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IMAGE ENHANCEMENT IN VIDEO ANALYTICS SYSTEMS

Recently, video analytics systems are rapidly evolving, and the effectiveness of their work depends primarily on the quality of operations at the initial level of the entire processing process, namely the quality of segmentation of objects in the scene and their recognition. Successful performance of these procedures is primarily due to image quality, which depends on many factors: technical parameters of video sensors, low or uneven lighting, changes in lighting levels of the scene due to weather conditions, time changes in illumination, or changes in scenarios in the scene. This paper presents a new, accurate, and practical method for assessing the improvement of image quality in automatic mode. The method is based on the use of nonlinear transformation function, namely, gamma correction, which reflects properties of a human visual system, effectively reduces the negative impact of changes in scene illumination and due to simple adjustment and effective implementation is widely used in practice. The technique of selection in an automatic mode of the optimum value of the gamma parameter at which the corrected image reaches the maximum quality is developed.

Keywords: *gamma correction, image enhancement, video analytics system, gamma parameter, histogram, computer vision, segmentation.*

Introduction

The main purpose of any video analytics system is to understand the situation in the scene [1]. And the way to achieve it is through the selection of all or certain objects in the scene of attention, determining cause-and-effect relationships between them, and predicting future events. Therefore, to make the only correct decision regarding the situation, high-quality images with good contrast and uniform illumination of all its areas are necessary. It is unrealistic to assume that applications of computer vision will process only perfect images while their running. Practice shows that everything is much more complicated. The quality of images obtained by the video processing system is affected by too many factors: technical parameters of video sensors, low or uneven lighting level, change in scene illumination level due to weather conditions (heavy cloud, fog, absence or presence of sunlight), time changes (day and night illumination level) or changes in scenarios in the scene (for example, bright light from headlights of a car or a moving train). Images taken in such conditions contain contrast distortion and low light intensity of the whole image and its parts, have a narrow dynamic range and high noise.

In practice, for example, low light conditions can lead to confusion of textures and objects, poor image recognition efficiency, poor segmentation, and visual quality for visual inspection. In some cases, poor quality of images obtained can lead to an incorrect decision regarding events in the scene, as well as to a complete failure of the system (for example, a face recognition system in low light conditions).

The need for a successful solution to the problem in obtaining quality data as a primary stage in the

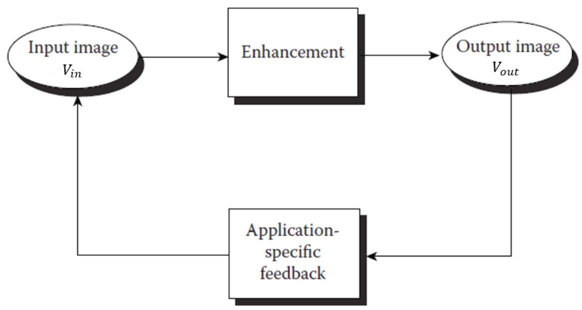


Fig. 1. Block diagram of an image enhancement process in an automated image processing system with feedback

whole process of image processing is substantiated by the fact that the functioning of video analytics systems provides maximum removal of a human from the process of collecting and processing images. This is because video systems receive too much video data and they are usually redundant and monitoring of images and adjustment of system parameters by a human operator is monotonous and difficult, but responsible. One of the options to increase the capabilities of video information processing systems is an automatic mode of operation, in which a person has an opportunity to intervene only to make decisions in some cases based on images, the enhancement of which should also be performed automatically.

Enhancements cover various aspects of image correction, such as saturation, sharpness, noise reduction, tonal adjustment, tonal balance, and contrast correction/enhancement. To convert images already taken by appropriate fixation devices into a state more suitable for both analysis and processing, a sufficient number of quality enhancement methods have already been developed, which can be divided into three groups: global, local, and hybrid.

Global methods are applied to the entire image and each pixel of the image must be changed under a single transformation function for the entire image. Local methods are used in cases where certain parts of the image need different types of enhancement, and their implementation is more complex. Hybrid methods combine features of both local and global groups. Occasionally, global contrast enhancement techniques may cause problems with insufficient or excessive pixel transformation in some parts of the image [2]. In some cases, this problem can be solved using local enhancement techniques, where the conversion of an image pixel depends on the information of adjacent pixels. However, sometimes in such a situation, due to a lack of global information about brightness, local artifacts can occur [3]. Since video analytics systems, as a rule, operate in extremely complex (in terms of illumination) conditions and with images far from an ideal quality, it is not always possible to use local and hybrid methods of image enhancement. It follows that the system must be balanced in determining parameters at which captured images and video sequences achieve the highest level of enhancement with available means and in automatic mode [4]. The last remark is especially important because of illumination changes over time (day/night, time movement of the sun), due to weather conditions (rain, clouds, shadows) and dynamic changes in scenarios (light of vehicle lights), etc.

Image Enhancement

Image enhancement boils down to improving display quality and analysis, with the result that one or more attributes of the image are changed. The choice of attributes and the way they are modified are specific to each application and often enhancement methods are developed empirically. The importance of the image enhancement procedure is especially relevant in a presence of feedback from the application (Fig. 1).

Much attention is paid to the development of methods for enhancing digital images [2, 5], especially in automated video analytics systems. And many of them are focused on improving over darkened or lightened images, which are a particular problem for automatic video processing systems.

Among the significant number of image enhancement methods, high efficiency has been proven by methods that use nonlinear transformation functions on the basis of the input data transformation process [6]. This group includes methods of enhancement based on gamma correction, which effectively reflects properties of a human visual system (Human Visual System, HVS) and due to simple adjustment and effective implementation has found wide application. Gamma correction, as one of the options for modifying the histogram, converts a uniform distribution of grey levels to increase the contrast of the image [7–8], providing high efficiency at low computational complexity.

Gamma Correction

Gamma correction methods are a family of general methods for modifying histograms obtained simply by a variable adaptive parameter γ.

Values of γ are usually determined experimentally by passing a calibration target with a full range of known luminance values through the imaging system (for example, the Macbeth diagram [9]). But often such calibration is not available or direct access to the imaging device is not possible, for example, when downloading an image from the Internet. Also, in most commercial digital cameras, a gamma parameter γ changes dynamically. It should be noted that with a significant expansion of various surveillance systems, video analytics, machine vision, etc., which usually use a wide range of different means of capturing images, and existing difficult illumination conditions, it is very important to eliminate poor lighting, contrast and more. All of the above forms the purpose of the work, which is to develop an efficient approach to providing a video analytics system with high-quality images of the scene in an automatic mode with elements of adaptation to changes in illumination.

This paper presents a novel, accurate, and practical method for estimating the optimal gamma parameter for a given image, which opens the possibility for further work towards obtaining enhanced images in video analytics systems. The method requires neither knowledge of the cameras used (model, settings, etc.) nor geometric calibration in contrast to [10] or [11], and it can be used in large variations of viewpoint and illumination of the scene. The paper presents a method for estimating the optimal value of a gamma parameter in automatic mode for video analytics, surveillance, and other applications in conditions of probable changes in scene illumination due to weather conditions, time changes, or changes in the scene scenario, excluding direct human intervention in the selection of this parameter.

It's common knowledge that the biggest problem for automated video processing systems is the lighting mode of the scene. This means that the quality of images at the input of a video system depends directly on illumination and a situation in the scene, which is an almost uncontrolled and unpredictable process. Due to unpredictable changes in lighting, images at the input of a system become darker or too light. In this case histograms of images also change their appearance. When illumination changes a majority of histogram bins shift towards minimum values (indicating an increase of the number of pixels that reflect darker intensity levels) or towards maximum values (indicating an increase of the number of pixels that reflect lighter intensity levels) of the lighting scale.

Correspondence of gamma correction to a human visual system and good results in its application in practice force researchers, to return to methods of image enhancement based on gamma correction and look for ways to automatically determine a parameter of gamma γ in image processing systems.

Gamma Correction and Images

Many devices used to capture, print, or display images typically use gamma correction, also known as a power-law transformation [6], on each pixel of the image. The power function as a transfer function is most often used in the form

$$V_{out} = AV_{in}^{\gamma}, \qquad (1)$$

where A is a coefficient and the input V_{in} and the output V_{out} are non-negative real numbers. In a general case, if $A = 1$, then the input and output values are in the range from 0 to 1 (in a normalized form). Figure 2 shows transformation functions at values of intensity levels from 0 to 255. If $\gamma = 1$, the characteristic of semitones is linear, and differences in luminance of the object in light and dark tones are the same. If $\gamma < 1$, then the brightness of the image is shifted to the darker side of the spectrum, otherwise, when $\gamma > 1$, the brightness of the image is shifted to the opposite lighter part of the spec-

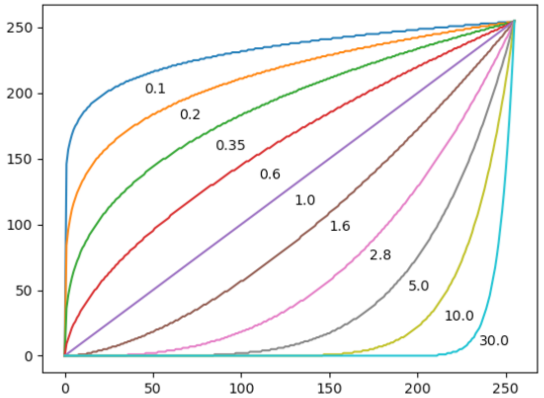


Fig.2. Power function of transformation at different values of gamma parameter

trum. This is seen in the histogram of the images (Fig. 3). The value of a gamma parameter equal to one ($\gamma = 1$) will not affect the brightness of the input image in any way.

Gamma is an image parameter that affects the intensity of pixels of the original image. However, not all image pixels are subject to change, but only those that have medium brightness, i.e. not the darkest and not the lightest. The intensity values of the darkest and lightest pixels remain unchanged. Which intensity values will not be affected, depends on the specific value of a gamma parameter. Thus, gamma adjustment only affects mid-tones.

Intuitively, image enhancement should lead to higher contrast, higher edge intensity, and the preservation of local and global information. The simulation results of the gamma parameter influence on the image quality using the developed software prove that:

1. the image quality varies depending on the value of a gamma parameter γ, and hence the distribution of intensity levels along the scale from 0 to 255;

2. the contrast of the image directly depends on the width of the range of intensity levels distribution: the wider the range of intensity levels distribution, the more pronounced the contours of objects;

3. the contrast of objects in the image directly reflects the ability to define contours of objects, for example, using a Canny edge detector.

When studying the influence of a gamma parameter on the image quality, it is also important to obtain a behaviour of some statistical characteristics of test images and their compliance with qualitative changes in variations of a gamma parameter γ. If for the test image of size $M\times N$ intensity levels of pixels are denoted through z_i, $i = 1, 2, 3, \ldots, L-1$, then a probability $p(z_k)$ of the intensity z_k in the image is estimated by the value

$$p(z_k) = \frac{n_k}{M\times N}, \tag{2}$$

where n_k is the number of pixels with the intensity z_k in the image and $M\times N$ is the total number of pixels.

Knowing $p(z_k)$ you can get such important quantitative characteristics of the image as:

1. *Mathematical* expectation (average value) of the intensity of the whole image

$$\mu = \sum_{k=0}^{L-1} z_k * p(z_k). \tag{3}$$

2. *A variance* of intensity as a magnitude of the scatter of intensity levels z around the mathematical expectation. The variance is a convenient measure of the image contrast, its dimension is equal to the square of intensity values. Often for convenience when comparing the contrast level instead of the variance they usually use the standard deviation σ (square root of the variance), because it has the same unit of measure as the intensity

$$\sigma^2 = \sum_{k=0}^{L-1} (z_k - m)^2 * p(z_k). \tag{4}$$

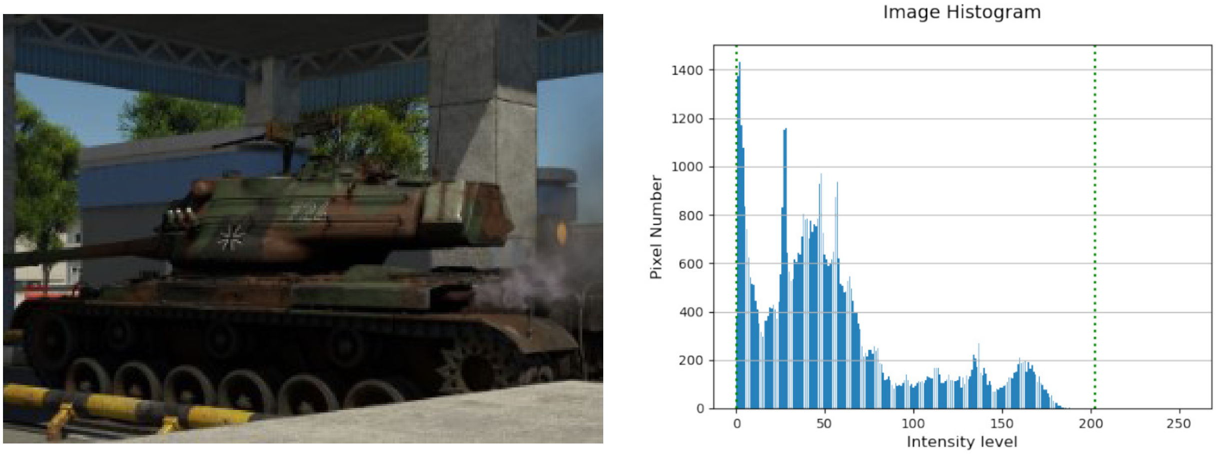
3. *Image entropy — a parameter that characterizes* the variability of intensity

$$E = -\sum_{k=0}^{L-1} p(z_k) * \log_2 p(z_k). \tag{5}$$

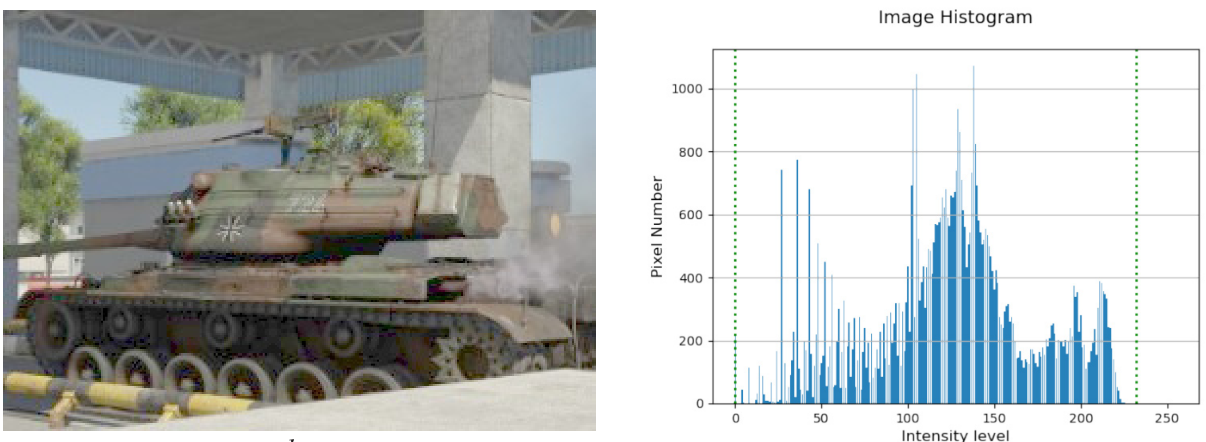
The entropy is equal to 0 for the region of constant intensity, i.e. when all $p(z_k)$ are zero and takes the maximum value in case of equally probable cases, i.e. when all $p(z_k)$ are equal to each other.

4. *The proportion* of image pixels that belong to edges in the image, relative to the total number of pixels of the entire image detected by, for example, a Canny edge detector

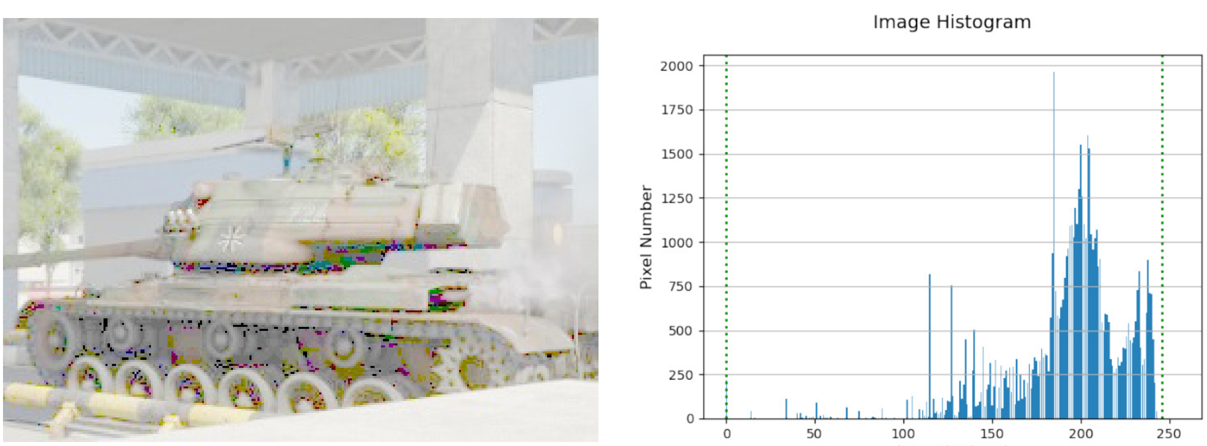
$$C = \frac{1}{M * N} * N_{contour}; \tag{6}$$



a



b



c

Fig. 3. Tank image and its histograms: *a* – the original image at $\gamma = 1$; *b* – the image at $\gamma = 2{,}5$; *c* – the image at $\gamma = 7{,}0$ (hereinafter, the vertical dotted reflect the first and last non-zero bins of the histogram)

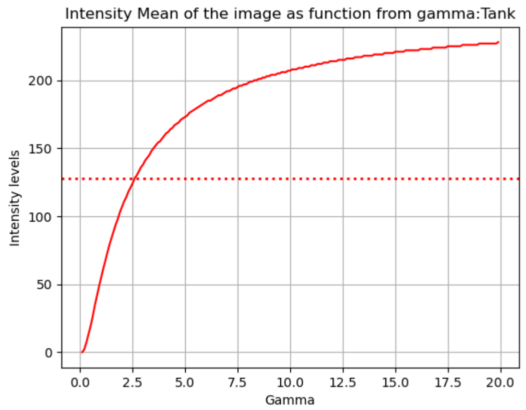


Fig.4. Dependence of the average intensity of the Tank image on a gamma parameter (dotted horizontal line shows the average value of the intensity scale, i.e. 128)

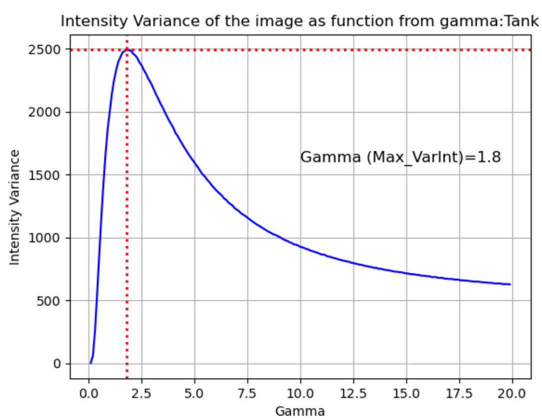


Fig.5. Dependence of the variance of image intensity on a gamma parameter

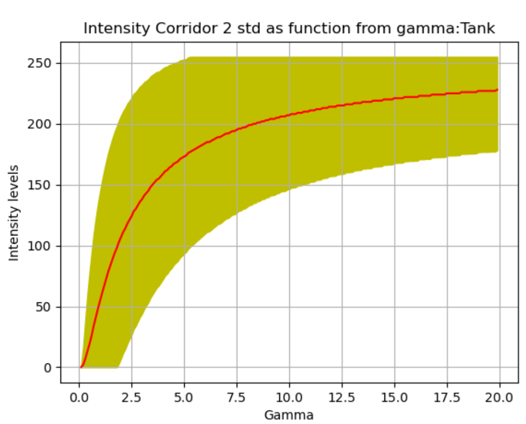


Fig. 6. The corridor with a width of ± 2 around the graph showing how the average value of image intensity depends on a gamma parameter

where $N_{contour}$ — the total number of pixels, that belong to edges in the image, detected by a Canny edge detector.

All the above-mentioned characteristics provide additional opportunities in determining the optimal parameter of gamma γ [12] without any additional means.

The results of simulation the influence of a gamma parameter on the histogram of the test Tank image (Fig. 2) state the fact of direct dependence of indicated statistical characteristics of the image:

1. The mathematical expectation or average value of the image intensity changes from 0 towards the intensity level 255 as the parameter gamma increases (Fig. 4).

2. The intensity variance σ^2, and hence the standard deviation σ, as a magnitude of the intensity scatter around the mathematical expectation, varies, reaching maximum at a certain value of a gamma parameter (Fig. 5). Having calculated variance values, it is possible to determine at which values of a gamma parameter the adjusted images should be assigned to the class of low or high contrast. This can be determined under the equation [13]:

$$g(I)=\begin{cases}\theta_1, & D\le 1/\tau,\\ \theta_2, & otherwise,\end{cases} \tag{7}$$

where $D = diff(\mu + 2\sigma), (\mu\text{-}2\sigma))$ and τ are parameters according to which the contrast of the image is determined, σ and μ are the standard deviation and the average intensity of the image, respectively. Using equation (7), it is possible to classify the image as low-contrast (when most of intensity values of the image pixel accumulate in a small range (Fig. 2*a*, *c*). The criterion in equation (7) is chosen according to the Chebyshev non-equation, which states that at least 75% of the values of any distribution are within 2σ around the mean on both sides [14]. This leads to a simplified version of the criterion for classifying the image as low-contrast, namely as $4\sigma \le 1/\tau$. In [13] determined that $\tau = 3$ is a suitable choice for characterizing the contrasts of different images.

The corridor with a width of $\pm\, 2\sigma$ around the graph representing how the average intensity of the image depends on a gamma parameter

(Fig. 6) shows that not all values of a gamma parameter corridor around the average intensity curve are equal to 2σ on both sides (at $\gamma<1{,}8$ and $\gamma>5{,}1$). This does not correspond to Chebyshev inequality [14], and thus leads to clustering values of intensity and, as a result, to low image quality.

Also, the small value of the intensity variance indicates a modest scatter of the values of the intensity and a small difference between the colors of the adjacent areas (Fig. 2,*a* and 2,*c*). From the graph showing how the intensity variance depends on a gamma parameter (Fig. 5), it is seen that the value of the intensity variance of the images in Fig. 2,*a* and 2,*c* are well below the maximum.

3. Entropy, as an indicator of variability of the intensity values, reaches its maximum value within limits of a gamma parameter, when the corridor fully corresponds to the value of $\pm 2\sigma$ (Fig. 7). The higher the value of entropy, the higher the intensity variability, which indicates a much larger amount of information that can be extracted from the image. The entropy (5) takes the maximum value in the case of equally probable values of intensity levels, i.e. when all $p(z_k)$ are equal to each other.

4. If the video analytics system is intended to select objects in the scene, then as an option, the ability to detect contours in the image, for example, using a Canny edge detector at different standard deviations of intensity (Fig. 8) can be taken as a quality estimation for selecting the gamma parameter. The percentage of defined pixels belonging to contours determined by the detector is taken as an estimate.

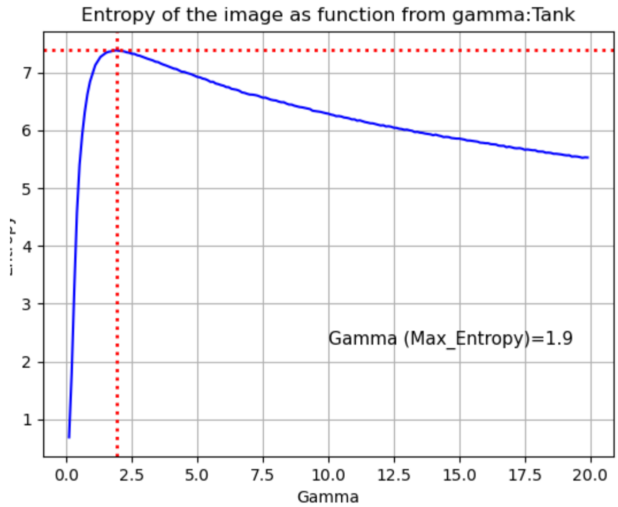


Fig. 7. Graph of the dependence of the image intensity entropy on a gamma parameter

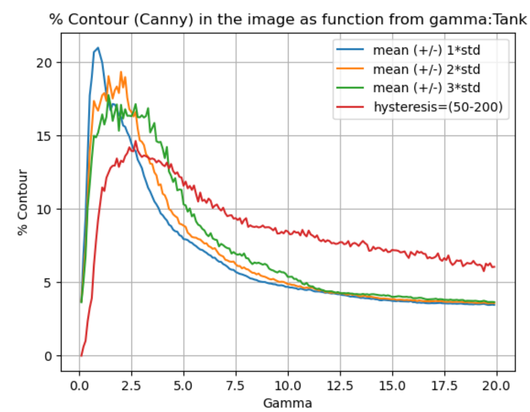


Fig. 8. Graph of the dependence showing the percentage of image pixels, which belong to contours in the image, detected by a Canny edge detector, from a gamma parameter

Gamma-Correction and an Image Histogram

A histogram (Fig. 3, right images) is a special diagram, which is somewhat similar to a mountain range, illustrating the distribution of all colors (for color images) or intensity levels (for gray images) in the image (the graph shows the number of pixels at each intensity level. A histogram allows you to determine whether the image contains enough details in shadows (left part of the histogram), in middle tones (middle part of the histogram), and the lightest areas of the image (right part of the histogram), that is very important for quality image correction.

A histogram provides an idea of a tonal diagram of the image (or type of image key). In the image in a lower key, details are concentrated in shadows; high-key images contain the most details in bright areas; and in the image in a middle key, details are concentrated in middle tones. The width of a histogram represents a tonal range of the image — the range of colors from the darkest pixels to the lightest — on a scale from 0 to 255. Pure black (0) is at the left end of the intensity scale, and pure white (255) is at the right end of the intensity scale.

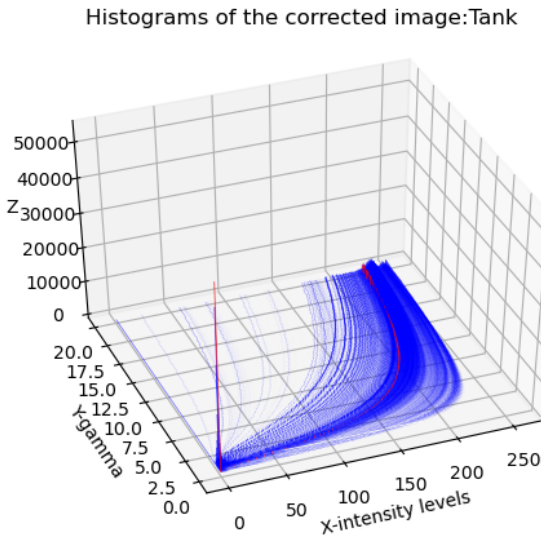


Fig. 9. The family of histograms (3D) of the Tank image at values of a gamma parameter from 0,1 to 20,0

Ideal from the point of view of color transfer is the situation when the histogram is distributed evenly over the entire area of the scale (Fig. 3, *b*), i.e. it is placed between the left and right edges of the histogram more or less evenly or at least without zero values at the edges. If, after all, similar zero values of the histogram take place at the edges (Fig. 3, *c* in the range of intensity levels 230–255), then, shifting the histogram in an appropriate direction and removing empty spaces at the edges, you can significantly improve the image quality — remove from it cloudy, grayish shades, etc.

To study histograms of images and the effect of gamma correction on the image quality, the program was developed. It gives an opportunity to set the value of a gamma parameter in the range of 0,1 and beyond with a certain step. The gamma parameter value of the image to be tested in the developed software has a value of 1. For certain studies, this parameter can be changed in one direction or another and analyze both the image and its histograms. Fig. 9 presents a 3D family of histograms of the Tank image at values of a gamma parameter from 0,1 to 20,0 in steps of 0,1. The program gives a complete idea of the distribution of histogram width, intensity values, mathematical expectation, and variance of intensity depending on a gamma parameter.

The result of these studies is to determine and select the best image in terms of ensuring an optimal segmentation of objects in the image and its visual representation to the human operator.

Given that a histogram of the image shows the relationship between intensity levels and their corresponding frequency in the image, you can adjust the gamma value based on calculated histograms, you can see that the range of intensity expands or narrows. But at the same time, there is still some share of both the darkest (black) and lightest (white) pixels (Fig. 2).

From the analysis results of a large number of test images and their histograms and [15–16], the following conclusions follow:

- in a dark image, gray levels (and, consequently, the histogram) are grouped at the lower end of the intensity scale (Fig. 3,*a*);
- in a uniformly bright image, gray levels are grouped at the upper end of the intensity scale (Fig. 3 *c*);
- in a brightly balanced contrast image, gray levels are more evenly distributed over a significant part of the range (Fig. 3,*b*);
- a narrow histogram indicates that a tonal range (and hence a difference between the darkest and lightest pixels) of the image is too narrow. Most likely, the image at the same time looks flat enough and it lacks details and contrast;
- too uneven ridge indicates that colors of the image are not balanced. Some colors may be enough in the image, but too few others;
- if the left edge of the histogram is a sharp peak, the image is likely to have shadows cut off (when shooting or scanning). If the peak is located on the right edge, bright areas of the image can be cut off;
- if the "mountain range" is shifted to the left (towards black, i.e. zero), and the "plain" stretches to the right, the image is underexposed (it is too dark);
- if the "ridge" is shifted to the right (towards white, i.e. 255), and the "plain" is on the left, the image is overexposed (it is too bright);
- the image with a good balance of dark and light colors gives a wide "mountain range", occupying the entire width of the histogram, quite long and uniform in height.

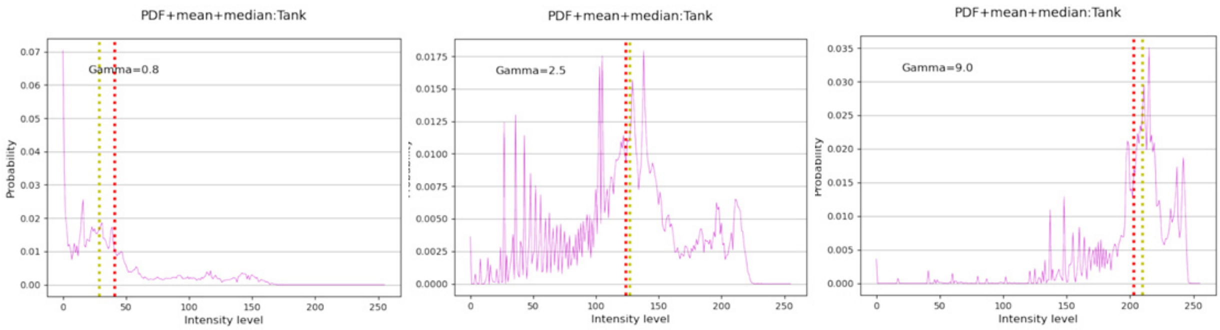


Fig.10. An example of changing the histogram peak position on the intensity scale of the Tank image depending on a gamma parameter (hereinafter dotted vertical lines reflect the average values of intensity levels — red and median — yellow)

Based on the above conclusions and analysis as well as modeling of the effect of gamma correction on a histogram and visual quality of test images, the following results were obtained:

1. When changing the gamma value from the minimum (γ_{min}=0,10) to the maximum (γ_{max}=20,0) the histogram passes the process of transforming the shape from the peak near zero bin of the histogram at γ_{min} to the peak near the 255 bin of the histogram at γ_{max} (Fig.10).
2. When changing the gamma value from the minimum value (γ_{min}=0,10) to the maximum (γ_{max}=30,0), the image changes from "very dark" to "very bright".
3. The most favorable image for visual perception corresponds to the most scattered histogram of the image (Fig. 3).

Thus, all of the above leads to the conclusion that the highest quality image in a whole set of images with different values of a gamma parameter corresponds to the value of a gamma parameter at which:

- the image histogram is mostly scattered throughout the intensity scale, that indicates the most possible scatter of intensity(variance) and the greatest dissimilarity of colors in adjacent areas of images, and hence the presence of more information in the image;
- the mathematical expectation of intensity is as close as possible to the average value of the intensity scale, that ensures compliance with the Chebyshev inequality when at least 75% of the values of any distribution are within 2σ around the mean value on both sides [14].

Also, the practice of applying the "rule of three sigmas" proves that in its implementation there is every reason to consider the law of distribution of a random variable normal. In this case, respectively, the law of distribution of values of image intensity is normal with all the consequences: mathematical expectation, mode, and median take the same value in some cases.

For more information on the distribution of intensity levels, it is appropriate to pay attention to the construction of a cumulative histogram of the image.

Gamma Correction and a Cumulative Histogram of the Image

A cumulative histogram of the image is nothing more than a function of the probability distribution of intensity levels. A distribution function in probability theory is a function that characterizes the distribution of a random variable. In our case, a random variable is the intensity of pixels, which takes values from 0 to 255. A value of the probability distribution function of intensity levels is a probability that the random variable X (pixel intensity level) will take a value less than or equal to x, where x — arbitrary real number.

It is necessary to pay attention once again to the above-mentioned statements, namely that:

1. the best image corresponds to the value of a gamma parameter, in which the histogram of intensity levels is scattered across its width;
2. the value of entropy takes the maximum in case of equal probability of certain intensity level occurrence, i.e. when all $p(z_k)$ from equation (5) are equal to each other.

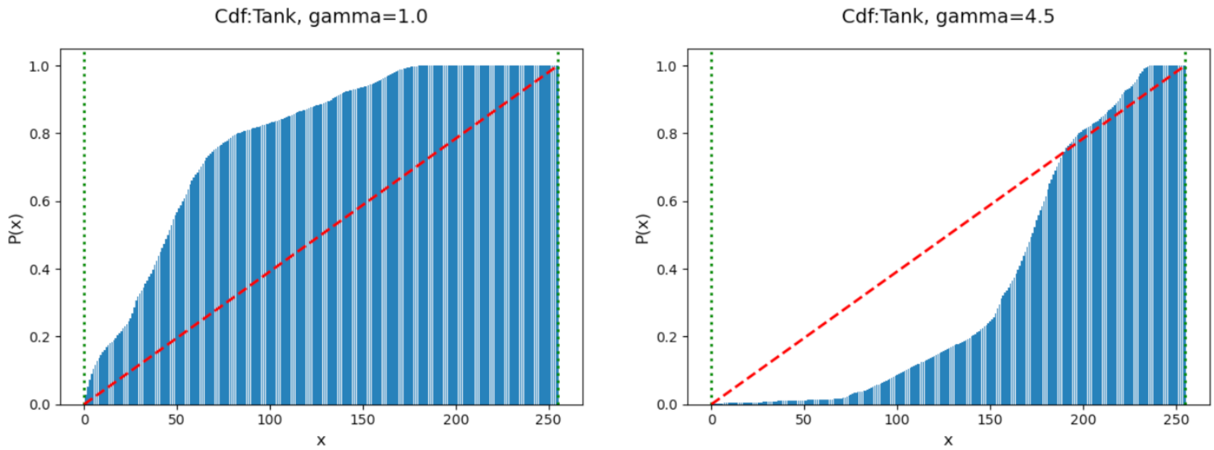


Fig. 11. Samples of cumulative histograms (normalized along the *y*—axis) of corrected images and the «identity line» of the "ideal" image-sample

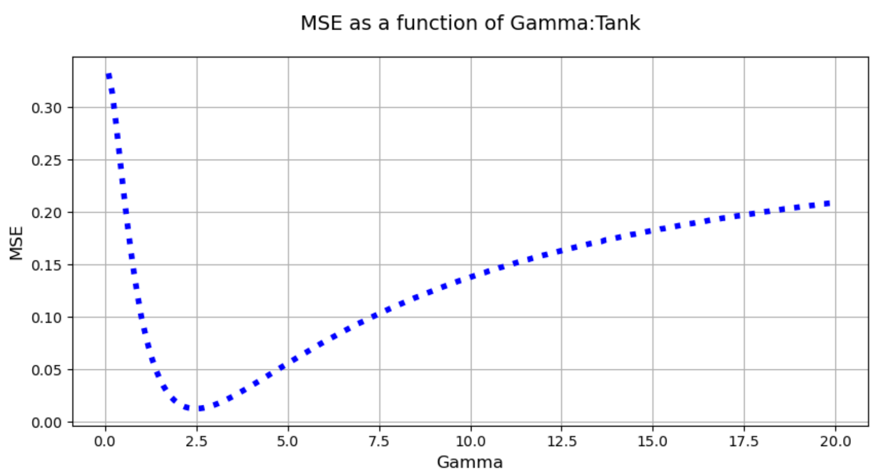


Fig. 12. Graph of the dependence of MSE values on a gamma parameter on an example of the Tank image (γ_{opt} =2,5)

These two statements lead to the conclusion that an "ideal" image will be with the following data: all intensity levels have the same probability of occurrence and the image histogram occupies the entire width of the intensity scale from 0 to 255. The probability function, in this case, takes a piecewise linear view from 256 intervals (the number of intensity levels) from 0 to 1,0 (or from 0 to the total number of pixels in the image without normalization). This conclusion makes it possible to consider the image with the above data as an "ideal" sample image to compare the images corrected by applying gamma correction with an appropriate parameter. The cumulative histogram of the "ideal" sample-image represents a graph in form of an up-going staircase with 256 (the number of bins of the image histogram) equal steps. Approximating the values of the cumulative histogram of the "ideal" sample-image leads to the conversion of the histogram into a straight line with coordinates (0,0) – (1,255) (Fig.11) or an «identity line» (hereinafter in the figures highlighted by a red dotted line) [17].

Fig.11 shows how the appearance of a cumulative histogram of the image changes after adjustment. Analysis of image histograms shows that the corrected image with the corresponding gamma parameter has the best appearance for visual representation when its cumulative histogram is as close as possible to the cumulative histogram of the "ideal" sample image. The degree of this comparison can be estimated using the Mean Squared Error (MSE) that is the average squared difference between the normalized cumulative histogram of the "ideal" sample image and the cumulative histogram of the adjusted image for each of the intensity levels:

$$MSE = \frac{1}{256}\sum_{k=0}^{L-1}\left[c(k) - Cdf(k)\right]^2, \qquad (8)$$

where $c(k)$ and $Cdf(k)$ are respectively values of the normalized cumulative histogram of the "ideal" sample-image and the cumulative histogram of the corrected image, k — the intensity level.

Thus, having determined the minimum value of MSE at a certain value of a gamma parameter, we can say that this value of a gamma parameter is optimal γ_{opt}. This value indicates that γ_{opt} is the only value from all considered values of a gamma parameter, which provides the maximum approximation of value distribution of the image intensity to the "identity line" of the "ideal" sample-image (Fig.12).

Experimental Results

Determining the optimal value of a gamma parameter γ_{opt} by the proposed method makes it possible to adjust the quality of images entering a processing unit of the video analytics system, automatically and without human intervention. The developed method for determining an optimal gamma parameter was tested on a large number of images with different characteristics and gave good results.

The conducted research of results allows us to draw the following conclusions:

1. The use of an "ideal" image sample, which has a uniform distribution of intensity levels across the intensity scale from 0 to 255, and the same probability values of intensity levels, as a reference for comparison is an effective mechanism for determining the optimal value of a gamma parameter.

2. The optimal value of a gamma parameter corresponds to the image for which:

- the most dispersed set of values of intensity levels throughout the intensity scale;
- values of statistical characteristics of a probability density function of image intensity are closer to a normal law of intensity dispersion: mode, median, and mean occupy positions in the middle (128) of the intensity scale;
- most levels of image intensity under the Chebyshev inequality fall in the range from $\pm 2\sigma$ to $\pm 3\sigma$ on both sides of the average image intensity;
- percentage of pixels belonging to contours in the image, which are detected by an edge detector, for example, a Canny edge detector at 2σ, 3σ, and hysteresis in the range of $50 \div 200$, is the maximum.

3. Variance and standard deviation of the intensity can in no case be used as a criterion for selecting the optimal value of a gamma parameter since for images with a wide dynamic range (for example, the Street image in Fig. 13 and the Knight image in Fig. 14 the peak of intensity shifts from the beginning of the scale towards the end of the scale, as a gamma parameter increases. This is especially evident in Fig.13,*h* and 13,*i*. Also, in Fig. 13,*h* it is seen that the curve of the average image intensity disperses with the main set of intensity values, which forms the image itself, due to the high peak at the beginning of the scale. Because of this, there is a situation where the average value of the image intensity is in the middle of the scale, the variance is largely due to peaks on both sides of the scale, and the ability of an edge detector to detect contours in the image decreases significantly. It is the proposed method that allows in such a situation to identify the optimal value of a gamma parameter with the most dispersed distribution of intensity levels.

4. Selecting the "ideal" sample image as a reference to determine the optimal value of a gamma parameter of adjusted images gives an additional advantage. Of course, for an image with a normalized cumulative histogram, a graphical representation of which is a line (as for the «ideal» sample image) with coordinates (0, 0) – (1, 256),


WDR OFF
WDR OFF

a

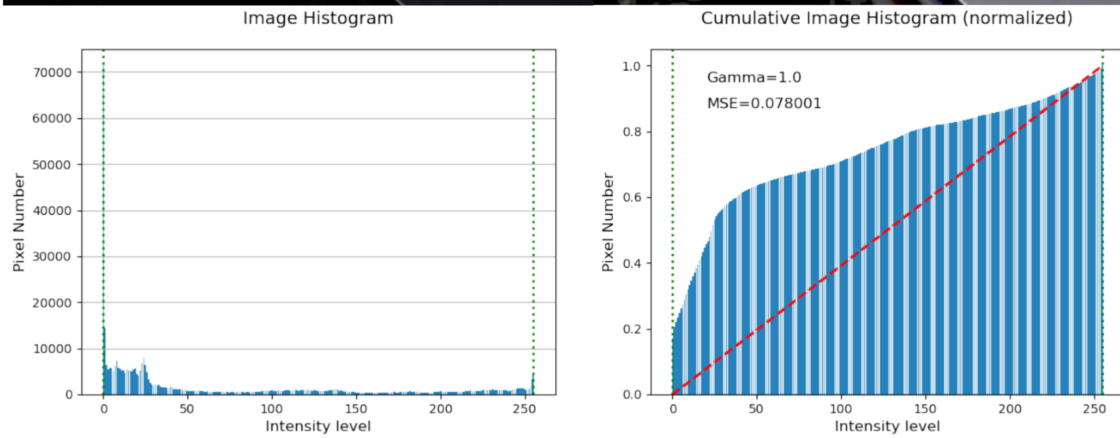


Image Histogram
Pixel Number
Intensity level
Cumulative Image Histogram (normalized)
Gamma=1.0
MSE=0.078001
Pixel Number
Intensity level

b

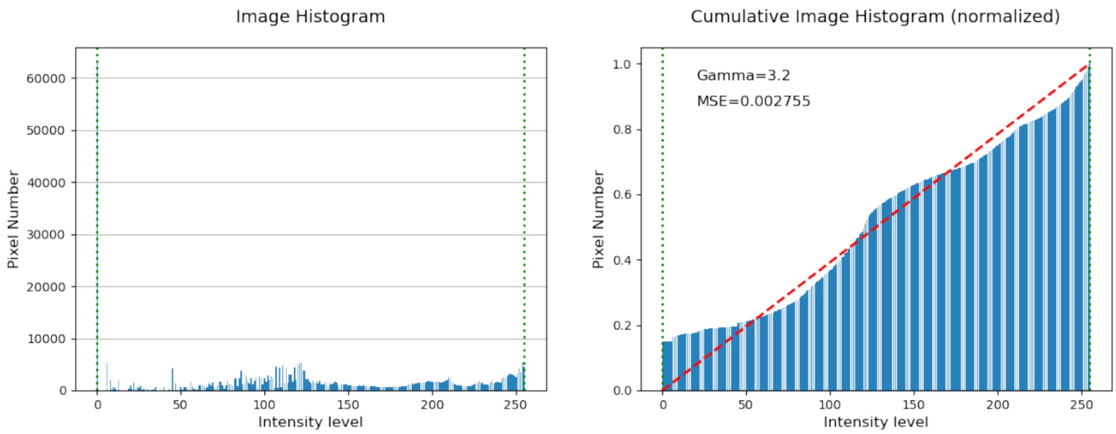
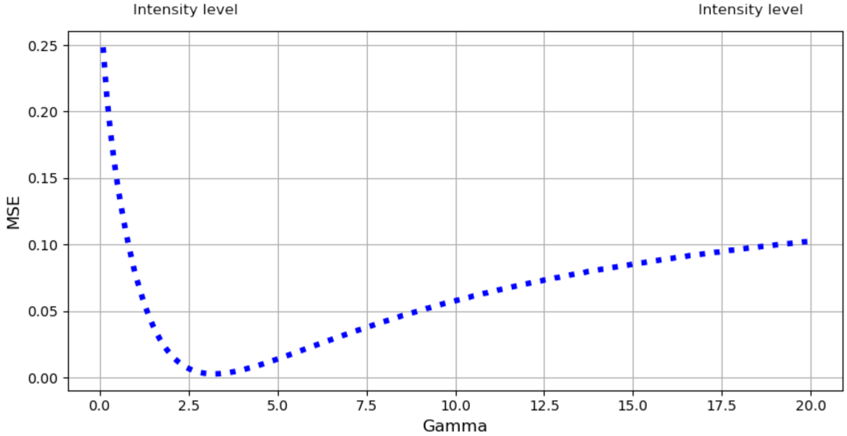


Image Histogram
Pixel Number
Intensity level
Cumulative Image Histogram (normalized)
Gamma=3.2
MSE=0.002755
Pixel Number
Intensity level

c


MSE
Gamma

d

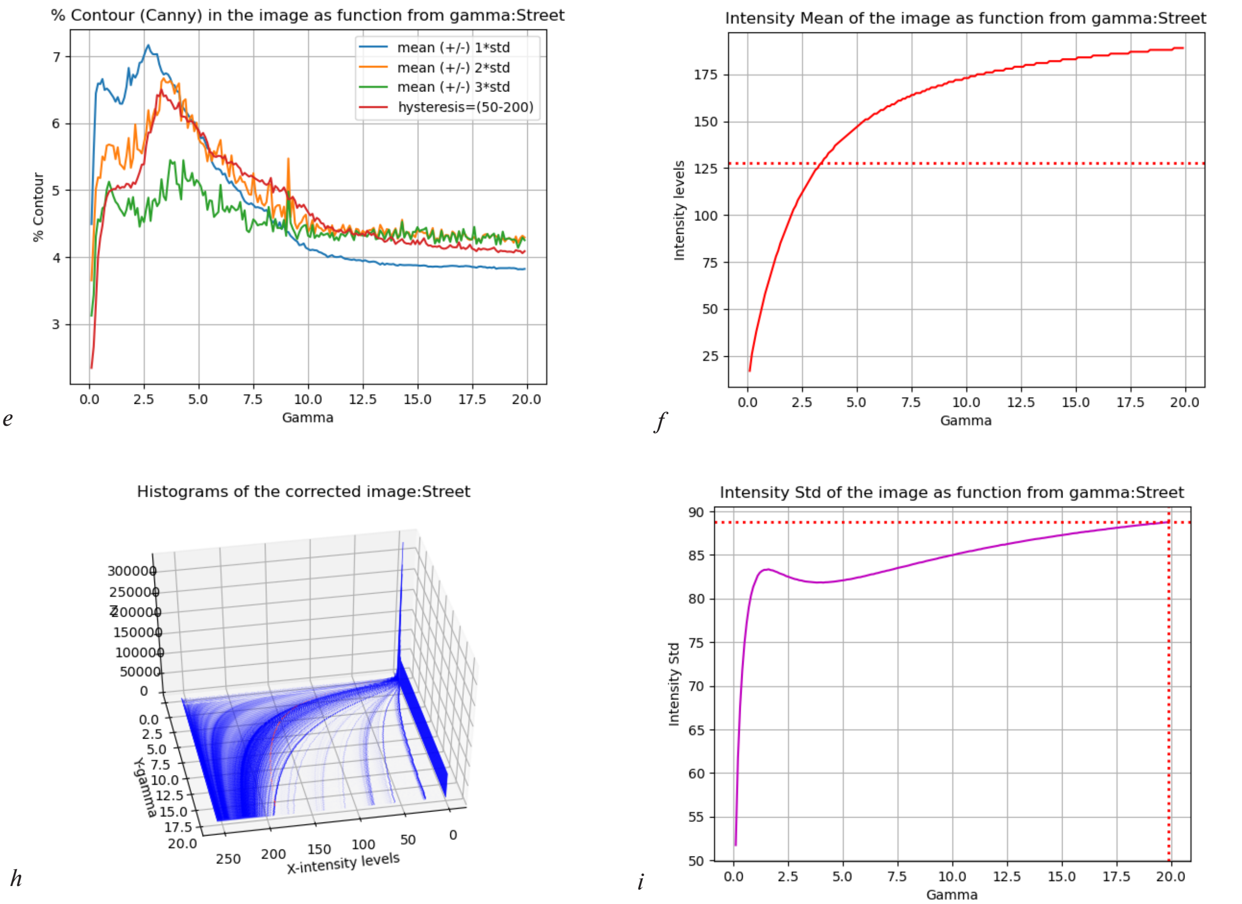


Fig. 13. Results of selecting the optimal value of a gamma parameter on the example of the Street image: *a* – the original and selected adjusted image; *b* – histograms of the original image; *c* – histograms of the image with a gamma parameter (γ_{opt} =3,2); *d* – selection of the optimal gamma parameter (γ_{opt} =3,2); *e* – proportion of image pixels belonging to edges detected by the Canny edge detector in the image with γ_{opt} =3,2; *f* – dependence of the average image intensity on a gamma parameter; *h* – the family of histograms of images at different values of the gamma parameter; *i* – dependence of the standard deviation of intensity on the value of the gamma parameter

the average intensity value is 128! Therefore, to determine the optimal value of a gamma parameter, you can also use the dependence of the average image intensity on the value of a gamma parameter (Fig. 13, *i*)). This graph indicates that the intersection point ordinate (*X*-axis) of the graph of dependence of the average image intensity on a gamma parameter with the average level (128) of intensity scale corresponds to the optimal value of the gamma parameter γ_{opt}.

Conclusions

A method has been developed for determining the optimal value of a gamma correction parameter of the image, which ensures the selection in automatic mode of the best quality scene image for further processing. To achieve the set goal of this work, the concept of an "ideal" image sample was introduced into the process of determining the optimal value of a gamma parameter, which

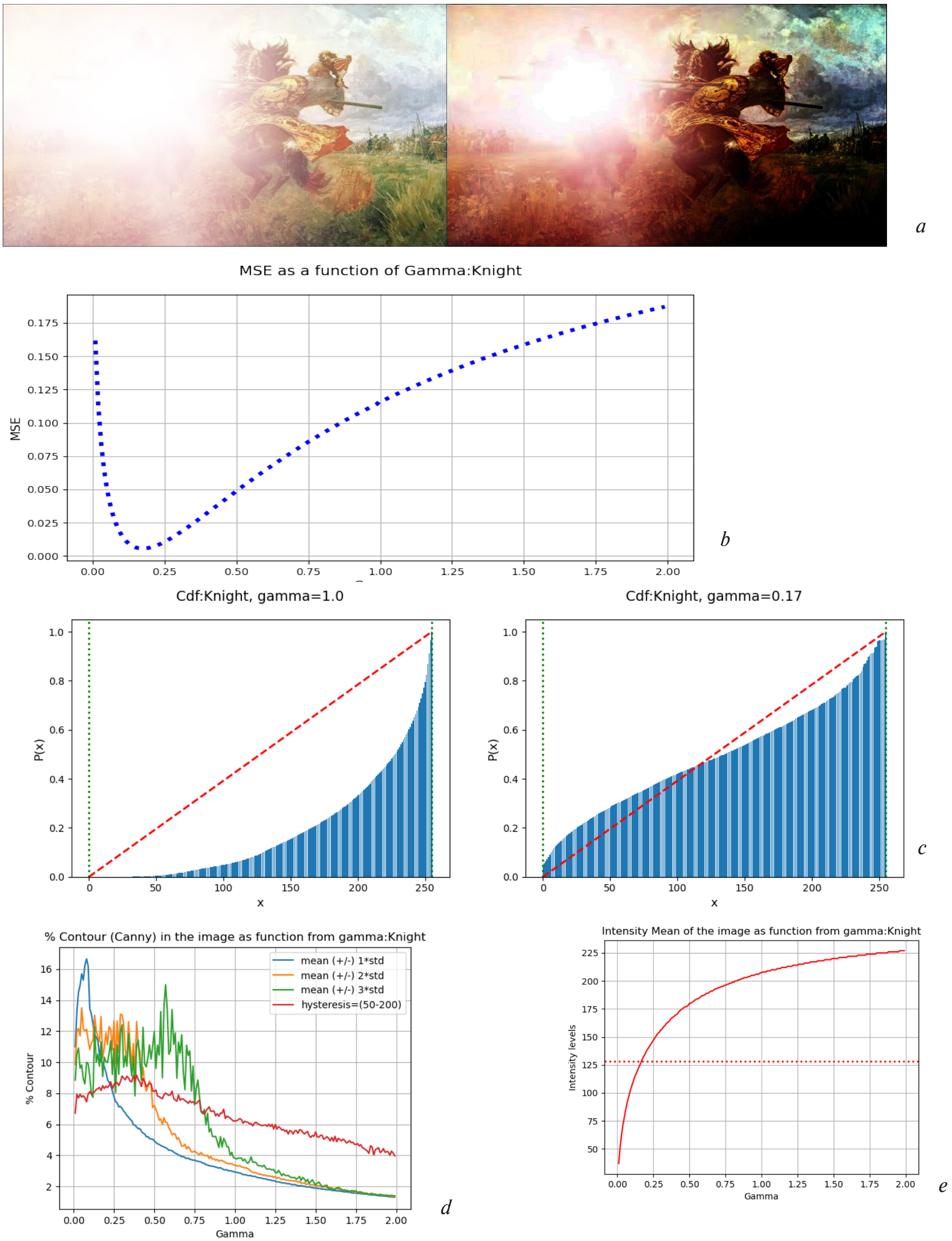


Fig. 14. Example of a very bright image: *a* — original and selected adjusted images; *b* — selection of the optimal gamma parameter ($\gamma_{opt} = 0{,}17$); *c* — cumulative histograms of original and adjusted images; *d* — a graph of dependence of detector edge Canny ability to determine the contours in the image at different values of the standard deviation of intensity; *e* — the intersection of the dependence curve of the average image intensity on a gamma parameter and the average level of intensity scale at γ_{opt}

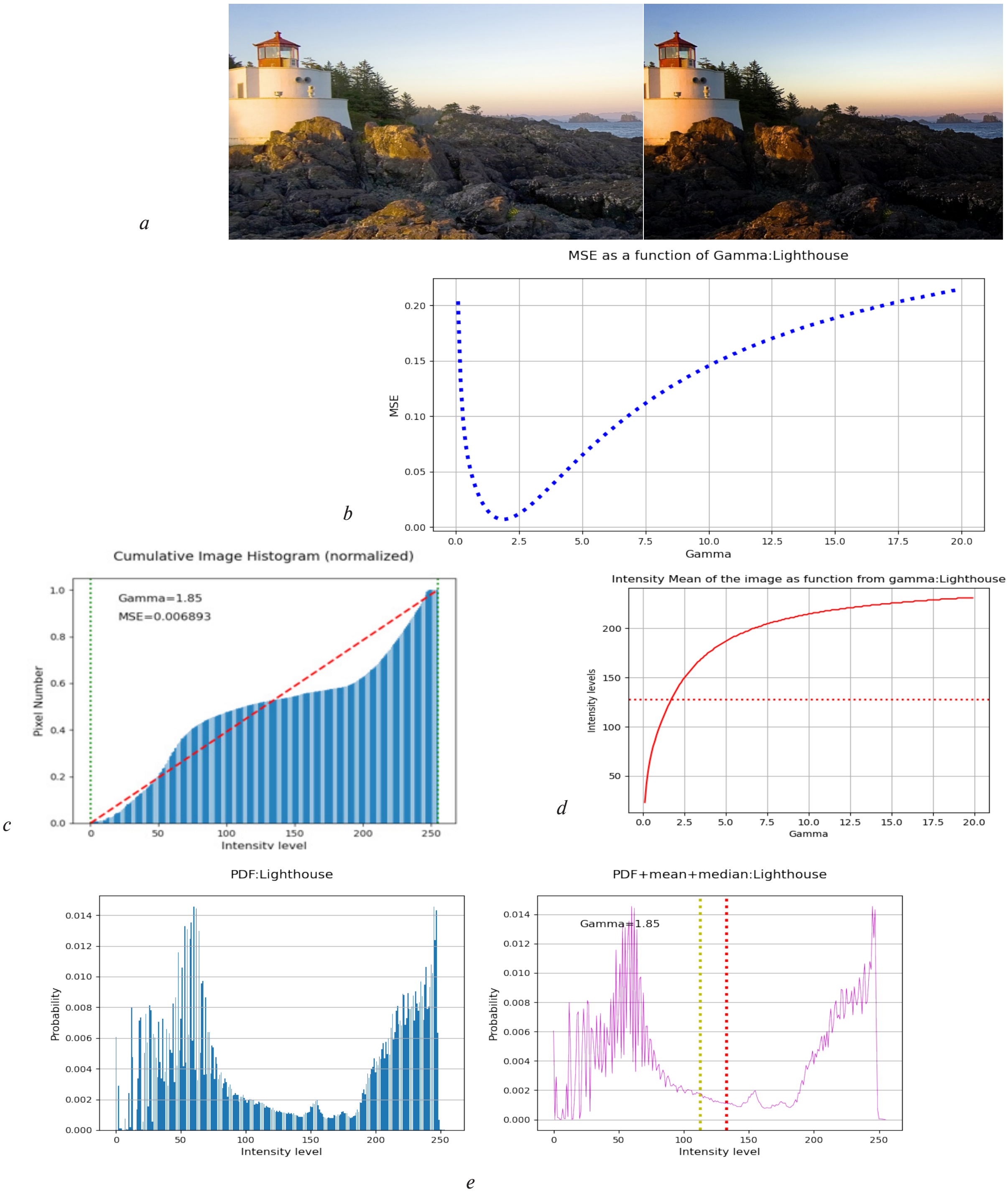


Fig. 15. Example of application of gamma correction to a darkened image: *a* — original and selected adjusted images; *b* — selection of the optimal gamma parameter (γ_{opt}=1,85); *c* — cumulative image histogram at γ_{opt}=1,85; *d* — the intersection of the dependence curve of the average image intensity on a gamma parameter and the average level of the intensity scale at γ_{opt}; *e* — the ordinary histogram and the contour of the corrected image histogram with a mean (red vertical line) and median (yellow vertical line)

is characterized by the same probability of the appearance of image intensity levels and the dispersion of the image histogram over the entire intensity scale. With such image data, the probability function of intensity levels takes a piecewise linear form with 256 intervals (in terms of the number of intensity levels) from 0 to 1,0 (or from 0 to the total number of pixels in the image without normalization). The cumulative histogram of such an "ideal" image sample represents a graph in the form of an ascending staircase with 256 (in terms of the number of intensity levels) equal steps, and the approximation of cumulative histogram values of the "ideal" image sample results in the transformation of the histogram into a straight line with coordinates (0, 0) – (1,255) (Fig. 11) or "identity line".

The method is based on minimizing the root-mean-square difference between the cumulative histogram of the gamma-corrected image and the corresponding histogram in the form of an "identity line" of the introduced "ideal" image sample.

The developed toolkit for automatic determination of the optimal value of the gamma parameter, and then of the best image for visualization and subsequent processing, significantly increases the efficiency of video analytics systems, segmentation, and image processing processes by reducing the negative effect of a scene illumination mode on image quality.

The proposed method is distinguished by the ability to bring the image quality to the highest possible level of quality in automatic mode and by the available elements of adaptability to changes in an illumination mode of the scene of attention. The effectiveness of the method allows it to be applied to a wide range of images and video sequences.

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ПОКРАЩЕННЯ ЗОБРАЖЕНЬ В СИСТЕМАХ ВІДЕОАНАЛІТИКИ

Вступ. Досягнення основної мети системи відеонаналітікі, а саме, розуміння сцени вирішується через процеси виявлення та розпізнавання об'єктів і встановлення причинно-наслідкових зв'язків між ними. Ефективність і якість роботи подібної системи безпосередньо пов'язано з обробкою великої кількості зображень і не завжди високої якості. Потреба в успішному вирішенні проблеми отримання якісних даних, як початкової ланки всього процесу обробки зображень, посилюється тим, що в системах відеоаналітики передбачається максимальне усунення людини від процесу збору і обробки зображень. Це обумовлено тим, що відеосистеми отримують занадто великі обсяги відеоданих і вони, як правило, надлишкові, а контроль зображень і регулювання параметрів системи з боку людини-оператора є монотонним і важким, але відповідальним. Одним з варіантів підвищення ефективності систем обробки відеоінформації є автоматичний режим функціонування, при якому людині залишається можливість втручання лише для прийняття рішень в окремих випадках на основі зображень, поліпшення якості яких має також виконуватися в автоматичному режимі.

Мета статті. Системи відеоаналітики функціонують в автоматичному режимі з великою кількістю зображень і відеопослідовностей та з мінімальним втручанням людини в процес їх здобуття і обробки. Однією з найвагоміших проблем, від вирішення якої залежить ефективність роботи системи відеоаналітики, є якість здобутих зображень, на які впливає багато зовнішніх чинників. Одним з них є зміни в режимі освітлення сцени, які складно не тільки усунути, а й передбачити (погодні умови, часові зміни, ситуація в сцені та інше). Зображення, зняті в таких умовах, містять спотворення контрасту і низьку інтенсивність освітлення як усього зображення, так і окремих його ділянок, мають вузький динамічний діапазон і сильний шум. Складнощі, що виникають в результаті змін освітлення, призводять не тільки до некоректної роботи всієї системи, а й до повного відказу. Все вищесказане формує мету роботи, яка полягає в розробці ефективного підходу до забезпечення системи відеоаналітики якісними зображеннями сцени в автоматичному режимі з елементами адаптації до змін освітленості.

Методи дослідження базуються на системному підході, програмному моделюванні, аналізі.

Результати. Розроблено метод для визначення оптимального значення параметра гамма-корекції зображень, при якому забезпечується вибір в автоматичному режимі найбільш якісного зображення сцени для подальшої обробки. Метод відрізняється здатністю приведення якості зображення до максимально можливого рівня якості в автоматичному режимі та наявними елементами адаптивності до змін у режимі освітленості сцени уваги.

Висновки. Розроблено метод для визначення оптимального значення параметра гамми-корекції зображень, при якому забезпечується вибір в автоматичному режимі найбільш якісного зображення сцени для подальшої обробки. Для досягнення поставленої мети цієї роботи в процес визначення оптимального значення параметра гамма введено поняття «ідеального» зразка зображення, яке характеризується однаковою ймовірністю появи рівнів яскравості зображення та розосередженням гістограми зображення по всій шкалі яскравості зображення.

При таких даних зображення функція ймовірності рівнів яскравості приймає кусочно-лінійний вигляд з 256 інтервалів (за кількістю рівнів яскравості) від 0 до 1,0 (або від 0 за загальною кількістю пікселів в зображенні без нормалізації). Кумулятивна гістограма такого «ідеального» зразка-зображення представляє графік у формі висхідних сходів з 256 (за кількістю рівнів яскравості) однакових сходинок, а апроксимація значень кумулятивної гістограми «ідеального» зразка-зображення призводить до перетворення гістограми в пряму лінію з координатами (0,0) – (1,255) (рис. 11) або «лінію ідентичності».

В основі методу лежить мінімізація середньоквадратичної різниці між кумулятивною гістограмою скоригованого за допомогою гамма-корекції зображення та відповідною гістограмою введеного «ідеального» зразка-зображення у вигляді «лінії ідентичності».

Розроблений інструментарій визначення в автоматичному режимі оптимального значення параметра гамма, а відтак і найкращого зображення для візуалізації та подальшої обробки суттєво підвищує ефективність систем відеоаналітики, процесів сегментації та обробки зображень за рахунок зниження негативного впливу режиму освітлення сцени на якість зображень.

Запропонований метод відрізняється здатністю приведення якості зображення до максимально можливого рівня якості в автоматичному режимі та наявними елементами адаптивності до змін у режимі освітленості сцени уваги. Ефективність методу дозволяє застосовувати його до широкого спектра зображень і відеопослідовностей.

Ключові слова: *гамма-корекція, покращення зображення, система відеоаналітики, гамма параметр, гістограма, комп’ютерний зір, сегментація.*