\sigma}$ and σ_G with the fitted surface (a) and the surface cross-sections

indices from 9 to 16 were textural ones. Some results are presented in Fig. 10 for σ=10. It is seen that values P_{vote} are obviously larger than 0.5 for test images with indices 1–8 and 10 (horizontal axis), i. e. the use of filtering is expedient. For textural images with indices 9 and 14–16, values of P_{vote} are about 0.5, i. e. there is no sense to apply denoising. Finally, for test images with indices 11–13 which are textural, the use of denoising is obviously the wrong decision. It is also seen that the BM3D filter usually provides a slightly larger P_{vote}, but, in general, the results for both filters are in coherence.

A typical example of data for textural images is presented in Fig. 11, where one can see noise-free test image (left) and dependences of P_{vote} on σ for two filters. The results are slightly better for σ equal to 5, 10, and 15. However, in all cases the values of P_{vote} are all smaller than 0.5, i. e. filtering is not worth applying. Moreover, it can decrease image visual quality.

One more portion of data is presented in Fig. 12. These are averaged (for all 16 test images) values of P_{vote} for all seven values of noise standard deviation. Both dependences start from P_{vote} about 0.5 for σ=3. This means that denoising is not needed (expedient). And there are two reasons behind this. The main is that noise with σ=3 is practically invisible in noisy images. The second reason is that filtering for such small values of σ produces small IPSNR and IPHVSM [23, 47]. Thus, it becomes not expedient to apply denoising for $PSNR_{inp}$ larger than 35 dB that corresponds to σ smaller than 5 (this condition has to be added to previous ones).

Then, for σ about 10, both filters (on the average) provide improvement of visual quality. This improvement becomes smaller for larger σ where for σ approximately equal or larger than 20 it is not worth to apply the standard DCT-based

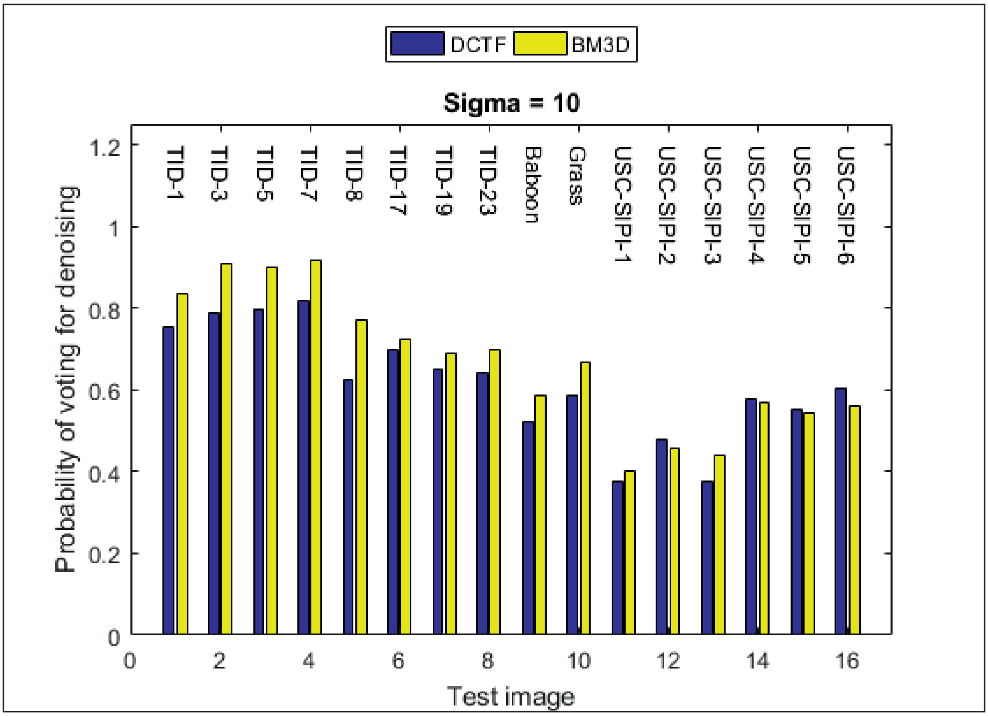


Fig. 10. Probability of voting in favor of denoising for 16 grayscale test images, σ=10, $PSNR_{inp}$=28.1 dB.

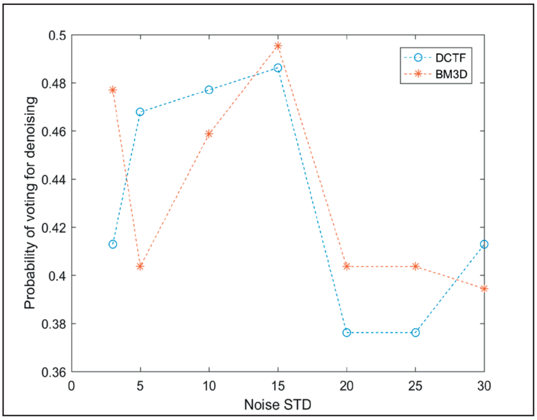


Fig. 11. A textural test image and dependence of of P_{vote} on σ for two considered filters

filter while the BM3D filter still improves visual quality. However, as it has been said above, the decision is individual depending upon an image to be processed.

Attempts to predict P_{vote} using different input metrics have been undertaken [54, 55]. However, currently the provided RMSE is not high enough (about 0.09) and additional efforts are needed to improve accuracy of prediction.

One more aspect of expedience of denoising is that it can influence solving final tasks in remote sensing. In this sense, it is possible to mark the following. Experiments carried out in [34] have shown that more effective denoising leads to better classification where quality of original images is rather low since they are corrupted by quite intensive speckle.

The data presented in [34] relate to probability of correct classification P_{cc} determined for all analyzed image pixels. However, a more detailed analysis of classification accuracy is possible using probabilities of correct classification for particular classes P_{pccc} as well as confusion matrix [7, 56, 57]. On one hand, direct connection between effectiveness of image denoising and criteria characterizing classification is not established yet. This is explained by several factors: different classifiers can be used, number of classes can be different, percentage of image pixels that belong to particular classes can vary in wide limits, etc. On the other hand, analysis carried out in [7, 56] shows the following.

Firstly, pre-filtering helps increasing P_{cc} especially if noise intensity in original images is high. If $PSNR_{inp}$ is about 35 dB, some improvement of P_{cc} can be observed [7] but it is not too large (for example, from 0.89 for noisy images to 0,91 for pre-filtered ones). The reason is that negative influence of class features' diversity and imperfectness of classifier (training) is larger than negative impact of the noise.

Secondly, denoising improves P_{pccc} for particular classes in different manner. There are classes that can be conditionally called „uniform" as water surface,

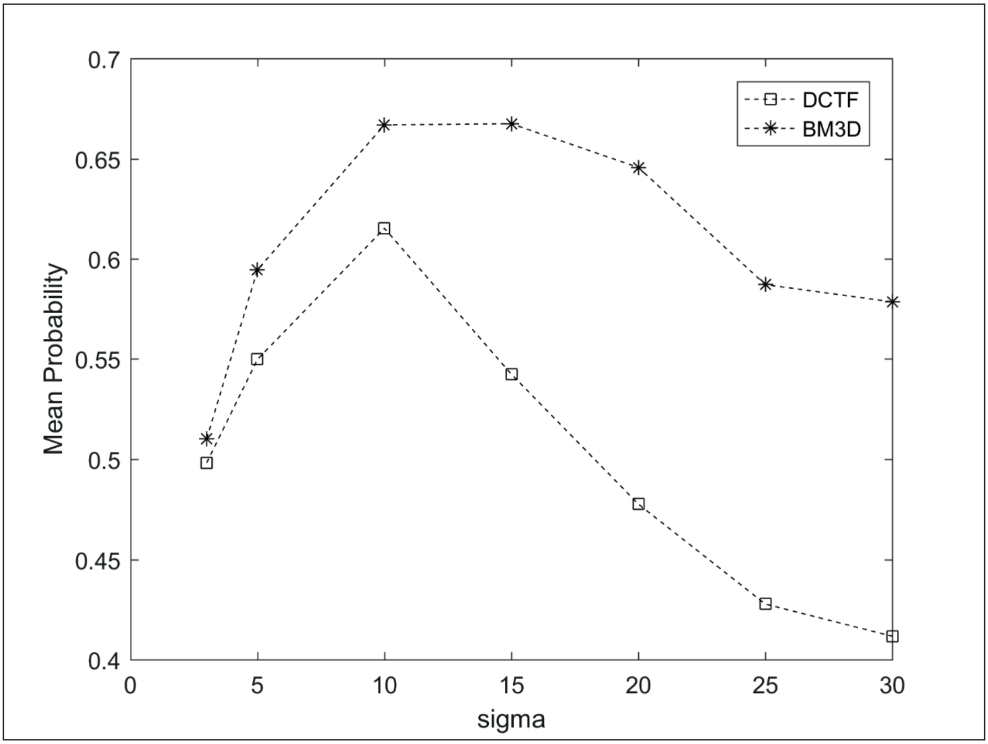


Fig. 12. Averaged values of P_{vote} for all seven values of noise standard deviation

meadows, etc., that mostly correspond to large size homogeneous objects in images. For them, improvement of P_{pccc} due to filtering is the largest and P_{pccc} highly correlates with conventional criteria of filtering effectiveness as MSE or PSNR. Meanwhile, there are classes that can be conditionally called „non-uniform" as urban areas, bushes, etc. They are often associated with small-sized objects and textures in images [58]. For these classes, improvement of P_{pccc} due to denoising is usually limited (quite small) and this parameter correlates more with visual quality metrics. This can be intuitively explained as follows. For such classes, there are many misclassifications especially in pixels near edges of objects. Then, preservation of edges in the process of denoising (that correlates with visual quality) is of great importance. This also explains why visual quality metrics are used in processing of remote sensing data [59].

CONCLUSIONS

It is shown that image denoising is not always needed. There are quite many practical cases when positive outcomes of filtering are negligible or, moreover, denoising leads to negative outcomes. Thus, there is the need in predicting effectiveness of denoising and decision undertaking is it worth applying filtering or it can be skipped with saving time and resources.

It is also demonstrated that prediction of denoising effectiveness is possible using adequate output metrics and input parameters that can be easily and quickly calculated. This makes prediction reliable and fast. Methodology of prediction is described and shown universal. Approaches for different types of noise are proposed and they are similar. Prediction is possible not only for single channel but also for multichannel images. Ways to improve accuracy of prediction that include the use of several input parameters and good approximating tools are studied and shown efficient. Simple rules to undertake decisions are given.

However, there is a wide space for future research. To name a few, interesting directions can be the following:

— to analyze opinions of observers or specialists concerning quality of specific types of images as medical or remote sensing ones especially if specialists have been trained to analyze filtered images;

— to continue analysis and design of metrics adequate for characterizing visual quality of filtered images;

— to pay attention to practically important cases of multichannel images and/or spatially correlated noise that have not been studied thoroughly yet;

— to carry out additional experiments with observers for understanding how they analyse (compare) noisy and denoised images and assess their quality;

— to study applicability of approaches to denoising effectiveness prediction based on neural networks, support vector machines, etc.;

— to establish dependences between quality metrics used in image denoising and measures (criteria) employed in image analysis (object detection, recognition, data classification).

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