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AUTOMATIC DETERMINATION OF FILTER COEFFICIENTS FOR LOCAL CONTRAST ENHANCEMENT

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Summary

This study proposes an algorithm whose main advantage is in enabling the automatic determination of non-linear homomorphic filter coefficients used for local contrast enhancement in digital image processing. The presented algorithm is tested in a real production environment. The obtained results are compared with relevant examples in literature, showing the advantages of the achieved results or a relatively high level of their correspondence with reference results. The proposed procedure can be used for various applications in mechatronics, robotics and automatized production systems.

Key words: *digital image processing, homomorphic filter coefficients, object dimensions measurement*

1. Introduction and relevant results review

The monitoring and supervising of industrial processes using digital image processing are mainly limited by image acquisition conditions. The choice of adequate equipment for image acquisition and the choice of disturbance elimination software are limited by the nature of measuring i.e. the industrial environment itself. Image processing is often performed in real time, requiring the use of fast and relatively simple algorithms, along with the use of the standard equipment for image acquisition. The quality of the obtained image is relatively poor, so it is necessary to perform the image post-processing. The basic method for image enhancement is based on grey level intensities and contrast transformations, edge emphasizing, noise reduction etc. Some improvement in this domain is realized by the introduction of an algorithm for automatic global contrast enhancement [1].

For medical images obtained by X-rays, good results are achieved by using the modification of homomorphic filtering functions in the logarithmic domain [2]. The combination of two non-linear filter types (wavelet transformation and homomorphic filtering) [3] also gave improved results. The image contrast modification can be achieved by changing parameters of the image segments [4]. By using homomorphic filtering, anisotropic filtering and algorithms based on the wavelet transformation, it is possible to improve the weak illumination and contrast of images [5].

Contrast enhancement using linear and non-linear methods is also analyzed [6]. Significant results are achieved by using high-pass filtering [7] as well as non-linear filtering with the use of the FT and IFT in the logarithmic domain [8]. Important progress in image enhancement is achieved by using non-linear methods in the filtering process [9]. T. Peli and J. S. Lim [10] have proposed an approach to the image enhancement using homomorphic filtering and local characteristics modifications, performed by non-linear coefficients multiplication. The homomorphic filtering parameter estimation, based on bimodal histograms of non-processed images [11], as well as the elimination of the industrial evaporation influence using non-linear filters [12] are also interesting and good approaches to achieving image enhancement.

2. Problem definition

Automatized industrial systems often use the digital image processing method for the product parameter evaluation. The simple system, used in the experiment in this study, has a fixed position camera and a fixed position diffuse light source (mercury lamp) (Fig. 1).

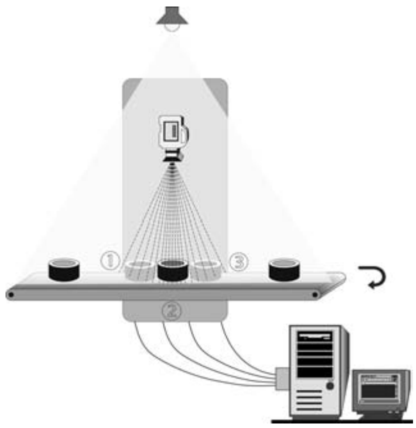

Fig. 1 Scheme of a simple industrial system

A typical task set for this system is the estimation of the monitored object dimensions. Using adequate procedures [13], [14], it is possible to measure dimensions of an object placed on a moving band, within certain tolerances. The occurrence of uneven illumination intensity, arising as a result of the object position change regarding the light source, the image quality and therefore the dimension measurement error will not always be the same in all image arrays. This problem can be solved by using a mobile light source [15], which additionally complicates the realization of the whole system, making it more expensive. For objects moving at a relatively low speed, it is possible to apply some of the methods for image enhancement. The best results, applicable in a real environment, are achieved by using local contrast change techniques, i.e. homomorphic filtering techniques. The homomorphic filtering method is commonly used for the removal of image multiplicative degradations. As the image degradation, which arises during the local contrast modification, should be within acceptable limits, it is necessary to establish criteria for the image parameter quality estimation. During the image filtering process automatization as well as the image quality estimation, it is necessary to obtain predictions that are in good correlation with MOS – Mean Opinion Score, which actually represents the average subjective estimation. For an adequate application of homomorphic mapping, it is necessary to determine the illumination coefficient α, and the reflection coefficient β, for each location of the observed object individually, which makes it more difficult for use in real conditions. In order to overcome this problem, a method for the automatic determination of homomorphic filtering coefficients is proposed in the following sections of this paper.

2.1 The basic theory of homomorphic filtering

According to the light-reflection model, every point of the digitalized image consists of the illumination and the reflection component product. The illumination component L(x,y) defines the illumination level of the whole image and corresponds to lower frequencies. The reflection component R(x,y) determines the local contrast and corresponds to higher frequencies. Each point of the digital image I(x,y) represents the product of these components, so their independent processing is needed to be performed in the logarithmic domain (A. Oppenheim, R. Schafer, T. Stockham [13]).

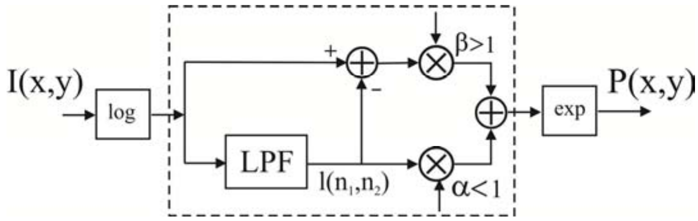

Fig. 2 Homomorphic filtering system (after A. Oppenheim, R. Schafer, T. Stockham)

2.2 Relevant equations for homomorphic filtering

The mathematical description of the image in the space domain is given by:

$$I(x,y) = R(x,y) \cdot L(x,y) \tag{1}$$

The transformation of the product components into a sum is performed in the logarithmic domain. Components separation is performed by using the LPF filter as well as by low-pass component subtraction from the logarithmic input signal in order to separate the high-pass component (Fig. 2).

$$log\ I(x,y) = log\ R(x,y) + log\ L(x,y) \tag{2}$$

$$i(n_1,n_2) = log\ I(x,y) \tag{3}$$

$$r(n_1,n_2) = log\ R(x,y) \tag{4}$$

$$l(n_1,n_2) = log\ L(x,y) \tag{5}$$

$$i(n_1,n_2) = r(n_1,n_2) + l(n_1,n_2) \tag{6}$$

$$r(n_1,n_2) = log\ I(x,y) - l(n_1,n_2) \tag{7}$$

After the signal is multiplicated by the non-linear coefficients α and β, their combination and anti-logarithming is performed in order to return into the space domain.

$$\beta \cdot r\ (n_1,n_2) + \alpha \cdot l\ (n_1,n_2) = p\ (n_1,n_2) \tag{8}$$

$$P(x,y) = e^{p(n_1,n_2)} \tag{9}$$

3. The modified homomorphic filtering model

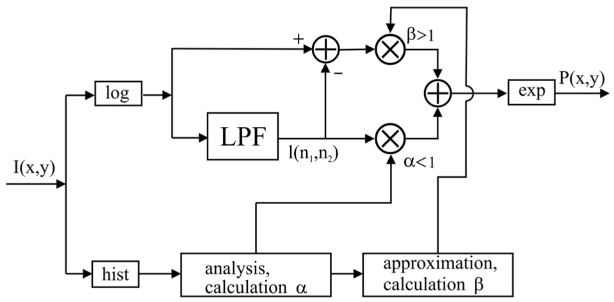

Fig. 3 Modified homomorphic filtering model

The performed experiments and analysis pointed to the functional connection between the image histogram shape and the illumination and reflection coefficient values. Their numerical values are most frequently determined in an experimental way. The modified homomorphic filtering model (Fig.3) implies the automatic determination of coefficients α and β values, based on the image histogram. The functional dependency determined between the coefficients and the shapes (i.e. characteristic parts of the histogram) is established based on a detailed analysis of the results obtained from a large number of performed experiments, according to [13] and [16].

The local changes in illumination are performed by choosing the value for the coefficient α, while the contrast local changes are performed by choosing the value for the coefficient β. It is determined by experiments that the illumination coefficient α is in direct proportion to the region surface of the object histogram, but in inverse proportion to the entire surface of the image histogram, and that there is a connection between these two coefficients, which can be approximated. After analyzing the image histogram parameters, the boundary values determination and the required surfaces, the homomorphic filtering coefficients α and β are calculated. Corresponding signals are multiplied by coefficients α and β and summed. The anti-logarithm result gives an image with improved characteristics. A block diagram of the proposed process is shown in Fig.4, with following labels:

NS – Non-processed image
1 – Histogram forming
2 – Global threshold
3 – Boundary values
4 – Object histogram surface
5 – Histogram total surface
6 – Logarithming
7 – Filtering
8 – Coefficients estimation
9 – Signal independent multiplication
10 – Combining
11 – Anti-logarithming
PS – Processed image

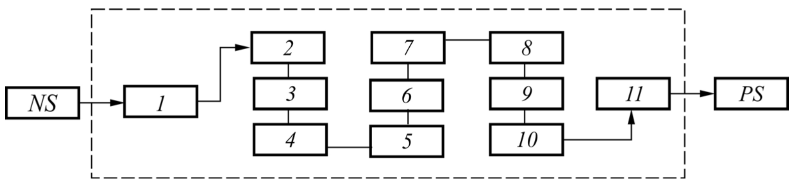

Fig. 4 Block diagram of the proposed homomorphic filtering process

3.1 The illumination coefficient α determination algorithm

Calculating limit value, which divides the histogram total surface into a part corresponding to the object and a part corresponding to the background, is very complex and determined by the encircled scene.

The simplest case is when the object is clearly distinguished from the background. In this case, the areas corresponding to the object and the background can be clearly noticed in the histogram, while between them, there is an area of low gray level intensities. This is the bimodal histogram. The illumination boundary value separating the object area from the background area in the histogram is placed in the region of low gray level intensities and represents the threshold which mostly corresponds to its minimal value. In these cases, object pixels are placed at the one side, while background pixels are placed at the other side of the threshold. Having in mind that these examples are very few in number, various methods of the threshold determination for cases when the object is not clearly distinguished from the background are developed and, over time, adopted. In such cases, the surface of the histogram part between the boundary value and the threshold is corresponding to the object and depends on the object characteristics and the spectrum of the registered gray level intensities, due to the fact that the threshold cannot be equated with the minimal boundary value in the histogram.

A number of algorithms for the automatic choice of the illumination threshold, based on the histogram are examined. The most frequently used are: the isodata algorithm, the background-symmetry algorithm, the watershed algorithm, the triangle algorithm and the greytresh algorithm based on Otsu's method. The *greytresh* algorithm is widely representative, because it can be used both for bimodal and multimodal histograms. It assumes the threshold determination, which is performed by using the method of minimizing the pixel intensity deviations from the image mean value and can be described by the following steps:

1. Determination of the possible boundary values domain.
2. Calculation of the object and background weighting coefficients, which define their appearance probability in the image.
3. Determination of the mean values for objects and background intensities.
4. Calculation of the object and background variances.
5. Calculation of the object and background sum of variances, multiplied by their weighting coefficients. This approach is repeated for all boundary values from the determined domain.
6. From a series of obtained results, the minimal value of the sum is adopted.
7. Determination of the gray level intensity corresponding to the minimal sum value, which is adopted for the boundary value.

The algorithm for the illumination coefficient determination, based on the image histogram, can be described by the following steps:

1. $y = \text{histogram(X)}$, - histogram forming and analysis;
2. $\left[y_{max},\ x_p\right] = max(y)$, - y_{max} – histogram maximum value, x_p – maximum location;
3. $x_d = min(y)$, - image minimum illumination;
4. $x_g = max(y)$, - image maximum illumination;
5. $x = x_g - x_d$, - image minimum and maximum illuminations determine the histogram width and define the image contrast;

6. $Q_{uk} = \int_{xd}^{xg} y dx$, - the histogram total surface;
7. $Q_{ob} = \int_{xd}^{xob} y dx$, - the histogram surface corresponding to the object;
8. $Q_{poz} = Q_{uk} - Q_{ob}$, - the histogram surface corresponding to the background;
9. $\alpha = \frac{Q_{ob}}{Q_{uk}}$, - illumination coefficient numerical value calculation.

The necessary surface values are calculated by the numerical integration of the histogram curve within certain limits. The lower limit value of the integral (*xd*) is determined by the image minimum illumination. The illumination threshold *(xob*), representing the histogram boundary value and dividing it into parts corresponding to the object and to the background, is determined by the greytresh algorithm. The upper boundary value of the integral (*xg*) is defined by the image illumination maximum.

The histogram parameter analysis implies the evaluation of the minimum and maximum value of the grey level intensities as well as the histogram curve maximum location and value determination. If the histogram maximum is in the nearest neighborhood of the mean value range, the illumination coefficient has a lower value, while the necessary global illumination change is smaller. Additionally, if the histogram peak is at a greater distance from the mean value range, the illumination coefficient has a greater value. For the illumination of insufficiently illuminated segments and for preserving the illumination of sufficiently illuminated segments as well as for the adequate quality change of a digital image, it is necessary to realize the corresponding non-linear characteristic managing changes of original image pixel values [11]. The value of the transformation coefficient α depends on the value of the pixel illumination level and differs for pixels belonging to the object and the background. The performed experimental researches from [13] pointed out that coefficients α and β need to satisfy the following conditions:

$$\begin{aligned} &\alpha \langle 1 \\ &\beta \rangle 1 \end{aligned} \tag{10}$$

3.2 Coefficients α and β functional dependence approximation

The illumination and reflection components form a single whole, pointing to the functional dependence between the illumination coefficient α and the reflection coefficient β.

These coefficient values are experimentally determined by the method presented in [13] and then adopted as reference values. It is found that satisfying results for the processed image quality are achieved by using the illumination coefficient values from the range 0.3-0.7. Outside of this range, the image is too bright or too dark, i.e. the quality of the resulting processed image is not satisfactory. Boundary values of the reflection coefficient β are also determined by performed experiments. Good results are achieved in the range 2-6. If the coefficient β value is smaller than the lower boundary value, the image does not have satisfactory contrast, while if the value of this coefficient is greater than the upper boundary value, significant image degradation occurs. Considering the fact that the conditions of adequate intervals for boundary values need to be satisfied, potential forms of coefficient functional dependency are assumed, and then the verification on concrete examples is performed as well as the analysis of the accuracy of the obtained results.

The form of this dependence can be determined by the histogram analysis and it can be approximated in the following three ways: by using the linear, power and trigonometric function.

3.2.1 Linear approximation

$$\begin{aligned} \beta &= k \cdot \alpha + n \\ \beta &= 10 \cdot \alpha - 1 \end{aligned} \tag{11}$$

Coefficients k and n are determined by the condition of the boundary points belonging to the previously defined intervals.

3.2.2 Power approximation

Power approximation is in the form of the second order function with negative sign of the square term:

$$\begin{aligned} \beta &= -a \cdot \alpha^2 + b \cdot \alpha - c \\ \beta &= -25 \cdot \alpha^2 + 35 \cdot \alpha - 6,25 \end{aligned} \tag{12}$$

Coefficients a, b and c are determined by solving the equation system along with the condition of boundary points as well as the central point belonging to the previously defined intervals.

3.2.3 Trigonometric approximation

Trigonometric approximation is defined by the following equation:

$$\begin{aligned} \beta &= p \cdot \sin(\alpha - q) + r \\ \beta &= 572,96245 \cdot \sin(\alpha - 0,3) + 2 \end{aligned} \tag{13}$$

Numerical values of coefficients p, q and r are determined by the condition of boundary points as well as the trigonometric curve bend point belonging to the given intervals.

4. Image quality estimation criterion

The creation and the application of the image processing algorithm raise the problem of the image quality estimation and the image classification according to its quality as well as a comparative (parallel) analysis of reference and processed image.

In this paper, we take advantage of the results of [15] which are presented in a summary form in the text that follows. The simplest way of the gray image qualitative characteristics estimation is the connection with its one-dimensional (1D) histogram. Since the histogram represents the distribution of the gray level values contained in a digital image, it can be considered as a discrete function in the range [0, L-1]:

$$h(i) = n_i \tag{14}$$

where i denotes the i-th of the gray level, while n_i denotes the number of image pixels possessing the i-th gray level. Image points are usually represented as 8-bit words, and so, the number of possible grey level intensities is $L = 256$. Dividing each histogram value by the total number of image pixels, the so called normalized histogram is obtained.

$$p_i = \frac{h(i)}{n} = \frac{n_i}{n}, \qquad i = 0,1,.....L-1 \tag{15}$$

where p_i denotes the appearance probability of the gray color i-th grey level. According to mathematical rules, the following has to be satisfied:

$$\sum_{i=0}^{L-1} p_i = 1 \tag{16}$$

Often used statistical characteristics for the image quality estimation are known as statistical characteristics of the first order:

1) **Mean value** (M)

$$m = \sum_{i=0}^{L-1} i p_i \tag{17}$$

2) **Variance** (STD)

$$\sigma^2 = \sum_{i=0}^{L-1} (i-m)^2 p_i \tag{18}$$

3) **Skewness** (SKEWNESS)

$$\mu_3 = \frac{\sum_{i=0}^{L-1} (i-m)^3 p_i}{\left(\sum_{i=0}^{L-1} (i-m)^2 p_i\right)^{\frac{3}{2}}} \tag{19}$$

4) **Kurtosis** (KURTOSIS)

$$\mu_4 = \frac{\sum_{i=0}^{L-1} (i-m)^4 p_i}{\left(\sum_{i=0}^{L-1} (i-m)^2 p_i\right)^{2}} - 3 \tag{20}$$

Information applicable for the image quality estimation is obtained by the determination of the quoted values of statistical characteristics. The **Mean value** indicates the level of image illumination and saturation. The **Variance** is a histogram outspread measure around the mean value. The **Standard deviation** σ is used more often than variance in the statistical analysis, and can be calculated as:

$$\sigma = \sqrt{\sum_{i=0}^{L-1} (i-m)^2 p_i} \tag{21}$$

Standard deviation σ, as well as variance σ^2, characterize the diagram outspread around the mean value, and they represent the measure of the image average contrast. The small value of the standard deviation assumes the small outspread of the image histogram around the mean value, indicating that the image has a small value of average contrast.

The standard deviation is particularly used for the texture analysis and description. The **Skewness** or the third order moment of the gray level distribution, represents the histogram symmetry measure around its mean value. The **Kurtosis**, or the fourth order moment is the histogram curvature measure related to the histogram mean value. After the partial determination, one can summarize the obtained results and indirectly define the image quality.

The image statistical characteristics determination is important due to the fact that images with similar characteristics also demand similar processing parameters. One-dimensional entropy is used as an image quality measure in this paper. In the field of information technology, the one-dimensional entropy of the gray image represents the measure of the contained information average quantity, which is generated by the source sending n independent messages, each with probability p_i. The mathematical relation describing the image entropy is:

$$H = \sum_{i=1}^{n} p_i \cdot I_i \tag{22}$$

where:

$$I_i = log_2 \frac{1}{p_i} \qquad I_i = -log_2\, p_i \tag{23}$$

I_i represents the information quantity transmitting the i-th message. This definition indicates the fact that the quantity of transmitted information is greater if a message with lower probability is generated. If the image is considered as the information source with independent pixels (messages), the one-dimensional entropy can be defined by the following equation:

$$H = -\sum_{i=0}^{L-1} p_i \cdot log_2\, p_i \tag{24}$$

where p_i is the estimated appearance probability of the gray nuance defined level, L is the number of gray scale intensity levels. $L = 256$ is common for an 8-bit image.

Theoretically, the maximum entropy of this image type is 8, corresponding to the case when all gray levels are equally represented. Entropy has the maximum possible value when gray level appearance probabilities are equal, whereas it has the minimum value in the case when all probabilities pi, except one, are equal to zero. In the image quality analysis domain, the image sharpness or, more precisely, the sharpness absence, is expressed by entropy. Accordingly, images with unclear edges have lower entropy value than images with sharp and clearly expressed edges.

5. Experimental results

5.1 Original images of a mobile object

Figure 5 shows three characteristic positions of a mobile object.

1 2 3

Fig. 5 Original images of cylinder

A case when an object is clearly distinguished from the background is assumed, i.e. when images are with bimodal histograms. This is the most frequent case in practice, when monitored objects are transported by a moving band. The image quality mark (estimate) is realized by the calculation of first order statistical characteristics, whose numerical values are given in Table 1.

Table 1 Original image frames 1, 2 and 3 - First order statistical characteristics

	M	STD	SKEWNESS	KURTOSIS	ENTROPY
1	51.6481	42.4734	3.6972	16.3157	6.1975
2	87.4152	63.8509	1.6796	4.8294	6.9425
3	49.3690	45.8004	3.0565	12.2493	6.4114

5.2 Reference model

Using the method presented by A.V. Oppenheim, R.W. Schafer and T.G. Stockham [13], values of the illumination coefficient α and the reflection coefficient β are determined, while the images obtained by this processing method are shown in Fig. 6. Coefficient values, as well as parameters for the image quality estimation, obtained by the use of this procedure, are taken as references. First order statistical characteristics of the images processed by the non-linear filter, according to this method [13], are given in Table 2.

1	2	3
$\alpha = 0.3231$	$\alpha = 0.5512$	$\alpha = 0.3711$
$\beta = 2.2054$	$\beta = 4.6785$	$\beta = 2.7113$

Fig. 6 Reference images and corresponding values of illumination α and reflection β coefficients

Table 2 Image frames 1, 2 and 3 – First order statistical characteristics of reference images

	M	STD	SKEWNESS	KURTOSIS	ENTROPY
1	148.7785	36.0633	2.0362	6.5890	6.7729
2	135.1315	54.2873	0.8689	2.5966	7.3534
3	121.6607	45.3606	1.8037	5.3062	7.1190

The first order statistical parameter analysis shows that the images, after transformation, possess sufficient amounts of illumination, contrast and edge sharpness. The quality of the realized images is in good correlation with the average subjective estimation.

5.3 Results obtained by the proposed algorithm

The proposed algorithm for the automatic determination of homomorphic filtering coefficients is applied for three assumed functional dependencies between the coefficients α and β, as follows: linear, power and trigonometric dependency.

5.3.1 Linear dependency between coefficients α and β

1	2	3
α = 0.3133	α = 0.5501	α = 0.3583
β = 2.1335	β = 4.5005	β = 2.5831

Fig. 7 $\beta = \beta(\alpha)$ - Linear dependency and corresponding values of illumination and reflection coefficients

Table 3 Image frames 1, 2 and 3 - First order statistical characteristics $\beta = \beta(\alpha)$ - Linear dependency

		M	STD	SKEWNESS	KURTOSIS	ENTROPY
I (original)	1	51.6481	42.4734	3.6972	16.3157	6.1975
P (after processing)		145.3431	36.3014	2.0988	6.6704	6.7097
I (original)	2	87.4152	63.8509	1.6796	4.8294	6.9425
P (after processing)		134.9684	53.9690	0.9104	2.6869	7.3262
I (original)	3	49.3690	45.8004	3.0565	12.2493	6.4114
P (after processing)		130.5219	43.4487	1.7806	5.2138	7.0693

5.3.2 Power dependency between coefficients α and β

1	2	3
α = 0. 3133	α = 0.5501	α = 0.3583
β = 2. 3631	β = 4.5605	β = 2.9228

Fig. 8 $\beta = \beta(\alpha) -$ Power dependency and corresponding values of illumination and reflection coefficients

Table 4 Image frames 1, 2 and 3 - First order statistical characteristics, $\beta(\alpha)$ - Power dependency

		M	STD	SKEWNESS	KURTOSIS	ENTROPY
I (original)	1	51.6481	42.4734	3.6972	16.3157	6.1975
P (after processing)		145.3792	36.4452	2.0646	6.5107	6.7331
I (original)	2	87.4152	63.8509	1.6796	4.8294	6.9425
P (after processing)		135.4562	55.0212	0.7988	2.4591	7.4046
I (original)	3	49.3690	45.8004	3.0565	12.2493	6.4114
P (after processing)		130.8471	44.1771	1.8094	5.5441	7.1286

5.3.3 Trigonometric dependency between coefficients α and β

1	2	3
$\alpha = 0.3133$	$\alpha = 0.5501$	$\alpha = 0.3583$
$\beta = 2.1334$	$\beta = 4.5892$	$\beta = 2.5799$

Fig. 9 $\beta = \beta(\alpha)$ – Trigonometric dependency and corresponding values of illumination and reflection coefficients

Table 5 Image frames 1, 2 and 3 - First order statistical characteristics, $\beta = \beta(\alpha)$ -Trigonometric dependency

		M	STD	SKEWNESS	KURTOSIS	ENTROPY
I (original)	1	51.6481	42.4734	3.6972	16.3157	6.1975
P (after processing)		145.3431	36.3014	2.0988	6.6704	6.7097
I (original)	2	87.4152	63.8509	1.6796	4.8294	6.9425
P (after processing)		134.8484	53.7106	0.9455	2.7630	7.3027
I (original)	3	49.3690	45.8004	3.0565	12.2493	6.4114
P (after processing)		130.5192	43.4447	1.7778	5.1922	7.0689

Figures 7, 8 and 9 show results obtained by the use of the proposed procedure. The numerical values of the coefficients and their deviations from corresponding values of the reference model for different dependencies are given in Table 6.

Table 6 Tabular view of the illumination coefficient α and the reflection coefficient β values, and their deviations from corresponding reference model values

	REFERENCE MODEL			LINEAR APPROXIMATION			POWER APPROXIMATION			TRIGONOMETRIC APPROXIMATION		
	1	2	3	1	2	3	1	2	3	1	2	3
α	0.3231	0.5512	0.3711	0.3133	0.5501	0.3583	0.3133	0.5501	0.3583	0.3133	0.5501	0.3583
β	2.2054	4.6785	2.7113	2.1335	4.5005	2.5831	2.3631	4.5605	2.9228	2.1334	4.5892	2.5799
Δα (%)	-	-	-	3.03	0.19	3.44	3.03	0.19	3.44	3.03	0.19	3.44
Δβ (%)	-	-	-	3.25	1.70	4.72	7.1	2.52	7.8	3.26	1.91	4.84

The numeric value of the illumination coefficient α is a variable which is conditioned by real environment conditions. With regard to the fact that the analyzed object is mobile in relation to the light source and the camera, its illumination is changing in time, and consequently the illumination coefficient value is also changing. The analysis of the first order of statistical characteristics (Tables 1, 2, 3, 4, 5 and 6) indicates that the image quality is approximately the same as separating of the reference model. Mean values deviations are negligible for all proposed approximations and their increase related to the original image characterize the global increase in the image illumination level (Figs. 5, 6, 7, 8 and 9). Similar standard deviation values indicate a negligible small difference between average contrasts. The skewness and kurtosis values in the reference and the actual image suggest similar histogram symmetry around the mean value, and uniform distribution of grey level intensities in the both images. In each of the cases, the entropy, as an image sharpness measure, has close numerical values and points to the edge sharpness increase related to the original image.

In the comparative analysis of the obtained results and the reference model [13], small deviations can be noticed, so that the obtained results are acceptable and applicable in real conditions. The proposed functional dependencies give approximately the same results for the reflection coefficient β, but they substantially differ in the realization quickness. The simplest way of the working speed estimation is the analysis of the execution time of the necessary mathematical operations. The minimum time required for the coefficient value estimation and calculation is for the linear approximation, while the maximum time is required for the power approximation, hence, the logical choice is the linear approximation.

6. Conclusion

The main advantage of the method and corresponding algorithm proposed in this paper is in enabling the automatic determination of non-linear homomorphic filter coefficients used for local contrast enhancement in digital image processing, when non-linear filters are in use, with slow speed of an observed object, and with the assumption that a clear difference exists between object and background. It is shown that the automatic change in the local contrast of the image is possible without substantial changes in its quality, which is illustrated by using the criterion for the image quality estimation. The comparative analysis of the illumination coefficient numerical values for the realized and for the reference model shows certain advantages of the realized model, or a relatively high level of correspondence with the reference results, while the errors are within acceptable tolerances. The smallest absolute value of the reflection coefficient deviation for all (each) of these analyzed image frames is realized by using linear approximation. Hence, the linear approximation is most appropriate for the use in real conditions. The algorithm is realized and examined in laboratory conditions with a simple system consisting of a moving band, a camera and a source of diffuse (white) light, used for measuring object dimensions. This procedure enables the automatic elimination of changes originated from the light source aging (and its replacement by another light source). The proposed procedure can be used for various applications in mechatronics, robotics and automatized production systems.

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