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AKAIKE INFORMATION CRITERION IN THE EDGE ANALYSIS OF THE SCREEN ELEMENT

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Original scientific paper
The analysis of the edge of the screen element is based on the selection of the linear sample on the paper – ink system in comparing models and reality. Although Yule and Nielsen suggested the Gaussian distribution for the description of the line spread function, our model, based on the stochastic approach of subsurface light scattering in paper, gives the complete description with the Lorentzian distribution. To determine which of the two proposed models, Gaussian or Lorentzian, gives a better approximation with respect to the measured data, Akaike information criterion has been used. As the observed profiles are asymmetric, both edges have been analyzed. It was not possible to distinguish which model better describes the resulting measurements, because of the extremely high value of the correlation coefficient for both models. Therefore the AIC method was applied using the routines in Origin 8.5 that was used to analyze the measured data. The Akaike weight demonstrates that the Lorentzian model better describes the LSF than the Gaussian model.

Keywords: *Akaike information criterion, line spread function, Monte Carlo approximation, screen element edge*

Akaikeov kriterij informacije u analizi ruba rasterskog elementa

Izvorni znanstveni rad
Analiza ruba rasterskog elementa temelji se na odabiru otisnutog linijskog uzorka na sustavu papir - boja i usporedbi modela i stvarnosti. Iako su Yule i Nielsen predložili Gaussovu raspodjelu za opis funkcije razmazivanja linije, naš model, temeljen na stohastičkom pristupu podpovršinskog raspršenja svjetlosti u papiru, daje cjelovit opis pomoću Lorentzove raspodjele. Da bi utvrdili koji od dva predložena modela, Gaussov ili Lorentzov, daje bolju aproksimaciju s obzirom na mjerene podatke, bio je korišten Akaikeov kriterij informacije. Kako su promatrani profili asimetrični, analizirana su oba ruba. Pri tome nije bilo moguće razlučiti koji model bolje opisuje rezultate eksperimenta, zbog iznimno visoke vrijednosti koeficijenta korelacije za oba modela. Stoga je korištena AIC metoda pomoću rutine u programu Origin 8.5 koji je korišten za analizu izmjerenih podataka. Akaikeova težina pokazuje da Lorentzov model bolje opisuje LSF od Gaussovog modela.

Ključne riječi: *Akaikeov kriterij informacije, funkcija razmazivanja linije, Monte Carlo aproksimacija, rub rasterskog elementa*

1 Introduction

Edge detection is one of the most common operations in image analysis, which results in the fact that multiple algorithms can be found in the literature to improve the detection of edges. The reason for this is that edges form the outline of the object. The edge is the boundary between the object and the background, and indicates the boundary between overlapping objects. This means that if the edges of the picture can be exactly identified then for all objects one can find the basic properties such as area, perimeter, shape, etc., which can then be measured. Since computer vision involves the identification and classification of objects in an image, edge detection is an essential tool. The importance of edge detection is usually motivated by the observation that under general assumptions about the process of creating an image, discontinuities in the brightness of the image can be assumed to match the discontinuity in depth, surface orientation, reflectance, or illumination. In this sense, the edges in the image domain present strong connection with the physical properties of the world. Display image information with respect to the edges is also compact in the sense that the two-dimensional image of the sample is presented by a set of one-dimensional curves. For these reasons, the edges were used as the main features in a large number of algorithms that are used in computer vision.

2 Edge detection

The reason for taking the line as basis for comparison of our model with the real situation lies in the fact that the line is one of the basic geometric shapes used in the screen reproduction. The importance of the quality of printed lines is reflected in the fact that the line appears frequently in the business graphics as an important element of tables, graphs, images, and of course in technical illustrations. Its quality is strongly correlated with the quality of the text, given that many of the desirable characteristics are common to line and the text: density, sharpness, edge quality, etc. For many printing techniques line quality is a measure of the basic variables of the printer, such as the consistency of the size of the droplets of an ink-jet printer. These variables affect not only the quality of the lines, but also some other aspects of print quality as the quality of the text, the uniformity of coverage area, etc. In this way, measuring the quality of printed lines can be used to predict much more general print quality. On the other hand, analysis of the line can be used to determine the interaction of the dye-substrate or dye - dye (if layers of other colours already exist). All of these reasons were the motive in the selection of the linear sample as an element for comparison of our model with the real situation.

Edge detection refers to the process of identifying and locating sharp discontinuities in the image. The discontinuities are abrupt changes in pixel intensity which characterize object boundaries in the scene. Classical methods of edge detection involve image convolution with the operator (2-D filter), which is designed to be sensitive to large gradients of the image while uniform areas assign the value of zero. There is an extremely large number of edge detection operators available, each designed to be sensitive to certain types of edges. The variables included in the selection of the edge detection operator:

- *Edge orientation*: operator geometry determines a characteristic direction in which it is most sensitive to the edges. Operators can be optimized to look for horizontal and vertical or diagonal edges.
- *Background noise*: edge detection is difficult for images which contain a lot of noise, because noise and edges contain both high-frequency content. Selected operator should try to reduce the impact of noise in the blurred and distorted edges. Operators used on images that contain a lot of noise typically have greater scope, so they can average out enough data and invalidate localized pixel noise. Consequently, these operators provide less precise localization of the detected edges.
- *The structure of the edge*: all edges are not involved in abrupt changes in intensity. Effects such as refraction or poor focus can result in objects with boundaries defined by the gradual changes in intensity. In such cases, the operator must be chosen so that it responds to such a gradual change. Newer techniques, based on the so-called wavelet, actually characterize the nature of the transition for each edge to differentiate, for example, the edges associated with hair from the edges associated with the face.

There are many ways to perform edge detection.

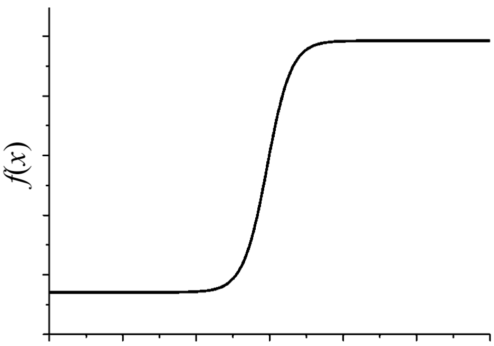

Figure 1 Edge profile of the cropped ideal image

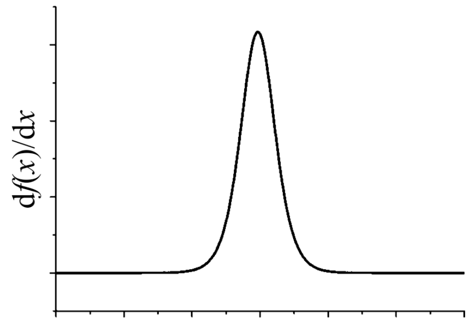

Figure 2 Derivation of edge profile

However, most of the different methods can be classified into two categories:
- Gradient: gradient method detects the edges by looking for maxima and minima of the first derivative of the image.
- Laplacian: to find the edges, the Laplacian method searches for positions in the image, in which the second derivative is zero. The edge has one-dimensional form of staircase and calculation of derivative of image can emphasize its location.

Suppose you have an image of the edge shown by the jump in intensity (Fig. 1).

If we take the gradient of this signal (which, in one dimension, is the first derivative with respect to x), we obtain the result shown in Fig. 2.

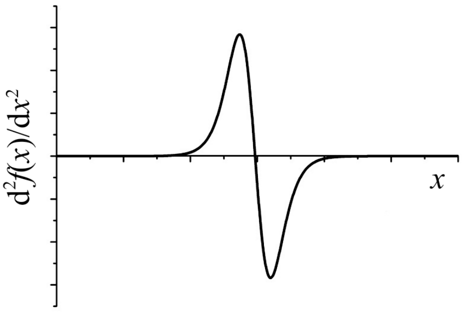

Figure 3 Second derivation of edge profile

Clearly, the derivative shows a maximum which is located in the middle of the edge in the original signal (if the signal is symmetrical). This method of locating the edge is the characteristic of "gradient filter" - family of edge detection filters and includes Sobel method [1]. Technically, it is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. Pixel location is declared as the location of the edge if gradient value exceeds a predetermined threshold value. As mentioned before, edges will have higher pixel intensity values than surrounding area. So with a certain threshold, we can compare the value of the gradient from the boundary values and detect edge whenever the threshold is exceeded. Further, when the first derivative is at a maximum, the second derivative is zero. As a result, the other alternative to find the location of the edge is finding zero value of the second derivation. This method is known as the Laplacian, and the second derivative of the intensity is shown in Fig. 3.

3 Line spread function

At printed pictures, paper base acts as an image system. Image reproduction can be considered to consist of two parts, the first one is the image formed on the substrate (input image) and the other one is the image detected by the optical system (image observed in reflected light - output images). Light scattering in the paper can affect the tonal characteristics of a printed raster tone reproduction (image). It is necessary to say that in our work by the term image we mean print that contains images and text respectively, as well as other elements that constitute a single print. Raster tone image is formed by variations in the average reflection, which is determined by the size of printed screen element. Photon migration from regions that are not covered by ink towards inked area tends to increase the absorption of photons and thus reduces overall reflection from printed screen elements - screen element actually becomes larger than its physical size. This effect is known as optical dot gain or the Yule-Nielson effect [2], and the size of the effect was determined by modelling the subsurface scattering of light using the Monte Carlo method [3]. Lateral light scattering in the paper has a major impact on the colour and tone reproduction [4]. The size of optical dot gain increment depends on the distance the photons undergo in the paper, which in turn depends on the characteristics of the scattering and absorption of elements that are components of the existence or absence of the final coating of the paper, on paper thickness, or on print technique. The method has shown that the system paper-dye has some features that other systems do not show. Influence of paper theoretically is shown with point spread function, which is conditional probability density function that characterizes the migration of photons in the paper [5]. Using the Monte Carlo method the function obtained by smearing the point can be approximated by the Lorentzian function, in contrast to previous descriptions that used to apply the Gaussian function.

For linear, isoplanar imaging systems transmission characteristics can be defined. It is a line spread function (*LSF*), which represents the distribution of radiation intensity of the image of infinitely narrow and of infinitely long slit (line source) of unit intensity. In a perfect imaging system radiation energy outgoing from a line source in an object plane will be concentrated in the line in the image plane. In practical systems, however, the optical irregularities result in "spreading" of ideal image lines which we perceive as blurred image of source line, and the *LSF* is a measure of this image blurriness, wherein the *LSF* is system transfer characteristic which provides the unique relationship between certain classes of arbitrary input image and corresponding outputs.

Starting from the very definition of the *PSF*, we calculated its shape as a function of the parameters of the paper. By the modelling of line profiles we wanted to examine the individual impact of each parameter, such as the scattering and absorption coefficients of the components of the paper, the percentage of the components, asymmetry parameters that are important for determining the contribution of cellulose fibres to the scattering, the type and thickness of the layers (if we take into account the coated paper), refractive index of the input layer of the coating and its thickness, type and shape of the surface of paper, and many other parameters that affect more or less the collective effect called optical dot gain. Previous approaches did not have the complexity required for a realistic description of the system, and their authors have presented approximations that have not always had plausible physical basis. Thus, at the end of the seventies, guided by an intuitive idea that the observed distribution of scattered light coming from a point source profile is bell cantered in the entry point, Yule and Nielsen suggested that the *LSF* was described by the Gaussian distribution [6]. Our model [3], based on the stochastic approach, shows that for a given set of parameters the complete description is done by the Lorentzian distribution, as shown in Fig. 4. The resulting function does not depend on the position in the plane of incidence, so that it can be regarded as a shift invariant function.

The optical dot gain is a direct consequence of the internal light scattering in the substrate, so that without prints of individual screen elements and their image analysis it would not be possible to verify the results that the model predicts. The model simulates the scattering of light in the substrate on which lines are printed and thereby the point spread function is generated which we use to simulate the reflectance profile of printed lines by means of convolution.

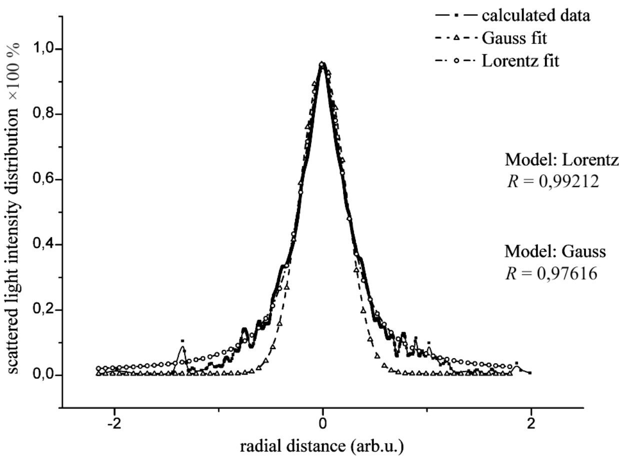

Figure 4 Comparison of the Lorentzian and Gaussian Profile (*R* – correlation coefficient) to the calculated one within the Monte Carlo approximation

Considering that our model, obtained in the framework of the Monte Carlo approximation, generates the point spread function we calculate corresponding *LSF* using equation (1):

$$LSF(x) = \int_{-\infty}^{\infty} PSF(x, y)\mathrm{d}y. \tag{1}$$

4 Measurement

To determine the line spread function, it was necessary to derive the previously measured line reflectance profiles. Numerical derivatives were carried out using the equation (2):

$$LSF = \frac{\mathrm{d}R}{\mathrm{d}x}. \tag{2}$$

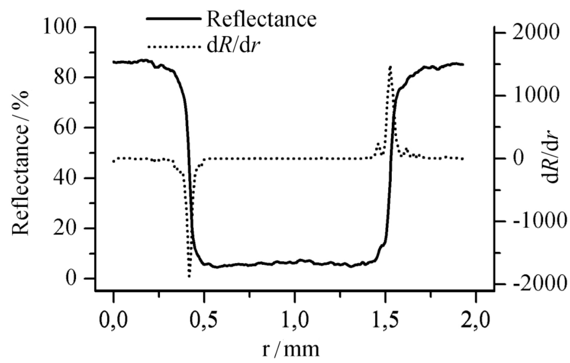

Figure 5 Comparison of reflectance profile of printed line (line thickness is 1 mm) on Arcoprint 120 g paper and its derivative across the profile line

It is evident that reflectance profile has a lot of noise, and the operation of derivation generates even more noise (Fig. 5) that complicates its analysis. Therefore, in order to reduce its impact we have used smoothing of reflectance profiles with the so-called percentile filtering. For a signal that has a "shot noise", where the noise appears as localized spikes, the method 50 % percentile filtering (median filtering) replaces the value of the signal at each point with the median set of points from its environment.

Smoothing of reflectance profile reduces the noise in the line wings area, where it is the most frequent. Thereby, the procedure does not affect the peripheral region lines of our interest, but only ensures that the wing d*R*/d*x* with its emphasised noise does not generate problems during approximation ("fitting") of the measured profile with the Gaussian and the Lorentzian distribution functions. Derivation of the reflectance profile of the left edge provides the *LSF* (Fig. 6), which describes a very good agreement with the Lorentzian profile, where it is evident that the wings of these two profiles do not coincide with the Gaussian function, which is confirmed by the calculated correlation coefficients: R_{Lorentz} = 0,9884; R_{Gauss} = 0,9605. A similar description applies to the right edge of the observed line (Fig. 7) where the correlation coefficients of the Lorentzian and Gaussian profiles with respect to the *LSF* profile values are: R_{Lorentz} = 0,9922; R_{Gauss} = 0,9605.

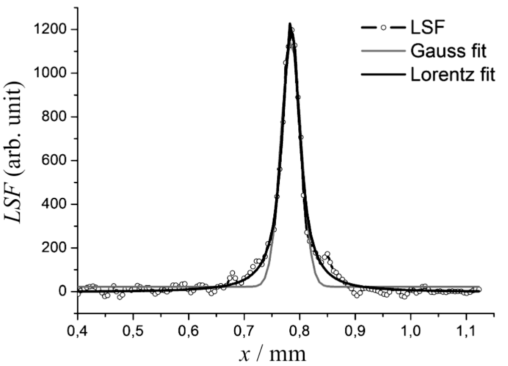

Figure 6 *LSF* of the left edge of printed line

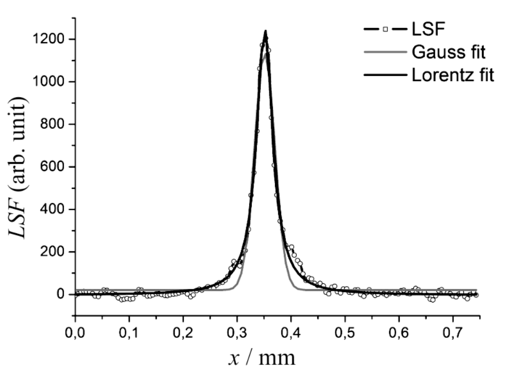

Figure 7 *LSF* of the right edge of printed line

Comparison of calculated *LSF* with the Lorentzian and Gaussian profile will show that the Lorentzian profile is a more suitable approach to describe subsurface scattering of light in the paper, which applies only to observation of relationships in the paper-ink system.

Medium (paper) on which lines were printed is given in Tab. 1.

The term wood free paper refers to all papers and boards that are manufactured exclusively from cellulose, with the possible addition of wood pulp, up to 10 % participation in the mass. Such papers are characterized by resistance to light and aging. The term natural paper refers to untreated (natural) papers that take the mentioned properties in the finishing process of production. In experiment we have used Arcoprint - uncoated wood free offset paper.

Table 1 Properties of the used paper in experiment

	Type	Opacity / % ISO 2471	Whiteness / % ISO 2470
ARCOPRINT 120 g/m²	uncoated: wood free offset	96 ± 2	110 ± 2

Table 2 Comparison of the obtained results of left and right *LSF*

HP INDIGO TURBO STREAM 1000 E PRINT				
ARCOPRINT 120 g/m²				
	w_{L}	w_{G}	R_{L}	R_{G}
Left *LSF*	0,03696	0,03631	0,98841	0,96248
Right *LSF*	0,03716	0,03766	0,99217	0,96053

Tab. 2 shows that the parameters w_{L} and w_{G} have almost identical values, and the same can be seen for the values for correlation coefficients R_{L} and R_{G} which are very close. However, it is possible to notice a certain difference, since coefficient R_{L} gets a little bit higher value of R_{G}, which means that the Lorentzian model better describes the *LSF* than the Gaussian model. This claim should be confirmed precisely, and for this purpose we used the Akaike information criterion.

5 Akaike information criterion (*AIC*)

Simplicity and economy is based on the concept of Occam's razor, which suggests that the simplest explanation is usually the most likely. It is a quality which is often aspired to in science. Cost-effectiveness is particularly evident in the issues of the model design, where scientist has to find a compromise between the bias and the inconsistencies of model. Here, the bias corresponds to the difference between the estimated value and the true value of the unknown parameters, while discrepancy indicates the precision of the estimates. Thus, a model with too many variables will have low precision, while the model with too few variables biased. The principle of multiple working hypotheses is to test the hypothesis of a single experiment and, according to the results, to formulate a new hypothesis that we are testing with new experiment [7]. Selection of model, which precedes the testing and the data that are available, requires several plausible models that we generate before performing the analysis. After the analysis, the indicators define which model is the best among the assumed models and measure the strength of evidence for each model.

Before the construction of the model, we must accept the fact that there are no realistic (true) models, but they just approximate the reality. The question then is how to determine the model that best approximates reality with respect to the measured data. In other words, we try to minimize the loss of information. Kullback and Leibler [8] solved such problems and developed a measure called Kullback-Leibler information, in order to present information lost when approximating the reality (i.e. a good model minimizes the loss of information). Several decades later, Akaike [9] proposes to use Kullback-Leibler information for model selection. He has established a relationship between the maximum likelihood, the estimation method used in many statistical analyses, and the Kullback-Leibler information. Data analysis often requires selection among several possible models, which could correspond to the measured data. Akaike information criterion (*AIC*) provides an objective way of determining which one among used models is the most economical and the method of selecting the model from a set of models. The chosen model is the one that minimizes the Kullback-Leibler distance between models and factual data (in our case the measurements). *AIC* is based on information theory, but heuristically we think of it as the criterion to find a model that describes well the measured data, wherein we have several parameters.

Statistical analyses frequently seek to estimate the size of the impact of certain variables on the response variable and its accuracy. In certain cases, we want to evaluate whether the effect is important enough to include in the model parameters predicted i.e. question arises of selecting a model. It is often the case in measurements where it is believed that a certain number of variables explain a process or pattern. While classical techniques, such as testing the null hypothesis, well suited for manipulative experiments, their widespread use and misuse in resolving issues such as parameter estimation and model selection, only reflect a slow migration of superior technology from distant world of statistics in disciplines that are dealing with graphics technology. Indeed, hypothesis testing is problematic because it indirectly addresses these issues (i.e. the effect is or is not significant), and the results do not seem very good at choice of the model [10]. However, a better approach for now does not exist [11, 12].

As is well known [13], three principles govern our ability to form conclusions in science:

1) the simplicity and cost-effectiveness,
2) several working hypotheses,
3) power of evidence.

AIC is defined, for one or several fitted model objects for which a log-likelihood value can be obtained, according to equation (3).

$$AIC = -2 \cdot \ln(likelihood) + 2 \cdot K, \qquad (3)$$

where the *likelihood* is the maximized value of the likelihood function for the estimated model, and K is the number of free parameters in the statistical model. *AIC* results are often presented as ΔAIC results or the difference compared to the best model (lowest *AIC*).

Table 3 Illustration of the parameters used in the *AIC* analysis of one of the measured profiles

Lorentzian model			Gaussian model		
$y = y_0 + \frac{2 \cdot A}{\pi} \cdot \frac{w}{4 \cdot (x - x_c)^2 + w^2}$			$y = y_0 + \frac{A}{w \cdot \sqrt{\frac{\pi}{2}}} \cdot e^{-2 \cdot \left(\frac{x - x_c}{w}\right)^2}$		
Correlation coefficient	0,98841		Correlation coefficient	0,96248	
Parameter	Parameter value (arb. unit)	Standard deviation	Parameter	Parameter value (arb. unit)	Standard deviation
y_0	9,75	3,5	y_0	11,14	3,4
x_c	0,48	$3,2 \times 10^{-4}$	x_c	0,48	$3,6 \times 10^{-4}$
w	0,037	$9,9 \times 10^{-4}$	w	0,036	$7,4 \times 10^{-4}$
A	92,6	1,7	A	69,2	1,1
			FWHM	0,048	

Criterion is rigorous and based on hard statistical principles (i.e. maximum similarity), but it is easy to calculate and interpret. Without going into detailed explanation and the mathematical representation, this method gives the "true" model more reliably than, for example, F-test [14, 15]. The authors also suggest that the F-test tends to choose more complex models, and conclude that the *AIC* is an effective and efficient approach.

In this paper, we used *AIC* model selection method in order to determine which one of the two proposed models of *LSF* (Lorentzian and Gaussian) better describes the results, because the correlation coefficients for both models are very high and do not differ much.

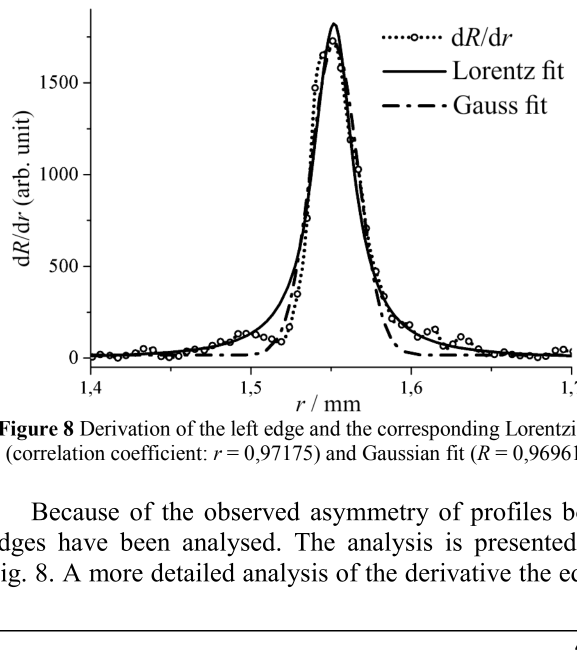

Figure 8 Derivation of the left edge and the corresponding Lorentzian (correlation coefficient: $r = 0,97175$) and Gaussian fit ($R = 0,96961$)

Because of the observed asymmetry of profiles both edges have been analysed. The analysis is presented in Fig. 8. A more detailed analysis of the derivative the edge that, after standardization to the unit, provides *LSF*, shows that *LSF* is not symmetric. That means that so called left and right edges do not exhibit the same properties. After fitting of corresponding derivative, Lorentzian and Gaussian function, we obtained the extremely high value of the correlation coefficient applied for both models. It is necessary to note that in both cases the fit converged and that was the tolerance criteria are met.

From the images it was not possible to distinguish which model better describes the resulting measurements. Therefore, the AIC method was applied for model selection using the routines in Origin 8.5 that was used to analyse the measured data. The result of applying AIC method showed strange behaviour. It has been shown that the left edge is better described by the Lorentzian function while the right edge is better described by the Gaussian function. Such behaviour indicates that the quality of the edge is determined predominantly by applied printing techniques. In both cases, it is evident that the "far wing" is better described by the Lorentzian function, and the second one, "closer wing", by the Gaussian function.

Table 4 Values obtained by AIC analysis of the left and right edge (N = number of points)

			Left edge		Right edge	
	N	Parameter	*AIC*	Akaike weight	*AIC*	Akaike weight
Lorentz model	188	4	1413,8	0,99896	1422,4	0,00101
Gauss model	188	4	1427,5	0,00104	1408,6	0,99899

From Tab. 4 it is evident that the left edge has higher Akaike weight for the Lorentzian model, which indicates that the description of the Lorentzian function for the left edge is better and vice versa, for the right side, which has higher Akaike weight for the Gaussian model, a better description is given by the Gaussian function.

6 Conclusion

Dot gain has two components - mechanical and optical, and in this paper, we focused on the study of the optical dot gain. Optical dot gain increase is a direct result of subsurface scattering of light in the paper. In this paper, the idea was to show a model of optical gain as a function of several parameters such as predictable results of scattering and absorption coefficients of the various components of paper, the refractive index of the input layer of paper coating, etc. Starting from the realistic physical assumptions, we modelled the subsurface scattering of light in the substrate of complex structure. Model used to simulate subsurface scattering of light in paper by means of the Monte Carlo method generated point spread function (*PSF*). Convolving *PSF* and model profiles we simulated reflectance profile of printed lines. Although, for the analytical form of the *PSF*, the Gaussian function is generally used, our simulations of subsurface light scattering profiles in the paper clearly show that a better description is given with a Lorentzian profile. To verify our hypothesis that the Lorentzian profile accurately describes the optical dot gain, we analysed the edge of our screen element (line). We took a measured reflectance profile and calculated the line spread function (*LSF*) of the system by calculating the numerical derivatives (gradient method). Comparison of thus obtained *LSF* with Lorentzian and Gaussian profile again points to the conclusion that the Lorentzian profile in the description of subsurface scattering of light in the paper-ink system, or in the description of the optical dot gain is more appropriate in comparison to previous approaches. However, it was shown that both Lorentzian and Gaussian fits have a high correlation with the resulting *LSF*. Therefore, to compare models, we used Akaike criterion which demonstrates that the Lorentzian model has greater Akaike weight, which suggests that it better describes the LSF than the Gaussian model, although both models have high correlation coefficients.

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