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AUTOMATION OF THE PROCESSING OF IMAGES OBTAINED WITH THE HELP OF AGRICULTURAL DRONES TAKING INTO ACCOUNT CONDITIONS OF LIMITED VISIBILITY

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The paper proposes new, more effective algorithms for the analysis and pre-processing of images obtained using drone cameras in order to automate processes in agriculture. A detailed analysis of modern methods of pre-processing images was conducted in the Matlab environment, and the possibilities of using this tool to improve the quality of digital images were considered. Based on the research results, software was developed that implements a number of advanced processing methods, in particular, contrast enhancement, noise removal, and adaptive filtering. The proposed algorithms allow for significantly improving the quality of images in low light conditions, which is especially relevant for the use of unmanned aerial vehicles in variable weather conditions, in particular in the morning, evening, or in cloudy weather. The developed methods are based on new approaches to improving the statistical characteristics of images, choosing an adequate noise model, and implementing low-frequency filtering that takes into account the specifics of the agricultural environment. The implementation of algorithms in the software package showed a significant improvement in image quality compared to traditional methods. The implementation of such solutions in the navigation and analytical systems of drones used in the agricultural sector will allow to increase the accuracy of collecting and analyzing information about the condition of crops, soil and other agricultural information. This, in turn, will contribute to increasing the efficiency of management, saving resources, reducing the environmental load, as well as forming a modern approach to agricultural production management with the involvement of remote sensing technologies.

Keywords: *locally adaptive contrast enhancement, histogram stretch function, local entropy, image processing, binary regions, high-contrast regions, adaptive transformation, visualization, technical vision, automated object recognition.*

Eq. 24. Fig. 9. Ref. 18.

1. Problem formulation

In modern agriculture, the implementation of remote sensing technologies using unmanned aerial vehicles (drones) is becoming increasingly important, which allows for rapid monitoring of crop conditions, soil moisture, detection of disease and pest outbreaks, and optimization of fertilizer application processes. Of particular value are images obtained from cameras capable of operating in different spectral ranges, in particular infrared and hyperspectral. They provide extended information on the physiological state of plants, the presence of stress factors or nutrient deficiencies [1-3]. Despite significant achievements in the field of aerial image processing, there are a number of challenges associated with high-quality image processing in conditions of limited visibility due to weather factors (fog, rain, clouds), variable illumination or dust in the fields. Such conditions lead to a decrease in the accuracy of automated data analysis, an increase in errors in plant condition classification, and a decrease in the efficiency of agrotechnological decision-making. Therefore, the problem of developing and improving image preprocessing methods adapted to adverse conditions, as well as artificial intelligence algorithms capable of compensating for the influence of noise and

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data loss, is relevant.

Thus, research in the direction of automating the processing of aerial photographs from drones in conditions of limited visibility is extremely promising and aims to ensure more reliable and accurate information collection for making effective decisions in the field of precision agriculture.

2. Analysis of recent research and publications

Despite significant achievements in the field of aerial image processing, there are a number of challenges associated with high-quality image processing in conditions of limited visibility due to weather factors (fog, rain, clouds), variable illumination or dust in the fields. Such conditions lead to a decrease in the accuracy of automated data analysis, an increase in errors in plant condition classification, and a decrease in the efficiency of agrotechnological decision-making. Therefore, the problem of developing and improving image preprocessing methods adapted to adverse conditions, as well as artificial intelligence algorithms capable of compensating for the influence of noise and data loss, is relevant.

Thus, research in the direction of automating the processing of aerial photographs from drones in conditions of limited visibility is extremely promising and aims to ensure more reliable and accurate information collection for making effective decisions in the field of precision agriculture.

3. The purpose of the article

The aim of the research is to develop and improve methods for automated image processing obtained using agricultural drones, taking into account conditions of limited visibility, in order to increase the accuracy and reliability of monitoring agrocenoses in the precision farming system.

The research aims to analyze existing algorithms for pre-processing digital images obtained from agricultural drones in order to identify their shortcomings in low light conditions; to develop new, more effective methods for filtering and extracting image contours, which will improve the quality of input data for subsequent pattern recognition; to investigate the impact of using different approaches to pre-processing on the accuracy of image analysis and the effectiveness of recognition algorithms. Special attention will be paid to the practical application of the proposed solutions in the field of precision farming, in particular in the tasks of monitoring crop conditions and detecting anomalies.

4. Results and discussion

Digital image processing encompasses a wide range of methods aimed at improving image quality, reducing noise, increasing contrast and sharpness, and correcting geometric and gradation distortions [1]. The main approaches to processing are classified into two areas: frequency domain and spatial domain.

Image processing in the frequency domain is based on the representation of an image as a set of frequency components. The goal of this approach is to modify the signal spectrum taking into account the model of human visual perception. The main methods include linear, inverse, and Wiener filtering, which allow for effective noise reduction based on predefined statistical characteristics [4, 5]. These approaches are particularly effective in cases where the spectral characteristics of the noise are significantly different from the signal.

Spatial image processing uses mathematical transformations such as the discrete Fourier transform, wavelet transform, Haar transform, etc. [6-9]. These tools allow for feature extraction, data compression, or dimensionality reduction. However, their real-time application is limited due to significant computational complexity. The most practical in applied problems is the use of spatial filters, which provide a balance between processing accuracy and computational costs [10-11].

A special place is occupied by rank methods, which are divided into structured and unstructured. Their key advantage is independence from spatial connections between pixels, which provides adaptability to local image features. Such methods are widely used for smoothing, boundary selection, increasing detail and statistical processing. The most famous example is median filtering, which demonstrates high efficiency in suppressing impulse noise. The implementation of rank algorithms is supported in technical modeling environments, in particular MATLAB [9, 11].

Another approach is difference methods or fuzzy masking methods, which are used to enhance the boundaries of objects in the image. The principle of operation is based on subtracting a smoothed (blurred) image from the original, which allows to enhance local contrast. Modern modifications of these methods include adaptive background modeling and nonlinear contrast transformations, which significantly improve the visual perception of objects [13]. To increase the contrast of images with a narrow dynamic range of brightness, histogram stretching methods are used. In particular, linear stretching or gamma correction is used, which ensure more uniform use of the entire available brightness range. These methods are characterized by simple implementation and high speed, which determines their popularity in practical applications [6].

The assessment of visual image quality is an important task in the fields of computer vision, digital signal processing and telecommunications [14]. Image quality depends on a number of technical parameters: signal-to-noise ratio, spectral properties, gradation accuracy, noise statistics and sampling parameters.

One of the basic criteria is contrast, which determines the degree of resolution of image elements. Due to the complexity of images (plot, detail), contrast is assessed based on combinations of elements, considering all elements to be equally important. In this case, human visual perception is taken into account, which affects the perception of contrast. To obtain the overall contrast value, a matrix of local contrasts is used, which is averaged to calculate an integral estimate [14].

Another approach is based on the hypothesis of normal brightness distribution [15]. It is known that an image with a normal brightness distribution is subjectively perceived as high-quality. Deviation from the normal distribution serves as a measure of distortion, which allows us to numerically assess the quality of the image, as well as establish the degree of use of gradations.

Another effective empirical approach takes into account several parameters:

1. The average brightness value ($\bar{L}$) reflects the adaptation of the human visual system. The optimal value is half of the maximum brightness range

$$LQ = (\bar{L} - LMAX/2) / (LMAX/2) \tag{1}$$

2. The completeness of the use of brightness gradations (KQ) - characterizes the number of active brightness levels in the image.

$$KQ = S / LMAX \tag{2}$$

3. Image sharpness (RQ) – estimated as the ratio of the brightness gradient to the signal drop.

$$RQ = RO / LMAX \tag{3}$$

where RO is the integral of the square of the derivative of the brightness.

4. Contrast (KC) is a generalized contrast that takes into account the difference between brightnesses regardless of the subject.

$$Q = k \cdot KC \cdot LQ \cdot KQ \cdot RQ \tag{4}$$

Alternative approaches assume that the user or operator can determine the weight of each quality parameter themselves [16]:

- linear model:

$$Q = a_1Q_1 + a_2Q_2 + \ldots + a_kQ_k. \tag{5}$$

- multiplicative model:

$$Q = Q_1\hat{}p_1 \cdot Q_2\hat{}p_2 \cdots Q_k\hat{}p_k. \tag{6}$$

Weighting factors (a_i or p_i) allow the assessment to be adapted to different types of distortions or image types.

Probabilistic model estimation is another method based on the analysis of the brightness histogram using the moments of the distribution. This approach forms a single probabilistic model for all parameters and provides a high correlation with the subjective quality assessment. It is especially effective for noise-free images, as it takes into account several characteristics at the same time. The more parameters are taken into account, the more accurate the estimate, although the computational complexity increases.

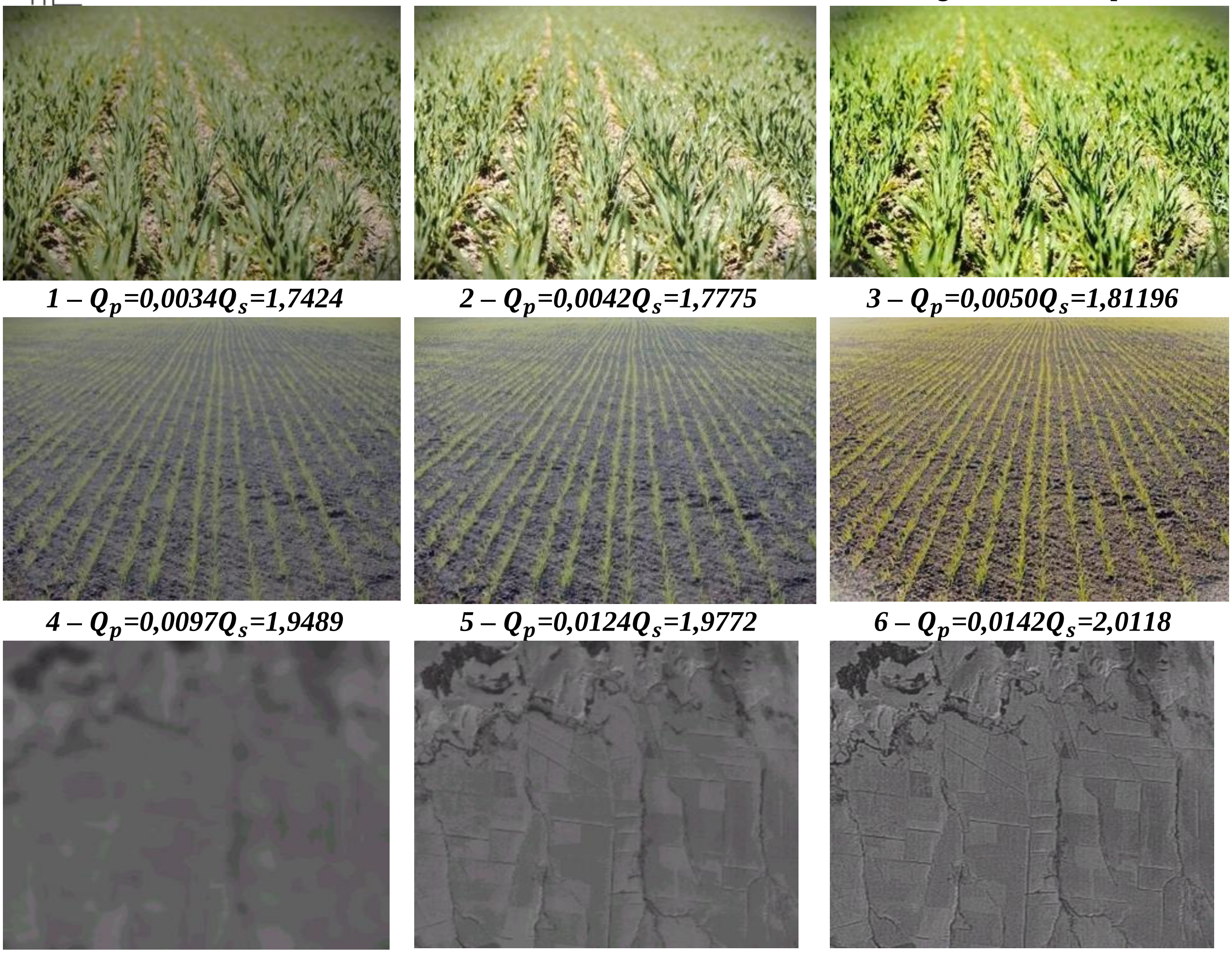
The method allows:

- compare the quality of images after processing;
- evaluate the effectiveness of different enhancement algorithms;
- test the method by applying, for example, local contrast enhancement and low-pass filtering.

As a result, a scale can be constructed – from degraded to improved image – according to the obtained quantitative quality estimates.

To test the method, the following strategy can be applied: the same image is processed by the method of local contrast enhancement and the method of low-pass filtering. As a result, we obtain a series of images – degraded, input and improved – corresponding to the lowest, average and highest quantitative quality estimates.

Fig. 1 shows the results of experimental studies and the corresponding quantitative quality estimates for three images that differ in nature.



1 – Q_p=0,0034Q_s=1,7424 ***2 – Q_p=0,0042Q_s=1,7775*** ***3 – Q_p=0,0050Q_s=1,81196***

4 – Q_p=0,0097Q_s=1,9489 ***5 – Q_p=0,0124Q_s=1,9772*** ***6 – Q_p=0,0142Q_s=2,0118***

7 – Q_p=0,0017Q_s=1,8081 ***8 – Q_p=0,0024Q_s=1,9439*** ***9 – Q_p=0,0037Q_s=2,1815***

Fig. 1. Demonstration of the use of the method of quantitative assessment of image quality

From Fig. 1, it can be seen that images that were blurred (first column) have the lowest quality score, while images processed by the enhancement method (third column) received the highest score. The obtained quantitative scores correlate well with visual perception. Studies of known methods for assessing image quality have shown that they are less effective compared to the proposed method. However, the disadvantage of this method is the incorrect assessment of the quality of noisy images, which is a common problem for all methods that use different measures of contrast when assessing image quality. This is due to the fact that the method does not provide correct identification of sharp brightness changes caused by noise or high-contrast areas.

In addition to those already mentioned above, objective assessments of image quality include [17, 18]:

- mean difference;
- normalized cross-correlation;
- correlation quality;
- maximum difference;
- image fidelity;
- laplasian mean square error;
- mean square error;
- maximum mean square error;
- normalized absolute error;
- normalized mean square error;
- norm L_p (Minkowski);
- signal-to-noise ratio;
- maximum signal-to-noise ratio;

Quality assessments are convenient to use, however, they do not always allow an objective assessment of image quality, especially from the point of view of its visual perception.

The problem of quantitative assessment of image quality still remains completely unresolved, but its solution is a key stage in the context of optimizing image transformations taking into account the peculiarities of human visual perception.

The image is one of the most informative and visual forms of data presentation during the diagnosis of materials and products in non-destructive testing processes, when visualizing human organs in medical practice, as well as in other applied fields. This necessitates the constant development of diagnostic methods based on visual information processing. At the same time, a significant drawback of most known approaches is the formation of images with a low level of contrast. Therefore, the main goal of methods for improving image quality is their transformation to a form with improved contrast, which provides increased information content.

Often, local distortions are observed in images caused by diffraction effects, imperfections of optical systems or defocusing. This necessitates the use of local transformations focused on adaptive processing. This approach allows us to isolate informative areas of the image and perform their selective correction. The methods of adaptive transformation of local contrast meet these requirements, which can be generally presented in the form of a structural diagram (Fig. 2), where the corresponding symbols are used.

$L, L(i, j)$ –the original image and its element with coordinates (i, j), respectively;

$C(i, j)$ – contrast of the image element with coordinates (i, j);

$F\big(C(i, j)\big)$ – transformed contrast value C(i, j);

ε, σ, H_S – characteristics of local neighborhoods (ε – entropy, σ – standard deviation, H_S – histogram extension function);

$L^*(i, j)$ – element of the processed image with coordinates (i, j).

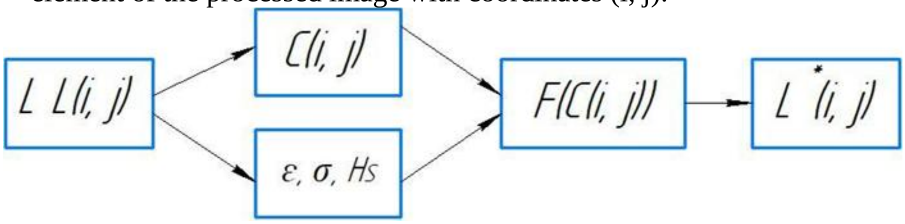


Fig. 2. Generalized structural model of image quality improvement methods based on adaptive local contrast transformation

The main stages of implementing adaptive local contrast transformation methods can be presented in the following sequence [17]:

Step 1. For each image element L(i, j), the local contrast value C(i, j) is determined in the selected neighborhood W centered at the point with coordinates (i, j).

Step 2. The statistical characteristics of the current sliding neighborhood W are calculated.

Step 3. The transformation (amplification) of the local contrast C(i, j) is performed, using nonlinear functions, while taking into account the statistical parameters $L^*(i, j)$ corresponding area W.

Step 4. An image with restored brightness values is formed, in which the local contrast is increased.

Steps 1 and 2 can be implemented both sequentially and in parallel.

Let's dwell on step 3 in more detail. Its essence lies in using nonlinear monotonic functions to transform the local contrast. In this case, to construct an adaptive function for transforming the local contrast, a power function is taken as a basis, for which the minimum (a_{min}) and maximum (a_{max}) exponent value a.

Adaptation is implemented by forming an additional term to a_{min}, which is determined based on local statistical characteristics in sliding neighborhoods. The histogram extent function is used as parameters describing the properties of such neighborhoods H_S, entropy ε and the standard deviation of the brightness of the surrounding elements σ. Therefore, depending on the task, the methods of this class may differ both in the choice of the local contrast transformation function and in the criteria characterizing the sliding neighborhood.

In the following, we will consider in more detail the proposed locally adaptive methods for improving image quality, analyze the use of local neighborhood characteristics in expressions for transforming local contrasts, and justify the feasibility of their use.

We consider a method for improving image quality based on adaptive transformation of local contrast. Adaptation in this method is carried out on the basis of the analysis of such a characteristic as the function of the length of the histogram of the elements of the local sliding neighborhood. For illustration, it is assumed that the values of the image elements are represented in the form of 8-bit integers, i.e.

$$L(i, j) \in [0,255]$$

The main steps of implementing this method are as follows.

Step 1. The local contrast is calculated for a given image element.

Step 2. The characteristic of the local sliding neighborhood is determined based on the histogram extension function.

$$H_s(W(i, j)) = \frac{L_{\max}(W(i, j)) - L_{\min}(W(i, j))}{H_{\max}(W(i, j))} \tag{7}$$

where $L_{max}(W(i, j))$, $L_{min}(W(i, j))$ – respectively, the upper and lower pixel intensity values of the local neighborhood centered at the element with coordinates(i, j);

$H_{max}(W(i, j))$ – the maximum value of the histogram of pixel intensity levels of the local neighborhood centered at the element with coordinates (i, j).

Step 3. We calculate the power transformation of the local contrast, which, thanks to the use of the histogram extension function of the moving neighborhood, has an adaptive nature:

$$C^*(i, j) = C(i, j)^{\alpha_{adapt}} \tag{8}$$

where

$$\alpha_{adapt} = \alpha_{\min} + (\alpha_{\max} - \alpha_{\min}) \frac{H_s(W(i, j)) - H_{s\min}(W(i, j))}{H_{s\max}(W(i, j)) - H_{s\min}(W(i, j))} \tag{9}$$

$H_{Smax}(W(i, j)$, $H_{Smin}(W(i, j)$ – respectively, the upper and lower values of the histogram extent function for the local neighborhood centered at the element with coordinates(i, j).

Step 4. Restoration of the transformed image element with enhanced local contrast.

Let us consider in more detail the implementation of steps 2 and 3 of the known method. In particular, the possible values of the histogram extension function are estimated H_S for sliding ca W, considering that images contain three characteristic types of local neighborhoods.

The first type characterizes homogeneous areas of the image in which approximately the same brightness levels of elements are observed; the histogram of such a local neighborhood is shown in Fig. 3.

From Fig. 3 it is clear that $L_{max} \approx L_{min}$, and therefore, according to expression (1), the function of the extent of the histogram of the local neighborhood $H_S(W(i, j))$ will be equal to zero.

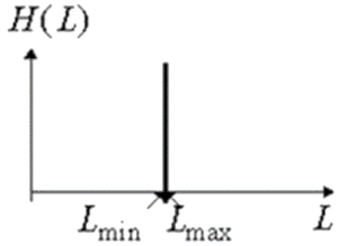


Fig. 3. Histogram of the brightness distribution of elements of a homogeneous environment

Enhancing local contrasts in such areas of the image is not advisable, as this may lead to additional distortions due to the amplification of the noise component.

For binary image areas with approximately the same quantitative ratio of elements L_{min} and L_{max} in the sliding neighborhood of W, a characteristic brightness histogram is presented in Fig. 4.

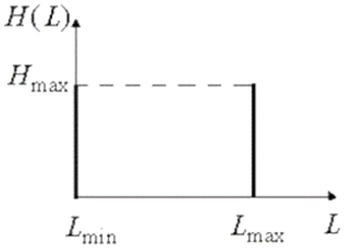


Fig. 4. Histogram of the local (binary) neighborhood, reflecting the distribution of brightness values of elements

Assuming that for dark and light elements of the binary neighborhood with approximately equal quantitative ratio, the maximum value of the histogram will be equal to

$$H_{s\max}\left(W(i,j)\right)=\frac{mn}{2} \qquad (10)$$

where m and n – dimensions of the sliding area W, expression (1) will have the form

$$H_s\left(W(i,j)\right)=\frac{L_{\max}\left(W(i,j)\right)-L_{\min}\left(W(i,j)\right)}{mn/2} \qquad (11)$$

If $L_{min}(W(i,j))=0$, $L_{max}(W(i,j))=255$, and the dimensions m · n of the local neighborhood are such that they allow the presence of elements with all possible brightness levels L϶[0,255], for example elements, then the histogram length function according to expression (10) will take the value

$$H_s\left(W(i,j)\right)=2$$

The third characteristic type of local neighborhood is one in which the image elements are present in approximately equal proportions for all possible brightness values in the range [0,255]. Such neighborhoods are characterized by a histogram of uniform brightness distribution, which is illustrated in Fig. 5. According to the assumptions made regarding the size of the local neighborhood and the shape of its histogram, the following conclusions can be drawn: that $H_{max}(W(i,j)=1$, $L_{min}(W(i,j)=0$, $L_{max}(W(i,j)=255$. In this case, the histogram extent function will take the value $H_S(W(i,j))=255$. For such an area, we will assume that it is high-contrast and does not require contrast enhancement.

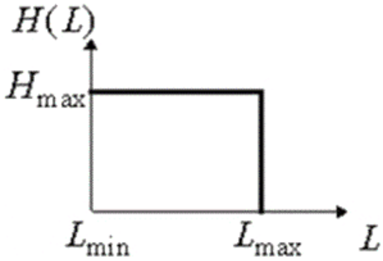


Fig. 5. Histogram of a moving average, characterized by a uniform distribution of the brightness values of the elements

The limiting cases of local neighborhoods were considered above. All other neighborhoods are characterized by such values of the histogram extension functions that are in the range [0,255].

Based on the analysis of the considered types of neighborhoods and the corresponding values of the histogram extension functions, it is possible to more objectively approach the formation of a step function of the local contrast transformation. It is most convenient to carry out such an analysis using a graphical representation of the local contrast transformation function

(Fig. 6, line 1). Note that 0 < a < 1 and a decrease in a corresponds to a higher local contrast enhancement, and an increase in it corresponds to a weaker enhancement.

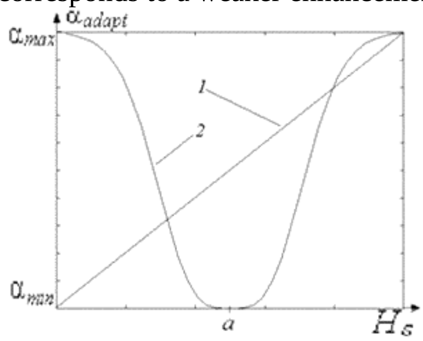


Fig. 6. Dependence of the exponent a of the local contrast transformation function on the histogram length function $H_S(W(i,j))$: 1– according to the known approach; 2 – within the proposed method

From Fig. 6 (line 1) it is seen that the maximum enhancement of local contrast is observed in homogeneous areas of the image (HS ≈ 0), which is not always desirable, since such areas are very sensitive to noise interference, and excessive enhancement of their contrast can lead to significant distortions. Experimental studies show that the maximum enhancement (C^{aadapt}) local contrasts should be exposed in sliding neighborhoods for which the histogram extent function takes a value corresponding to the middle of the range $H_S \in [0,255]$.

In accordance with the above, we propose to use a step function for local contrast transformation, the nature of the change in the degree index of which corresponds to curve 2 in Fig. 6.

Analytical definition of the parameter a_{adapt} (Fig. 6, curve 2) is given by the following expression:

$$\alpha_{adapt} = \alpha_{\min} + (\alpha_{\max} - \alpha_{\min})\left[1 - \exp\left(-\frac{(H_s - \alpha)}{0,0392}\right)\right]^s \tag{12}$$

where a is the value of the histogram extent function, which corresponds to the most informative areas of the image ($a \approx 0.5$); S is a constant coefficient ($S > 1$).

The proposed expression (6) for the modified static transformation allows for a more accurate classification of different types of local image neighborhoods and adaptively enhance their contrast depending on the values of the local characteristics of these neighborhoods.

The method of contrast enhancement using the histogram extent function is effectively used for processing a wide class of images. Analysis of the characteristics of sliding neighborhoods allows for the identification of image areas by contrast level and for differentiated processing on them, which provides more accurate processing of fine details.

At the same time, two main requirements are imposed on images: they should not contain a large amount of impulse noise and significant homogeneous dark or light areas. In the first case, this can lead to incorrect determination of the histogram extent function, in the second - to ineffective contrast enhancement. In case of non-compliance with these requirements, it is recommended to apply preliminary filtering or gradation correction of the image.

There is also a method of adaptive transformation of local contrasts, in which the parameter characterizing the sliding neighborhood is determined by analogy with entropy.

Entropy can be used to characterize the smoothness of local neighborhoods. Therefore, based on the measure of a priori uncertainty of the brightness values of the neighborhood elements, a local contrast transformation function is formed. The main steps of implementing the method are as follows.

Step 1. We calculate the local contrast of the image element (i, j).

Step 2. To determine the local entropy of the image in the sliding neighborhood W with the dimension m· n elements and the values L(i, j) we use the expression

$$\varepsilon = \sum_{(i,j)\in L} \frac{\left(P(i,j)\log_2 P(i,j)\right)}{\log_2(nm)} \tag{13}$$

where

$$P(i,j) = \frac{L(i,j)}{\sum\limits_{a=-\left[\frac{n}{2}\right]}^{n-\left[\frac{n}{2}\right]-1} \sum\limits_{b=-\left[\frac{m}{2}\right]}^{m-\left[\frac{m}{2}\right]-1} L(i+a, j+b)} \tag{14}$$

Step 3. We calculate the step transformation of the local contrast, which, due to the use of local entropy, becomes adaptive:

$$C^*(i,j) = C(i,j)^{\alpha_{\min} + (\varepsilon(i,j) - \varepsilon_{\min})(\alpha_{\max} - \alpha_{\min})/(\varepsilon_{\max} - \varepsilon_{\min})} \tag{15}$$

where $\varepsilon_{\max}$, $\varepsilon_{\min}$ – upper and lower values of the entropy of the sliding neighborhood W with the size of m·n elements.

Step 4. We restore the image according to the expression, which is determined from the expression for determining the local contrast.

Note that the entropy of the local neighborhood of the image is defined as the sum of the products of the probabilities of the neighborhood elements with different brightness values by the logarithm of these probabilities, taken with the opposite sign.

According to expression (14), the brightness value L(i, j) should be perceived as the probability of the brightness of the (i, j)th element of the neighborhood. With this approach, formula (13) for determining the entropy of the neighborhood does not correspond to the generally accepted definition of probabilistic entropy, but is one of the varieties of improbability entropy. According to expression (13), the local neighborhood should be considered as some complex system consisting of simple subsystems - neighborhood elements, and from these positions to search for the entropy of the neighborhood. In addition, this approach to determine the entropy of the local neighborhood requires significant computational costs.

To increase the efficiency of the described method, it is proposed to use a classical probabilistic approach to determining entropy. Then in the algorithm described above, step 2 will consist in calculating ε according to expression (13), but with the calculation of probabilities P(i, j) as

$$P(i, j) = \frac{H\left(L(i, j)\right)}{n \times m} \tag{16}$$

where $H(L(i, j))$ – histogram value for an element with brightness value L(i, j).

In addition, we have proposed a local contrast transformation expression to modify step 3 of the known approach.

$$C^*(i, j) = C(i, j)^{\alpha_{\min} + (\alpha_{\max} - \alpha_{\min})((\varepsilon(i,j) - \varepsilon_{\min})/(\varepsilon_{\max} - \varepsilon_{\min}))^s} \tag{17}$$

where $S > 1$– Nonlinear contrast enhancement parameter.

The proposed processing method is most effective for images that have a uniform histogram of brightness distribution and do not contain noise. Based on the visual and quantitative analysis of the results of experimental studies, we note that the proposed method is more effective in comparison with known methods of this class.

The well-known three-stage technology for increasing image contrast was considered above. However, it does not sufficiently take into account adaptation to local features of the image. To eliminate this drawback, it is proposed to use adaptive definition of the power exponent in the class of power functions of nonlinear transformation of local image contrasts. However, in this case, the effectiveness of the method is insufficient. To increase it, it is proposed to additionally evaluate the local neighborhoods W of the image taking into account the mean square deviations relative to the brightness of the central element L(i, j) and on that basis to form a function of nonlinear transformation of local contrasts of brightness of image elements.

Let us define the magnitude of the exponent a as follows:

$$\alpha = \alpha_{\max} - K \frac{\bar{L}}{\sigma(i, j)} \tag{18}$$

where K – normalizing coefficient, $0 < K < 1$, $\bar{L}$ – arithmetic mean brightness value of the original image

$$\bar{L} = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} L(i, j) \tag{19}$$

where N, M – image dimensions ($i = \overline{1, N}$, $j = \overline{1, M}$),

σ·(i, j) – the root mean square deviation of the brightness levels of image pixels in the local neighborhood W, which is calculated by the expression

$$\sigma(i, j) = \left(\frac{1}{nm} \sum_{a=-\left[\frac{n}{2}\right]}^{n-\left[\frac{n}{2}\right]-1} \sum_{b=-\left[\frac{n}{2}\right]}^{n-\left[\frac{n}{2}\right]-1} \left[L(i + a, j + b) - \bar{L}(i, j) \right]^2 \right)^{0,5} \tag{20}$$

Note that the software implementation of the proposed method takes into account the case when σ·(i, j)=0, setting some limiting minimum value σ_{min}. That is, the current mean square deviation of the brightness values of the image elements σ·(i, j) is assigned σ_{min}in the event thatσ·(i, j) <σ_{min}.

It is characteristic of expression (20) that when the image elements that fall into the sliding neighborhood W differ little in value from the central element of the neighborhood L·(i, j), this leads to small values of the mean square deviation σ·(i, j). As a result, we obtain a significant decrease in the coefficient a from a_{max} in expression (18), which is adequate to increase the contrast enhancement. If the image elements in the sliding neighborhood W differ significantly from the central element of the neighborhood L·(i, j), then this leads to larger values of the mean square deviation σ·(i, j). Therefore, the value of the degree a will differ less from a_{max}, in expression (18), which is adequate to increase the contrast enhancement. If the image elements in the sliding neighborhood W differ significantly from the central element of the neighborhood L·(i, j), then this leads to larger values of the mean square deviation σ·(i, j). Therefore, the value of the degree a will differ less from $0 < \alpha < 1$.

We also note that the value of the normalizing coefficient K must be chosen based on the analysis of the values of σ, observing that $a \in [a_{min}, a_{max}]$. The choice of the value of K significantly affects the efficiency of the method. Using the global arithmetic mean value of the brightness $\bar{L}$ allows you to adapt the generalized transformation algorithm to a specific image, since the value reflects the level of adaptation to the brightness of the human visual system when perceiving the image. Therefore, using the standard deviation $\sigma\cdot(i, j)$ as a quantitative assessment of the smoothness of the image in the sliding neighborhood W, we obtain a direct dependence of the degree a on σ(i, j). This allows us to generally implement adaptive enhancement of local contrasts during their step transformations.

Contrast enhancement is one of the important tasks of image processing, pattern recognition, and machine vision. Solving this task is directly related to increasing the probability of correct image perception. Recently, methods for improving images have been developed that are based on nonlinear transformations of local contrasts taking into account the peculiarities of human vision. The implementation of these methods consists of performing three main steps:

Step 1. Determination of the quantitative measure of local contrast.

Step 2. Increase according to a certain law of some quantitative measure of local contrast.

Step 3. Restoration of an element of the transformed image with enhanced local contrast.

Such transformations are performed for each element of the image.

A new approach to increasing image contrast is proposed, which is based on the transformation of the local contrast histogram.

Having considered the histograms of the distribution of local contrast values of real images, we note that in most cases they have small values, occupying approximately a third of the permissible range (Fig. 7).

Therefore, real images are characterized mainly by small local contrast values. The histogram of the distribution of local contrast values of an image that has been processed by some method of contrast enhancement will have the form presented in Fig. 8.

Analyzing the histograms of the distribution of local contrast values of the original and processed images, we can assume that the histogram in Fig. 8 is obtained as a result of nonlinear stretching of the histogram in Fig. 7.

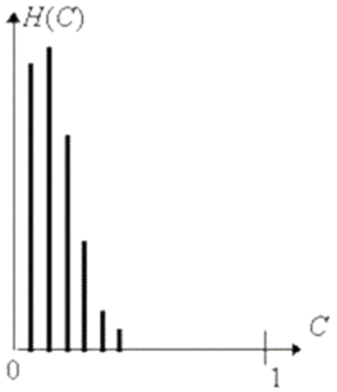


Fig. 7. Typical histogram of the distribution of local contrast values of the original image

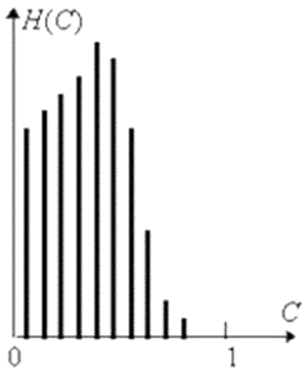


Fig. 8. Histogram of the distribution of local contrast values of an image processed by some contrast enhancement method

A method for increasing image contrast based on the proposed approach is considered. Its implementation includes stages similar to the described three-stage scheme, with the exception of the stage of nonlinear transformation of local contrasts, which is considered in more detail.

To implement this transformation of local contrast, the following mathematical relationship is used:

$$C^*(i,j)=\begin{cases} B_0+\left(\frac{R}{2}-A_0\right)\left(\frac{C(i,j)-C_{\min}}{\hat{C}-C_{\min}}\right)^{\alpha} & для\, C(i,j)\le\hat{C} \\ R-A_0+\left(\frac{R}{2}-A_0\right)\left(\frac{C_{\max}-C(i,j)}{C_{\max}-\hat{C}}\right)^{\alpha} & для\, C(i,j)>\hat{C} \end{cases} \quad (21)$$

where $C(i, j)$ – local contrast value of the source image element with coordinates (i, j), $C^*(i, j)$ – enhanced local contrast value of the image element with coordinates (i, j); R –the largest allowable value of local contrast R=1; C_{min}, C_{max} – the interval of variation of the local contrast of the original image from minimum to maximum, $\hat{C}$ – determining the mathematical expectation of local contrasts, for example, by calculating the arithmetic mean of the local contrast values of image pixels, A_0, B_0 –constant displacement coefficients; a – power indicator(a < 1).

Let us analyze the local contrast transformation function (21). To do this, consider the graphs of two functions – the step transformation and the proposed function (15), which are presented in Fig. 9. The local contrast step transformation function is calculated by an expression of the type $F[C(i,j)]=C^{\alpha}$, where a < 1.

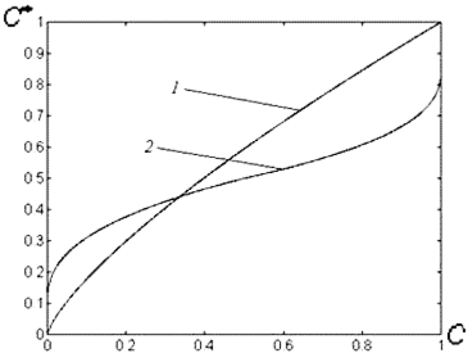


Fig. 9. Graphical representation of local contrast transformation functions:
1 – step function; 2 – function defined by expression (21)

From Figure 9 it is seen that the proposed function provides better amplification for small values of local contrast. The values of local contrasts for real images have exactly this level. However, in practical implementation, a special case of expression (21) is used. It consists in performing transformations only for such local contrasts that satisfy the condition $C(i,j)\le\hat{C}$ .In general, the proposed method allows for effective enhancement of image contrast.

An original technique for improving image quality by enhancing local contrasts is considered. Its essence lies in the quantitative assessment of local contrast for each image element, its subsequent nonlinear enhancement and updating of the corresponding image element with changed brightness, which provides an increase in local contrast compared to the original image. Structurally, the procedure for enhancing local contrast consists of three main stages and is used for each element L(i, j) with coordinates (i, j) of the original image L(i, j) ϵ L.

However, the use of the described method shows that its effectiveness is insufficient for processing images containing small details. The reason is that local contrast is determined by the formula, where its value is proportional to the degree of difference between the central element of the image and the surrounding background in terms of brightness. The constituent elements of this formula are the direct values of the elements or their averaged values, which leads to an incomplete description of the texture of the local area.

The most complete description of such texture characteristics as uniformity, roughness and graininess is provided by statistical methods.

One of the simplest methods of describing texture is to use the moments of the histogram of the image element intensities. Let L be a random variable that determines the discrete intensity of the image, and H(L(i, j)) be the corresponding histogram values. It is known that the nth moment about the mean value of L(i, j) is given by the formula

$$\mu_n(L)=\sum_{(i,j)\in W}\left(L(i,j)-\overline{L}\right)^2 H\left(L(i,j)\right) \quad (22)$$

where $\overline{L}$ – the mean value of the brightness levels of the elements within the local neighborhood W.

From expression (22) it follows that μ_0=1, a μ_1=0. The second moment, called the variance and denoted by $\sigma^2(L)$, is used to describe texture. It is also a measure of intensity contrast and is applied to characterize surface uniformity. In some studies, the following expression has been proposed as a preventive measure of texture contrast:

$$C(i,j) = 1 - \frac{1}{1 + k\sigma^2(L)} \tag{23}$$

where $\sigma^2(L)$ – variance in the neighborhood n·m, k = 0.8 – normalization coefficient. C (i, j) according to expression (23) is equal to zero for neighborhoods with constant intensity and unity for large values $\sigma^2(L)$. This property of expression (23) fully meets the requirements for determining local contrast. Thus, by analogy with the known approach, the developed method uses a contrast measure calculated according to expression (23).

At the first stage of the algorithm, the local contrast is determined for each image element according to expression (23).

The second stage involves performing a nonlinear transformation of the local contrast C (i, j).

At the final, third stage, the image is restored by calculating a new brightness value $L^*(i,j)$ for the element with coordinates (i, j), which is determined based on the formula (23).

$$L^*(i,j) = \bar{L}(i,j) + \left(\frac{C^*(i,j)\cdot n\cdot m}{1 - C^*(i,j)} - \sum_{\gamma(i,j)\in W_2 - W_1} \left(\bar{L}(i,j) - L(i,j)\right)^2 H\left(L(i,j)\right) \right)^{0,5} \tag{24}$$

The proposed procedure is applied sequentially to each image element. The developed method implements statistical determination of local contrasts, which allows taking into account key texture characteristics, in particular, uniformity, roughness, and graininess. Due to this, the method is advisable to use for processing images with a high level of detail and the presence of small structural elements.

5. Conclusion

In the course of the research, an analysis of various methods of preprocessing, analysis and selection of contours in digital images was carried out. The main types of images, the features of their perception, as well as transformation methods aimed at improving visual quality and informativeness were considered. A detailed review of modern digital processing methods was conducted, in particular: rank methods, difference methods, dynamic range stretching methods, histogram transformations and local contrast transformations. For each group of approaches, advantages and limitations were outlined, the conditions for their most effective application were determined, and areas requiring further scientific development were identified in order to improve algorithms and increase their productivity. Particular attention was paid to the implementation of image enhancement methods in autopilot systems of unmanned aerial vehicles used in the agricultural sector. Improving image quality provides more accurate reproduction of spatial details and contours of objects, which allows the drone to navigate the environment more effectively, increases navigation accuracy and adapt to changing operating conditions. This, in turn, contributes to the optimization of agricultural processes, the rational use of resources, the reduction of negative impact on the environment and the expansion of the functional capabilities of unmanned technologies.

The use of these methods is also the basis for the integration of artificial intelligence elements, which makes drones more autonomous, capable of self-learning and making decisions in real time. Thus, image enhancement is a key factor in the development of modern autopilot systems in agriculture, ensuring increased production efficiency, saving energy and material resources, as well as the formation of environmentally sustainable agricultural technologies of the future.

Further research should be focused on the development of adaptive and energy-efficient image processing algorithms capable of operating in real time in various field conditions. The combination of image enhancement methods with artificial intelligence systems and the use of multimodal data is promising, which will increase the accuracy and reliability of the analysis of agricultural objects. Another important area is the creation of standardized databases and the introduction of three-dimensional reconstruction technologies for a comprehensive assessment of the condition of crops and the environment.

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АВТОМАТИЗАЦІЯ ОБРОБКИ ЗОБРАЖЕНЬ, ОТРИМАНИХ ЗА ДОПОМОГОЮ СІЛЬСЬКОГОСПОДАРСЬКИХ ДРОНІВ, З УРАХУВАННЯМ УМОВ ОБМЕЖЕНОЇ ВИДИМОСТІ

У статті запропоновано нові, більш ефективні алгоритми аналізу та попередньої обробки зображень, отриманих за допомогою камер дронів, з метою автоматизації процесів у сільському господарстві. У середовищі Matlab проведено детальний аналіз сучасних методів попередньої обробки зображень і розглянуто можливості використання цього інструменту для підвищення якості цифрових зображень. За результатами дослідження розроблено програмне забезпечення, яке реалізує *низку сучасних методів обробки, зокрема підвищення контрастності, усунення шумів та адаптивну фільтрацію. Запропоновані алгоритми дають змогу суттєво покращити якість зображень в умовах недостатнього освітлення, що є особливо актуальним для використання безпілотних літальних апаратів у змінних погодних умовах, зокрема вранці, увечері або за хмарної погоди. Розроблені методи ґрунтуються на нових підходах до поліпшення статистичних характеристик зображень, вибору адекватної моделі шуму та реалізації низькочастотної фільтрації з урахуванням специфіки аграрного середовища. Упровадження алгоритмів у програмний пакет продемонструвало істотне покращення якості зображень порівняно з традиційними методами. Реалізація таких рішень у навігаційних та аналітичних системах дронів, що використовуються в аграрному секторі, дасть змогу підвищити точність збору та аналізу інформації про стан посівів, ґрунту та інших об'єктів сільськогосподарського призначення. Це, своєю чергою, сприятиме підвищенню ефективності управління, економії ресурсів, зниженню екологічного навантаження, а також формуванню сучасного підходу до управління аграрним виробництвом із залученням технологій дистанційного зондування.*

Ключові слова: *локально-адаптивне підвищення контрастності, функція розтягування гістограми, локальна ентропія, обробка зображень, бінарні області, висококонтрастні ділянки, адаптивне перетворення, медична візуалізація, технічний зір, автоматизоване розпізнавання об'єктів.*

Ф. 24. Рис. 9. Літ. 18.

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