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The Influence of Light Intensity on the Operation of Vision System in Collaborative Robot

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ABSTRACT

Human-robot collaboration can be a powerful tool for increasing productivity in production systems by combining the strengths of humans and robots. Assembly operations, in particular, have shown great potential for utilizing the unique abilities of both parties. However, for robots to efficiently perform assembly tasks, components and parts must be presented in a known location and orientation, which is achieved through a process called parts feeding. Traditional automation methods for parts feeding, such as vibratory bowl feeders, are limited in their ability to accommodate variations in parts design, shape, location, and orientation, making them less flexible for use in human-robot collaboration. Recent advancements in machine vision technology have opened up new possibilities for flexible feeding systems in human-robot assembly cells. This paper explores the application of the vision system in the collaborative robot ABB Yumi and its ability in object detection. In this case, the characteristic of the vision system was determined experimentally by changing the light intensity on the test rig. The system was validated, if the angle of incidence of light affects the stability of the vision system. The results of the study demonstrate the efficiency of vision system in collaborative robot and provide insights into its industrial application.

Keywords: collaborative robot; vision system; ABB Yumi; robotics.

INTRODUCTION

The industrial sector is undergoing a shift from Industry 4.0 to Industry 5.0 [1], integrating the principles of both. One of the ongoing challenges is the need for flexibility and productivity, especially with the increasing demand for customized products. Industrial robots have played a crucial role in meeting these requirements, especially during the COVID-19 pandemic [2, 3]. However, companies also need the flexibility of manual systems to offer a variety of products, particularly in the assembly phase [4, 5], which is the final stage where all product variants are present.

Manual assembly systems offer flexibility, but they also have downsides, such as low accuracy and difficulty in maintaining repeatability. These systems also pose ergonomic problems and increase the risk of occupational injuries, which could affect competitiveness and worker well-being. Industry 5.0 aims to create a human-centered workplace where the operator's welfare is maximized, which conflicts with the introduction of occupational hazards [6, 7].

To address these challenges, collaborative robots (cobots) have gained popularity [8-10]. Cobots combine the productivity of automatic systems with the flexibility of manual ones and work directly with operators without requiring fences. They can perform burdensome and exhausting tasks, improving not only ergonomics but also cognitive workload. Moreover, cobots can work alongside human operators in the same space and time, eliminating the need for additional safety measures typical of industrial robots [11, 12].

One of the challenges in the application of the collaborative is its accuracy of positioning using the user frame as a reference system is determined by both the robot's repeatability and the accuracy of the user frame calibration with respect to the robot's fixed reference system [13]. As a result, the use of different calibration methods may result in varying levels of positioning accuracy, even with the same movement repeatability of the cobots. Typically, there are two methods adopted to perform a calibration procedure: 1) mechanical methods and 2) vision-based methods [14]. While the mechanical methods have been used for the decades, the vision-based systems are relatively new and they have the advantage that the selection method is based on taken images of the element [15].

Vision-based calibration methods have gained interest in the scientific community working on cobots due to their speed, despite being less accurate than mechanical methods. These methods rely on computer vision algorithms to extract useful information from images. In recent years, a variety of innovative procedures have been developed that adopt these algorithms. For instance, a calibration procedure using a custom L-shaped 3D printed tool with three holes has been described by Marques de Araujo et al. [16]. The tool is carefully placed on the workpiece to calibrate with respect to a CNC machine tool, and the holes are accurately detected by a Circular Hough Transform algorithm applied to the RGB image of the calibration tool acquired by the stereo vision system mounted on the machine arm. Other automatic calibration methods based on the camera calibration algorithm are presented by Du et al. [17], where the user frame is estimated by analyzing the chessboard pattern to extract the camera coordinate system and parameters.

Nevertheless, the vision systems face some problems, which can have external or internal origin [18, 19]. They can be as following: quality of lighting, quality of image, quality of calibration and the position (height or angle) of taking the image. In the reference of Golnabi et al. [20], the deeper insight of factors influencing the vision system reliability is described. In this paper, we focus on the accuracy of the vision system embedded into the end-effector of the collaborative robot YuMi IRB 14000 by variable light of intensity. The effect of the experiment is finding the range of the lighting intensity by which the least number of failures of vision system have occurred. Moreover, the system is validated by the variable angle of incidence and the same value of lighting intensity. The aim of validation is to cross-check if the angle of incidence have the impact on the stability of the vision system and in fact the number of failures.

The remainder of the paper is following. In Section 2, the experimental test rig consisting of collaborative robot, conveyor belt, PLC controller, elements with QR codes and luxmeter is described. Next, in Section 3, the experiment is described focusing on calibration and experimental element. In Section 4, the results obtained are discussed and the validation of the vision system is conducted. In the end, conclusions summarize the paper.

Experimental test rig

The experimental test rig used for the analysis consists of a few crucial devices to provide sufficient conditions for conducting the experimental series. First of all, the main device is the dual-arm collaborative robot ABB IRB 14000 YuMi (Figure 1), which arms are equipped with the Cognex vision system. Additionally, to prepare the full layout for the pick&place operation, the other devices and elements have been used, which are specified in Table 1 and are presented in Figure 2.

In Figure 2, the simplified scheme of the experimental test rig is shown. In order to conduct the sequence, the mutual communication between devices was needed. Starting with the applied PLC controller (1), it was the heart of the whole test rig, that its inputs and outputs received and sent and received signals from the conveyor belt (5) and the vision system (3). After taking the image with vision system, the recognised elements used in the experiment with the attached QR code on their top (4) were taken by the vacuum system in the gripper (3) and placed at the starting point of the conveyor belt. The vacuum system was connected to the oil compressor (8) to provide the suction chamber in the gripper. Next, after the recognition, that the element is on the conveyor it was transferred to the next sensor (6) and then collected with the second arm and placed on the place plate (7). For the need of the experiment, the experimental elements with QR codes and pick and place plates were printed with the FDM (Fused Deposition Modelling) method (Figure 3). The mass of the element was equal to 7[g], that it didn't have the influence on the dynamics of each robot's arm.

Before using the vision system, its camera was prepared for operation with the grid calibration method with the grid spacing equal to 5 mm. The vision system integrated in YuMi robot allows for various type of element recognition exemplary by its shape (square, round), colour, size

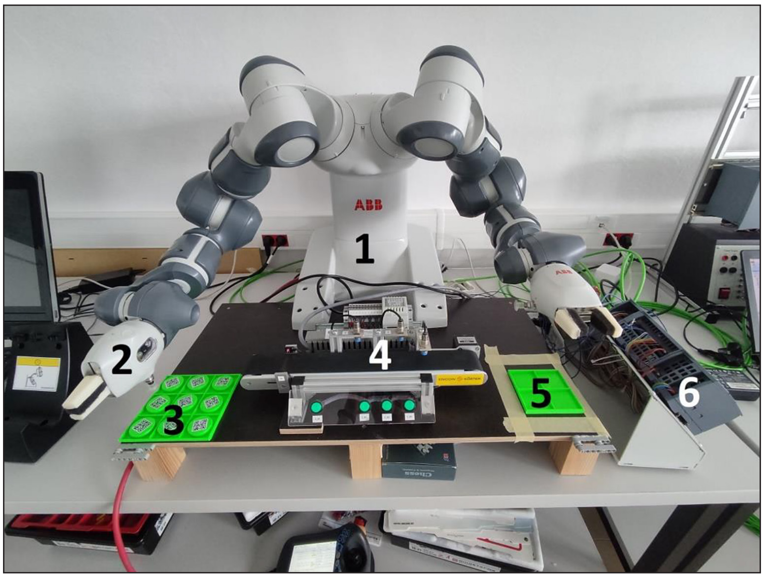

Fig. 1. Collaborative robot YuMi IRB 14000 used in the experiment. In Figure, the most important elements are marked, i.e. 1 – collaborative robot ABB IRB 14000 YuMi, 2 – vision system in the robot arm, 3 – place plate with elements, 4 – conveyor belt, 5 – pick plate, 6 – PLC controller

Table 1. Devices and softwares used in the experimental test rig for the pick&place operation

Device	Type
PLC Controller	Siemens Simatic S7-1200 (1)
Robot	ABB YuMi IRB 14000 (2)
Vision system	Cognex In-Sight® 7000 (3)
Conveyor belt	Encon Köster (5)
Oil compressor	Airpress L6-45 Silent (8)
Photoelectric sensor	Omron E3TFT142M (6)
Light meter	Voltrcraft MS-1300 (range for light intensity 200-50000 lux)
Robot offline-programming software	RobotStudio ABB 2022.3.2

Note: numbers in the 'Type' column refer to the numbers assigned to elements in Figure 2.

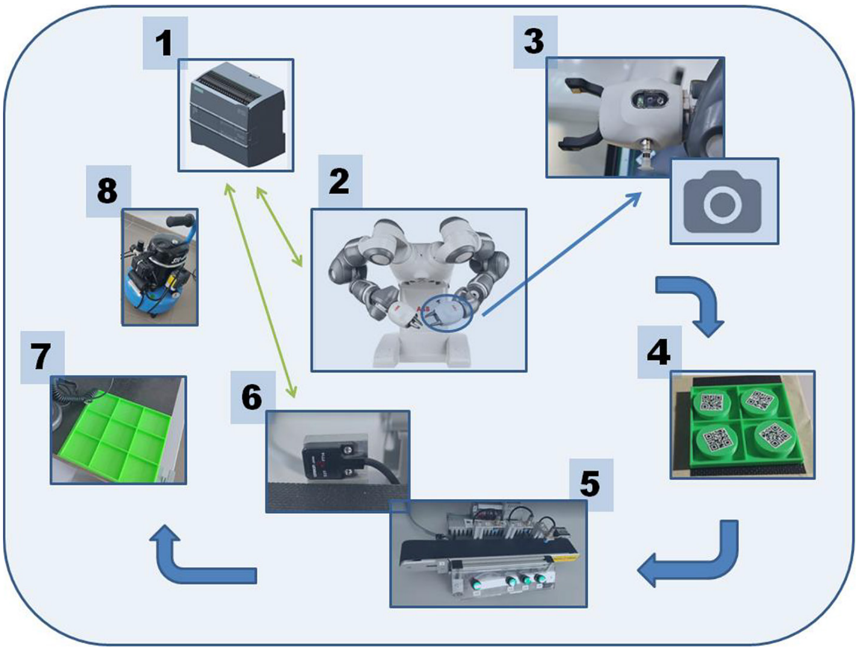

Fig. 2. Collaborative robot YuMi IRB 14000 used in the experiment

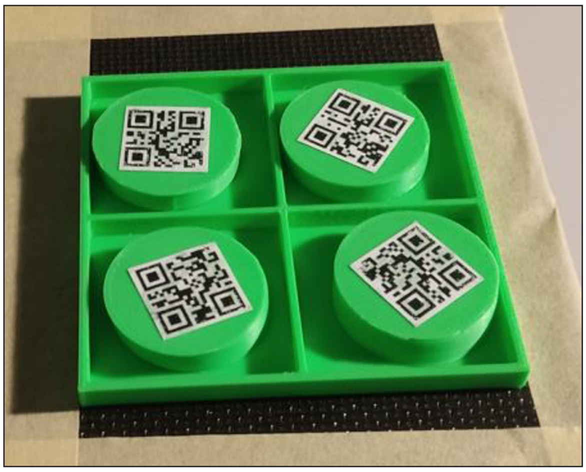

Fig. 3. 3D printed elements with QR codes used in the experiment

or QR code as it was in the experiment [21, 22]. The advantage of using QR codes for the element recognition is its universality and the fact that it is commonly used in industrial applications [23, 24]. QR code is scalable, easy to scan, reproducible and can store quite good enough amount of information (e.g. code for the specific automotive part) [25, 26]. The alternative approach in the recognition of the specific state can be the application of the neural networks, which is based on the considered state. Referring to the study of Wang et al. [27], he proposes the automatic image recognition by its 5 state starting with state "too dark" to "too bright". Moreover, the QR code recognition is based on artificial intelligence methods as it is described in the following reference [28], this is a quite good alternative to improve the pick&place or assembly process.

EXPERIMENTAL PROCEDURE

As one of the factors influencing the accuracy of the vision system is the value of light intensity, the decision was made to investigate it. Namely, the accuracy of the vision system by the different values of light intensity was tested. For the analysis, 9 different values of light intensity were chosen in the range of 30 to 700 lux, which values are specified in Table 2. The light intensity was measured at the pick place, from where the elements were collected by one of the robot's arms. The light in the mentioned place was controlled by dimming with roller blinds and brightening by adding an additional source of light. Following

a)

b)

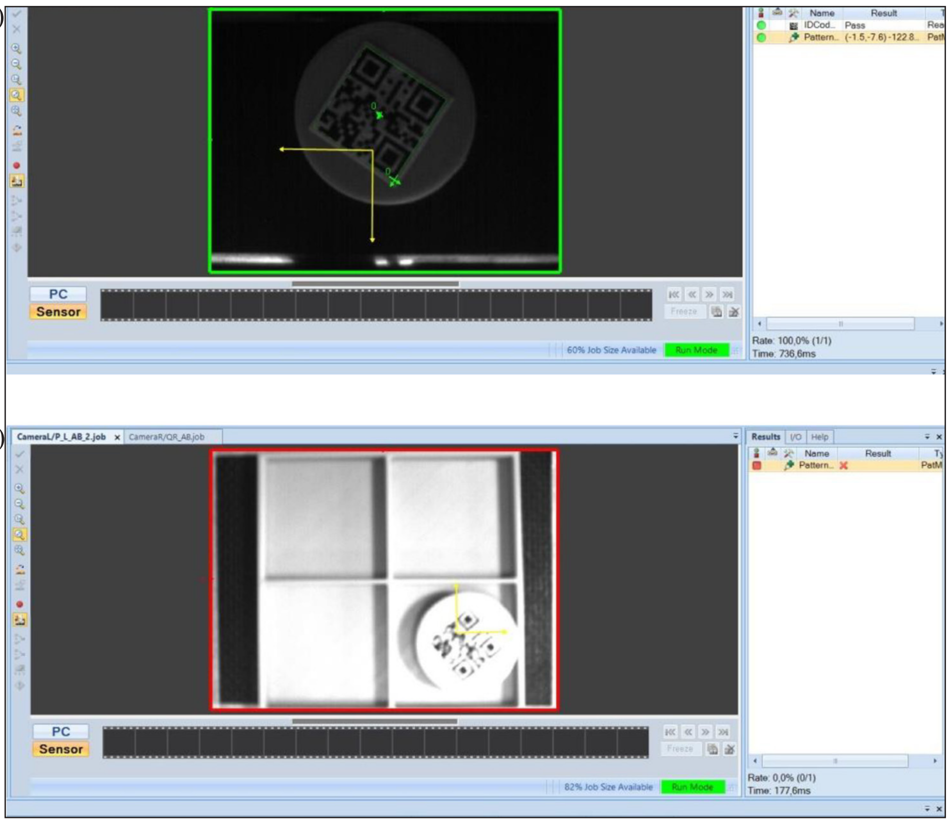

Fig. 4. Screens from RobotStudio software connected with Integrated Vision in SmartGripper by (a) underexposure, (b) overexposure

the manual of Integrated Vision, in order to obtain good lighting in the element identification some rules should be followed such as avoiding light distribution, reflections, shadows and glare [29]. Achieving optimal results in image processing and ensuring excellent performance and reliability requires adapting lighting techniques to specific scenarios and areas. While no single universal lighting technique exists, a solid understanding of the fundamental principles of image processing enables effective adjustments of lighting conditions to capture high-quality input data. Implementing such adjustments can significantly enhance performance and robustness in various applications. After setting the desired light intensity level, the experimental setup was launched from RobotStudio software, where the program's listing was initiated. The display from the vision system camera was visible in the same software (Figure 4). In mentioned Figure 4, two exemplary screens in RobotStudio are presented that the element is a) underexposed (low level of light intensity) and b) overexposed (high level of light intensity). Additionally, in the same Figure two cases are presented when the vision system recognized the element a) green frame around the taken image, and when the vision system failed b) red frame around the taken image. For each considered level of light intensity, there were 100 hundred attempts taken. Firstly, the vision system took a photo of pick plate and recognized the number of elements with QR code (usually 4), and later after the recognition the element could be picked up. The attempt was taken as passed when the object was recognized and transferred from the picking plate on the conveyor. The failed attempt instead, was in the case when the element wasn't recognized and the whole system stopped, requiring the manual restart of the setup. The results obtained are presented and interpreted in the next Section.

RESULTS

As it was described in the previous Section, the 9 values of the light intensity were chosen to cross-check the accuracy of the vision system. Moreover, the idea is to find the range of the light intensity when the whole setup works smoothly without any interruptions. In Table 2, the values of considered light intensity are presented with the results of the number of failures by each of them. As can be observed, the highest number of failed attempts is observed for the smallest considered value of light intensity by 30[lux], when the element is underexposed. Certainly, the result obtained is related to the small value of light intensity, which is why not in any case the vision system can recognize the QR code despite the fact of using embedded flash. A similar situation, but with a smaller number of failed attempts occurs with the light intensity equal to 40 and 60[lux]. The situation is getting better by the light intensity equal to 70[lux], by which there are 14 failed attempts. This value can be treated as a step value for the latter validation of the vision system setup. In the range of light intensity between 100 and 600[lux], failed attempts occur occasionally, and this range of light intensity can be taken as a reference to the optimal range for the system's operation. The tendency of the number of failures is increasing with the level of light intensity, and 18 failed attempts occurred by 700[lux]. Based on the results obtained it is recommended to find the optimal range of light intensity level. In Figure 4, the results of failed attempts are presented in the domain of light intensity, and actually, 3 areas can be characterized that are marked in the same Figure:

I. underexposure area characterizing low level of light intensity (Figure 5 – red zone),
II. area for optimal operation of the vision system (Figure 5 – green zone),
III. overexposure area characterizing high level of light intensity (Figure 5 – yellow zone).

In order to define potential area of optimal light intensity the cubic function (Figure 5 – green line) was plotted to find the minima of fitting it to the results points. The minima of the cubic function is close to the light intensity equal

Table 2. Details for conducted experiement by different values of light intensity

Light intensity [lux]	Number of tests [–]	Number of failures [–]
30	100	79
40		52
60		34
70		14
100		0
200		3
400		5
600		7
700		18

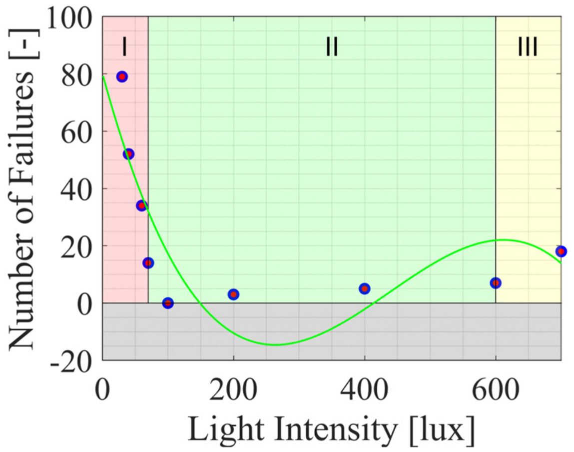

Fig. 5. Number of failures of vision system in the domain of variable angle of incidence. Green curved line corresponds to the cubic fitting to the results obtain of number of failures

Table 3. Cubic fitting function to the results obtain for number of vision systems failures

Cubic fitting function
$y = -1.74e\text{-}6\ x^3 + 0.002282\ x^2 - 0.8397\ x + 80.07$

to 250[lux], while the other points in the found green area shouldn't be rejected and the system should operate smoothly without serious interruptions. In Table 3, the function for obtained cubic fitting is presented.

VALIDATION

After finding the dependence of level of light intensity on the robustness of the vision system, the another factor is taken into account. System is cross-checked if the angle of incidence has an influence on the vision system's operation by the constant value of light intensity, which for the case is chosen as 70[lux]. For the analysis of impact of angle of incidence on the vision system's accuracy, 4 different angle were chosen that are specified in Table 4. For the change of angle of incidence, the additional source of light was applied, that was set in the specific position. In Figure 6, two exemplary positions of the lamp are presented with angles of incidence equal to a) 0° and b) 30° while the light intensity in the picking place was kept constant equal to 70[lux] for all considered angles. Similarly to the previous experiment, for each angle of incidence, 100 attempts were taken and the number of failed attempts was counted.

The results of conducted experiment are collected in Table 4, and what can be observed that the number of failed attempts oscillates between 10 and 20 cases for each angle of incidence. Additionally, the results are visualized in Figure 7, and after adding the linear to the results obtained it can be observed that there is no specific dependence between angle of incidence and number of failures. Moreover, the coefficient of determination of the fitting function is calculated and is equal to $R^2 = 0.01143$, what proves no correlation between number of failed attempts and angle of incidence. If the coefficient of determination is close to $R^2 = 1$, then there is an increasing correlation between two factors, while the value is close $R^2 = -1$ there is a decreasing correlation. After its determination it can be stated that there is no dependence between of the angle of incidence on the operation of the vision system, while the value of the light intensity is kept constant. In the next step of the research, the cross-correlations between two or more features influencing the vision system will be considered, such it is described in the following research by Pratomo et al. [30]. In this case the number of cases can be studied exemplary with the Principal Component Analysis (PCA).

CONCLUSIONS

As collaborative robots are one of the fastest groups of robots that are applied in industrial applications, recently they became the issue of various research [25,26]. The conducted research aimed to find the optimal lighting conditions for

Table 4. Details for conducted experiement by different values of angle of incidence

Light intensity [lux]	Number of tests [–]	Angle of incidence [°]	Number of failures [–]
70	100	0	16
		15	13
		30	12
		60	15

Table 5. Linear fitting function to the results obtain for number of vision systems failures and coefficient of determination

Linear fitting function
$y = -0.007619\ x + 14.2$
$R^2 = 0.01143$

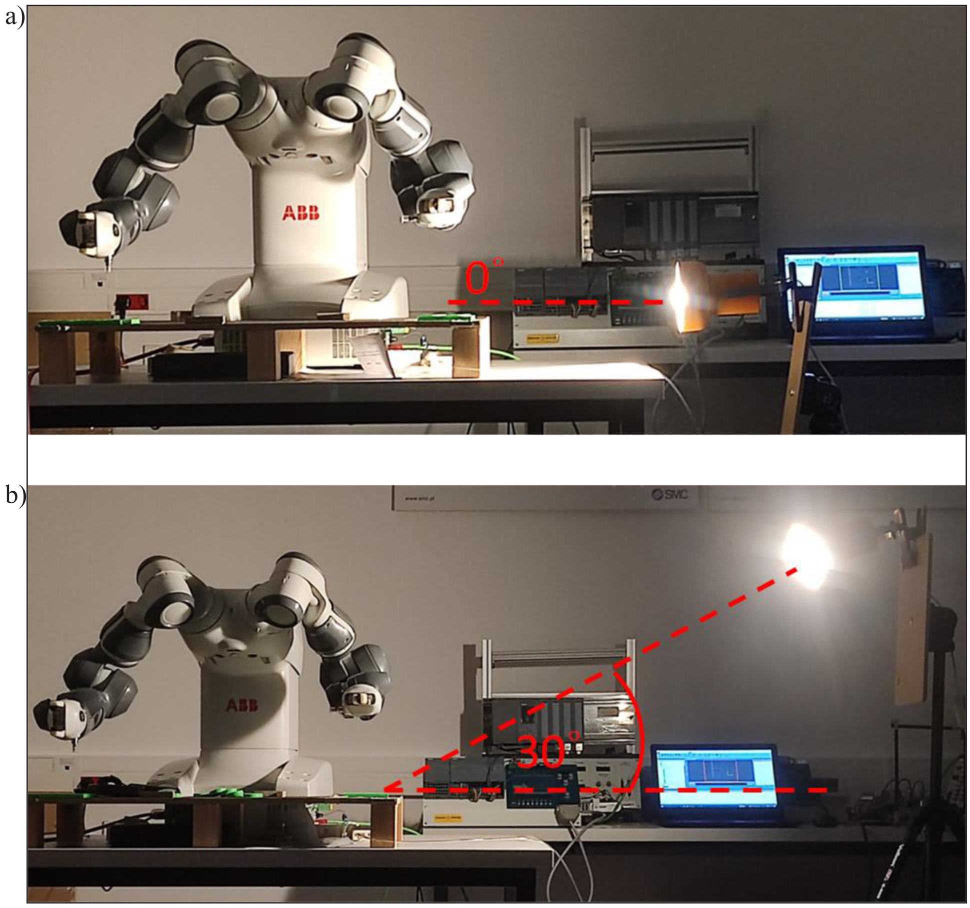

Fig. 6. Experiment with different angle of incidence (a) 0°, (b) 30°

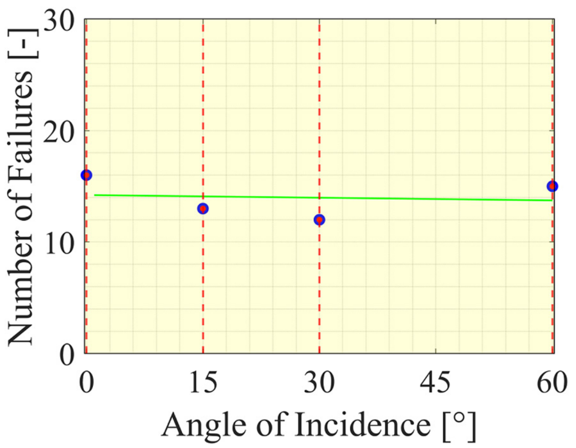

Fig. 7. Number of failures of vision system in the domain of variable angle of incidence. Green straight line corresponds to the linear fitting to the results obtain of number of failures

the vision system, which is embedded in the gripper of the ABB YuMi collaborative robot. For the few levels of light intensity, the experiment was conducted with the element on which the QR code was printed. After the analysis of results obtained, the range of light intensity for which the vision system operated smoothly was observed between 100-600[lux]. When the element was under or overexposed, numerous failed attempts occurred in the recognition of the QR code. In order to cross-check the vision system, the additional test was conducted by the constant light intensity and various angles of incidence. The range of angle of incidence was between 0° to 60°, and the attempt consisted of 100 counts. Results obtained in the second experiment showed that there is no correlation between the angle of incidence and the number of failed attempts, the value of the calculated coefficient of determination was close to 0, which means a very weak correlation between the two factors. This observation proved that the level of light intensity plays a crucial role in the proper operation of the vision system in the industrial robot. The future tests with the vision system in YuMi collaborative will be referred to the variable light intensity in time during the assembly process. Then, the real-time light intensity measurements would be conducted, the analysis could be extended with the comparison of different types of element recognition, i.e. different colors, surface quality or shape of the element.

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