Type of Blur and Blur Parameters Identification Using Neural Network and its Application to Image Restoration

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ABSTRACT

The original solution of the blur and blur parameters identification problem is presented in this paper. A neural network based on multi-valued neurons is used for the blur and blur parameters identification. It is shown that using simple single-layered neural network it is possible to identify the type of the distorting operator. Four types of blur are considered: defocus, rectangular, motion and Gaussian ones. The parameters of the corresponding operator are identified using a similar neural network. After a type of blur and its parameters identification the image can be restored using several kinds of methods.

Keywords: Neural network, image restoration frequency domain

1. Introduction

As a rule, blur is a form of bandwidth reduction of an ideal image owing to the imperfect image formation process. It can be caused by relative motion between the camera and the original scene, or by an optical system that is out of focus. Today there are different techniques available for solving of the restoration problem including Fourier domain techniques, regularization methods, recursive and iterative filters [1, 2]. All of the existing techniques are directed to the obtaining of a solution for the deconvolution problem. A problem is that without a good estimation of the blur parameters these filters show poor results. If incorrect blur model is chosen then the image will be rather distorted much more than restored. Many of different algorithms for blur identification and identification of its parameters exist today, for

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example, the maximum likelihood blur estimation or regularization approach [3]. The disadvantage of these algorithms is their computing complexity and relatively high level of the misidentification.

In this paper we would like to present an original solution of this problem. The background for our solution is based on the learning of the specific distortions that are implied by the distorting operator in the Fourier spectrum amplitude. To identify the distorting operator, its mathematical model and its parameters, we will consider this problem as a problem of pattern recognition.

To solve the classification problem, we will use a neural network based on multi-valued neurons (MVN) [4]. It will be used for the recognition (identification) of the distorting operator or kind of blur. A similar MVN-based neural network will be used to recognize the corresponding distorting operator parameters. The multi-valued neurons have many wonderful properties. The most important of them are a high functionality and simplicity of learning.

We will consider here the classification for the four types of blur: defocus, rectangular, motion and Gaussian ones. The preliminary results for the blur and type of blur identification problem have been presented in [5], but just motion and Gaussian blur have been considered. In this paper we present the results of a significant development of the approach presented in [5].

After a type of blur and its parameters identification the image can be restored using several kinds of methods. Some fundamentals of image restoration will be considered. The image restoration (using the information obtained by the neural network) by Tikhonov regularization will be presented.

2. Multi-valued neuron and its learning

As it was mentioned above, we will use a neural network based on multi-valued neurons (MVN) for the blur and blur parameters identification. Let us consider some fundamentals of MVN, its learning and networks based on it.

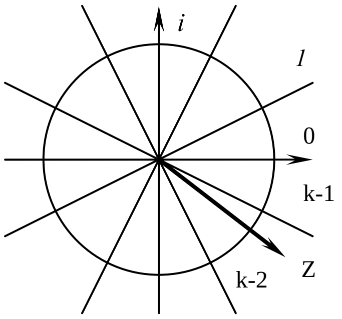
MVN has been deeply considered in [4]. MVN performs a mapping between n inputs and a single output. The mapping is described by multiple-valued (k-valued) function of n variables $f(x_1, \ldots, x_n)$ via their representation through n+1 complex-valued weights $w_0, w_1, \ldots, w_n$:

$$f(x_1, \ldots, x_n) = P(w_0 + w_1 x_1 + \ldots + w_n x_n) \tag{1}$$

where $x_1, \ldots, x_n$ are variables, on which the performed function depends. Values of the function and of the variables are k^{th} roots of unity: $\varepsilon^j = \exp(i2\pi j/k)$, $j \in \{0, k\text{-}1\}$, i is an imaginary unity. P is the activation function of the neuron:

$$P(z) = \exp(i2\pi j/k), \ if \ 2\pi j/k \le \arg(z) < 2\pi\,(j+1)/k \tag{2}$$

where j=0, 1, ..., k-1 are values of the k-valued logic, $z = w_0 + w_1 x_1 + \ldots + w_n x_n$ is the weighted sum , arg(z) is the argument of the complex number z. The equation (2) is illustrated in Fig. 1.



$$P(z) = \varepsilon^{k\text{-}2}$$

Fig. 1. Definition of the MVN activation function. If the weighted sum is equal to z then the output is equal to $\varepsilon^{k\text{-}2}$

For MVN, which performs a mapping described by the k-valued function, we have exactly k domains. Geometrically they are the sectors on the complex plane (Fig. 1).

The MVN learning is based on the same background as the perceptron learning. It means that if the weighted sum is going to the "incorrect" domain then the weights might be corrected in some way to direct the weighted sum into the correct domain. Let us consider this process in the details. If the desired output of MVN on some element from the learning set is equal to ε^q then the weighted sum should belong exactly to the sector number q. If the actual output is equal to ε^s, it means that the weighted sum belongs to the sector number s. A learning rule should correct the weights to move the weighted sum from the sector number s to the sector number q. The following correction rule for learning of the MVN has been proposed [4]:

$$W_{m+1} = W_m + C_m (\varepsilon^q - \varepsilon^s)\ \overline{X}\ , \tag{3}$$

where W_m and W_{m+1} are the current and the next weighting vectors, $\overline{X}$ is the complex-conjugated vector of the neuron's input signals, C_m is the scale coefficient.

Learning algorithm, which is based on the rule (3) is very quickly converging.

3. MVN-based neural network and its application to the blur identification

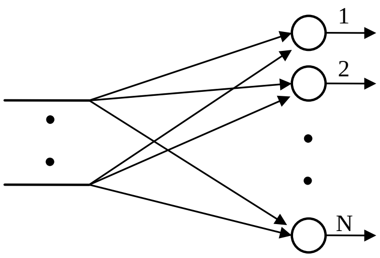
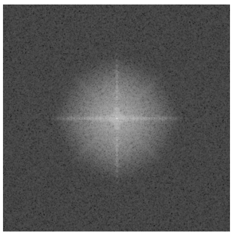


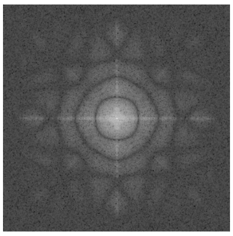
Fig. 2. MVN based neural network for pattern recognition

We will use here a single-layered MVN-based neural network, which contains the same number of neurons as a number of classes we have to classify (Fig.2). An idea of this network has been proposed in [4]. Each neuron has to recognize pattern belonging to its class and to reject any pattern from any other class.

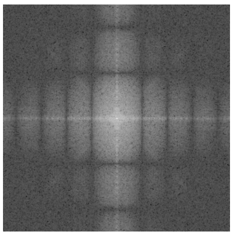
Any blur leads to the specific distortion of the image Fourier spectrum amplitude. The amplitude "disappears" in some areas. A character of this disappearance is very specific for the different types of blur (Fig. 3 illustrates this important property). Thus the Fourier spectrum amplitude contains the important information about the signal properties (existence and character of the blur, in particular). This means that it is possible to use this property for the blur and its parameters identification. A neural network has to be taught to distinguish a specific behavior corresponding to each type of blur independently on the particular image.



(a) Gaussian blur, var=4



(b) Defocus blur, r=6



(c) Rectangular blur 8x4

Fig. 3. Fourier spectrum amplitude's distortion implied by the different blurs

To organize the learning process for the network, the following reservations of the domains has been used. The output values 0,..., $k/2$-1 of the i^{th} neuron correspond to the classification of object as belonging to i^{th} class. The output values l,..., k-1 correspond to the classification of object as rejected for the given neuron and class (k is taken from (2)). To prepare the data for the learning and further recognition we used the normalization procedure based on the logarithmic quantization.

To test abilities of the blur and blur parameters identification, we used four kinds of blur: Gaussian, Defocus, 1D horizontal motion and rectangular ones. The images of different nature have been used: landscapes, satellite optical images, face images. The images were blurred by the mentioned blurs with the different parameters. To make our model more realistic, we corrupted the images by zero-mean Gaussian noise with the dispersion 0.3σ.

For the blur identification 140 images have been taken. Since a spectrum amplitude behavior for the rectangular and defocus blurs is often very similar, we use two-stage blur identification. Three classes have been considered on the first stage: Gaussian, 1D motion, Rectangular/Defocus. The testing results are very good: 95-97% of the correct identification. If the corresponding blur was classified as "Rectangular/Defocus", we used additional single-layered neural network of two neurons to identify if it is rectangular or defocus. For the 94% of the images the identification is correct. The rest of 6% corresponds to defocus with a small radius (4) and the rectangular blur 1x1.

For blur parameters recognition 25 classes with different rectangular blurs were created. Steps for rectangular blur parameters are equal to 2 pixels in both directions (i.e. 1x1, 1x3, …, 1x5, 3x1, …, 3x5, …. 5x5). These 25 classes contain 500 images in the testing set (20 per class), and 12 images per class in the learning set, which is 300 images. To test the Gaussian blur variance identification 5 classes were distinguished (variance 1 to 5, 200 images per class). Respectively, the defocus blur radius identification has been tested for the 15 classes (radius from 2 to 16, 500 images per class), 1D horizontal motion blur has been tested for the 16 classes (motion from 3 up to 18 pixels).

As the result, a recognition rate for the parameters identification is: for the Gaussian Blur 93.5% successful, for the defocus blur 94.1% successful, for the motion blur 98.1% successful and for the rectangular blur 95.6% successful.

4. General approach to the restoration problem

The image restoration problem is usually formulated the obtaining of the non-distorted image $z(\zeta,\eta)$ from the given equation:

$$Az + n = u(x, y) + n(x, y) = \tilde{u}(x, y)\,, \qquad (x, y) \in W, \tag{4}$$

where $A : Z \rightarrow U$ (*Z, U* –metric spaces) is a given linear or nonlinear operator, $z \in Z$, $u \in U$, $n(x, y)$ is a noise, $\tilde{u}(x, y)$ is an output distorted image.

It is evident that whatever method we use to obtain the restored image, it must comply in a certain way with the basic equation (4). So the most general formulation of the restoration problem can be reduced to the following functional's minimization:

$$z^* = \inf_{z \in Z} \rho_U (Az, \tilde{u})\,, \tag{5}$$

where ρ_U is a certain metric in *U*. In general it is possible to use different definitions of a distance ρ_U between two images.

The simplest way to guarantee the uniqueness and stability of the solution is to formulate "a priory" information about the original image using a functional $\Omega(z)$ that possesses stabilizing properties [6]. In this case the image restoration problem can be reduced to the conditional or unconditional optimization problem, in particular to the Tikhonov minimization [2]:

$$z^* = \inf_{z \in Z} \{\rho_U (Az, \tilde{u}) + \alpha\Omega(z)\}\,, \tag{6}$$

where α is the parameter of the regularization. Usually it is assumed that the original image is a smooth function with respect to Sobolev space, and stabilization functional in (6) is $\Omega(z) = \|z\|^q_{W^p_q}$. It is necessary to point out that the opportunity of obtaining a family of solutions that depend on a parameter α is very important. This allows us to control the visual quality of the image restoration interactively in the absence of a mathematical criterion of visual image quality.

5. Simulation results

To identify a type of blur and then to identify its parameters we used the neural network and the algorithm presented here. Then the images have been restored using the Tikhonov's regularization.

Let us consider the restoration example of the originally (optically) blurred image taken by the digital camera on the street (Fig.3). This image didn't participate in the learning process of the neural network. The blur on the image has been identified as motion with parameter 6 (in every color channel). Tikhonov's filter has been used for the restoration

(a) The original blurred image (b) The restoration result.

Fig. 3. Restoration of the originally (optically) blurred image.

6. Conclusions and future work

The main result of the presented work is the effective neural solution for the recognition of the blur and for the identification of its parameters. The results of this identification can be used for the image restoration using the Tikhnov's filter, for example. The future work will be directed to the consideration of more blurs, including the combinations of several different blurs and to the further development of the restoration technique.

7. References

1. W.K.Pratt, Digital Image Processing, Second Edition, N.Y.: Wiley, 1992.
2. A.N.Tikhonov, V.Y.Arsenin, Solutions of ILL-Posed Problems, N.Y.: Wiley, 1977.
3. Y.L. You and M. Kaveh, “A Regularization Approach to Joint Blur Identification and Image Restoration”, *IEEE Trans. on Image Processing*, vol. 5, pp. 416-428, 1996.
4. I.N..Aizenberg, N.N.Aizenberg, J.Vandewalle “*Multi-valued and universal binary neurons: theory, learning, applications*”, Kluwer Academic Publishers, Boston/Dordrecht/London, 2000.
5. I.Aizenberg., N.Aizenberg, T.Bregin, C.Butakov, E.Farberov, N.Merzlyakov, O.Milukova “Blur Recognition on the Neural Network based on Multi-Valued Neurons”, *Journal of Image and Graphics*. Vol.5, 2000
   Tianjin, China, *Proceedings of the First International Conference on Image and Graphics (ICIG’2000)*, Tianjin, China, August 16-18, 2000, pp.127-130.
6. O.P.Milukova “ On Justification of Image Model”, *SPIE Proceedings*, vol.3348, pp283-289, 1998.