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MODEL OF FORMATION OF LOCAL DISTORTION OF IMAGES

Physical process of blurring emergence has been analyzed. Model of local distortion formation, which emerges as a result of movement of an object of attention or a registration device, has been built. Mechanism of buffer area formation between moving object of forefront and immovable background, i.e. transition area between an area of full blurring and non-distorted area, has been studied.

Key words: methods of distortion elimination, deconvolution, function of point scattering, model of local distortion.

Introduction

Blurring is such a distortion type that emerges as a result of dynamic changes of objects of attention or background during frame exposure.

Existing methods of blurring elimination are based on a mathematical model of blurring. The model is built on nature and feature of distortion and describes changes of colors of image points while blurring. Hereby considering the notion “blurring”, we mean “global distortion” not “local”, which is its more complicated form.

Despite the existence of few sufficiently effective algorithms of reconstruction of images distorted by blurring, there is no method to restore such an image with no lost features of informational content. The value of such losses is a measurement of effectiveness of the reconstruction algorithm.

To understand the reason of such losses, first of all it is necessary to check the correctness of chosen model of image blurring. Typically this verification should be completed via procedure of blurring simulation on non-distorted image. Aiming at this, the image is artificially distorted by some motion based on previously known parameters (trajectory and uniformity). Further, according to previously determined metrics we make a comparison with the image that has been distorted in a natural way while exposure of a movable object by the device with matrix sensitive to the light.

Analysis of methods of distortion elimination

Methods of distorted image reconstruction, which are based on deconvolution transformation, are one of the most used in practice.

We differentiate algorithms of both blind and not blind convolution among deconvolution algorithms in scientific literature. A part of methods have a priori nature, and some of them anticipate the use of special hardware.

Despite the type, the use of blurring center, i.e. PSF, for all algorithms is characteristic for all algorithms. The blurring center is Point Spread Function (PSF) that caused blurring (distortion) of an image.

Signal distortion under influence of some blurring center (core) means that each distorted image point is a result of wrapping operation. The wrapping operation can be presented as follows [ ]:

$$d_i = \sum_j h_{i,j} c_j \ , \tag{1}$$

where $h_{i,j}$ – discrete point spread function is an array (matrix), every element of which determines proportion of light from the point j, which is present in the point i; d – value of the intensity function in the point i after wrapping operation; c – primary intensity function value in the point i, i.e. such value that existed before the wrapping operation.

As a rule, image distortion, caused by wrapping, is eliminated by one of deconvolution methods. All algorithms based on deconvolution use bijective homomorphisms, i.e. such PSF that performs reverse transformation to the primary image.

Not blind deconvolution algorithms [5] anticipate the presence of sweep function, i.e. it is presumed about the type of distortion and basing on this assmption the function of image processing is built.

Blind deconvolution [4, 5] is based on the assumption about unknown center of blurring as far as distortion can be caused by different factors and by different influence. That is why a blurring center is calculated during an algorithm work in blind deconvolution.

There are following algorithms of blind deconvolution:

Richardson–Lucy algorithm [4]**.** One of the oldest algorithms (suggested in 1974). Iterative algorithm of restoration of blurred image by known blurring center. The algorithm is based on assumption that the point of not-distorted image is distributed by Poisson distribution.

Taking into account this assumption, at every step of iteration any point of blurred image is calculated as from its previous value, values of other points from preceding iteration step, values of points of primary distorted image, and known blurring center by the following formula [4]:

$$c_j^{t+1} = c_j^t \sum_i \frac{d_i}{c_i} h_{i,j} \ , \tag{2}$$

where

$$c_i = \sum_j c_j^t h_{i,j} \ . \tag{3}$$

Iterations are repeated up to obtaining the most probable deconvolved image by determined criterion.

The disadvantage of the Richardson-Lucy algorithm is the necessity to know the discrete Point Spread Function in advance. If the distortion has been caused by some unknown factors, the algorithm becomes useless for image restoration.

Tikhonov Filter is smoothing filtration with the help of the least squares with connection. Problem formulation of matrix type with next optimization problem solution lies in its base.

Wiener Filter lies in calculating such an estimate f' with minimum mean-square error of noise.

Donatella Algorithm anticipates the use of partial differential equations with antireflective boundary conditions for deconvolution. The algorithm peculiarity lies in elimination of deconvolution ringing effects, which is caused by image blurring, by asymmetric discrete Point Spread Function.

Christiansen-Hanke Algorithm is further compatible development of Donatelle Algorithm and Tikhonov Filter and is based on the use of antireflective boundary conditions. Due to the use of Tikhonov Filter elements, it demonstrates better results than the Donatella Algorithm. Nevertheless, its disadvantage is the necessity of previous PSF determination.

Neelamani Algorithm is one of the type of wavelet deconvolution. The algorithm is determined by previous Fourier transform of an input image with the further use of wavelet transform to eliminate noises.

Rav-Aka Algorithm [2] is based on the use of two images blurred by the same blurring center.

Yuan Algorithm [2] is based on the use of two images, one of which is blurred and the other comprises noises, which are characteristic for both images with the same blurring center.

Ben-Ezra-Najjar Algorithm [3]**.** To calculate blurring center, an image of video series and a frame image are to be used during the registration process. The algorithm allows obtaining an output frame of high quality, but has limited applied application because of the necessity of simultaneous photographing and video recording.

Raskar algorithm [3] is hardware-dependent algorithm. During the process of registration a camera shutter should open and close with high frequency to minimize losses of minute image elements, which are commensurable with the size of a grain of camera resolution.

Shan Algorithm [3] is a classic iterative algorithm of blind deconvolution and is based on processing of one frame. At every step of iteration the blurring center value as well as processed frame is updated. Simultaneous frame cleaning from noises of output image is characteristic feature of the algorithm. Shan Algorithm is considered to be one of the most effective algorithms. The algorithm efficiency lies in frame cleaning from blurring, caused by the camera motion or by the registered object.

Problem setting

The main task lies in developing the model of local distortion formation, which provides the development of reconstructive algorithms of blurring elimination, which emerge as a result of motion of an object of attention or a registration device.

Model of local image distortion formation

Similar to distortion from defocusing of optical system, blurring nature lies in the following: information about the color of every point is distributed all over the image by some law. The difference between different types of distortion lies in the law, by which the distribution occurs. The law is determined by PSF.

To simplify the representation of local distortion formation model, let's consider one dimensional case, i.e. the action of some PSF on a certain vector $\{c_i | i = 1..4\}$, which elements are pixel values of a set image.

In case of any blurring, the intensity function value at the point of blurring area obtains color intensity. In particular, in case of horizontal blurring per a pixel as a result of distortion every pixel values and a value of a preceding (left) pixel by the coordinate are added and divided by two: $c_i' = (c_i + c_{i-1})/2$. This formula results from the following: as far as the left pixel comes on the given one during its movement, during exposure both values managed to reflect in the position.

As a result we obtain a new distorted image:

$$\frac{(c_1+c_0)}{2}\left|\frac{(c_2+c_1)}{2}\right|\left|\frac{(c_3+c_2)}{2}\right|\frac{(c_4+c_3)}{2}$$

This is the model of ideal distortion.

The blurring analysis above dealt with a general case with no regard of its type. In accordance with the classification there are global (full) and local (partial) blurrings. The final is more complicated than the first. That is why let's dwell upon the formation model of the local blurring, which covers not the whole image but some its part. Hereby, the rest is not distorted.

On the contrary to the full blurring that is formed as a result of movement of a camera on immovable background, the partial blurring has different mechanisms of formation. In compliance with this it is necessary to consider different models of distortion.

There are several types of local changes. One of them is formed when a camera, which exposes a frame with the moving object in it, is fixed.

The scheme of formation of such blurred area is the following. At the moment t_n shutter closes. During this period the moving object has moved to some distance, which taking into account discrete nature of a digital photo can be estimated by a finite number of pixels *m*. This makes possible to divide the time period $\Delta t = t_n - t_0$ into *m* equal interims. During every interim each pixel of the movable object left imprint of its value of intensity function at the other point via overlapping of own intensity function value and the previous value at the same point. As a result values of intensity function in inner object pixels collide on the values of other pixels of the same object and the classic deconvolution problem emerges.

At the end of blurring section the situation is different. The ends can be considered the area along the perimeter of an object in the movement direction and with the width of *m* points (buffer area). In the area the mix of values of intensity function of the moving object and values of intensity function of immovable background pixels occurs. As far as the exposure time was sampled into *m* periods, it can be considered that during time unit $\tau=1/m$ intensity function value of every point of the buffer area is formed with τ part of the color value of the moving object and $(1-\tau)$ part of the value rest, which in its turn is formed as a result of additive overlapping in the same proportion of intensity function values, which belong to the object and background, which the object is moving over.

For the limit object pixel, any intensity function value will be determined by the described correlation. For the next object pixel its intensity function value $c(x_i, y_i)$ will be calculated by the scalar product of vectors $\mathbf{v} = (\tau, \tau, (1-2\tau))$ i $\mathbf{F}_i = (f(x_i, y_i), f(x_{i-1}, y_i), f_ф(x_i, y_i))$:

$$c(x_i, y_i) = \mathbf{v} \cdot \mathbf{F}_i. \tag{4}$$

Here $f_ф(x_i, y_i)$, $f(x_i, y_i)$, $f(x_{i-1}, y_i)$ – values of intensity function in the given and limit pixels. By the similar scheme intensity function values will be determined in every buffer area point. The final buffer area pixel value will be equal to the value of intensity function, which will comprise background color value τ.

The described above approach of formation of intensity function values in buffer area pixels will be named as the *operation of weighing intensity function values*, and the vector **v** – *weighing operator*. It should be noted that the indicated above parameters of the operator **v** are possible only under the condition of uniform motion. In case of nonuniform motion these parameters would be different and formed by the rule: *the less period of object pixel stay at the position, the less is its part of intensity function value in the resulting value.* However, the regularity obtained for the case of uniform motion will be preserved for the *j* pixel of the buffer area and can be written as follows:

$$c_j = a_j f_j + \left(1 - a_j\right) b_j , \quad a_j = \sum_{i=1}^{j} h_i , \tag{5}$$

where $j \in [0; m]$; h_i – i-e not null value of discrete PSF h; b_j – value of intensity function of background at the given point; f_j – integrated value of intensity function in pixels of any moving object, which were at the given position during the object motion.

By the other words, the configuration and dimension of the matrix PSF depend upon velocity, uniformity, motion trajectory, and frame exposure time. Arrangement of not null elements of the PSF matrix repeats the object motion trajectory for the period while the light-sensitive matrix exposured the given frame. The matrix elements values are proportional to the object velocity during the period from t_n to t_{n+1}, which is equal to $1/m$ of frame exposure time, where m – a number of not null matrix elements. Appropriately, during uniform motion not null matrix elements will be almost equal, and during linear motion they will be built in a line. A row vector results from the strict horizontal motion, and a column vector – from the strict vertical motion.

Hereby, it can be concluded that the buffer area under research repeats the PSF configuration: in case, if PSF is a vector-column of five elements, then the buffer area width will be 5 points of the moving object image.

The approximate example of buffer area can be areas of the image in Fig. 1, marked by the arrow with the caption "50 px". The instance is not correct completely, as far as the mentioned image is an example of the full not local blurring. Despite this, the given area is formed for the buffer area in case of the partial blurring by the rule of a chessboard, i.e. a black square of the chessboard with the even value of intensity function comes on (during its motion) the previous impress of a white square of uniform color. That is why the black square can be considered as a forefront moving object, uniformly colored, and a white square – as an immovable background of uniform color as well.

More proper example that fully illustrates the idea of buffer zone can be taken from the following natural image (Fig. 1). Drawn nearer separation of both buffer areas is illustrated in Fig. 2.

Fig. 1. Drawn nearer separation of buffer areas of partial distortion by the motion from a previous image

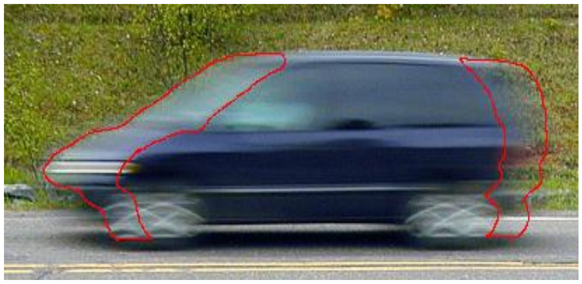

Fig. 2. Natural image, partially distorted by motion

Conclusions

Physical process of local blurring emergence and detailed mechanism of formation of distorted image by partial motion have been analyzed. Mechanism of buffer area formation between moving object of forefront and immovable background, i.e. transition area between an area of full blurring and non-distorted area, has been studied.

Obtained methodology of buffer area determination can be base for developing effective deconvolution methods for elimination of global and local distortions, which emerge as a result of movement of an object or registration device.

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