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DEVELOPMENT OF ALGORITHMS FOR DETECTING DEFECTS IN THE CODE SEQUENCE STRUCTURE ON THE SURFACE OF MODULATION DISKS

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Abstract. This study investigates algorithms for detecting and localizing defects in code sequence structures on modulation disk surfaces. It targets small anomalies in lithographically patterned elements that can cause readout errors or reduced measurement accuracy. A multi-level image-processing model combines Gaussian smoothing, adaptive thresholding, morphological operations, and contour-based segmentation. Processing stages are formalized as mathematical operators for reproducible implementation. Defects are characterized using perimeter- and area-based metrics, and their area distribution is approximated by a normal law. A spatial model computes defect centroids, enabling comparative quality assessment of disk samples. The software provides an interface for tuning thresholds, visualizing contours and defect-area plots, and exporting results. Tests on real defective disks confirm the method's reliable detection of local structural violations and its suitability for diagnostic systems.

Keywords: modulation disks, automated inspection, code sequence, microstructural anomalies, image preprocessing, morphological analysis, contour segmentation.

INTRODUCTION

The integration of automated surface inspection methods into the technological workflow of optical and micromechanical components, particularly modulation disks, plays a crucial role in ensuring the accuracy and reliability of photoelectric measurement systems [1–3]. Previous studies have reported that the formation of high-precision coded structures on transparent substrates using photolithographic techniques is often accompanied by the emergence of local defects. These defects may result from technological inaccuracies, residual stresses, or surface contamination [4–6]. In response to the growing demands placed on the metrological performance of encoding systems, the development of effective technical diagnostic procedures for the detection of defects within code sequences at submicron structural resolution has become increasingly relevant.

Traditional inspection methods based on visual assessment and manual surface marking of modulation disks are significantly outperformed by modern approaches utilizing computer vision systems (Fig. 1). These advanced systems enable automated processing of digital images, integration with production lines, and real-time adaptation to new requirements through the implementation of neural network algorithms [7]. The development of corresponding algorithms for the structured analysis of modulation disks is considered a ***priority direction*** in advancing the technology of high-precision optomechanical component fabrication and verification.

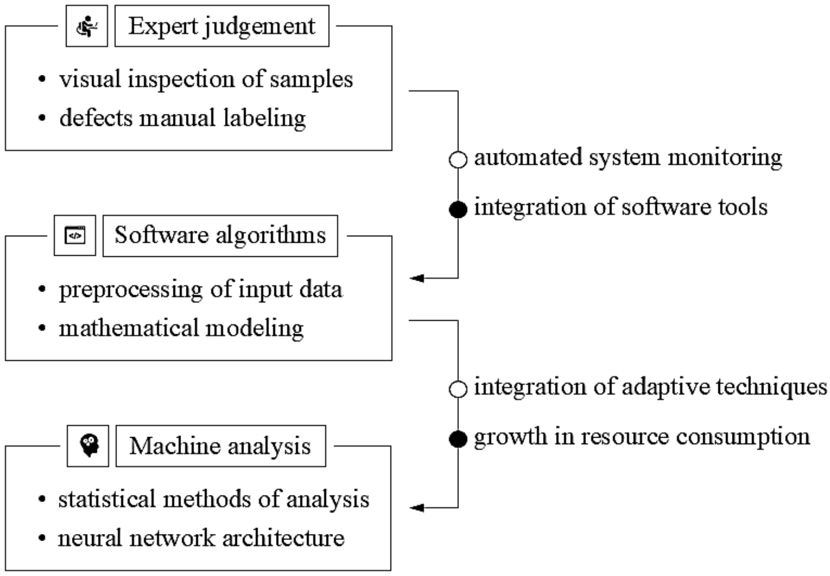


Fig. 1. Evolution of automated inspection tools for code sequences on modulation disks

An analysis of scientific studies devoted to the automation of defect detection in binary structures formed during the photolithographic deposition of code sequences reveals the active development of two principal approaches: classical algorithmic solutions [7–10] and machine learning-based methods [7; 11–14]. The first category focuses primarily on traditional image preprocessing techniques, including filtering, adaptive thresholding, segmentation, and morphological transformations [8–10]. These methods allow for both the restoration of the digital image matrix and the basic detection of structural anomalies. However, such approaches exhibit limited adaptability to changes in illumination, local distortions, and micro-scale defects, which are common in coded patterns produced by photolithographic processes. The second category of research emphasizes the use of neural network architectures, particularly convolutional neural networks (CNNs), autoencoders, and transformer-based models [11–14], which offer superior classification accuracy and enhanced generalization in the presence of incomplete input data and high noise levels. Nevertheless, the implementation of these solutions imposes substantial computational demands, often requiring graphics processing units (GPUs) or tensor accelerators, which complicates their deployment in software systems operating in real-time environments [11–14]. Furthermore, training neural network models necessitates the preparation of large datasets of annotated digital images with labeled defects, which may be infeasible in production settings with a limited number of representative samples. These considerations highlight the need for a comprehensive methodology that combines the efficiency of classical image processing algorithms, the flexibility of machine learning techniques, and the optimization of computational resources. Such an approach should aim to strike a balance between defect detection accuracy, processing speed, and adaptability to real-world industrial operating conditions.

The aim of this study is to develop a mathematically grounded approach for detecting defects in the structure of code sequences on the surface of modulation disks by integrating image preprocessing techniques, morphological analysis, and statistical interpretation of the results. The primary focus is placed on constructing a comprehensive methodology based on thresholding and contour analysis, employing adaptive filters, shape moments, and area distribution approximation of the detected defects. Given the constraints of computational resources and the need for integration with embedded control systems, the study does not explore the broad application of resource-intensive neural network models. Instead, it proposes an efficient software-based algorithmic solution that prioritizes detection accuracy, processing speed, and feasibility for deployment in industrial environments. The proposed model is designed to ensure the identification of local structural anomalies within code sequences, with the potential for future enhancements tailored to the specific characteristics of high-precision optomechanical components.

PROBLEM STATEMENT: DEFECT DETECTION IN THE BINARY STRUCTURE OF A CODE SEQUENCE

The present study addresses the task of automatic defect detection in a binary structure formed on the surface of a modulation disk as a result of photolithographic reproduction of a code sequence. The corresponding structure is composed of a periodic or quasi-periodic set of elements, which are read by optoelectronic sensors with high spatial resolution [4–6]. The occurrence of defects in such structures—such as geometric distortions, fragmented damage, local darkening, or bright artifacts—can lead to positioning errors, signal readout failures, and degradation of the specified level of metrological accuracy.

The defect detection task is formalized as a process of digital image analysis, where the code sequence is represented as a binary mask corresponding to a two-dimensional matrix $\mathbf{BM}(x, y) \in \{0;1\}$, which contains pixel values obtained after thresholding the input data. The input dataset, in turn, is defined as a grayscale image matrix $\mathbf{GI}(x, y) \in [0;255]$. The objective of the software algorithm is to localize and classify regions that potentially deviate from the expected geometry of the binary structure. To achieve this, a sequence of filtering and morphological operations is applied, resulting in a set of contours $\{C_n\}$, where each $n \in [1;N]$ denotes a distinct object in the input image matrix, indicating a possible defect in the binary sequence structure. For each contour C_n, the corresponding area S_n and perimeter P_n are calculated based on the number of points forming the contour. A contour C_n is classified as defective if its geometric parameters fall outside the empirically or calibration-defined thresholds: $S_{\min}$, $S_{\max}$, $P_{\min}$ and $P_{\max}$, which are set according to the objectives of the inspection system (see Fig. 2). Thus, the problem of defect detection in a code sequence structure is reduced to the construction of a computational procedure capable of reliably localizing anomalous regions based on geometric features of contours formed through morphological image processing

The selected approach avoids the use of complex machine learning models by implementing a software algorithm with controllable parameters, which can be adapted to the limited computational resources of the hardware platform within the automated inspection system.

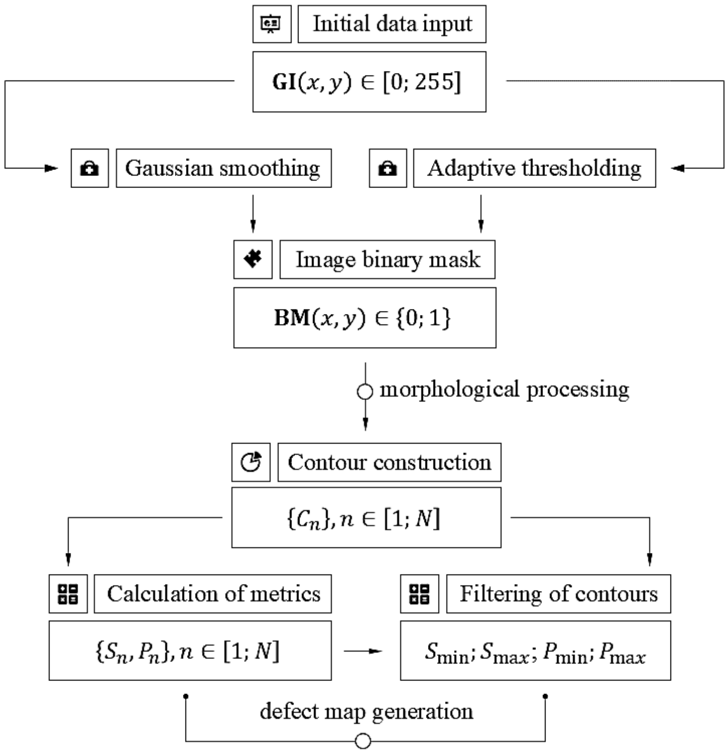


Fig. 2. Algorithmic flowchart for processing the digital image matrix for defect detection

MATHEMATICAL MODEL FOR DEFECT RECOGNITION IN THE CODE SEQUENCE STRUCTURE ON THE SURFACE OF MODULATION DISKS

The formalization of the defect recognition procedure within the code sequence structure on the surface of a modulation disk is based on the development of a mathematical model comprising the stages of digital image preprocessing, morphological filtering, geometric contour analysis, and statistical evaluation of the parameters of the detected objects. The proposed model describes image transformations as a sequence of operations applied to the input image matrix and the resulting binary mask, thereby ensuring algorithmic modularity, reproducibility of results, and adaptability to specific application requirements.

At the first stage, the digital image matrix is converted into grayscale format, which reduces computational costs and enables processing based on the brightness values of each element $GI(x, y) \in [0;255]$. To reduce the negative impact of high-frequency noise and eliminate digital artifacts that may be mistakenly identified as defects, a Gaussian smoothing procedure is applied. The Gaussian smoothing method is based on the convolution of the image matrix with a two-dimensional kernel G, which is mathematically formalized as:

$$GI_G(x, y) = (GI * G)(x, y), \text{ де } G(i, j) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{i^2 + j^2}{2\sigma^2}\right).$$

The parameters of the two-dimensional Gaussian kernel were selected to ensure a balance between background smoothing and the preservation of image components. Following the smoothing stage, adaptive thresholding is applied to convert the image into binary form while accounting for local variations in illumination. Each pixel $GI_G(x, y)$ is mapped to a corresponding value in the binary image $BM(x, y)$ based on the average brightness $\mu_{GI}(x, y)$ within a local neighborhood of size $\Delta x \times \Delta y$, which was set to 11×11 pixels in this study, while the threshold offset parameter $\Delta\mu$ was determined empirically and adjusted using an interactive control element:

$$\begin{cases} BM(x, y) = 1 \text{ при } GI_G(x, y) > \mu_{GI}(x, y) - \Delta\mu, \\ BM(x, y) = 0 \text{ при } GI_G(x, y) \le \mu_{GI}(x, y) - \Delta\mu. \end{cases}$$

In the software implementation, inverse thresholding was applied, meaning that the binary mask is interpreted with reversed polarity and is formalized as $BM(x, y) = 1$ when $GI_G(x, y) < \mu_{GI}(x, y) - \Delta\mu$. As a result of the aforementioned transformations, a binary mask $BM(x, y) \in \{0;1\}$ is obtained, in which potentially defective regions are highlighted as connected components with high contrast relative to the background. This stage is critically important for ensuring the clear formation of contours in the subsequent steps of morphological analysis of the image matrix.

After adaptive thresholding is applied, the binary mask matrix may contain residual noise, small-size artifacts, and structural distortions in the components of visual objects. To improve the quality of defect detection, classical morphological operations are used, allowing for the restoration of object shapes within the binary image matrix and the stabilization of the subsequent contour analysis stage. The fundamental morphological operation in this context is the morphological closing operation (MCO), which is implemented by sequentially performing dilation and erosion procedures on the binary mask matrix. The application of the closing operation to the binary mask $BM(x, y)$ is mathematically formalized as:

$$BM_{MCO}(x, y) = (BM \oplus MK) \ominus MK.$$

where MK is the structural element that defines the shape and size of the morphological window (Morphological Kernel, MK). In the software implementation used in this study, a 5×5 pixel kernel was applied, with all elements set to $MK(x, y) = 1$. The closing operation enables the suppression of digital artifacts that cause internal holes, contour breaks, and distortions in the overall shape of visual objects. This is followed by the application of the morphological opening operation, which is performed in reverse sequence:

$$BM_{MOO}(x, y) = (BM \ominus MK) \oplus MK.$$

The opening operation, in turn, is intended to remove small-size artifacts from the image that do not correspond to actual visual objects, eliminate isolated noise, and preserve the core geometry of larger objects. Thus, the sequential application of closing and opening operations enables the formation of a refined binary mask in which local defects have clearly defined boundaries without internal breaks or extraneous artifacts. This is critically important for the accurate extraction of contours in the subsequent stage. The structural element of the kernel MK plays a key role in the quality of the restored image matrix. The selected rectangular kernel of 5×5 pixels ensures symmetric filtering of digital artifacts and thus enables proper processing of both horizontal and vertical components. If necessary, the shape and size of the structural element can be adapted according to the specific characteristics of the defects.

After the morphological processing of the image, a refined binary mask is formed, reflecting potential regions with structural anomalies. The next step is the contour detection procedure (CDP), which identifies closed sequences of pixels that define the boundaries of connected components. Each contour is treated as a separate object that may correspond to a local defect. For each detected contour $\{C_n\}$, containing $n \in [1; N]$ points, the perimeter P_n and area S_n are calculated, serving as the fundamental geometric features:

$$\left[\begin{array}{l} S_n = \dfrac{1}{2}\left|\sum_{m=1}^{M_n} (x_m\, y_{m+1} - x_{m+1}\, y_m)\right|, \\ P_n = \sum_{m=1}^{M_n} \sqrt{(x_m - x_{m+1})^2 + (y_m - y_{m+1})^2}\,, \end{array}\right.$$

where M_n is the number of points in contour C_n. The contour C_n is classified as containing a defect based on the threshold value pairs $\{S_{\min}; S_{\max}\}$ and $\{P_{\min}; P_{\max}\}$, if at least one of the following conditions is satisfied:

$$\left[\begin{array}{l} S_n < S_{\min}, \\ S_n > S_{\max}, \end{array}\right. \quad \left[\begin{array}{l} P_n < P_{\min}, \\ P_n > P_{\max}. \end{array}\right.$$

Thus, a controllable feature set is formed for each detected defect in the following form:

$$D_n = \{P_n, S_n, X_n, Y_n\},$$

where $\{X_n, Y_n\}$ are the coordinates of the centroid of the corresponding contour C_n. The resulting set $\{D_n\}$ serves as an analytical basis for subsequent visual and statistical analysis. After classifying contours as defective based on geometric criteria, a set of the areas of the detected objects $\{S_n\}$ is formed. To analyze the statistical characteristics of the distribution, the mean area $\overline{S}_n$ and the standard deviation σ_S are estimated as follows:

$$\left[\begin{array}{l} \overline{S}_n = \dfrac{1}{N}\sum_{n=1}^{N} S_n\,, \\ \sigma_S = \sqrt{\dfrac{1}{N}\sum_{n=1}^{N} (S_n - \overline{S}_n)^2}\,. \end{array}\right.$$

The corresponding parameters make it possible to quantitatively characterize the variability of the geometric properties of the defects and to identify the presence of anomalous objects whose areas significantly deviate from the mean level. To visualize the statistical distribution, a histogram of defect areas is constructed and supplemented by a normal distribution approximation. In this case, the probability density is modeled by the function:

$$f_S = \frac{1}{\sqrt{2\pi}\,\sigma_S} e^{-\frac{(S_n - \overline{S}_n)}{2\sigma_S^2}}\,.$$

The parameters $\overline{S}_n$ and σ_S are considered maximum likelihood estimates (MLE) for the normal distribution. The proximity of the empirical distribution toa normal profile serves as an indicator of the homogeneity of the detected defect class. Deviations from the normal distribution may indicate the presence of foreign objects or structural inhomogeneities.

SOFTWARE-BASED DEFECT RECOGNITION IN THE CODE SEQUENCE STRUCTURE ON THE SURFACE OF MODULATION DISKS

To validate the functionality and effectiveness of the proposed approach, a software implementation of the defect identification algorithm for the code sequence structure of a modulation disk was developed. The corresponding software module integrates stages of preprocessing, morphological filtering, contour analysis, defect classification, and statistical evaluation of defect parameters. The user interface provides interactive tools for adjusting thresholding and classification parameters and enables visualization of processing results, including graphical representation of detected defects, histogram construction of defect areas, and tabular output of coordinates and numerical characteristics.

The defect identification algorithm was implemented as a modular Python application with a graphical user interface. The system architecture is based on the principles of separating image processing logic, parameter control, result visualization, and data export to external formats. This structure ensures flexibility, scalability, and ease of modification for individual stages of the algorithm. The software algorithm consists of three key components:

1. The graphical data processing module is responsible for the step-by-step transformation of the input image matrix, including Gaussian smoothing, adaptive thresholding, morphological filtering, contour detection, and the calculation of geometric and statistical parameters of the detected objects. The core element is the “ImageProcessor” class, which implements the main logic for binary mask analysis and the formation of the defect feature set.

2. The Graphical User Interface (GUI) is implemented using the “Tkinter” library. This component enables image loading, interactive adjustment of the adaptive thresholding value, visualization mode switching, display of analysis results, and result saving. The interface is divided into functional panels: the control panel, the visualization area, and the text fields for statistics and coordinates.

3. The result-saving mechanism enables the export of detected defects in graphical PNG and tabular CSV formats. The defect mask, annotated image with highlighted objects, and centroid coordinates can be saved as separate files for further use in technical inspection systems or external analysis.

To implement the aforementioned functions, the following external libraries were used: “OpenCV” for image loading, preprocessing, morphological operations, contour detection, and calculation of geometric parameters; “NumPy” for vectorized data processing and basic statistical computations; “Matplotlib” for generating histograms and visualizing the area distribution of detected defects; “Pandas” for constructing tabular structures and exporting results in CSV format; and “Scipy.stats” for approximating the area distribution using a normal distribution curve. The architectural design is based on a clearly structured separation of component functions, enabling both local testing of individual modules and integration of the system into a broader software environment for technical inspection and machine-based analysis.

The defect detection algorithm is implemented using the methods of the "ImageProcessor" class and automated through interaction with the graphical user interface elements. The system's operational logic involves the sequential execution of the following stages:

- loading the grayscale image matrix, which reduces computational complexity by excluding color components;
- Gaussian smoothing with a fixed kernel to reduce noise levels and prepare the image for thresholding;
- adaptive thresholding using a local mean, with an adjustable offset parameter controlled via a slider;
- morphological filtering, including a closing operation to eliminate internal breaks and an opening operation to remove noise;
- contour analysis to determine the geometric characteristics of connected components (perimeter and area) and evaluate their compliance with predefined threshold criteria;
- classification of contours as defects based on whether their area or perimeter exceeds or falls below the specified threshold values.

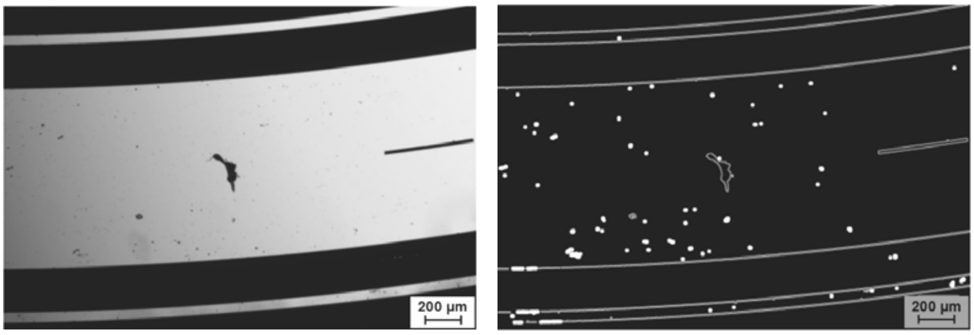
The interface allows the user to modify key processing parameters in real time, such as the threshold offset for adaptive image binarization, the minimum perimeter value for classifying an object as defective, and a visualization mode toggle that enables or disables the overlay of circles on the centroids of detected defects. These parameters make it possible to adapt the algorithm's sensitivity to various lighting conditions, image scales, and defect types.

To evaluate the accuracy of the core functionalities performed by the modular Python application, verification was carried out using real microphotographs of modulation disk surfaces. The processing results demonstrate the system's ability to effectively detect defects originating from the photolithographic process by isolating anomalous regions based on geometric and statistical criteria. Figs. 3–5 present the processing outcomes for microimages of code sequence samples "1", "2", and "3", respectively, showing the original grayscale microimage, the binary mask with overlaid contours (green contours indicate objects without defect features, while white circular markers denote objects classified as defective), as well as the histogram of detected defect areas with an overlaid normal distribution curve and corresponding statistical data:

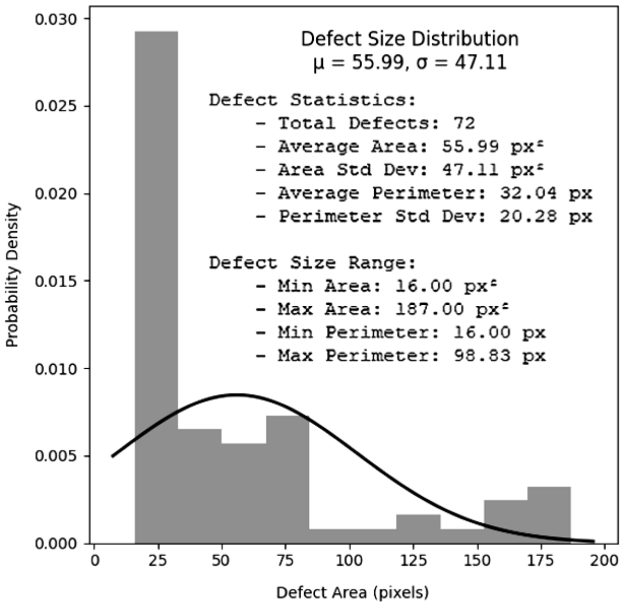
- total number of detected defects;
- average defect area;
- average defect perimeter;
- range of defect areas;
- range of defect perimeters.

The histograms constructed based on defect areas characterize the structure of the sample and visualize its variability. To approximate the empirical distribution, a normal distribution model was applied using the parameters of mean defect area and standard deviation. The obtained parameters represent maximum likelihood estimates and reflect a distribution skewed toward lower values, which is typical for defects associated with microcracks, scratches, and contamination particles. It should be noted that statistical indicators provide insight not only into the number but also the nature of the defects. For instance, a high standard deviation indicates significant variability in defect sizes, which may suggest inconsistency in the technological process. Additionally, the coordinates of defect centroids can be used for targeted adjustment of the photolithography system and for initiating subsequent stages of detailed inspection.

Fig. 3 presents the results of applying the algorithm to code sequence sample "1", demonstrating the system's capability to effectively localize both isolated anomalies and small-scale digital artifacts, thereby enabling a comprehensive assessment of the processed surface condition.



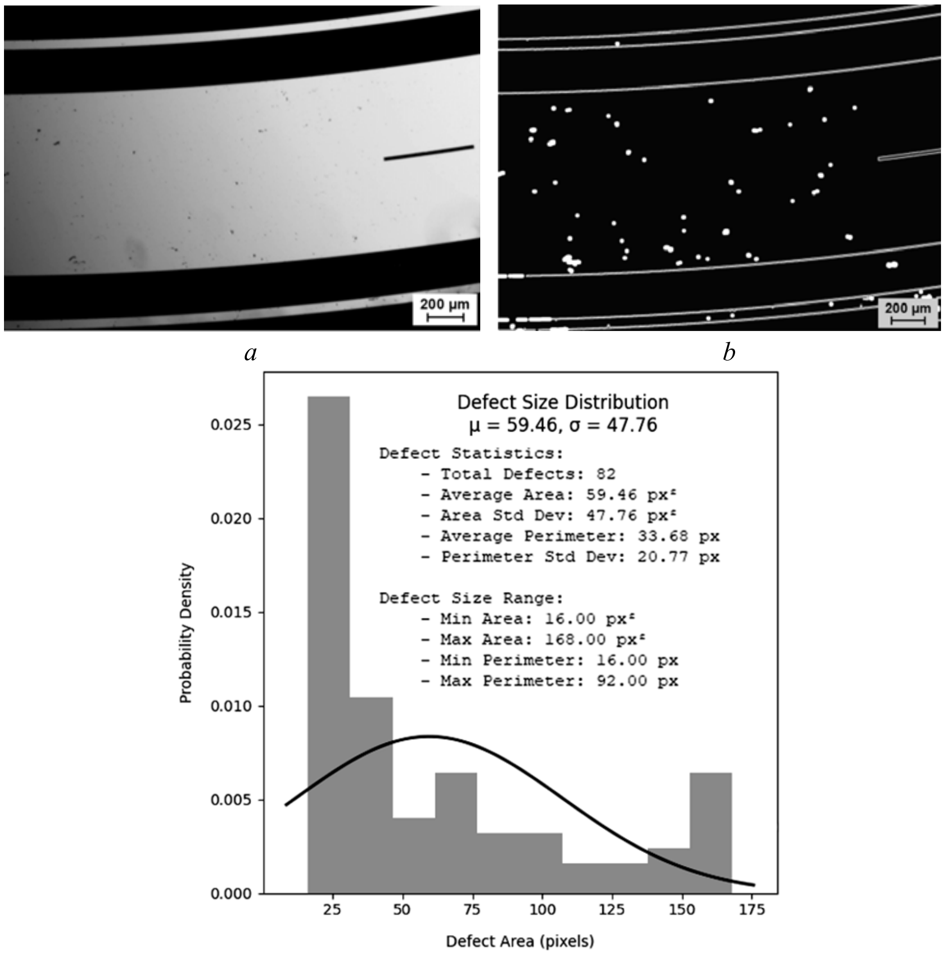
a *b*



c

Fig. 3. Processing results for code sequence sample "1": *a* — original grayscale microimage; *b* — binary mask with overlaid contours; *c* — histogram of detected defect area distribution

Fig. 4 shows the analysis results for code sequence sample "2", indicating a higher total number of defects but with a lower maximum area and less pronounced dominance of a single large defect. This suggests a different nature of structural disturbance in the binary code sequence compared to sample "1", potentially associated with dust or contamination deposition processes or exposure instability in certain regions.



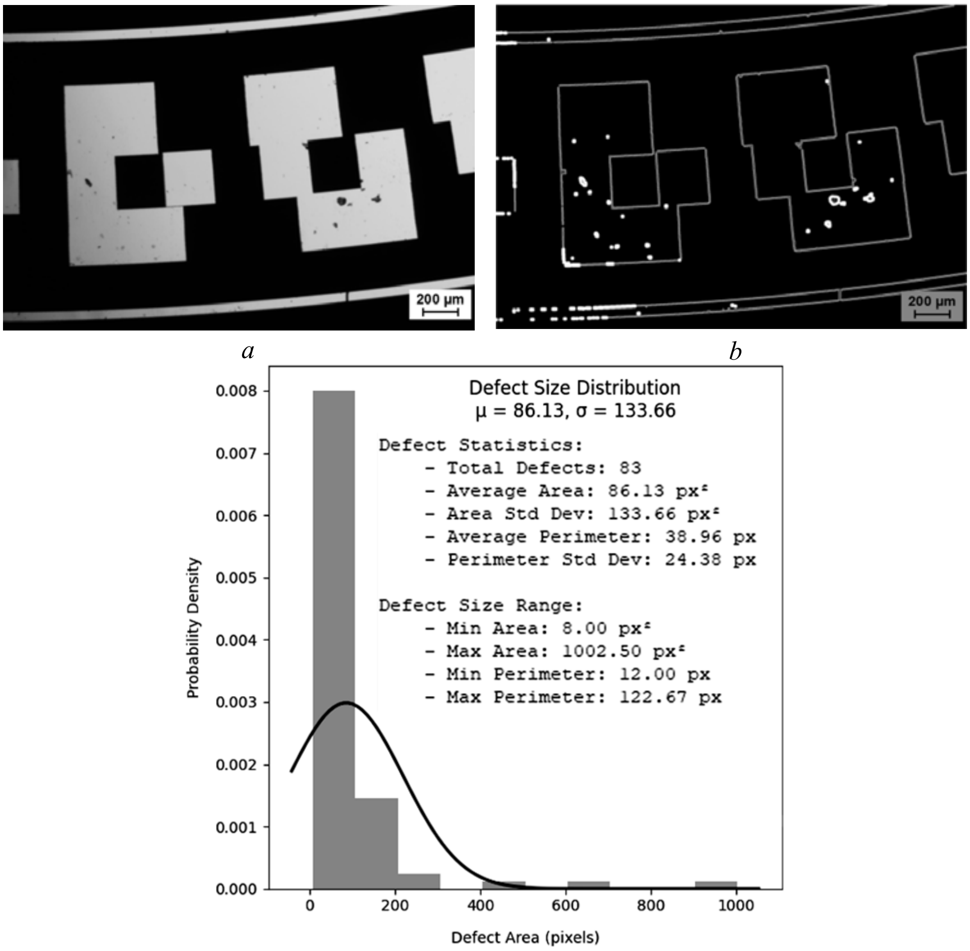
a *b*

c

Fig. 4. Processing results for code sequence sample “2”: *a* — original grayscale microimage; *b* — binary mask with overlaid contours; *c* — histogram of detected defect area distribution

Fig. 5 presents the processing results for code sequence sample “3”, which contains high-contrast geometric structures and noticeable foreign inclusions. Sample “3” is characterized by greater area dispersion and the presence of pronounced macro-scale defects. This is confirmed by both the numerical characteristics and the shape of the histogram, where the normal distribution curve exhibits strong asymmetry. Such results indicate localized disruptions during fabrication or damage incurred during operation.

The presented results confirm the stability and consistency of the algorithm’s performance under varying input conditions, such as defect geometry, image contrast, and noise variability. Thus, the proposed approach demonstrates high sensitivity to local structural anomalies while maintaining robustness against background artifacts and digital noise. The analysis of defect area distribution histograms shows that the system can adapt to changes in the nature of damage and maintain the reliability of statistical evaluation even in cases of asymmetric or anomalous distributions. As part of future improvements, it is planned to extend the algorithm by integrating machine learning classifiers for automatic defect type identification, incorporating spatial context in the analysis of centroid distribution, and optimizing processing procedures for implementation on computational modules of embedded machine analysis systems operating in real time.



a *b*

c

Fig. 5. Processing results for code sequence sample “3”: *a* — original grayscale microimage; *b* — binary mask with overlaid contours; *c* — histogram of detected defect area distribution

CONCLUSIONS

The article presents a comprehensive methodology for the automatic detection of defects in the binary structure of a code sequence on the surface of modulation disks, combining image preprocessing methods, morphological analysis, and statistical evaluation of the geometric characteristics of objects. A mathematical model is proposed that describes the stages of smoothing, adaptive thresholding, filtering, and contour detection, followed by classification based on area and perimeter. The developed software module provides a complete processing cycle of the input image: from conversion into a binary mask to the visualization of detected defects and construction of histograms with normal distribution approximation. The modular system architecture and the presence of a user interface that allows adjustment of key parameters enable the adaptation of the program to variations in image quality, scale, and the nature of defects. Experimental verification on samples of binary code sequences of modulation disks demonstrated the algorithm's ability to detect both microdefects and local structural anomalies of considerable area. The stability of results under varying processing parameters confirms the algorithm's adaptability and its suitability for implementation in technical diagnostic systems under constrained computational resources. Further extension of the software functionality is possible through the use of machine learning classifiers, application of spatial contextual analysis, and integration with real-time hardware platforms to enable autonomous monitoring.

Conflicts of interest. There are no conflicts to declare.

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РОЗРОБЛЕННЯ АЛГОРИТМІВ РОЗПІЗНАВАННЯ ДЕФЕКТІВ У СТРУКТУРІ КОДОВОЇ ПОСЛІДОВНОСТІ НА ПОВЕРХНІ МОДУЛЯЦІЙНИХ ДИСКІВ / Д.Ю. Манько, Є.В. Беляк, А.А. Крючин, Р.М. Іщенко, В.В. Заварзіна

Анотація. Дослідження присвячено алгоритмам виявлення та локалізації дефектів у структурах кодової послідовності на поверхнях модуляційних дисків. Воно спрямоване на невеликі аномалії в літографічно структурованих елементах, які можуть спричинити помилки зчитування або зниження точності вимірювання. Багаторівнева модель оброблення зображень поєднує гауссове згладжування, адаптивне порогове визначення, морфологічні операції та сегментацію на основі контурів. Етапи оброблення формалізовано як математичні оператори для відтворюваної реалізації. Дефекти характеризуються за допомогою метрик на основі периметра та площі, а їх розподіл за площею апроксимується нормальним законом. Просторова модель обчислює центроїди дефектів, що дає змогу виконувати порівняльне оцінювання якості зразків дисків. Програмне забезпечення надає інтерфейс для налаштування порогів, візуалізації контурів та графіків площ дефектів, а також експорту результатів. Тести на реальних дефектних дисках підтверджують надійне виявлення локальних структурних порушень та придатність методу для діагностичних систем.

Ключові слова: модуляційні диски, автоматизований контроль, кодова послідовність, порушення мікроструктури, попереднє оброблення зображень, морфологічний аналіз, контурна сегментація.