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Application of the Cognex Vision system in modern industry: design and implementation of an inspection application for a cable clip manufactured using FDM 3D Printing Technology

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Abstract: The paper presents the design and implementation of the Cognex vision system in the quality control process of cable holders manufactured using 3D FDM printing technology. The image processing algorithm developed in the InSight Explorer software achieved an accuracy of 95-96%. The vision system enables the automation of the quality control process, eliminating errors caused by human factors and improving production efficiency. The analysis confirms the system's effectiveness in detecting manufacturing defects, such as the absence of a mounting hole or underfill, contributing to cost reduction and increased efficiency in industrial enterprises.

Keywords: Vision systems; Quality control; 3D FDM printing; Industrial automation; Image processing algorithms

Zastosowanie systemu wizyjnego Cognex w nowoczesnym przemyśle: projekt i implementacja aplikacji kontroli uchwytu kablowego wykonanego technologią FDM w druku 3D

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Streszczenie: W artykule przedstawiono projekt oraz implementację systemu wizyjnego Cognex w procesie kontroli jakości uchwytów kablowych wytworzonych technologią druku 3D FDM. Opisano zastosowanie algorytmu przetwarzania obrazu opracowanego w programie InSight Explorer, który osiągnął dokładność na poziomie 95-96%. System wizyjny pozwala na automatyzację procesu kontroli, eliminując błędy wynikające z czynnika ludzkiego i zwiększając efektywność produkcji. Analiza wyników potwierdza skuteczność systemu w wykrywaniu wad produkcyjnych, takich jak brak otworu montażowego czy niedolań, co przyczynia się do redukcji kosztów i zwiększenia wydajności w przedsiębiorstwach przemysłowych.

Słowa kluczowe: Systemy wizyjne; Kontrola jakości; Druk 3D FDM; Automatyzacja przemysłu; Algorytmy przetwarzania obrazu

1. Introduction

In an era of rapid and dynamic advancement in modern technologies, as well as increasing demands for higher quality in components and production efficiency, including the elimination of human error, vision systems are continuously gaining importance as key tools supporting the automation of industrial processes. Advanced vision systems, utilizing

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various types of image processing algorithms and machine learning, enable automated analysis of the visual characteristics of manufactured components for tasks such as inspection, identification, geometric dimension measurement or sorting. Vision systems can also assist collaborative robots (cobots) in assembly applications [1,2]. The wide range of applications spans various industries, including automotive, pharmaceuticals, food production, and many others, where precision and reliability in quality control are critical factors for maintaining a company's growth pace and/or increasing profit. Modern vision systems based on artificial intelligence algorithms, machine learning, and deep learning allow for maximizing profit and efficiency while simultaneously reducing the number of customer complaints due to defective products. These algorithms are thus one of the key trends in the industry and vision systems [3,4]. This article will focus on presenting the current technological solutions in visual inspection. A practical, custom-engineered case related to the quality control of manufactured components will also be presented.

A vision system, also known as machine vision, is a configuration of interconnected electronic devices designed to process and interpret images, mimicking the functionality of the human sense of sight [5]. Similar to a human in a quality control position, a properly selected and programmed vision system can distinguish between well-made and defective components, and then transmit the data to a sorting or palletizing robot, which will move them to the appropriate location [6]. An example of a pick-and-place application performed at a workstation using a vision system integrated with a cobot is presented in the figures below (Fig. 1 - Fig. 3).

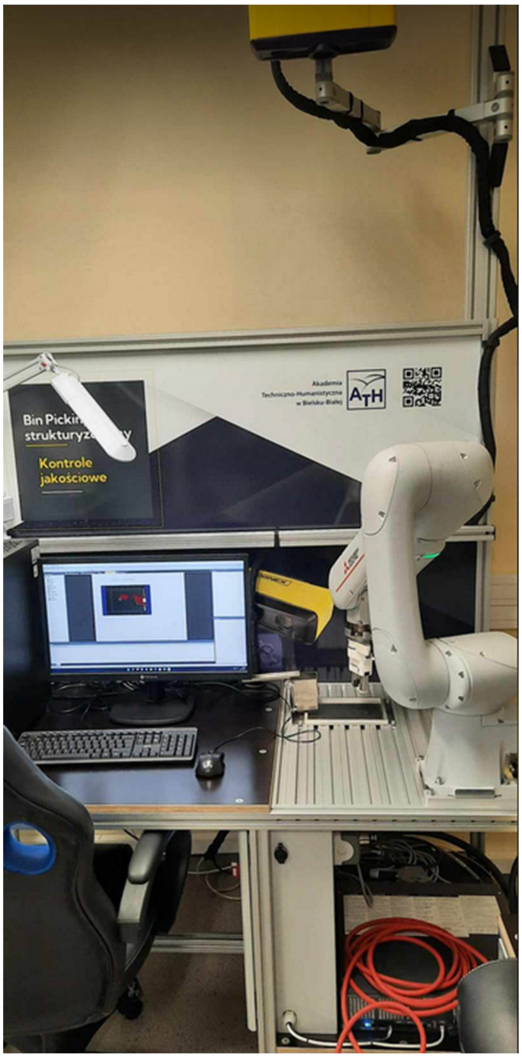

Figure 1. Pick-and-place workstation with a cobot

Figure 2. Vision system coupled with cobot

Figure 3. Cobot work cycle in a pick-and-place application

New methods and solutions in the field of vision inspection that improve productivity are displacing earlier, traditional solutions from the market. Historically, the evolution of vision systems can be divided into several breakthrough stages, namely [7-11]:

1. Proprietary boxes – one of the first types of machine vision, where such a system could only inspect a single specific component. Changing the detected defect or component was only possible by completely rebuilding the system.

2. Embedded boards – specialized systems were integrated into smaller versions compared to the first prototypes. These were used where space-saving was crucial.

3. PC Vision – this involves the processing, analysis, and interpretation of images, machine learning, and the use of artificial intelligence in vision systems, with the computer acting as the core system working with a separate camera.

4. Modular cameras – built to allow easy reconfiguration of the camera, including changing the illuminator, lens, or other parts.

5. Vision sensors – devices that operate automatically without the need for a computer (after initial configuration).

6. 3D laser profilometers – used to create clouds of points via a laser beam, enabling the generation of a 3D model of the object for quality assessment and measurement.

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These stages are symbolically represented by the vision system manufacturer Cognex in Figure 4.

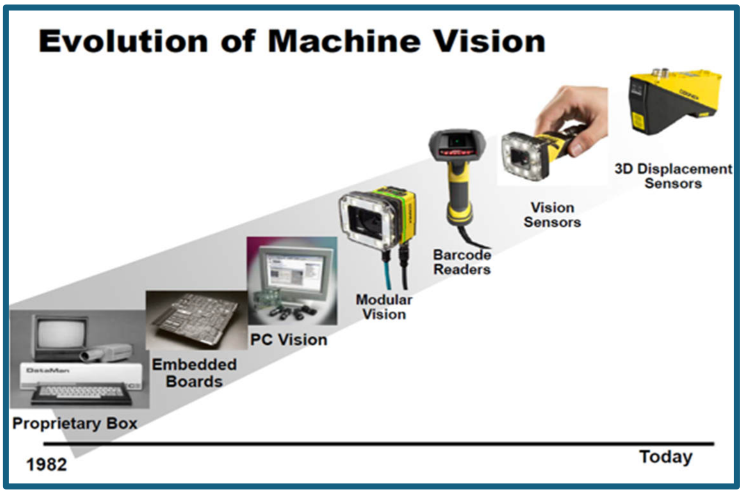

Figure 4. Evolution of Cognex Machine Vision [7]

2. Project description

The object of analysis is a mounting component for electrical cables. Due to its specific functional requirements, the component demands a level of quality that ensures proper functionality. Given the small size of the object, visual inspection is significantly challenging. To address this, a practically implementable vision system has been proposed, utilizing a modular camera and software designed to classify cable mounting components. Automating the quality control process reduces the number of personnel responsible for monitoring and inspecting finished products within the company, which in turn increases the accuracy and speed of the quality control process, minimizes errors caused by human factors, and boosts efficiency—resulting in lower production costs. The vision system is an advanced and modern solution that combines data acquisition and archiving capabilities with advanced image analysis software.

As part of the project, a modular camera will be used, allowing flexible adaptation of the system to the specific needs of the production process at relatively low cost.

For the purpose of this study, several dozen samples of a cable holder model, produced using FDM 3D printing technology, have been prepared. A schematic of the component, along with selected dimensions, is shown in Figure 5.

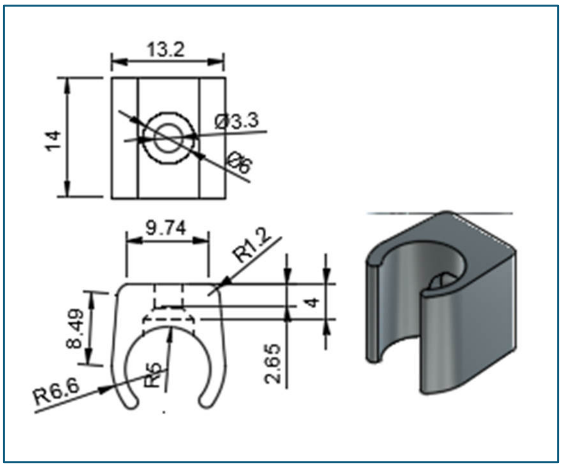

Figure 5. Schematic model of the component with example dimensions

As can be observed in the figure above, the proposed object is not easy to measure or classify using conventional methods (such as caliper). In the case of manual sorting and classification by quality control personnel, every produced unit must undergo at least one inspection performed by a human. This introduces a high risk of error and the potential for defective components to be packaged, which could lead to future complaints and additional costs.

The samples have been divided into three categories. The first category consists of correctly manufactured parts. The second category comprises underfilled samples, while the third category includes parts without a central hole. Therefore, the vision system will be used to automatically detect and categorize parts as follows:

1. Parts missing the central hole,
2. Underfilled parts,
3. Correctly manufactured parts that meet the requirements.

This project assumes that the defects in the produced parts are repeating, and the defects are predictable, meaning the locations and types of defects are known and defined. Schematic examples of both defective and non-defective products are presented in the figures below.

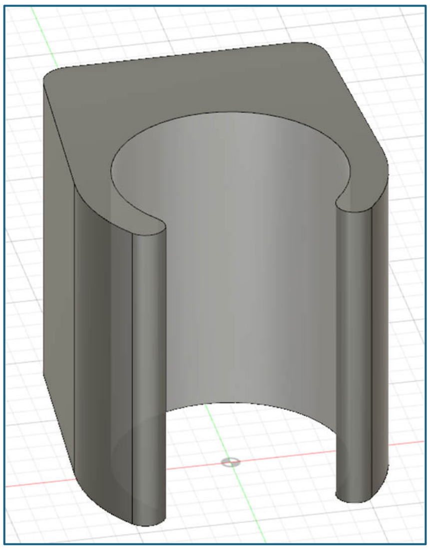

Figure 6. Model of a defective component – missing mounting hole

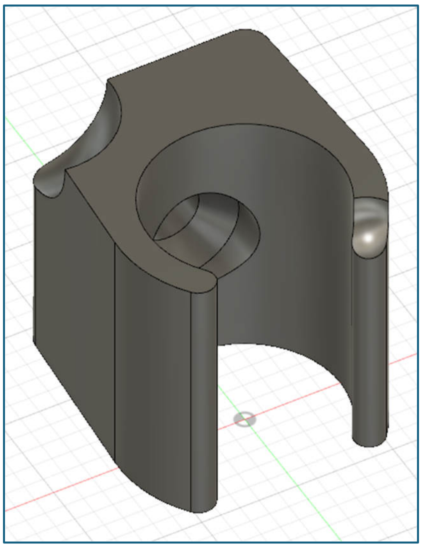

Figure 7. Model of a defective component – underfilling present

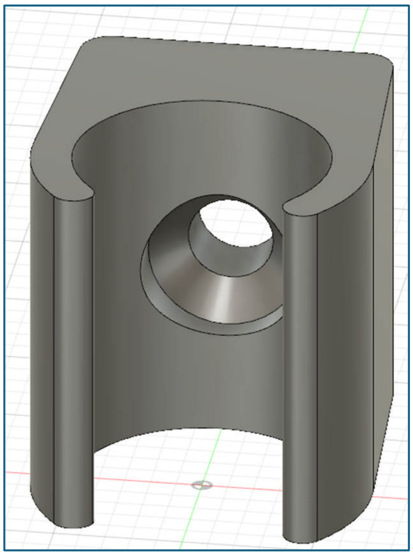

Figure 8. Model of a properly manufactured component

Samples (simulating models of components produced by the company) were created for the purposes of this project using 3D printers and the FDM method. The color chosen for the finished components was yellow—a color that poses significant challenges for vision systems. The printed models are presented in the figures below.

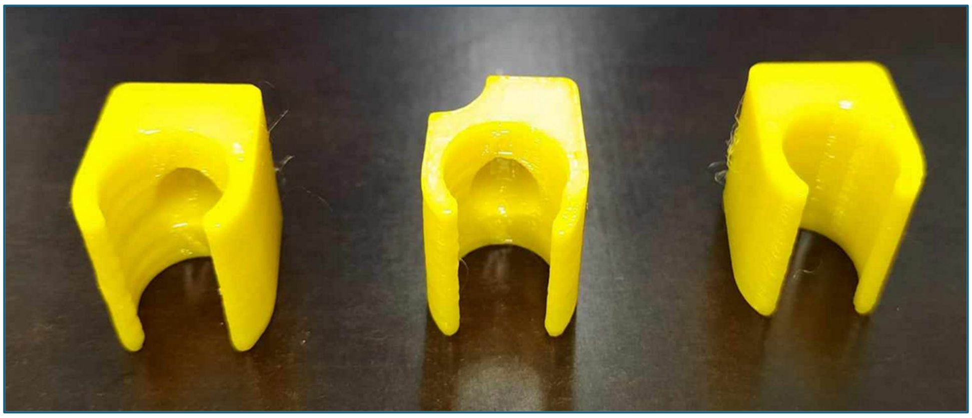

Figure 9. Cable holder models produced with the FDM method using a 3D printer

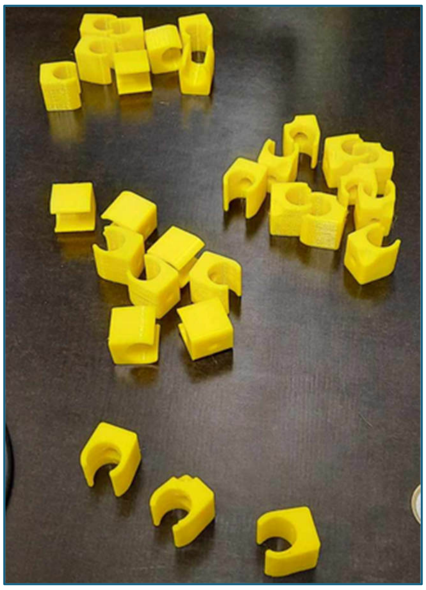

Figure 10. Grouped cable holder models produced with the FDM method using a 3D printer

To standardize the course of the tests, a darkroom model was utilized (also created using the FDM method with a 3D printer). This darkroom features a specially designed base to ensure that each component is positioned in the same manner. This design is intended to minimize the influence of the component's placement and the background on the inspection process. In the actual implementation of the project, the finished components could move along a specially covered conveyor belt after being properly positioned. The 3D model of the darkroom and the assembly concept are presented in the figure below.

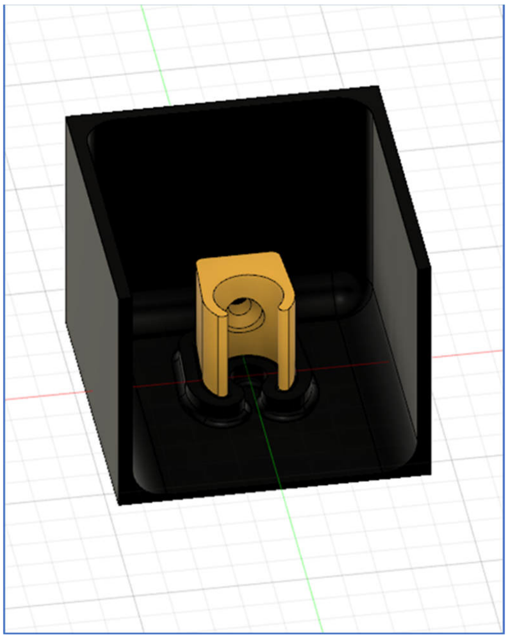

Figure 11. Darkroom model to be used in the project

The schematic of wiring diagram of the vision system used in the project is presented in the figure below.

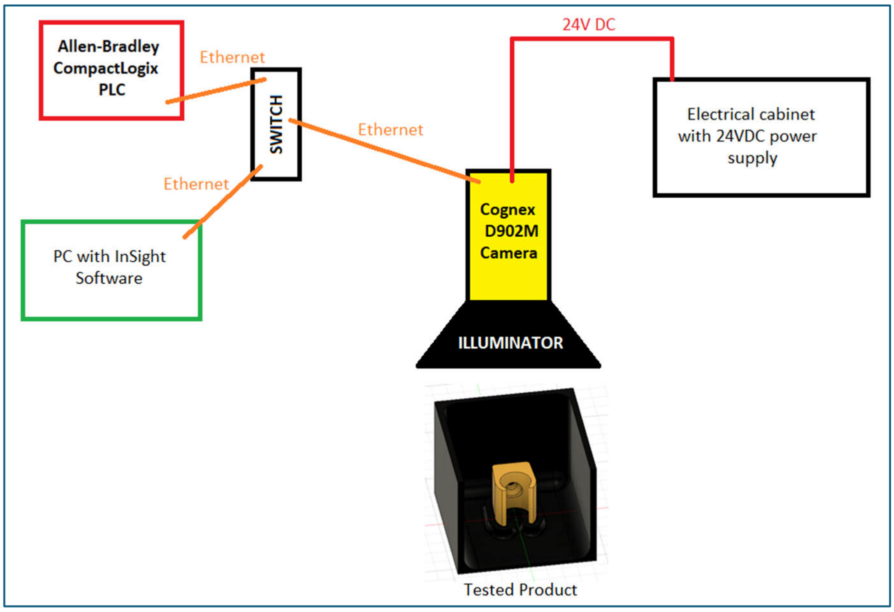

Figure 12. Schematic overview of the vision system

The project was implemented using the InSight Explorer software and a collection of images taken with the previously mentioned darkroom and the Cognex D902M vision camera. The entire quality control cycle is managed by the Allen-Bradley Compact GuardLogix PLC controller. Each component was captured in the form of photographs three times—to average the results and to check how the program behaves with the same component processed a second and third time. During the initial trials of the system, a darkroom printed in gray was used. The combination of yellow and gray produced the following final effect, shown in the figure below.

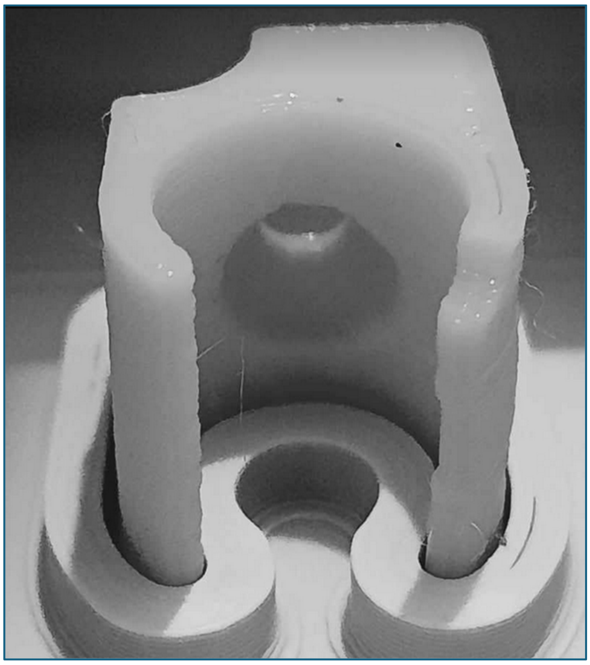

Figure 13.Yellow model on gray background

As can be observed, the contrast between the model and the background is low. Additionally, the influence of external lighting on the resulting image is visible (the formation of shadows). This caused some issues with the classification of the model by the vision system algorithm. To minimize this effect as much as possible, it was decided to print the darkroom in black and paint its walls in a matte black color. The intention was to increase the contrast between the background and the classified component, as well as to reduce the shadow effect by increasing the intensity of the lighting generated by the illuminator built into the modular camera. The painted darkroom along with the classified component is shown in the figure below.

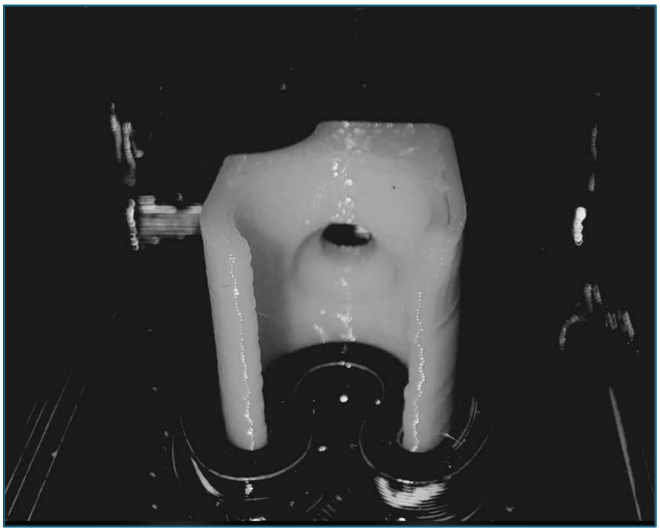

Figure 14. Darkroom painted black

In the figure above, bright spots caused by incomplete painting of the darkroom in certain areas can be observed. It can be unequivocally stated that the use of black improved the contrast and nearly completely eliminated the shadow effect (except for the shadows cast on the surface of classified component). To entirely eliminate the shadow effect, additional illuminators could be used so that the component is evenly illuminated from all sides. While this is possible in laboratory conditions, it is not always feasible in industrial settings; hence, it was decided to keep only the illuminator built into

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the camera. As part of the test, a procedure was carried out to adjust the settings of the vision camera to minimize the influence of shadows on the final result (the obtained image subjected to the vision algorithm). After making the necessary adjustments, the effect shown in the figure below was achieved.

Figure 15. Obtained final effect after changing camera settings

A compromise was reached regarding the intensity of the object's illumination, the exposure time of the software shutter and the angle of the camera tilt relative to the object. The contrast has decreased, but the shadow effect has also been minimized. The image is sharp, and even individual printing layers can be observed. The matte paint has, in some places, achieved a reflective effect due to the significant increase in exposure time and the power of the illuminator. The selection of parameters for the camera taking the pictures is problematic and requires experience from the operator and programmer. Changing one parameter synergistically affects others. For example, increasing the camera's shutter opening time without changing the intensity of the illumination generated by the camera’s illuminator will result in overexposed images, making them unsuitable for processing by the algorithm due to too low a contrast. Similarly, decreasing the shutter opening time will yield an underexposed and dark image—desired product details will not be "captured," and the assessment by the algorithm will be incorrectly performed or even impossible to carry out (error messages such as #ERROR will be displayed). The final selected parameters are presented in the figure below.

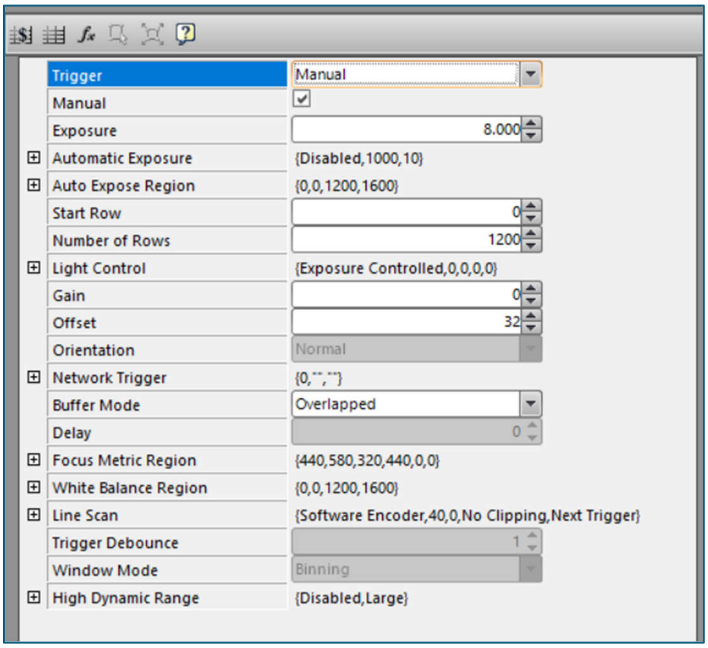

Figure 16. Final settings of vision system

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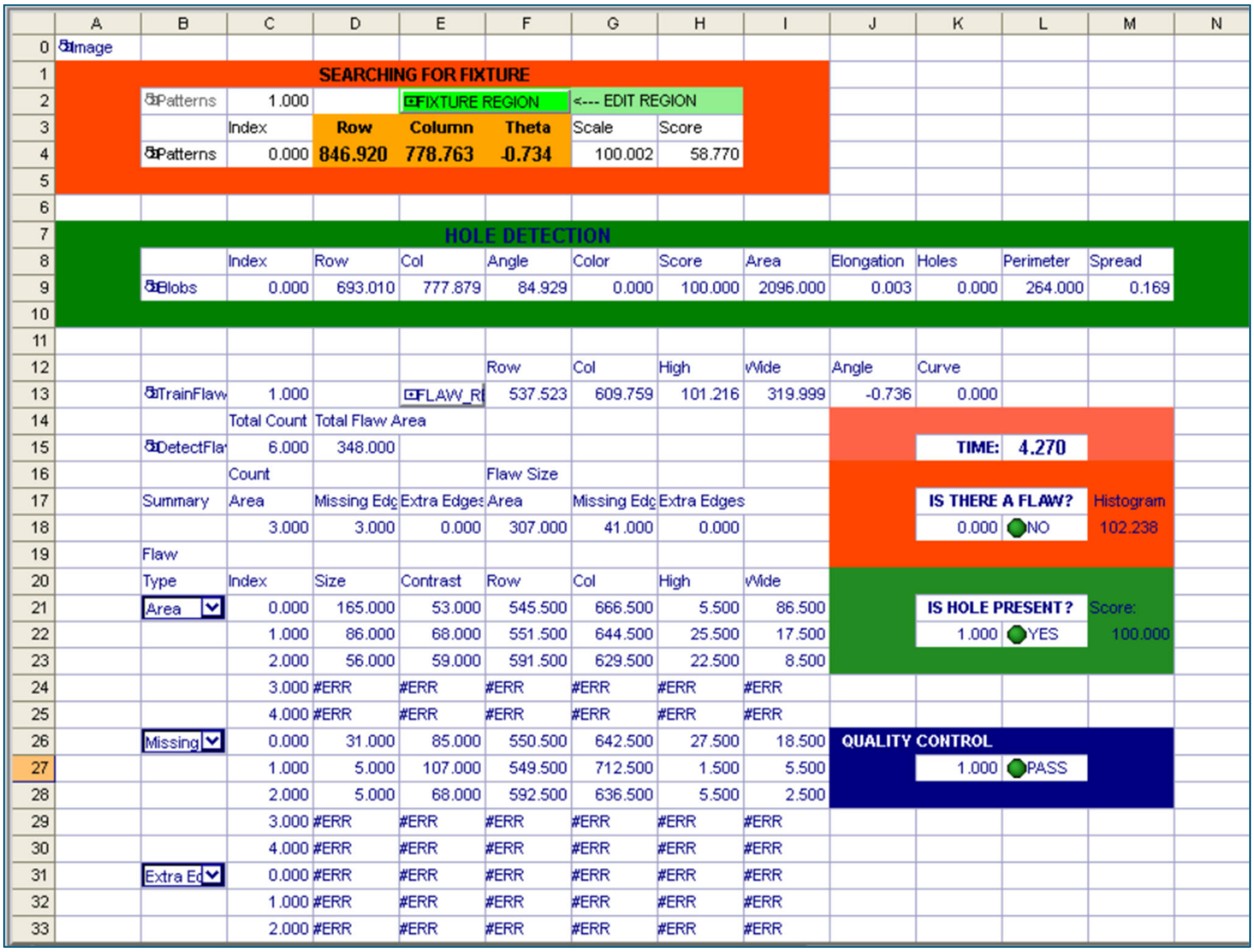
As can be observed in Figure 16 above, the number of adjustable parameters in Cognex systems is vast, and each parameter synergistically influences the others. While automatic parameter tuning algorithms can be used, they will only provide preliminary settings—often requiring additional adjustments, and sometimes complete changes and reconfiguration of the system.

After the technical preparation of the camera, its physical setup, and the selection of parameters, the next step was to create the algorithm in the InSight Explorer software. The program is structured in a Spreadsheet view reminiscent of Excel. However, it operates on slightly different principles; individual cells do not contain a single value but rather a whole set of functions and data. The finished program is presented in the figure below.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
0	Image													
1					SEARCHING FOR FIXTURE									
2		Patterns	1.000		FIXTURE REGION		<--- EDIT REGION							
3			Index	Row	Column	Theta	Scale	Score						
4		Patterns	0.000	846.920	778.763	-0.734	100.002	58.770						
5														
6														
7						HOLE DETECTION								
8			Index	Row	Col	Angle	Color	Score	Area	Elongation	Holes	Perimeter	Spread	
9		Blobs	0.000	693.010	777.879	84.929	0.000	100.000	2096.000	0.003	0.000	264.000	0.169	
10														
11														
12						Row	Col	High	Wide	Angle	Curve			
13		TrainFlaw	1.000		FLAW_RI	537.523	609.759	101.216	319.999	-0.736	0.000			
14			Total Count	Total Flaw Area										
15		DetectFla	6.000	348.000							TIME:	4.270		
16			Count			Flaw Size								
17		Summary	Area	Missing Edg	Extra Edges	Area	Missing Edg	Extra Edges			IS THERE A FLAW?		Histogram	
18			3.000	3.000	0.000	307.000	41.000	0.000			0.000	NO	102.238	
19		Flaw												
20		Type	Index	Size	Contrast	Row	Col	High	Wide					
21		Area	0.000	165.000	53.000	545.500	666.500	5.500	86.500		IS HOLE PRESENT?		Score:	
22			1.000	86.000	68.000	551.500	644.500	25.500	17.500		1.000	YES	100.000	
23			2.000	56.000	59.000	591.500	629.500	22.500	8.500					
24			3.000	#ERR	#ERR	#ERR	#ERR	#ERR	#ERR					
25			4.000	#ERR	#ERR	#ERR	#ERR	#ERR	#ERR					
26		Missing	0.000	31.000	85.000	550.500	642.500	27.500	18.500	QUALITY CONTROL				
27			1.000	5.000	107.000	549.500	712.500	1.500	5.500		1.000	PASS		
28			2.000	5.000	68.000	592.500	636.500	5.500	2.500					
29			3.000	#ERR	#ERR	#ERR	#ERR	#ERR	#ERR					
30			4.000	#ERR	#ERR	#ERR	#ERR	#ERR	#ERR					
31		Extra Ed	0.000	#ERR	#ERR	#ERR	#ERR	#ERR	#ERR					
32			1.000	#ERR	#ERR	#ERR	#ERR	#ERR	#ERR					
33			2.000	#ERR	#ERR	#ERR	#ERR	#ERR	#ERR					

Figure 17. Vision system algorithm

As shown in the figure above, the system algorithm consists of several modules that are an original solution made up of grouped ready-made functions available in the InSight Explorer software. These modules are described below.

The SEARCHING FIXTURE module is used to locate the characteristic shape of the base and position the coordinate system (ROW, COLUMN, THETA) for further referencing of other functions to the established system. This reduces the image processing time since the entire image needs to be scanned only once during the referencing phase, and subsequent functions relate only to selected segments of the image—where defects and quality issues can be expected.

The HOLE DETECTION module is responsible for detecting the presence or absence of the mounting hole. It consists of the BLOBS function, which detects clusters of pixels in the image, and a built-in algorithm analyzes and checks whether these pixels are arranged in the appropriate shape (a circle with specified tolerance). The output of the BLOBS algorithm includes a variable called SCORE, which describes the algorithm's confidence level regarding the presence of the hole. If the confidence level falls below a specified threshold, the hole will not be detected or reported in the program.

The IS THERE A FLAW? module checks whether flaws exist or not in areas where material defects or omissions occur. This module operates by comparing the learned image (a good piece) with the current image. Its output is the result of the GetTotalFlawSize function, which describes the size of the defect in pixels using the HISTOGRAM variable. As one might guess, even nearly identical images differ at the pixel level, which introduces uncertainty into the algorithm. The maximum allowable defect size was experimentally determined. If the algorithm's output exceeds this threshold, it indicates with certainty that a defect is present, and the product is faulty.

The IS HOLE PRESENT module visually presents the result of the HOLE DETECTION module along with a YES / NO description.

The QUALITY CONTROL module is the final composition of the results from the individual modules, summarizing their outcomes. It yields two possibilities—PASS or FAIL. This provides a binary representation—clear and straightforward—indicating whether a given element has been manufactured correctly or not.

3. Results

The algorithm developed in the InSight Explorer software demonstrates correct operation and achieves an estimated accuracy of 95%, which exceeds the accuracy of quality control employees, approximately 85%. An important factor to consider is the system's efficiency, which operates without breaks and is not susceptible to fatigue. In the case of inspecting 1,000 product pieces, a quality control worker may make a higher number of errors compared to an automated vision system. The analysis showed that the algorithm incorrectly classified a part without a hole as correct, on average, once in every hundred cases. Regarding the detection of omissions and defects, the misclassification of a defective product as correct occurred on average 3 times out of 100 attempts. In total, this results in about 3-4 misclassifications for every 100 trials, leading to an overall system accuracy of 95-96%.

4. Summary

The conducted research and implementation of the Cognex vision system for quality control of assembly components manufactured using FDM 3D printing technology confirmed the high effectiveness of automating this process. The developed algorithm, operating in the InSight Explorer environment, achieved an estimated accuracy of 95-96%, surpassing the standard accuracy of quality control employees, which is around 85%. The vision system demonstrated great stability, eliminating the influence of human factors such as fatigue, allowing for consistently high performance. Automated quality control not only reduces the number of errors associated with manual inspections but also significantly speeds up the entire process, leading to increased production efficiency and cost reduction. The results indicated that the system is particularly effective in detecting the absence of a mounting hole, where misclassification occurred only once in 100 cases, as well as in detecting omissions and defects, with an accuracy level of 3-4 errors per 100 attempts. The conclusion drawn from the analysis is that the implementation of a vision system in the production process of components with complex geometry, such as cable holders, is both cost-effective and efficient. The reduction of production errors, lower costs associated with claims, and increased efficiency of control processes suggest that such solutions are the future of modern industry. The integration of vision systems with other automation technologies, such as collaborative robots (cobots), can further enhance the efficiency and quality of production across many industrial sectors.

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