A model for generation a motion-blurred image of a radiating object’s shadow from a series of high-quality images

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Abstract. The paper proposes a model of the reconstruction process for a series of images of the shadow casted by radiating cylindrical object and diffraction pattern from a motion-blurred image generated by an optical device at unequal speeds of an object's movement and image generation by the device. Using the proposed model, methods and their software implementation, separate images of the shadow of the radiating objects and diffraction patterns were generated in order to obtain a motion-blurred image, which can later be stored in a database and used as a template for recognizing the trajectory and speed of an object's movement, measuring its individual parameters, etc. The proposed model and methods can be improved and used in the future to optimize the optical monitoring system for the parameters of the radiating cylindrical objects, such as wire or optical fiber in the high-temperature process of their manufacture. Heated wire with a diameter of 200 microns made of NiCr alloy and carbon fiber with a diameter of 7 microns were used as the test objects for carrying out experiments.

1. Introduction

High-precision measurements and monitoring of any object parameters using optical methods require using a high-quality image transmitted to the input of a machine (computer) from a radiation receiver (a matrix of photovoltaic cells) [1, 2].

During the monitoring process, especially when the object \( V_{obj} \) is moving at a high speed, the generation of the high-quality image may be quite a difficult task for the radiation receiver that generates the image \( V_{image} \) at a speed equivalent to the object's movement speed \( V_{obj} \). At unequal speeds of the generation of image \( V_{image} \) and the object's movement \( V_{obj} \), the generation is not possible at all, so image processing methods are used to solve problems of obtaining a high-quality image (not blurred by movement).

Image processing methods such as Tikhonov regularization, Wiener filtering, etc. allows to restore an image that was initially distorted by blurring [3-5].

The main limitation of these methods is that only one image can be obtained as a result which can then be processed to measure the parameters of the object imaged. In this case, there is a high probability that the image processing algorithm for the measurement procedure will be slightly increased by introducing correction procedures in the measurement method and some coefficients.

This limitation is logical and requires no explanation. There are many factors that are difficult to manipulate in the image restoration process.
In this paper, we propose a model for reconstructing a series of images from a motion-blurred image, but it is only suitable for a specific case.

2. The proposed model of image reconstruction

Figure 1 shows a traditional model of the image distortion/reconstruction process (figure 1, a) and the proposed model of the reconstruction process for a series of images obtained from a motion-blurred image (figure 1, b) [3].

The proposed model is based on previously known parameters:

- the object's movement speed range;
- region in three-dimensional space in which the object moves;
- value range for the object parameters measured;
- image generation speed of the radiation receiver;
- specifications of the radiation receiver;
- value of the center wavelength selected by using a narrow-band light filter in the optical system;
- modulation transfer function (including frequency response) of the optical system.

As can be seen from the given parameters, the proposed method is designed for specific tasks.

The key difference of the proposed model is that the motion-blurred image transmitted to the input is represented by an image generated by averaging the brightness from the $n$-th number of all quality images that could be formed over a given time interval.

A distinctive feature of the model is the use of machine learning methods for pattern recognition (the block "image processing procedure" in figure 1, b), as well as databases allowing you to store most of the information, which is a disadvantage. However, improving the reconstruction model and machine learning methods in the future could reduce the cost of local system resources for storing information and improve the quality of recognition.

3. The proposed model of image generation

Initially, we need to determine how to generate a single image. There are several ways to do this:

- a complete physical and mathematical model describing the formation of an image of the object's shadow and diffraction pattern in the optical system of the device when the object is illuminated by a point source;
- an incomplete physical and mathematical model with additional correction coefficients;
- a model using pre-calibration.

The model from para. 3 was used (figure 2).

Figure 2 shows a scheme for calibrating the optical device based on the image parameters of the object's shadow and diffraction pattern.
Figure 3 shows a scheme for generating an image of the radiating object shadow and diffraction pattern based on the relationship between parameters obtained from two calibrated images.

The mathematical model of the diffraction pattern generation as a function of the required diameter is as follows (graphically shown in figure 3, a).

The value $k_s$ versus the difference of the segment $\Delta d$, which is accounted for one percent, is expressed as

$$k_s = \frac{\Delta d}{100} = \frac{d_{\text{max}} - d_{\text{min}}}{100},$$

where $\Delta d$ is the difference between the maximum and minimum diameter of the object.

The $k_p$ difference between the specified and minimum diameters is expressed as a percentage
The required segment $x_{need}$, which value depends on the relationship between the parameters of two diffraction patterns (two images), is expressed as

$$x_{need} = k_pk_s + x_{min}.$$  \hfill (4)

To obtain the brightness value $y_{need}$, it is necessary first to set $y_{max}$ and $y_{min}$, since in some cases the values can be inverted, and in this case

$$k_p = 100 - \left( d_{need} - d_{min} \right)/k_s. $$  \hfill (5)

The value $k_s$ versus the brightness difference $\Delta y$, which is accounted for one percent, is expressed as

$$k_s = \Delta_y/100 = \left( y_{max} - y_{min} \right)/100, $$  \hfill (6)

where $\Delta y$ is the difference between the maximum and minimum brightness values.

The brightness value $y_{need}$ is expressed as

$$y_{need} = k_pk_s + y_{min}. $$  \hfill (7)

The mathematical model for generating an image of the diffraction pattern along the Z-axis can be expressed as follows (graphically shown in figure 3, b).

To generate the motion-blurred image $I_{blur}$ of the object moving longitudinally at a constant speed $V_{obj}$, an expression equivalent to the average value of all images was used which is as follows

$$I_{blur}(x, y) = \frac{\sum_{i=0}^{n} I_i(x, y)}{n}, $$  \hfill (9)

where $n$ is the number of images in the series.
5. Proposed recognition model

This paper describes a "simplified" method for recognizing a series of images. The algorithm for recognizing a series of images consists of the following steps:

- the resulting motion-blurred image is compared with known template images that are stored in the database;
- the pattern comparison is performed using a certain number of markers and errors (standard deviation) of each of the signals that correspond to the coordinates of marker;
- a result obtained after determining the closest template is a series of images forming this template. The same "reconstructed" images are used for measuring the diameter, and surface temperature of the product.
- As a result of comparing the resulting motion-blurred images with templates, we obtain:
  - the signal comparison values in individual coordinates (as a percentage) on which the markers are set;
  - an overall evaluation of the comparison (convergence) of the image and the closest template (as a percentage);
  - a series of images forming a template image.

6. Main parameters of the experiment

The values of the parameters used in the experiment are shown below. The table shows the main parameters for generating motion-blurred images.

From the work [6], it is known that in the process of dieless drawing the temperature range $T_{\text{max}}$ of the product surface area located in the center of deformation is 700-900 °C, while the speed range of product drawing $V_{\text{vol}}$ is 9-15 mm/min.

The parameters of the optical monitoring device used were as follows [1].

- the matrix resolution (number of pixels along the row and column) is 1920x1080 elements;
- the physical size of the pixel side $l_{\text{px}}$ (there are 4 photovoltaic cells in the pixel design that register radiation in the specified spectral regions and are located behind the Bayer filter) is 2.7 microns [8];
- the frequency of generating, processing and transmitting $V_{\text{im}}$ images at this resolution of the matrix is 30 images/second. Due to the presence of a narrow-band light filter in the design of the optical system, which highlights a narrow range of wavelengths with a central wavelength
of 532 nm, the frequency has decreased to approximately 5 images/second. This can be explained by the electronic part of the radiation receiver, when radiation from the required wavelength range cannot be transmitted to some of the elements, or when the generated signal is too small;

- the focal lengths $f_1$ and $f_2$ are equal to 50 mm and 175 mm, respectively;
- the distances $a_0$ and $b$ are 235 mm and 17 microns, respectively.

### Table. Parameters for generating motion-blurred images

| $T_{im}$ (msec) | $l_x$, $l_y$ (µm) | $V$ (mm/sec) | $V$ (mm/min) |
|----------------|------------------|--------------|---------------|
| 500            | 27               | 0.06         | 3.6           |
|                | 67.5             | 0.15         | 9             |
|                | 135              | 0.3          | 18            |
|                | 270              | 0.6          | 36            |
| 200            | 27               | 0.15         | 9             |
|                | 67.5             | 0.375        | 22.5          |
|                | 135              | 0.75         | 45            |
|                | 270              | 1.5          | 90            |
| 100            | 27               | 0.3          | 18            |
|                | 67.5             | 0.75         | 45            |
|                | 135              | 1.5          | 90            |
|                | 270              | 3            | 180           |
| 50             | 27               | 0.6          | 36            |
|                | 67.5             | 1.5          | 90            |
|                | 135              | 3            | 180           |
|                | 270              | 6            | 360           |

7. Generated images

Figures 5-7 show motion-blurred images generated by the parameters set above.

During the study of the motion-blurred images of the object moving along the $X$-axis, it was found that the maximum brightness that corresponds to the center of the first diffraction extremum of the distorted image is always at the border between image of the product's shadow and beginning of the first diffraction extremum of the original image.

It is obvious that the brightness of the image on the area of the object's heated surface (the deformation zone) on its slurred image is reduced to an average value when summing up a group of images. Depending on the signal-to-noise characteristic, the average brightness value may have larger or smaller errors.

Currently, it is difficult to perform such reconstruction process of a series of images, in which it would be possible to obtain high-precision results of measurements of geometrical and energy parameters of the object due to the inconsistency between main and required characteristics and parameters of the radiation receiver and optical systems.
Figure 5. Generated motion-blurred images when moving the object along the X-axis: a-g is the object with a diameter of 200 microns; d-z is the object with a diameter of 7 microns.

Figure 6. Generated motion-blurred images when moving the object along the Y-axis: a-g is the object with a diameter of 200 microns; d-z is the object with a diameter of 7 microns.

Figure 7. Generated motion-blurred images when moving the object along the X- and Y-axes: a-g is the object with a diameter of 200 microns; d-z is the object with a diameter of 7 microns.

Figure 8. A motion-blurred image generated when moving the object along the Z-axis (the object's diameter is 200 microns).

Figure 9. Generated motion-blurred images when changing the diameter of the object with original diameter of 200 microns.
8. Conclusions

The total accuracy of the method, taking into account that the speed of the product movement is a constant value or a value with some minor deviation in the given range, is influenced by the number of pattern sample, resolution of the matrix of photoelectric elements, signal-to-noise characteristic of each of the photoelectric elements, pitch (equal to the size of photovoltaic element) of the object's movement in space, minimum resolution of the optical system and scale of depicted shadows.

To date, the proposed method for reconstructing a series of images is the simplest, but it requires large resources of the information storage device.

To improve this method, the use of machine learning methods can be suggested. This will reduce the requirements for the volume of the information storage, but the large computing resources of the processor and RAM are required.

Further researches will be focused on improving the proposed method for reconstructing a series of images to solve problems of monitoring several parameters of a long length product at the same time during its high-temperature manufacturing.

References

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