Parameter Estimation of a Laser Measurement Device Using Particle Swarm Optimization

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***Abstract* – The two-dimensional object's position or object's edge can be estimated from its multi-exposure shadow projection. This can be done using two bare Laser diodes projecting the object's edge onto a CCD or CMOS sensor without the need of any additional optical elements such as collimation lenses. For simple triangulation methods, Sensor- and laser diode position play a very important role. The overall accuracy is mostly determined by the uncertainty of that parameters. This paper presents a possible approach to determine that parameters. Since deterministic methods suffer from badly shaped error functions, stochastic methods can deliver very good results, ending up in the global optimum. When using particle swarm optimization, it could be shown, that the remaining residual error of an estimated projected edge position can be significantly reduced. This error immediately effects the overall object's position estimation accuracy, which can also be increased, in case the geometrical system parameters were determined using particle swarm optimization.**

***Keywords* – CCD image sensors, Semiconductor Lasers, Diffraction, Image edge detection, Position estimation, Particle swarm optimization**

I. INTRODUCTION

In many cases, common contact-less optical methods for determining an 2D object's position use so-called shadow methods. The shadow of an opaque measurement object which is exposed by a light source, is projected onto a light sensitive sensor. Therefore, the object's projected edge position on the sensor can be obtained. In result the position of an object, or geometrical object parameters, like thickness or diameter could be determined, given the position of several projected edges [1].

The idea of getting rid of very expensive additional optical elements which were needed for collimating the light source's light beam, is essential when setting up small measurement systems. This also leads directly to savings in production costs, system dimensions, and reduced complexity of such measurement devices. A small measurement device could be well-integrated directly into applications like wafer production- or testing systems like it is proposed in [2].

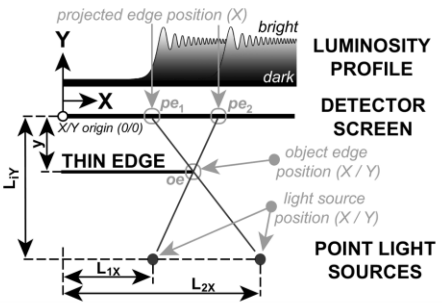

Fig. 1 Working principle for position measurements, projecting object's edges with two light sources onto a sensor.

Our test setup proposes a linear CCD sensor array and two bare, off-the-shelf Laser diodes, placed in a distance of L_{iY} to the sensor. These two Laser diodes sequentially expose one single sharp edge of an opaque object onto the sensor. The shown setup relies on sequential exposure, therefore only one single edge is projected in one step by one single light source. Every single exposure will generate a shadow, a diffraction pattern respectively, which is projected onto the sensor (Fig. 1). By finding this projected edge position on the sensor, as well as due to the known the light sources positions, it is obvious that the objects edge position (X/Y) could be easily determined with triangulation methods.

In this paper, it is proposed that the very first pixel of the CCD sensor is placed in the X/Y coordinate origin at (0/0), and its orientation is in X direction only, therefore, the projected edge position on the sensor will also be only a function of X. The object's edge is also considered to be very thin. This plays an important role, since the enhancement of the Laser diodes photometric stereo basis can increase the edge position estimation accuracy, but also scales down the measurement area (Fig. 2). In any case, it must be maintained that both light sources expose the same edge. Especially with thick objects this problem can be nicely illustrated (Fig. 3). To overcome that

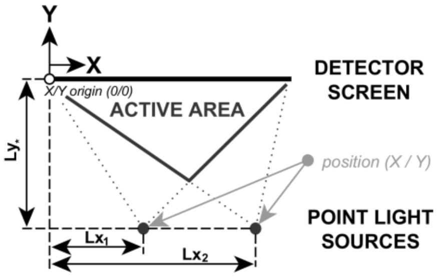

Fig. 2 active measurement area, by increasing the distance in between the two sources, the active measurement area gets smaller

problem, in this paper the object's edge will always be considered as very thin, assuming a straight knife edge.

Particle swarm optimization can be utilized to determine the exact light source position highly accurate. In a real-world application, the projected edge is influenced by noise as well as laser speckles, the geometrical setup, the used edge detector and the underlying edge projection model. Therefore, the projected edge position is always detected with some error. This error, which is going to be optimized, won't always have only a single flat or nicely shaped valley. Therefore, deterministic methods might not converge to the global optimum when optimizing L_{iX} and L_{iY}. In that case, stochastic methods like the proposed particle swarm optimization, can deal a lot better with badly shaped error functions, which were strongly influenced by different sorts of noise.

With particle swarm optimization, the inaccurate parameters L_{iX} and L_{iY}, can be adjusted in a way to significantly increase the accuracy of the estimated X/Y object position, its edge respectively, independent of the edge detector used (e.g. simple thresholding). It is obvious that the proposed method can be envisaged to be used in combination with any suitable edge detector. The estimation accuracy of the objects X/Y edge position will be improved, regardless of the used projected edge detection algorithm. By defining a residual error as function of the projected edge position, the particle swarm optimizer can alter the particle positions to minimize the remaining residual projection error. The X/Y objects edge position estimation error is then reduced implicitly.

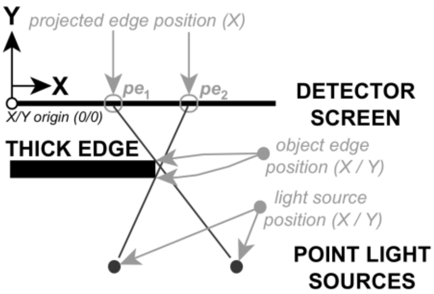

Fig. 3 both light sources expose different edges, in result an edge position estimation is not possible

II. RELATED RESULTS

The first indispensable step is determination of the projected edge position on the sensor, since this information is needed for estimation of the unknown objects edge position. When exposing an edge using narrowband point light sources, e.g. laser diodes, a diffraction pattern will be generated. This pattern, which also strongly depends on the geometrical parameters of the measurement setup, will be projected onto the sensor. By using the known solutions of Fresnel Integrals for an opaque half plane [3], which is the edge in our case, the Luminosity on the sensor can be calculated using (1-2).

As it can be obtained by equation (1) (where $C(\zeta)$ is the Fresnel cosine integral and $S(\zeta)$ the Fresnel sine integral), the theoretical exposure intensity at any arbitrary point x on the sensor can be determined unambiguously (k is the wavenumber, y the distance in between the edge and the screen, x the position in X direction on the sensor). Thereof follows the relative intensity at the projected edge's position on the sensor by 25% of I_0 (Fig. 4). By using that knowledge, it seems obvious that very simple thresholding

$$I_{rel}(\zeta) = \frac{I_0}{2} \cdot \left\{ \left[\frac{1}{2} - C(\zeta) \right]^2 + \left[\frac{1}{2} - S(\zeta) \right]^2 \right\} \qquad (1)$$

$$\zeta = \sqrt{\frac{k}{2 \cdot y}} \cdot x \qquad (2)$$

will work for determining the projected edge position on the sensor [4].

In case the projected edge position should be determined more accurate, in terms of getting better resolution than the sensors pixel size is, some other different methods can be envisaged.

Some simple geometrical models, for detecting the projected edge position were introduced in [5], since in some cases, e.g. high amounts of additive noise, simple thresholding does not perform well.

More robust and advanced methods, enabling the projected edge position to be determined with subpixel resolution were presented in [6].

In [4] it was also shown, that triangulation methods for object position estimation, using bare laser diodes can perform well, although without using any collimation optics. If optical elements should be omitted, it comes to

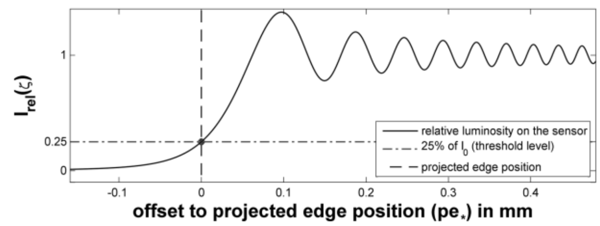

Fig. 4 diffraction pattern generated by a point light source and a sharp edge projected onto the CCD sensor, given a sensor-object edge distance (y) centered around the projected edge position (pe).

some severe disadvantages. For example, for object or edge position measurements, the light source positions must be known precisely. The performance of the position estimation is directly influenced by the uncertainty of the Laser diodes L_{iX} and L_{iY} positions.

For any real-world application, it is obvious, that the positioning of the Laser diodes is not trivial. Also in an automatic placement process, depending on the mounting standard and component tolerance, the Laser diode position will vary from device to device from a few tens of micrometers up to several millimeters.

With the versatile particle swarm optimization, as introduced in [7], it is possible to determine the Laser diodes position in order to improve the objects edge position estimation, without the need of an accurate placement of the used laser diodes.

III. DESCRIPTION OF THE METHOD

To improve the object edge position estimation error, a calibration step is introduced. First, several edge positions must be processed as accurate as possible, to determine the light source positions. Once this is done, the objects edge position can be later identified more precisely, due to the optimized light source position. This chapter describes this calibration step in detail.

A. Description of the test setup

In our test setup, a linear drive table with a positioning precision of 200nm was used to move a very thin knife edge towards given points in the X/Y measurement plane preserving some given boundaries. Some of these points, object edge positions respectively, were marked with x in Fig. 6, as well as the object edge position boundaries [oe_{xmin}=0.02, oe_{xmax}=0.03, oe_{ymin}=-0.035, oe_{ymax}=-0.025] are indicated by the dark rectangle. *M* different object edge positions ($\mathbf{oe}_m$(X,Y)) were exposed by *I* light sources consecutively and the sensor data is collected. Any edge detector could then estimate the detected projected edge position $de_{i,m}(X)$ given the sensor pixel data. These detected edge positions are biased by some estimation error (Fig. 5), depending on the used edge detectors accuracy and the geometrical parameters of the setup.

In our case, the object edge position $\mathbf{oe}_m$ (linear drive table position feedback), as well as the light source positions (L_{iX}, L_{iY}) are considered to be known.

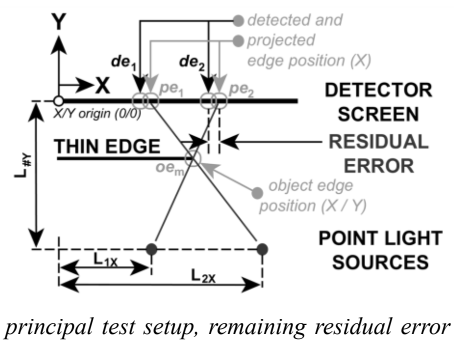

Fig. 5 principal test setup, remaining residual error with an inaccurate point light source position

The complete geometrical setup used, is shown in Fig. 6. Up to six laser light sources were available. For estimating the object edge position in the last step, with the optimized system parameters, $\mathbf{oe}_{m,est.}$, one single pair of two sources is used. The available light sources were placed at some fixed positions on a PCB:

$$\mathbf{L}_{(1:6)X,Y} = \begin{bmatrix} 20.325, -65.543 \\ 24.797, -65.499 \\ 29.269, -65.455 \\ 33.741, -65.411 \\ 38.212, -65.367 \\ 42.684, -65.323 \end{bmatrix} \text{mm}$$

This fixed positions should be maintained by a pre-assembled printed circuit board. Therefore, the resulting theoretically projected edge positions $pe_{i,m}$ and the remaining residual error r_i for each light source, can be easily calculated.

$$pe_{i,m} = f\left(\mathbf{L}_{iX,Y}, \mathbf{oe}_{mX,Y}\right) \tag{3}$$

$$r_i = \sqrt{\frac{1}{M}\sum_M \left(pe_{i,m} - de_{i,m}\right)^2} \tag{4}$$

Typically $\mathbf{L}_{iX,Y}$ is not precisely known or may be displaced by some few hundred micrometers, as well as the edge detector will have some remaining residual error when estimating the detected projected edge positions. Therefore $\mathbf{L}_{iX,Y}$ can be adopted to optimize the remaining residual error r_i, given the detected projected edge position $de_{i,m}$ and the projected edge position $pe_{i,m}$.

$$\text{find } [\mathbf{L}_{iX,Y}] : r_i = \min\left(r_i\left(pe_{i,m}, de_{i,m}\right)\right) \tag{5}$$

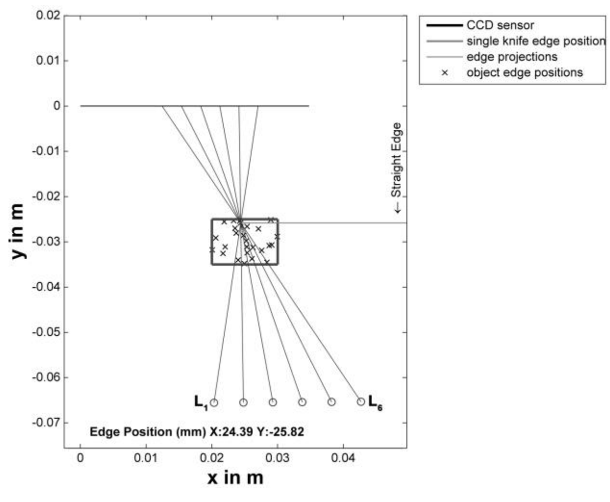

Fig. 6 complete geometrical testsetup, one distinct object edge position with edge projections caused by sequential exposure with light sources at different positions, the edge is projected at different positions onto the sensor, additional object edge test positions were marked with x

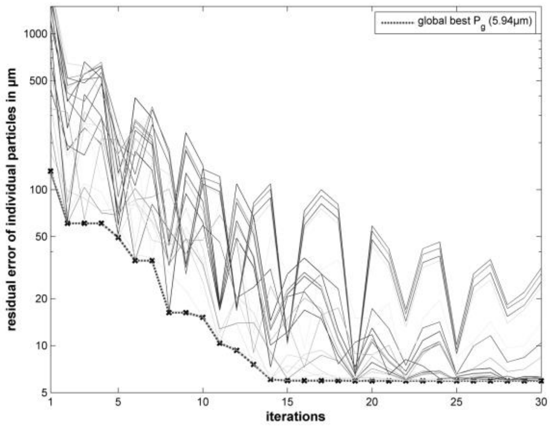

Fig. 7 individual evolution of the light source particle error, all particles move towards the global optimum. (c1=0.75, c2=0.9, w=0.8)

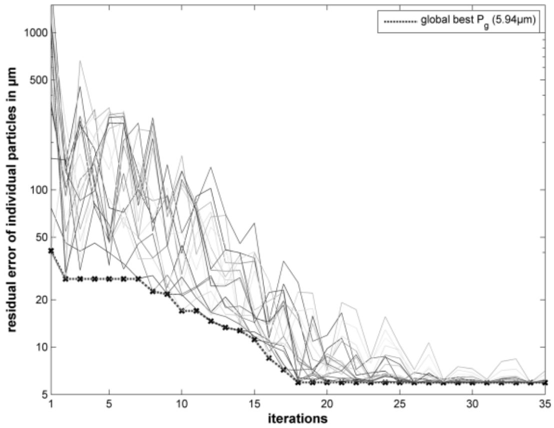

Fig. 8 individual evolution of the light source particle error, all particles move towards the global optimum. (c1=0.75, c2=1, w=0.8)

B. Description of the particle swarm optimization step

The following steps (eq. 6-14) can be simultaneously computed for light source one to six since the defined error criteria r_i is independent of the others light source position. In principle, the particle swarm optimizer is initialized for each light source with *P* Particles $\mathbf{X}_p$, each representing one distinct light source position ($\mathbf{L}_{i,pXY}$) preserving given boundaries (e.g. ± 2mm) for one starting light source position ($\mathbf{L}_{iXY}$), and initial random velocities $\mathbf{V}_p$ in X and Y direction.

$$\mathbf{X}_p = \begin{bmatrix} \boldsymbol{L}_{i,1XY} \\ \vdots \\ \boldsymbol{L}_{i,PXY} \end{bmatrix} \qquad \mathbf{V}_p = \begin{bmatrix} \boldsymbol{V}_{i,1XY} \\ \vdots \\ \boldsymbol{V}_{i,PXY} \end{bmatrix} \qquad (6)(7)$$

Each particle maintains its individual best $\mathbf{P}_p$, as well as the whole particle swarm its global best light source position $\mathbf{P}_g$. The velocity and position update in each step ($t \rightarrow t+1$) is influenced by an inertial $\mathbf{I}_p^t$,a cognitive $\boldsymbol{C}_p^t$ and a social component $\mathbf{S}_p^t$.

Inertial Component	$\mathbf{I}_p^t = w \cdot \mathbf{V}_p^t$	(8)
Cognitive Component	$\mathbf{C}_p^t = c_1 \cdot r_1^t \cdot [\mathbf{P}_p - \mathbf{X}_p^t]$	(9)
Social Component	$\mathbf{S}_p^t = c_2 \cdot r_2^t \cdot [\mathbf{P}_g - \mathbf{X}_p^t]$	(10)
Velocity Update	$\mathbf{V}_p^t = \mathbf{I}_p^t + \mathbf{S}_p^t + \mathbf{C}_p^t$	(11)
Particle Update	$\mathbf{X}_p^{t+1} = \mathbf{X}_p^t + \mathbf{V}_p^t$	(12)

c_1, c_2 were some predefined constants and r_1^t, r_2^t some randomly generated numbers in the interval of [0,1]. After (8-12), the error criteria (4) is evaluated and $\mathbf{P}_p$ as well as $\mathbf{P}_g$ were updated.

Particle Update	$\mathbf{P}_p = \text{best}(\mathbf{P}_1^t \cdots \mathbf{P}_P^t)$	(13)
Global Update	$\mathbf{P}_g = \text{best}(\mathbf{P}_1 \cdots \mathbf{P}_P)$	(14)

The Update process can be stopped after a various number of iterations. Typically, 10-15 update steps were necessary to compute the optimal light source position.

C. Particle swarm parameter choice

The right choice of c_1, c_2 and w plays an important role, regarding convergence of the particle swarm optimizer. Different problems may need adopted parameters. By the choice of c_1 as well as also c_2 the convergence speed can be influenced. The greater c_1 is, the more one particle moves towards his personal best position. The greater c_2 is, the more the particle will move towards the global best position of all particles. When considering that each light source is optimized separately, the evolution of the error of each iteration and particle of one single source, can be found in Fig. 7.

In Fig. 8 the parameter c_1 was only slightly changed, but the convergence velocity of the particle swarm is immediately affected, thus the whole swarm converges faster to its global optimum.

By the choice of w, the exploration of the whole parameter space is handled. If w is small, the particles tend to explore the parameter space less than compared to higher values of w. In Fig. 9 the evolution of all particles in the parameter space is illustrated. There it can be seen, how the global best particle moves through its parameter space from iteration to iteration. The error corresponding to the particle positions of Fig. 9 is shown in Fig. 7.

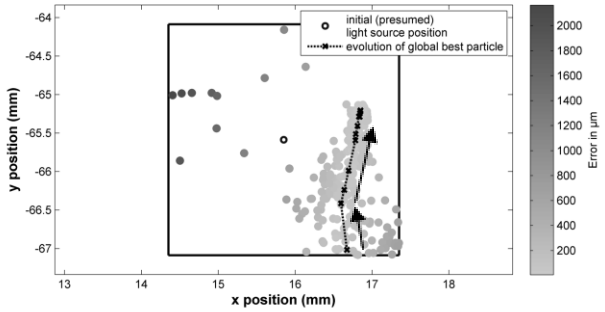

Fig. 9 evolution of 20 initialized particles towards the best light source position, the middle of the bounding box marks the initial start position at (X=15.8528mm, Y=-65.5872mm)

D. Object edge position estimation

The object edge position can be estimated ($\mathbf{oe}_{m,est.}$) by straight forward extending the light rays from the light source to the detected edge position ($de_{i,m}$) and determining the point of intersection of both rays (Fig. 5) afterwards.

$$k_{i,m} = \frac{L_{iY}}{L_{iX} - de_{i,m}} \tag{15}$$

$$d_{i,m} = - k_{i,m} \cdot oe_{mX} + L_{iY} \tag{16}$$

Equation (18-19) follows when determining the intersection point of the two light rays in (17).

$$k_{1,m} \cdot oe_{mX} + d_{1,m} = k_{2,m} \cdot oe_{mX} + d_{2,m} \tag{17}$$

$$oe_{X,est.} = \frac{d_{1,m} - d_{2,m}}{k_{2,m} - k_{1,m}} \tag{18}$$

$$oe_{Y,est.} = k_{1,m} \cdot oe_X + d_{1,m} \tag{19}$$

IV. RESULTS AND DISCUSSIONS

The proposed particle swarm optimization method for optimizing the light source position was tested with real measurement datasets, and the geometrical setup proposed in Fig. 6.

A. Residual error of the projected edge position (r_i)

For a set of around M=1000 different object edge positions, the remaining residual error r_i was evaluated. Using the presumed laser diode position (PCB Placement) and a simple threshold model, $r_i \approx 0.8\text{mm}$, for the projected edge position of each light source. For the particle swarm optimization step we achieved nice results by using the following initial conditions:

$$[c_1,\ c_2] = [0.75, 0.9]; \qquad w = 0.8; \tag{20}$$

Fig. 7 shows how the error r_i changes for a population size of P=20 particles for one light source over 30 iterations. Fig. 9 shows the X/Y position of the light source particles, which nicely accumulate towards the global optimum during the iterations. With that parameters (20), the particle swarm converged for several test-runs almost in every run to the global optimum, which was obtained at e.g. $L_{1X} = 21.252\text{mm}, L_{1Y} = - 64.978\text{mm}$ with a residual error $r_i \approx 3.73\mu\text{m}$. Additionally, we tested a variation of w during iterations:

$$w_{start} = 0.5; \quad w_{end} = 0.9 \tag{21}$$

$$w^t = \text{linearinterp}(w_{start}:w_{end}) \tag{22}$$

Therefore (8) is adapted to:

$$\textit{Inertial Component} \qquad \boldsymbol{I}_i^t = w^t \cdot \mathbf{V}_i^t \tag{23}$$

With that modification, the particles tend to explore the parameter space even at a higher iteration number, when the particle swarm is more and more grouped. This also leads directly to an improvement of the convergence speed as well as convergence in different test runs. The algorithm converged for every light source in nearly every of 50 different test runs to the global optimum of r_i . The iteration limit was set to 50 iterations for each particle swarm.

With the proposed method, it is possible to achieve very good light source position estimation results. The remaining residual error r_i, which is mainly caused by displacement of the laser diodes, can be significantly reduced from several hundred (Table 1), to a few micrometers (Table 2). The optimized light source positions $\mathbf{L}_{(1:6)X,Y,opt.}$ clearly differ from the starting presumed positions $\mathbf{L}_{(1:6)X,Y}$.

$$r_{1..6} \approx \begin{bmatrix} 3.7 \\ 3.7 \\ 3.0 \\ 2.6 \\ 2.8 \\ 5.0 \end{bmatrix} \mu\text{m} \quad \text{with} \quad \mathbf{L}_{(1:6)X,Y,opt.} = \begin{bmatrix} 21.252, -64.978 \\ 25.699, -65.045 \\ 30.212, -65.144 \\ 34.689, -64.974 \\ 39.205, -64.907 \\ 42.728, -64.905 \end{bmatrix} \text{mm}$$

B. Object edge (oe) position accuracy regarding the light source position uncertainty

It is obvious that the remaining residual error directly effects the estimated object edge position (X/Y) accuracy. Also, the greater the x distance in between the used laser diode pair is, the more accurate the estimated object edge position ($\mathbf{oe}_{m,est.}$) becomes, since the object edge position is determined simply by the point of intersection of the projection rays (Fig. 5) (Eq. 15-19).

The object edge position can be estimated by any two out of the six used sources. For easy comparison three light source pairs are going to be compared (light source 1/6, 2/5, 3/4). For the whole set of 1000 object edge positions, each position preserving the boundaries shown in Fig. 6, also as mentioned in section III - A, the detected edge was determined firstly without optimizing the light source positions of all 6 sources (Table 1).

After using the particle swarm optimizer to determine

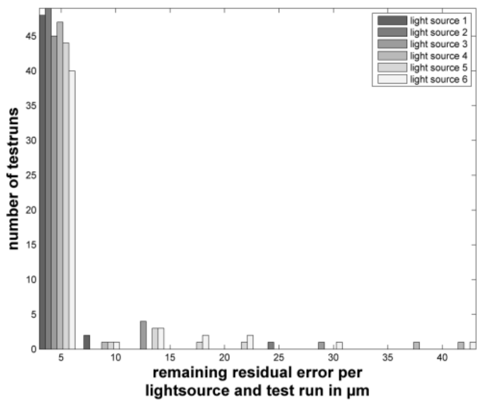

Fig. 10 result for 50 independent test runs of the particle swarm optimizer (iteration limit -50 iterations reached) the light source position more accurate $\mathbf{L}_{(1:6)X,Y,opt.}$ the results were much more reasonable. Indeed, it can be said that the error in X/Y position decreases if the most outer positioned light sources (1/6) were used (Table 2).

Although for our measurements a CCD sensor with a pixel size of 4.7µm was used, the results show impressing, that also with a relatively simple threshold model, a good object edge position estimation performance can be achieved.

Table 1

	object edge RMS error (X)	object edge RMS error (Y)
light sources: 1/6	419µm	282µm
light sources: 2/5	411µm	327µm
light sources: 3/4	409µm	304µm

Table 2

	object edge RMS error (X)	object edge RMS error (Y)
light sources: 1/6	2.23µm	5.38µm
light sources: 2/5	4.74µm	13.03µm
light sources: 3/4	7.09µm	22.25µm

V. CONCLUSIONS

The parameter estimation for the light source position (X/Y) is essential when accurate position measurements were considered. To overcome real world positioning problems, regarding this light-source position, the relative light source - sensor position respectively, a calibration routine using particle swarm optimization was introduced. Using that optimization method, it was shown that it is possible to determine the light source positions, with a very easy, straight forward to implement solution, since the main core of the particle swarm optimizer is only about 30 lines of code, including initialization. Additionally, this approach shows very good convergence, which can be seen in Fig. 8. The choice of the particle swarm optimizer parameters c_1, c_2 and w influences the convergence of the algorithm at most. In several test cases with a set of different datasets, it was proven that is nearly impossible to end up far away of the global optimum. Also, the variation of w during the iterations is a possible approach, which can lead to a convergence improvement. There are also other techniques for extending the particle swarm approach, like differential evolution, proposed in [8], which can deliver better convergence, whilst exploring the parameter space even more. Since our error function r_i was not that badly shaped, it can be stated that simple particle swarm optimization was sufficient for our optimization problem.

The results show that increasing the stereo basis, the x-distance in between two light sources respectively, directly increases object edge position estimation accuracy, when using simple intersection method. In that case, it should be maintained that only very thin edges were measured, otherwise both light sources wont expose the same edge of the object, which leads to measurement errors.

Increasing the stereo basis, also sizes down the utilizable measurement area and should be adjusted to the envisaged application.

With the proposed methods, it can be said, that using very simple thresholding and a straight forward to implement particle swarm optimization, it is possible to obtain reasonable object edge position estimation results down to the scale of the used sensors pixel size and even below.

When using a more sophisticated edge detector for determination of the projected edge position which is able to achieve subpixel resolution [6], the object edge position (X/Y) estimation error can be further lowered down.

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