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Analysis and improvement of methods and means for eliminating distortions in image and video signals

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The main purpose of this article was to study existing image processing methods, binarization and noise reduction, and to develop an improved adaptive thresholding algorithm. The analysis of methods and tools for eliminating distortions in image and video signals is an urgent task in numerous fields, including medicine, computer vision, and document science. The article discusses in detail the existing binarization and noise reduction methods, highlighting their advantages and limitations. However, the main achievement is the development and implementation of an improved adaptive thresholding algorithm. This algorithm considers the specific features of the image and automatically adapts the binarization threshold for better processing quality. It is a significant contribution to the field of image processing and can be used in various fields, including medical diagnostics and visual object detection in images.

Keywords: Adaptive thresholding, Analysis of image processing methods, Image binarization, improved adaptive thresholding algorithm, Reducing noise in images.

Introduction. In the field of image processing, converting raw visual data into a more advanced and usable form is a fundamental step. Whether it's document identification, medical diagnostics using X-rays, or a host of other applications, image processing plays an important role in extracting meaningful information from visual content. However, this conversion process is often accompanied by various challenges, one of the most important of which is noise.

Noise in the context of images refers to unwanted variations or distortions that interfere with the discernment of the image's essence. Overcoming this challenge is essential for accurate and reliable image analysis. In this study, we thoroughly investigate various image processing techniques, in particular those designed to reduce noise and perform adaptive thresholding. Our goal is not only to introduce and analyze these methods but also to present an improved adaptive thresholding algorithm as a valuable addition to the existing arsenal of techniques.

The methods studied include median equalization [1], Gaussian equalization [2], bilateral equalization [3], Gathos thresholding [4], maximum entropy thresholding [5], wavelet transform [6], a mathematical method for analyzing signals and images, finds various applications in the field of medicine due to its ability to analyze signals and images with high resolution in both the time and frequency domains. Recently, it has been widely used for medical purposes to store, compress and transmit large data sets, as well as to analyze biomedical signals such as (ECG) and (EEG).Sauvola thresholding [7], Bernsen thresholding [8], Niblack thresholding [9], and the improved adaptive thresholding algorithm. Each of these methods is thoroughly investigated in terms of their applicability, advantages, and limitations.

The essence of "intelligent" programs is that using data from sensors that signal changes in environmental parameters as quickly and as accurately as possible, special algorithms engage higher-level automation to perform adequate actions. CPS goes beyond the conventional product, system, and application architecture [10].
They combine traditional information technologies: from receiving data from sensors with their processing using built-in computing power or using cloud technologies, to traditional operational control and management technologies [11].

There are many needs for filtering signals in images. Digital images are exposed to various types of noise during capture, storage, or other factors affecting their quality, so it is necessary to remove these noises by preserving the image as much as possible [12]. In today's world, images and videos are everywhere. From video surveillance to medical imaging and entertainment, they are essential to our lives. However, these images and videos often contain large amounts of data that require a significant amount of memory and bandwidth. This led to the development of various methods of reducing the size of image and video signals while preserving their quality. Despite these efforts, images and video signals can still be distorted by various factors such as noise, compression, and transmission errors [13]. A noisy image becomes a problem for information retrieval. The process begins with improving the quality of the image by applying various filters that can subjectively improve the image [14].

Eliminating distortion in video and image signals is critical for a variety of reasons, ranging from aesthetic considerations to technical requirements [15, 16]. Distortions can significantly degrade the quality of the result, making it difficult to view or interpret. It can alter the colors and contrast [17].

1. Median equalization

The Median Equalization method is based on analyzing and modifying the histogram of an image. The main goal is to equalize the distribution of pixel brightness using the median of the histogram. Let's take a closer look at this method using mathematical formulas.

The Median Equalization method is based on the analysis of the histogram of pixel brightness in the input image. A histogram is a graphical representation of the number of pixels for each brightness value from 0 to 255 (in the case of 8-bit images).

Steps of the method:

Histogram calculation: First, a histogram is created, where the X-axis shows the brightness value, and the Y-axis shows the number of pixels with this brightness value in the image.

Finding the median: The median of a histogram is defined as the luminance value that divides the histogram into two equal halves. This means that half of the pixels have luminance less than or equal to the median, and the other half have luminance greater than or equal to the median.

Replace pixel values: Each pixel in the image is replaced with the median value. This results in a luminance distribution in which half of the pixels have a value less than or equal to the median and the other half have a value greater than or equal to the median.

The median has a value of that divides the histogram into two equal planes below the histogram graph. This can be expressed mathematically as:

$$m = arg\,\min_{i}\left|\sum_{j=0}^{i} H(j) - \sum_{j=i+1}^{255} H(j)\right|$$

where $H(j)$ −intensity (brightness) of pixels in the image.

Advantages of the Median Equalization method:

Improved contrast: By equalizing the brightness distribution, the image becomes more contrast, and details stand out.

Reduces the effect of "overexposure" and "backlighting": Areas that are too bright or too dark become less visible.

Limitations of the Median Equalization method:

Loss of information: Because all pixels with the same brightness are replaced by the median, some detail may be lost.

Computational complexity: Calculating the histogram and median can be computationally intensive, especially for large images.

The result of the algorithm is shown in Figure 1:

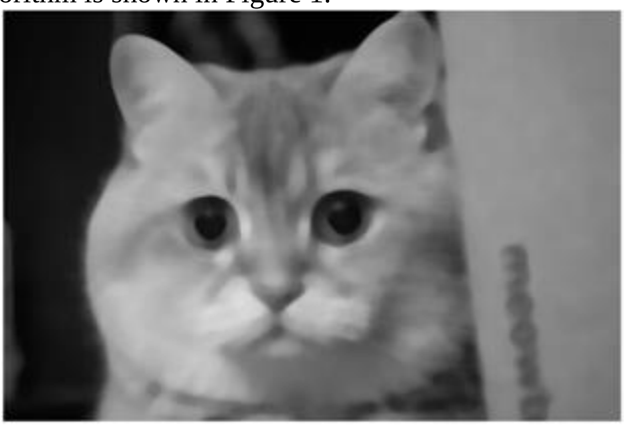

Fig.1 Median filter realization

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2. Gaussian equalization

Gaussian Equalization is another effective image-processing method for improving contrast and equalizing brightness distribution. This method uses the Gaussian function to modify the brightness of pixels, which helps to make the image more expressive and preserve its details.
The Gaussian Equalization method is based on the idea of using the Gaussian function to create a new distribution of pixel brightness. The main goal is to make the pixel brightness distributed according to a Gaussian law, where values close to the mean have a higher probability of occurrence and values that deviate from the mean have a lower probability.
Steps of the method:
Generation of the Gaussian function: First, a Gaussian function is created that defines the new pixel brightness distribution. The Gaussian function has parameters, such as mean ( ) and variance ( ), which can be adjusted as needed.
Replace pixel values: Each pixel in the image is replaced with a value determined by the Gaussian function of its original brightness.
The Gaussian function has the following form:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

Advantages of the "Gaussian Equalization" method:

Improved contrast: By distributing the brightness according to a Gaussian law, the image becomes more contrasty and expressive.

Preservation of details: This method improves contrast without losing detail in the image.

Limitations of the Gaussian Equalization method:

Computational complexity: Calculating the Gaussian function for each pixel can be a resource-intensive operation, especially for large images.

Parameter settings: Choosing the right values for the mean and variance is important and can affect the result.

The result of the algorithm is shown in Figure 2:

Fig.2 Gaussian filter realization

3. Bilateral equalization

Bilateral Equalization is a powerful image processing algorithm aimed at improving contrast and correcting luminance distribution. This method combines bilateral filtering and histogram equalization techniques to achieve the desired results.

The Bilateral Equalization method combines two key stages of image processing: bilateral filtering and histogram equalization.

First, a bilateral filter is applied to the input image. The bilateral filter preserves image details by taking into account both spatial and luminance information. This helps reduce noise and improve the overall image quality. The image is passed through a bilateral filter, where each pixel is evaluated based on its brightness and spatial location. The filter takes into account the proximity of pixel brightness and their distance in space.

$$I_{filt}(x,y) = \frac{1}{W_{total}(x,y)} \sum_{p \in \Omega} I(p) W_{spac}(\|p-(x,y)\|) W_{inten}(|I(p)-I(x,y)|)$$

where

$I_{filt}(x,y)$ −new pixel value after bilateral filtering;

$I(p)$ −is the pixel value at the point$p$;

W_{spac} −is a weighting function for spatial proximity;

W_{inten} −is a weighting function for the difference in brightness;

Ω −is the set of all neighboring pixels;

W_{total} −is the normalization term.

After filtering, the histogram is equalized for the entire image. This ensures that the brightness distribution is equalized.

$$I_{eq}(x,y) = \frac{CDF[I(x,y)] - \min(CDF)}{\max(CDF) - \min(CDF)} L$$

where

$I_{eq}(x,y)$ −new pixel value after histogram equalization;

CDF −is a function of the cumulative brightness distribution;

L −is the number of brightness levels.

Advantages of the Bilateral Equalization method:

Contrast: The method improves the contrast of an image while preserving details and structure.

Noise reduction: Bilateral filtering helps reduce noise in an image.

Corrects uneven lighting: Histogram equalization flattens the brightness distribution, which can be useful for correcting uneven lighting.

Limitations of the Bilateral Equalization method:

Computational complexity: Bilateral filtering can be a resource-intensive operation, especially for large images.

Requires parameter selection: Bilateral filter and histogram equalization parameters need to be adjusted to achieve optimal results.

4. Gathos thresholding

Gathos, Thresholding is an approach to image binarization that uses a local threshold to determine which pixels in an image should be considered an object and which should be considered a background. This method is especially useful when processing images with uneven lighting or large contrast changes.

Firstly, the image I is divided into small local blocks or windows W_i . Each window has its own size, for example, 3x3, 5x5, or 7x7 pixels.

For each local block W_i, a local binarization threshold is calculated T_i. This threshold can be calculated in several ways, but the Gathos Thresholding method uses a statistical measurement approach.

$$T_i = kW_{iavg} - W_{iavg}$$

where

W_{iavg} –average value of the brightness (or intensity) of pixels in the block.

After the local thresholds are calculated, the image is binarized, meaning that each pixel takes on the value of "object" or "background" depending on whether its brightness exceeds the corresponding local threshold.

The results of binarization for all local blocks are combined to obtain the final binary image.

Advantages of the Gathos Thresholding method:

Local adaptation: The Gathos Thresholding method uses local thresholds to binarize each block individually. This allows the method to effectively handle images where pixel intensity varies significantly across the image area or has uneven illumination.

Reducing the impact of noise: Local binarization helps to reduce the impact of noise because the threshold for each block is calculated based on statistical measurements in that block. This makes the method robust to small noise in certain areas of the image.

Adaptability to contrast: Gathos Thresholding can effectively binarize images even with significant contrast changes in different parts of the image.

Disadvantages of the Gathos Thresholding method:

High computational complexity: Calculating local thresholds for each block can be computationally expensive, especially for large images and/or large block sizes.

Parameter selection: Determining the optimal values of parameters such as block size and k in the thresholding formula can be a task that requires experimentation.

The need for debugging: Differences in image regions may require parameter adjustments for optimal binarization.

Loss of detail: Under certain conditions, where the difference between adjacent blocks is large, the method can lead to loss of detail.

5. Maximum entropy thresholding

Maximum Entropy Thresholding is one of the image binarization methods that tries to choose a threshold that maximizes the entropy of the object region in the image.

This method uses statistical characteristics of the image to automatically determine the optimal binarization threshold.

First, a histogram $H(i)$ of pixel brightness is calculated, showing how many pixels have a certain brightness value.

For each potential binarization threshold T, the entropy of the object and background regions is calculated. Entropy is a measure of uncertainty or randomness in a region. The threshold that maximizes the sum of the entropies of the object and background regions is selected as the optimal binarization threshold.

Divide the histogram into two parts: $H_1(i)$ for brightness values from 0 to T and $H_2(i)$ for values from $T+1$ to $maxT$. Calculate the probabilitiesP_1, P_2:

$$P_1 = \sum_{i=0}^{T} \frac{H(i)}{N}\ ,\ \ P_2 = \sum_{i=T+1}^{maxT} \frac{H(i)}{N}$$

Calculate the entropies of the object and background regions:

$$E_1 = -\sum_{i=0}^{T} P_1 \log_2(P_1)\,, E_2 = -\sum_{i=T+1}^{maxT} P_2 \log_2(P_2)$$

Calculate the total entropy for the current threshold:

$E(T) = E_1(T) + E_2(T)$

The threshold value is chosen to maximize the entropy function. The maximum entropy method is effective for binarizing images with complex brightness distributions and different illuminations. It allows automatic thresholding without prior knowledge of the image structure, making it useful for a variety of image-processing applications.

Advantages of the maximum entropy method:

Automated approach: The method requires no prior knowledge of the image structure or threshold parameters. It automatically determines the optimal threshold based on image statistics.

Efficiency in difficult lighting conditions: The method works effectively with images that have complex brightness distributions and different lighting conditions.

Application in various fields: This method can be used in a variety of image-processing applications that require automatic image binarization.

Disadvantages of the maximum entropy method:

Computational complexity: Calculating the entropy and choosing the optimal threshold can be computationally expensive, especially for large images.

Sensitivity to noise: The method can be sensitive to random noise in the image, which can lead to incorrect binarization.

Dependence on parameters: The method includes parameters such as T (threshold) and a number of objects that can affect the binarization results.

6. Sauvola thresholding

The Sauvola Thresholding method involves calculating a binarization threshold for each pixel in the image based on local statistical characteristics. Below is a more detailed description of this method.

The first step in the Sauvola method is to create two auxiliary "integral" images:

The first integral image is created using a square aperture covering the entire image area. For each pixel in this image, the average luminance of the pixels within the aperture is calculated.

The second integral image is also created using a square aperture. For each pixel in this image, the sum of the squares of the pixel brightnesses within the aperture is calculated, and then the square of the average pixel brightness from the first integral image is subtracted from this sum.

The following rules are applied in the main processing cycle for each image pixel:

If the brightness of the current pixel is less than the global minimum (predefined by the parameter), then this pixel is considered an object and is set to "1" in the binary image.

If the brightness of the current pixel is greater than the global maximum (also set by the parameter), then this pixel is considered the background and is set to "0" in the binary image.

If the brightness of the pixel remains between the global minimum and maximum, the formula that determines the binarization threshold for the current pixel is applied.

For a pixel that lies between the global minimum and maximum, the binarization threshold is determined:

$$t(x,y) = \mu(x,y)\left[1 + k\left(\frac{S(x,y)}{R} - 1\right)\right]$$

where

$t(x,y)$ −is the binarization threshold for a pixel;

$\mu(x,y)$ −is the average value of pixel brightness within the square aperture for a pixel;

$S(x,y)$ −is the sum of the squared brightness of pixels within a square aperture for a pixel;

k −is a parameter that can be adjusted to adjust the threshold value;

R −is the maximum possible value of the sum of squared brightness in a square aperture.

The Sauvola Thresholding method automatically determines the binarization threshold for each pixel based on local statistical characteristics, making it effective for images with variable lighting and noise.

Advantages of the Sauvola Thresholding method:

Automated approach: The method automatically determines the binarization threshold for each pixel based on local image properties, making it effective in variable lighting and noise conditions.

Contrast consideration: The method takes into account local contrast, which improves the quality of binarization in images with different lighting conditions and large contrast changes.

Parameterized approach: The method includes parameters, such as k, that can be adjusted to achieve optimal results in specific conditions.

Disadvantages of the Sauvola Thresholding method:

Computational complexity: Calculating local statistical characteristics for each pixel can be computationally expensive, especially for large images.

Sensitivity to parameters: Properly tuning parameters such as k and R is important to achieve the best results, and this may require experimentation.

Parameter dependence: Although the method automatically determines the binarization threshold, it still depends on manually defined parameter.

7. Bernsen thresholding

Bernsen Thresholding is an image binarization method that uses the local statistical characteristics of each point in an image to determine the binarization threshold. The basic idea of this method is to compare the brightness of points within a square aperture and determine whether the current pixel is part of an object or background in the image.

First, you select a square aperture around the current pixel in the image. This aperture is usually an odd size and is placed around the pixel. The aperture moves across the image, starting at the top left corner and ending at the bottom right corner.

For each aperture, the brightness values of the pixels inside it are found. The minimum brightness value Min and maximum brightness value Max among these pixels are found.

The average value Avg is calculated as the arithmetic mean between Min and :

$$Avg = \frac{Min + Max}{2}$$

For each pixel in the image, its brightness is calculated, and this brightness is compared with the value. If the brightness of a pixel is greater than plus a certain constant (set by the user), the result of binarization of this pixel is "0" (background); otherwise, it becomes "1" (object).

However, if Avg is less than the contrast threshold (which is also set at the beginning of the algorithm), the current pixel becomes the one selected for the "unspecified pixel". This means that in this case, it can take the value of the background or object, depending on the selected mode for ambiguous pixels.

The result of the algorithm is shown in Figure 3:

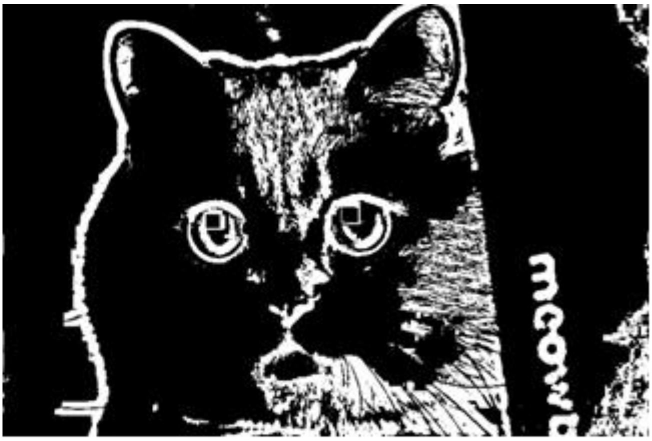

Fig.3 Bernsen method realization

Advantages of the Bernsen Thresholding method:

Simplicity: The method is relatively simple to implement and easy to understand in terms of concept. It does not require complex calculations or many parameters.

Local adaptation: The method uses a local approach to binarization, which allows it to work well on images with variable illumination and contrast.

User-controlled sensitivity: The user can adjust the E constant to achieve the desired level of sensitivity to luminance differences.

Disadvantages of the Bernsen Thresholding method:

Dependence on the E parameter: To obtain optimal results, the user must adjust the E parameter, and an incorrectly selected E can lead to unsatisfactory results.

Aperture shape limitation: The method uses a square aperture, which may be insufficient for some types of objects in the image.

Computational complexity: If the aperture value is large or the image is large, it may result in a high computational load.

8. Niblack thresholding

The Niblack binarization method is a method that uses local statistical characteristics to determine the binarization threshold for each pixel in an image. The basic idea behind the method is to vary the brightness threshold from point to point based on the local standard deviation of a sample of pixels in the surrounding area.

First, you select the size of the square aperture around the current pixel in the image. The aperture size should be chosen so that it preserves local image details while reducing the effects of noise.

For each image point in the aperture, the average brightness μ and standard deviation s of the pixels within the aperture are calculated. The average μ and standard deviation s are calculated using the following formulas:

$$\mu(x,y) = \frac{1}{N}\sum_{i=1}^{N} I(x_i, y_i)$$

where

N −number of pixels in the aperture;
$I(x_i, y_i)$ −pixel brightness.

$$s(x,y) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I(x_i,y_i) - \mu(x,y)\right)^2}$$

The brightness threshold for each point is calculated using the formula:
$B(x,y) = \mu(x,y) + ks(x,y)$

Based on the calculated threshold B, each pixel is determined to be part of an object or background. If the brightness of the pixel is greater than or equal to the threshold, it is considered part of the object (value "1"); otherwise, if the brightness is less than the threshold, it is considered background (value "0").

Advantages of the Niblack Thresholding method:

Local adaptation: The method uses a local approach to binarization, which allows it to take into account changes in contrast and illumination in an image. This makes it effective for images with uneven lighting.

Reducing the impact of noise: The use of standard deviation allows the method to be less sensitive to noise in the image.

Adaptable aperture: The size of the square aperture can be selected to preserve local image details.

Disadvantages of the Niblack Thresholding method:

Dependence on the k parameter: To achieve optimal results, the user must adjust the k parameter, and an incorrectly selected k can lead to unsatisfactory results.

Limited performance on images with complex textures: The method may produce inconclusive results on images with complex textures or details.

Computational resource requirements: The large aperture size and high image dimensionality can result in a high computational load.

9. Improved adaptive thresholding algorithm

Traditional binarization methods do not always provide the required quality of blood cell isolation with high accuracy and low noise. The new algorithm aims to reduce noise and improve object separation.

First, the size of the square aperture used for image processing is determined. This aperture size is fixed for the entire algorithm.

An additional image is created that reflects the intermediate result of binarization of the main image. This intermediate binarization step is performed based on a pre-selected binarization method, such as a gradient binarization algorithm.

For each point of the source image, an aperture with the dimensions determined earlier is selected again. For each specific aperture, all values of the P parameter are selected that correspond to the gradient between any two points in the aperture and are less than the specified value of the binarization parameter B. All these values of the P parameter are adjusted upward based on the inverse normal distribution for the discrete area.

The values of P that have been adjusted to be greater than the binarization parameter B mark points on the supplementary image. This adds new boundary points to the supplementary image that were not previously selected.

The correction operation of the P parameter values can be performed several times, depending on the image characteristics and the required binarization quality. This approach allows us to improve the binarization result and highlight the boundaries of objects more accurately.

The algorithm takes into account the specifics of object boundaries, providing selective processing of individual boundary areas and reducing the requirements for points that have not been binarized but are close to the defined boundary points.

The result of the algorithm is shown in Figure 4:

Fig.4 Adaptive method realization

10. Comparison of image processing quality using PSNR and SSIM metrics

PSNR (Peak Signal-to-Noise Ratio) is a metric used to measure the quality of a recovered signal or image after processing compared to the original signal. It expresses the ratio between the peak of the signal (the maximum possible value) and the noise in the signal. PSNR is measured in decibels (dB) and provides information about how much the recovered signal differs from the original. A high PSNR value indicates a high quality of the recovered signal, since the noise in the signal is insignificant compared to the signal.

$$PSNR = 10 \log_{10} \frac{M^2}{MSE}$$

where

M −maximum possible pixel intensity (usually 255 for 8-bit images);

MSE −the average square deviation between the original and processed images, and it is calculated as the sum of the squares of the difference between the corresponding pixels of the two images divided by the number of pixels.

SSIM (Structural Similarity Index) is a metric used to measure the similarity between two images. It takes into account the structural similarity between the pixels of the images, not just their brightness and contrast. SSIM generates a value between -

1 and 1, where 1 indicates that the two images are identical. A high SSIM value means that the images are highly similar.

$$SSIM = \frac{(2\mu x \mu y + c_1)(2\sigma xy + c_2)}{(\mu x^2 + \mu y^2 + c_1)(\sigma x^2 + \sigma y^2 + c_2)}$$

where $\mu x \mu y$ –represent the average luminance values (mean luminance) of the two images being compared;
σxy –is the covariance between the pixel brightness of the two images;
c_1, c_2 –constants introduced to prevent division by zero. They are used to smooth the numerator and denominator of the formula.

In this research paper, PSNR and SSIM metrics were used simultaneously to analyze the image processing quality assessment (see Table 1, Table 2). PSNR measures the noise level, while SSIM considers structural similarity, helping to find out how well the details and structure of the image are preserved. Combining these two metrics will provide a more objective assessment of image processing quality.

Table 1

Results of comparing algorithms for PSNR-metric

Algorithm name	**PSNR**
Median filter	10.5941
Gaussian filter	11.7413
Bilateral filter	14.7256
Gatos	9.4192
Max entropy	8.6929
Niblack	16.7198
Bernsen	15.2910
Sauvola	16.6869
Adaptive	16.8234

Table 2

Results of comparing algorithms for SSIN-metric

Algorithm name	**SSIN**
Median filter	0.7027
Gaussian filter	1.9965
Bilateral filter	2.5834
Gatos	0.9950
Max entropy	1.6929
Niblack	1.1081
Bernsen	1.0005
Sauvola	1.2749
Adaptive	3.040

As can be seen from the comparison results, the adaptive image processing method produces the best results among the considered methods. With higher PSNR values and improved structural similarity to the original images, the adaptive method proved to be the most effective in providing high-quality image processing. Its ability to adapt to different conditions and highlight details makes it an ideal choice for image-processing tasks.

Conclusions. Several methods and algorithms are intensively used in the field of image processing to optimize and improve visual information. These techniques have a wide range of applications, including document identification, medical image analysis, and many other fields. However, one of the key problems is the presence of noise in the images, which can significantly complicate the analysis and processing. In this study, various image processing techniques aimed at reducing noise and performing adaptive thresholding were thoroughly reviewed. One of the goals of this paper is not only to present and analyze these methods but also to develop an improved adaptive thresholding algorithm that can be an important contribution to the field of image processing. Adaptive thresholding algorithm has 3.040 for SSIN-metric and 16.8234 for PSNR-metric. Which is the best among others algorithms. Each of the methods was carefully considered in the paper, their advantages and limitations were determined, and the details of the improved adaptive threshold algorithm were considered. Considering the characteristics of specific images and the desired level of accuracy, the most suitable method of image processing for specific tasks was selected.

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Аналіз та удосконалення методів та засобів усунення спотворень в сигналах зображень та відео

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Основною метою цієї статті було дослідження існуючих методів обробки зображень, бінаризації та шумозаглушення, а також розробка вдосконаленого адаптивного алгоритму порогової обробки. Аналіз методів та інструментів для усунення спотворень у зображеннях і відеосигналах є актуальним завданням у багатьох галузях, зокрема в медицині, комп'ютерному зорі та документознавстві. У статті детально розглянуто існуючі методи бінаризації та шумозаглушення, виокремлено їхні переваги та обмеження. Однак головним досягненням є розробка та реалізація вдосконаленого адаптивного алгоритму порогової обробки. Цей алгоритм враховує особливості зображення та автоматично адаптує поріг бінаризації для кращої якості обробки. Він є значним внеском в область обробки зображень і може бути використаний в різних сферах, включаючи медичну діагностику та візуальне виявлення об'єктів на зображеннях.

Ключові слова: адаптивне порогове визначення, аналіз методів обробки зображень, бінаризація зображення, вдосконалений алгоритм адаптивного порогового визначення, зменшення шуму в зображеннях.

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