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Problems of image restoration in metallography

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Abstract

In optical inspection and in metallography in particular it is necessary to reduce to minimum distortions on an image so to obtain highest possible measurement preciseness measuring object size on its image. One among methods to solve this problem is image restoration.

Difficulty of image restoration is stipulated for following factors:

- PSF of the device is not determined a priori;
- PSF may have complex structure (non-linear and spatially non-invariant).

Regarding to this, the division of image restoration task into several stages, is proposed:

1. Image fragmentation into areas where PSF is linear and spatially invariant
2. PSF estimation in all image areas.
3. Formulation and solution of reverse task of the original image restoration in the proposal that PSF is determined approximately.
4. Image reconstruction (composition).

Difficulties of each stage:

1. Presence of essential geometric distortions. Since the model of distorting system supposed to be linear and pulse characteristic is spatially invariant, so real blurred and, probably, noisy image should have blureness degree uniform within all fragment. By this, the fragment is to include objects with contrast differences of brightness.
2. PSF estimation could be obtained by a priori method (using test body) or aposteriory method (using blurred image). By aposteriory method of PSF determination the main difficulty is the correct choice of PSF restoration window size: at one hand, not more than one border should get into the window, at the other hand, the noise should not cause false border detection.
3. Main difficulty in realization of fragment restoration algorithm is the choice of the inverse problem regularization (IPR) parameter. The procedure of automated selection of IPR parameter by minimum artifacts criteria, is realized.
4. The difficulty of the composition stage is the necessity of restoration of fragment size upto initial, as well as exclusion of visible borders between fragments. This task is solved by addition of compensation frames to each fragment.

All algorithms described are realized in MatLab environment.

keywords: optical inspection , metallography, Sufficient geometric distortions, fragment restoration algorithm

Introduction

In order to obtain highest possible measurement preciseness measuring object size on its image, the image distortion is to be minimized. It is an important task in optical inspection when applying portable complexes for metallographic analysis. Digital image restoration (or, more closely, digital restoration of an image) is one among methods to solve this problem.

In the paper presented, the image restoration algorithm developed by authors, and main difficulties arising by its software realization, are described.

1. Mathematical model of optical electronic imaging system.

The construction of mathematical model of optical electronic system bringing distortions into images obtained, is the first important stage of image restoration. Main elements of real optical electronic imaging system (OEIS) of portable complexes for metallographic analysis, are: microscope, digital video- or photocamera, and the computer with imaging/analyzing software installed. Each of elements listed is the block that performs some conversion of an input image into the output one. Generalized model of OEIS could be presented as block diagram as shown on Fig.1. Mathematical model of such imaging system is described by equations relating inputs and outputs for all elements.

Fig. 1. Structural diagram of the generalized model of imaging system

On Fig.1 $G(\alpha,\beta)$ is object brightness distribution on the surface under inspection, $F_R^0(x,y)$ - is brightness distribution in the image, $F_R^{Э}(x,y)$ is the charge distribution on image sensor, and $F_R(m_1,m_2)$ is real digital image.

The image restoration algorithm presented in the given paper is based on the assumption that real optical system is linear with spatially invariant pulse characteristic (point scatter function, PSF). This condition could be provided by image fragmentation. Relation between functions described above, could be presented as:

$$F_R^0(x,y) = \iint H(x-\xi, y-\eta) G(\xi,\eta) d\xi d\eta ,$$

where $H(x,y)$ is the pulse characteristic of the optical, $\xi = M\alpha$, $\eta = M\beta$, M is the scale factor of the optical system;

$$F_R^{Э}(x,y) = Q\{F_R^0, x, y\} ,$$

where $Q\{\cdot\}$ is the generalized transfer function of optical-to-electric signal converter, this conversion is understood as element-by-element,

$$F_R^P(m_1,m_2) = \iint F_R^{Э}(\xi,\eta) P(\xi - m_1\Delta x, \eta - m_2\Delta y) d\xi d\eta ,$$
$$F_R(m_1,m_2) = IK\{F_R^P(m_1,m_2)\} ,$$

where first equation represents image spatial discretization process, $\Delta x, \Delta y$ are discretization intervals, $P(x,y)$ discretization pulse form, $IK\{\cdot\}$ is the generalized transfer function of element-by-element sampling.

For image restoration, in the given paper it is proposed to use the mathematical model of digital distorting system (Fig.2), establishing quantitative correlations between samples of the obtained $F_R(m_1,m_2)$ and initial $F_I(m_1,m_2)$ images.

Fig. 2. Model of digital distorting system

Assuming that the distorting system is linear and spatially invariant, we define the ratio between its input and output with the equation of 2D-convolution

$$F_R(m_1,m_2) = \sum_{n_1}\sum_{n_2} h(m_1 - n_1, m_2 - n_2) F_I(n_1,n_2), \quad (1)$$

where $h(i, j)$ is the pulse characteristic of the system (PSF), by this $\sum_{i,j} h(i, j) = 1$. Thus, the problem of digital image restoration comes to the inverse of the digital distorting system (1).

2. Algorithm of image restoration.

Image restoration process includes following main steps:

1. Fragmentation of an image to the areas of linearity and spatial invariance of PSF.
2. Estimation of PSF at each image fragment.
3. Formulation and solution of the inverse task of initial image restoration by the assumption that PSF is determined approximately.
4. Image recomposition.

3. Estimation of distorting system PSF a posteriori.

The estimation of system PSF is carried out using point or linear lengthy objects. Borders of metal grains are the objects of such kind. Following steps are assumed by PSF restoration process:

1. Spatial differentiation of the initial image and construction of gradient image.
2. Detection of points corresponding to extremal gradient values.
3. Detection of directions of maximum brightness differences in the neighbourhood of points detected (neighbourhood size is the parameter of PSF restoration algorithm)
4. Construction of line spread function (LSF) for directions found in given neighbourhoods.
5. Averaging of LSF.
6. Differentiation of averaged LSF.
7. Reconstruction of PSF by LSF derivative considering circle symmetry of PSF.

4. Problems arising by PSF restoration.

Experiments showed following main problems by PSF restoration.

1. In case if neighborhood in which PSF is determined, is chosen too big (or there is noise in central point of neighborhood, but object edge is absent), the distribution of maximum brightness differences could be non-monotonous. Theoretically it should be strictly increasing with inflection point in the line segment centre. As the result, its derivative will take on negative values, and therefore PSF will also be negative in some points, which brings significant error in restoration process.
2. Maximum gradients, by which average value of brightness distribution is determined, could fall onto same line segment (i.e. there is a superposition of these elements' windows and coincidence of maximum brightness difference directions). This also brings errors into PSF restoration process.

5. Algorithms for error reduction by PSF restoration.

Two approaches are proposed to compensate influence of negative factors described in p.1 above. The first one is based on that gradients with non-monotonous brightness distribution in its neighborhood, are discarded. If all maximum gradients are discarded, the neighbourhood in which PSF is restored, should be reduced. The second one is based on that negative values of brightness distribution derivative are replaced with zero values, and then PSF is restored.

So to avoid negative factors described in p.2 above, a special algorithm was developed. The algorithm checks if two gradients by which PSF is restored, would not fall on parallel and crossing line segments.

6. Digital image restoration algorithm.

Developed methods to compensate distortions caused by optical-electronic system, are based on Tikhonov method of regularization for incorrect task solution.

Proposed inverse task solution algorithm assumes following main steps.

1. Extension of restoration area up to the size of the carrier of system pulse characteristic.

2. The transfer function of the restoration filter is chosen in following form:

$$h_{в}^{\alpha}(u,v)=\frac{h^{*}(u,v)}{|h(u,v)|^{2}+\alpha Q(u,v)},$$

where α is regularization parameter, $h(u,v)$ and $Q(u,v)$ are obtained as the result of application of discrete Fourier transform to the pulse characteristic of the system, and to the stabilizer.

$$h(u,v)=\sum\sum h(i,k)\exp(-\frac{2\pi j}{N}(ui+vk)),$$
$$Q(u,v)=\sum\sum Q(i,k)\exp(-\frac{2\pi j}{N}(ui+vk)).$$

Stabilizer $Q(u,v)$ is sectionally continuous non-negative even function, by that:

a) $Q(u,v)>0$ by $(u,v)\neq 0$, $Q(0,0)\geq 0$;

b) by $|u|,|v|$ big enough $Q(u,v)\geq C>0$ (C is the constant);

c) for each $\alpha>0$ the transfer function of the restoration filter is the function with integrable square.

3. Regularized solution of the equation of convolution type is determined using:

$$G_{\alpha}(u,v)=\frac{1}{N^{2}}\sum\sum\frac{h^{*}(u,v)}{|h(u,v)|^{2}+\alpha Q(u,v)}F(u,v)\exp(\frac{2\pi j}{N}(ui+vk)),$$

4. The algorithm for search of optimal regularization parameter α is used.

7. Difficulties arising out of digital image restoration and methods of its solution.

There are following problems arising by numeric realization of image restoration algorithms.

1. Sufficient non-recoverable errors appear on the border of the area restored (Fig.3) in connection with that the function $F(m_1,m_2)$, which sets digital image, is defined on the limited area (square or rectangle). So to reduce restoration errors on image borders, the area

restored could be extended to the size of local carrier of convolution kernel (PSF). It's always possible because estimation of unknown PSF is the preliminary step of image restoration. After extension of restoration area the solution is searched within all extended area, and border effects appear on in extension zone. Fig.4 shows the result of restoration algorithm application with preliminary extensuion of restoration area (for elimination of stripes at the borders of restored image).

2. Since the image obtained with portable optic microscope has different blureness in the center and near edges, the image is to be fragmented to areas of uniformity of blureness degree, in which PSF spatially invariant. Restoration algorithms are applied in each area separately. The difficulty arising by such approach to image restoration, is in subsequent image assembling. So to avoid distortions at edges it is necessary to extend restoration area. One of the approaches to solve this task, is in following: the image is fragmented to square areas of PSF uniformity; each area is extended up to size of PSF carrier with black compensation frame. Then the restoration algorithm is applied; as the result the given image area can displace and loose symmetry relatively to the frame. So to assemble restored areas it is necessary to apply frame removal algorithms for each area. Frame removal procedure can be based on statistic algorithms of image border search.

Fig. 3. Left to right: initial image, "defocused" (blurred) image, restored image

Fig. 4. Image restoration with preliminary extension of restoration area. Left to right: initial image, "defocused" (blurred) image, and restored image

3. As it is known, the preciseness of PSF estimation on defocused image depends strongly on quality of brightness differences "object-background". Therefore, in case of low-contrast image PSF could be restored with big errors. To avoid this, it is proposed to use defocused image of test body (micrometric ruler, etc.) with big enough contrast differences for PSF estimation (Fig.5).

Fig.5. Left – initial image of test body, right – "defocused" image of the same test-body

4. Automation is important when realizing algorithms of image restoration in optical inspection. Following problem was solved regarding to this. Application of Tikhonov's method of regularization to inverse tack solution comes to the construction of regularizing operator sequence, depending on some parameter. One of restoration difficulties is in selection of optimal regularization parameter providing best possible restoration. To solve this problem, special test body for which regularization parameter selection is easy, is proposed for use.

8. Automation of digital image restoration algorithm.

For automation of the process of optimal regularization parameter selection, different test bodies were researched. It is established that optimum result is obtained using test image of square with upper white and lower black halves (Fig. 6). This test image is distorted with PSF identified using initial image, and then restored in parallel with initial image.

The algorithm of automatic regularization parameter selection (ARPS) is based on more clear appearing of stripe-shape structure on test image. It allowed to develop automatic ARPS detecting the moment the stripes begin to appear on image borders and selecting regularization parameter by these conditions.

Fig. 6. Test image for stripe-shape structure detection

On Fig. 6 the sequence of test images obtained after algorithms application, is shown. On Fig.7 the sequence of images restored with algorithm of automatic restoration by different regularization parameters. The interval of α parameter was chosen between 10^{-8} and 10^{-15}. $\alpha = 7{,}9 \cdot 10^{-11}$ and $\alpha = 7{,}9 \cdot 10^{-12}$ were selected as optimal parameter values as algorithm was applied (on Fig. 7 - images 2 and 3).

Fig.6. Change of test image by regularization parameter variation

Fig. 7. The example of image restoration using algorithm for automatic selection of optimal regularization parameter.

Conclusions.

Numeric results of the application of developed algorithms for restoration of defocused and noised images obtained at the output of optical-electronic system, allow to make following conclusions.

1. The algorithm for automatic selection of optimal regularization parameter demonstrated high effectiveness by Tikhonov's method application. The test image was very useful in this case.
2. Proposed algorithms increase measurement preciseness for 6-10% in average.

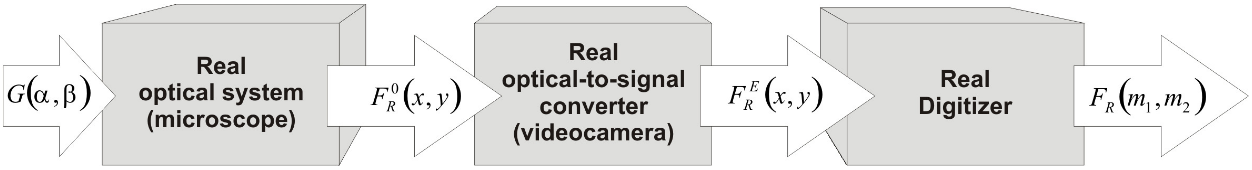


Fig. 1. Structural diagram of the generalized model of imaging system

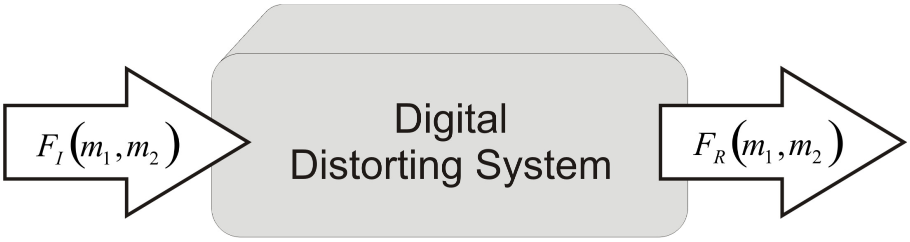


Fig. 2. Model of digital distorting system

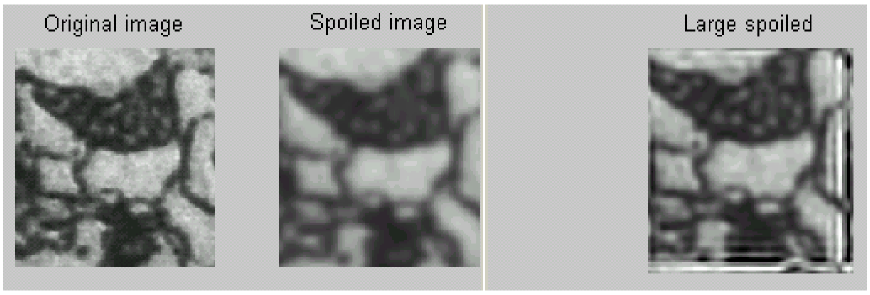


Fig. 3. Left to right: initial image, "defocused" (blurred) image, restored image

Fig. 4. Image restoration with preliminary extension of restoration area. Left to right: initial image, "defocused" (blurred) image, and restored image

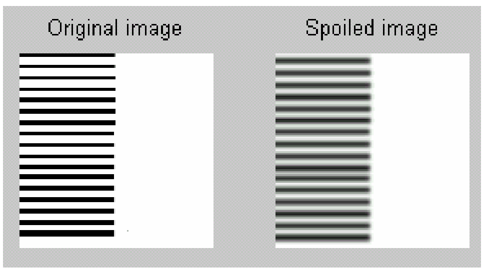
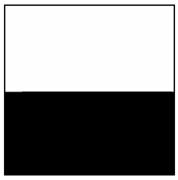


Fig.5. Left – initial image of test body, right – "defocused" image of the same test-body



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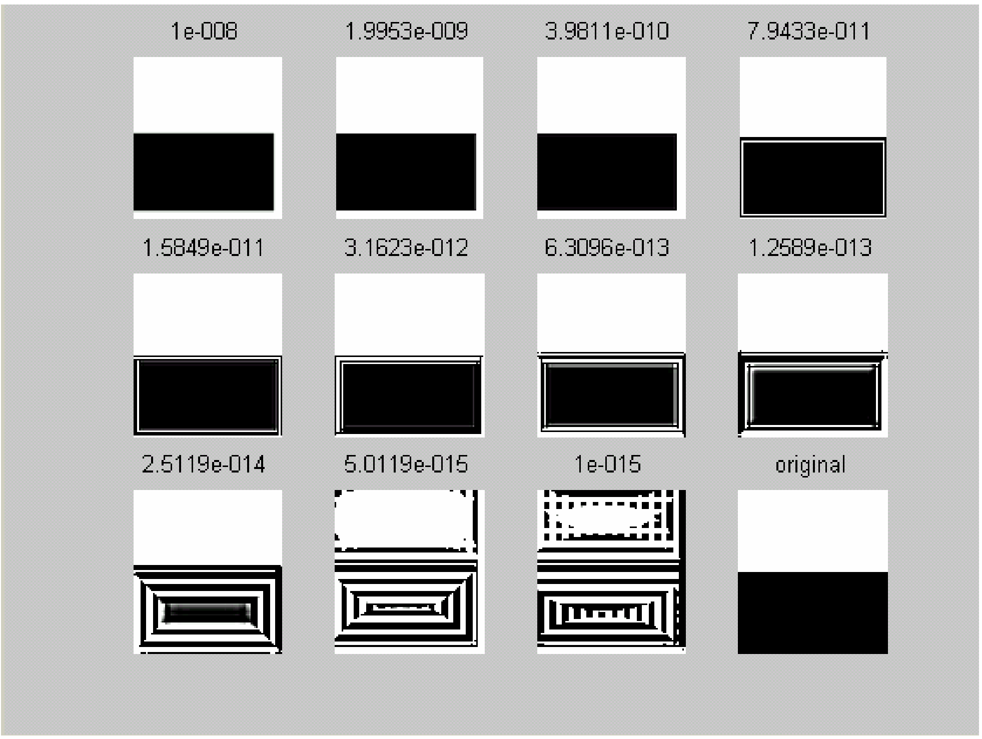

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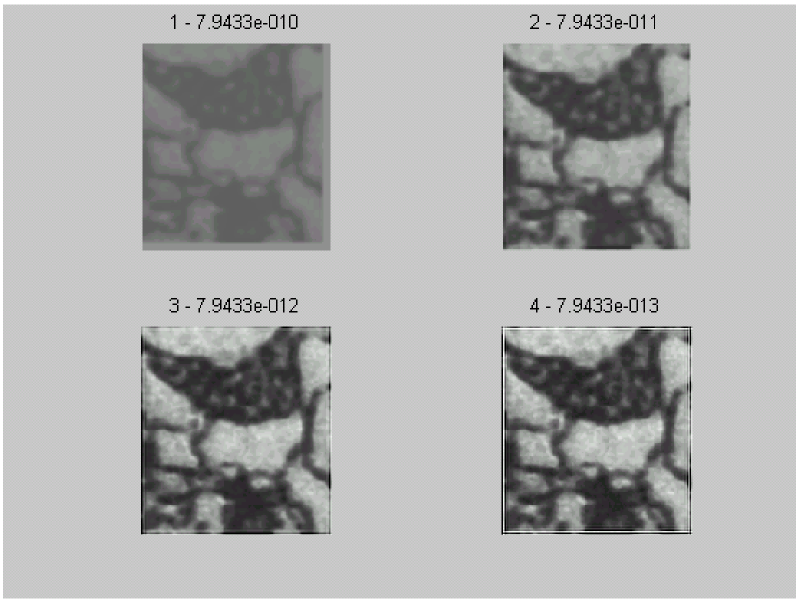

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