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ALGORITHM OF OPTICAL MONITORING FOR REAL-TIME EVALUATION OF GRAIN FRACTIONATION EFFICIENCY BASED ON THE STRUCTURAL CHARACTERISTICS OF THE FLOW

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The problem of improving the efficiency of quality control in grain fractionation processes within post-harvest grain handling is addressed. It has been established that conventional methods for evaluating the quality of obtained fractions, which rely on laboratory sample analysis, are labor-intensive, time-delayed, and incapable of providing real-time monitoring of the technological process. This necessitates the development of new approaches based on modern digital technologies.

An algorithm for optical quality control of the grain fractionation process is proposed, based on the application of computer vision techniques and analysis of the grain flow structure. The algorithm includes the formation of a stable optical scene, acquisition of digital images of the grain flow, their preprocessing, grain kernel segmentation, extraction of geometric and optical features, classification of objects into fractions, and subsequent statistical analysis of the obtained data.

A distinctive feature of the proposed approach is the use of structural characteristics of the grain flow to evaluate the efficiency of the fractionation process. Based on the determination of the quantitative and qualitative composition of fractions, integral indicators are introduced to characterize fraction purity, impurity content, and the degree of material separation. This enables an objective assessment of process quality directly during operation.

The developed algorithm enables the implementation of an automated monitoring and control system for grain fractionation. The use of feedback based on optical analysis results allows for real-time adjustment of equipment operating parameters, including the feed rate of grain material and separation settings, thereby improving process efficiency and reducing losses. The proposed approach provides a foundation for the development of intelligent quality control systems and digital twins of post-harvest grain processing operations.

Keywords: *optical monitoring, computer vision, grain fractionation, grain quality, flow structure, classification, automation, post-harvest processing.*

Eq. 3 Fig. 4. Ref. 21.

1. Problem formulation

Ensuring food security in Ukraine under current conditions remains one of the key challenges for the agro-industrial sector, particularly in view of the need to improve the efficiency of utilizing harvested grain. A significant share of agricultural product losses occurs during post-harvest processing stages, among which grain fractionation plays a crucial role. The quality of this process directly affects the commercial characteristics of grain, its grading, suitability for storage, and further processing [1-3].

Grain fractionation is a complex technological process aimed at separating the grain mass into individual fractions based on size, aerodynamic, and other physico mechanical properties [4, 5]. The efficiency of this process is determined by indicators such as the purity of the obtained fractions, impurity content, uniformity of grain size distribution, and minimization of losses of the target product. Insufficient fractionation efficiency leads to reduced grain quality, increased energy consumption for subsequent processing, and higher product losses [6].

Existing methods for monitoring fractionation quality are typically based on periodic sampling followed by laboratory analysis. Such approaches are characterized by high labor intensity, delays in obtaining

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results, and the inability to promptly influence the technological process [7-9]. Moreover, they do not account for the dynamic nature of the grain flow and the variation of its parameters in real time.

In this context, the development of non-destructive, continuous, and real-time methods for monitoring the quality of grain fractionation processes becomes particularly relevant [10]. The application of computer vision technologies and digital image processing opens up new opportunities for analyzing the structure of the grain flow directly during its motion [11]. However, existing approaches are primarily focused on the identification of individual kernels or the determination of their characteristics and insufficiently account for the relationship between flow structure and the efficiency of the technological process.

Thus, a scientific and practical task arises to develop an optical monitoring algorithm capable of evaluating the efficiency of grain fractionation in real time based on the analysis of the grain flow structure, while also enabling automated control of process operating parameters.

2. Analysis of recent research and publications

In modern scientific research, considerable attention is paid to the application of computer vision and machine learning technologies for solving problems related to grain quality control and the optimization of technological processes in agriculture. Computer vision is regarded as an effective tool for automated image analysis, enabling the acquisition of objective information on the morphological, geometric, and color characteristics of grain in a non-contact and non-destructive manner [12, 13].

In studies devoted to the classification of grain materials, a typical pipeline has been established, including image acquisition, object segmentation, feature extraction, and subsequent classification. A review of current research indicates that both classical pattern recognition methods (such as SVM and k-NN) and modern deep learning approaches - particularly convolutional neural networks (CNNs) - are widely used, demonstrating high accuracy and robustness to variations in imaging conditions [14-16]. Various types of imagery are employed, ranging from standard RGB images to multispectral and hyperspectral data, which significantly expand the range of detectable grain characteristics.

Systematic reviews indicate that computer vision technologies are already widely applied in precision agriculture for tasks such as crop classification, defect detection, product quality assessment, and monitoring of production processes [17]. In particular, it has been established that the integration of artificial intelligence algorithms with high-performance computing resources (e.g., GPUs) enables the development of high-speed real-time analysis systems.

A distinct research direction is associated with the application of deep neural networks for phenotyping and analysis of grain crops, where computer vision is used to determine growth parameters, quality attributes, and grain condition. Such approaches allow for the automation of large-scale data acquisition and significantly improve evaluation accuracy [18-19]. At the same time, a number of studies highlight the limitations of existing methods, which are primarily focused on the analysis of individual kernels or small sample sets, thereby complicating their application in high-throughput continuous-flow processes.

Studies in the field of automated grain quality control also demonstrate the high efficiency of machine learning methods for classifying grain based on morphometric and color features, achieving accuracy levels exceeding 90% in tasks involving the recognition of different grain types [20, 21].

At the same time, it is emphasized that conventional monitoring systems are predominantly based on the analysis of static images or discrete samples, which limits their applicability for continuous monitoring of technological processes.

Thus, the conducted analysis indicates that, despite the significant advancement of computer vision and machine learning methods for assessing the quality of grain materials, there remains an insufficient number of studies focused on analyzing the structure of grain flow and evaluating the efficiency of fractionation processes in real time. This necessitates the development of new algorithmic approaches that integrate image processing techniques with the analysis of process parameters, enabling real-time control of grain fractionation quality.

3. The purpose of the article

The objective of this study is to develop an optical quality control algorithm for the grain fractionation process that enables real-time evaluation of the separation efficiency of the grain flow based on the analysis of its structural characteristics.

4. Results and discussion

To achieve the stated objective, the following key scientific and applied tasks must be addressed: to substantiate an approach for forming an informative optical scene that ensures the acquisition of stable and high-quality images of the grain flow; to develop an image preprocessing algorithm aimed at noise reduction, illumination normalization, and enhancement of object contrast; to implement effective segmentation methods for isolating individual kernels within the flow, taking into account possible partial overlap and non-uniform imaging conditions; to construct a system of informative features describing geometric, morphological, and optical parameters of the kernels; to develop a classification algorithm for assigning objects to fractions based on the extracted features using machine learning methods; to propose an approach for statistical analysis of the grain flow structure that enables the determination of quantitative and qualitative characteristics of individual fractions; to establish a system of indicators for evaluating fractionation efficiency, including fraction purity, impurity content, degree of separation, and losses of the target product; and to ensure the possibility of generating control actions for the technological process based on optical monitoring results.

The implementation of these tasks will provide a foundation for the development of automated monitoring and control systems for grain fractionation processes, aimed at improving efficiency, reducing product losses, and ensuring stable quality of the obtained fractions.

The real-time grain fractionation efficiency evaluation system consists of an illumination module, a high-speed camera, and a computational unit. A key challenge is image stabilization under conditions of high dust concentration and vibration.

The proposed optical quality control algorithm for the grain fractionation process is based on the analysis of the grain flow structure and involves a stepwise processing of digital images aimed at determining quantitative and qualitative characteristics of fractions in real time. In general, the algorithm comprises nine interconnected stages: 1) formation of the optical scene; 2) acquisition of digital images; 3) image preprocessing; 4) grain segmentation; 5) feature extraction; 6) object classification; 7) statistical analysis of the flow; 8) evaluation of fractionation quality; and 9) generation of the control signal (Fig. 1).

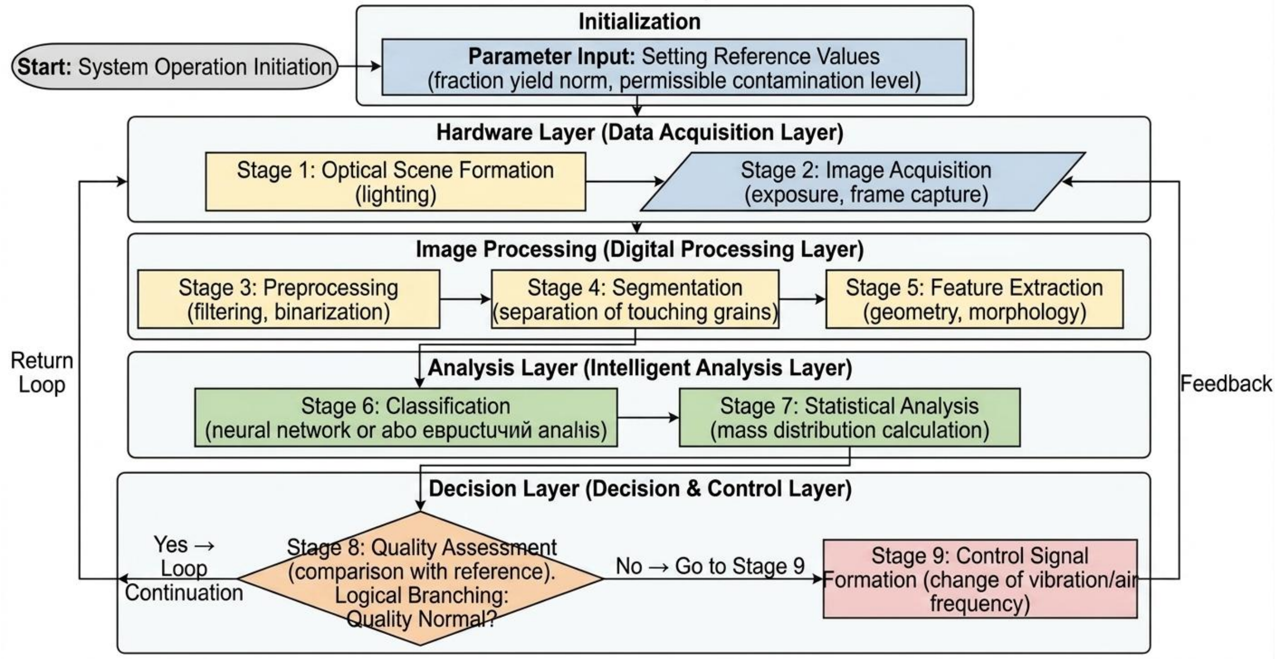

Fig.1. Flowchart of the algorithm for optical quality control of the grain fractionation process

At the first stage, an optical scene is established to ensure stable and controlled conditions for image acquisition. The key requirements include uniform illumination, elimination of glare, a high-contrast background, and a monolayer flow of grain material. Such conditions significantly improve the reliability of subsequent image analysis by reducing systematic and random errors already at the acquisition stage.

The second stage involves capturing a digital image of the grain flow using an industrial camera. The main parameters - resolution, frame rate, and exposure time - must be carefully synchronized with the movement speed of the grain to prevent motion blur and object duplication. Proper configuration at this stage directly determines the accuracy of all further processing and classification procedures.

During the preprocessing stage, the image is prepared for further analysis. To reduce noise and improve image quality, smoothing is applied using a Gaussian filter [4]:

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

where (x, y) are the pixel coordinates; (x_c, y_c) are the coordinates of the filter window center; σ is the standard deviation that defines the degree of blurring (the larger the value, the stronger the smoothing effect).

Additionally, contrast enhancement techniques may be used to improve the visibility of individual grain particles and their boundaries, which facilitates more accurate segmentation in subsequent steps.

Median filtering is also applied, which effectively removes impulsive noise. In addition, illumination normalization and contrast enhancement are performed to ensure clear delineation of grain boundaries. These procedures help stabilize image characteristics under varying acquisition conditions and improve the robustness of subsequent feature extraction.

Image segmentation is carried out through binarization using either a global or adaptive threshold. The Otsu method allows automatic determination of the optimal threshold value by minimizing intra-class variance. This approach is particularly effective for images with bimodal intensity distributions, where foreground and background are well separated:

$$\sigma_W^2(t)=q_1(t)\sigma_1^2(t)+q_2(t)\sigma_2^2(t) \quad (2)$$

where q_1 and q_2 are the probabilities of the two classes separated by the threshold t; σ_1^2 and σ_2^2 are the variances of these classes.

This formulation ensures that the optimal threshold maximizes the separability between foreground and background regions. In practical applications, it provides a robust and computationally efficient way to perform segmentation even in the presence of moderate noise.

After binarization, morphological operations are applied to remove noise and restore the shapes of objects, as well as edge detection algorithms (in particular, the Canny method), which ensure precise localization of grain boundaries. These procedures improve the structural integrity of segmented objects and reduce the influence of artifacts caused by imperfect thresholding.

At the feature extraction stage, each grain is characterized by its geometric (area, length, width), morphological (compactness, elongation), and optical (intensity, color) properties. The use of a scale factor enables conversion from pixel-based measurements to real-world physical dimensions. This provides the basis for quantitative analysis of grain quality and further classification or sorting tasks.

Object classification is performed using machine learning methods, in particular convolutional neural networks (CNN), which enable automatic extraction of informative features and ensure high recognition accuracy. As a result, each grain is assigned to a corresponding fraction or classified as an impurity. These models are capable of capturing complex nonlinear relationships between visual features, which significantly improves classification robustness under variable operating conditions.

Based on the classification results, a statistical description of the grain flow is generated, including the number of objects in each fraction, their percentage composition, mean parameter values, and variance. Such aggregated information provides a comprehensive assessment of the material quality and allows monitoring of technological process stability. The generalized indicator for the *j*-th fraction is defined as:

$$P^j=\frac{\sum_{i=0}^{Nj}p_{i,j}}{\sum_{j=0}^{J}\sum_{i=0}^{Nj}p_{i,j}}, \quad (3)$$

where P^j is the indicator characterizing a specific property of the j-th class of objects in the grain material sample; $p_{i,j}$ is the indicator characterizing a specific property of the i-th object belonging to the j-th class of the grain material sample; Nj is the number of objects in the j-th class of the grain material sample; J is the total number of classes of objects in the grain material sample.

This formulation allows aggregation of individual object-level measurements into class-level descriptors, which is essential for robust statistical evaluation of grain quality. In practical applications, it also supports comparative analysis between different fractions and improves interpretability of classification results (Fig. 2).

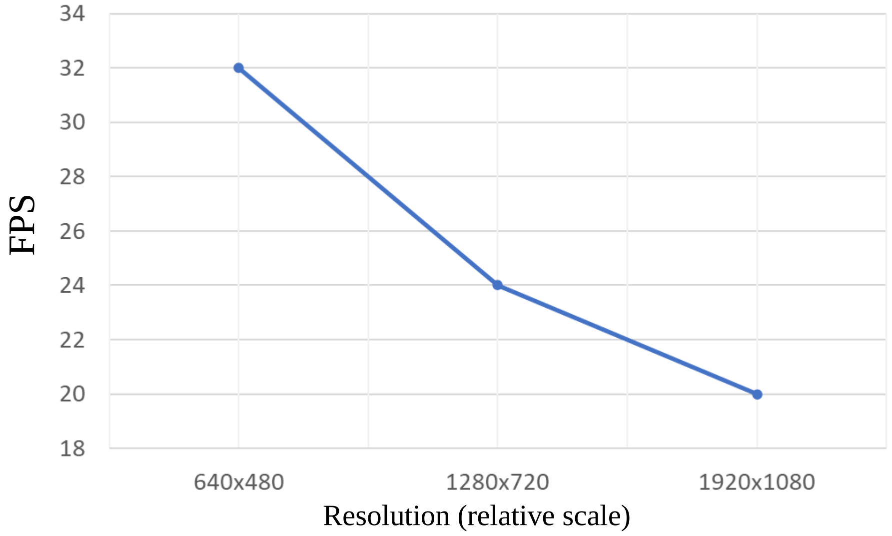

Fig. 2. Dependence of system performance (FPS) on resolution

A key stage of the algorithm is the evaluation of the fractionation process quality. For this purpose, integral indicators are introduced that characterize fraction purity, impurity content, and the degree of separation. In particular, the fraction purity coefficient is defined as the ratio of the number of target grains to the total number of objects in the fraction, while the impurity coefficient represents the proportion of foreign inclusions. These indicators provide a quantitative basis for assessing the efficiency and stability of the separation process under different operating conditions.

At the final stage, a control signal is generated for regulating the technological process. Based on the obtained indicators, adjustments are made to equipment operating parameters such as grain feed rate, layer thickness, or separation modes. This enables the implementation of a closed-loop control system and increases the overall efficiency and adaptability of the fractionation process in real time.

To implement such an algorithm, it is most effective to use an object-oriented approach. Below is a code structure based on the OpenCV and PySide/Tkinter libraries (Fig. 3). Each method of the class corresponds to a specific stage of the algorithm’s block diagram. This modular design improves code readability, simplifies maintenance, and allows flexible extension of individual processing stages without affecting the overall system architecture.

The developed algorithm was tested on two types of input scenes (Fig. 4): a grain mass of maize on a dark (a) and a light (b) background. It was found that the use of adaptive binarization (Otsu’s method) makes it possible to reduce the segmentation error on a light background to 2,1%, compared to 1,5% on a dark background. This confirms the robustness of the approach under varying illumination and contrast conditions.

In addition, the presence of touching grains in both scenes required the implementation of the Watershed algorithm to ensure accurate estimation of the number and area of each individual object. This approach significantly improves object separation in dense flows and enhances the reliability of quantitative measurements.

```
import cv2
import numpy as np
import time

class GrainQualityControlSystem:
    def __init__(self): # 1. Initialization block
        self.reference_values = {"purity": 0.95, "target_fraction": 0.85}
        self.is_running = False
        self.camera = None

    def setup_hardware(self): # Stage 1 & 2: Camera and lighting setup
        self.camera = cv2.VideoCapture(0)
        self.camera.set(cv2.CAP_PROP_EXPOSURE, -5) # Мінімізація розмиття
        print("Hardware Layer: Camera and Lighting initialized.")

    def preprocess(self, frame): # Stage 3: Pre-processing
        gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
        blurred = cv2.GaussianBlur(gray, (5, 5), 0)
        _, thresh = cv2.threshold(blurred, 0, 255, cv2.THRESH_BINARY + cv2.THRESH_OTSU)
        return thresh

    def segment_grains(self, binary_img): # Stage 4: Segmentation
        dist_transform = cv2.distanceTransform(binary_img, cv2.DIST_L2, 5)
        _, last_fg = cv2.threshold(dist_transform, 0.7 * dist_transform.max(), 255, 0)
        return last_fg

    def extract_features(self, segmented_img): # Stage 5: Feature extraction
        contours, _ = cv2.findContours(segmented_img.astype(np.uint8), cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
        features = []
        for cnt in contours:
            area = cv2.contourArea(cnt)
            if area > 100: # Фільтр шуму
                features.append(area)
        return features

    def classify_and_analyze(self, features): # Stage 6 & 7: Classification and Statistics
        total_count = len(features)
        if total_count == 0: return 0
        main_fraction = [f for f in features if 200 < f < 500]
        efficiency = len(main_fraction) / total_count
        return efficiency

    def decision_layer(self, current_efficiency): # Stage 8 & 9: Evaluation and Management
        if current_efficiency < self.reference_values["target_fraction"]:
            self.send_control_signal("INCREASE_VIBRATION")
        else:
            print("Quality OK")

    def send_control_signal(self, signal):
        # Реалізація протоколу (UART/Modbus/MQTT)
        print(f"CONTROL SIGNAL SENT: {signal}")

    def run(self):
        self.setup_hardware()
        self.is_running = True

        while self.is_running:
            ret, frame = self.camera.read()
            if not ret: break
            # Sequential execution of stages
            processed = self.preprocess(frame)
            segmented = self.segment_grains(processed)
            features = self.extract_features(segmented)
            efficiency = self.classify_and_analyze(features)
            self.decision_layer(efficiency)

        self.camera.release()
        cv2.destroyAllWindows()

# System startup
if __name__ == "__main__":
    system = GrainQualityControlSystem()
    system.run()
```

Fig. 3. Structure of the program code in the Python language

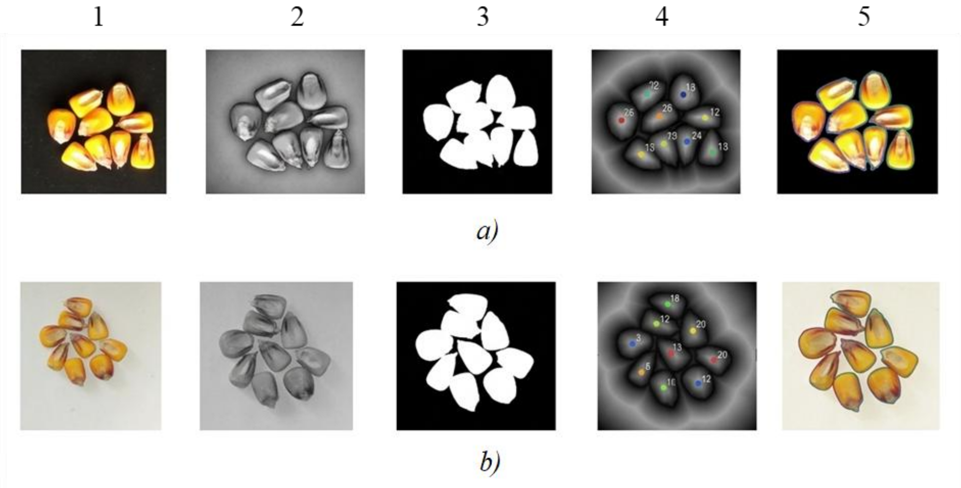

Fig.4. Stages of segmentation of touching maize grains on dark (a) and light (b) backgrounds using the WaterShed method: 1 – input image; 2 – preprocessing; 3 – thresholding; 4 – localization stage; 5 – contour detection

The localization stage image demonstrates the local maxima of the distance map. Each such maximum serves as a unique identifier (seed) for an individual grain. These markers are critically important for initializing the Watershed algorithm, as they define the object centers from which boundaries propagate, enabling accurate separation of touching grains.

This approach significantly reduces over-segmentation and improves the stability of object detection in dense grain flows. As a result, it ensures more reliable estimation of both the number and geometric parameters of individual grains.

Thus, the proposed algorithm provides a comprehensive analysis of the grain flow, enables real-time evaluation of the fractionation process quality, and establishes a foundation for the development of intelligent automated control systems in post-harvest grain processing.

Overall, the integration of computer vision and machine learning techniques enhances process transparency, improves decision-making accuracy, and contributes to increased efficiency and consistency of grain processing operations.

5. Conclusion

Based on the analysis of global experience in digital object identification, it has been established that the most effective approach for analyzing dense flows of grain materials is a combination of Otsu thresholding and Watershed-based morphological segmentation. This combination ensures reliable separation of touching objects and provides segmentation accuracy at the level of 97,9 - 98,5%, depending on background conditions. As a result, a solid theoretical foundation for the development of an adaptive control algorithm has been formed.

An optical control algorithm has been developed that covers the full data processing cycle: from optical scene formation to the generation of control signals for separator actuators. A key feature of the algorithm is the use of local maxima labeling of the distance transform, which ensures accurate separation of touching maize grains and reduces fraction counting error to below 2,0%. In particular, the segmentation error was experimentally determined to be 1,5% for dark backgrounds and 2,1% for light backgrounds, confirming the robustness of the proposed approach.

Experimental validation of the algorithm on maize grain images with different background conditions confirmed its operability and efficiency. It was found that the proposed sequence of digital processing enables real-time evaluation of fractionation efficiency with a processing speed of up to 20 - 30 frames per second, depending on hardware configuration. The coefficient of fraction purity can be determined with an accuracy of ±1,5%, while impurity detection reliability exceeds 96%.

The implementation of the developed algorithm provides a basis for creating closed-loop automated control systems for post-harvest grain processing. The use of real-time feedback allows dynamic adjustment of technological parameters (feed rate, layer thickness, separation режимs), leading to an overall increase in fractionation efficiency by 10 - 15% and a reduction in grain losses by up to 8 -12%.

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АЛГОРИТМ ОПТИЧНОГО МОНІТОРИНГУ ДЛЯ ОЦІНЮВАННЯ В РЕАЛЬНОМУ ЧАСІ ЕФЕКТИВНОСТІ ФРАКЦІОНУВАННЯ ЗЕРНА НА ОСНОВІ СТРУКТУРНИХ ХАРАКТЕРИСТИК ПОТОКУ

Розглянуто проблему підвищення ефективності контролю якості в процесах фракціонування зерна. Встановлено, що традиційні методи оцінювання якості отриманих фракцій, які базуються на лабораторному аналізі проб, є трудомісткими, мають значну часову затримку та не забезпечують можливості оперативного (реального часу) контролю технологічного процесу. Це зумовлює необхідність розроблення нових підходів, заснованих на сучасних цифрових технологіях.

Запропоновано алгоритм оптичного контролю якості процесу фракціонування зерна, що базується на застосуванні методів комп'ютерного зору та аналізі структури зернового потоку. Алгоритм включає формування стабільної оптичної сцени, отримання цифрових зображень зернового потоку, їх попередню обробку, сегментацію зернівок, виділення геометричних та оптичних ознак, класифікацію об'єктів за фракціями, а також подальший статистичний аналіз отриманих даних.

Відмінною особливістю запропонованого підходу є використання структурних характеристик зернового потоку для оцінювання ефективності процесу фракціонування. На основі визначення кількісного та якісного складу фракцій введено інтегральні показники, що характеризують чистоту фракцій, вміст домішок та ступінь розділення матеріалу. Це дає змогу здійснювати об'єктивну оцінку якості процесу безпосередньо під час його виконання.

Розроблений алгоритм забезпечує реалізацію автоматизованої системи моніторингу та керування процесом фракціонування зерна. Використання зворотного зв'язку на основі результатів оптичного аналізу дозволяє в реальному часі коригувати параметри роботи обладнання, зокрема швидкість подачі зернового матеріалу та налаштування сепарації, що підвищує ефективність процесу та зменшує втрати. Запропонований підхід формує основу для створення інтелектуальних систем контролю якості та цифрових двійників технологічних процесів післязбиральної обробки зерна.

Слід зазначити, що впровадження такого підходу дозволяє суттєво скоротити час прийняття технологічних рішень і підвищити стабільність роботи обладнання в умовах змінних навантажень. Це особливо важливо для високопродуктивних зернопереробних ліній, де навіть незначні відхилення можуть призводити до втрат якості продукції.

Ключові слова: *оптичний моніторинг, комп'ютерний зір, фракціонування зерна, якість зерна, структура потоку, класифікація, автоматизація, післязбиральна обробка.*

Ф. 3 Рис. 4. Літ. 21.

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