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DEVELOPMENT AND INVESTIGATION OF AN OPTOELECTRONIC SYSTEM FOR AUTOMATED INSPECTION OF MICRODEFECTS IN LAYERS OF ADDITIVELY MANUFACTURED PARTS

The study employs a comparative analysis of non-destructive testing (NDT) methods, the theory of acoustic wave propagation to examine the limitations of ultrasonic testing (UT), and computer vision algorithms for surface defect identification. The mathematical framework is based on the evaluation of ultrasonic wave propagation velocity in anisotropic media and correlation analysis of visual descriptors associated with defects. Critical limitations of conventional ultrasonic testing for porous structures fabricated via fused deposition modeling (FDM) have been identified, primarily due to significant signal attenuation and temperature-induced drift. An integrated approach to optical inspection is proposed, enabling differentiation of defect types (warping, under-extrusion, stringing) based on their morphological characteristics without mechanical interaction with the specimen.

A hardware–software complex for optical inspection has been developed and experimentally validated. The system provides automated defect detection based on geometric and textural features, enabling a reduction in production losses within digital manufacturing processes based on additive technologies. It has been demonstrated that the implementation of an optical monitoring system allows for the identification of precision defects with a characteristic size of 0.1 mm or greater, resulting in a 15–20% reduction in production losses through real-time adjustment of printing parameters.

Keywords: *additive manufacturing, fused deposition modeling (FDM), 3D printing, defectoscopy, non-destructive testing, ultrasonic testing, artificial intelligence, surface defects, computer vision, optical monitoring.*

Problem Statement. The current stage of industrial development is characterized by the intensive integration of additive manufacturing (AM) technologies into digital production cycles. The transition to layer-by-layer object fabrication methods ensures a significant reduction in the duration of research and development (R&D) activities, as well as optimization of technological pre-production processes. According to industry analyses [1], the implementation of AM technologies enables an average increase in unit production profitability of approximately 23%, accompanied by a substantial reduction in capital expenditures required for deployment of manufacturing capacities.

Despite the rapid proliferation of 3D printing across engineering, medicine, and other domains, a critical barrier to its large-scale industrial adoption remains the instability of quality indicators of finished products. The complexity of physicochemical processes governing layer formation leads to the occurrence of specific surface and structural defects, necessitating the development of precision automated inspection systems. Therefore, the development of efficient optoelectronic defectoscopy tools constitutes a relevant scientific and engineering task aimed at ensuring the reliability and repeatability of additive manufacturing processes [2].

Analysis of Recent Research. The complexity of physicochemical processes accompanying layer-by-layer extrusion of thermoplastics results in a wide range of structural inconsistencies that significantly degrade the operational characteristics of manufactured parts [5, 7]. Studies [3, 5, 8] indicate that one of the most critical defects is interlayer delamination, caused by insufficient adhesion between consolidated layers. The primary factor underlying this phenomenon is the violation of the thermal gradient and insufficient melt temperature at the extruder, which inhibits polymer chain diffusion at the interlayer interface. As a result, localized strength degradation and the formation of interlayer cracks occur, ultimately leading to structural failure under operational loading conditions [8].

Research findings [5, 6] also confirm the significant role of defects related to geometric precision, particularly thermally induced deformation (warping). This phenomenon is attributed to the development of substantial internal stresses in the polymer during phase transitions and non-uniform crystallization. It is noted that the thermal regime is a dominant parameter: excessive material fluidity at elevated temperatures leads to the formation of material accumulation and loss of contour definition, whereas insufficient temperature in the printing zone impedes extrusion and reduces structural isotropy [8].

In addition to macrostructural deviations, other studies [3, 4, 5] emphasize the presence of surface microdefects, such as retraction artifacts (stringing) and under-extrusion. These anomalies, caused by improper adjustment of dynamic filament feed parameters, directly reduce density, hermeticity, and aesthetic quality of the parts. The systematization of these studies indicates the necessity of developing intelligent visual inspection systems for the real-time detection of such defects.

In summary, the identified defects can be classified as follows (Table 1).

Table 1 – Classification of Defects in Additive Manufacturing Processes

Defect Category	Occurrence Frequency (%)	Primary Factors
Physical (Mechanical)	40%	Geometric deviations, surface roughness, nozzle wear
Thermal	30%	Deformation (*warping*), delamination, overheating
Pre-processing	20%	Slicing errors, incorrect orientation, G-code parameter misconfiguration
External/Random	10%	Contamination, power supply disturbances, vibrations, humidity

This classification confirms the necessity of developing an optical inspection system capable of identifying multimodal defect types at different stages of the fabrication process.

The primary objective of the proposed system is the defectoscopic inspection of parts while fully preserving their structural integrity and geometric parameters. Within the framework of non-destructive testing (NDT) methods, particular attention is given to ultrasonic testing (UT), whose theoretical foundations and hardware limitations require detailed analysis in the context of the stated problem. The functional advantages and limitations of ultrasonic testing for the diagnostics of additively manufactured parts were analyzed (Tables 2 and 3).

Table 2 – Functional Advantages of Ultrasonic Testing in the Diagnostics of Additively Manufactured Parts

Parameter / Characteristic	Description of Advantages and Technical Capabilities
Resolution	Enables identification of precision defects (microcracks, voids, inclusions) with linear dimensions from 0.1 mm.
Depth Penetration Capability	High efficiency in inspecting objects of significant thickness and internal structures, exceeding classical optical vision systems.
Spatial Localization	Capability for precise determination of spatial coordinates, depth of occurrence, and geometric configuration of defects in 3D space.
Operational Efficiency and Automation	High scanning speed of large surfaces; generation of digital datasets for subsequent intelligent processing and archiving.
Methodological Flexibility	Adaptability in selecting techniques (pulse-echo, through-transmission, or phased array methods) depending on part geometry complexity.
Non-destructive Testing	Complete verification of internal structure without compromising integrity or physicomechanical properties of the object.

The identified limitations of acoustic methods substantiate the feasibility of transitioning to non-contact optoelectronic inspection systems. The application of computer vision techniques enables real-time monitoring of surface geometry and texture without mechanical interaction with the object, ensuring a high probability of defect identification even under conditions of thermodynamic instability in the working zone.

Objective of the Study. The objective of this work is the development and experimental validation of a hardware–software complex for optical inspection that provides automated defect detection based on geometric and textural features, thereby enabling a reduction in production losses within digital manufacturing processes based on additive technologies.

Table 3 – Technical and Physical Limitations of Ultrasonic Testing for Inspection of Additively Manufactured Parts

Limiting Factor	Description of the Issue and Its Impact on Inspection Reliability
Structural Anisotropy	The layered structure of FDM parts induces intensive scattering and attenuation of acoustic waves, reducing the signal-to-noise ratio (SNR).
Geometric Complexity	The presence of lattice structures and internal cavities prevents stable acoustic coupling between the transducer and the object.
Coupling Medium	The requirement for immersion liquids or coupling gels, which may penetrate porous polymer structures and alter their physicomechanical properties.
Temperature Drift	The dependence of sound velocity on thermoplastic temperature complicates in-situ monitoring due to high thermal gradients within the part.
Signal Interpretation	The presence of technological interlayer interfaces generates multiple false echo signals, necessitating complex filtering and signal processing algorithms.

Main Content. During the course of the study, specific boundary conditions were established under which defects associated with the pre-processing stage were excluded from consideration. Within the experimental framework, pre-print preparation conditions were assumed to be conditionally ideal, allowing the analysis to focus exclusively on internal anomalies arising directly during layer formation.

The authors propose a machine vision method based on the integration of a high-resolution camera directly into the printer architecture. The optical axis of the camera is positioned strictly perpendicular to the build surface, ensuring the acquisition of high-precision images of each intermediate layer. The result of this process is a structured dataset of images, the analysis of which enables the operator to verify structural integrity and identify latent internal defects.

The software implementation of the proposed method requires modification of motion control algorithms. To ensure unobstructed surface capture, it is necessary to move the extrusion head outside the camera field of view after the completion of each layer. In this study, the corresponding G-code configuration was implemented using the PrusaSlicer software environment. To automate the image acquisition process, the following command sequence was introduced in the *"Before layer change G-code"* section:

G1 X200 Y200; Move the extruder to a fixed position outside the part

G4 P500; Pause for 500 ms to stabilize the camera and suppress vibrations

; Trigger command for camera shutter activation (depending on the interface)

The algorithmic implementation involves modifying the control G-code such that, upon completion of each layer, the system initiates the return of the extruder to a predefined position outside the printing area. Simultaneously, the logical state of a designated GPIO pin is altered, serving as a synchronization signal between the printer control board and the image processing module. The reception of this signal acts as a trigger for image capture.

The hardware modification of the printer involves the integration of a machine vision system comprising a camera and an auxiliary computing module. The use of a dedicated microcomputer, such as the Raspberry Pi 4, is justified by the need to isolate the primary printer controller from computationally intensive media processing tasks. This approach ensures the stability and efficiency of core printing operations, as the secondary board performs parallel processing and archiving of captured images. The selection of the Raspberry Pi platform is conditioned the availability of a sufficiently powerful processor with an integrated graphics unit, adequate RAM capacity (from 2 GB), and a high clock frequency, which are critical for real-time image analysis.

When selecting an image sensor for the machine vision system, a key requirement is the ability to operate under elevated temperature conditions. Most commercially available solutions exhibit similar technical specifications but lack adequate thermal protection. For industrial additive manufacturing systems, where the temperature within the build chamber may exceed 100 °C, this constitutes a critical limitation. An effective engineering solution is the spatial decoupling of system components: relocating the electronic control module to a low-temperature zone, while placing only the optical unit (lens) within the high-temperature environment. Among available hardware solutions, the Raspberry Pi HQ Camera module is particularly suitable for implementing this architecture. This camera offers high resolution and flexible interfacing capabilities, enabling integration into customized cooling systems or the use of extended ribbon cables to position the processing unit outside the thermal chamber.

At the stage of control program preparation (slicing), the geometry of the part is decomposed into distinct structural elements (*feature types*), classified according to their spatial arrangement. The key components include external perimeters (*external perimeter*), internal infill structures (*internal infill*), as well as solid bottom and top layers (*solid infill* and *top solid infill*) (Fig. 1).

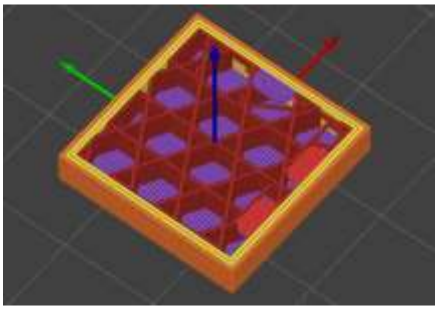

Figure 1 – Examples of Geometric Elements:
External perimeter (yellow), Internal infill (dark red), Solid infill (purple), Top solid infill (red)

The visual inspection methodology is primarily based on the analysis of the morphology of extruded filament lines (“strands”) within the specified regions. The principal quality criteria are structural homogeneity and stability of the geometric parameters of the deposited lines. In particular, a reduction in cross-sectional area or non-uniformity of the deposition pitch indicates under-extrusion, excessive cooling rates, or partial degradation of nozzle throughput (Fig. 2). Conversely, pronounced irregularity and material accumulation are indicative of over-extrusion.

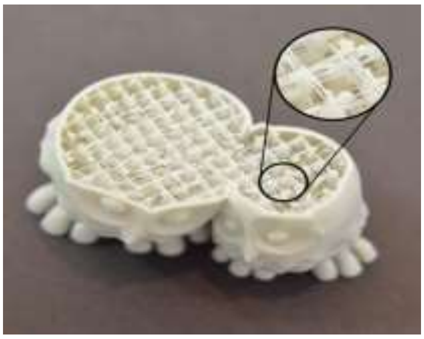

Figure 2 – Example of a Printing Defect

The identified defects have a physical origin and are caused dynamic variations in printing process parameters, including deviations of the actual filament diameter from its nominal value and changes in the hydrodynamic resistance of the nozzle (due to clogging or thermal deformation). Since direct real-time monitoring of these parameters is technically complex from a hardware perspective, the analysis of high-resolution layer-by-layer images provides a representative assessment of the stability of the technological process.

The architecture of the proposed algorithm is based on the synergy of two approaches: deterministic analysis of the control G-code and empirical training of a neural network. The use of G-code data ensures precise positioning of extrusion trajectories, which serves as a reference basis for the initial phase of artificial intelligence (AI) model training. This enables the formation of high baseline accuracy of the system, followed by iterative optimization of recognition performance during practical operation.

At the first stage of the study, a conceptual information model of the analysis system was developed, reflecting the interaction of data flows between software and hardware components (Fig. 3). Based on this model, specialized software was designed and implemented using the Python programming language. The functional algorithm of the system involves layer-by-layer analysis of part geometry with subsequent decomposition into elementary extrusion trajectories. The processing pipeline includes the generation of a reference digital representation of each layer, based on the nozzle movement coordinates.

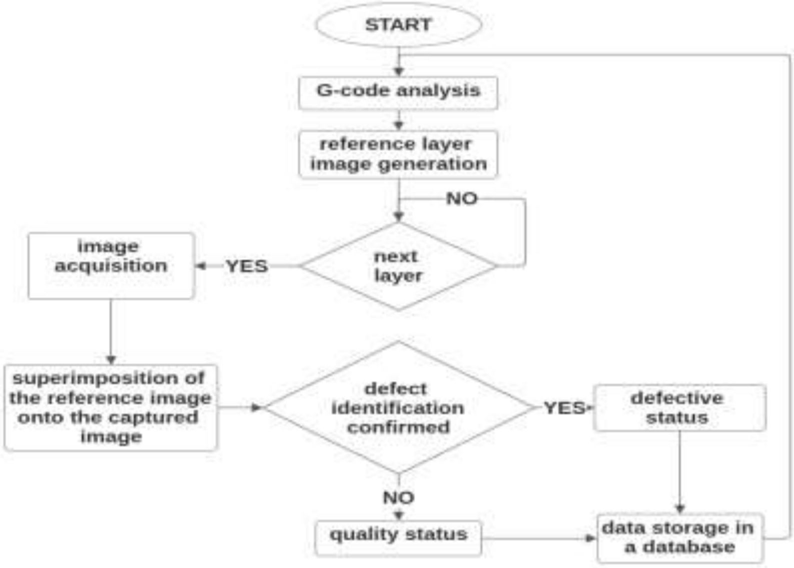

Figure 3 – Information Model of the Analysis System

The visualization results are structured into an organized array of graphical data, examples of which are presented in Fig. 4 and Fig. 5. The generated image database serves as a reference dataset for subsequent verification of the actually printed layers and for the detection of deviations from the prescribed geometric model.

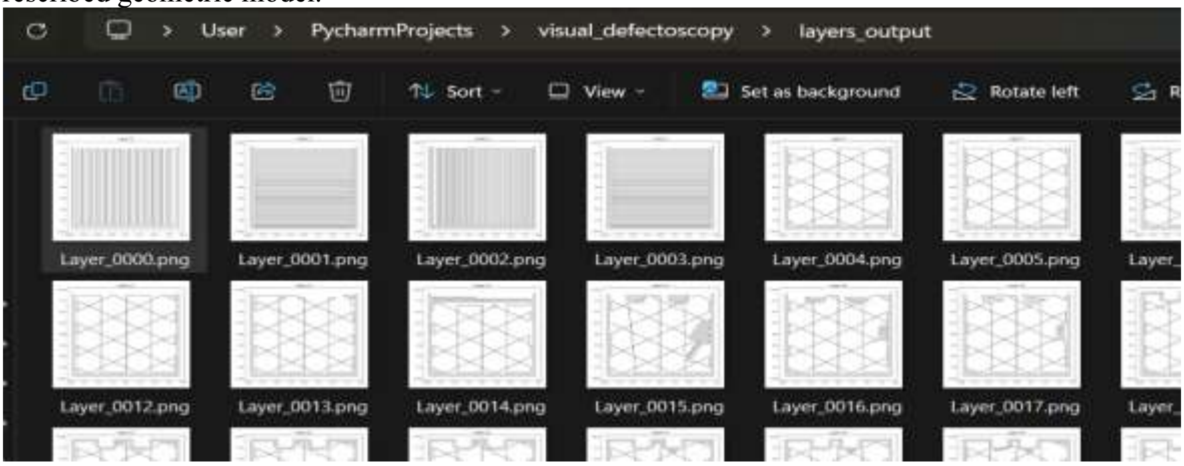

Figure 4 – Example of a Generated Directory Containing Layer Representations

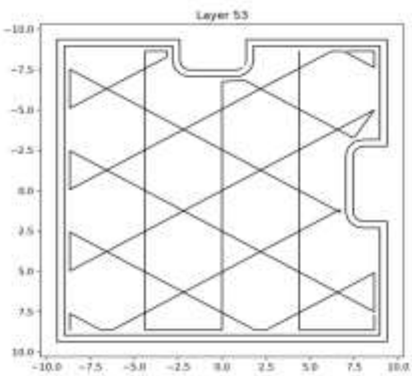

Figure 5 – Example of a Generated Layer Representation

The next stage involves a superposition operation, i.e., overlaying the reference digital layer model onto the actual image acquired by the machine vision system directly during the manufacturing process [9]. This procedure ensures spatial synchronization between the theoretical extrusion trajectories and the actual material deposition pattern, enabling precise determination of regions of interest for analysis.

The algorithm performs sequential iteration along the extrusion vector, verifying the correspondence of actual parameters to the predefined criteria (Fig. 6), including line width, structural continuity, and geometric congruence (compliance with the boundaries of the calculated trajectory). The processing result for each segment is represented as a binary evaluation: confirmation of compliance with specified tolerances (positive result) or identification of a structural anomaly classified as a manufacturing defect (negative result).

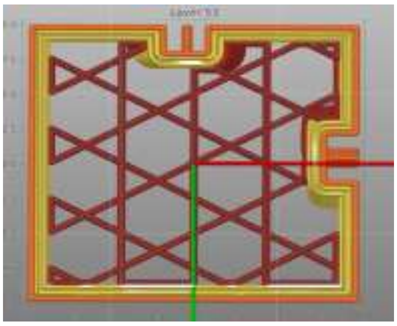

Figure 6 – Superimposed Layer Representation on a Simulated Layer Image

To validate the proposed method, an experimental setup was designed and assembled, on which a series of test runs with layer-by-layer photographic recording of the additive manufacturing process was conducted. The evaluation of the developed algorithm enabled the acquisition of empirical data regarding the accuracy of structural anomaly identification.

For comparative analysis and to illustrate the system's effectiveness, two representative samples were selected: a reference sample with parameters corresponding to the prescribed digital model (Fig. 7), and an experimental sample containing morphological defects (Fig. 8). The visualization results confirm the capability of the algorithm to clearly differentiate regions of stable extrusion from areas with geometric deviations of the layer.

Figure 7 – Defect-Free Part (Part0)

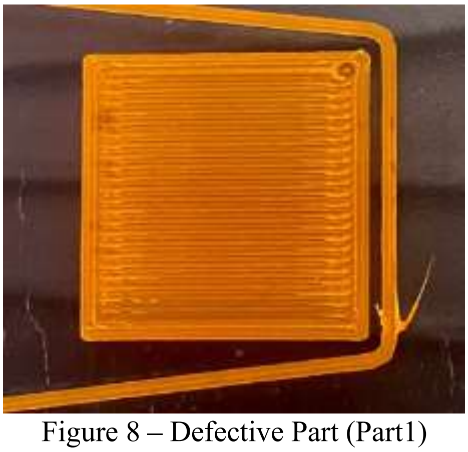

Figure 8 – Defective Part (Part1)

The generated array of images was processed using the developed algorithm, the results of which are presented in Fig. 9.

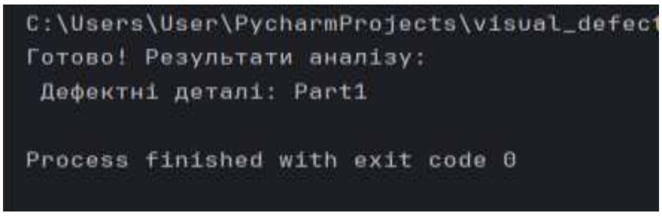

Figure 9 – Obtained Results

Conclusions. The analysis procedure was performed iteratively: for each layer, a reference digital representation was generated and superimposed onto the actual photographic capture to verify extrusion lines. As a result of validation, the reference sample without structural anomalies (*Part0*) was correctly identified by the system as defect-free, confirming the validity of the baseline algorithm.

Given the complexity of unambiguous defect classification, an adaptive system training methodology is proposed, comprising the following stages:

- Sensitivity calibration**:** establishment of minimum deviation thresholds for detecting potential anomalies (e.g., variations in line width, structural discontinuities), followed by their classification.
- Verification and filtering**:** execution of mechanical testing of samples to determine the correlation between detected optical anomalies and actual physicomechanical properties of the part. If nominal characteristics are preserved, recognition parameters are adjusted accordingly.
- Knowledge base formation**:** development of a structured dataset containing defect types and their corresponding mathematical descriptors (e.g., critical gradient of line discontinuity relative to the trajectory vector).
- Definition of admissible tolerances**:** determination of a relative error coefficient that defines the maximum allowable number of non-critical deviations per unit area of a layer.

Systematic training according to the proposed methodology enables minimization of Type II errors. It should be noted that the training process must be adapted to specific types of polymer materials (or their groups), as variations in texture, optical properties, and rheological behavior of different filaments significantly influence the visual characteristics of the deposited layers.

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РОЗРОБКА ТА ДОСЛІДЖЕННЯ ОПТИКО-ЕЛЕКТРОНОЇ СИСТЕМИ АВТОМАТИЗОВАНОГО КОНТРОЛЮ МІКРОДЕФЕКТІВ ПОВЕРХНІ ДРУКОВАНИХ ВУЗЛІВ

В роботі використано порівняльний аналіз методів неруйнівного контролю (НК), теорію поширення акустичних хвиль для дослідження обмежень ультразвукової дефектоскопії (УЗД) та алгоритми комп'ютерного зору для ідентифікації дефектів поверхні. Математичне моделювання базується на розрахунку швидкості поширення ультразвуку в анізотропних середовищах та кореляційному аналізі візуальних дескрипторів браку. Встановлено критичні обмеження класичної УЗД для пористих структур, виготовлених методом FDM-друку, що зумовлені високим загасанням сигналу та температурним дрейфом. Авторами запропоновано інтегрований підхід до оптичної дефектоскопії, який дозволяє диференціювати типи дефектів (warping, under-extrusion, stringing) за їх морфологічними ознаками без механічного впливу на виріб. Розроблено та апробовано програмно-апаратний комплекс оптичного контролю, який забезпечує автоматичне виявлення браку за геометричними та текстурними ознаками, що дозволяє знизити частку виробничих втрат у процесах цифрового виробництва на основі адитивних технологій. Доведено, що впровадження системи оптичного моніторингу дозволяє ідентифікувати прецизійні дефекти розміром від 0,1 мм, що забезпечує зниження виробничих втрат на 15-20% за рахунок оперативного коригування параметрів друку.

Ключові слова: *адитивні технології, FDM-друк, 3D друк, дефектоскопія, неруйнівний контроль, ультразвукова дефектоскопія, штучний інтелект, дефекти поверхні, комп'ютерний зір, оптичний моніторинг.*

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