Multi-Focus Image Fusion Based on Cellular Automata Method

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***Abstract*—image merging is a process of obtaining one image from multiple. The resulting image carries more information about the photographed scene, than each of the originals. Such an image can be more useful when we deal with human or image processing system. Algorithms that performed this task are used in a wide applying in practical: computer vision, robotics, medicine, forensics, etc. In general, the problem of limited depth of field optical relieving device is solved. The article outlines the general provisions forming multi- focus mages, shows the classification of existing algorithms. In addition, the image distortion process of the blurring formation outside the focal plane was examined. The authors propose an algorithm of forming multi-focus images based on cellular automata. The results of the algorithm implementation are described in this article. Moreover, it is considered popular methods for assessing the quality of the images from different viewpoints.**

I. Introduction

Image merging is used in photo computing. Image fusion is a sub-field of image processing in which two or more images of a scene are combined into a single composite image that is more informative and is more suitable for visual perception and for digital processing. We categorize the fusion methods based on the input data of the fusion process and also based on directly pixels processing [1]. In general, image obtaining methods can be classified into four main groups:

- multi-camera image obtaining;
- image getting via panorama scene;
- at different times survey in order to detect changes between them or to synthesize realistic images of objects;
- with various focal lengths image capture (multi-focus method).

In the main, the methods based on image fusion with various focal lengths can be classified on two groups: spatial domain and transformed domain [2]. In the first techniques fusion directly takes place on the pixel values. At the same time, in transformed domain method the images are first transformed into multiresolution components. It is noted that image fusion is generally carried out at four different levels according to abstraction primitives: signal level, pixel level, feature, and decision level [3].

Signals from different cameras in signal-based fusion are fused to create a new signal which has a better signal-to-noise rate value than the original. Image fusion in pixel level refers to generating of fused image in which the pixel values are based on the pixel values of the initial image.

Feature-based fusion requires the extraction or segmentation of various features of the source images. Moreover, the fusion process is based on those extracted features of the original images. In decision level fusion multiple algorithms are combined to get the final fused n. Then the obtained information is then combined applying the decision rules [4, 5].

Notwithstanding, all mentioned above fusion approaches blur the sharp edges or leave the blurring effects in the fused image. The key challenge of multi-focus image fusion is to obtain the fused image without blurring.

II. Multi-focus image fusion merging

A. Defocused image mathematical model of blurring

To describe the distortions arising in the image the model of an ideal single lens system is used. Most real-world optical system may be reduced to the model. The described scheme is shown in Fig. 1:

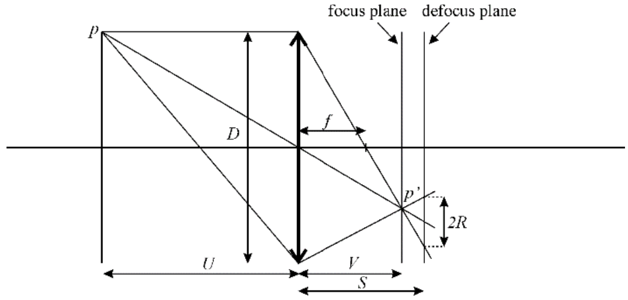


Fig. 1. Scheme of the ideal single lens system

In this case p – a point object. The image p' of p is constructed in optical lens with a focal length *f*. The distance from the object to the lens is U, whereas V is the distance from the lens to the image. Therefore, the lens formula is defined as:

$$\frac{1}{f} = \frac{1}{U} + \frac{1}{V} \tag{1}$$

The camera has got an aperture with the size *D*. The charge-coupled camera located at a distance S from the lens. Hence, if $V \neq S$, image of the object on the matrix will be a blur with radius, which is calculated as:

$$R = \left|\frac{1}{2} DS \left(\frac{1}{f} - \frac{1}{U} - \frac{1}{S}\right)\right| \tag{2}$$

Sign of the module needs for generalization to the case of the formula $V > S$, i.e. matrix closer to the lens than the image. The value R may be selected, for instance, based on the pixel size of the sensor matrix. Thus, according to the value of R far and near border and depth of field (DOF) can be found as:

$$U_{far} = U \frac{f(1 - 2\frac{R}{D})}{1 - 2\frac{RU}{D}} \tag{3}$$

$$U_{near} = U \frac{f(1 + 2\frac{R}{D})}{1 + 2\frac{RU}{D}} \tag{4}$$

$$DOF = U_{far} - U_{near} \tag{5}$$

When $D \to \infty$, accordingly $DOF \to 0$, since $U_{far} \to U$ и $U_{near} \to U$. Otherwise, when the diaphragm drops significantly decreases the illumination image, that a variety of practical applications, such as microscopy, is unacceptable. Besides, in addition to directly blurring of p', it shifts radially from the main optical axis of the system. Even so, mentioned effect doesn't influence essentially to quality of purposed method and visual perception of the scene in vast majority of cases [6].

B. Generalized image merging algorithm

Terminology in this field of computational photography is not yet established. In a number of sources, the resulting image is called as «multi-focused» other «full-focused», «overall-focused» or simply «fused». We will continue to adhere to the first mention.

Multi-focused image is a combination of several images of the same scene taken with different focal lengths. The first and the most important stage of all image fusion techniques are to compute focus value of original images or the parts of them. In the better part of the works the mentioned below approaches of focus value assessment are used [7]:

- Histogram entropy method,
- Energy of image gradient,
- Tenengard method,
- Spatial frequency,
- Laplacian energy,
- M2 focus measure,
- Grey-level variance,
- Digital cosine transform based on focus measure (DCT-based).

At once, pixels with greater values of these measurements, when source images are compared, are considered to be in focus and selected as the pixels of the fused image. Once the focus measure is done, there are different fusion rules to fuse the images [8]. One is selecting the sharp pixels with maximum of focus value in the spatial domain to Multi-Scale decomposition (MSD) transform image information in the high-frequency via multiscale approximation. The ordinary scheme of image fusion is shown in Fig. 2 [4].

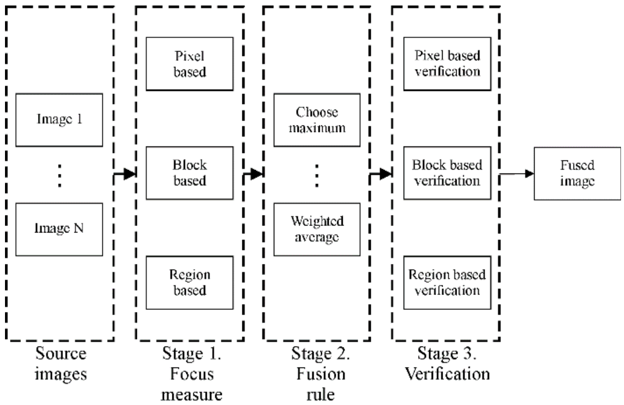


Fig. 2. Scheme of multi-focused image merging

The last stage: checking the result of fusion is an optional.

C. Cellular Automata Method

The proposed algorithm is based on a cellular automaton and refers to a group of spatial techniques [9] blending of images, as well as takes into account the content of the image. All stages of the method are described in Algorithm 1.

The suggested above method allows merging different multi-focused images with both in quality and speeding efficiency. It is noticed that the choice of the parameter α depends on the situation and the constraints imposed by the characteristics of the scene, the object of interest and the used equipment. Onwards, we will discuss various approaches to evaluate the quality of algorithms.

Algorithm 1 Multi-focus image fusion based on cellular automata method

1: Focus evaluation computation for each pixel in each of the original images. Matrix $G(I_k)$ calculation
2: Searching for maximum of focus evaluation $\max G(I_k) = G_{max}(k)$ for each k from n matrix $G(I_k)$
3: Threshold matrix binarization $G(I_k)$ with threshold $\alpha G_{max}(k)$, where α – variable parameter
4: Matrix label creating M in obedience to the rule:

$$M_{i,j} = \begin{cases} 0, \forall\, k: G_{i,j}(I_k) < \alpha G_{max}(k) \\ k, \exists!\, k: G_{i,j}(I_k) \geq \alpha G_{max}(k) \\ \max k, \exists\, k: G_{i,j}(I_k) \geq \alpha G_{max}(k) \end{cases} \quad (6)$$

5: Cellular automata method implementation based on matrix label in pursuance of the following scheme:

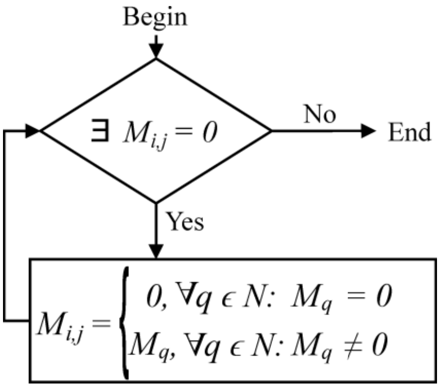


Fig. 3. Block diagram of cellular automata method. Therein N – a set of pixels from 8-tuply connected domain around (i, j), q – a pixel from this set

6: Assignment of a pixel (*i, j*) in the final image values corresponding to the pixel (*i, j*) of the image $M_{i,j}$.

III. Image quality assessment

Image quality describes an image deteriorated in comparison with some ideal image − reference. Processing system, such consideration, can make some distortion and artifacts in the resulting images, hence − an assessment of their quality is an important task. All variety of methods and evaluations of image quality can be divided into two large groups: methods based on reference standards and methods without the use of a reference. In the first case processed image is compared with the reference image, whose quality is considered ideal. The second way alludes that such comparison is not occurred [10].

A. No reference evaluation

When the reference image is not available as in mentioned above case the following metrics are used to test the performance of the fused algorithms. These methods aren't based on the knowledge of pixels [11, 12].

Entropy

Entropy is an index to evaluate the information quality of an image. If the entropy value becomes higher after fusion, it is an indication that the information quality has increased and the fusion performance has improved.

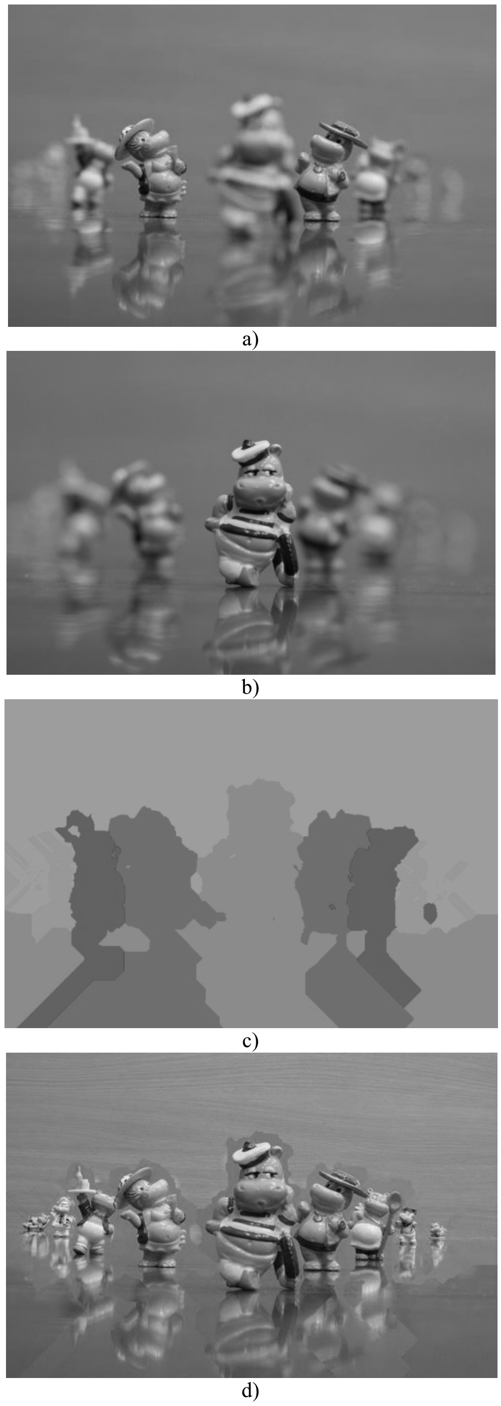


Fig. 4. The results of proposed method processing: a, b) examples of original images, c) label matrix M, d) multi-focused image

Using entropy, the information content of an image is:

$$E = -\sum_{i=0}^{G} p(i) * log_2 p(i) \quad (7)$$

where G – is the number of gray levels in the image's histogram (255 for a typical 8-bit image), and $p(i)$ – is the normalized frequency of occurrence of each gray level, i.e., the histogram of the image. Importantly that entropy is also sensitive to noise and other unwanted rapid fluctuations.

Spatial domain

Spatial frequency [13, 14] measures the overall activity level in a fused image. An assessment is calculated as:

$$SF = \sqrt{RF^2 + CF^2} \quad (8)$$

here RF and CF are the row frequencies, determined as:

$$RF = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=2}^{N}(I(i,j) - I(i,j-1))^2} \quad (9)$$

$$CF = \sqrt{\frac{1}{MN}\sum_{i=2}^{M}\sum_{j=1}^{N}(I(i,j) - I(i-1,j))^2} \quad (10)$$

Mutual Information

This metric is conceptually close to the mutual information [15] in reference metrics; however, due to the absence of a reference image some changes were made. Let A и B — original images, a F – image after merging. Consequently, the mutual information can be determined as:

$$FMI(A,B) = MI(F,A) + MI(F,B) \quad (11)$$

This evaluation represents the similarity of mutual and original images. There is also a high metric value corresponds to a higher quality of the algorithm.

There are more accurate methods for calculating the similarity between two images based on the idea of calculating a cross-entropy, but they are usually more computationally costly.

Divergence or the distance between the mutual distribution and the composition of the marginal distributions of image pairs can be used as a measure of their similarity. Divergence action class using mutual information is the class of *f*-information or *f*-divergence. *F*-measures of information are [16]:

$$I_\alpha = \frac{1}{\alpha(\alpha-1)}\left(\sum_{i=0}^{255}\sum_{j=0}^{255}\frac{p_{i,j}^{\alpha}}{(p_i p_j)^{\alpha-1}} - 1\right) \quad (12)$$

$$M_\alpha = \sum_{i=0}^{255}\sum_{j=0}^{255}\left|p_{i,j}^{\alpha} - (p_i p_j)^{\alpha}\right|^{\frac{1}{\alpha}} \quad (13)$$

$$\chi_\alpha = \sum_{i=0}^{255}\sum_{j=0}^{255}\frac{|p_{i,j} - p_i p_j|^{\alpha}}{(p_i p_j)^{\alpha-1}} \quad (14)$$

Herewith, I_α is defined whereas $\alpha \neq 0$, $\alpha \neq 1$ and reduced to the Shannon mutual information in case $\alpha = 1$. At the same time, M_α assigned if $0 \le \alpha \le 1$, a χ_α – when $\alpha > 1$.

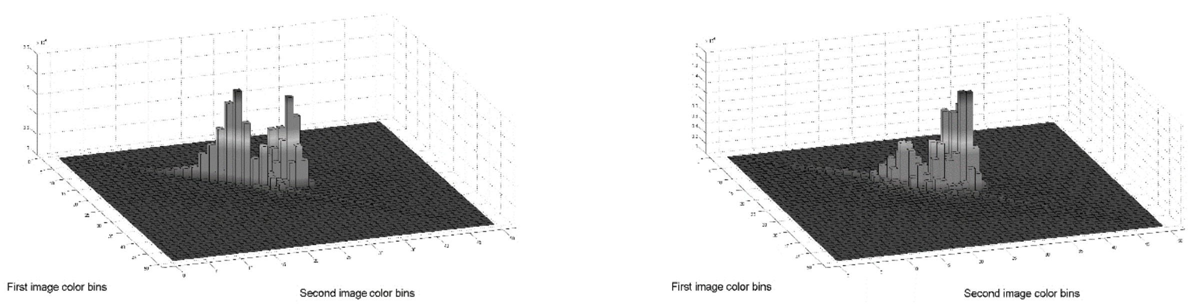
For some above metrics evaluation $p_{i,j}$ – a mutual elements probability density distribution of brightness of images must be calculated. This probability can be evaluated, for instance, via a histogram.

For two 8-bit single-channel images X and Y, each of which has a size of $M \times N$, the value ($p_{i,j}$) can be represented as a two dimensional histogram, which size is 255×255.

$$p_{i,j} = \sum_{p=1}^{M}\sum_{q=1}^{N}\begin{cases}1, \text{if } I(X_{p,q}) = i \text{ and } I(Y_{p,q}) = j \\ 0, \text{otherwise}\end{cases} \quad (15)$$

where $I(X_{p,q})$ – the intensity of the pixel at coordinates (p, q) of X.

An example of a mutual probability density for two pairs of images is shown in Fig. 5.



a) b)

Fig. 5. 2D mutual probability density for two pairs of images a) Fig. 4a and Fig. 4d b) Fig. 4b and Fig. 4d

IV. Quality assessment

A. Image database

To assess the quality of algorithm based on cellular automata own database photographed images was formed.

This database includes four scenes contingently, which are called «numbers», «toys», «soldiers» and «robot». The example of toys's scene is depicted in Fig. 4a and 4b at the same time the instances of the other scenes are illustrated in Fig. 6.

The images from testing database have following characteristics: *.JPG format of storage, 786 × 523 pixels resolution, appearance in color (RGB color space), having 8 bit to pixel. Each of scene is contained from five to eight testing image from database.

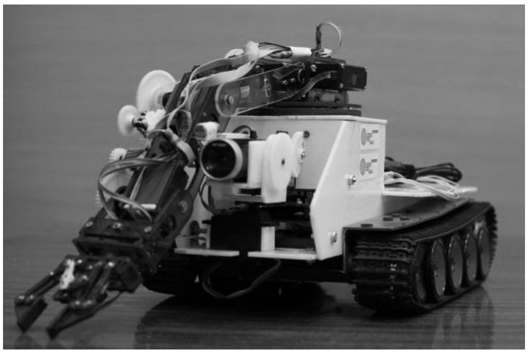
An essential part of proposed approach quality estimation is to assess temporal characteristics of the method, which are corresponded in Fig. 7.

Thus, it is possible to make a several conclusions based on these results. Firstly, the running time is positively correlated with the value of the parameter α, indicating that the inappropriate usage of high values of the parameter. Secondly, this time depends on the image content, while maintaining the number of pixels. Moreover, worth noting is a substantial reduction in the execution time of the algorithm, if $(\alpha - 1\%)\ mod\ 11 = 0$, presumably this is due to the peculiarities of implementation. Note that the algorithm can be significantly accelerated using parallel computing on the GPU, as stage 5 of Algorithm 1, which occupies most of the CPU time is performed for each pixel independently.

V. Conclusion

To sum up, usage the mentioned above algorithm allows to synthesize of multi-focus image according to the quality aspects, which are necessary in a specific task, as well as to assess the effectiveness of their applying. It is vital to note that merging images used in a wide range of applications: cameras image processing, medical, judicial and military applications, etc. Synthesis algorithm based on cellular automata, developed by a group of authors, is used for the fusion of images, which were taken with the camera to produce the final image with an extended depth of field that allows getting a better view of the considered scene. Most effectively proposed algorithm works in the presence of sharp boundaries of objects, but this, in turn, leads to the appearance of halos around them. In additional to all, the developed algorithm shows better results when working with scenes in which there are multiple objects at different distances from camera. Further development of the algorithm is aimed at reducing the impact of artifacts halo around the clear boundaries of objects in the scene. The most promising way to achieve this result is to use Gaussians and Laplace pyramids [17], which allow merging the image on the label matrix, which is obtained via Algorithm 1. It is also planned to further improve the no reference methods for the quality fusion algorithms assessment based on information metrics [18].

a)



b)

c)

Fig. 6. The image samples from testing database a) numbers b) robot c) soldiers

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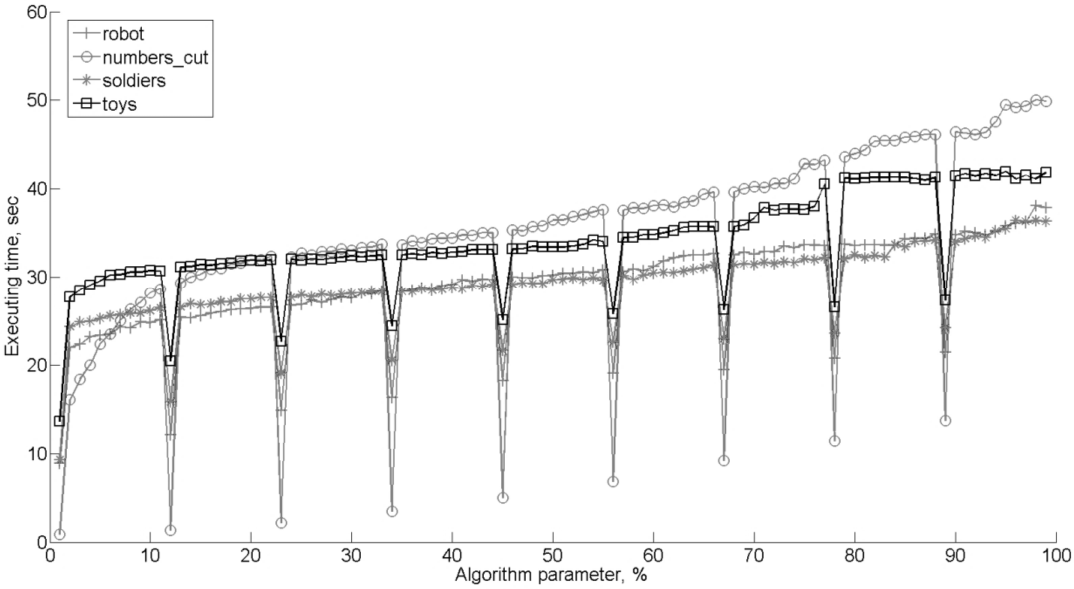

Fig. 7. Temporal characteristics of the algorithm based on cellular automata method on different testing images

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