Numerical Tests-Based Assessment of the Procedures of Blurry and Noisy Image Enhancement

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Abstract— An extension of the test-based method of multi-aspect numerical assessment of the quality of image enhancement procedures on blurry and noisy images is presented. The principles of construction of the tests affected by various types and intensity of blurring and noising are described. Linear models of blurring have been defined. Formal definitions of measurable parameters characterizing the quality of image enhancement procedures are proposed. Comments on the errors and applicability limitations of the proposed testing method are also given. In a numerical experiment, the utility of the method by comparative assessment of 18 various image enhancement procedures is proven. Remarks concerning the properties of several widely-known image enhancement procedures are formulated. Concluding remarks about the utility of the presented method of image enhancement procedures assessment are given.

Keywords- *image processing, image filtering, blurry images enhancement, noisy image enhancement*

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I. INTRODUCTION

In numerous application areas (e.g. medical diagnosis, biological, ecological, geophysical research etc.), experimental data are provided in the form of blurry and noisy images. In such a case, the shape, size, inner structure and number of real objects being of interest are not directly available for observation and analysis. Computer-aided image enhancement is then a desirable step preceding other qualitative or quantitative image analysis procedures. For image quality enhancement, a large variety of linear and non-linear procedures has been proposed [1–8]. They usually are aimed at enhancement of selected image quality aspects: contrast reinforcement, background equalisation, contour sharpening, noise reduction, etc. Assessment of the quality of a so-enhanced image can be solved by measuring adequately defined image quality parameters [9–12]. However, as shown in [13], the type of image enhancement procedure affects also the final results of morphological or statistical image analysis. For instance, improving image contrast in a biological specimen influences the result of counting the details exceeding a fixed luminance threshold level, and may change statistics and the final diagnostic decision that are based on it. This shows that numerical evaluation of image enhancement procedures plays a substantial role in the case of image enhancing as a preliminary step in quantitative image analysis. The main difficulty in image enhancement consists of a contradiction between the tendency to contour enhancement and noise damping. In the former case, higher spatial frequency components should be reinforced; while in the latter, their relative level should be rather reduced. Therefore, if blurring and noise in an image co-occur, then a combination of high- and low-pass image filtering is desired. However, image quality assessment and image enhancement procedures assessment are different problems; the latter requires an appropriate approach to be solved. The problem of choosing an image enhancement procedure, the most appropriate to a given application problem, is thus of great practical importance. A typical example of such a problem is that of choosing an optimal scale at which image features should be most effectively extracted [14]. A similar problem of decision rules quantitative assessment is well known in the pattern recognition and data clustering domain [15–17]. However, those methods cannot be directly applied to image enhancement procedures. It is thus desirable to have a powerful method of numerical assessment of the properties of image enhancement procedures. This, in general, can be solved by comparison of images [18], one of them being used as a standard. Such a method, based on a set of standard tests, was proposed in [19]. The main idea of the method is based on two assumptions: 1) if a procedure correctly restores disturbed basic image elements (i.e. patterns), then it should correctly restore the image as a whole; 2) basic image elements can be chosen as standards suitable for numerical evaluation of the distortion level before and after using the image enhancement procedure.

The proposed tests-based method makes possible the evaluation of various image enhancement aspects, such as: contrast and/or distinctiveness improvement, image phase-shifting tolerance, etc. The standard tests-based method proposed in [19] is here presented in an extended form, aimed at testing the effectiveness of blurred and noisy images enhancement procedures. For this purpose, a new series of tests imitating blurry and noisy images is proposed. The paper is organised as follows: in Section II the principles of blurred and additive noise-affected standard tests generation are presented and the principles of standard tests-based image enhancement procedures assessment are shortly outlined. Section III contains an example of blurred and noisy image enhancement procedures application to comparative assessment of a dozen of typical image enhancement procedures. In Section IV final conclusions are recapitulated.

II. METHOD AND MATERIALS

The test-based method of assessment of image enhancement procedures consists of the evaluation of the distance between ideal patterns and enhanced images of standard tests obtained by controlled transformation and distortion of the ideal patterns. A general scheme of the proposed method of testing the procedures is shown in Fig. 1.

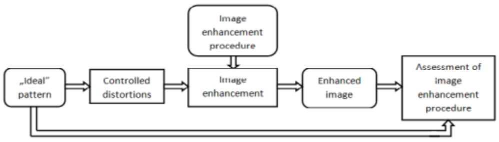

Figure 1. Test-based assessment of image enhancement procedure.

In our approach as ideal patterns, three first-order morphological spectra components [9]: checker, horizontal line and vertical line have been chosen, as shown in Fig. 2.

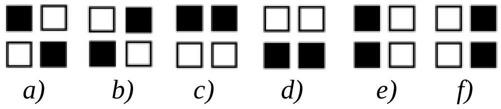

Figure 2. Basic image elements: *a), b)* checkers, *c), d)* horizontal lines, *e), f)* vertical lines.

The ideal patterns are then reproduced at different scales and different contrast levels, as described in [8].

In the case of blurred and/or noisy images enhancement, standard tests should be generated according to the following, extended sequence of transformations:

basic (ideal) binary patterns → artificially blurred and noise-added patterns → scale and phase-differentiated blurred/noisy patterns → scale-, phase- and contrast-differentiated blurred/noisy patterns

The subsequence of operations: blurring → noise addition has been chosen according to an assumed model of the most common image forming process: the contours of a well-defined physical or biological object are blurred in the image acquisition process, and noise in the succeeding image processing steps is added. However, in some cases, the order of the process can be reversed as: noise addition → blurring. The results in the two cases are different, as shown in Fig. 3

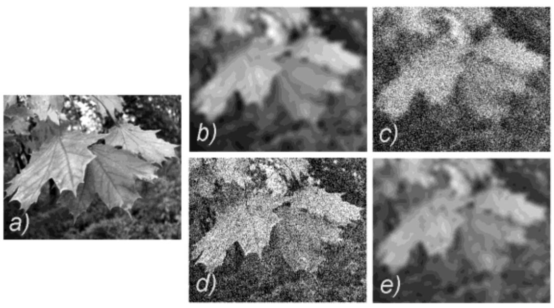

Figure 3. Results of different ways of distorted image formation: a) original image, b) blurring, c) blurring + noise addition, d) noise addition, e) noise addition + blurring effects.

Restoring the original image is evidently more difficult in case c) than in e). Therefore, this type of test was chosen in our experiments. However, in general, the generation of tests should simulate the assumed real image forming process. For testing the power of blurred and noisy image enhancement procedures, the test-cards described in [19] have been additionally affected by artificial distortions consisting of: a) blurring, b) noise addition. For any image enhancement procedure assessment, the number of classes of standard tests should be chosen according to the type of distortions expected to affect the real images in a given application domain.

A. Blurring

The reference sets described in [19] and named: shifted vertical lines (*v*') , shifted horizontal lines (*h*') and shifted checkers (*x*') are blurred in the following way.

1) It is assumed that the blurring effect does not depend on the direction (isotropy) and position (homogeneity) on the test-cards.

2) The blurring effect is described by a set of $(2k+1)\times(2k+1)$ square matrices $\boldsymbol{W}_k$, $k=1,2,\dots,$ called *blurring kernels*; the natural numbers k being called the *blurring ranges*. The blurring kernel has the following form:

$$\boldsymbol{W}_k = \begin{array}{|c|c|c|c|c|c|c|}\hline w_k & w_k & w_k & w_k & w_k & w_k & w_k \\ \hline w_k & \dots & \dots & \dots & \dots & \dots & w_k \\ \hline w_k & \dots & w_1 & w_1 & w_1 & \dots & w_k \\ \hline w_k & \dots & w_1 & w_0 & w_1 & \dots & w_k \\ \hline w_k & \dots & w_1 & w_1 & w_1 & \dots & w_k \\ \hline w_k & \dots & \dots & \dots & \dots & \dots & w_k \\ \hline w_k & w_k & w_k & w_k & w_k & w_k & w_k \\ \hline \end{array} \qquad (1)$$

3) The following model of blurring is assumed: *a*) For any k, the elements $w_0, w_1,\dots, w_k$ called *weight coefficients* are non-negative real numbers surrounding w_0 as shown in (1); and such that $w_0 \geq w_1 \geq \dots \geq w_k \geq 0$; *b)* If n_k, S_k denote, respectively, the number and the sum of weight coefficients w_k in W_k then

$$S_\kappa = \eta \cdot S_{\kappa-1} \qquad (2)$$

for $\kappa = 1,2,3\dots,k$. The coefficient η, $\eta \geq 0$, is called a *blurring level*; it is assumed that $\eta = 0$ in non-blurred basic patterns.

Under such assumptions it can easily be shown that:

$$n_0 = 1,\ n_k = 8k \ \text{ for } k = 1,2,3,\dots; \qquad (3)$$

$$S_k = \frac{w_0(\eta^k - 1)}{\eta - 1} \qquad (4)$$

The coefficient S_k is used to calculate a normalising coefficient:

$$g_k = \frac{1}{S_k} = \frac{\eta - 1}{w_0(\eta^k - 1)} \qquad (5)$$

keeping the mean luminance level unchanged after the blurring operation.

If $\boldsymbol{X} = [\xi_{ij}]$, $i = 1,2,\ldots,I$, $j = 1,2,\ldots,J$ is an $I \times J$ bitmap (i.e. an image-describing matrix whose elements ξ_{ij} denote pixel values) then the elements ζ_{pq}, $p = 1,2,\ldots,I$, $q = 1,2,\ldots,J$ of a blurred image are given by the formula:

$$\zeta_{pq} = \sum_{\{i,j:\gamma(i,j)=0\}}^{k} w_\gamma \cdot \xi_{ij} \tag{6}$$

where $\gamma = \gamma(i,j) = max(|p–i|, |q–j|)$. In other words, for calculation of ζ_{pq} the kernel is imposed on the image $\boldsymbol{X}$ so that the element w_0 matches ξ_{ij} such that $i=p, j=q$; ζ_{pq} is then given as the sum of the ξ_{ij} multiplied by the respective weights w_η. In the calculation, the lacking values of ξ_{ij} (for $i,j < 0$, $i > I$, $j > J$) are set to 0.

B. Noising

Many noise generating programs are included into widely available image processing libraries (viz. Matlab, ImagePro Plus, Corel Photo Paint X4). In our experiments, it was assumed that noise should be spatially uncorrelated and equally distributed with a fixed spatial density d [%] over the image area. Two types of noise intensity probability distribution were taken into consideration: a) Gaussian, b) uniform. In both cases, the mean value of noise intensity equals 0. The intensity of Gaussian noise is described by the variance σ, while in uniform noise by the length ε of interval, both given in % of the total luminance interval equal 256. The resulting signal + noise values are approximated to the nearest integers and are cancelled on the 0 and 255 levels. In Fig. 4, examples of non-blurred noisy "shifted checkers"-type tests are shown. The columns from 1–4 correspond to the increased scale of basic elements: 2, 4, 8 and 16 pixels, the rows correspond to decreased contrast-levels: 0–255, 0–127, 0–63, 0–31, 0–15, 0–7, 0–3, and 0–1. The size of a testing window is thus 64×64, i.e. it contains at least 16 basic windows of 16×16 size. This is important for the testing accuracy evaluation. Fig. 4*a* presents a clear test, Fig 4*b,c* – tests covered by Gaussian noise with 100% spatial density, the noise intensity levels being, respectively, 25% and 50%.

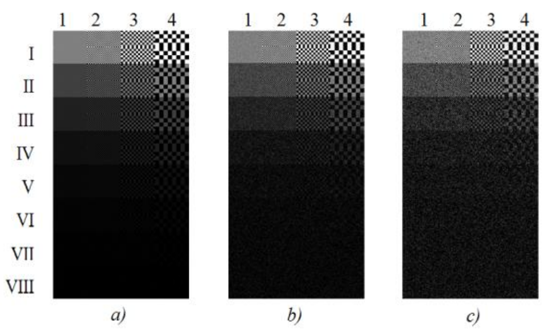

Figure 4. Shifted checkers (x') tests: *a)* clear, *b)* added 25% Gaussian noise, *c)* added 50% Gaussian noise; 100% spatial noise density.

C. Method of testing

The method of testing the image enhancement procedures consists of calculation of strongly defined parameters characterising the difference between some "ideal patterns" and the patterns affected by controlled distortions (i.e. blurring, noise addition), and then subjected to enhancement by the examined procedures. The following parameters are calculated:

a) Primary pattern reconstruction error (*PRE*):

$$d_{x',r,s} = \frac{1}{M}\sum_{\mu=1}^{M} |z_\mu - y_\mu| \tag{7}$$

where M denotes the total number of pixels in a testing window (e.g. M= 32×32=1024); z_μ is a pixel value of a transformed (i.e. distorted and filtered) test; and y_μ is a pixel value of an "ideal" testing image. The primary quality score of a tested procedure depends on the type of the test (which in the experiments described below is limited to the "shifted checkers" denoted by x'), the contrast-level r, and the scale-level s [19].

The secondary pattern reconstruction errors are obtained by averaging (Av) of the primary *PRE* over all testing windows corresponding to the averaging parameters (r, s or both, r and s):

b) Secondary r-independent pattern reconstruction error:

$$G_{x',s} = Av_{(r)}(d_{x',r,s}), \quad r \in [\mathrm{I, II,\ldots, VIII}]. \tag{8}$$

c) Secondary s-independent pattern reconstruction error:

$$G^*_{x',r} = Av_{(s)}(d_{x',r,s}), \quad s \in [1,\ldots,4]. \tag{9}$$

d) Total pattern x' reconstruction error:

$$Q^*_{x'} = Av_{(r,s)}(d_{x',r,s}). \tag{10}$$

The measured *PRE*s are additionally denoted by a subscript q corresponding to the type of image enhancement procedure subjected to examination.

D. Remarks on testing errors

Two basic sources of errors in the testing filters by the aforementioned method should be taken into consideration: 1) border effects and 2) statistical errors.

Border effect errors are caused by the fact that, for shifted filtering procedures, the peripheral data z_m in Equation (4) are incorrectly calculated by capturing some pixel values in the adjacent testing windows. However, this is not the case in covering filtering procedures (like wavelets or *MS* filters), whose testing windows are covered exactly by the basic windows.

In testing the noise-resistance of filters, it should be taken into consideration that the data x_n in Equation (4) are instances of some random values, and so are also the estimates $d_{x',r,s}$, $G_{x',s}$, $G^*_{x',r}$ and $Q^*_{x'}$. Their variances are then inversely proportional to the minimum number M^* of basic windows (characterising a tested filter) totally covering the testing window (e.g. for a Laplace 5×5 filter and 64×64 testing window size $M^* \cong 164$ and this number of statistically independent data should be taken into account in the error of testing evaluation). However, if in this case the testing windows are affected by Gaussian noise with 50% density and 25% intensity then ½ x 164 = 82 testing windows are affected by noise, and its initial intensity will be reduced by $\sqrt{82} \cong 9$ times.

III. Comparative Assessment of Image Enhancement Procedures

The method of image enhancement procedures testing has been proven by numerical experiments consisting in comparative assessment of the quality of a set of typical image enhancement procedures. The following procedures were tested: 1) High-pass edges enhancement filters: Laplace 7x7 and 5x5 pixels, 2) Sobel, 3) Roberts, 4) Canny, 5) Sharpen, 6) Higauss 7x7 pixels, 7) Hipass, 8) Morphological closing with 3x3 structural cross-element, 9) Morphological opening with 3x3 structural cross-element, 10) Top hat 7x7 pixels, 11) Variance, 12) Morphological spectra (*MS2*)-based filters reinforcing the 2nd-order components, as shown in Table 1.

TABLE 1. Weights assigned to the *MS*2 components

\ *MS* comp. Filter \	*SS*	*SV*	*SH*	*SX*	*VS*	*VV*	*VH*	*VX*	*HS*	*HV*	*HH*	*HX*	*XS*	*XV*	*XH*	*XX*
MS2/AA	1.5	6	6	1	6	6	6	1	6	6	6	1	6	6	6	1
MS2/BB	1	1.5	1.5	1	1.5	1.5	1.5	1	1.5	1.5	1.5	1	1.5	1.5	1.5	1
MS2/CC	1	3	3	1	3	3	3	1	3	3	3	1	3	3	3	1
MS2/DD	2	1.5	1.5	1	1.5	1.5	1.5	1	1.5	1.5	1.5	1	1.5	1.5	1.5	1
MS2/EE	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1
MS2/FF	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1
MS2/HH	1	1	1	4	1	1	1	1	1	1	1	1	1	1	1	1
MS2/LL	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1

Roughly speaking, the filters *MS2/AA – DD* with various strengths relatively reinforce the *MS*2 components representing the middle-size elongated structures. Their parameters have been intuitively chosen. The filters *MS2/EE* and *-HH* with various strengths reinforce the component *SX* representing small grains, while *MS2/FF* reinforces the component *XS* representing the middle-size grains.

A similar experiment of comparative assessment of 18 various, linear and nonlinear image enhancement procedures was performed. For this purpose, an *x'*-type test blurred with parameters k=2, η = 0.5 and affected by uniformly distributed additive noise of 50% intensity and 100% spatial density was used. Here, besides seven MS2 linear filters, the Laplace 5×5, Sobel and Roberts filters, Canny, sharpen HiGauss 7×7, Hipass, morphological closing by 3x3 structural cross-element, morphological opening by 3x3 structural cross-element, Top hat 7×7 , and variance procedures were all taken into consideration [1–4,11–13]. The results are shown in Fig.5.

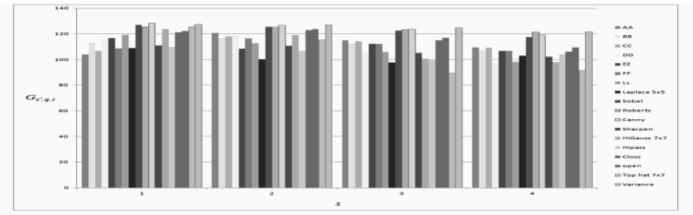

Figure 5. $G_{x',q,s}$-based comparative assessment of 18 image enhancement procedures tested by *x'*-type blurred and noisy tests, as a function of the scale *s* of basic patterns.

It can be remarked that the Laplace 5×5 filter is relatively the most effective in blurry and noisy image enhancement, similar to the HiGauss 7×7 filter. The Sobel, Roberts and Canny procedures are relatively the less effective ones; this is because they are typical contour enhancement procedures. The *MS*2-based filters are placed in the middle of the error-scale; however, they offer great flexibility to be adjusted to a given type of visualised pattern.

IV. Conclusions

Computer-aided image analysis requires preliminary image processing aimed at image contrast reinforcement, removing the effects of blurring and of noise addition. The properties of the procedures should be strongly controlled, independent of a visual control of the quality of the resulting images. For this purpose, a test-based method of image enhancement procedures' quantitative evaluation was proposed in [19]. In this paper, the method has been extended to testing the quality of the procedures used for the enhancement of blurry and noisy images. The proposed testing method makes possible the particular numerical assessment of the quality of linear or nonlinear procedures with respect to various types of basic patterns, contrast levels, scales, various intensities and ranges of blurring; and various types and intensities of additive noise. It also admits a more global assessment of procedures by averaging their particular quality parameters (i.e. pattern reconstruction errors) over the sets of test parameters. The method may be particularly useful in choosing the most effective multi-parameter image enhancement procedures, when the number of possible instances of a procedure is very high and the differences in their quality cannot easily be detected by visual examination of the resulting images. Moreover, the general test-based method can be extended to any other type of noise or blurring. Using the test-based method in the assessment of image enhancement procedures quality seems to be an important step in reducing one of sources of error in computer-aided morphological and/or statistical analysis of images in various experimental domains.

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