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Gaussian-Based Approach to Subpixel Detection of Blurred and Unsharp Edges

Anna Fabijańska
Lodz University of Technology
Institute of Applied Computer Science
18/22 Stefanowskiego Str., 90-924 Lodz, Poland
Email: anna.fabijanska@p.lodz.pl

***Abstract*—In this paper the problem of edge detection with subpixel accuracy is considered. In particular, the precise detection of significantly blurred edges is regarded. A new method for subpixel edge detection is introduced. The method attempts to reconstruct image gradient function at the edge using the Gaussian function. The results of subpixel edge detection in the artificially created and the real images obtained by the introduced approach are presented and compared with the results of previously proposed methods. In particular, the moment based methods, the gravity center method and the parabola fitting method are considered in the comparison. The presented results prove the robustness of the introduced approach against the averaging and the Gaussian blur. Additionally, the comparison shows, that the introduced approach outperforms the existing state-of-art methods for subpixel edge detection.**

I. Introduction

EDGE detection is the problem of crucial importance in image processing. Edges define location and geometric features of objects present in the scene. Therefore, in a typical vision system, edge detection is performed during low level processing and provides information for operations performed in the following stages, such as quantitative analysis, target recognition or image coding etc.

Recently, the requirements for edge detection accuracy rapidly increase. Satellite remote sensing, telemetry, photogrammetry, medical image analysis, industrial inspection, geometrical measurement and other applications where accuracy is at premium require precision of tenths or even hundredths of pixel.

The traditional, well-established methods for edge detection such as gradient operators (Sobel, Prewitt, Roberts), Canny edge detector, operator LoG etc. all belong to pixel level. Therefore, they are mostly insufficient for practical applications of modern machine vision. Due to their low precision of edge location and extracted wider edges, these approaches more and more often have difficulties in meeting the actual accuracy requirements of vision systems. Therefore, the development of subpixel techniques for edge detection has become one of the hotspots of the current research in image processing. Some work has already been done on this problem. However, the major methods for subpixel edge detection are still to be developed. It should be also underlined that while there has been substantial work performed on the detection of clear and well defined edges at subpixel accuracy, a little has been done on the subpixel edge detection in low contrast images containing blurred, noisy and unsharp edges [1][2].

This paper presents a new method which is a step forward through introducing subpixel analysis into edge detection. In particular, it considers precise edge detection of significantly blurred edges. As the already proposed methods deal mostly with sharp, regular and well defined edges the introduced approach can be considered like a novelty.

This paper is organized as follows. Firstly, in Section 2 background on subpixel edge detection is given. Then, in Section 3 the proposed method for subpixel edge detection is introduced. Section 4 presents results of the new algorithm obtained for synthetic images. Resistance of the method to Gaussian blur and averaging is tested. Next, in Section 5 results of edge detection obtained for real images are shown. Finally, Section 6 concludes the paper.

II. Background on subpixel edge detection

The main idea behind subpixel edge detection is to divide pixel into classes by determining edge location inside a pixel. Such approach is fundamentally different to the classical image processing where pixel is the basic and indivisible image component which is fully qualified to one class.

Subpixel edge detection is a challenging task. The discrete structure of a pixel grid causes irreversible loss in image intensities, influences shape of the objects present in the image and reduces edge information. Therefore, edge position inside a pixel can only be estimated with some probability.

The need of edge detection at subpixel level was firstly mentioned by the researchers in the late 70's [3]. Since then the issue of image processing with subpixel accuracy gained an interest of scientists and several approaches to this problem were proposed. Recently, methods for subpixel edge detection can be qualified into three main groups:

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1) curve fitting methods;
2) moment based methods;
3) reconstructive methods.

They are briefly characterized in the following subsections.

A. Curve fitting methods

Curve fitting methods determine subpixel edges by fitting various curves into edge points determined with a pixel accuracy. Firstly, for edge detection at pixel level the traditional edge detectors are used. Then, fitting is performed in an image plane in order to obtain continuous border.

This methodology was used by Yao and Ju [4] who fitted cubic splines into spatial data points provided by Canny operator or by Breder [5] who applied B-spline interpolation. Similar approach was also proposed by Kisiworo [6] who used deformable models to obtain subpixel edge position.

The accuracy of subpixel edge obtained using curve fitting methods is strongly limited by the accuracy of edge detection at pixel level. These methods are also sensitive to badly defined edge points which can deform the resulting shape of the object. Therefore, curve fitting methods yields reasonable results only in applications where shape of the object is known a priori and edge is accurately located at pixel.

B. Moment based methods

Moment based approaches determine edge position by relating image moments into parameters of subpixel edge. Methods which use image intensity moments (regarding only pixel intensities) and spatial moments (regarding both pixel intensities and spatial information about pixel neighborhood) have been proposed.

History of the moment based approaches dates back to 80's when Machuca and Gilbert [7] proposed the first method using image moments to determine edge position. The method integrates region containing the edge in order to determine its position using moments found within the integrated region. The moments are defined based on properties of vector from the given pixel to the gravity center of a pixel square neighborhood. Although Machuca and Gilbert's method has no ability to determine edge with subpixel accuracy it was an inspiration for the following approaches to the considered problem.

Tabatabai and Mitchell [8] proposed a method for subpixel edge detection which fits three intensity moments into the ideal step edge. In their approach the ideal edge is defined as sequence of one intensity followed by the sequence of the second intensity. The moments are defined as a sum of pixel intensity powers and do not consider any spatial information. The main drawback to this method is that it determines edges only in non-decreasing or non-increasing intensity sequences.

Geometric moment approach developed by Lyvers [9] fits moments into 2D model of an ideal edge. This model is described by four parameters which indicate subpixel edge position. The relation between the parameters of an ideal edge and image moments is established; then edge subpixel position is determined. This procedure requires evaluation of six moments by convolving an image with circular masks. As a result, the method is computationally complex. Additionally, geometrical moments proposed by Lyvers are not orthogonal, what makes the method lacks optimality in information redundancy. Approach proposed by Ghosal and Mehrotra [10] eliminates this weakness by fitting orthogonal Zernike moments into Lyvers' edge model. Additionally, the complexity of the method is decreased as only three masks are required. Zernike moments have difficulty in describing small objects, however they are most commonly applied for subpixel edge detection. Recently, Bin [11] put forward orthogonal Fourier-Mellin moments (OFMM) proposed by Sheng and Shen [12] into the Lyvers' edge model. However, determination of subpixel edge position using OFMMs requires application of seven circular masks what causes complexity of the method.

The main drawback to moment-based approaches is lack of clear criteria for classifying pixels as edge or non-edge. Moreover, they produce response (i.e. parameters of subpixel edge) for every set of pixels containing change in image intensity and work properly only in a close neighborhood of the edge pixel. Therefore in the current form they can mostly be used to refine position of the properly defined coarse edges.

C. Reconstructive methods

Reconstructive approaches to subpixel edge detection attempt to restore continuous information about an edge from the discrete intensity sample values. These sample values are provided by the traditional methods to edge detection such as Sobel, Canny or LoG. Next, different interpolation, approximation and extrapolation techniques are applied.

The continuous image information can be reconstructed independently in the vertical and the horizontal direction or simultaneously in both directions. In the first case one dimensional image intensity functions are retrieved in every direction and the final result is a superposition of results obtained in each direction. For reconstruction performed in all directions simultaneously two-dimensional function is found. In both cases the coordinates of the characteristic points of the reconstructed image function (i.e. local extremes, zero crossings, inflection points, etc.) indicate edge position with subpixel accuracy. In order to diminish the complexity of edge detection, image intensity function is often reconstructed in some neighborhood of a coarse border. Therefore, firstly, standard feature selection is applied in order to determine the coarse edge. Then this location is refined to subpixel level by adapting local feature pattern in the closest neighborhood.

The reconstructive approaches to subpixel edge detection can be divided into following groups:

1. ***methods reconstructing image intensity function*** [13] which determine subpixel edge position based on properties of function modeling image intensity at the edge; these methods however are in minority, due to lack of characteristic points of image intensity function at the edge;
2. ***methods reconstructing image first derivative function*** [14], [15] which retrieve image gradient function at the edge based on gradient sample values provided by operators like Sobel, Prewitt [14] or Canny [15] - most commonly second order polynomial is fitted into gradient sample values in a small (3 - 5 pixels) neighborhood; several approaches using wavelet transform instead of image first derivative have also been proposed [19], [20];
3. ***methods reconstructing image second derivative function*** [16]–[18] which reconstruct continuous image 2nd derivative function at the edge based on sample values provided by operator LoG; most commonly image derivative function is linearly interpolated in the neighborhood where the 2nd image derivative function changes its sign [16], [17] then coordinates of the zero-crossings of the reconstructed derivative function determine edge position with subpixel accuracy.

D. Other methods

There are also several subpixel edge detection methods which do not meet the classification presented in the previous subsections. One of them is approach used by Stanke [23] or Ji [24] where subpixel edge position is indicated by center of gravity of a gradient peak. Bie and Liu [25] applied quad-tree decomposition to divide pixels into subpixels while Kisworo [6] determined subpixel edge using image energy computed based on image intensities and their Hilbert transform. Some methods based on curvelets [21][22] have also been proposed.

Regarding the classification presented in the preceding subsections, the method introduced in this paper is a combination of reconstructive and curve fitting methods. More detailed description of the method is given in the following part of this paper.

III. THE PROPOSED METHOD

The proposed method attempts to retrieve continuous edge information at the edge from the discrete image data. Reconstruction is performed only in the neighborhood of the edge. Therefore, the method starts from defining the coarse edge location. Then edge position is refined to subpixel level. Finally, continuous edge is obtained via cubic spline interpolation. The detailed description of the above mentioned steps is given in the following subsections.

A. Coarse edge determination

For the coarse edge determination Sobel gradient masks are applied. Input image L is convolved with the horizontal h_x and the vertical h_y gradient masks in accordance with Equation (1).

$$\nabla L \approx \sqrt{(h_x \otimes L)^2 + (h_y \otimes L)^2} \tag{1}$$

where $\otimes$ denotes convolution. The gradient image ∇L is next thresholded with a global threshold T. The value of T is determined using ISODATA algorithm [26]. The applied threshold selection method is an iterative approach which starts from assigning an arbitrary initial threshold. Then mean intensities of pixels above the initial threshold and below the initial threshold are computed and the new threshold is obtained as their average. The procedure is repeated based upon a new threshold as long as the threshold value changes.

When value of T is determined thresholding is performed in accordance with Equation (2). The operation produces binary image corresponding with the region of the highest gradient.

$$\nabla L'(x) = \begin{cases} 1 & for \;\; \nabla L \geq T \\ 0 & for \;\; \nabla L < T \end{cases} \tag{2}$$

Finally, the coarse edge is obtained as a result of skeletisation performed on the binary image $\nabla L'(x)$ in accordance with Equation (3) [27].

$$\partial L = \bigcup_{n=0}^{N} \left[(\nabla L' \Theta nH') - (\nabla L' \Theta nH') \circ H \right] \tag{3}$$

where: H denotes structuring element (see Fig. 1), Θ and $\oplus$ denote erosion and dilation respectively, $\circ$ denotes morphological opening and:

$$N = \max\{n | \nabla L'(x) \Theta nH' \neq \emptyset\} \tag{4}$$

$$H' = \{-h \mid h \in H\} \tag{5}$$

$$nH = \begin{cases} \overbrace{\{\bar{0}\} \oplus H \oplus \ldots \oplus H}^{n} & for \;\; n = 1,2,\ldots \\ \{\bar{0}\} & for \;\; n = 0 \end{cases} \tag{6}$$

Equation (3) is iterated until the convergence with the structuring elements shown in Figure 1 and all their 90° rotations.

0	0	0
X	1	X
1	1	1

X	0	0
1	1	0
X	1	X

Fig. 1 Structuring elements used for skeletisation.

Successive steps of the coarse border determination in a sample image are presented in Figure 2. Particularly, Figure 2a presents input image. In Figure 2b gradient image is shown. The result of global ISODATA thresholding is presented in Figure 2c. Finally, Figure 2d presents the coarse border.

B. Refining edge to subpixel level

In this step of the algorithm, reconstruction of gradient profile at the edge is performed. Gaussian function given by Equation (7) is fitted along the normal direction of edges into a gradient sample values provided by Sobel operator.

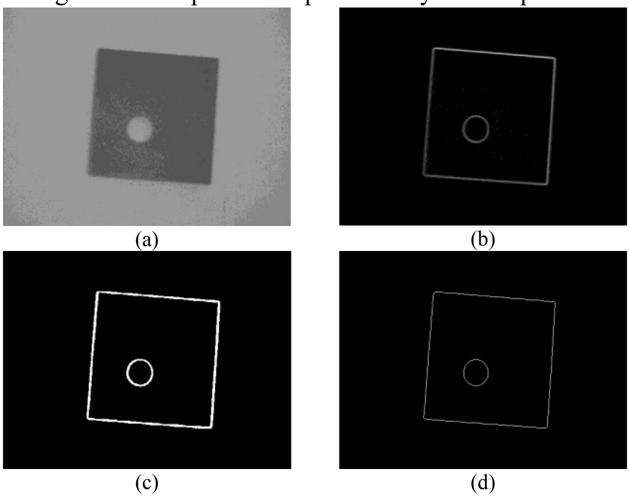

Fig. 2. Successive steps of coarse border determination; (a) input image; (b) gradient image; (c) image after ISODATA thresholding; (d) coarse edge.

$$f(x) = Ae^{\frac{-(x-\mu)^2}{2\sigma^2}} \qquad (7)$$

where $f(x)$ denotes gradient value at location x. The fitting is performed in a neighbourhood of every pixel from the coarse edge. It's linear neighbourhood in the gradient direction (the horizontal or the vertical) is considered. Several pixels on each side of the coarse edge are used.

The main idea of the proposed method is presented in Figure 3. In particular, in Figure 3a direction of a linear neighbourhoods used for gradient reconstruction are indicated. Figure 3b explains the idea of Gaussian function fitting along the normal direction of the edge. The figure presents 3D surface plot where gradient intensity is represented as a third dimension.

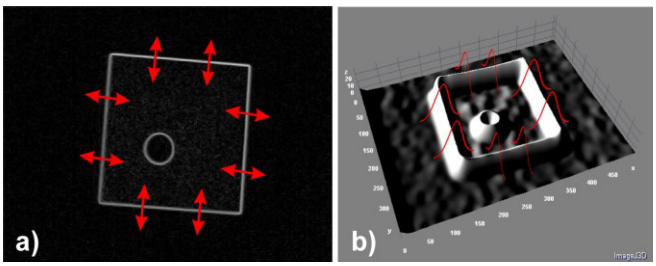

Fig. 3. The main idea of the proposed method; (a) direction of linear neighborhoods used for gradient reconstruction; (b) an idea of Gaussian function fitting along the normal direction of the edge presented in 3D surface plot.

Parameters of the Gaussian function fitted into a gradient sample values determine properties of the edge. Specifically:

– σ - describes a blur level of the edge;

– A - corresponds with gradient maximum value at the edge;

– μ - determines subpixel position of the edge pixel.

An example Gaussian function fitted into the discrete gradient sample values in a neighbourhood of pixel at location $x=27$ is presented in Figure 4. Empty circles correspond with gradient sample values shown under the graph. The coordinate μ of the maximum of the approximating Gaussian function indicates the edge location with subpixel accuracy.

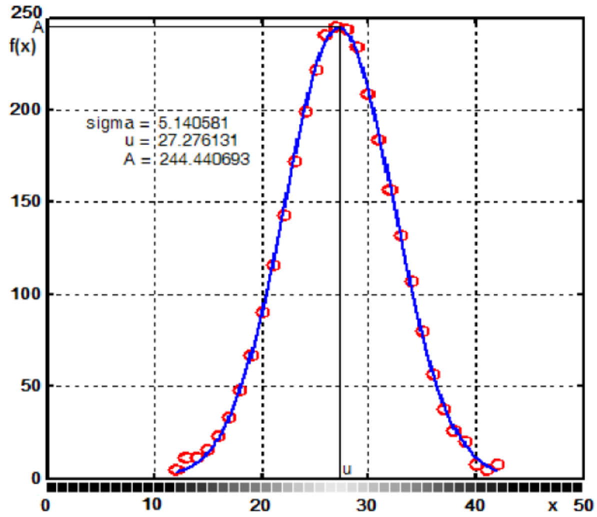

Fig. 4. Gaussian function fitted into gradient sample values.

Parameters of the Gaussian function are obtained via multidimensional unconstrained nonlinear minimization using Nelder-Mead algorithm [28]. This is an effective and computationally compact, simplex based method for finding a local minimum of a function of several variables. The algorithm works iteratively and uses only function values, without any derivative information. Each iteration of the simplex-based direct search begins with a simplex (i.e. a generalized triangle in n dimensions), specified by its n_s+1 vertices and the associated function values. One or more test points are computed, along with their function values, and the iteration terminates with bounded level sets.

The initial estimates for the fitting are as follows:

– for A – the maximum gradient value in the current neighbourhood;
– for μ – x coordinate of the central pixel in the regarded neighbourhood in case of the horizontal fitting and y coordinate of the central pixel in the regarded neighbourhood in case of the vertical fitting;
– for σ – size of a neighbourhood used for gradient function reconstruction.

C. Edge linking

In the last step of the algorithm edge linking is performed. It aims at obtaining continuous border from the subpixel positions of the coarse edge points determined in the previous step.

Firstly, the coarse edge is represented by means of chain code i.e. connected sequence of straight line segments of a specified length and direction; 8-connectivity segments are considered [29]. Despite the information about the succeeding pixel, each node of the chain contains information about the corresponding subpixel position.

Next, Cubic spline interpolation is performed over the subpixel positions corresponding with the consecutive pixels in the chain code in accordance with Equation (8).

$$F(x) = \sum F_i(x) \tag{8}$$

where: $x \in [x_i, x_{i+1}]$, $x_{p'0}=x_0<x_1<\ldots<x_{n-1}<x_n=x_{p'k}$ and:

$$F_i(x) = a_i(x-x_i)^3 + b_i(x-x_i)^2 + c_i(x-x_i) + d_i \tag{9}$$

$$F_i(x_i) = y_i, F_i(x_{i+1}) = y_{i+1} \tag{10}$$

$$F'_{i-1}(x_i) = F'_i(x_i), F''_{i-1}(x_i) = F''_i(x_i) \tag{11}$$

$$F''_0(x_0) = 0, F''_{i-1}(x_n) = 0 \tag{12}$$

IV. TESTS ON SIMULATED DATA

Firstly, the proposed method for subpixel edge detection was tested on the simulated data to verify if it works correctly. Specifically, the robustness of the method against the Gaussian blur and the averaging was investigated. In order to present robustness of Gaussian function in determining blurred edge position, the third step of the algorithm (i.e. edge linking) was not performed on the presented results.

Geometrically created 8-bit grayscale image of a circle was used to test the performance of the proposed approach. The circle of radius 50 pixels was centered at the position (75.0, 75.0). The intensity of the background was 52 while the intensity of the circle was 255.

The assessment of edge detection quality was made by means of:

- coordinates of the determined circle center;
- an average radius of the determined circle;
- standard deviation of the radius of the determined circle.

Coordinates of the circle center were defined as a center of gravity of the determined subpixel edge points and computed in accordance with the Equation (13).

$$\begin{cases} x_c = \dfrac{1}{k}\sum_{i=1}^{k} x_i \\ y_c = \dfrac{1}{k}\sum_{i=1}^{k} y_i \end{cases} \tag{13}$$

where k is number of subpixel edge points and x_i, y_i denote coordinates of i-th subpixel edge point. Radius was defined as an average distance of subpixel edge points from the real circle center (i.e. (75.0, 75.0)). This is expressed by Equation (14).

$$\bar{r} = \frac{1}{k}\sum_{i=1}^{k}\sqrt{(75-x_i)^2 + (75-y_i)^2} \tag{14}$$

The test image was distorted by:

- Gaussian filter of an increasing radius (from 1 to 10);
- an average filter of an increasing size (from 1 to 10).

Results provided by the proposed method (series: *gauss*) were compared with the previously proposed approaches to subpixel edge detection, such as:

- Tabatabai and Mitchell's method [8] (series: *tabatabai*);
- Zernike moments approach [10] (series: *zm*);
- parabola fitting approach [14][15] (series: *par*);

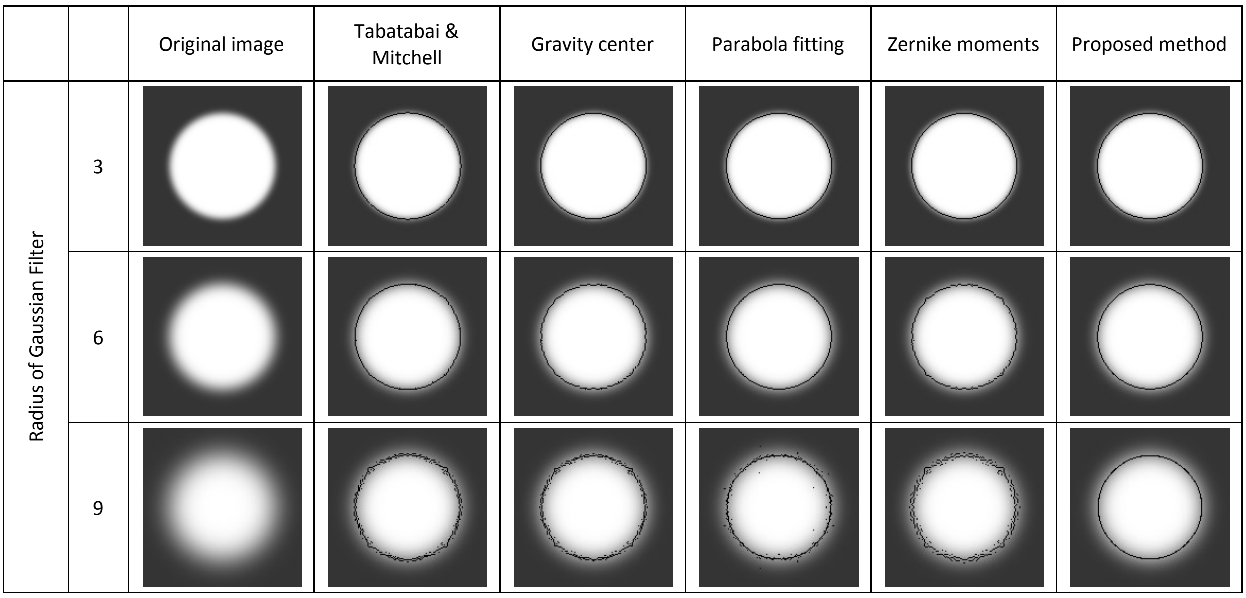

Fig. 5. Results of edge detection at sub-pixel level in images distorted by Gaussian blur.

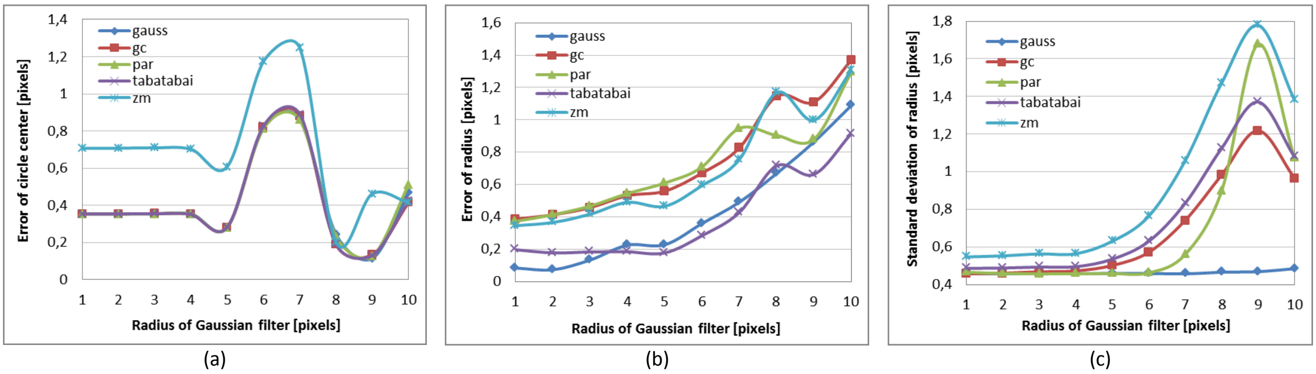

Fig. 6. Results of edge detection at sub-pixel level in images distorted by Gaussian filter.

– gravity center approach [23][24] (series: *gc*).

In all the cases the neighborhood equal to the diameter of the filter used to distort the image was regarded while determining edge position.

The results of edge detection in images distorted by the Gaussian blur are presented in Figures 5 and 6. Specifically, Figure 5 shows edges obtained with subpixel accuracy rounded to the closest pixel. Method used for edge detection is indicated above each column. Radius of the Gaussian filter used for blurring is given at the beginning of each row.

Figure 6 presents the comparison of edge detection results at subpixel level. Specifically, Figure 6a shows the error of circle center determination in function of radius of Gaussian filter used for blurring. The error is expressed by means of Euclidean distance between the real and the determined (in accordance with Eq. (13)) circle center. Figure 6b presents the error of circle radius determination in function of radius of Gaussian filter used for blurring. The error is expressed by means of the difference in length between the real and the determined (in accordance with Eq. (14)) radius. Finally, Figure 6c presents standard deviation of the circle radius in function of radius of Gaussian filter used for blurring.

Results of edge detection in images distorted by an average filter are presented in Figures 7 and 8. As previously, Figure 7 shows edges obtained with subpixel accuracy rounded to the closest pixel while Figure 8 presents comparison of edge detection results at subpixel level. The error of circle center (Fig. 8a), the error of radius (Fig. 8b) and the standard deviation of radius (Fig. 8c) are presented in function of size of an average filter used for blurring.

The results presented in Figures 5-9 prove the robustness of the proposed method against the Gaussian blur and the averaging.

Firstly, based on visual assessment (Fig. 5, Fig. 7), it should be underlined that only the proposed Gaussian fitting approach produces continuous and regular edges for a wide range of blur corruption. This is in the case of both: the Gaussian blur and the averaging for all regarded dimensions of filter used for image corruption. The other regarded approaches to subpixel edge detection produce continuous and regular edges only for low level of blur. With increasing blur, increases irregularity and discontinuity of the determined edge. This is also proved by graphs on Figures 6c and 8c showing standard deviations of the determined radius in function of radius of blurring filter.

Considering the comparison at subpixel level (Fig. 6,

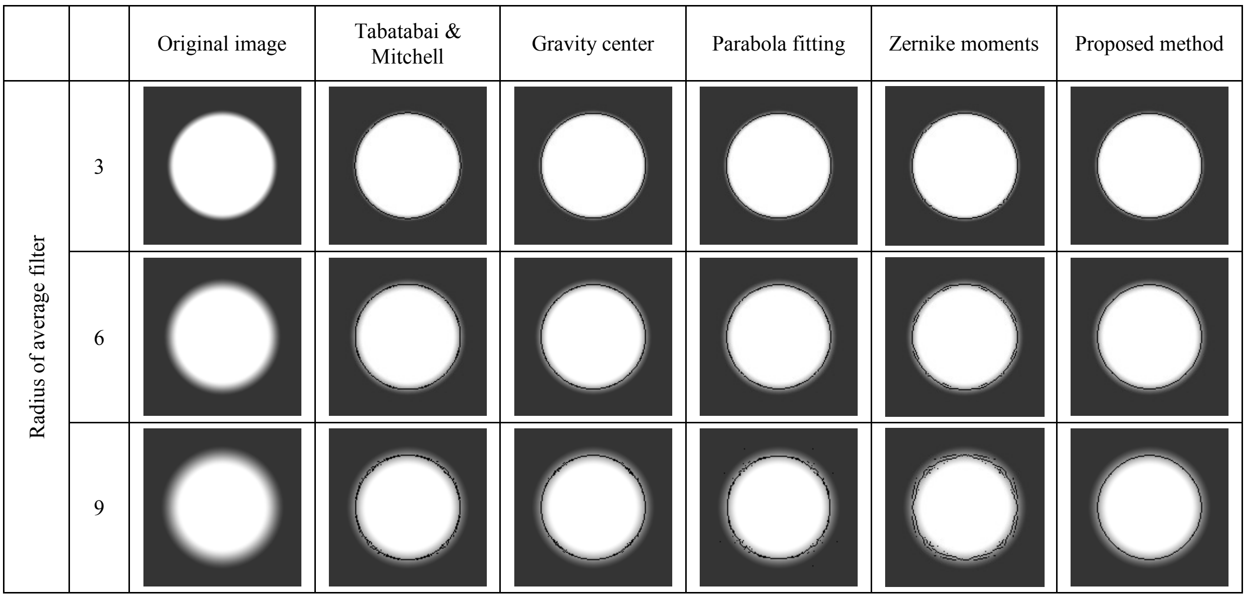

Fig. 7. Results of edge detection at sub-pixel level in images distorted by an average filter.

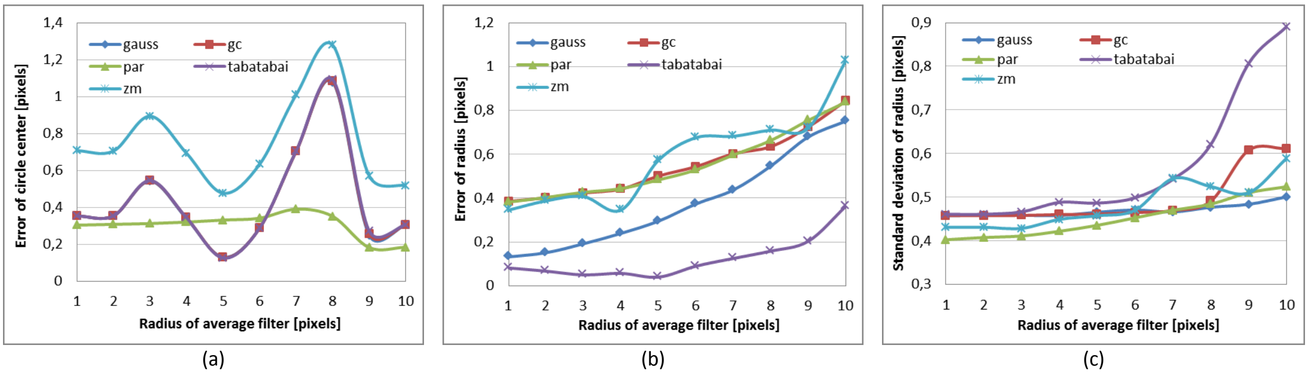

Fig. 8. Results of edge detection at sub-pixel level in images distorted by an average filter.

Fig. 8) it is clear that the best results are provided by the proposed method. In the case of Gaussian, blur the error of circle center determination is similar for all tested methods (see Fig. 8a). However, the smallest errors of an average radius provide the Gaussian fitting approach and Tabatabai and Mitchell's method (see Fig. 8b). Having in mind irregularity of edges provided by the second method, Gaussian fitting approach is superior in the case of Gaussian blur corruption. In the case of averaging, the error of an average radius provided by the proposed method is indeed higher than the error of Tabatabai and Mitchell's method, however, due to a very high standard deviation of radius of the latter method again Gaussian fitting approach can be regarded superior.

It should be also underlined, that Zernike moments approach fails when applied to blurred images (by both: Gaussian blur and averaging) - specifically for high level of blur the method produces the most irregular and discontinuous edges from all tested methods. Parabola fitting approach yields reasonable results for low and medium level of blur corruption, but for very blurry images the method has some problems with stability and produces edge points which significantly outstand from the border. Gravity center approach is always stable and for low level of blur produces continuous edges. However for increasing blur the method changes object shape. It can be observed that for large blur the determined edges become squarer.

Here, it should be concluded, that results obtained for the synthetic images prove correctness of the introduced method, its robustness against blurred edges and its superiority over other approaches to subpixel edge detection.

V. Tests on Real Data

In the next step, the tests on real images were performed in order to define the scope of applicability of the introduced method for subpixel edge detection. Specifically, images of heat-emitting specimens of metals and alloys obtained from the computerized system for high temperature measurements of surface properties [30][31] were considered. Due to the intense thermal radiation, usage of gas protective atmosphere and application of infrared filters the images are characterized by low contrast and blurred edges. Sample images obtained from the regarded system are shown in Figure 9. They present specimens of: copper at 853°C (Fig. 9a), steel at 797°C (Fig. 9b), copper at 1265°C (Fig. 9c) and steel at 1104°C (Fig. 9d).

Results of subpixel edge detection in sample images from Figure 9 are presented in Figure 10. Ten pixels at each side of the coarse edge pixel was regarded while refining edge position. Edges provided by the proposed approach are compared with results provided by other approaches. Specifically, the coarse edges are presented in the first row. The second row shows results of refining edge position using the proposed Gaussian fitting approach. The following rows presents edges provided by the gravity center approach, the parabola fitting approach, the Zernike moments approach and Tabatabai and Mitchell's method respectively. The results are rounded to the closest pixel. Interesting regions of specimen border are highlighted by red rectangles and magnified. In order to present robustness of the Gaussian function in determining blurred edge position, the third step of the algorithm (i.e. edge linking) was not performed on the presented results.

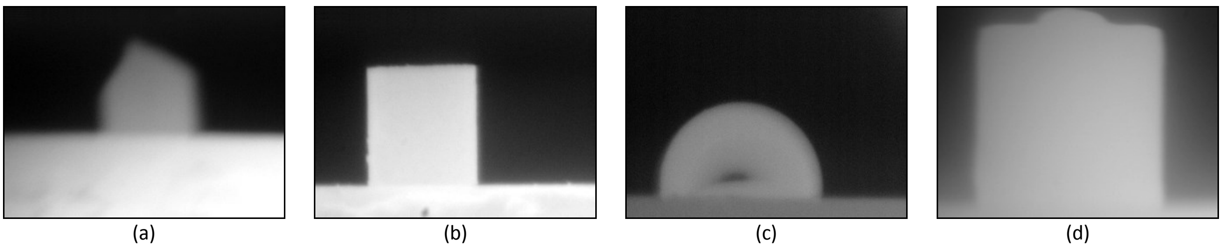

Fig. 9. Sample images of heat-emitting specimens of metals and alloys; (a) copper, 853°C; (b) steel, 797°C; (c) copper, 1265°C; (d) steel, 1104°C.

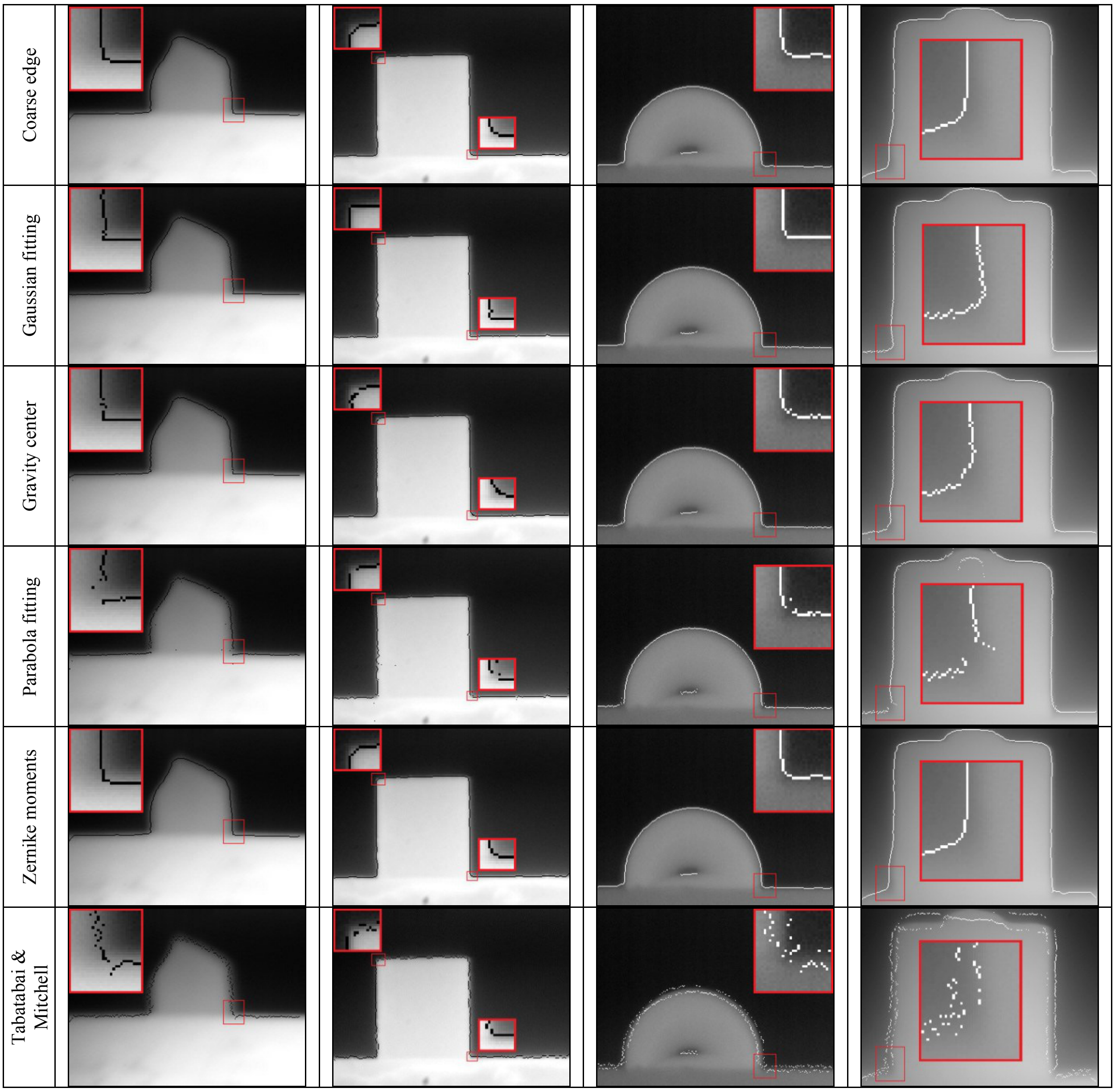

Fig. 10. Results of subpixel edge detection in images of heat-emitting specimens of metals and alloys. The original images are shown in Figure 9. Method used for edge detection is indicated at the beginning of each row.

Results shown in Figure 10 clearly show, that the proposed method significantly improves quality of edge detection in images of heat-emitting specimens of metals and alloys and outperforms other regarded approaches.

Firstly, it should be underlined that Zernike moments approach and Tabatabai and Mitchell's method fail when applied to the images of heat-emitting specimens. Subpixel edge provided by Zernike moments approach is at pixel level identical with the coarse edge. At subpixel level the differences between the coarse and the refined edge are negligible. In the case of the considered class of images Tabatabai and Mitchell's method becomes unstable and provides jagged, discontinuous, irregular and ambiguous edges what is unacceptable. Also parabola fitting approach has some problems with the continuity and the stability as it determines subpixel position of singular edge points visibly outstanding from the edge location. It is especially in the case when the supposed edge position is not in the center of the neighborhood of the coarse edge regarded while refining its position.

Both: the gravity center approach and the proposed Gaussian fitting approach are stable and provide continuous edges. However, the gravity center approach is sensitive to blur - it has problems in describing corners and rounds them off. In the examples shown in Figure 10 it is especially visible in contact of specimen, base and background or in case of image of steel at 797°C (Fig. 9b). Moreover, the gravity center approach tends to move border from the object when big neighborhood is used while refining the edge position.

The most significant increase in edge detection accuracy can be observed when the proposed Gaussian fitting approach is used. Subpixel edges produced by the introduced method are regular. Moreover, they are continuous what diminishes number of edge information to be guessed during edge linking and makes the results more unequivocal. Additionally, improved edge fits closely specimen shape. Corners are sharp and well defined. This makes the method adequate for the considered class of images.

VI. CONCLUSIONS

In this paper problem of edge detection at subpixel level was considered. Specifically, precise edge detection in blurred images was regarded. The reconstructive method for subpixel edge detection was introduced. The method firstly determines the coarse edge using Sobel gradient masks, thresholding and skeletisation. Then it attempts to reconstruct continuous image gradient function at the coarse edge using Gaussian function. Position of the maximum of the reconstructing Gaussian function indicates edge position with subpixel accuracy.

The correctness and robustness of the method was proven by tests performed on geometrically created synthetic images under a wide range of blur corruption. Obtained results clearly show that the proposed method significantly improves quality of edge detection. The refined edges are continuous and much more regular than those provided by the previously proposed approaches to subpixel edge detection. The more blurred is the edge, the difference is more significant. The advantage of the Gaussian function based method can be seen both: in accuracy and the stability of the obtained subpixel edge position.

Tests performed on the real images obtained from the high temperature industrial vision system proved that the introduced method can be particularly useful in case of low contrast images with blurred and unsharp edges. In consequence it can be successfully applied in a wide spectrum of machine vision applications where accuracy is at premium.

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