НЕЙРОІНФОРМАТИКА ТА ІНТЕЛЕКТУАЛЬНІ СИСТЕМИ

НЕЙРОИНФОРМАТИКА И ИНТЕЛЛЕКТУАЛЬНЫЕ СИСТЕМЫ

NEUROINFORMATICS AND INTELLIGENT SYSTEMS

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NOISY DISTORTED IMAGES RECOVERY USING BLIND DECONVOLUTION

The problem of noisy and linearly distorted images recovery is considered. For the solving the blind deconvolution method is proposed. This method ensures contour preservation and high quality of restoration.

Keywords: color images, deconvolution, linear distortions, disturbance, contours.

INTRODUCTION

The practice of preparing printing of publications involves the processing of a variety of images. These images may be distorted due to the conditions of photographing (motion effects, defocus, low light), or because of improperly selected digitization modes. Traditional methods for improving such defects use a variety of digital filters and ways to correct the brightness, contrast and sharpness, which are implemented in popular graphics packages. This approach to the problem of image enhancement based on heuristics, which result depends on the characteristics of human visual perception.

In contrast to enhancement, image reconstruction is based on the modeling of the distortion and the use of inverse models to restore the original image – this approach is also called deconvolution. Restoration can be done if you know the operator of distortion, or if it is not known («blind deconvolution») [1, 2]. Spatial distortion operator is often called the point spread function (PSF).

Deconvolution methods with a known distortion operator are very sensitive to differences between the model and the real distortion. Moreover, the effectiveness of such methods is greatly reduced in the presence of noise, which only increases the discrepancy.

However, in practice, the distortion operator is rarely known, especially in the printing industry. In general, the reconstruction problem is very ill-defined – in fact there are an infinite number of solutions corresponding to the possible combinations of «distortion + noise». The developed models describe the distortion rather limited cases characterized by a small number of parameters, and do not allow us to formulate a more general description. For example, to model the defocus function is typically used with a uniform intensity distribution in a circle of a given radius, to model the blurring – function with the intensity distribution along a line segment of fixed length and location [3, 4], although the actual distortions are more complex, they often described by more complex dispersion functions, and are usually accompanied by noisy.

To solve these problems methods using several predefined point spread function [5, 6] were developed. Some methods are based on the idea total variance (TV) reducing – for the regularization of ill-posed problems [7]. This idea reflects the fact of the presence of several types of areas on the images that can be distinguished by the variance – is of textures, borders and smooth changes tone, because the action of recovery methods to these areas is different.

STATEMENT OF THE PROBLEM

Task of the image restoring can be viewed as a special case of the variational problem for changes in space variables. When you move the operator along of the image plane processed neighborhood differ in the brightness level and the deviation between the calculated value and the measured (or given) brightness in the image should be minimum by the norm

$$L(f,x)=S(x)=\left\|f(x)-g(x)\right\|_n, \qquad (1)$$

here $f(x)$ – the original image, $g(x)$ – measured distorted image, and for the deviation estimates is most often used rule which leads to the least squares method. $L(f,x)$ – function, which depends on the original image, the spatial coordinates x and their possible changes. In the L_2 case the formulation (1) includes only the similarity term

$$S(f,x,t)=\left\|f\nabla g-g_t\right\|_2, \text{ where } g_t=\frac{\partial g}{\partial t}. \qquad (2)$$

The motion of the operator on the image plane also occurs in time, and changes in brightness are some indissoluble process, also called optical flow. Properties of the flow are described by the brightness continuity equation [2]

$$f(x,t)\nabla g(x,t)+g_t(x,t)=0. \qquad (3)$$

Obviously, the first term – a member of the optical flow similarity, can not be determined, when the spatial gradient is equal to zero (in areas with constant brightness), so that the function (1) is required to add another regularizing term that depends on the spatial derivative:

$$L(f,\nabla f,x)=S(f,x)+R(f,\nabla f,x). \qquad (4)$$

One possible regularizer is a smoothness parameter. If the brightness of pixels varies strongly in one direction, the similarity will be the dominant term of the smoothness term, and vice versa – when little change in intensity occures, smoothness term becomes dominant. In areas of contours derivatives became discontinuous, so the restriction of smoothness (3) is not uniform. This heterogeneity may be modeled by the modified smoothness term.

At the points of image heterogeneity the smoothness constraint may be weak or disappear. Modified smoothness term should include the control function, which disables the restriction on the smoothness in the relevant conditions. One approach to such modification is presented in [6], where the construction of the regularizer used a set of contour detectors d_Θ. The outputs of these detectors are formed in accordance with the expression

$$y_\Theta(x)=d_\Theta * x, \qquad (5)$$

the result of their joint action:

$$f_\Theta(x)=\sqrt{\sum_{\theta\in\Theta} y_\theta(x)^2}, \qquad (6)$$

(here Θ – the set of detectors orientations). Then a regularized term of equation (4) becomes:

$$R(x)=\lambda\sum_i\left(\left[f_{\theta i}(x)+\varepsilon\right]^q\right), \qquad (7)$$

where ε – a small parameter for finding the filter's result in the zero neighborhood, λ – regularization parameter. As a result of the iterative image reconstruction procedure a regularizer takes the form shown in Fig. 1.

Such regularizer allows to modify the smoothness term of constraints (3) depending on the type of the image, but the function (7) has a fundamental defect – its derivative has a discontinuity at $f_{\theta i}=0$, and in the rest of the domain the derivative can be calculated only by numerical methods iteratively with the transform to the frequency domain and back. All these factors seriously slow down the action even considered regularizer estimated its authors.

The aim of this work is to develop a method for blind deconvolution of color digital images in the presence of linear distortion and noise, with maximum preservation of contours, textures and smooth tone gradations for on-line image processing.

BLIND DECONVOLUTION METHOD

In the restoration problem for modeling distortions use

$$g(x)=f(x)*h(x)+\xi(x), \qquad (8)$$

where $h(x)$ – the point spread function modeling the distortion, $\xi(x)$ – additive noise.

The proposed method finds a local minimum of

$$C(x,h)=\frac{1}{2}\left\|g(x)-f(x)*h(x)\right\|_2+\frac{1}{2}\rho R(x), \qquad (9)$$

where $R(x)$ – regularizing function providing contour strengthening in images without affecting the smooth tonal

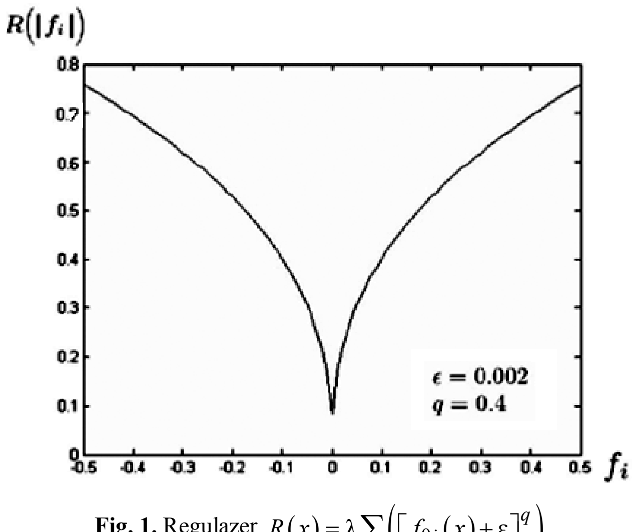

Fig. 1. Regulazer $R(x)=\lambda\sum_i\left(\left[f_{\theta i}(x)+\varepsilon\right]^q\right)$

area. We propose to use a term based on the Cauchy function:

$$R(x)=1-\frac{1}{1+\frac{x^2}{\sigma^2}}=\frac{x^2}{x^2+\sigma^2}. \qquad (10)$$

Here σ – the width function parameter. The graph of this function is shown in Fig. 2.

In this case, the objective function becomes:

$$C(x,h)=\frac{1}{2}\left\|g(x)-f(x)*h(x)\right\|_2+\frac{1}{2}\rho\frac{\|h\|_2}{\|h\|_2+\sigma^2}. \qquad (11)$$

Minimization of this function is associated with the solution of the equation

$$\nabla C_h=-\left(g-h^T f\right)f+\rho\frac{dR}{dh}=0, \qquad (12)$$

that allows to enter a recursive algorithm for distorting operator estimating in the form:

$$\begin{cases} h(k+1)=h(k)+\eta(k+1)\left(g(k+1)-h^T(k)f(k+1)\right)f(k)+\\ \qquad +\rho\frac{\sigma^2}{\left(\|h(k)\|^2+\sigma^2\right)}h(k)=0,\\ g(k+1)=h^T(k)f(k+1), \end{cases} \qquad (13)$$

where $\eta(k)$ – learning step parameter, $g(k)$ – image estimation after deconvolution, k – number of iteration step.

EXPERIMENTAL RESULTS

The task of deblurring the image differs from the usual task of improving that the quality of solutions to be evaluated objectively. Using the quadratic error as a measure of quality is not justified – the error is calculated in the color space RGB, do not reflect the features of the non-linearity of human visual perception. For this reason, there are cases when filtering methods or recovery, providing the minimum mean square error, do not allow to get an image that is acceptable from a visual point of view.

In this problem, apply assessment increase the signal / noise ratio (increase in signal to noise ratio – ISNR) [6]:

$$ISNR=10\log_{10}\frac{\sum_i\left(y_i-x_{0i}\right)^2}{\sum_i\left(x_i-x_{0i}\right)^2}, \qquad (14)$$

where x_0 – the original image, y – distorted, x – restored, i – pixel number.

Feature of such quality measure is the need for an uncorrupted image. Under this conditions the experiment includes the step for forming blur and noise with the specified parameters. Model image includes extensive flat areas and areas of sharp tone gradations (Fig. 3).

For the blur modeling used the point spread function as a disk with radius of 16 pixels, a two-dimensional Gaussian function blur with radius of 10 pixels, the scattering function as a segment length of 20 pixels to simulate motion blur. Noise component is modeled by Gaussian and Poisson noise:

– distortion 1 – Gaussian Blur, Gaussian noise with $\mu=0$, $\sigma=0{,}005$;

– distortion 2 – Gaussian Blur, Gaussian noise with $\mu=0{,}2$, $\sigma=0{,}005$;

– distortion 3 – blur with distorting operator as a disk with a Gaussian noise $\mu=0{,}2$, $\sigma=0{,}01$;

– distortion of 4 – motion blur, Poisson noise with $\alpha=0{,}1$.

The method effectiveness was compared with the standard methods: regularization by the least squares method, Lucy-Richardson method, maximum likelihood blind deconvolution, deconvolution with the Wiener filter. Distortion parameters, models, and the results of the deconvolution using the proposed and standard methods are given in Table 1.

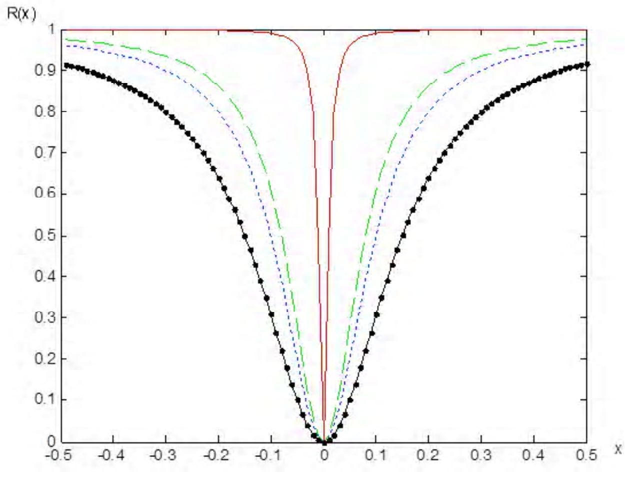

Fig. 2. Graph of the function $R(x)=\frac{x^2}{x^2+\sigma^2}$. The solid line shows the graph for σ = 0,01, long dashed lines – to σ = 0,08; short dotted line – to σ = 0,1, dot-dash – to σ = 0,15

Fig. 3. Model picture

Table 1. The parameters of distortion and noise, and the results of the deconvolution

Deconvolution method	Deconvolution method error, ISNR			
	Distortion 1	Distortion 2	Distortion 3	Distortion 4
Предложенный метод	4,5456	0,2065	0,2556	5,7870
Regularization by the least squares method	22,0797	3,1352	3,1872	22,8988
Lucy-Richardson method	5,9725	14,4450	13,7564	7,4408
Maximum likelihood blind deconvolution	5,9643	14,4152	13,5574	7,5277
Deconvolution with the Wiener filter	5,2415	1,8289	3,5633	19,4166

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ВОССТАНОВЛЕНИЕ ИСКАЖЕННЫХ ЗАШУМЛЕННЫХ ИЗОБРАЖЕНИЙ С ПОМОЩЬЮ СЛЕПОЙ ДЕКОНВОЛЮЦИИ

Рассмотрена проблема восстановления изображений, подверженных действию шума и линейных искажений. Для решения предложен метод слепой деконволюции, который обеспечивает сохранность контуров при высоком качестве восстановления.

Ключевые слова: цветные изображения, деконволюция, линейные искажения, помеха, контуры.

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ВІДНОВЛЕННЯ ВИКРИВЛЕНИХ ЗАШУМЛЕНИХ ЗОБРАЖЕНЬ ЗА ДОПОМОГОЮ СЛІПОЇ ДЕКОНВОЛЮЦІЇ

Розглянуто проблему відновлення зображень, що зазнають дії шума та лінійних викривлень. Для вирішення запропоновано метод сліпої деконволюції, який забезпечує збереження контурів разом з високою якістю відновлення.

Ключові слова: кольорові зображення, деконволюція, лінійні викривлення, завада, контури.

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