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DEVISING AN APPROACH TO SELECTING FILTERING METHODS FOR RELEVANT IMAGES OF ROAD DEFECTS

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This study investigates the process of selecting filtering methods for the corresponding images of road defects, provided that the textures and edges of the depicted damage are maximally preserved. The results are aimed at solving the task of ensuring the overall quality of pre-processing of defect images by selecting an effective filter corresponding to the type of depicted road defect.

An approach to selecting filtering methods for the corresponding images of road defects has been devised. Compared to conventional approaches, which are usually based on only one criterion, the devised approach is based on multi-criteria selection of an effective method. The approach algorithm combines the evaluation of the filtering results by the peak signal-to-noise ratio (PSNR) and the visual evaluation method based on established criteria. This is explained by the fact that the multi-criteria filter selection method produces a better integrated result compared to conventional ones as evidenced by the results of experimental testing. In particular, the practical implementation of the approach in the Python programming language (USA) and its testing based on images of 5 types of linear and planar damage types has been carried out.

Based on the results of testing, it was found that the PSNR of the results of processing images of longitudinal cracks with a nonlocal averaged filter is 15.26% higher than when using the Gaussian filter, which is proposed in other studies. The PSNR of the results of processing images of potholes with a bilinear filter is 15.5% higher than when using the Gaussian filter.

Such results indicate the possibility of effective application of these filters in practice for rapid pre-processing of large arrays of images of such defects

Keywords: noise pollution, road damage images, peak signal-to-noise ratio, image filtering

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1. Introduction

A current technique to reduce the risks of ineffective operational maintenance of a road network is to implement monitoring technologies and analyze various factors in order to assess their impact on the degree of object degradation. One of the significant factors influencing the condition of roads is road surface defects, which worsen the transport and operational characteristics of the network.

Automatic recognition of defects in images of transport construction objects is an important innovative tool. Conventional image processing methods make it possible to solve problems within a certain class only. In addition, these methods do not take into account noise pollution of images, changing lighting conditions, and the presence of a background with complex textures, as well as the inaccuracy of determining the geometric dimensions of damage from two-dimensional images. Since noise makes images grainy and discolored, hiding small details, its reduction while ensuring appropriate image brightness is crucial for accurate recognition of types of defects in images of infrastructure objects.

Thus, the relevance of our chosen research area relates to the need to devise an approach to selecting filtering methods for relevant images of road defects. This will make it possible to categorize techniques for recognizing and eliminating noise in images, taking into account the type of damage to the coating of infrastructure objects. From a practical point of view, such a methodological approach could become a digital tool for rapid pre-processing of defect images for the purpose of their subsequent correct recognition for taking management decisions regarding the maintenance of a road network.

2. Literature review and problem statement

A number of current studies consider an approach to detecting and categorizing road surface defects in images of road sections using machine learning methods obtained from photographs and video frames during their scanning [1–3]. At the same time, combined methods for pre-processing images (denoising) have been used to solve the problems of detecting, recognizing, and categorizing road surface defects with acceptable accuracy. In particular, this is recognition and noise reduction using artificial intelligence methods [1], the use of additional sensors when capturing images [2], or a combination of these methods [3]. Although these papers emphasize the problem of eliminating noise in images for the purpose of further identifying road surface damage, the solutions to this issue are reported in fragmentary form [2] or are too complicated [1, 3] since the predominant focus of those studies was on the direct classification of road defects using methods for recognizing depicted objects.

Study [4] emphasizes the importance of pre-processing images of road surface damage. In this case, the main phase of preprocessing falls on the identification and removal of noise from the image. The study outlines a wide range of noise removal methods. However, it does not provide specific tools or approaches to selecting filters that have proven effective when applied to image processing of certain types of road defects [4]. This is due to the fact that the work focuses on direct image processing and machine learning to detect cracks on the depicted roads.

It was established in [5] that a large amount of texture noise on the surface of highways and other infrastructure objects reduces the performance of detecting damage edges. The authors proposed performing image segmentation and reducing noise using machine learning methods. The results of testing the approach are successful but the study examines only one type of damage – cracks – since the authors took an existing data set on photofixation of this damage for practical implementation. No testing under field conditions and on images of other defects was carried out.

To remove noise from an image, researchers in [6] used a combination of image signal processing and discriminative machine learning. To remove redundant information in order to improve the noise reduction effects, advanced filtering algorithms using convolutional neural networks were used. However, the testing was performed on the Berkeley Segmentation (BSD) dataset with 432 natural images. Thus, it is not possible to establish whether this method could be applied to pre-processing images of road defects.

The cited studies mainly try to solve the problem of identifying and minimizing noise in technical images using modern filtering methods [7–11]. In particular, in [7] it is proposed to apply a nonlocal average filter. This can be effective for images of infrastructure objects since it is necessary not only to remove noise pollution but also preserve the edges of damage, small details, and the texture of the road surface. However, the application of this filter requires testing since studies [7, 8] have not demonstrated that this method could be applied to images of transport construction objects for the purpose of further damage identification.

Papers [9–11] give a more detailed consideration of the effectiveness of the application of the nonlocal averaged filter from both a theoretical and a practical point of view. However, its application is considered from the point of view of natural images [11] or available in open databases, degraded by Gaussian noise [9, 10]. It is impossible to establish whether these techniques [9, 10] could be applied to images of damage to the road network. This is largely due to the fact that images of defects contain other types of noise, such as "salt and pepper", speckle, and periodic noise, and not only Gaussian noise.

Thus, studies [1–3] emphasize the existing problem of devising approaches to eliminating noise in images of road defects. However, there are no specific solutions to this problem since the focus is on defect recognition, and not on selecting an effective filter for the image of this defect during pre-processing.

In [4], the need for pre-processing images of infrastructure objects is emphasized because the noise in such images can lead to subsequent incorrect recognition of the type of defect, texture, and its size [5]. However, the proposed solutions relate only to a formal set of similar data, which does not take into account the existing nature of images of different types of defects.

In recent studies [6–11], concerning the selection of image filtering methods, there is no convincing evidence of the application of modern methods, techniques, approaches to recognizing and eliminating noise in images of road damage as most of these solutions concerned images of natural objects [7, 8, 11] or open image databases [9, 10]. In addition, the type of noise present in the image is not taken into account. In addition, criteria for applying a particular image denoising method to a specific type of depicted defect, taking into account the preservation of textures and its edges, require additional clarification.

Separately, it should be noted that the damage database includes more than 20 types only for cement-concrete road surfaces if the type of materials used is neglected. In addition, photofixation of various types of damage to infrastructure objects is associated with the accumulation of an extremely large number of images [1–3]. This creates the problem of rapid pre-processing of large arrays of depicted defects [1, 3]. In addition, in the earlier studies, the efficiency of filters is assessed mainly by only one criterion [6–11]. For example, the maximum peak signal-to-noise ratio (Peak Signal-To-Noise Ratio – PSNR) [11] was used as the criterion, which does not take into account the need to simultaneously ensure correct recognition of the type of defect, texture, and its size.

Thus, there is a problem of ensuring the overall quality of pre-processing of defect images, taking into account their specificity. Therefore, there is a need to conduct research aimed at devising an approach for selecting an effective denoising method for the appropriate type of depicted defect, which is solved by solving a multi-criteria problem. This will subsequently make it possible, having an appropriate array of photofixation results and using this approach, to build an expanded database of types of depicted damage with their corresponding filtering methods. The results could be integrated in an information and analytical system for automated pre-processing of road condition photofixation results.

3. The aim and objectives of the study

The aim of our study was to devise an approach that would make it possible to select an effective filtering method corresponding to the type of depicted road defect. This would make it possible, taking into account the type of damage to the infrastructure objects' coating, to process the image using selected effective methods of eliminating digital noise. In practice, this could contribute to increasing the informativeness of the images at the stage of their subsequent processing in order to clarify the type of damage, texture, and its geometric dimensions.

The specified goal was achieved by gradually completing the following tasks:

– to state a multi-criteria problem of selecting filtering methods corresponding to images of defects and to develop an algorithm to solve it;

– to devise a methodology for performing experiments on selecting filtering methods corresponding to images of defects;

– to test the approach to selecting filtering methods corresponding to images of road defects.

4. The study materials and methods

The object of our study is the process of selecting filtering methods for the corresponding images of road defects, provided that the textures and edges of the depicted damage are maximally preserved.

The principal hypothesis assumes that the use of a multi-criteria filtering method selection system based on a combination of analysis of the results according to the established criteria and compliance with the accepted range of the PSNR indicator could provide a significant improvement in the overall quality of pre-processing of defect images. Compared to a conventional approach, which is usually based on only one criterion (for example, maximum PSNR), such an approach could make it possible to form an approach to selecting an effective method for filtering depicted defects by solving a multi-criteria problem.

In the process of conducting the study, an assumption was adopted – the principal hypothesis could be confirmed if experimental testing showed that the multi-criteria filter selection method gave a better integrated result compared to the conventional one.

The basic simplification accepted in the study is to consider only 5 types of depicted defects, which belong to two types (linear and planar), without taking into account the volumetric parameter of damage since the assessment of this parameter at this stage requires additional consideration and analysis of other filtering methods, in addition to those selected for testing.

The use of criteria for selecting an effective image denoising method applied to a specific type of depicted defect will make it possible to build a high-quality initial image database for further processing. This will allow for more accurate and rapid recognition of depicted defects, their textures and sizes at the next stages, which will subsequently affect decision-making regarding road network management. The approach is based on the use of image filtering methods (nonlocal averaging, median, Gaussian filter, and bilinear filtering) [4, 7, 8, 10], which were identified as the most applicable to images of infrastructure objects. To analyze the quality of the image obtained after processing with filters, the method of visual evaluation of processing results in combination with a multi-criteria approach and the method of determining the peak signal-to-noise ratio (PSNR) [11] were used. Thus, our research methodology was based on the analysis of methods for solving problems of effective image denoising [1–11] in combination with methods for evaluating processing results.

For further testing of the research results, the Python programming language (USA) was employed with the use of the OpenCV library (USA). In this case, the peak signal-to-noise ratio (PSNR) indicator was used in the program algorithm to quantify the experimental results.

The approach was validated using available photographs of five types of road defects that we recorded in Ukraine. In this case, images of longitudinal and transverse cracks, a network of cracks, potholes, and ruts were selected for the experiment. Visual evaluation of the results of image processing of all groups of defects according to the criteria of "defect clarity", "blurring of the entire image", "texture smoothing" showed that the use of the nonlocal average filter method is the most acceptable. However, for effective processing of images of planar defects, such as potholes and ruts, bilinear filtering is also possible. The evaluation of the efficiency of the filters by the PSNR indicator confirmed the effectiveness of the nonlocal averaged filter for removing noise in defect images. The greatest effect of this method was demonstrated by an increase in the PSNR indicator by 15.26% when processing images of longitudinal cracks processed by the nonlocal averaged filter compared to the use of the Gaussian filter.

5. Devising an approach to selecting filtering methods for relevant images of road defects: results

5. 1. Statement of the multi-criteria problem of selecting filtering methods for relevant images of defects; an algorithm for solving it

The following extraneous noises and artifacts are most often found in images of defects at infrastructure objects:

– digital noise (fuzzy (blurred) image, graininess, inclusions, stripes, etc.);

– shadow noise from natural objects (trees, bushes, clouds, etc.);

– shadow noise from urban objects (buildings, structures, road construction) and equipment (tripods, rails, shooting equipment, measuring devices, etc.);

– shadow noise from road users (vehicles, pedestrians) or the crew conducting the shooting;

– digital noise as a result of existing traces of wheels of road vehicles or aircraft in the landing zone of airfield surfaces (graininess, shadow noise, etc.);

– optical artifacts (spots and drops on the windshield when shooting from the car interior or on the glass of photo equipment during precipitation);

– physical artifacts (contamination of the surface of the coating with clay, sand, soil or other material, water on the surface in the area of potholes or subsidence, foreign inclusions, spots of bitumen or mastic, spillage of fuel and lubricants, etc.).

The task to select filtering methods for the corresponding images is reduced to identifying such methods that could satisfy the conditions for recognizing noise in images of road defects. According to theoretical research, all filtering methods are categorized as follows (Table 1).

Considering the specificity of road defect images, further research should be conducted to analyze and test in practice the nonlocal averaging, median, Gaussian filter, and bilinear filtering.

Table 1

Description of the most common image filtering methods

Method ID	Description
Spatial methods (classical filters)	These methods work directly with the pixels of an image, changing the value of each pixel based on its neighbors. They are the simplest and fastest ways to process images
Averaging filter	This filter replaces the value of each pixel with the average value of the pixels in its neighborhood (kernel). This is an effective way to smooth out noise, but can result in blurring of sharp edges and details
Median filter	Each pixel is replaced with the median value of the pixels in its neighborhood. This method is very effective for removing impulse noise (such as "salt and pepper") because the median is less sensitive to sharp outliers than the mean. It preserves the edges of objects better than an averaging filter
Gaussian filter (cv2.GaussianBlur)	This filter uses a weighted average for each pixel, where pixels closer to the center of the kernel are given a higher weight. This method is best for smoothing noise and achieving a soft focus effect, as it creates a more natural blur than the averaging filter
Bilinear filtering (cv2.bilateralFilter)	Unlike other spatial filters, this method takes into account not only spatial proximity, but also the similarity of pixel values. It smooths noise without blurring edges and contours, making it ideal for photo processing
Frequency methods	These methods work with an image in the frequency domain, using the Fourier transform to analyze and change the frequency components
Frequency domain filtering (Fourier transform)	The image is first transformed using the Fourier transform into a frequency spectrum. Then, filters are applied to this spectrum, either removing high frequencies (smoothing) or low frequencies (edge extraction). The spectrum is then converted back to the spatial domain using the inverse Fourier transform
Methods based on convolutional neural networks (DNN)	These are modern approaches that use deep learning to automatically filter images, learning from large datasets
Autoencoders, GAN, DnCNN	Autoencoders are used to remove noise by compressing an image in a "hidden" representation and then restoring it. The network learns to reproduce the image, but without noise. GANs (Generative Adversarial Networks) consist of two networks: a generator that creates a noise-free image, and a discriminator that tries to distinguish the "real" (clean) image from the "fake" (restored) one. This allows for high-quality filtering. DnCNN (Denoising Convolutional Neural Network) is a specialized convolutional network for denoising that can effectively deal with various types of noise, showing exceptional performance. These methods are much more powerful than classical filters, but require large computational resources and significant amounts of data for training

The averaging filter calculates the average value of all pixels in a certain window (kernel). Each pixel (x, y) in the output image I_{out} is calculated as the arithmetic mean of the pixels in a window of size $m \times n$ around the corresponding pixel (x, y) in the input image In

$$I_{out}(x,y)_b = \frac{1}{m \cdot n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} I_{in}(x+i, y+j), \quad (1)$$

where m and n are the kernel sizes; I_{in} is the input image.

The median filter replaces the value of the center pixel with the median of all pixels in the window

$$I_{out}(x,y)_{md} = md\left\{I_{in}(x+i, y+j) \middle| i, j \in wd\right\}, \quad (2)$$

where md is the median of all pixels; wd is the set of pixels in the kernel (window).

The Gaussian filter uses a weighted average, where the weights are determined by a two-dimensional Gaussian function. In this case, pixels that are closer to the center of the kernel have a higher weight

$$I_{out}(x,y)_G = \sum_i \sum_j G(i,j) \times I_{in}(x-i, y-j), \quad (3)$$

where $G(i, j)$ is the value of the Gaussian kernel, which is calculated from the formula

$$G(i,j) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{i^2+j^2}{2\sigma^2}\right)}, \quad (4)$$

where σ is the standard deviation, which determines the degree of blurring.

Bilinear filtering smooths the image while preserving the contours. It takes into account two parameters: spatial proximity (as in the Gaussian filter) and similarity of intensity values (color similarity)

$$I_{out}(x,y)_{bf} = \frac{1}{W}\sum_{i,j} I_{in}(i,j) \times f_s(i,j,x,y) \times f_r\left(I_{in}(i,j), I_{in}(x,y)\right), \quad (5)$$

where f_s – spatial Gaussian filter, which is defined by the following formula

$$f_s(i,j,x,y) = e^{-\left(\frac{(i-x)^2+(j-y)^2}{2\sigma_s^2}\right)}, \quad (6)$$

where σ_s – standard deviation for spatial filter; f_r – band filter (color Gaussian)

$$f_r\left(I_{in}(i,j), I_{in}(x,y)\right) = e^{-\left(\frac{\left\|I_{in}(i,j)-I_{in}(x,y)\right\|^2}{2\sigma_r^2}\right)}, \quad (7)$$

where σ_r – standard deviation for color filter; W – normalizing coefficient

$$W = \sum_{i,j} f_s(i,j,x,y) \times f_r\left(I_{in}(i,j), I_{in}(x,y)\right). \quad (8)$$

Before choosing a filtering method, it is important to determine what type of noise is present:

– Gaussian noise – digital noise that is evenly distributed, similar to "fog";

– Salt-and-Pepper noise – digital noise that is random white and black dots;

– Speckle noise – multiplicative noise;

– Periodic noise – noise that appear s in the form of regular patterns (bands).

Since noise assessment is a fundamental task in image quality analysis, there is a need to quantify its level. Classically, this process can be performed using one of the following noise measurement methods:

1. Determining the peak signal-to-noise ratio (Peak Signal-To-Noise Ratio – PSNR), which serves as a benchmark for assessing image quality. The essence of this method is to compare the number of pixels in the original image with the values of the reproduced image after filtering.

2. The method of evaluation using the mean square error (MSE). This method, on the contrary, makes it possible to evaluate the quality of the output image by calculating the average value of the squares of the differences between the corresponding pixels of the input and output images.

In particular, the most widespread method for evaluating image quality is the PSNR indicator, which is measured in decibels (dB)

$$PSNR = 10 \times \log_{10}\left(\frac{I_{\max}^{2}}{MSE}\right), \tag{9}$$

where $I_{\max}$ is the maximum possible brightness value of an image pixel; for an 8-bit image, $I_{\max}=255$; MSE is the mean square error

$$MSE = \frac{1}{m \times n} \times \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[I(i,j) - K(i,j)\right]^{2}, \tag{10}$$

where m and n are the image dimensions (height and width in pixels); $I(i,j)$ is the pixel value at position (i,j) of the original image; $K(i,j)$ is the pixel value at the same position in the processed image.

It is believed that the higher the PSNR value, the better the image quality. The optimal PSNR values for processed images are values in the range from 30 dB to 50 dB.

Thus, the task of selecting filtering methods for the corresponding road defect images can be represented as maximizing the overall efficiency of the filtering method

$$F(x) = I_{out}(x,y) \rightarrow \\ \rightarrow \max,\ F(x) \in \left\{F(x)_{k}\right\}, \tag{11}$$

where k is the index of the element in the set "type of depicted damage" (x) – "effective image filtering method" ($F(x)$); under the following constraints:

$$\begin{cases} I_{out}(x,y) \in V, \\ I_{out}(x,y) \notin R, \\ PSNR \in [30,50], \end{cases} \tag{12}$$

where V is the clarity of the defect in the image after its processing according to the visual assessment (set by the expert); R is the level of blurring of the entire image after processing (set by the expert).

Thus, the proposed approach, which involves selecting an effective filter for the type of depicted road defect (11), (12), will make it possible to build a database on the types of depicted defects with their corresponding filters.

During the study, it was decided to implement the proposed approach using the Python programming language (USA) and the OpenCV library (USA). The step-by-step implementation of the proposed approach is represented in the form of an algorithm (Fig. 1).

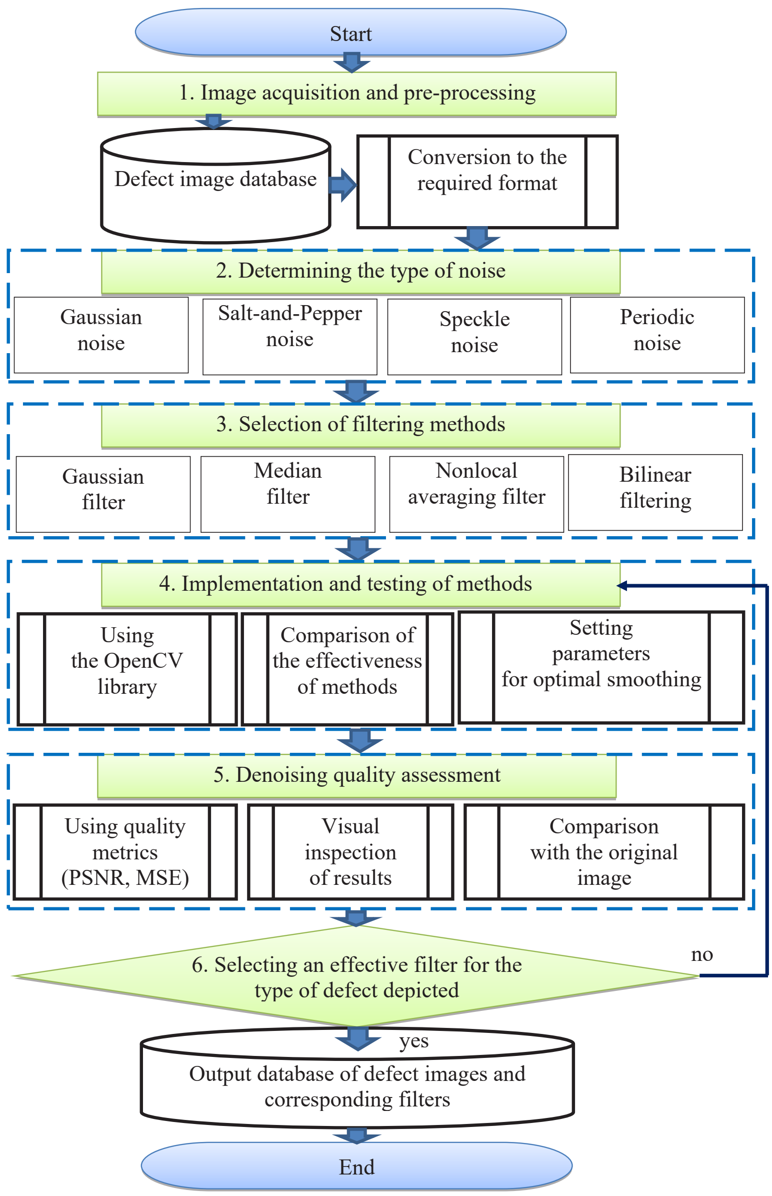

Fig. 1. Algorithm for implementing the proposed approach

The implementation of the proposed algorithm (Fig. 1) from a practical point of view makes it possible to preprocess defect images taking into account the effectiveness of the applied filter for the type of damage.

5. 2. Methodology for performing experiments on selecting filtering methods appropriate for defect images

The proposed approach was implemented in the form of program code in the Python environment (USA) using the OpenCV library (USA):

```
# Importing the OpenCV library
import cv2
import matplotlib.pyplot as plt

# Reading an image from a specified path and changing its color format
def noise_reduction(image_path):
  img_noise = cv2.imread(image_path)
  img_noise_rgb = cv2.cvtColor(img_noise,cv2.COLOR_BGR2RGB)

# Image processing with a Gaussian filter
  gaussian_blur = cv2.GaussianBlur(img_noise, (5,5), 1)
  gaussian_rgb = cv2.cvtColor(gaussian_blur, cv2.COLOR_BGR2RGB)

# Image processing with a median filter
  median_blur = cv2.medianBlur(img_noise,5)
  median_rgb = cv2.cvtColor(median_blur, cv2.COLOR_BGR2RGB)

# Image processing with bilinear filtering
  bilateral_filter = cv2.bilateralFilter(img_noise, 9,100,100)
  bilateral_rgb = cv2.cvtColor(bilateral_filter, cv2.COLOR_BGR2RGB)

# Image processing with a nonlocal averaging filter
  nonlocal_mean = cv2.fastNlMeansDenoisingColored(img_noise, None, 10,10,7,21)
  nonlocal_rgb = cv2.cvtColor(nonlocal_mean, cv2.COLOR_BGR2RGB)
  plt.figure(figsize=(14,8))

# Output of the processed image using all methods
  tup = [("Noise Image", img_noise_rgb),
       ("Gaussian Img", gaussian_rgb),
       ("Median Img", median_rgb),
       ("Bilateral Img", bilateral_rgb),
       ("Nonlocal Img", nonlocal_rgb)]
  for t in range(len(tup)):
    plt.subplot(2,3,t+1)
    plt.title(tup[t][0])
    plt.imshow(tup[t][1])
    plt.axis("off")

# Calculating PSNR between original and processed image
def calculate_psnr(original, filtered):
  mse = np.mean((original.astype(np.float64) – filtered.astype(np.float64)) ** 2)
  if mse == 0:
    return float('inf')
  max_pixel = 255.0
  psnr = 20 * np.log10(max_pixel / np.sqrt(mse))
  return psnr

  psnr_gaussian = calculate_psnr(img_clean, img_gaussian)
  psnr_median = calculate_psnr(img_clean, img_median)
  psnr_nonlocal = calculate_psnr(img_clean, img_ nonlocal)
  psnr_bilateral = calculate_psnr(img_clean, img_bilateral)

  print(f"PSNR Гаусового фільтра: {psnr_gaussian:.2f} дБ")
  print(f"PSNR Медіанного фільтра: {psnr_median:.2f} дБ")
  print(f"PSNR Нелокального усередненого фільтра: {psnr_nonlocal:.2f} дБ")
  print(f"PSNR Білінійного фільтра: {psnr_bilateral:.2f} дБ")
  print(«-» * 30)
  print(«Чим вище значення PSNR, тим краще.»)

noise_reduction("NameImage.JPG")
```

As a result of the program execution, five images and PSNR values for each filter will be obtained. The person who will make a decision regarding the processed images should visually evaluate the result and compare it with the value of the derived PSNR indicator. Visual evaluation of the result means analyzing the image to see whether the applied filter has preserved important contours and whether so-called "artifacts" have appeared because, for further assessment of defects in infrastructure objects, it is important that the clarity of key details, in particular, damage contours, is preserved. Thus, the optimal filter for an image is a balance between effective noise removal and preservation of important information.

5. 3. Testing the approach to selecting filtering methods for relevant images of road defects

According to the previously formed database of road defects, five types were selected for the experiment: longitudinal and transverse cracks, a network of cracks, potholes, and ruts. By their nature, longitudinal and transverse cracks, as well as a network of cracks are linear damages, and potholes, ruts are planar. At the same time, when photographing the damages, a section of the road with a cement concrete base and asphalt concrete pavement, built from the same road construction materials, was selected. The next step was to test the devised approach to selecting filtering methods for relevant images of road defects (Fig. 2–6).

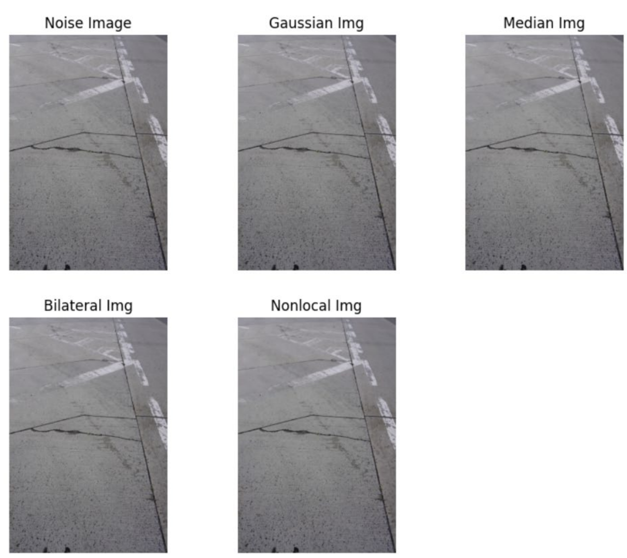

Fig. 2. Results of processing images of longitudinal cracks (output from the program)

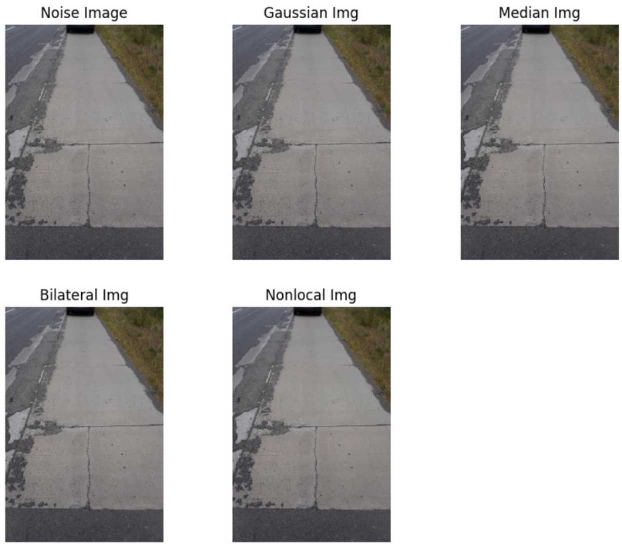

Fig. 3. Results of processing images of transverse cracks (output from the program)

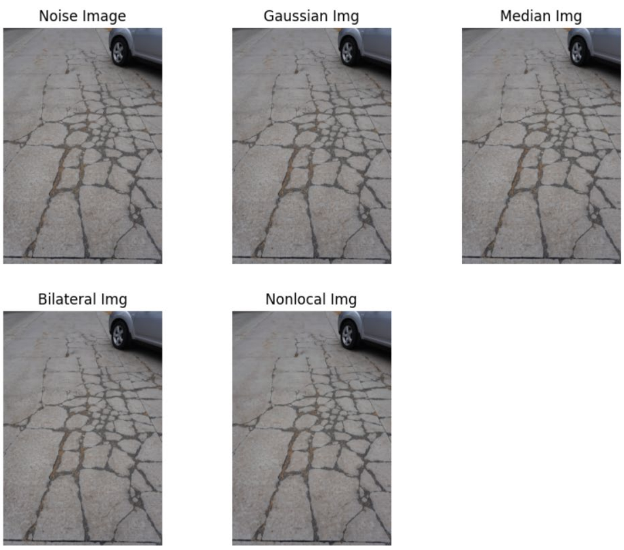

Fig. 4. Results of processing images of crack mesh (output from the program)

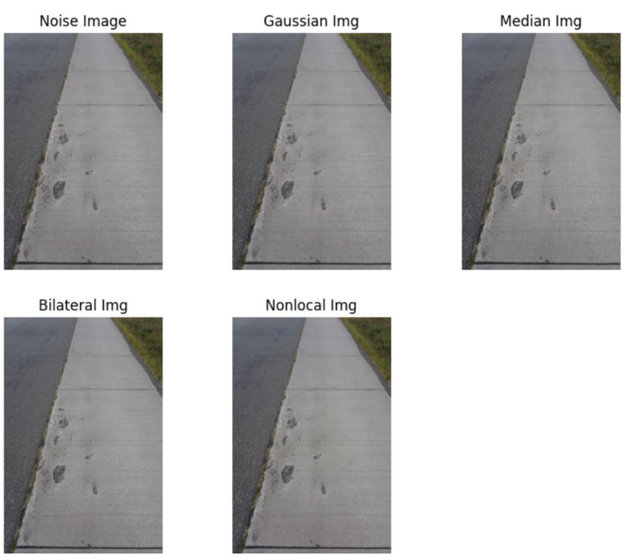

Fig. 5. Results of processing pothole images (output from the program)

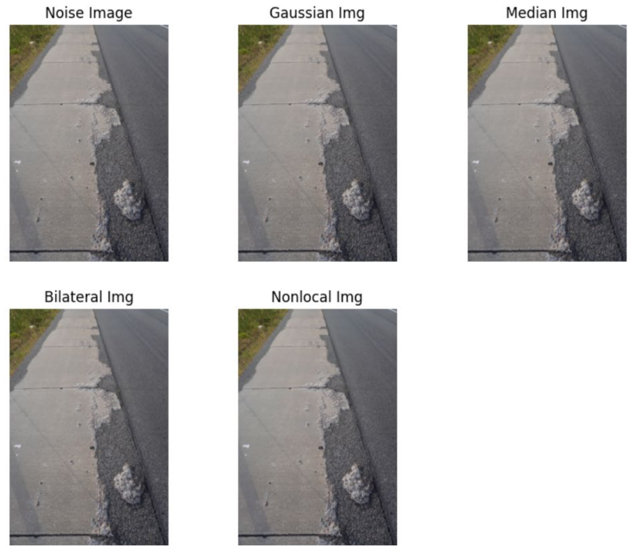

Fig. 6. Results of processing rut images (output from the program)

At the same time, for the visual assessment by the expert of the results of processing by filters of images derived from the program (Fig. 2–6), three criteria were assigned: "defect clarity", "blurring of the entire image", "texture smoothing". The value of the PSNR indicator for each filter was determined programmatically (lines of program code 39–58). The results from visual assessment and based on the PSNR indicator for each filter are listed in Table 2.

Table 2

Evaluating image processing results

Indicator	Type of defect in the image				
	Longitudinal crack	Transverse crack	Crack grid	Pothole	Rut
Gaussian filter					
PSNR	32.1	33.2	36.5	38.1	41.1
Defect clarity	–	–	–	–	–
Blurring the entire image	+	+	+	+	+
Texture smoothing	+	+	+	+	+
Median filter					
PSNR	33.5	34.3	37.5	39.2	41.0
Defect clarity	–	–	–	–	–
Blurring the entire image	+	+	–	–	–
Texture smoothing	+	+	+	+	+
Bilinear filtering					
PSNR	34.5	35.2	37.8	44	42.8
Defect clarity	–	–	–	+	+
Blurring the entire image	+	–	–	–	–
Texture smoothing	–	+	+	–	–
Nonlocal averaged filter					
PSNR	37	39.1	41	44.2	43
Defect clarity	+	+	+	+	+
Blurring the entire image	–	–	–	–	–
Texture smoothing	–	–	–	–	–

Fig. 2–6 and Table 2 demonstrate the results of applying various noise removal methods, namely Gaussian, median, nonlocal averaged filters, and bilinear filtering. The most effective in each case is the one that best preserves image details while removing noise.

Performing a visual assessment of the results of processing the image of longitudinal cracks (Fig. 2), it was found that the best method for minimizing noise for such defects is the nonlocal averaged filter. At the same time, the Gaussian and median filters smooth the texture of the road surface and partially blur the edges of the cracks. The bilinear filter preserves the reflection of the edges of the cracks but loses some of the fine details. Using the nonlocal averaged filter, it was achieved to preserve the texture of the road surface and the clarity of the crack reflection.

This filter also demonstrates high results when applied to images with transverse cracks on the road (Fig. 3), preserving the clarity of fine details in the image. In particular, experts noted that Gaussian and median filters blur the boundary between the road surface and the curb, and the bilinear filter partially smoothes the edges of the cracks.

According to the visual assessment by the experts of the results from processing the image of the crack grid (Fig. 4), the nonlocal average filter method also turned out to be the most effective. It is this method that best preserves the fine details of the cracks, while effectively removing noise. Other methods noticeably smooth the depicted cracks, which are important details for further processing.

The results from processing the images of potholes (Fig. 5) showed that the most visually effective filtering methods are the bilinear and nonlocal average filter. It was thanks to their use that the clarity of the pothole edges was achieved, which is very important for further processing to determine its size. The Gaussian filter noticeably blurs the image as a whole, and the median filter smoothes the edges of the pothole.

The bilinear and nonlocal average filter also demonstrated the best results when evaluating the results of processing images of ruts on a road (Fig. 6). These filters, unlike the median and Gaussian, preserve clear rut boundaries and the texture of the road surface in the image, which makes it possible to for better object discrimination.

Evaluating the efficiency of the filters by the peak signal-to-noise ratio (PSNR) also showed that the nonlocal average filter is the most effective for removing noise from defect images (Fig. 7).

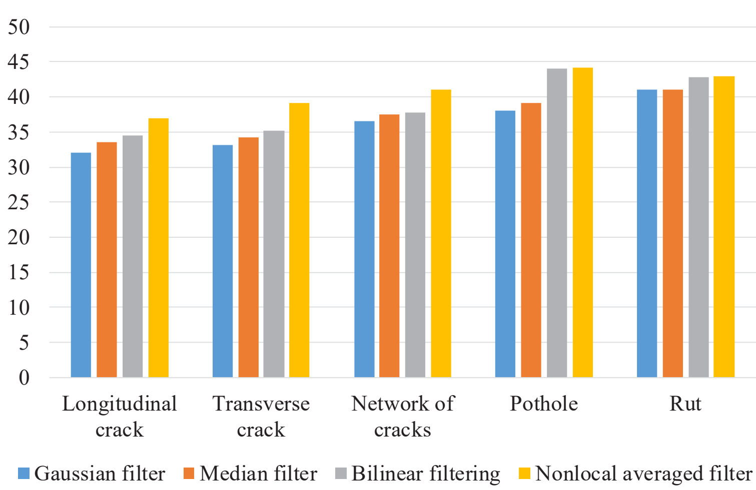

Fig. 7. Determining Peak Signal-to-Noise Ratio (PSNR)

In particular, for example, the PSNR value for images of longitudinal cracks processed by a nonlocal average filter was 7.2% higher than when processed by bilinear filtering, as well as 10.44% higher than when processing these images by a median filter, and 15.26% higher than when using a Gaussian filter.

Thus, for images of all types of road damage taken for assessment, the nonlocal average filter method turned out to be the most effective. Visual evaluation of the processing results confirmed that it best preserves important details and textures in the images, while successfully removing noise. This is explained by the fact that this method makes it possible to compare each pixel with other similar pixels throughout the image, and not only in a local area, which is an advantage over other filters. The bilinear method can be used to process images of potholes and ruts on road objects, since it preserves the boundaries of large damage. Gaussian and median filters are the least effective for processing such specific images, since when they are used, the image clarity is lost and important details are blurred.

Thus, the results of our study showed that for optimal noise removal it is advisable to combine several methods or use adaptive approaches to a specific type of depicted defect. Such results indicate the possibility of forming an initial database of images of road defect types and corresponding filters. This will make it possible to quickly process large arrays of photofixation data of a certain type of damage using a filter already assigned to the database, which has proven its effectiveness taking into account the preservation of textures and edges of depicted damage.

6. Discussion of results of testing the approach to selecting filtering methods for appropriate images of road defects

The devised approach to selecting filtering methods for images of defects is based on a mathematical model (1) to (12). In this case, the task of selecting a method for filtering images of defects of infrastructure objects is reduced to maximizing the overall efficiency of the filtering method (11) under existing constraints (12). The software implementation of the devised approach in the Python programming language (USA) in combination with the OpenCV library (USA) was performed according to the proposed algorithm (Fig. 1). This makes it possible to pre-process defect images taking into account the efficiency of the applied filter for the type of damage. Subsequently, this will allow for a clearer recognition of the geometric parameters of the damage and existing textures. Unlike [4, 5], which proposes the application of image segmentation and filtering methods at the pre-processing stage to the entire array of collected data of the same type, the proposed approach takes into account the type of depicted defect. This became possible due to the advantage of the devised approach, related to the fact that when selecting an effective filter for a specific image of damage, a visual analysis of the obtained images is carried out according to three criteria and the efficiency of the filters is assessed by the PSNR indicator. In particular, unlike [7–11], in which it was not determined by which criteria it was necessary to carry out a visual analysis, in our study criteria such as defect clarity, blurring of the entire image, texture smoothing effect are adopted. Directly due to the application of these criteria in the proposed approach, the quality conditions of the original depicted infrastructure objects are satisfied, taking into account their specificity.

The devised approach was tested on images of 5 types of damage, of which three are linear in nature and two are planar (Table 2, Fig. 2–6). A visual analysis of the obtained images was carried out according to the criteria of "defect clarity", "blurring of the entire image", "texture smoothing" (Table 2). The results of our analysis revealed that for all types of road damage taken for assessment, the nonlocal averaged filter method is the most effective. It was confirmed that this filter best preserves important details and textures in the images, while successfully removing noise (Table 2, Fig. 2–6). That confirmed that the nonlocal averaged filter method makes it possible to compare each pixel with other similar pixels throughout the image. This is the advantage of our method over other filters when applied to the recognition and removal of noise in images of road defects.

In addition, according to the results of the testing, it was found that the bilinear filtering method can be used to process images of potholes and ruts on road objects since it preserves the boundaries of large damage (Fig. 5, 6). Thus, the effectiveness of the bilinear filtering method for images of planar defects was confirmed. The efficiency of the filters was evaluated by the peak signal-to-noise ratio (PSNR), which was determined programmatically. The evaluation results confirmed the effectiveness of the nonlocal averaged filter in eliminating noise in defect images (Table 2, Fig. 7). The value of the PSNR indicator for images of longitudinal cracks processed by the nonlocal averaged filter was 7.2% higher than when they were processed by bilinear filtering, as well as 10.44% higher than when these images were processed by the median filter, and 15.26% higher than when using the Gaussian filter. This allows for the effective application of the nonlocal averaged filter method to images of linear damage to infrastructure objects. It is confirmed that, in terms of PSNR, the bilinear filtering method is the most effective for processing images of planar damage. In particular, when removing noise from images of potholes using this method, the PSNR was 15.5% higher than when using the Gaussian filter.

Thus, our results could subsequently become an important component of information and analytical systems for road network management as the initial database is formed on the basis of qualitatively processed images of road defects for further clarification of the type of defect, recognition of its size and texture. This is an important element for making management decisions regarding the application of corrective actions – assigning or non-assigning a certain type of repair and restoration measures.

The limitation of the proposed approach is that only three criteria are used in the visual assessment of the obtained images – "defect clarity", "blurring of the entire image", "texture smoothing". The disadvantage of the devised approach to the selection of filtering methods for the corresponding images of road defects is that at this stage it can be used to select a filtering method only to eliminate digital noise. That is, the existing shadow noise caused by foreign objects present in the images, optical and physical artifacts are not taken into account. This shortcoming will be taken into account at the next stage of the research – when designing an information and analytical system for recognizing defects at infrastructure objects from photo-spectral images. In addition, in further research, a database of visual assessment criteria will be built and approaches to justifying their choice will be proposed.

7. Conclusions

1. We have stated a multi-criteria problem of selecting filtering methods appropriate for defect images; an algorithm to solve it has been developed. To this end, various means and technologies for eliminating noise in images were analyzed, and various approaches to filtering were investigated taking into account the specificity of images from infrastructure objects. It was determined that the choice of the filtering method depends on the type of noise. In particular, Gaussian noise can be effectively eliminated using a Gaussian filter or neural network methods. Impulse noise (Salt-and-Pepper) is better removed by a median filter. Speckle noise can be reduced using bilinear filtering. Spatial methods (averaging, median, bilinear filters) are simple to implement and provide fast processing but could lead to loss of detail in images. Frequency methods (Fourier transform) allow for effective filtering of certain noise frequencies but require complex setup. Deep neural networks demonstrate the best quality of image cleaning but require significant computational resources and pre-training of models. Taking into account the specificity of images of road defects, including the typical digital noises present, it is proposed in our study to perform denoising using the methods of nonlocal averaging, median, Gaussian filter and bilinear filtering. The task of selecting filtering methods appropriate to images of defects is reduced to maximizing the overall efficiency of the filtering method under the established constraints. An algorithm for step-by-step implementation of the proposed approach has been developed, which makes it possible to build a database of defect images and corresponding filters at the output.

2. The software implementation of the approach to selecting the methods of filtering corresponding to the images of defects was carried out according to the proposed algorithm in the Python programming language (USA) in combination with the OpenCV library (USA). The algorithm takes into account that the criteria for selecting an effective filter for a specific image of damage are the results from visual analysis of the obtained images and a satisfactory value of the PSNR indicator. Thus, the program developed in this way is a full-fledged tool for constructing the initial database for further clarification of the type of defect, recognition of its size and texture.

3. Our approach was tested on the basis of images of 5 types of damage, which are linear and planar in nature. As a result of the visual analysis of the obtained images according to the criteria of "defect clarity", "blurring of the entire image", "texture smoothing", it was established that for all types of road damage taken for assessment, the nonlocal averaged filter method is the most effective. In addition, the results of the testing showed that the bilinear filtering method can be used to process images of planar nature (potholes and ruts) on road objects since it preserves the boundaries of large damage. Further evaluation of the efficiency of the filters by the peak signal-to-noise ratio (PSNR) confirmed the effectiveness of the nonlocal averaged and bilinear filters in eliminating noise in images of various types of defects. In particular, the greatest effect of applying the nonlocal averaged filter method to the image of a linear type of damage (longitudinal cracks) was recorded at 15.26% compared to the use of the Gaussian filter. The greatest effect of the bilinear filtering method was achieved for the image of a planar type of damage (pothole), which was 15.5% compared to the use of the Gaussian filter. This allows the nonlocal averaged filter method to be effectively applied to images of linear damage, and the bilinear filtering method to images of planar damage to infrastructure objects. Thus, the devised approach was used to select effective filters for images of specific types of defects. This makes

it possible to build a database of types of depicted defects with their corresponding filters to subsequently serve as a tool for rapid preliminary processing of large image arrays.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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