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Abstract. The main purpose of this paper is to present an algorithm for correcting motion blurred gray scale images iteratively by determination of edge parameters like the edge width. These parameters are used to describe a motion point spread function for the usage in a closed-loop deconvolution algorithm. The image restoration works well with motion blurred images with additional noise and was tested with realistic and synthetic motion blurred images. Furthermore the variation of the edge position in the image was determined by four different edge detection methods in pixel domain to proof the functionality of the restoration algorithm.

1. Introduction
Increasing measuring speed of optical geometric measures without strobe illumination respectively short exposure time involves motion blurring effects at image acquisition by the relative moving of CCD-camera and measuring object. Optical coordinate measuring machines (CMM) provide information about position, velocity and acceleration data, which are used for describing motion point spread function (PSF) kernels. The PSF kernel is used for processing a Richardson-Lucy (RL) deconvolution algorithm. After deconvolution of the basic image with the estimation of the motion PSF kernel, the edge qualities in the corrected image are determined and if it is necessary the procedure starts again by creating a new motion PSF kernel and recalculation of the corrected image.

1.1. State of the art
For 30 years, many works have been done to remove motion blur, which can be principally broken up in two steps: motion estimation and deconvolution. Much effort has been put into the first step and some remarkable results have been published. Some methods use parametric PSF model in blur estimation [14] and some other use segmentation techniques to handle multiple motions [5], [10] in a single image. And some methods use image constraints in blur estimation: Fergus et al. [4] use a certain statistical distribution for natural image gradients; and Joshi et al. [16] predict the underlying sharp image as image prior. And some other methods acquire multiple images: Bascle et al. [15] de-blurred a sequence of motion blurred images of a moving object to recover a single sharp image; Yuan et al. [13] use a pair of images, one blurry and one noisy, to produce a high quality image that can not be obtained by simply de-noising the noisy image or de-blurring the blurred image standalone. Furthermore, Ben-Ezra et al. [11] take advantage of additional attached image acquisition hardware to record the motion path of the camera. All of above mentioned methods are intent to estimate an as
accurate as possible PSF kernel. Given the estimation of PSF we shift to the second step to recover the de-blurred image. We have experimented with a variety of current most popular deconvolution algorithms, including Wiener filter deconvolution, Richardson-Lucy (RL) deconvolution, Regularized Wiener deconvolution and blind deconvolution, all of them are available as Matlab routines. Furthermore, Schuon [12] performed a quantitative comparison of deconvolution algorithms although in Matlab environment that are already in use or proposed in the literature. These methods bring ringing artifacts into the restored image and are sensitive to noise. Besides these frequency domain methods there are image-space methods that use image priors: The simplest of these is a least squares deconvolution, which was improved and proposed by Levin et al. [10]. One downside of these methods is that they are more time consuming.

1.2. Placement of our work

All of the above mentioned work concentrates on the motion de-blur for the photographs in the natural scenes, where there are RGB color channels and complex textures and motion blurs usually caused by complex camera shake. The criterion for the goodness of the restored image is usually the visual sense of human. Until now there is no work that applies a deconvolution algorithm for motion de-blur in the area of metrology, such as our application, i.e. optical geometrical measures, which has its own features and requires specific treatments in motion de-blur process. In the following, we summarize some features of motion de-blur in the geometrical measures:

- The image is usually in bitmap format, (i.e. 8 bit grayscale image with only one channel)
- There are usually no complex textures in the scene. (only simple geometric elements, such as line, circle and arc, remain in the scene)
- During a short exposure time the motion can be considered as a constant velocity, linear motion.
- The edge width in the blurred image is usually much larger than one in the photograph.
- The restored images should have the sharp textures without distortions regarding the origin shape.
- The location of the restored sharp edge should be predictable. The determination of the location of the restored sharp edge for a synthetically motion blurred image is in one dimension investigated.

In view of above-mentioned features in optical geometric measures we proposed a simple effective iterative deconvolution algorithm to realize the motion de-blurring with little effort. At first, based on the one-dimension gray scale curve the length and the location of the blur area is calculated with a novel approach developed by us. It is very helpful to repeat this course row by row in the image, if there is a non-linear edge profile. Then the length of the blurry area is directly used to generate the PSF kernel, which is parameterized as one-dimensional blur vector. Secondly, given the PSF kernel we reconstruct the latent image with the Richardson-Lucy (RL) algorithm, which is in many ways proven to be the best choice and will be described in next section. As mentioned above the restored image by RL contains more or less ringing, which is against the following deconvolution and the further edge detection. Therefore we wipe off the ringing outside the blurry area by filling the constant gray scale value, with which the continuity along the x-axis in the image has to be preserved. The “clean” image with less noise will be delivered to the next iteration, such procedures continue until the edge width becomes sharp enough.

2. Principles and foundations

The main condition for appliance of the introduced algorithm is a linear uniform motion between CCD-camera and measuring object at image acquisition. Other basic are the deconvolution algorithm of Richardson-Lucy used for restoration and the approach for calculation of the point spread function input parameter, which is defined by the blurred edge.
2.1. Image acquisition under linear uniform motion

The CCD-camera for capturing the intensity distribution of the measuring scene is in linear uniform motion at image acquisition time. Concerning this assumption, the pixels of CCD-matrix integrate over the moving intensity distribution over the complete exposure time. The light intensity of the measuring scene is averaged on the pixels in moving direction. An abstracted model (Fig. 1 left), consisting of an ideal edge in perpendicular direction toward the moving direction and an absolutely dark background, clarifies the context. In comparison to the synthetic model predictions, the realistic image capturing (Fig. 1 right) in motion delivers similar results.

A realistic image furthermore consists of two additional effects: optical distortions and defocusing are described by a further point spread function, which is convolved with the origin image. During acquisition time the noise at the pixel is another influence in capturing the intensity distribution.

2.2. Edge analysis criteria

The main parameter of the closed loop deconvolution algorithm is the edge width. The used analysis criterion works as follows:

1. Given is the intensity curve along a search line $grayvalue[i] \in i \in 1..n$
2. Calculate the differences between the adjacent pixels in the intensity curve: $Diff[i] = grayvalue[i+1] - grayvalue[i] \in i \in 1..n - 1$
3. Calculate the sum of the adjacent four (by default) elements of $Diff$:
   $Sum[i] = \sum_{j=0}^{i+3} Diff[j] \in i \in 1..n - 4$
4. If $Sum[i]$ has a high-low transition then:
   • Find the minimum of $Sum[i]$ and the corresponding position $pos_{min}$
   • In $i \in 1..pos_{min}$ find the last $Sum[i] \geq 0$ and the corresponding position $pos_{left}$
   • In $i \in pos_{min} + 1..n - 4$ find the first $Sum[i] \geq 0$ and the corresponding position $pos_{right}$

![Fig. 1: moving image capturing (left synthetic, right realistic)](image-url)
5. Else if $\text{Sum}[i]$ has a low-high transition then:
   - Find the maximum of $\text{Sum}[i]$ and the corresponding position $\text{pos}_{\text{max}}$
   - In $i \in 1..\text{pos}_{\text{min}}$ find the last $\text{Sum}[i] \leq 0$ and the corresponding position $\text{pos}_{\text{left}}$
   - In $i \in \text{pos}_{\text{min}} + 1..n - 4$ find the first $\text{Sum}[i] \leq 0$ and the corresponding position $\text{pos}_{\text{right}}$

6. Finally calculate the length of the blurred edge in pixel: $\text{Length} = \text{pos}_{\text{right}} - \text{pos}_{\text{left}} + 1$

2.3. Richardson-Lucy-Algorithm (RL)
The Richardson-Lucy method is an iterative restoration algorithm that maximizes a Poison statistics image model likelihood function, which is more applicable to very low light conditions. [7] The algorithm begins with a first approximation of the de-blurred image, typically the constant average intensity of all pixel gray scale values in the blurred image. The approximation is refined at each iteration with a correction factor based on the ratio between the blurred image and the approximation. The algorithm ends at a user defined number of iterations, e.g. default: 15 cycles. For the more details the reader can survey the papers of Jiang et al. [17] and Schuan [12] and Matlab product help [18]. If the PSF is known and the additive noise is low in the image, the Richardson-Lucy algorithm is more effective.

3. Closed-loop algorithm
The coordinate measuring machine (CMM) accelerates and controls at a reference speed and collects motion images at a fixed frame speed. After image acquisition by the CCD-camera with logging of position and synchronization data of the CMM, the interesting images and the associated data are separated for further post processing. Fig. 2 shows the basic steps of this post processing algorithm.

Initially an area of interest edge (AOI) is selected on the motion blurred image and the associated edge parameters: edge width and edge rise are determined. Assuming that the optical system was focused on the edge, the determined edge width is associated with the motion between CCD-camera and the
measuring object. With the information about edge width and motion direction it is possible to create a motion PSF kernel. This kernel is used for deconvolution using the Richardson-Lucy algorithm. After the deconvolution, the first iteration output de-blurred image is inspected again for the edge parameter. If the determined edge width in the de-blurred image is smaller than a predefined threshold edge width, the de-blurred image is ready for an edge detection criterion like gradient, threshold or dynamic threshold method. If the de-blurred image edge width is insufficient regarding to the predefined threshold, the algorithm runs again till the solution gets sufficient.

4. Verification of the algorithm
For testing the algorithm realistic and synthetic motion blurred images are processed in the closed-loop algorithm. Dependent on the edge widths of the origin images, the algorithm creates a sufficient solution by de-blurring a realistic image after a finite count of iteration loops. The first subchapter 4.1 introduces the results of the algorithm for application with realistic image examples. Furthermore for optical geometric measures it is necessary to determine the edge location using pixel and sub pixel edge detection methods, hence a quantitative analysis is performed using synthetic example.

4.1. Quality of restoration for real captured images
Fig. 3 shows the result of the restoration on a real image captured in the controlled coordinate measuring machine environment. As shown in Fig.3, a very sharp edge, which has a sufficient edge quality, is obtained after only three iteration loops. The method converges very quickly and is insensitive to the existing noise in the real image. The Richardson-Lucy deconvolution generates artifacts at the boundaries of the image, which are eliminated by resizing the de-blurred image and are delivered for the next iteration. Therefore the algorithm is applicable for edges located in the middle of the image to avoid artifacts in the area of the edge. The conclusion of this example is, that geometrical measures with dynamic motion captured images without strobe illumination are possible, if the whole measuring scene is divided into several sub AOIs for a separated motion blur restoration.

![Fig. 3: motion blurred and restored images](image)

4.2. Edge detection results using synthetical generated images
Generally geometrical measures in optical metrology are based on different edge detection algorithms in pixel and sub pixel domain. [1] In this section the verification of the restoration results and the influence of our image restoration algorithm on the edge position in the image are determined by using four different methods for edge detection in pixel domain without using sub pixel detection methods. The proof of edge location is done by using a synthetic image including an ideal edge and a well-known position of the edge, which is located at 127th pixel. (See Fig.4 left (1)) This image is synthetically blurred, as shown in Fig. 4 left (2), and afterwards restored with our restoration algorithm in the first and second iteration (see Fig. 4 left (3) and (4)). Fig. 4 - right depicts the related gray scale curves of the line areas of interest, which are perpendicular located to the edges.
The edge detection of the four image states is limited by the threshold of the used method. The gradient method is not applicable for edge detection of the first blurred image (Fig. 4, left (2)). One of the causes for this is the internal gradient threshold, which differentiates between valid and invalid edges. The edge detection results of the four different image states are diagrammed in Fig. 5. [2] The four methods detect different edge positions, especially the correlation method creates insufficient results after blurring and de-blurring the images in comparison with the other methods. By comparison of the edge locations of images (Fig. 4 left (1) and (4)), the average locations of all methods except the correlation method diversify less than four pixels. The utilization of sub pixel methods for increasing the accuracy of the edge detection is not necessary, because the blurring and the following restoration create a movement of the edge location in pixel domain as mentioned above. However the restoration results are sufficient for accurate optical geometric measure of dynamic blurred images.
5. Conclusion
The introduced algorithm gives excellent restoration results if the size of the AOI enclosing the edges in motion direction is large enough. The outcome of this is that the artifacts have no impact to the edge which is preferably placed in the middle of the area of interest. The detected edge position in the restored AOI has only small deviations from the origin edge position in the still un-blurred AOI. The presented algorithm gives the possibility for accurate geometric measure of motion blurred images.

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