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MASTER'S FINAL PROJECT

Programming of a Robotic Gantry for Material Position Correction

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Master's degree in Robotics and Computer Science

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COMPANY/ORGANISATION IN WHICH THE PROJECT WAS CARRIED OUT: Mondragon Assembly S. Coop.

DECLARATION OF ORIGINALITY

I, Borja Palacios Paniagua

Declare that this Master's Final Project is original, the result of my personal work, and that it has not been previously submitted to obtain another degree or professional qualification. Ideas, formulations, images and illustrations taken from outside sources have been duly cited and referenced.

Abstract

Robotic gantry systems are essential in automation, offering the precision and adaptability needed for advanced manufacturing. This thesis focuses on programming a robotic gantry system for correcting material positions, an operation critical for ensuring quality in industrial processes like assembly and packaging.

The problem arises from the challenge of detecting and aligning materials in real-time, especially given variations in material, lighting, and positioning errors. These issues directly impact the efficiency and reliability of the manufacturing process, necessitating advanced solutions.

The proposed work addresses these challenges by leveraging:

- A robust machine vision system for detecting material edges and positions accurately.
- Kinematic models to calculate corrections in position and orientation.
- Calibration methodologies for aligning vision systems with gantry reference frames.

The project integrates image processing algorithms and systematic calibration steps to enhance the detection accuracy and system reliability. The work is particularly significant as it aligns with industry trends toward higher precision and automation.

Keywords: robotic gantry, material position correction, machine vision, calibration, kinematics.

CERCS codes: **T111** Imaging, image processing, **T120** Systems engineering, computer technology, **T125** Automation, robotics, control engineering, **T170** Electronics, **T210** Mechanical engineering, hydraulics, vacuum technology, vibration acoustic engineering.

Laburpena

Robotika gantry sistemak automazioan funtsezkoak dira, fabrikazio aurreraturako behar den zehaztasuna eta moldagarritasuna eskainiz. Tesi honek hari-posizioak zuzentzeko gantry robotiko bat programatzea du helburu, eta horrek muntaketa eta paketatze prozesuetan kalitatea bermatzeko zeregin kritikoa betetzen du.

Arazoa hariak denbora errealean detektatzeko eta lerrokatzeko erronkan datza, bereziki materialaren, argiztapenaren eta posizionamendu akatsen aldakuntzak kontuan hartuta. Arazo hauek zuzenean eragiten dute fabrikazio prozesuaren eraginkortasunean eta fidagarritasunean, irtenbide aurreratuak beharrezkoak bihurtuz.

Lan honek honako hauek erabiliz aurre egiten die erronka horiei:

- Hariaren ertzak eta posizioak zehaztasunez detektatzeko ikusmen makina sistema sendoa.
- Posizioaren eta orientazioaren zuzenketak kalkulatzeko eredu zinematikoak.
- Ikusmen sistemak gantry erreferentzia esparruekin lerrokatzeko kalibrazio metodologiak.

Proiektuak irudi-prozesatzeko algoritmoak eta kalibrazio urrats sistematikoak integratzen ditu, detekzioaren zehaztasuna eta sistemaren fidagarritasuna hobetzeko. Lana bereziki garrantzitsua da zehaztasun eta automaziorako industriaren joerekin bat datorrelako.

Hitz gakoak: gantry robotikoa, hariaren posizioaren zuzenketa, ikusmen makina, kalibrazioa, zinematika.

CERCS kodigoak: **T111** Irudigintza, irudi-prozesamendua, **T120** Sistema-ingeniaritza, ordenagailu-teknologia, **T125** Automatizazioa, robotika, kontrol-ingeniaritza, **T170** Elektronika, **T210** Ingeniaritza mekanikoa, hidraulika, huts-teknologia, bibrazio- eta akustika-ingeniaritza.

Resümee

Portaalroboti projekteerimine materjalide positsioneerimise korrigeerimiseks

Portaalrobotid on automatiseerimises olulised, need pakuvad täpsust ja kohanemisvõimet, mis on vajalikud keerukates tootmisprotsessides. Käesolev magistritöö keskendub portaalroboti programmeerimisele materialide positsioneerimise parandamiseks, automaatsel päikesepaneelide koostamise liinil.

Probleem seisneb materialide reaalajas tuvastamise ja joondamise keerukuses, eriti arvestades materiali materjali, valgustuse ja positsioneerimisvigade varieeruvust. Need probleemid mõjutavad otseselt tootmisprotsessi tõhusust ja usaldusväärsust ning nõuavad keerukaid lahendusi.

Käesolev töö lahendab neid probleeme järgmiselt:

- Usaldusväärne masinnägemise süsteem materialide servade ja positsioonide täpseks tuvastamiseks.
- Kinemaatilised mudelid positsiooni ja orientatsiooni korrektsioonide arvutamiseks.
- Kalibreerimismeetodid nägemissüsteemide joondamiseks portaalrobotiga.

Projekt ühendab täpsustatud pilditöötlusalgoritmid ja kalibreerimissammud, et parandada tuvastamise täpsust ja süsteemi töökindlust. Töö on eriti oluline, kuna see vastab tööstuse trendidele, mis liiguvad suurema täpsuse ja automatiseerimise suunas.

Marksõnad: portaalrobot, materiali positsiooni korrigeerimine, masinnägemine, kalibreerimine, kineemaatika.

CERCS koodid: **T111** Pilditehnika, **T120** Süsteemitehnoloogia, arvutitehnoloogia, **T125** Automatiseerimine, robootika, control engineering, **T170** Elektroonika, **T210** Masinaehitus, hüdraulika, vaakumtehnoloogia, vibratsioonakustiline tehnoloogia.

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Symbols and abbreviations

AI Artificial Intelligence

OOP Object Oriented Programming

LiDAR Light Detection and Ranging

HMI Human Machine Interface

OPV Organic Photovoltaic

EVA Ethylene-Vinyl Acetate

ROI Region Of Interest

PLC Programmable Logic Controller

PC Personal Computer

SDG Sustainable Development Goals

1. Introduction

This research project focuses on developing a section of an automated machine for producing flexible solar panels in diverse sizes and designs. The study examines a particular working area of this machine, with visual representations provided to enhance understanding of spatial relationships and component functionality.

The core challenge involves implementing precise pick-and-place operations between multiple collection and placement points, though the current implementation focuses on adjusting a single collection point affecting one placement location. While theoretically performable by human operators, the required precision and repeatability make automated robotic systems essential for this application within an industrial production environment.

The system under examination incorporates a gantry mechanism operating in coordination with three material supply conveyors, each handling different components (barrier, EVA, and OPV). Current adjustments specifically target the OPV material positioning to ensure consistent placement before subsequent processing stages. These later stages involve trimming operations on the outer layers while maintaining protective margins around the encapsulated photovoltaic material.

Material positioning inconsistencies necessitate the implementation of machine vision technology to detect actual component placement and calculate necessary gantry adjustments. This automated correction system compensates for inherent variability in material feeding processes that would otherwise compromise manufacturing precision.

The developed solution requires integration with existing production cycles while maintaining operational flexibility. This includes provisions for manual operation when needed, such as for system verification or diagnostic purposes without disrupting normal production workflows.

System reliability is ensured through implementation of safety protocols that prevent erroneous positioning commands in case of detection failures. The design allows for autonomous operation while providing maintenance personnel with diagnostic and correction capabilities through the human-machine interface screen when required.

1.1 Background

This task represents a small yet critical component within the broader machine operation. The gantry system operates in the second of five sequential processing zones, where its primary function involves assembling the various layered materials that constitute the solar panel. The specific composition of each panel varies according to the selected production recipe. Following this assembly stage, the partially completed panels undergo numerous additional processing steps before reaching their final form.

Given this context, it should be noted that the full complexity of the complete machine system falls beyond the scope of this thesis. The overall project involves collaborative development efforts extending beyond Mondragon Assembly S. Coop. [1] in Aretxabaleta (a municipality in Spain's

Basque Country region), including contributions from Orange's headquarters in France and various equipment suppliers who provide and configure specialized machinery for this application.

The research focuses specifically on the described positioning correction system rather than attempting to address the machine's comprehensive functionality. This targeted approach reflects the distributed nature of development responsibilities across multiple engineering teams and partner organizations.

1.2 State of the art

The integration of gantry robotics, machine vision, and artificial intelligence has revolutionized industrial automation, particularly in precision material positioning tasks. This state-of-the-art review focuses on the application of these technologies in solar panel assembly, a critical process in renewable energy manufacturing. Mondragon Assembly, a leader in automation solutions, has been at the forefront of implementing advanced robotic systems for solar panel production. This review explores advancements in gantry robotics, machine vision, AI, and object-oriented programming (OOP) within this context, highlighting their integration and the challenges faced.

Gantry Robotics: Overview and Advancements

Gantry robots, also known as Cartesian robots, are widely used in industrial automation due to their high precision, repeatability, and ability to manage heavy payloads. Operating on a three-axis Cartesian coordinate system (X, Y, Z), they provide linear motion along each axis, and in some cases, a fourth degree of freedom with tool rotation. Recent advancements have enhanced their capabilities, including the implementation of high-speed actuators and controllers. Modern gantry robots now feature high-performance servo motors and advanced motion controllers, enabling faster and more accurate movements. The use of EtherCAT communication protocols has significantly reduced latency and improved synchronization between axes.

Another key development is modular design, which allows for customization based on specific application requirements, such as varying workspace sizes and payload capacities. Additionally, collaborative robotics has improved safety by integrating features such as force sensing and safety-rated sensors, enabling gantry robots to collaborate with human operators securely. [2]

Machine Vision in Robotics

Machine vision plays a crucial role in automated systems that require precision. When processes cannot rely entirely on pre-defined positioning due to variations or external factors, vision systems provide real-time correction, ensuring accurate material placement during assembly. Image processing techniques have become indispensable, as they can be adapted to a wide range of applications.

Key technological advancements include high-resolution cameras and sensors, along with 3D vision systems and depth sensors such as LiDAR and structured light. These technologies enable the capture of highly detailed images, facilitating precise object detection. A notable improvement is the use of time-of-flight cameras, which enhance depth perception, particularly in dynamic and unstructured environments. [3]

Advances in image processing algorithms have also improved object detection, recognition, and pose estimation. Convolutional neural networks and feature-based matching techniques have optimized material identification in automated environments, allowing robots to detect objects and determine their orientation and position with unprecedented accuracy. Additionally, the integration of edge computing and GPU-accelerated processing has significantly reduced latency in vision-based systems, enabling robots to make instant decisions based on visual data, improving efficiency and adaptability.

Object-Oriented Programming (OOP) in Robotics

Object-oriented programming (OOP) is essential in robotics for structuring complex systems, enhancing code reusability, and promoting modularity. OOP principles (encapsulation, inheritance, and polymorphism) enable efficient software development, fostering scalability and reducing redundancy in robotic systems.

Encapsulation simplifies software design by bundling data and the methods that operate on it into self-contained units. This abstraction is particularly useful for designing modular subsystems such as motion controllers, sensor interfaces, and actuator drivers. By enforcing clear boundaries between components, encapsulation improves maintainability and reduces the likelihood of errors.

Inheritance enhances code reusability by allowing new classes to be created based on existing ones. Instead of rewriting similar functionalities, developers can define a base class with common attributes and behaviours and extend it into specialized subclasses. This structure reduces code duplication, facilitates software updates, and streamlines the integration of new robotic models.

Polymorphism provides flexibility by allowing a single interface to represent multiple object types, enabling dynamic behaviour in robotic applications. For instance, a sensor interface might be implemented by distinct types of sensors, such as LiDAR, cameras, or ultrasonic sensors, allowing seamless switching without modifying the main control logic.

OOP is also fundamental in developing robotic frameworks and middleware, such as the Robot Operating System, which relies heavily on object-oriented design patterns. By structuring software into reusable components, OOP supports innovation, efficiency, and scalability in robotic applications. [4]

Application of Robotics, Machine Vision, and AI in Solar Panel Assembly: The Case of Mondragon Assembly

The integration of gantry robotics, machine vision, and AI has significantly impacted solar panel assembly, enhancing precision, efficiency, and sustainability. These technologies contribute to high-quality production while minimizing material waste and energy consumption.

One of the most critical applications is precision material positioning, where vision-guided gantry robots accurately place solar cells and other components during assembly. Equipped with advanced vision systems, these robots achieve millimetre-level precision, ensuring optimal alignment of solar cells on substrates.

Quality inspection has also benefited from automation, with machine vision systems detecting defects such as cracks, misaligned cells, and surface irregularities. By automating defect detection, manufacturers can significantly reduce waste and improve production efficiency. Additionally, adaptive control algorithms powered by AI allow robotic systems to adjust to variations in material placement and environmental conditions, increasing precision and reducing downtime.

Mondragon Assembly exemplifies the successful implementation of these technologies. The company specializes in customized automation solutions tailored to the specific needs of solar panel manufacturers. By integrating advanced machine vision and AI, Mondragon Assembly enhances precision and efficiency while prioritizing sustainability, developing solutions that reduce waste and optimize energy consumption. [1]

Challenges and Future Directions

Despite the significant advancements in gantry robotics, machine vision, and AI, several challenges remain. Calibration and alignment are crucial for achieving high precision, as misalignment can lead to errors in material positioning. Variations in lighting, occlusions, and moving objects can also impact vision system performance, requiring robust algorithms and adaptive lighting solutions. Additionally, real-time processing of high-resolution images demands substantial computational resources, necessitating ongoing advancements in hardware and software optimization.

Future research should focus on developing more robust and adaptive vision algorithms, integrating AI for predictive maintenance.

Conclusion

The integration of gantry robotics and machine vision has transformed precision material positioning in industrial automation, particularly in solar panel assembly. Advances in motion control, vision systems, and adaptive algorithms have enabled robots to perform complex tasks with high accuracy and efficiency. Addressing challenges such as calibration, dynamic environments, and computational complexity will further enhance these systems, with edge computing playing key roles in their continued evolution.

1.3 Objectives

This project addresses specific technical tasks that contribute to a broader industrial machine development effort by Mondragon Assembly. The work focuses on two core technical goals:

1. Precise detection of incoming material positions using machine vision techniques, including real-time image processing and feature recognition.
2. Automated correction of material positioning to ensure the gantry system places materials with ±0.5 mm accuracy.

While this tight positional tolerance is primarily an aesthetic requirement, the system could tolerate greater deviations without affecting solar panel functionality. The vision and positioning systems must be fully integrated with the machine's main control program, requiring careful calibration of cameras and actuators. The project provides valuable learning opportunities in several technical areas: developing machine vision applications, integrating complex electromechanical systems, mastering precision calibration methods, troubleshooting automated processes, and implementing sustainable manufacturing solutions. These skills have broad applicability in industrial automation beyond this specific application.

The work represents one component of a larger manufacturing system being developed through collaboration between Mondragon Assembly and international partners. While the complete machine involves greater complexity across its five processing zones, this project specifically targets the vision-guided positioning system in the second zone. The solution must maintain compatibility with the overall production sequence while allowing for manual operation when needed. Safety considerations include preventing erroneous gantry movements during vision system failures. The implementation allows for autonomous operation while providing maintenance personnel with diagnostic and override capabilities through the human-machine interface when required.

The technical approach emphasizes practical, production-ready solutions rather than theoretical exploration, with all components designed for reliable industrial operation. The methods developed could potentially be adapted to similar material handling applications in other manufacturing contexts.

1.4 Project Planning

The planning of the project depended on how the assembly of the machine was going. The limitations of availability to work with the machine once it was assembled was also a key point and the organization with other partners was crucial for a correct management of time and resources. The Gantt´s Chart where all this is visible can be found in Annex A.

1.5 Specifications

1.5.1 Resources

To conduct this project successfully, the following resources will be required:

- Hardware:
    - Gantry Robot System: A high-precision gantry system capable of accurately positioning and releasing components.

  - Cameras and Lenses: High-resolution cameras for machine vision tasks. Cameras model is Basler acA4600-7gc and the lenses are VS Technology VS-0818VM. [5]
  - Actuators and Motors: Precision actuators and motors to position the incoming materials accurately based on visual feedback.
  - Processing Units: Computers or edge devices with sufficient computing power to manage real-time image processing.
  - Calibration Tools: Tools for the precise calibration of cameras and actuators to ensure proper alignment and positioning.
- Software:
  - Programming Languages: Python, C++, TwinCAT or similar for implementing control algorithms and integrating vision systems.
  - Machine Vision Software: Software for image processing, such as OpenCV, or proprietary software solutions. TwinCAT also provides their own Vision tool.
  - Control Software: Software to manage the integration of actuators, cameras, and sensors.
- Personnel:
  - Robotics Engineers: Professionals with expertise in robotics, programming, and integration.
  - Vision System Experts: Specialists in computer vision to develop and fine-tune the detection system.
  - Technicians: Staff for hardware setup, calibration, and maintenance.

1.5.2 Requirements

For the project to be executed successfully (meaning, to achieve the positioning target with a precision of ±0.5 mm) the required time must align with the cycle time. However, this timing is not critical in this instance, as the process operates at a low cadence. The following requirements must meet:

- Technical Requirements:
  - High-Precision Calibration: The cameras and actuators must be calibrated to achieve a positioning accuracy of ±0.5 mm.
  - Integration of Systems: Seamless integration between vision systems, actuators, and control software for synchronized operation.
  - Environmental Adaptability: The system should be able to manage variations in material characteristics or environmental conditions (for example, lighting conditions, surface irregularities).
- Operational Requirements:
  - Automation of Misalignment Detection: Machine vision system must be capable of automatically identifying misalignment in the incoming materials.
  - User Interface: An intuitive interface should be developed for operators to monitor and control the system.

1.5.3 Specific Conditions

- Working Environment:

    - The system should be designed to work in a manufacturing environment with controlled conditions, such as temperature, humidity, and lighting, to ensure reliable operation.
    - The gantry robot must be capable of functioning in tight spaces with high precision, without interference from other machinery or obstacles.
- Safety Protocols:
    - The design must comply with safety regulations, ensuring that the robot operates safely in proximity to human operators.
    - The gantry robot should have emergency stop features, collision detection, and safety barriers to prevent accidents.
- Maintenance and Upkeep:
    - The system should be designed for easy maintenance, including regular calibration checks, software updates, and hardware inspections.
    - There should be a troubleshooting system for identifying and resolving issues promptly.

1.5.4 Standards and Regulations (UNE Standards)

To ensure compliance with industry standards and safety regulations, the project should adhere to the following UNE standards and other relevant guidelines: [6]

- Regulation (EU) 2023/1230 on Machinery. This regulation establishes health and safety requirements for the design and construction of machinery placed on the European market. It also governs the application of the CE marking, which is mandatory for machinery intended for use within the EU. Compliance with this regulation is essential to ensure that the machinery meets the necessary legal and safety obligations.
- UNE-EN ISO 10218-1: Robotics – Safety Requirements – Part 1: Industrial Robots. This standard outlines the safety requirements for industrial robots, including those related to physical interaction with humans and safeguards for accident prevention.
- UNE-EN ISO 12100: Safety of Machinery – General Principles for Design – Risk Assessment and Risk Reduction. This standard provides guidelines for risk assessment and risk reduction when designing machinery, including robotic systems.
- UNE-EN 62061: Safety of Machinery – Functional Safety of Electrical, Electronic, and Programmable Electronic Control Systems. This standard specifies the requirements for the functional safety of machinery control systems, ensuring that robotic systems are safe and reliable.
- UNE 166002: Innovation Management – R&D and Innovation Management Systems. This standard provides guidelines for the management of R&D and innovation activities in organizations, ensuring the proper management of the technological advancements related to robotics and automation.
- UNE-EN ISO 13849-1: Safety of Machinery – Safety-Related Parts of Control Systems. This standard covers the design and integration of control systems that are responsible for safety functions, including robotic systems.
- UNE-EN 60204-1: Safety of Machinery – Electrical Equipment of Machines – Part 1: General Rules. This standard defines the electrical safety requirements for machinery and automated systems.

- UNE-ISO 14001: Environmental Management Systems – Requirements with Guidance for Use. If the project focuses on sustainability, compliance with this standard ensures that environmental impact is minimized, and proper management of resources is in place.
- UNE-EN 61508: Functional Safety of Electrical/Electronic/Programmable Electronic Safety-Related Systems. This standard specifies requirements for the functional safety of electrical, electronic, and programmable electronic systems, applicable to robotics systems where safety is a concern.

By following these standards and regulations, the project will ensure not only technical success but also compliance with safety, quality, and sustainability standards.

2. Development

The project begins with a thorough analysis of the gantry correction requirements, encompassing several fundamental aspects: calibration procedures, kinematic considerations, and the derivation of essential parameters for subsequent calculations. These parameters primarily consist of positional data obtained from the vision system, specifically the coordinates of designated reference points on the incoming materials that serve as inputs for the positioning algorithms.

Material dimensions will vary depending on the recipe but primarily change in length rather than width (see Table 1). This ensures positioning calculations remain consistent, as the images from both cameras remain unchanged whether the material is longer or shorter (within defined limits).

Table 1 Size of materials

Material	Barrier	OPV	Encapsulant
Width (mm)	560-1150	510	560-1150
Length (mm)	550-2000	500-1900	550-2000
Thickness (μm)	120-200	126	120-200

Prior to performing any calculations, it is necessary to establish and define the various reference coordinate systems within the gantry's operational framework. Understanding their spatial relationships and orientations is crucial for accurate position corrections. Visual references (Figure 1, Figure 2 and Figure 3) provide comprehensive views of Zone 2, both with and without internal machinery and conveyors, facilitating this spatial comprehension.

The system configuration reveals three material processing units located externally to Zone 2, each associated with a dedicated conveyor. These units, manufactured by Pasquato and colloquially referred to as "pasquatos", perform critical material handling functions. Each machine contains a roll of specific material (barrier, EVA, or OPV) and precisely cuts it to required dimensions before feeding it onto the respective conveyor for subsequent processing in Zone 2.

This configuration highlights the integrated nature of the system, where external material preparation directly influences the gantry's positioning tasks. The "pasquatos" cutting accuracy contributes to - but does not eliminate - the need for the vision-based correction system, as final placement precision depends on multiple factors including material properties and conveyor dynamics. The relationship between these external machines and the gantry's coordinate systems forms a fundamental part of the correction algorithm's development.

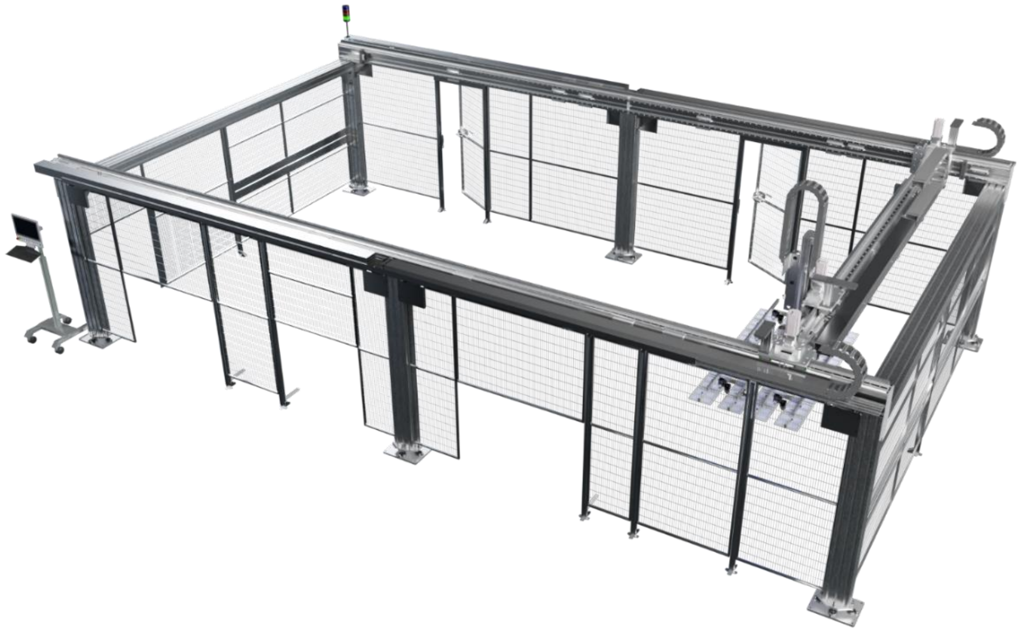

Figure 1 Zone 2 of the production line without machines

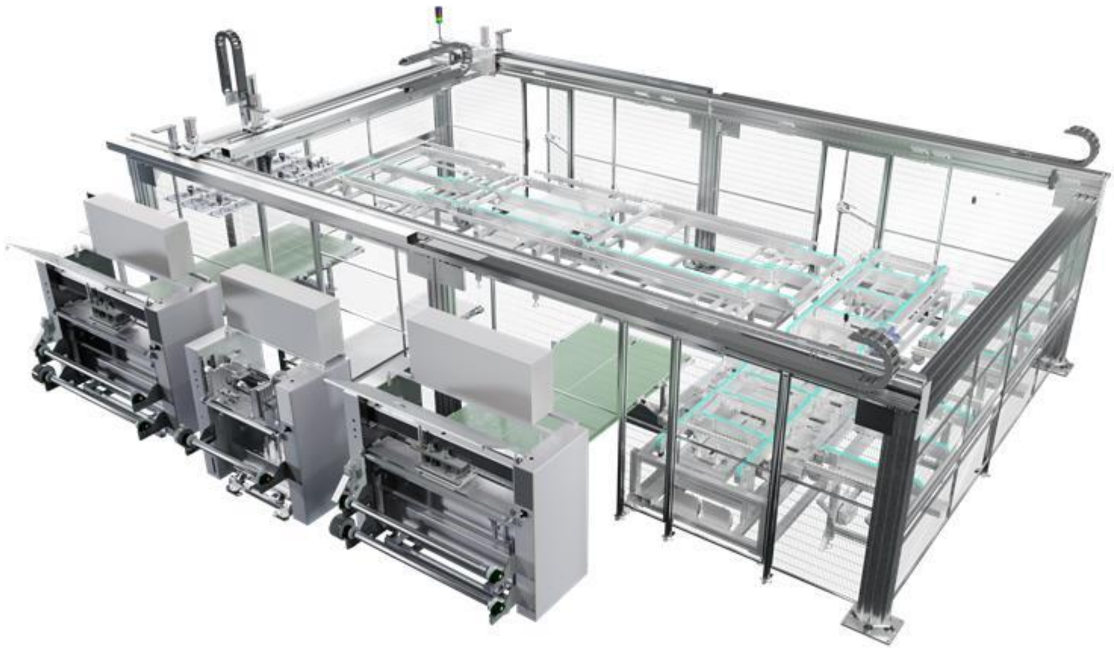

Figure 2 Zone 2 of the production line with machines and conveyors

Figure 3 Real image of zone 2, in Mondragon Assembly facilities

Gantry-Tool reference systems

The gantry system operates within a global coordinate system where the origin point (0,0,0) is located at the bottom-right corner of the gantry structure (as shown in Figure 1), with the positive Z-axis oriented downward. Positive rotation follows the positive direction of rotation as defined by the axis orientation. All pick-and-place positions are defined and programmed within this fixed reference frame.

The end effector (visible in Figure 4) features an innovative modular design consisting of 32 individual 3D-printed components arranged in an 8×4 matrix configuration. The cameras and lights are marked with red circles in the image. This versatile design enables:

1) Adaptive material handling through selective vacuum activation.

2) Compatibility with various material sizes by controlling specific electro-valves.

3) Efficient reconfiguration for different production requirements.

The matrix configuration provides multiple pickup points that can be independently activated, allowing the system to manage different material formats without physical tool changes. When combined with the vision system's positional data, this setup enables precise material placement regardless of incoming material dimensions or orientation.

All positional corrections calculated by the vision system are transformed into this global coordinate system before being executed by the gantry. The downward Z-axis orientation reflects the machine's working direction and matches the physical movement of the gantry head during material pickup and placement operations. This coordinate system standardization ensures consistency across all automated processes in Zone 2.

The tool's modular nature complements the precision requirements (±0.5mm) by providing multiple contact points that can compensate for minor material variations while maintaining the specified placement accuracy.

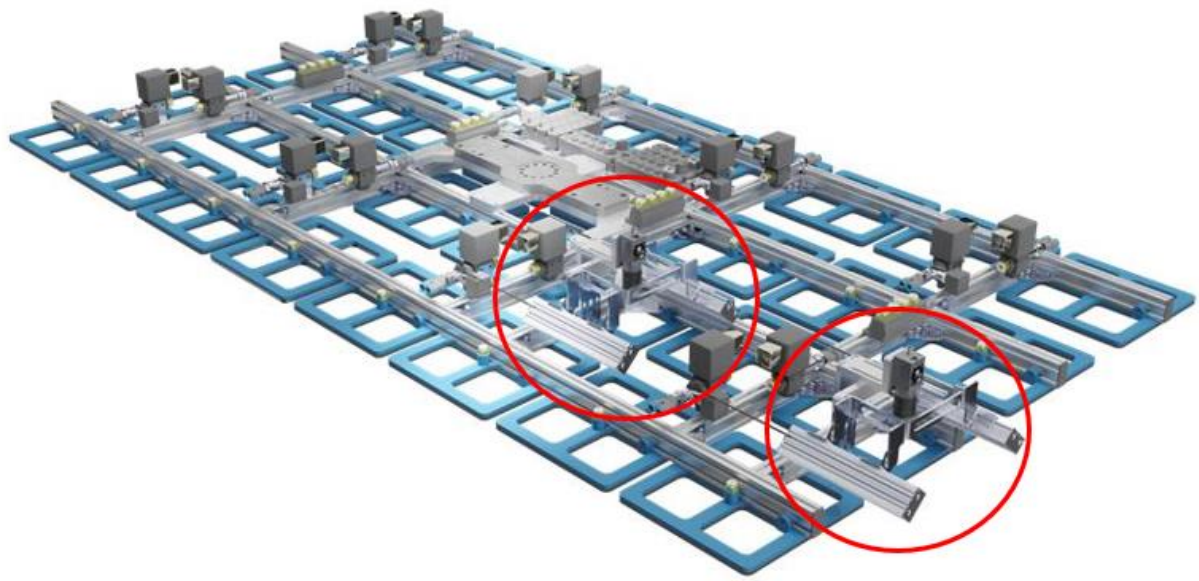

Figure 4 Tool for Pick-Place operations

Cameras reference systems

The camera coordinate systems are established during the calibration phase, with their axes intentionally aligned to match the gantry's positive axis orientation. However, each camera's origin point is determined dynamically based on the specific calibration image used to derive the extrinsic parameters. The calibration process involves several key steps:

Axis Alignment:

- Cameras are configured to maintain consistent positive axis directions with the gantry system.
- This alignment ensures coordinate system compatibility between vision data and mechanical movements.

Calibration Process:

- Implemented through TwinCAT software (partial interface shown in Figure 5).
- Utilizes precision chessboard patterns (24×15 grids with 3×3 mm squares).

Algorithm requires subtracting 1 from row/column counts (23×14) because it detects intersection lines inside the pattern.

Reference Point Definition:

- 'Extrinsic Origin' establishes the image reference point at the chessboard's top-right corner.
- 'World Coordinates' parameter defines axis orientation and positive directions.
- Default values are maintained for most parameters.
- Image encoding set to BayerBG to match camera acquisition settings.

Mathematical Transformation:

- Intrinsic parameters are first obtained through calibration.
- Rotation matrices are then applied to align all camera images with the global coordinate system.

The calibration creates a direct mathematical relationship between pixel coordinates and real-world positions, enabling accurate conversion of vision system detections into gantry movement commands. The chessboard's known geometry serves as the fundamental reference for determining both intrinsic camera properties and their spatial relationship to the gantry's working volume.

This standardized calibration approach allows different cameras to provide spatially consistent data regardless of their physical mounting positions, which is critical for maintaining the system's ±0.5mm positioning accuracy requirement. The process also accounts for potential lens distortions, ensuring measurement precision across the entire working area.

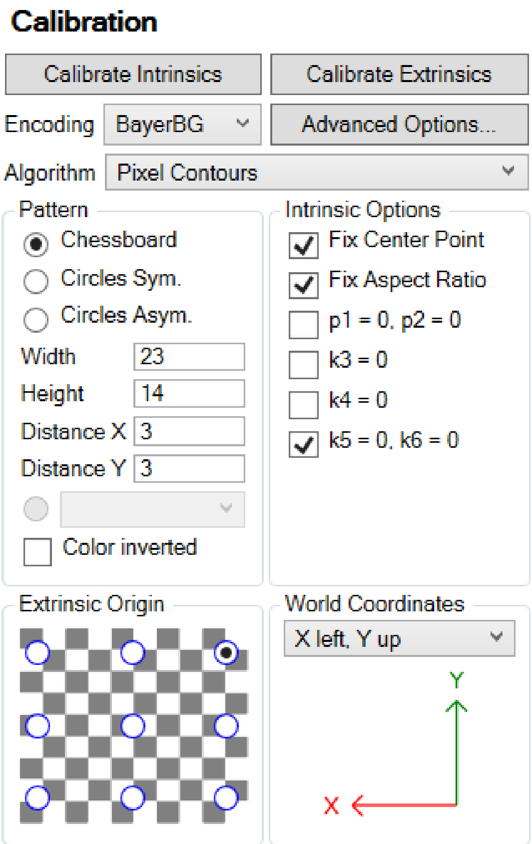

Figure 5 Detail of calibration software

2.1 Calibration

The camera calibration requires a special board with two aligned chessboards and a reference circle (shown in Figure 6). This board has three mounting holes that attach to a calibration carrier, which is a machined plate with matching holes. The specifications of both the calibration carrier and the calibration board can be found in Annex B and Annex C.

The chessboard patters (24×15 grids with 3 mm squares, so 72x45 mm) are used for calibration, while the circle serves as an additional reference point. The three-hole mounting system ensures repeatable positioning during calibration. This setup allows accurate calibration of all cameras relative to the gantry's coordinate system, maintaining the required ±0.5mm positioning precision. The calibration process follows the standard TwinCAT procedure described previously.

Key features:

- Dual chessboard pattern.
- Mechanical mounting for precise, repeatable positioning.
- Compatibility with multiple conveyor configurations.

The calibration validates both the camera parameters and their spatial relationship to the gantry's working volume.

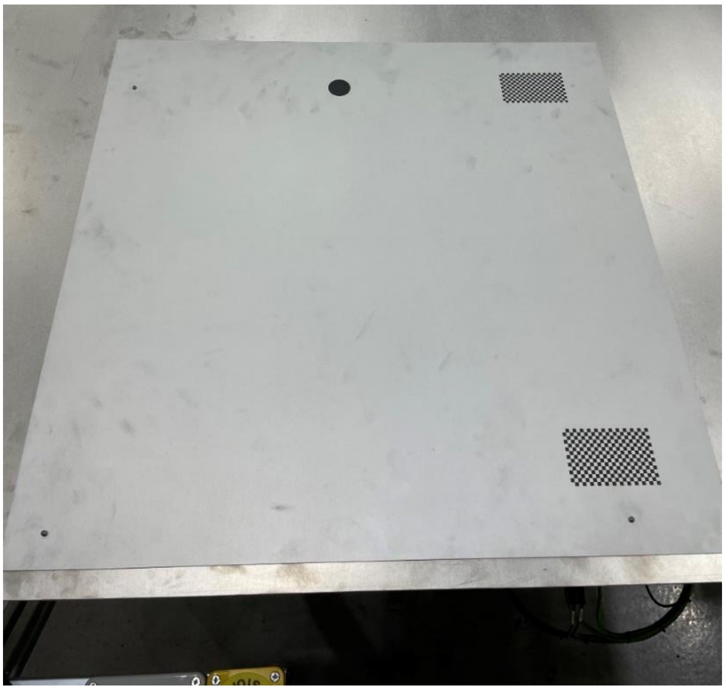

Figure 6 Calibration board pinned with calibration carrier

2.1.1 Distortion correction and *pixel-mm* relation

The calibration board is positioned at the same height where production imaging occurs, ensuring the cameras' field of view matches operational requirements (see Figure 7). The cameras are located to 450 millimetres of distance in the Y direction of the gantry when the tool is not rotated, this is why the calibration board contains the chessboard patterns to that exact distance. If patterns and cameras were aligned, both cameras would see the chessboard pattern is nearly same position.

For calibration:

- A series of 7-9 images per camera are captured while moving either the gantry or calibration board to cover all areas within the cameras' field of view.
- While additional images could theoretically improve calibration, the number is limited due to:
  - Significant increase in processing time.
  - Potential software failures without indication of which specific image caused errors.
  - Minimal benefits that do not justify the additional time investment.

Key calibration parameters:

- The height is carefully calculated to:
  - Achieve the desired field of view.
  - Ensure clear visibility of the chessboard patterns.
- Chessboard patterns provide the reference points for calibration.

This approach delivers reliable calibration while maintaining efficient workflow. The chessboards enable calculation of both the cameras' internal parameters, and the calibration process establishes accurate positioning references for production operations. [7]

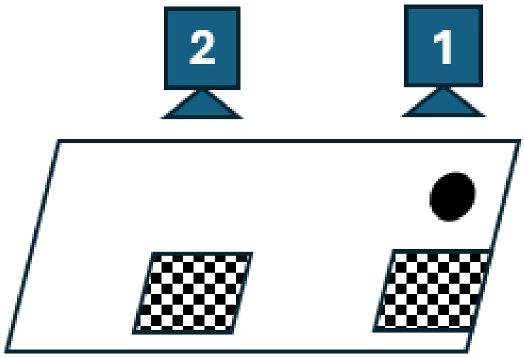

Figure 7 Configuration of cameras and calibration board for image calibration process

These images are introduced into the calibration software of the TwinCAT Vision and after this, the undistorted images and the *pixel* to *mm* (patterns dimensions are known, if not, the conversion would be *pixel* to pattern) conversion can be obtained with the obtained information.

2.1.2 Angle between camera 1 and gantry

In other words: rotation of the pixel matrix relative to the gantry coordinate system. The calibration process begins by positioning the calibration board on the conveyor with the reference circle centred in the camera's field of view, after which an initial reference image is captured. While keeping the calibration board stationary, the gantry then moves systematically to capture a total of nine images (see Figure 8) arranged in a 3×3 grid pattern, three vertical positions (up, centre, down) and three horizontal positions (left, centre, right). This methodical approach ensures comprehensive coverage of the camera's working area while maintaining optimal focus and lighting conditions throughout all image captures. The resulting image set provides the necessary data points for accurate calculation of the position of the camera relative to the gantry.

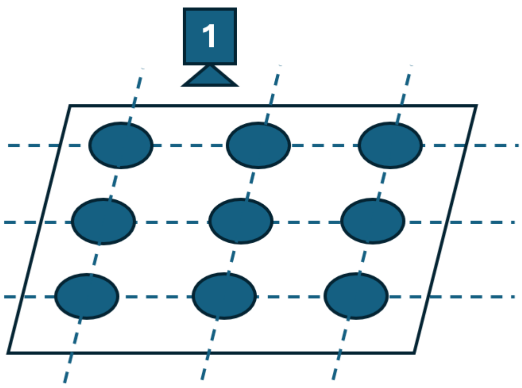

Figure 8 Configuration of camera 1 and calibration board for angle between camera and gantry calculation

The obtained images can be seen in Figure 9. The height of the camera was higher than the one settled for the acquiring during the process, in order to have a bigger distance between points so that the calculations could be more precise.

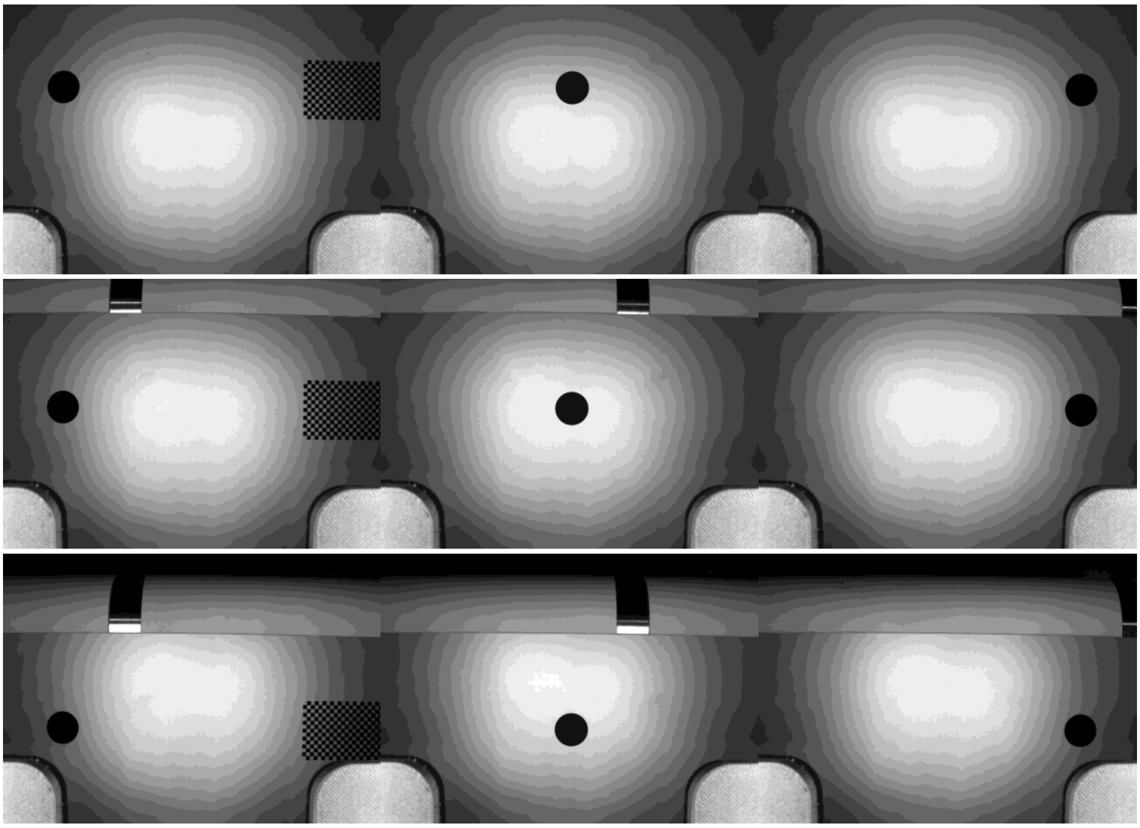

Figure 9 Obtained images for angle between camera 1 and gantry calculation

Following image acquisition, the circle centres are automatically detected using TwinCAT's built-in functions, with the results exported to an Excel file for angle calculation between reference points in both axes. While theoretically these angles should measure precisely 0° and 90° respectively, minor deviations are typically observed. As illustrated in Figure 10, the measured points show slight angular misalignment, with an average deviation of 0.388°. This angular discrepancy represents the relative orientation between the camera's coordinate system (pixel matrix which is transformed to millimetres) and the gantry's movement axes, a parameter that will be accounted for in subsequent calibration adjustments.

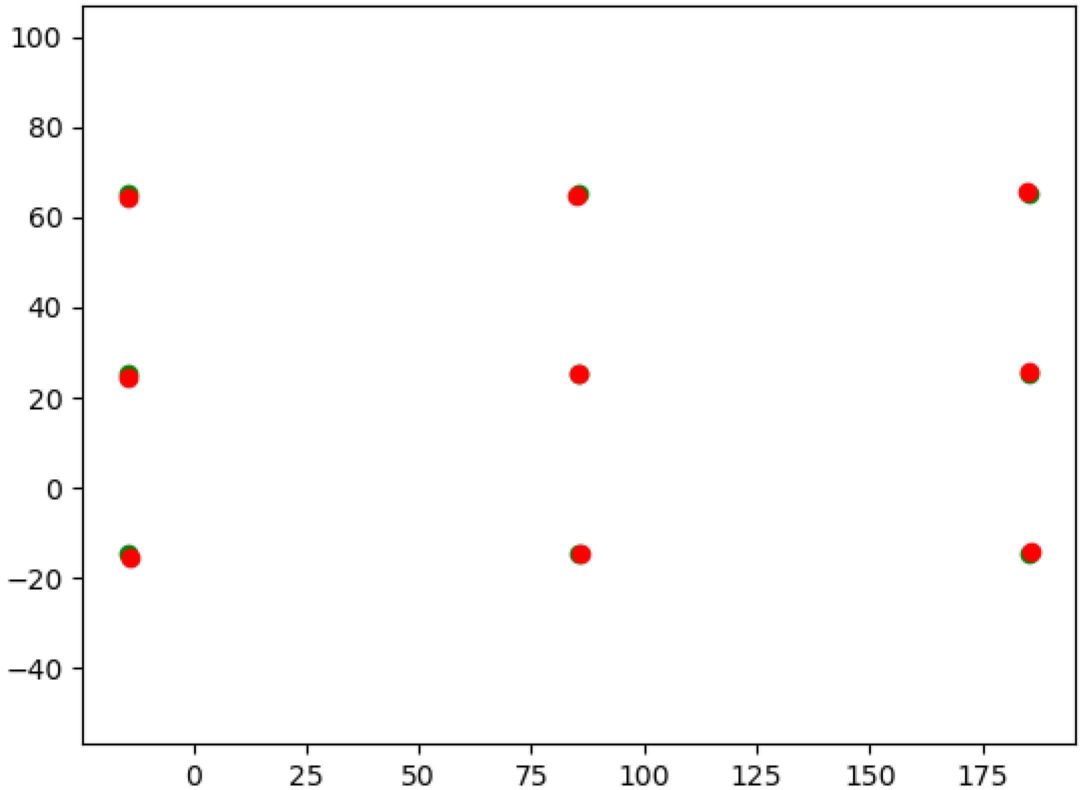

Figure 10 Graphical representation of actual gantry position and detected points for angle calculation

Green dots: Gantry position (X, Y, scaled).

Red dots: Image results (X, Y).

2.1.3 Estimation of rotation centre

This calibration process involves maintaining the calibration board's circle in a fixed position while rotating the tool through various angles, as depicted in Figure 11. For each angular position, an image is captured (camera 1 is used for this), and the circle's centre is determined. These centre points are subsequently processed through a circle-fitting algorithm, with the resulting circle's centre identifying the system's precise rotational centre. This calculated rotation centre serves as a critical reference for compensating positional deviations during operational movements. The camera 1 is used for this calibration because it is further from the centre of rotation, and with smaller rotations there are bigger deviations of the circle.

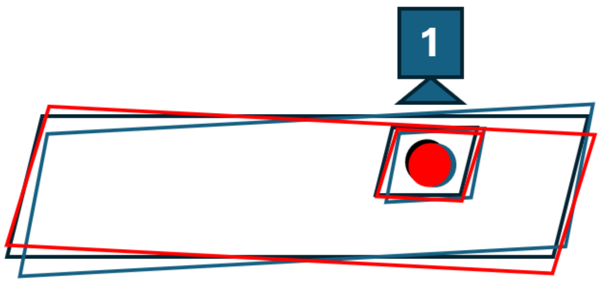

Figure 11 Configuration of camera 1 and calibration board for obtaining the rotation centre

In the Figure 12, it can be seen how the acquired images were.

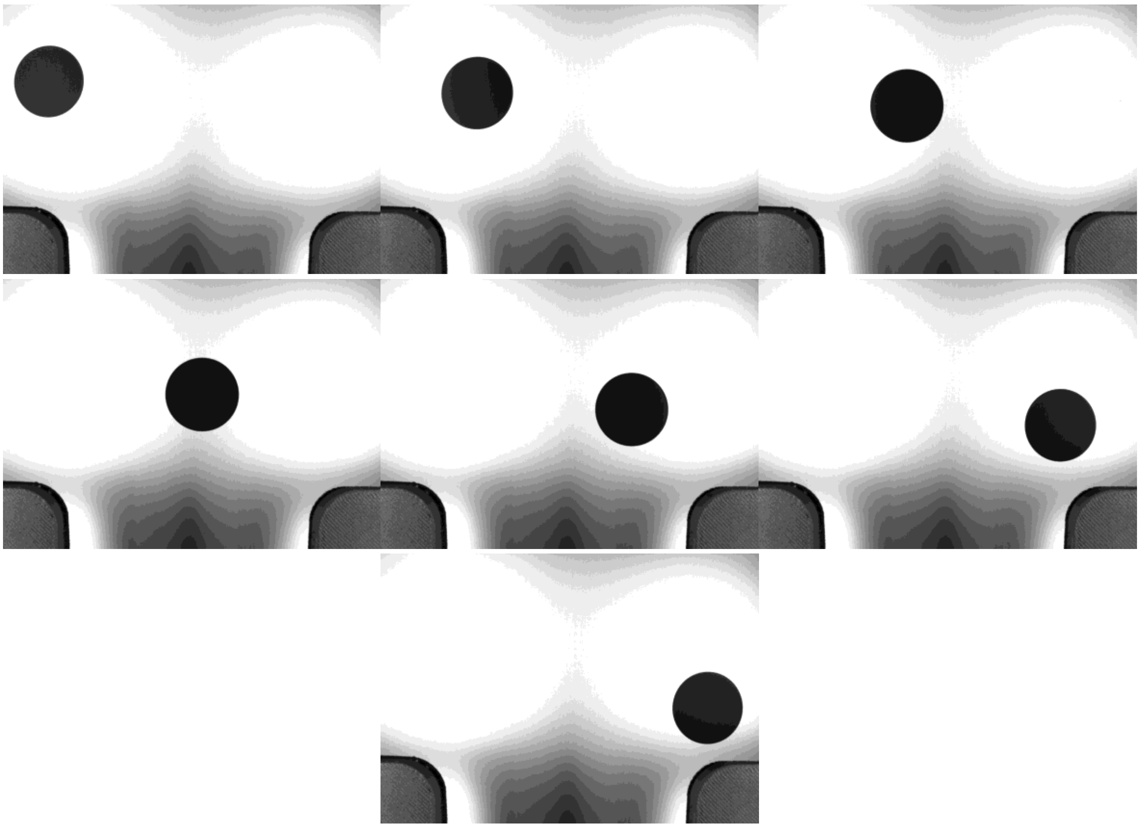

Figure 12 Obtained images for the calculation of rotation centre

Once all images are captured, they are processed using image analysis software (such as OpenCV or MATLAB) to detect the circular markers' centres. The initial processing stage involves image cleaning and binarization to isolate the target circle, as demonstrated in Figure 13. This preparatory step enhances detection accuracy by removing background noise and non-essential features before the actual centre-point calculation is performed. The resulting binary image contains only the clearly defined circular marker used for subsequent precision measurements.

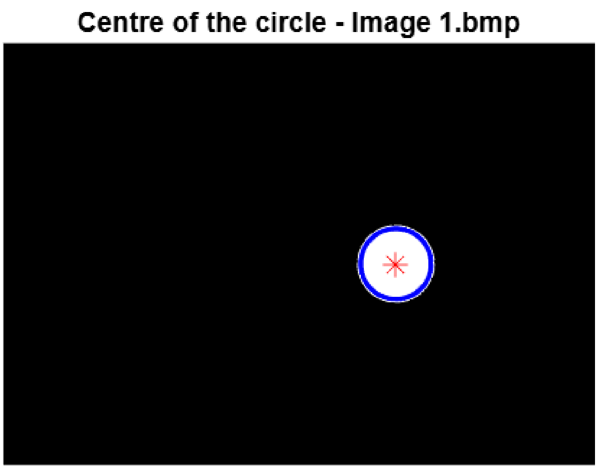

Figure 13 Processed image for obtaining the location of the circle

After processing all images, the coordinates of the detected circle centres are compiled into an array. Using least-square method (implemented through MATLAB's library in this case), the optimal circle encompassing these points is calculated, with its centre representing the system's rotational reference point (as visible in Figure 14). The absolute magnitude of this centre's coordinates carries the operational significance, while the sign convention proves irrelevant as it merely reflects the arbitrary choice of coordinate system orientation during data input.

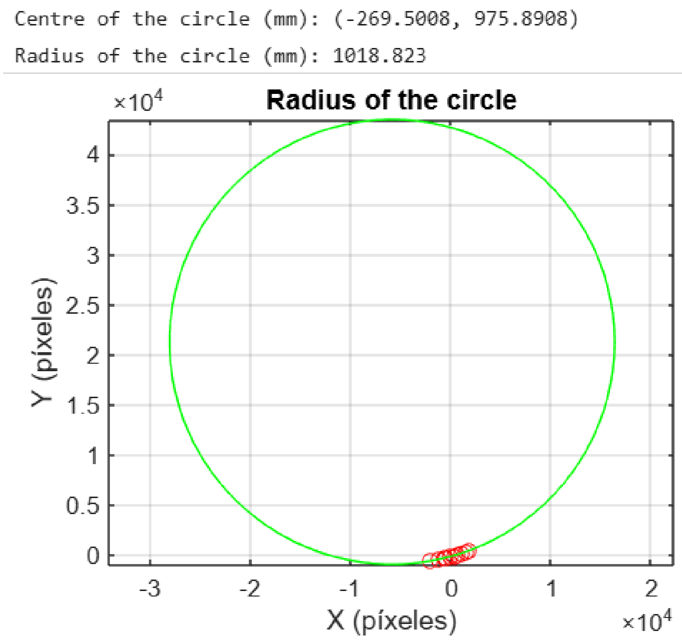

Figure 14 Estimation of the rotation centre

2.1.4 Improvement of the calculation of rotation centre

Following the initial MATLAB analysis, the same calibration procedure was implemented in TwinCAT with an adjusted camera height to accommodate a wider rotational range. By increasing the field of view, the system captured more distant points along the circular path during gantry rotation, enhancing measurement accuracy through greater angular separation between reference points. In other words, angle of the sector of the circle used for calibration is larger, and the arc fitting algorithm works better.

This critical calibration requires only a single execution, as the determined rotational radius remains constant unless mechanical disassembly occurs. The precision of this calculation proves essential, any error propagates through subsequent corrections, with inaccuracies becoming increasingly magnified at larger adjustment angles. The enhanced spatial distribution of measurement points across the expanded field of view provides more robust data for the circle-fitting algorithm, ultimately yielding more reliable positional corrections during operational use.

The image results are introduced into the Excel file, and this gives back the results and a graphical representation of the points, similar to Figure 14. The executed calculations are these:

$$(x^2 - a) + (y^2 - b) = r^2$$

Eq. 1

x: detected X point in millimeters (known).

y: detected Y point in millimeters (known).

a: X coordinate of the circle's center point in millimeters (unknown).

b: Y coordinate of the circle's center point in millimeters (unknown).

r: radius of the circle in millimeters (unknown).

$$x^2 + y^2 - 2ax - 2by + a^2 + b^2 - r^2 = 0$$

Eq. 2

$$x^2 + y^2 + Dx + Ey + F = 0$$

Eq. 3

$D = -2a.$

$E = -2b.$

$F = a^2 + b^2 - r^2.$

$$\begin{bmatrix} x_1 & y_1 & 1 \\ x_2 & y_2 & 1 \\ x_n & y_n & 1 \end{bmatrix} \begin{bmatrix} D \\ E \\ F \end{bmatrix} = \begin{bmatrix} x_1^2 + y_1^2 \\ x_2^2 + y_2^2 \\ x_n^2 + y_n^2 \end{bmatrix}$$

Eq. 4

$$A \cdot X = B$$

Eq. 5

Least square method is used for calculating X matrix at this point, and then the important values, which are a and b are obtained.

2.1.5 Carrier origin

This step establishes the precise origin coordinates (X, Y) and angular alignment of the carrier in the place points of conveyors 2.1 and 2.5 (see Figure 15).

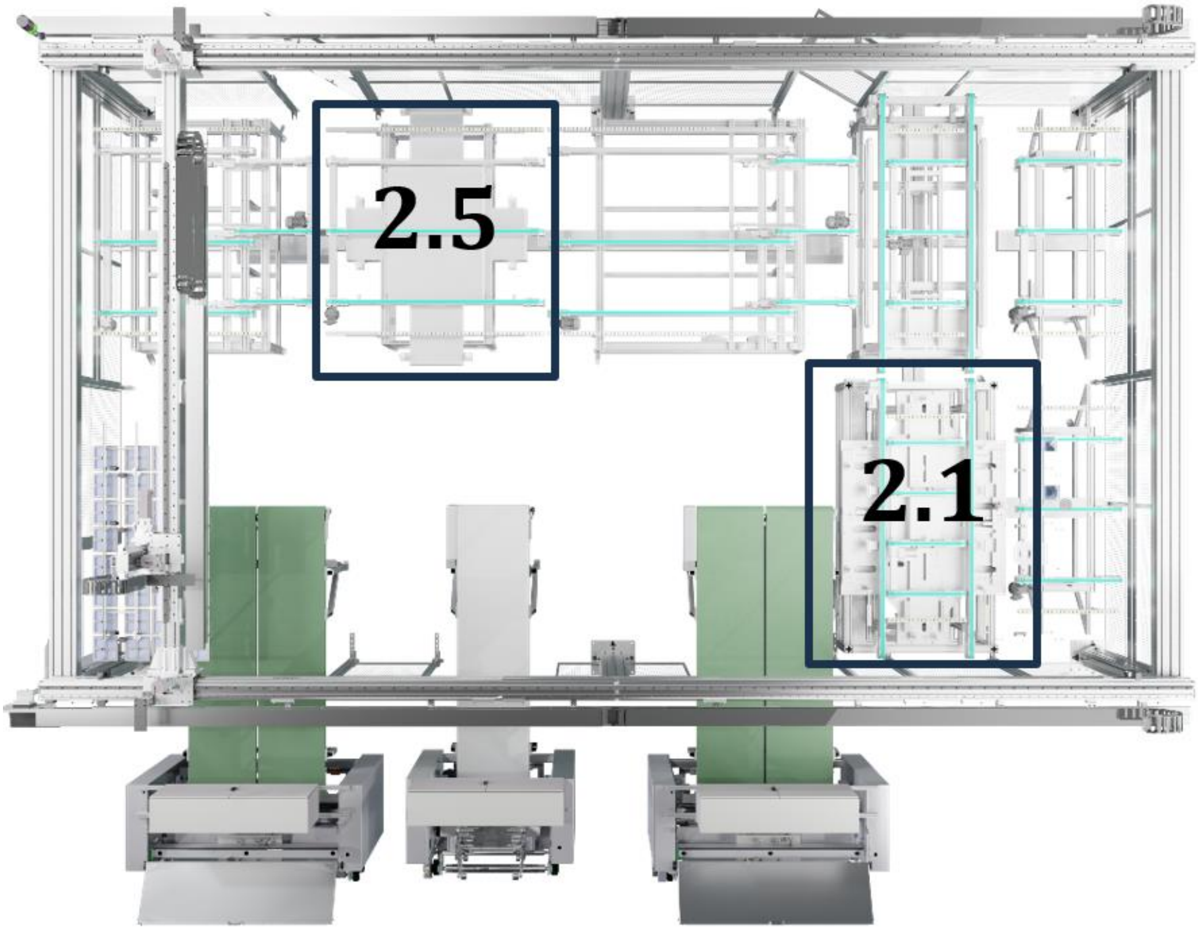

Figure 15 Top view of zone 2, detailing 2.1 and 2.5 conveyors

The procedure involves:

- Positioning the Calibration Board: the calibration board is securely placed on the machined 'calibration carrier', using alignment pins to ensure correct positioning. See Figure 6.
- Alignment Validation:
    - The gantry is moved to a position where the chessboard patterns appear in approximately the same location and orientation as they will at the pick point. The closer this position is to the actual pick point conditions, the smaller the correction the gantry will need to apply, assuming the material consistently arrives in the same place. This gantry position (X, Y, and angle) will be saved as the place point for each conveyor.
- Image Acquisition & Reference Setup:
    - Each camera captures an image of chessboard pattern.
    - The first image determines the corner position (in pixels), while the second detects the pattern's angular orientation. This is how the material has to be detected in pick point.
    - These values are stored as persistent references, ensuring future pick-and-place operations replicate this alignment.

- Recipe-Based Adjustments:
    - The calibration is performed once for the carrier's midpoint, corresponding to the default placement position for single-OPV recipes.
    - For double-OPV recipes, predefined offsets in X (and Y, if angular correction requires it) are applied.
    - For EVA and barrier materials, predefined offsets in Y (and X, if angular correction requires it) are applied.

This process guarantees that the system consistently picks and places materials in the optimal position unless recalibration is performed. Any deviation in this setup would propagate errors, particularly as correction angle increases.

In Figure 16, a complete image of a carrier is shown. This exact carrier is the one used for calibration, even if the machined holes are not easily seen here.

Figure 16 Example of a carrier over a conveyor

2.1.6 Calibration angle between pick and place conveyors

Although the machine is designed with the assumption that all conveyors are aligned, in practice, slight misalignments may occur. Since the current system only corrects for the OPV conveyor, the relative alignment between the OPV conveyor and conveyor 2.1 must be determined. However, this procedure should ideally be performed for all pick-and-place conveyors to ensure future compatibility.

Instead of the conventional approach (which involves capturing multiple images of chessboards and performing complex calculations), a more straightforward and accurate method is employed. This alternative eliminates potential detection errors and ensures precision through physical alignment verification, although it's not exactly a scientific method.

Initial Material Pick:

- The gantry picks a material sheet from any one of the conveyors.

Calibration Board Placement:

- The calibration board is correctly positioned on the target conveyor (one conveyor at a time).
- For conveyors 2.1 and 2.5, the board is mechanically centred using pneumatic actuators.
- For the conveyors where materials are picked, the board is manually aligned to the conveyor's edge. This ensures consistency without requiring additional tools.

Manual Alignment Verification:

- Using manual gantry movements, the edge of the picked material is carefully positioned over the side line of the two chessboards on the calibration board.
- The exact angle at which this alignment is achieved is recorded.

Unlike the standard calibration, the material's corner does not need to align precisely with the chessboard pattern corner, the only requirement is that the edge matches the separation line.

Repeating for all conveyors:

- Without releasing or moving the picked material, the same process is repeated for the remaining conveyors.
- Each conveyor's alignment angle is noted for future reference.

Advantages of This Method:

- Simplicity: does not require complex image processing or chessboard corner and edge detection.
- Future proofing: once performed, this data remains valid unless mechanical changes occur.

Critical Considerations:

- Manual alignment on non-reference conveyors relies on the conveyor's edge as a guide, ensuring reproducibility.
- If the machine's configuration changes, the process must be repeated.

This method guarantees that all pick-and-place operations maintain high accuracy, particularly when angular corrections are applied during material handling.

2.2 Vision detecting program

The edge detection program was developed using TwinCAT Vision, following Beckhoff's technical documentation as a foundation. Mondragon Assembly provided sample images representative of actual production conditions, enabling the implementation of a robust vision processing pipeline. For the better understanding of the process and the different used techniques, academic research was essential. [8]

1. Image Acquisition Verification. The system first confirms successful image reception before proceeding with analysis.

2. Colour Space Conversion. Input images in BayerBG format are converted to grayscale for processing, while retaining colour versions for visualization purposes only.

3. Edge Enhancement. A dual-direction Sobel filter (X and Y axes) highlights gradients, with absolute values combined to create a composite edge map. The Canny algorithm further refines edge detection for optimal feature extraction

4. Morphological Processing. Two closing operations are applied to enhance edge continuity. Additional morphological operations were tested but rejected due to diminishing returns in accuracy versus increased processing time

5. Feature Extraction. Edge points are detected in predefined regions of interest. Detected points undergo linear regression to determine dominant edge lines

6. Geometric Calculations. The system calculates:

    - Angular deviation of each edge relative to the image's X-axis
    - Precise intersection point of detected edges. This intersection point serves as the primary positional reference for material alignment

7. Visual Feedback. All detected features are overlaid on the original image for verification

Implementation Considerations:

- Processing efficiency was prioritized to maintain machine cycle times.
- The current implementation represents a baseline configuration that will be refined using actual production images once the machine is operational.
- Future optimizations may include:
    - Adaptive thresholding improvements.
    - Dynamic region-of-interest selection.
    - Enhanced noise reduction techniques.

2.2.1 Line fitting improvement

The edge detection program provided by Beckhoff [9] demonstrated varying performance across different material types, as visible in the test images. While the first two cases showed reasonably good detection with minor deviations, the third case exhibited clear fitting errors. These results indicated the need for algorithmic refinements to achieve consistent precision. For this preliminary evaluation, the same images originally sent to Beckhoff were used to test potential improvements, despite recognizing that any modifications might overfit the solution to these specific test cases.

The translucent materials presented no detection challenges, performing equally well under different lighting conditions (see Figure 17). The visual results show blue lines representing detected edges and purple dots (visible in all images shown below, but they are more clearly discernible in the transparent material detection, Figure 18) marking the actual edge points used for extrapolation. Notably, when processing slightly warped material sheets, the straight-line fitting approach naturally couldn't perfectly follow the curved edges, even though the edge point detection itself remained accurate. This limitation highlights an important consideration for future algorithm development.

This trial phase served primarily to observe how different materials responded to various filter parameters. While the current implementation may not generalize perfectly to all possible production images, it provided valuable insights for subsequent refinements. The preprocessing approach will undoubtedly require further adjustments once the machine is operational and real production images become available. These initial tests confirmed both the strengths of the current edge detection method and the specific areas needing improvement for robust industrial application.

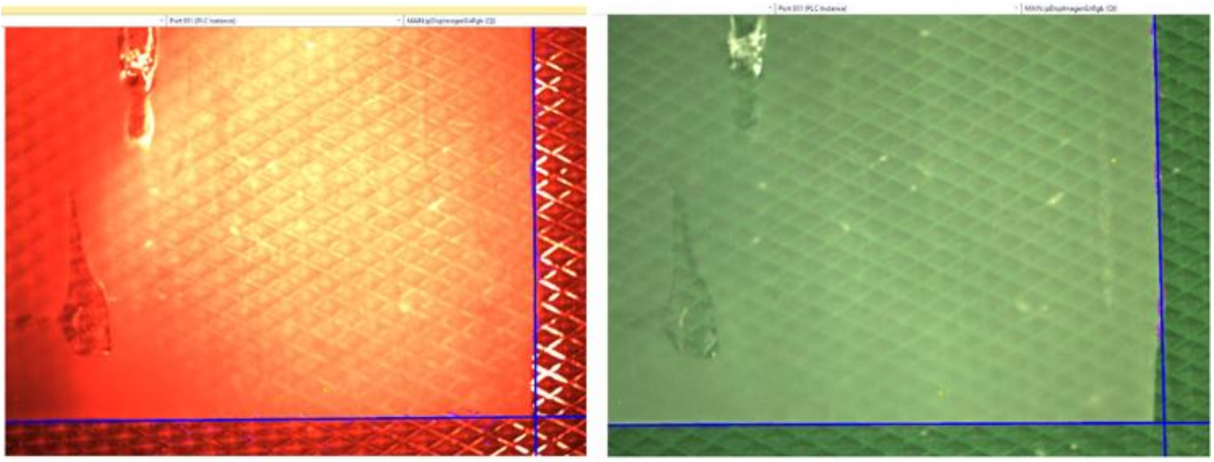

Figure 17 Detection of translucent material, with (left) and without (right) illumination

The transparent material demonstrates reasonably good detection performance even without additional lighting (as visible in Figure 18), though implementing a basic filtering process to remove outlier points from the edge detection data could further enhance accuracy. When analysed under lighting conditions, the vertical edge detection shows notable deviation, yet examination reveals that many of the reference purple points - which determine the edge position - are correctly placed along the true edge, especially in the upper and lower regions.

A straightforward solution involves applying percentile-based filtering to systematically eliminate erroneous points. This approach would retain the accurately positioned points while discarding outliers, significantly improving the overall detection reliability. Such filtering would be particularly effective because: the majority of points are already well-positioned, and the problematic points tend to cluster in identifiable patterns that can be statistically filtered. This adjustment would maintain the system's responsiveness while substantially increasing detection precision, especially for the challenging vertical edge cases observed in illuminated conditions.

The proposed method offers a computationally efficient solution that could be readily implemented within the existing processing pipeline without requiring major algorithmic changes or additional hardware components.

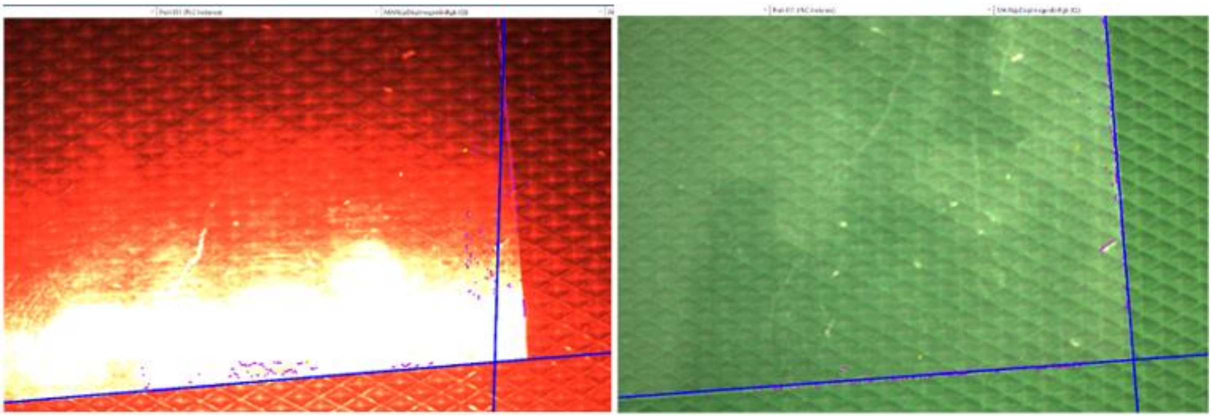

Figure 18 Detection of transparent material, with (left) and without (right) illumination

The OPV material presents the most demanding detection scenario, as evidenced in Figure 19. Analysis of the illuminated sample reveals that strategic lighting of the corner region produces a more defined edge profile in this critical area. By concentrating detection efforts specifically on this well-lit corner zone - rather than attempting uniform edge detection across the entire material - the system could achieve substantially improved positional accuracy.

This targeted approach offers several advantages:

- The corner region typically provides the most geometrically stable reference point.
- Focused illumination minimizes light scattering effects common in OPV materials.
- Reduced processing area enables higher analysis resolution for the most critical alignment features.
- Computational resources can be prioritized for the highest-value detection task.

Implementation would require:

- Precise directional lighting aligned with the corner geometry.
- Adjusted region-of-interest parameters in the vision algorithm.
- Validation testing to confirm detection reliability across material batches.

This solution maintains the system's operational speed while solving the particular challenges posed by OPV materials, where traditional edge detection methods struggle with consistency. The approach could be further enhanced by combining it with the previously discussed percentile filtering for outlier rejection.

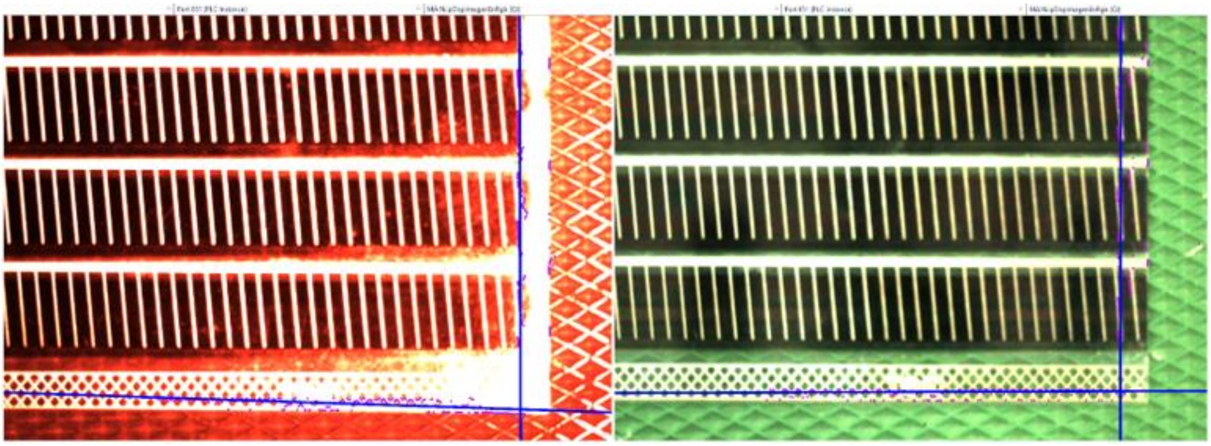

Figure 19 Detection of OPV material, with (left) and without (right) illumination

The entire processing currently takes approximately 400ms, though this measurement was taken on a non-industrial computer using a single core to process the full image. On an industrial PC, the processing time would be considerably faster. Additional optimizations could be implemented by using regions of interest (ROI) to reduce the analysis area and by leveraging multiple cores for parallel processing. The 400ms measurement encompasses the complete image processing pipeline, including result rendering, generation of diagnostic images for each processing step, and all geometric calculations such as corner point detection, edge angle determination, and inter-edge angle analysis.

Given these performance characteristics, several parameters were adjusted to enhance detection accuracy. The original implementation only applied two morphological operations, leaving room for improvement. Testing revealed that while increasing to three or four operations boosted computation time, it also improved edge detection quality for both transparent and OPV materials. The improvement varied between vertical and horizontal edges, though perfect fitting remained elusive.

During this optimization process, it became clear that different materials and image orientations required distinct processing approaches. This realization led to a restructuring of the program into two separate "cases", each with customized parameters for material type and edge orientation. Key adjustable parameters included the detection search area and the number of morphological operations. The refinement process was iterative, with continuous visual feedback guiding parameter adjustments until optimal fitting was achieved. The final results, categorized by material type, are presented in Images X.

Translucid

The detection for this material is decent, but illumination has to be considered when the final configuration is decided. See Figure 20.

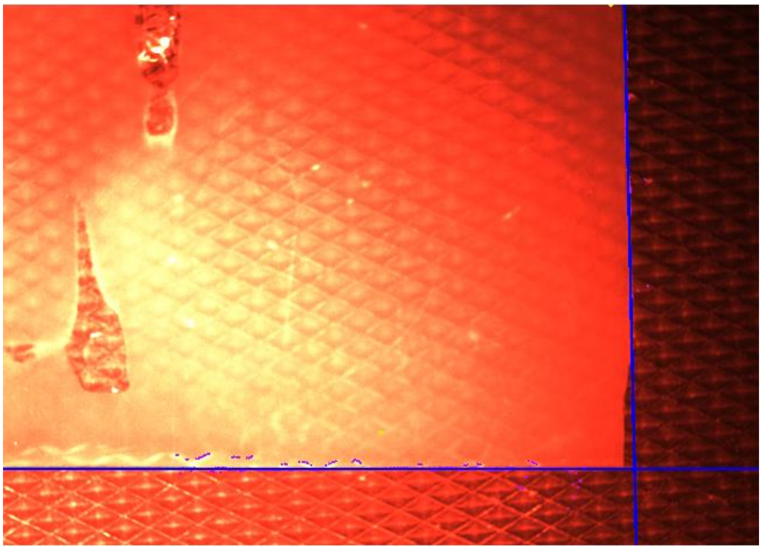

Figure 20 Optimized detection of translucent material

Transparent

As it happened with the translucid material, here the illumination is the key for a correct detection. It can be seen that now the edges are much better than before, but the difference of illumination in the Y axis makes it complex for the detection. See Figure 21.

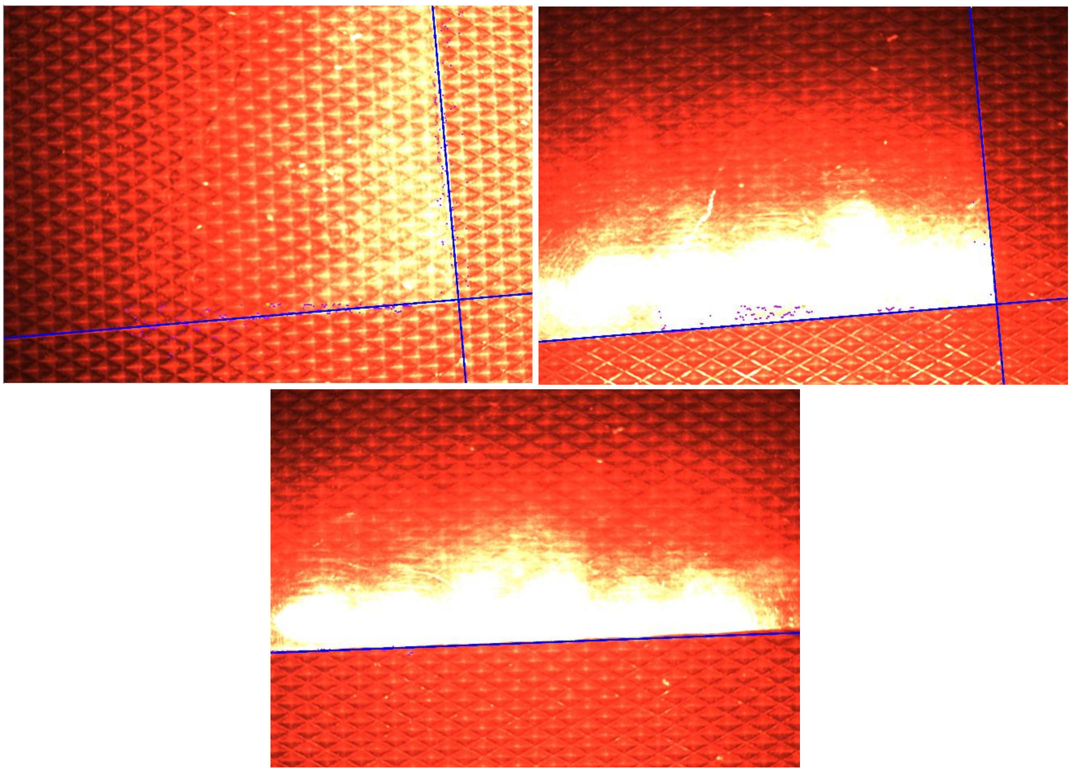

Figure 21 Optimized detection of transparent material with different illuminations for corner image (top left and top right) and illuminated side edge image

OPV

This was and still is the most complex material for the detection. The "holes" in the horizontal edge and the different patterns in the vertical edge make difficult to identify correctly the edges, even if the results now are much better. Illumination is also a key factor here because it can make the detection zones in the image much clear, as seen in the examples of Figure 22.

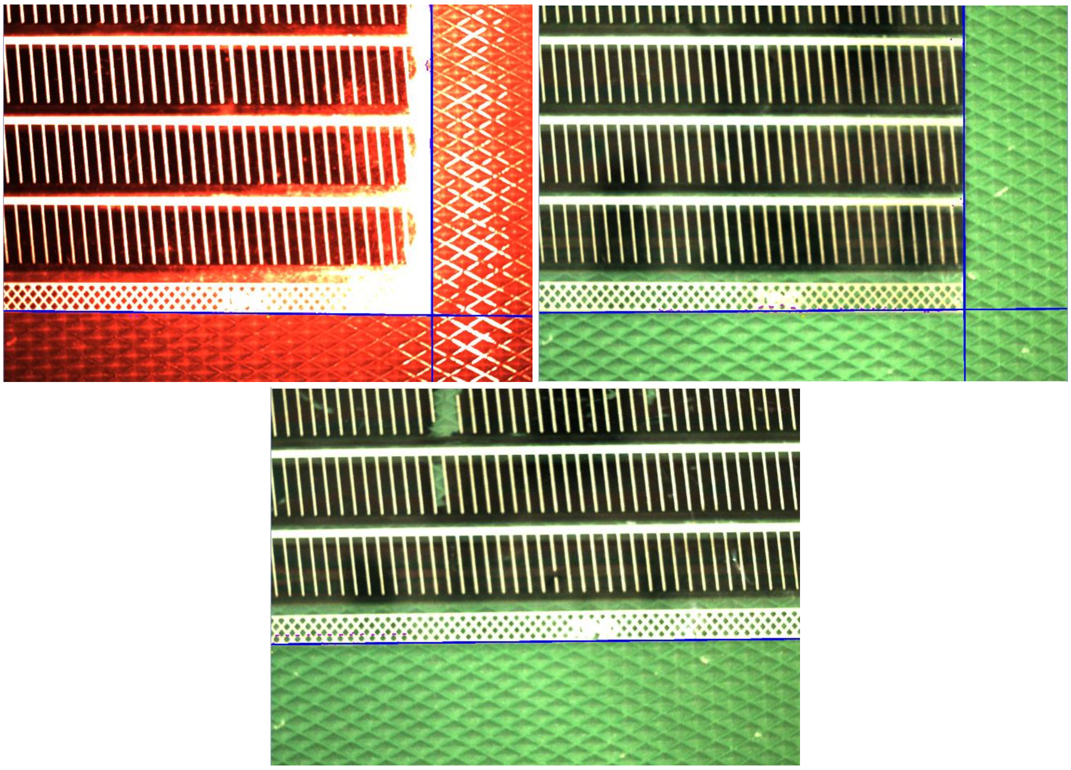

Figure 22 Optimized detection of OPV material with different illuminations for corner image (top left and top right) and illuminated side edge image

Nevertheless, it is important to note that these materials and backgrounds are not the ones that will ultimately be used in the machine. This preliminary process was carried out to assess the requirements for processing the actual images. This approach was necessary because, at this stage of the project, the machine's cameras were not yet available, forcing the team to proceed without them.

To clarify, the only material from these trials that will be used in the final setup is the OPV. However, since OPV is a highly expensive material, a substitute material was employed during the programming phase.

3. Theoretical calculations

With all calibrations completed and the vision program fully implemented, the material's position can be determined through kinematic calculations. The system collects the material from one of three pre-corrected pick points and precisely places it at the designated release point, making necessary adjustments to both position and angle. This process builds on previously established documentation while incorporating the latest refinements to the positioning methodology.

Before performing any calculations, the vision system's detection parameters for the material cells must be defined. This critical parameter determines how the material's location is identified and must be established at the outset. The current configuration uses the material's corner as the reference point, as specified in earlier documentation. Camera 1, mounted on the tool's edge, serves dual purposes: detecting the exact coordinates of the corner point and measuring its angular orientation. These measurements are cross verified with angle data from camera 2, which provides the reference values for final angle correction.

The coordinate system's origin point was established during carrier initialization (section 0) and remains dynamic in the process. To maintain system accuracy, this reference point is updated with each calibration cycle, ensuring consistent precision throughout operations. This approach allows for continuous refinement of the positioning system while accounting for potential variations in the operational environment.

Step 1

Take the data about the position and angle of the material from vision program and obtain the deviation of the obtained point with reference to the established origin. This established origin is where the material’s corner would be ideally found.

$$P_{Origin} = P_{CameraOrigin} - P_{CalibrationOrigin}$$

Eq. 6

$$P_{deviated} = P_{Detected} - P_{Origin}$$

Eq. 7

$P_{CalibrationOrigin}$: Point in pixels of the images where the corner should be detected, it has been converted to millimetres.

$P_{CameraOrigin}$: Origin point of the camera, where the (0,0) in pixels and millimetres is located.

$P_{Detected}$: Detected point in pixels of the material’s corner. It is converted to millimetres.

Step 2

Calculate the coordinates of the centre of the material in relation to the rotation centre.

$$P_{deviated_{refRC}} = P_{deviated} + RC$$

Eq. 8

RC: Distance to the rotation centre

Step 3

Calculate the turning command of the material. This means to settle the rotation that the tool has to do to pick the material correctly aligned. It depends also on the angle obtained in the calibration and any offset that wants to be added.

$$COM_{\varphi} = \gamma_{GantryCalibration} - \delta_{Edge} + \beta_{Offset}$$

Eq. 9

β_{Offset}: Offset rotation angle (optional)

$\gamma_{GantryCalibration}$: Detected angle of the lateral edge when calibration was executed.

δ_{Edge}: Detected angle of the material

Step 4

Rotate the point obtained in *Step 3* with a rotation matrix in *Z* being the angle the one detected in the material. Then obtain the new reference subtracting the distance to the rotation centre.

$$P_{AngleCorrected} = COM_{\varphi} \cdot P_{deviated_{refRC}}$$

Eq. 10

$$P_{Correction} = P_{AngleCorrected} - RC$$

Eq. 11

Step 5

Finally, the correction command is calculated considering the corrected point from *Step 5*, the pick point and any offset that may be added. The correction is rotated to correct the angle between camera 1 and gantry, and the angle of the tool fixed for pick and vision points (in this case, -0.5°).

$$P_{CorrectionGantry} = R_{-(\vartheta_{calib}+\sigma_{PickPoint})} \cdot P_{Correction}$$

Eq. 12

$$PickPoint_{(x,y)} = RecipePoint - P_{CorrectionGantry} + Offset$$

Eq. 13

ϑ_{calib}: Angle between camera 1 and gantry, obtained in calibration.

$\sigma_{PickPoint}$: Angle of the tool when doing the vision and pick operations.

The correction angle was obtained in **Step 3**, named COM_{φ}.

4. Code Integration

Following successful testing of both the vision program and correction program in separate projects, the integration into the machine's main code can now proceed. The software used in this project is TwinCAT 3, which has been previously mentioned in this document. For the execution of the part related to this thesis, the TwinCAT Vision extension is required, as it includes libraries for image processing functions, among others, and allows the cameras to be integrated into the project file.

The original vision code existed as a single comprehensive document where execution depended on manually input cases, source images, and various parameters to generate output values and processed images.

The current task involves restructuring this code into discrete methods called as needed during operation. Since the machine programming follows Object-Oriented Programming principles, a specific organizational structure must be maintained. The required methods include camera status verification, image acquisition, image preprocessing, and edge detection functionality.

The process logic follows the sequence outlined in Figure 23, which shares similarities with the previously described workflow. The vision cycle initiates when called by the gantry program, which first positions the gantry according to the current recipe step requirements. The vision cycle requires specific input parameters including material type and image capture location (corner or side). Progression to subsequent steps occurs automatically once the camera achieves acquisition state and successfully loads the image - both conditions handled within a single method.

Image preprocessing follows immediately after successful image loading. This step operates without error checking since the preprocessing parameters were rigorously determined through extensive image analysis to ensure optimal detection performance. The established parameters guarantee consistent, reliable preprocessing outcomes.

Edge detection and validation occur next, with failed edge detection triggering error handling. Detected edges undergo further analysis to verify positional values and angular relationships fall within expected parameters. Successful edge detection requires identification of either:

- Both vertical and horizontal lines for corner images
- A single horizontal line for side images

Final validation examines numerical values to prevent acceptance of incorrect detections, such as angles significantly deviating from the expected 90° orientation. This comprehensive checking ensures only properly identified features proceed through the system.

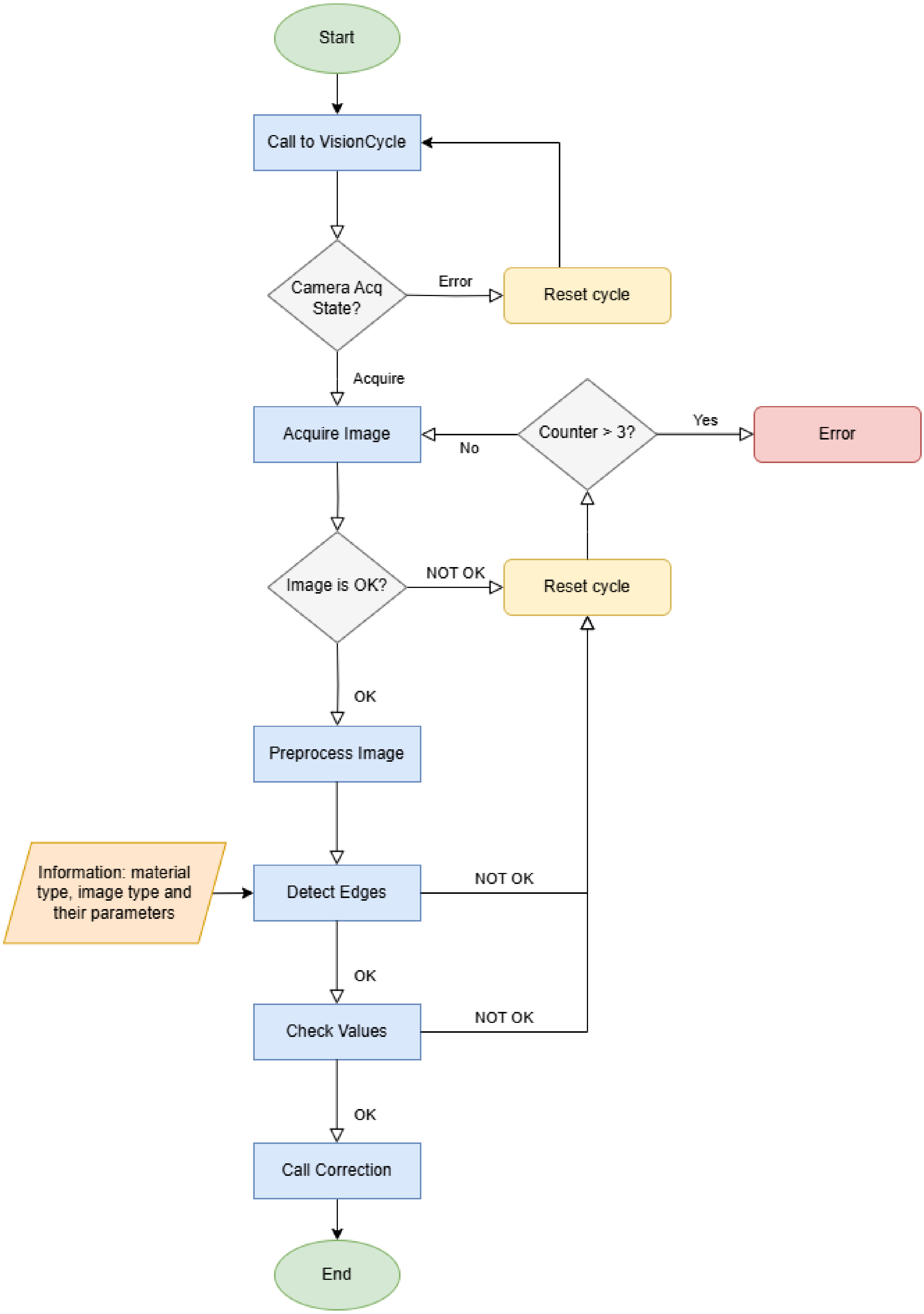

Figure 23 GRAFCET of vision cycle

Following completion of the vision cycle, the correction cycle begins using the previously validated values. This cycle requires no separate methods for different tasks as it handles a single consistent operation. The inputs consist of edge positions in pixel coordinates (converted to millimetres) and the panel's rotation angle relative to the horizontal axis.

The correction cycle calculates the pick offset. Two approaches were considered: correcting at the pick point or at the place point. Correcting at the pick point was selected as the optimal solution for several reasons:

- Ensures proper material pickup with verified vacuum engagement.
- Maintains safety margins when handling double OPV material recipes.
- Prevents potential collisions that could occur with large corrections at the place point due to tight machine clearances.

The correction cycle's Grafcet (see Figure 24) demonstrates simpler logic compared to the vision cycle. Operating as a single continuous process, it reliably processes inputs without error states. The cycle performs straightforward coordinate transformations and rotations before passing the results to subsequent operations.

This streamlined approach guarantees consistent output by applying precise mathematical operations to the input data, maintaining system reliability throughout the placement process. The deterministic nature of the calculations ensures input data always produces correct output values when processed through this cycle.

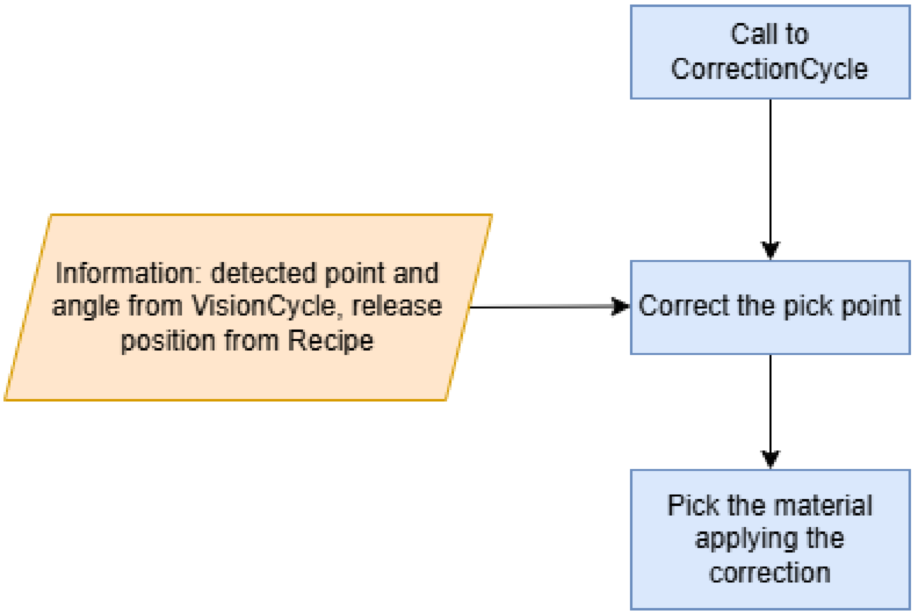

Figure 24 GRAFCET of correction cycle

4.1 Manual mode acquisition

Although unrelated to the correction process, the system incorporates a dedicated image acquisition feature to facilitate quick capture of reference images. This functionality enables direct image collection without executing the complete pick-and-place cycle. Operators can initiate captures through the HMI interface, with acquired images automatically saved to a designated folder on the PLC desktop.

The implementation includes a specialized pop-up interface (shown in Figure 25) providing these capabilities:

- Individual camera activation for targeted image capture.
- Independent control of lighting systems (on/off).
- Immediate image processing through dedicated screen buttons.

This streamlined approach significantly reduces the time required for obtaining detection reference images while maintaining full manual control over the acquisition process. The system ensures all captured images are stored and readily accessible for subsequent analysis or system calibration purposes.

The interface design prioritizes operational efficiency, allowing quick toggling between cameras and lighting conditions without interrupting normal machine functions. This proves particularly valuable when establishing new detection parameters or troubleshooting vision system performance.

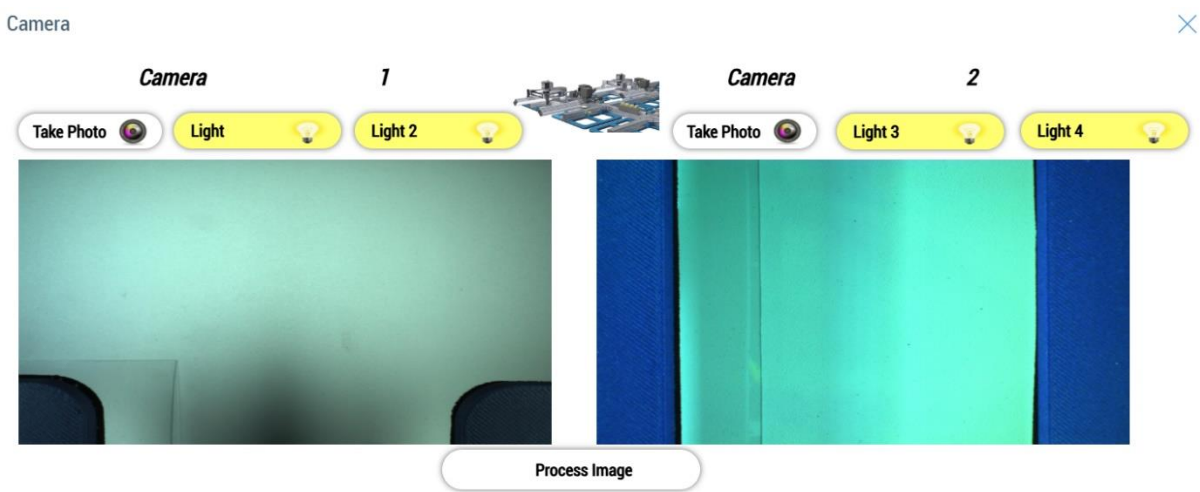

Figure 25 HMI screen for cameras manipulation

While creating this method of acquisition, it was noticed that all the operations related with the vision (with image acquisition to be more precise), had to be run in an apart task in the PLC, as it has to be processed in a lower frequency. This is just because the different executed operations with images require more execution time than the usual tasks executed in the main cycle.

The HMI screen is located outside the zone 2, as shown in Figure 26, and it has a certain mobility that is limited to the length of the cable connected to it. This allows to see what is happening inside the zone 2 while operating with the HMI screen.

Figure 26 Current location of the HMI screen, in Mondragon Assembly facilities

5. Results

The results are primarily presented through visual documentation, with correction values varying by a few millimetres depending on the material's conveyor positioning while maintaining consistent placement accuracy across cycles. Figure 27 shows grayscale captures (the standard format for saved images in the PLC memory, at approximately 15MB each, versus 45MB in RGB) while Figure 28 displays an HMI screenshot of edge detection in RGB format for clarity. In the corner detection image, horizontal edge points are marked in red and vertical edge points in yellow, with most points aligning beneath the black fitted lines. The visible points, though potentially appearing as outliers, confirm accurate detection when properly aligned. This visual documentation ensures reliable verification of the correction process while optimizing file storage efficiency.

The simplified image acquisition functionality, though separate from corrections, allows operators to capture reference images directly via the HMI without executing full pick-and-place cycles. The dedicated pop-up interface (see Figure 25) enables individual camera control, lighting adjustment, and immediate image processing, storing files in a designated PLC folder. This streamlined approach facilitates quick calibration and troubleshooting while maintaining operational efficiency.

Following the vision cycle, the correction cycle processes validated inputs (converting pixel coordinates to millimetres and measuring panel rotation) to calculate pick point corrections. Correcting at the pick point ensures proper material handling and prevents collisions, especially in double-OPV recipes. The correction Grafcet (see Figure 24) operates as a continuous process, applying translations and rotations before passing results onward. This deterministic approach guarantees reliable output without intermediate error states, maintaining precision throughout placement.

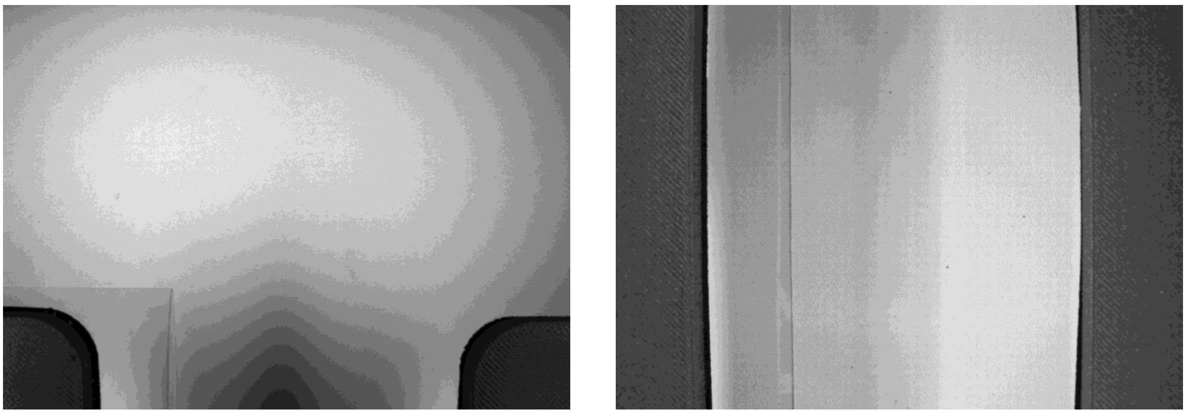

Figure 27 Acquired images of camera 1 and 2

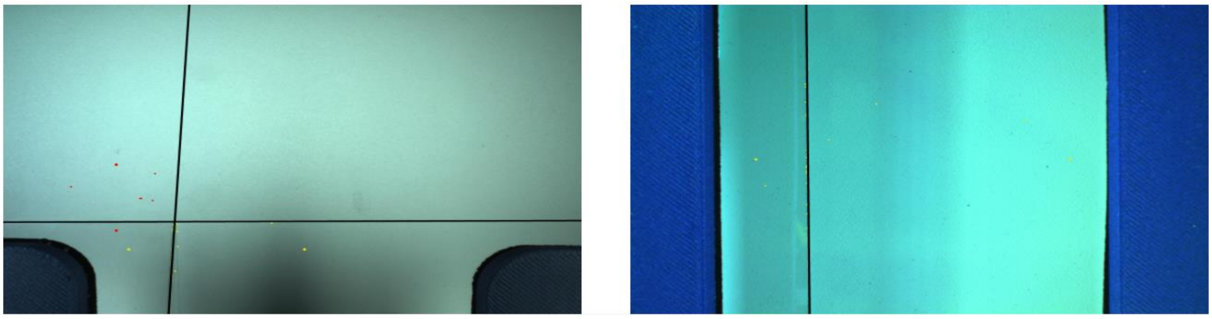

Figure 28 Processed images of camera 1 and 2

5.1 Possible failure solution

When an acquisition returns illogical values (significantly deviating from normal material detection parameters), operator intervention becomes necessary. The HMI provides several corrective options for resolvable issues: expanding the detection area to accommodate misaligned material or adjusting image filtering parameters when lighting conditions have changed. For non-resolvable cases, the system can eject problematic material from the conveyor. Persistent detection failures require production stoppage for thorough investigation and resolution.

A dedicated HMI pop-up element (currently in development) will provide operators with enhanced control capabilities. This interface will allow real-time visualization and manual adjustment of detection areas, along with modification of morphological filter parameters while observing the resulting changes. The interface design emphasizes immediate visual feedback for all parameter adjustments.

Figure 29 illustrates a sample detection area overlay on test images, noting that production configurations may differ from this example. The visualization demonstrates the system's detection methodology while clarifying that actual production parameters are subject to optimization based on specific operational requirements. This approach maintains system flexibility while ensuring operators can effectively troubleshoot detection issues when they occur.

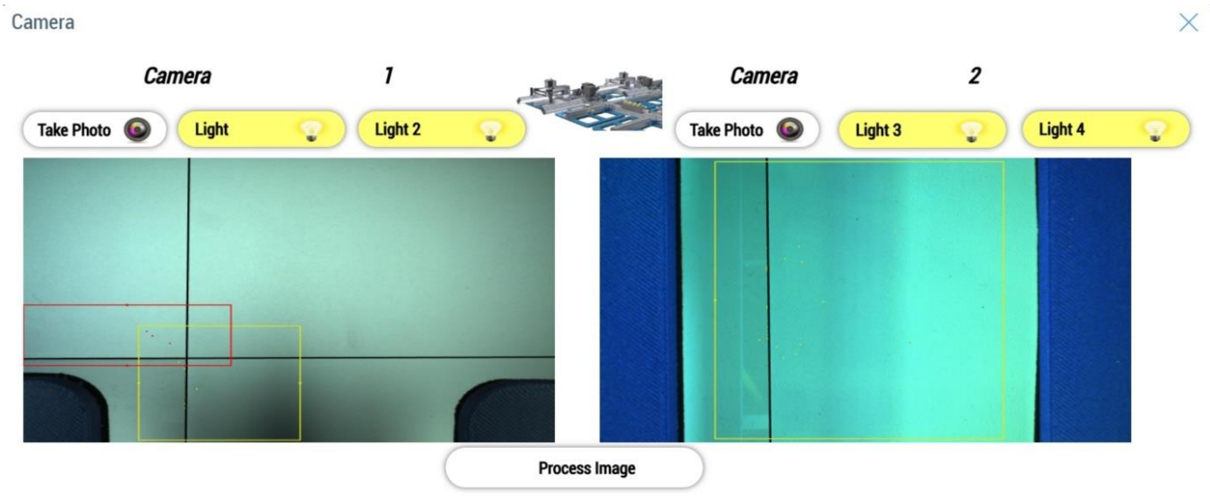

Figure 29 Processed images in the HMI screen, with detection borders

5.2 Production results

Following the complete correction cycle, the results demonstrate successful alignment of OPV material within the specified tolerance of ±0.5 mm. Figure 30 shows precise sheet alignment with adjacent positioning, where the minimal visible gap stems from inherent material width variations.

The substitute material used during project development (500 mm wide rolls) exhibits slight dimensional inconsistencies between rolls. These natural variations account for minor gaps or overlaps between sheets. To maintain the achieved positioning accuracy, the system requires width measurement whenever a new roll is loaded, enabling automatic compensation of these minimal offsets.

The results confirm the system meets its primary objective of maintaining ±0.5 mm placement precision while accommodating real-world material variations through the implemented correction protocol. This performance level ensures reliable operation under normal production conditions while providing necessary tolerance for material inconsistencies.

Figure 30 Placed OPV sheets over the carrier after correction

When position correction wasn't applied, satisfactory results were still achieved in most cases due to the machine's good repeatability in material ejection and conveyor stopping. However, occasional minor deviations did occur. While these would typically only represent cosmetic issues, testing revealed potential scenarios where material positioning could fall outside acceptable tolerances.

In such cases, the vision and correction system become vital to prevent more serious operational problems. The implemented solution ensures consistent placement accuracy regardless of these rare but possible variations in material delivery. This preventive approach maintains quality standards while accounting for all potential real-world operating conditions.

6. Economic report

The economic report of this project cannot accurately be explained because it belongs to a way bigger project where many people work on it, there are internal and external costs that are private, and sometimes the labour done was not strictly related to this ongoing project.

The only costs that can be related only to this thesis project (not to the complete machine) are the cameras, the lenses, and the working time of the student, which, as explained before, was not exclusively to this project. Nonetheless, the cameras were already available in the company, so there was no need of buying new ones. As mentioned in the specifications, the cameras model is Basler acA4600-7gc and the lenses are VS Technology VS-0818VM.

7. Conclusions

The results demonstrate successful execution of material detection and correction, with repeated testing confirming consistent repeatability and accuracy. The detection process for OPV material followed the previously documented methodology using a substitute material, as the organic and expensive nature of OPV prevents its use for testing purposes.

The substitute material exhibited undulations that complicated detection and occasionally reduced accuracy, particularly when lighting conditions caused shadow detection instead of edge recognition. While OPV material is not expected to present identical challenges, detection parameters have been proactively adjusted to minimize potential errors from similar issues.

The lights of camera 2 were repositioned to improve edge detection in the image. This adjustment was essential, as previously, for the same image, the angle would vary by approximately $\pm 0.2^\circ$, which could result in the material being misaligned at the placement point.

After the adjustment, it has been observed that the angle now varies only by $\pm 0.03^\circ$ for the same image, an acceptable result that leads to imperceptible deviations.

Implementation for the remaining two materials remains pending, with future adaptation contingent on long-term process performance. A potential challenge involves lighting conditions, as the white OPV conveyor enhances detection contrast against dark OPV material, while the green conveyors used for other materials demonstrate reduced light reflection. This difference creates significantly darker images under identical lighting conditions, requiring potential adjustments for optimal detection accuracy.

8. Future lines

Development is currently underway to implement HMI panel functionality for direct modification of detection parameters. This ongoing improvement will provide data to prioritize future optimization efforts. Until now, detection and correction processes have been exclusively applied to OPV material, as outlined in previous conclusions. The other two materials have not required identical treatment due to their subsequent edge-cutting stage, which accommodates minor misalignment. Unlike OPV material where precise positioning is critical, these materials tolerate greater positional variance.

Consideration is being given to adapting a similar correction process using Camera 1 for the remaining materials. While the horizontal axis remains observable, enabling angle correction through methodology analogous to OPV edge detection, the system cannot reliably determine absolute position without knowledge of the material's corner location. This limitation risks creating more operational complications than solutions, necessitating careful evaluation of whether enhanced precision justifies the required execution time and resource allocation.

Additional unknown challenges may emerge following project transfer to the final customer in Greece. Although unlikely, variable lighting conditions at the new location may necessitate parameter adjustments, while other unforeseen complications could demand alternative solutions. The system's adaptability to these potential changes remains an important consideration for future implementation phases.

9. Sustainable Development Goals

As part of this project's sustainability assessment, key metrics and objectives were input into the SDG Tool web. [10]

The tool generated a visual summary (Figure 31) and an analytical report (https://www.sdgtool.com/scripts/present_project.php?proj=2657c55e), which corroborate the alignment of this project with Sustainable Development Goals.

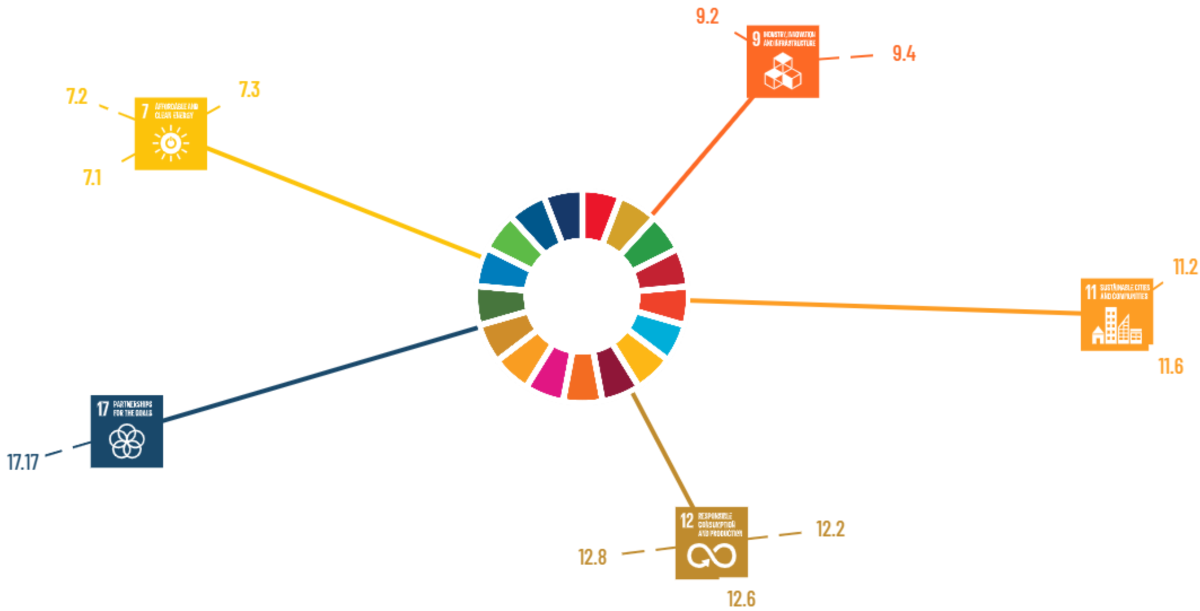

Figure 31 Sustainable Development Goals

10. Acknowledgements

I would like to thank my supervisor Jon Altube, and my work mates for their help and guidance during this thesis. I also thank my reviewer, Priit Kull, for his valuable feedback.

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May 20th, 2025

Bibliography

[1] M. A. S.Coop.. [En línea]. Available: https://www.mondragon-assembly.com/es/solar-automation-solutions/.

[2] M. Dynamics, «Macron Multi-Axis Gantry System is Used in Automated Optical Inspection Station for Large Solar Panel Manufacturer,» [En línea]. Available: https://www.macrondynamics.com/job-stories/solar-panel-inspection/.

[3] K. America, «Vision Systems for the Solar Industry,» [En línea]. Available: https://www.keyence.com/products/vision/vision-sys/industries/solar/.

[4] I. Institute, «Aplicaciones prácticas de la programación orientada a objetos,» [En línea]. Available: https://immune.institute/blog/programacion-orientada-a-objetos/.

[5] V. Technology. [En línea]. Available: https://vst.co.jp/en/machine-vision-lenses-en/fixed-focal-length-en/vs-vm-series/.

[6] U. N. Española. [En línea]. Available: https://www.en.une.org/.

[7] R. a. A. Group y E. a. C. S. D. f. M. Unibertsitatea, CV2-ZhangCalibration (Unpublished), 2024.

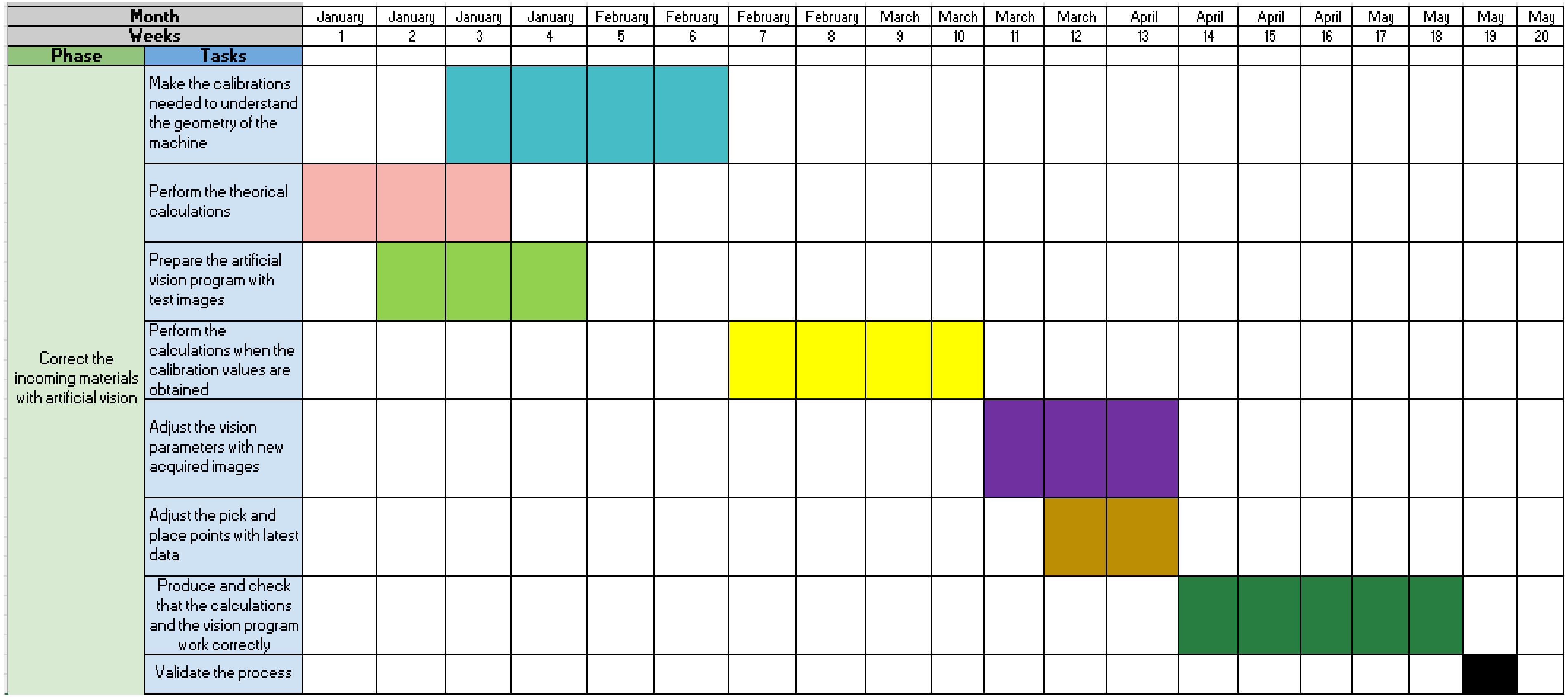
[8] R. a. A. Group y E. a. C. S. D. f. M. Unibertsitatea, IP2-ImageEnhancement, 2023.

[9] Beckhoff. [En línea]. Available: https://infosys.beckhoff.com/english.php?content=../content/1033/tcinfosys3/index.html&id=.

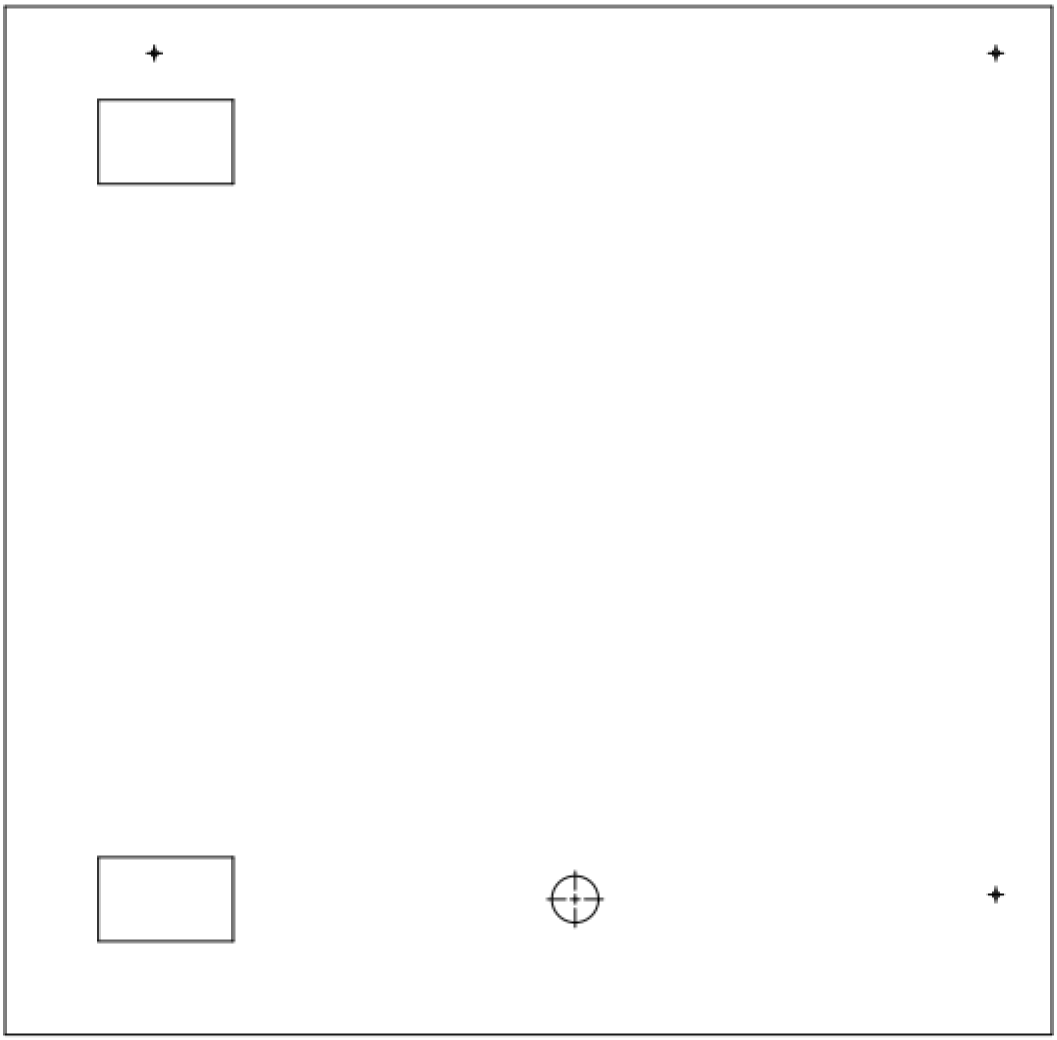
[10] SDG. [En línea]. Available: https://www.sdgtool.com/.

11. Annexes

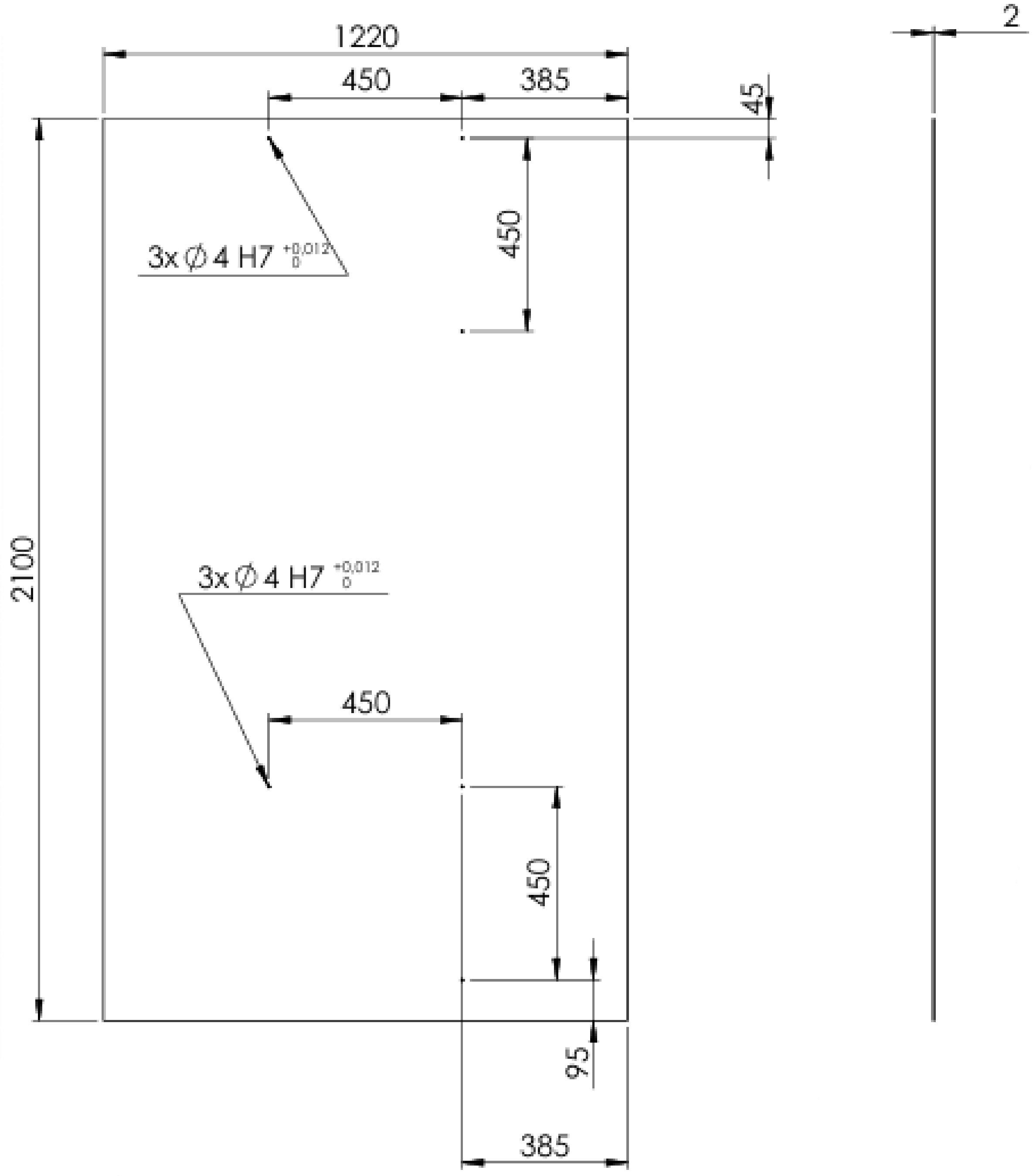
Annex A. Gantt's Chart



Annex B. Calibration Board's AutoCAD file



Annex C. Dimensioned drawing of the Calibration Carrier



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