

A new approach on restoration of dynamic measurement uncertainties in optical precision coordinate metrology

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Abstract. This paper presents a new approach to the restoration of dynamic influenced measurement uncertainties in optical precision coordinate metrology (OPCM) using image sensors to measure geometrical features. Dynamic measurements within the context of this paper are based upon relative motion between the imaging setup (CCD-camera and optical system) and the measuring object respectively the measuring scene. The dynamic image acquisition causes image motion blur effects, which downgrades the uncertainties of the measurand. The approach presented deals with a new technique to restore motion degraded images using different methods to analyze important image features by extending the famous state of the art Richardson-Lucy image restoration technique using a new convergence criteria based on the variation of the detectable sub-pixel edge position of each iteration.



1. Introduction

The primary objective of the new approach is to obtain accurate measurands on dynamic measurements in optical coordinate metrology (OPCM). Besides the measurement accuracy it becomes more and more important to provide measurement results at a reasonable time due to economic reasons. The computation time needed to process acquired images in a suitable way for metrological applications allocates a small amount of the complete measurement time needed to finalize a measurement task (often accelerated by multicore CPU-architectures and GPU-processors). Acquiring static images often consumes a higher amount of time due to repositioning the camera and freezing the drives. Therefore the image acquisition process actually is a bottleneck in the whole process chain. Within the context of this paper a static measurement describes the measurement object in rest relative to the imaging sensor respectively the camera and the lens. A dynamic measurement instead depicts the measuring object in motion during the measurement process [1]. The goal of the dynamic measurement is the decrease of the time consumption at the achievement of a constant measurement accuracy as on static measurement. High precise measurements in OPCM require high quality imaging of the measurement scene. Influences like distortion effects caused by the optical system, noise during the sensor integration time, analog-digital-conversion (ADC) and others reduce the measurement accuracy on static and dynamic measurements too. A dynamic measurement usually causes blur effects in the image due to the relative motion between measuring object and image sensor during image acquisition, so-called motion blur. For metrological purposes the blur effects at intensity transitions (“edges”) are the major problem since they are used to interpolate subpixel-precise edge positions (SPEPs). Image blur effects increase the measurement uncertainty U [2] and therefore downgrade the measurement accuracy. The reachable uncertainty of the image measurement increases with the velocity of the relative motion. Figure 1 also depicts an dynamical acquired scene of a measuring object in horizontal motion and the overlay of a typical region-of-interest, which is used for a search line based detection of SPEPs.

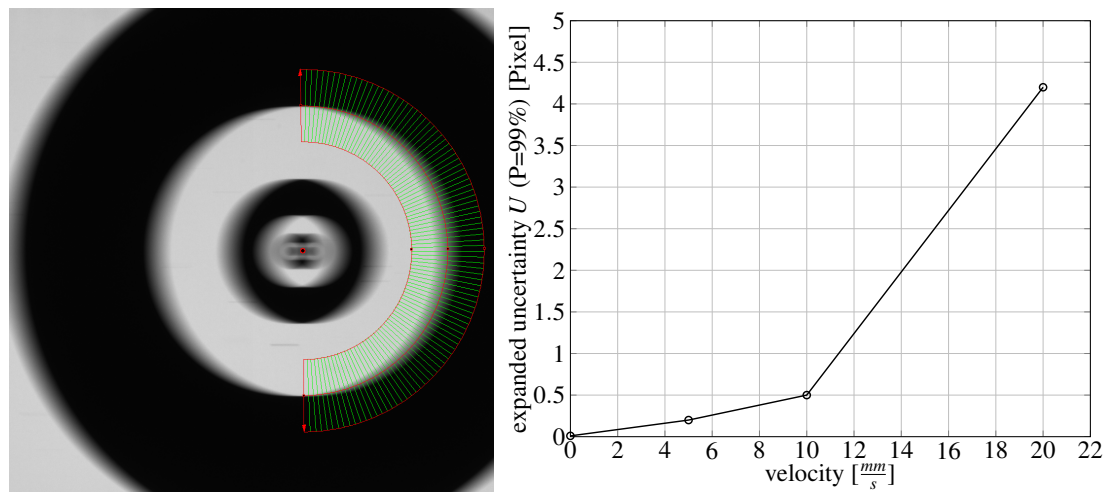


Figure 1. left: horizontal motion degraded image, right: measurement accuracy downgrade by increased uncertainties caused by motion-blur-effects [2]

2. State of the Art

2.1. Dynamic measurement in optical precision coordinate metrology

The state of the art approach to reduce image blur effects is to “freeze” the measuring scene for a short time. A common technique for this approach is to use strobed illumination during

the shutter time of the CCD-camera, image capturing in a very short exposure time [3, 4]. These methods demand in both cases a powerful illumination of the measuring scene or a high electronic amplification, which yields higher image noise as the biggest disadvantage. The noise effects are degradational influences to the measurement of geometrical features and also to the reachable measurement uncertainties. Another simple method in combination with the other above mentioned approaches is the reduction of the motion velocity at the exposure time [3], which is counterproductive in regard to the advantage of saving of time of the dynamic image acquisition.

2.2. Image degradation process

When modeling the imaging process using linear system theory, the ideal image, described as $f(x, y)$, is transformed into the captured image $g(x, y)$ by convolving (*) the ideal image with a degradation function $h(x, y)$ which is superposed by noise effects $n(x, y)$ during the image acquisition process (equ. 1 [5]).

$$g(x, y) = h(x, y) * f(x, y) + n(x, y) \quad (1)$$

The image degradation function $h(x, y)$ is modeled as a superposition of different degradation kernels like the optical lens degradation kernel $h_{optic}(x, y)$ for the static measuring scene. The optical degradation kernel contains diffraction and optical distortion effects, depending on the analytic model used. For the dynamic measurement there is an additional image degradation function called motion blur kernel $h_{motion}(x, y)$ which depends on the CCD-sensors integration time, the relative motion velocity \vec{v} , the motion direction as angle α , the lens-magnification β and the constant pixel-distance on the image sensor d_{pixelX} , d_{pixelY} (see equ. 2).

$$h(x, y) = h_{optic}(x, y) + h_{motion}(x, y) \quad (2)$$

In case of linear uniform motion, a simple estimation of $h_{motion}(x, y)$ is used to restore the image $g(x, y)$ using iterative non-blind deconvolution methods like the Richardson-Lucy algorithm [6].

2.3. Iterative image restoration

Different non-blind deconvolution algorithms are applicable for the restoration of motion blurred images with knowledge of the blur kernel $h(x, y)$. Iterative deconvolution methods like the Richardson-Lucy algorithm (RLA) yield sufficient results on restoration of motion blurred images using a fixed number of iterations to calculate the unblurred estimation $\hat{f}(x, y)$. The image estimate of RLAs current iteration is calculated using the following equation 3 [7]:

$$\hat{f}_i = \hat{f}_{i-1} \cdot \left(h * \frac{g}{h * \hat{f}_{i-1}} \right) \quad (3)$$

The main issue on the restoration using the RLA is the estimation of the blur kernel function and the proper iteration stop criteria.

3. Extended Richardson-Lucy-Algorithm

The major problem when using the iterative RLA is to find an adequate number of iterations or any other useful convergence criteria. When using iterative deconvolution algorithms like RLA in OPCM, the image region to be restored especially the edge transitions are very important to yield precise SPEPs. In OPCM, an area in the image, so called region-of-interest (ROI), is selected to obtain measurements results. Such ROIs consist of search lines (see figure 1), which define the direction to interpolate the image-subpixeling. The new approach utilizes the

variations of typical motion influenced properties in the image, which vary on each RLA iteration of the restoration. One of these properties is the width of the intensity transition (so-called edge-width [8]) x_W along the motion direction, another property is the detectable subpixel-precise edge positions \vec{x}_{SPEP} [9]. Since common ROIs are not suitable for the restoration tasks, new types of ROIs (figure 2) are proposed, which compute the edge position $\vec{x}_{SPEP,j,i}$ and the edge-width $x_{W,j,i}$ for every search line j in every iteration i in the adjustable motion direction, which is requested from the drive controller of the coordinate measuring machine (CMM).

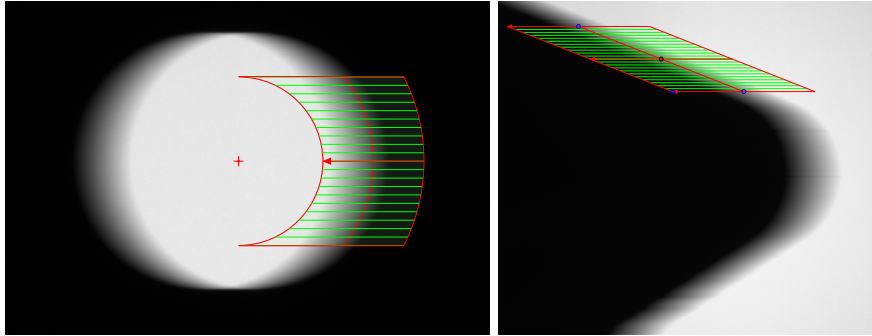


Figure 2. special regions-of-interest for the restoration task: left: *restoration-arc-ROI*, right: *restoration-line-ROI*

Figure 3 illustrates the full flow chart of the proposed extended RLA. The motion angle α (angle between horizontal image axis and motion vector) during exposure time of the sensor is used for the definition of the restoration-ROI in the image as illustrated in figure 2. The first step of the extended RLA starts with an initial analysis of the image based on the defined restoration-ROI, figure 3 - step 1. Every search line j of total $counts_{SL}$ is used for the estimation of the subpixel-precise edge position $\vec{x}_{SPEP,j}$ and the edge-width $x_{W,j}$. The averaged edge-width \bar{x}_W and the motion direction angle α are used for computing the motion point-spread-function $h(\bar{x}_W, \alpha)$. Under the pre-condition of an uniform linear motion, the point-spread-function in case of a pixel-grid-synchron motion is a vector of the size $[\bar{x}_W, 1]$ estimated by following equation:

$$h(\bar{x}_W, \alpha, x) = \frac{1}{\bar{x}_W} \quad x = [0..\bar{x}_W] \quad (4)$$

Non pixel grid motion angles are produced by rotation of the motion vector and bilinear interpolation [6]. Afterwards the motion point-spread-function is extended to the image size by zero padding. The main iteration loop of RLA is processing the image estimate $\hat{f}_i(x, y)$ for every iteration i , figure 3 - step 2. The further step 3 is calculating the edge properties SPEP and edge-width again. The current iterations scalar distance value d of the SPEPs estimated from current and last RLA iteration is calculated component-by-component in the following way by the distance vectors absolute value:

$$d = |\vec{x}_{SPEP,j,i} - \vec{x}_{SPEP,j,i-1}| \quad (5)$$

$$d = \left| \begin{pmatrix} x_{j,i} \\ y_{j,i} \end{pmatrix} - \begin{pmatrix} x_{j,i-1} \\ y_{j,i-1} \end{pmatrix} \right| = \left| \begin{pmatrix} d_x \\ d_y \end{pmatrix} \right| = \sqrt{d_x^2 + d_y^2} \quad (6)$$

Afterwards the convergence criteria are checked by comparing the estimated values with pre-defined threshold values (figure 3 - step 4). This loop procedure is repeated until the conditions are true.

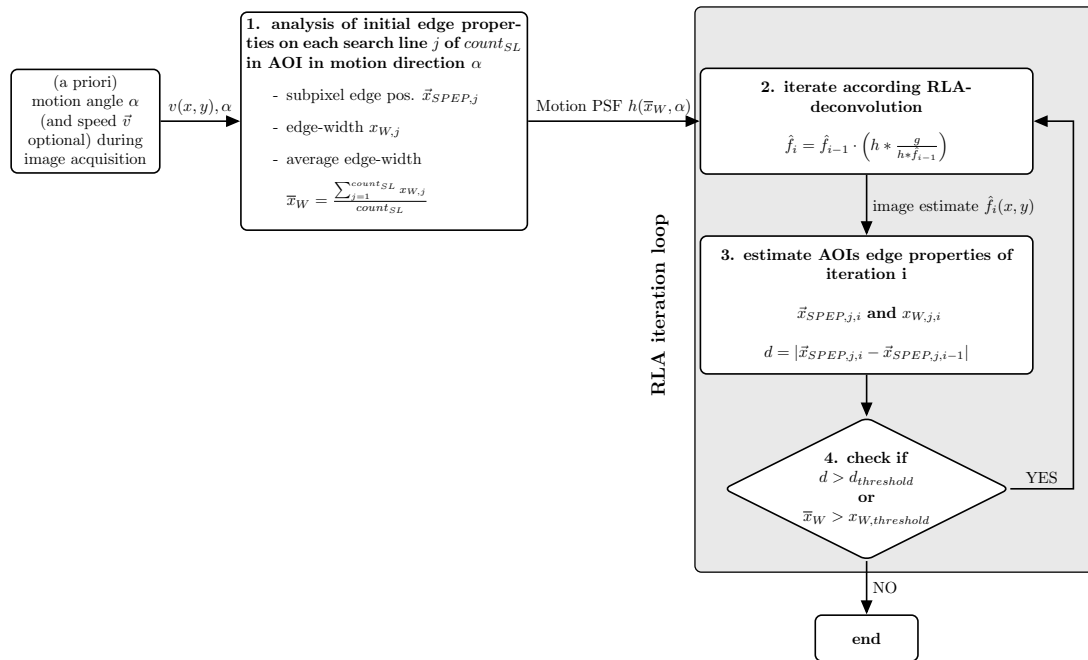


Figure 3. Extended RLA for motion blur restoration of images used for measurements in OPCM

4. Experimental results

The new algorithm was tested on different motion acquired images and delivered sufficient results on the restoration. Figure 4 depicts the restoration levels of an selected image restored by the proposed algorithm. The image edges were sharpened in a sufficient way to reduce the reachable uncertainty of the measurement. As seen in figure 5 a) the edge-width decreases on each iteration of the algorithm. The example image was sharpened from 58 pixel edge-width to a value of 10 pixel in only 38 RLA iterations. The distance of the SPEPs between two iterations are also decreasing, see figure 5 b). The charts of both values have an asymptotic characteristics, therefore pre-defined threshold values ($d_{threshold}, x_{W,threshold}$) as stopping criteria could be used. The distance value of the SPEPs $d_{threshold}$ converges to zero with a noise depending ripple.

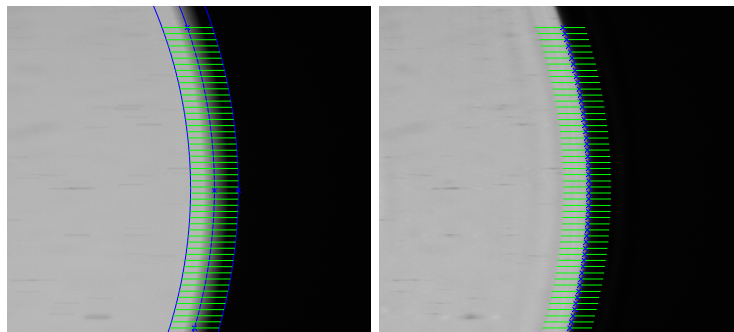


Figure 4. motion blurred image, left: before extended RLA restoration, right: after extended RLA restoration

For a subpixel-precise estimation of the edge position, an edge-width in the range of 5 to 10 pixel necessary for the interpolation. These values are estimated on real static images and mainly

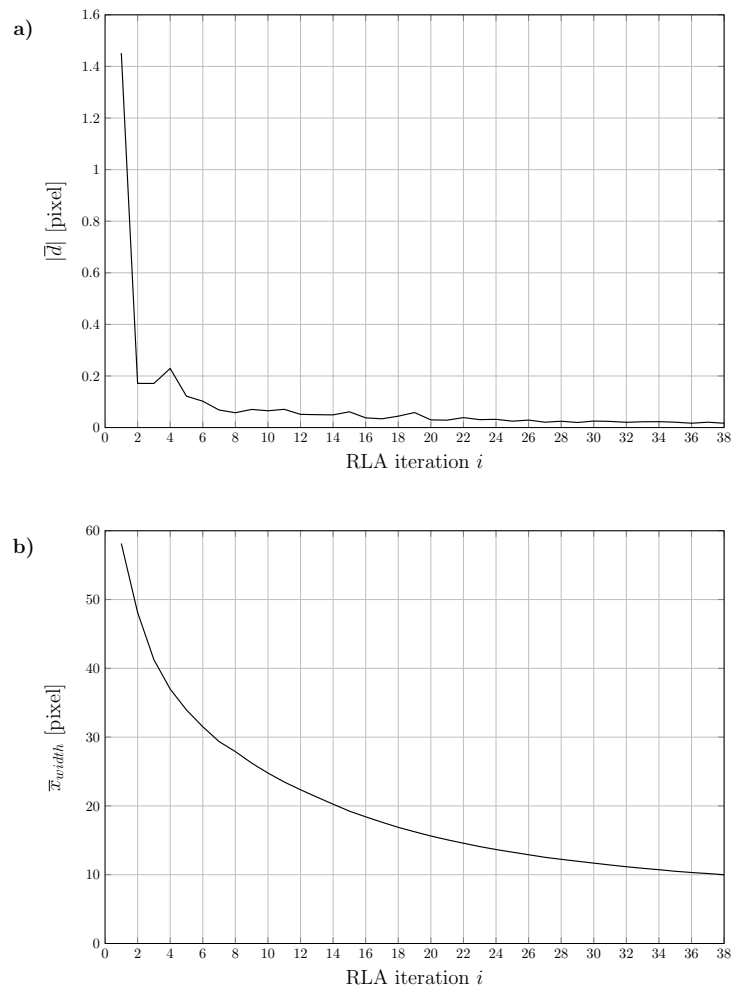


Figure 5. a) average edge-width, b) average SPEP distance vs. RLA iteration

depending on the diffraction effects of the lens system. Hence the threshold value $x_{W,threshold}$ is a-priori defined for the breaking condition to a value of 10 pixel. The SPEPs distance threshold $d_{threshold}$ is also a-priori defined to a value of 0.05 pixel and yields a good ratio of performance and accuracy of the algorithm.

5. Summary

We presented within this paper a new approach on the restoration of motion blurred images in the field of dynamic measurement using image sensors in the optical precision coordinate metrology. The proposed algorithms are based on an extension of the Richardson-Lucy iteration with special remark to image properties regarding to the uncertainties for measurement applications. The deconvolution algorithm yields a good performance on motion blurred grayscale images and delivers sufficient results to the intensity edge transitions, which are important for the measurement application.

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