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ITERATIVE METHOD FOR BLIND EVALUATION OF MIXED NOISE CHARACTERISTICS ON IMAGES

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A new method for blind estimation of mixed noise parameters is proposed. The method is based on line fitting into a set of cluster centers obtained from scatter-plot of local variance and mean estimates. Improved estimation of cluster centers is performed on basis of fourth-order statistical moment analysis. The estimation results for the proposed method are compared to the results for other known methods using images from TID2008 database. It is shown that the proposed method provides estimation accuracy comparable to the estimation accuracy of the method based on maximum likelihood estimation of image and noise characteristics (which is considered the best among the existing methods). An advantage of our method is that it is considerably faster.

Introduction

Image is one of the most convenient and intuitive forms of information presentation. That is why subsystems that perform image acquisition (forming), processing and storage have become an inherent integral part of most of modern information systems [1, 2].

The images obtained in such systems might be used for several different purposes as visualization, automatic analysis, retrieval of additional information that might be interesting or useful for customers [2]. For example, one of trendy and promising tendencies in modern photographic systems is estimation of visual quality of the obtained image followed by giving a user some recommendations on the feasibility of re-shooting with other parameters or different perspective [1].

As it is seen, image quality assessment and, sometimes, image enhancement can be needed in many applications at initial stages of image processing. One of the main factors influencing image visual quality is noise that should be characterized by a set of statistical parameters (such as probability density function, variance, type if not additive, etc.).

Information about noise statistics is directly or indirectly taken into account in many non-reference visual quality metrics [2]. Such information is also often used for setting filtering parameters in many noise removal algorithms, for example, sigma-filter or for the family of DCT-based filters. Recently, a method for prediction of image filtering efficiency [3] was proposed that allows estimating the feasibility of filtering a considered image. To work correctly, this method needs information on noise type and characteristics.

Noise characteristics in images are usually influ-

enced by a lot of factors that can be both internal and external with respect to an imaging system. So, information about noise characteristics is often a priori unknown and it should be extracted directly from a processed image [4]. Since modern information systems are characterized by large amount of produced data (for example, hyperspectral remote sensing systems create snapshots consisting of hundreds or thousands component images corresponding to different spectral channels [2]), that should be done in a blind (automatic) manner.

Gaussian additive model has been traditionally used to describe noise on images obtained by optical imaging sensors. Therefore, many blind methods for noise variance evaluation [4 – 6] were designed under assumption of this model. Later, it has been shown that noise in many real-life images has to be described by a more complex model, namely, by a mixture of signal-independent and signal-dependent noise [7]. For radar images, noise model has a form of mixture of additive and multiplicative noise components [8] whilst for optical and hyperspectral images a mixture of additive and quasi-poisson noise components has been adopted [7].

During recent decade, several methods for mixed noise characteristics' evaluation have been designed. These methods can be divided into, at least, three groups: methods operating in spatial domain [8, 9], methods performing in spectral domain [6, 10], and methods based on maximum likelihood estimation of image and noise characteristics [11]. Methods for blind estimation of noise characteristics should satisfy a lot of different and, often contradictory, requirements. The main of them are acceptable accuracy and high computational efficiency (ability to operate in accepted time

limits). The methods that work in spatial and spectral domains are usually characterized by rather high computational efficiency, but they often provide significantly biased estimates for highly textured images. In turn, the methods based on maximum likelihood estimation of image and noise characteristics are able to provide more accurate estimates for complex structure images but they require a lot of computations [11]. So, improvement of existing methods for noise characteristics evaluation and designing of the new ones that meet the aforementioned requirements still remains topical.

Statement of the research problem

The common approach to the mixed noise characteristics evaluation is to get a scatter-plot of local variance (standard deviation) and local mean estimates obtained for some set of image blocks, to fit a polynomial curve into it and to take parameters of the fitted polynomial as noise characteristics estimates. For the considered noise model in the form of mixture of signal-independent and signal-dependent noise, a simple polynomial of the first order (line) can be used [8]. In this case, the zero order polynomial coefficient (term) corresponds to the signal-independent (additive) noise variance estimate and the first order polynomial coefficient corresponds to the signal-dependent noise parameter estimate.

It should be noted that if an image is corrupted by the aforementioned mixture of additive and quasi-poisson noise, line should be fitted into a scatter-plot of local variance and mean estimates as:

$$\hat{\sigma}_{loc_m}^2 = \hat{\sigma}_a^2 + \hat{k} \cdot \hat{I}_{loc_m}, \quad (1)$$

where $\hat{\sigma}_{loc_m}^2$ is the noise variance estimate in the m -th image block; \hat{I}_{loc_m} denotes the mean estimate in the m -th image block; $\hat{\sigma}_a^2$ is additive noise component variance estimate; \hat{k} denotes quasi-poisson noise component gain estimate.

If an image is distorted by the mixture of additive and multiplicative noise, fitting should be done into the scatter-plot of local variance and squared mean estimates:

$$\hat{\sigma}_{loc_m}^2 = \hat{\sigma}_a^2 + \hat{\sigma}_\mu^2 \cdot \hat{I}_{loc_m}^2, \quad (2)$$

where $\hat{\sigma}_\mu^2$ is relative variance estimate of multiplicative noise component.

Since the only difference between methods for evaluating the characteristics of mixed noise for the models (1) and (2) is in the scale along the horizontal axis, all the mentioned methods for mixed noise characteristics evaluation may be tested for any of the considered models (1) or (2). Therefore, further analysis will be conducted for the noise model (1). Additional interest to

considering such a noise is due to the fact that it is present in raw optical images including those obtained by home cameras and built-in mobile phone cameras with which almost everyone deals in his/her everyday life.

Whereas for many practical applications high performance is one of the leading requirements, let us focus on noise evaluation methods working in spectral domain. Another reason of choosing this group of methods relates to their ability to provide higher accuracy of estimation for highly textured images in comparison to the methods operating in spatial domain.

Although most methods for estimating mixed noise parameters are based on curve fitting into a scatter-plot or its “derivative” (e.g., a set of cluster centers), properties and accuracy of these methods depend upon many factors as how local estimates in blocks are obtained, are all image blocks taken into account or not, how fitting is performed (using LMSE or robust fitting, weighted or non-weighted, in one or several iterations) and so on. Let us, as a good example, consider the mixed noise characteristics evaluation method described in [10]. The main stages of this method are the following.

1. Image is pre-segmented and homogeneous regions are detected. For image pre-segmentation, the method [12] is used since it does not require a priori information on noise type and statistics; the outcome of the method [12] is a pre-segmented image that usually has from five to fifteen levels. Then a discrimination map is obtained for the segmented image. This map discriminates the blocks that can be considered quasi-homogeneous from other ones that relate to edges and textures with high probability.

2. Scatter-plot cluster centers ($\hat{\sigma}_{clc}^2; \hat{I}_{clc}$) ($\hat{\sigma}_{clc}^2$ is variance estimate and \hat{I}_{clc} is mean estimate within c -th cluster) are estimated. The estimate \hat{I}_{clc} is obtained as mean of the corresponding cluster elements (points) after pre-segmentation. For obtaining the $\hat{\sigma}_{clc}^2$ estimates, the method [5] is used. Briefly the idea of method [5] is the following. For all image blocks belonging to homogeneous regions, the 2D DCT (Discrete Cosine Transform) coefficients $D_i(k,l)$ are calculated and grouped according to spatial frequencies (defined by indices k and l). Then, for all high frequency coefficients, estimates of percentile kurtosis coefficient (PCK) and median absolute deviation (MAD) are obtained. The final variance estimate is calculated as the squared median of MAD estimates for spatial frequencies with PCK estimates within the acceptable range, i.e. if coefficients distribution is close to Gaussian.

3. Through the found cluster centers, robust line $Y = a + bX$ fitting is carried out and the determined

parameters a and b are accepted as the estimates of $\hat{\sigma}_a^2$ and \hat{k} . The fitting is carried out using double weighted least mean squares (DWLMSC) method with restrictions imposed on non-negativity of both estimates [9].

Let us analyze performance of the method [10]. Recall that for performance analysis it is expedient to analyze a set of images that have different properties (complexity, texture content). One opportunity to do this is to exploit images from TID2008 database [13]. This database contains 25 noise-free color test images. These images are of different complexity and can be divided into three groups: low textured images (# 3, 4, 7, 9, 10, 20, 23), medium textured images (# 2, 6, 11, 12, 15, 16, 17, 18, 19, 21, 22, 24, 25) and highly textured images (# 1, 5, 8, 13, 14). Availability of noise-free color images allows getting 75 grayscale test images (R, G, and B components of 25 color images), to add noise with desired statistics to them, and to apply the considered blind estimation methods.

Scatter-plots of local variance and mean estimates with marked cluster centers and two fitted lines: true (solid) and the line obtained using method [10] (dashed) for two highly textured images (# 8 and 13) from TID2008 database corrupted by mixed noise ($k = 1$, $\sigma_a^2 = 30$) are shown in Fig. 1. As it is seen, cluster centers estimates can be significantly biased with respect to their true positions. This essentially decreases general accuracy of the method. Obviously, for improving overall accuracy of the method, one way consists in modifying the procedure of obtaining cluster centers. This is the main goal of the present study.

The proposed mixed noise evaluation method also consists of three main stages, namely

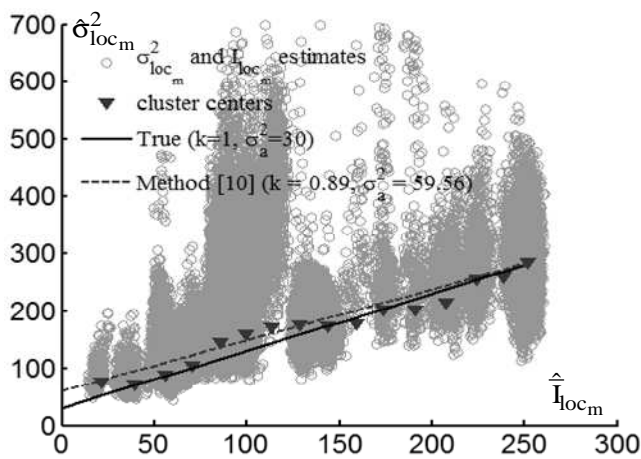
1. Image segmentation and cluster mean estimates (\hat{I}_{clc}) obtaining;
2. Cluster variance estimates ($\hat{\sigma}_{clc}^2$) obtaining using the method [25];
3. Line fitting through the obtained cluster centers using the DWLMSC method. The cluster weights are calculated proportionally to the final cluster sizes.

For the method [10] considered in the previous section, the scatter-plot cluster centers were significantly biased from their true positions. This fact is mainly due to the large number of abnormal local variance estimates (see Fig. 1) obtained in blocks belonging to heterogeneous areas (containing edges, textures, small sized objects etc.) that have not been eliminated by segmentation and homogeneous regions detection algorithms. That's why the image segmentation algorithm and the homogeneous region detection method were modified.

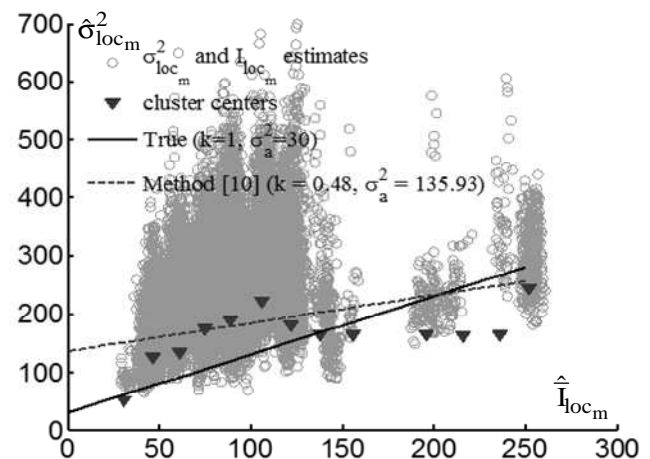
For each separate cluster in the image, the following algorithm of data processing is proposed.

1. An image is divided into overlapping blocks of size 8x8 pixels.
2. For each block, the mean estimates \hat{I}_{loc_m} are calculated. To avoid clipping effect, only the blocks with $30 \leq \hat{I}_{loc_m} \leq 225$ are taken into account in further processing.
3. Maximal $\hat{I}_{loc_{max}}$ and minimal $\hat{I}_{loc_{min}}$ mean estimates are determined.

Description of the proposed method



(a)



(b)

Fig. 1 Scatter-plots of local variance and mean estimates with two fitted lines: true (solid) and the obtained line using the method [10] (dashed) for images # 8 (a) and # 13 (b) from TID2008 database corrupted by mixed noise

4. The range from minimal to maximal cluster means $\hat{I}_{loc_{min}} \dots \hat{I}_{loc_{max}}$ is divided into n sub-intervals (by default we propose to use $n = 10$), the blocks with \hat{I}_{loc_m} within c -th ($c = \overline{1, n}$) sub-interval are assumed to belong to the c -th cluster.

5. Cluster mean estimates \hat{I}_{cl_c} are calculated as average intensity values within a cluster:

$$\hat{I}_{cl_c} = \hat{I}_{loc_{min}} + (c - 0,5) \frac{\hat{I}_{loc_{max}} - \hat{I}_{loc_{min}}}{n}.$$

At the second stage, to obtain $\hat{\sigma}_{cl_c}^2$ estimates, the method [14] is applied within each cluster. Briefly the idea of this method is in the following.

1. For all blocks referred to the c -th cluster, 2D DCT is applied.

2. Fourth central moment ($\hat{\mu}_{4_m}^{Spat}$, $\hat{\mu}_{4_m}^{Spec}$) and variance estimates ($\hat{\sigma}_{Spat_m}^2$, $\hat{\sigma}_{Spec_m}^2$) are calculated in spatial and spectral (DCT) domains.

3. Modes of local variance estimates distributions in spatial ($\hat{\sigma}_{Spat_{mode}}^2$) and spectral ($\hat{\sigma}_{Spec_{mode}}^2$) domains are determined. For this purpose, the interquantile method described in [4] is used.

4. Modified kurtosis estimates in spatial and spectral domains are obtained as:

$$\hat{K}_{Spat_m} = \sqrt{\hat{\mu}_{4_m}^{Spat} / \hat{\sigma}_{Spat_{mode}}^4},$$

$$\hat{K}_{Spec_m} = \sqrt{\hat{\mu}_{4_m}^{Spec} / \hat{\sigma}_{Spec_{mode}}^4},$$

and the modes of these estimates ($\hat{K}_{Spat_{mode}}$ and $\hat{K}_{Spec_{mode}}$, respectively) are determined.

5. A block is supposed to be homogeneous if both conditions $\sqrt{\hat{\mu}_{4_m}^{Spat} / (\hat{\sigma}_{Spat_{mode}}^2 \cdot kc)^2} \leq Th_1$ and

$\sqrt{\hat{\mu}_{4_m}^{Spec} / (\hat{\sigma}_{Spec_{mode}}^2 \cdot kc)^2} \leq Th_1$ are satisfied. Here kc is a correction factor determined as:

$$kc = \begin{cases} (\hat{K}_{Spat_{mode}} / \hat{K}_{Spec_{mode}})^2 & \text{if } \hat{K}_{Spec_{mode}} < \hat{K}_{Spat_{mode}} \\ (\hat{K}_{Spec_{mode}} / \hat{K}_{Spat_{mode}})^2 & \text{if } \hat{K}_{Spat_{mode}} \leq \hat{K}_{Spec_{mode}} \end{cases}$$

and Th_1 is a predetermined threshold (the recommended value is $Th_1 = 2.3$).

6. For the detected homogeneous blocks, the method [5] is applied and cluster variance estimate $\hat{\sigma}_{cl_c}^2$ is obtained. This estimate is taken as “corrected” ($\hat{\sigma}_{corr}^2$)

noise variance estimate and the earlier obtained mode of local variance estimates in spatial domain $\hat{\sigma}_{Spat_{mode}}^2$ is taken as “preliminary” ($\hat{\sigma}_{prel}^2$) noise variance estimate.

7. If relative difference $|\hat{\sigma}_{corr}^2 - \hat{\sigma}_{prel}^2| / \hat{\sigma}_{corr}^2$ occurs to be larger than the predetermined threshold Th_2 (the recommended $Th_2 = 0.15$), modified kurtosis estimates are recalculated using “corrected” variance estimate:

$$\hat{K}_{Spat_m} = \sqrt{\hat{\mu}_{4_m}^{Spat} / \hat{\sigma}_{corr}^4},$$

$$\hat{K}_{Spec_m} = \sqrt{\hat{\mu}_{4_m}^{Spec} / \hat{\sigma}_{corr}^4}.$$

8. After that, conditions $\hat{K}_{Spat_m} \leq Th_1$ and $\hat{K}_{Spec_m} \leq Th_1$ are checked and the refined homogeneous regions map is obtained.

9. For blocks assumed homogeneous at step 8, the method [5] is applied and the obtained noise estimate is taken as the “corrected” one while the previous “corrected” estimate is taken as “preliminary”. After such reassignment, the steps 7-9 are repeated until the relative difference between “preliminary” and “corrected” estimates becomes less than Th_2 .

Results analysis

Fig. 2 shows the scatter-plots of local variance and mean estimates obtained in homogeneous regions detected according to the proposed method. Cluster centers are marked by square markers, the true line is solid and line fitter through the marked cluster centers is dashed. The presented scatter-plots were obtained for highly textured images # 8 and 13 from TID2008 database, true noise parameters are the following: $k = 1$, $\sigma_a^2 = 30$. Comparing these scatter-plots to the ones presented in Fig. 1, we can see that number of abnormal (particularly excessive) local estimates is significantly less and cluster centers are located closer to the true lines. As a result, the obtained noise parameters' estimates are also less biased than for the method [10].

The noise characteristics estimates for all images from TID2008 database are presented in Fig. 3. The results are shown not only for the proposed method and the basis method [10], but also for two other methods: the percentile method [6] operating in spectral domain and the method [11] based on maximum likelihood estimation of image and noise characteristics. The true noise parameters are shown by bold solid horizontal lines, dashed lines above the true line and under it are

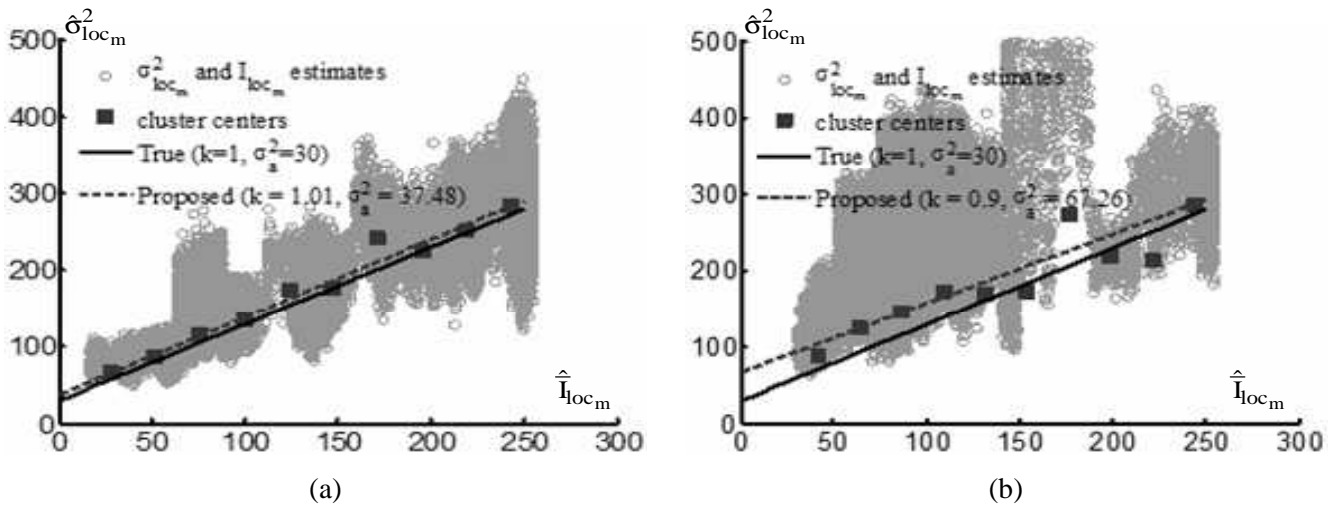


Fig. 2 Scatter-plots of local variance and mean estimates with two fitted lines: true (solid) and the obtained line using the proposed method (dashed) for images # 8 (a) and 13 (b) from TID2008 database corrupted by mixed noise

the borders of acceptable range of noise parameter estimates. It has been shown [15] that for practical use the relative noise characteristics estimation error should be within the range $-0.2 \dots 0.2$ for both mixed noise components. Image indexes (DI) are plotted along the abscissa axis, for each index three noise parameter estimates obtained for red, green and blue color components, respectively, are shown. The results for different methods are presented by curves with markers of different shapes: square for the basic method [10], triangular for the proposed method, diamond for the method [6] and round for the method [11].

As we can see, for all methods the estimates of signal-dependent noise parameter are more accurate (almost all the estimates are within the acceptable range) than the estimates of signal-independent noise parameter (there are many biased, in particular, overestimated values). The reason of such phenomenon consists in

In Table 1, we provide mean (median) noise parameter estimates obtained by averaging (or median finding, respectively) the results for all images from TID2008 database for each method. To assess how far the values of individual estimates are located from the averaged value standard deviation (STD) and median absolute deviation (MAD) estimates are presented as well.

The method [6] provides very unstable results (see Fig. 3): only a small part of estimates falls into the limits, other estimates are significantly overestimated or underestimated, some estimates are even negative. Mean and median values of the processed (over the database) estimates are inside the acceptable range, but this is achieved mainly due to the fact that biases of the estimates have opposite signs, so the STD and MAD values for this method are relatively high.

According to data in Table 1, the accuracy of the method [10] is comparable to the method [6], wherein,

Table 1. Averaged by TID2008 database mixed noise parameter estimates for different methods

Method	Estimate	Mean	STD	Median	MAD
Method [10]	$\hat{\sigma}_a^2$	41.77	19.75	36.54	12.18
	\hat{k}	0.94	0.15	0.96	0.10
Proposed	$\hat{\sigma}_a^2$	32.78	10.53	31.47	7.26
	\hat{k}	0.998	0.107	0.997	0.071
Method [6]	$\hat{\sigma}_a^2$	34.99	25.98	36.25	18.5
	\hat{k}	1.09	0.28	1.06	0.21
Method [11]	$\hat{\sigma}_a^2$	31.97	5.53	30.77	3.94
	\hat{k}	1.01	0.07	1.01	0.05

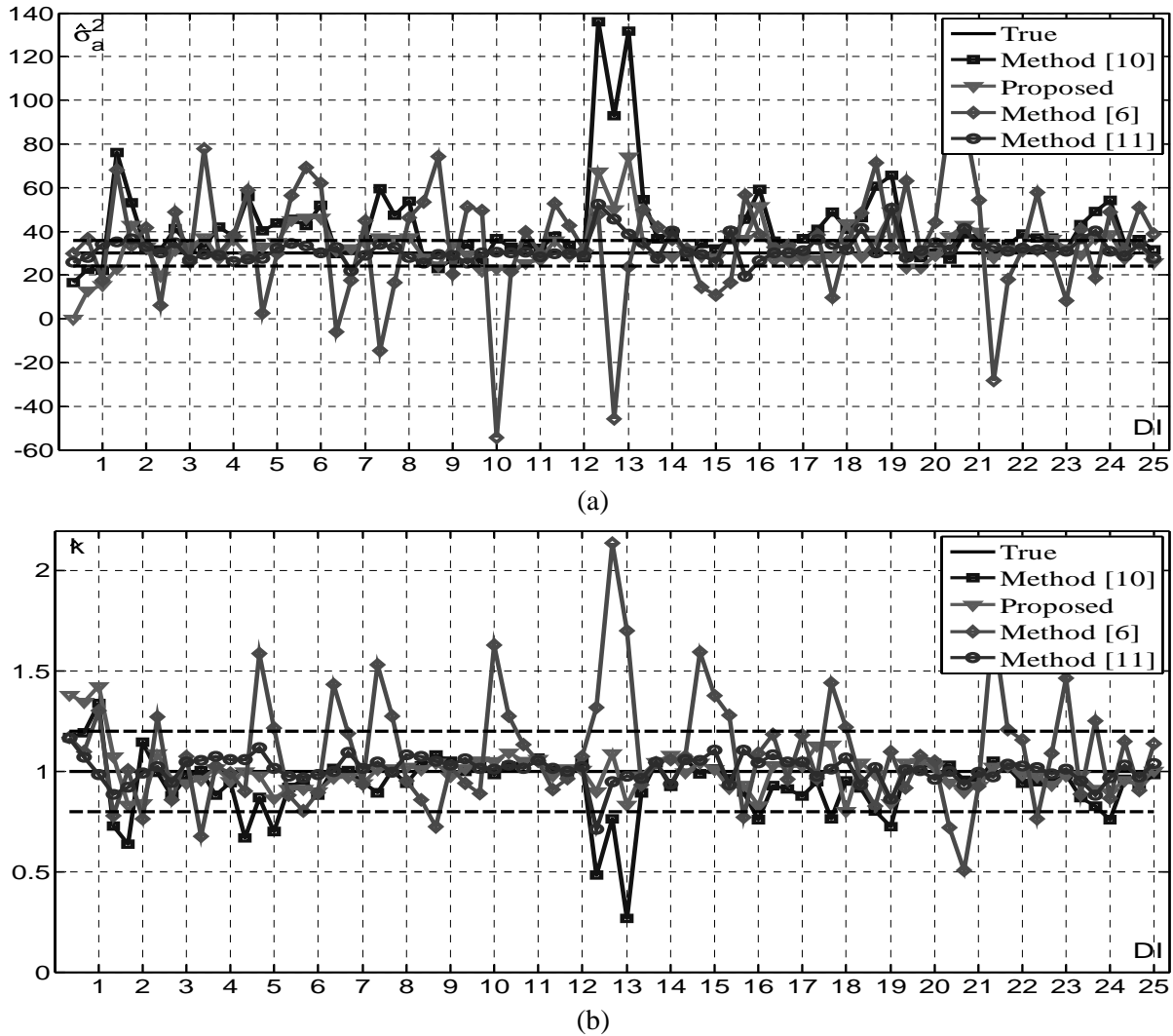


Fig. 3 Scatter-plots of local variance and mean estimates with two approximation lines: true (solid) and obtained using proposed method (dashed) for images # 8 (a) and 13 (b) from TID2008 database corrupted by mixed noise

the method [6] demonstrates slightly better estimation accuracy for the additive noise component, but essentially loses in \hat{k} parameter estimation accuracy. It is worth saying that STD and MAD values are smaller for the method [10] that indicates higher stability of estimation results for this method.

The method [11] provides the best accuracy among the considered methods, although for some highly and medium textured images this method also provides estimates outside the limits. In particular, for red and green components of highly textured image #13 and blue component of medium textured image #19 the estimate values are 1.4 times higher than the upper limit of the acceptable range, and more than 1.5 times higher than the true variance value (see Fig. 3).

The mean estimates averaged for TID2008 database (as well as their median) for this method in all cases are in the desired limits, and STD and AMO values are the

smallest (see Table 1). Concerning the proposed method, analyzing data in Fig. 3 and Table 1 we can see that it provides noticeably more accurate results in comparison to the basic method [10]. For most “problematic images” for the method [10] images, the estimates obtained by the proposed method occur to be either in the limits or are essentially less biased. The results from Table 1 also indicate the higher stability of estimation results for the proposed method as its STD and AMO values are up to 1.5 times smaller in comparison to the corresponding values for the method [10].

According to data presented in Fig. 3 and Table 1, the accuracy of the proposed method is comparable to the accuracy of the method [11]. Averaged estimates and the medians for the proposed method in all cases are in the desired limits, and STD and AMO of these estimates are also small enough (see Table 1). It should be noted that the averaged \hat{k} parameter estimates for the proposed method in some cases are even closer to the correspond-

ing true value than for the method [11], wherein the STD and AMO values are only slightly higher.

It was noted earlier that the methods of the third group (to which the method [11] belongs), require significant computational costs, and, therefore, are characterized by low efficiency (time to process a single image from TID2008 database (one component of a color image) in Matlab programming environment on a computer with a dual-core processor at 2.5 GHz is about five minutes). Performance of the proposed method is a bit lower in comparison to the basic method [10], but as it has been shown, this method provides essentially higher estimation accuracy. In comparison to the method [11], the estimation accuracy of the proposed method is slightly lower, but its computation efficiency is significantly higher (the process of obtaining noise parameter estimates for a single TID2008 database image takes about 1 minute (in Matlab environment on the same CPU)).

Conclusions

The blind mixed noise characteristics evaluation method is proposed. The main feature of the method is cluster-wise use of homogeneous regions detector based on analysis of the fourth-order statistical moment. The proposed method provides significantly higher estimation accuracy in comparison to other heuristic methods. Accuracy of the proposed method is comparable to the accuracy of the state-of-the-art method based on maximum likelihood estimation of image and noise characteristics while performance of the proposed method is several times higher.

Despite a significant increase in accuracy, the obtained noise parameters estimates are still essentially biased mainly due to the image content influence. This demonstrates the need for further improvement of the method and that is what our future research will be devoted to.

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