Automated Visual Inspection Model For Screw Detection on The Moving Objects In Industrial Quality Control

[1]Sasa Arsovski, [2]Adrian David Cheok, [3]Chong Yoe Yat

Abstract— *Modern industrial automated visual inspection models provide new methods and solutions in industrial visual quality control application. In this paper, we present automated visual inspection (AVI) model based on the normalized cross-correlation template matching algorithm for real-time screw detection on a moving object. The model can recognize products and detect screws on moving objects. We present the implementation challenges and provide guidelines for successful industrial application. We present experimental results, and discuss model constraints, and implementation parameters settings, showing that the proposed model is very sensitive both to object distance from the camera and a small rotation of the object during template detection on moving objects. The problem of vibrations in real industrial environments and our proposed solution that signi_cantly improves model accuracy is also presented. Our findings show that the model can outperform humans in visual quality control process.*

Keywords— Machine Learning, Computer vision, Vision control, Template

I. INTRODUCTION

Machine learning shows promising results in computer vision automation and enable numerous forms of applications in the industrial automation especially in the Automated Visual Inspection. Automated Visual Inspection (AVI), according to authors in (Davies, 1998) is a quality control that ses cameras connected to the computer systems.

With the latest advances in computer vision algorithms, object detection and object recognition techniques, in general, become more accurate. Computer vision object detection is a set of methods for image processing aimed to identify real-world objects in digital images. Advances in artificial intelligence and Deep Learning launched numerous research in order to develop, analyze and implement, models for object tracking, visual question answering, image segmentation, text recognition, self-driving cars, image recognition, image captioning, pose estimation, image compression, image synthesis, and face recognition. Artificial intelligence computer vision systems can be implemented in the video surveillance, medical image analysis, face detection and recognition, object detection, and many other fields.

In the industry, visual inspection is the part of the quality control process and it is usually carried out by human experts. According to the authors in (Pesante-Santana & Woldstad, 2000), the quality inspection task performed by

1, Raffles University Malaysia, 2, Imagineering Institute, Malaysia, 3, UTM, Malaysia

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humans is prone to a significant amount of errors. Research presented in (Drury, 1992) indicate that human experts can find only 80% of the defects. In addition, human experts require training to develop their skills and they are slower than computer vision models. Our research will show that in the real industry environment, AVI models can be successfully implemented as a part of the visual quality control processes.

As shown in Table I, authors in (Malamas, Petrakis, Zervakis, Petit, & Legat, 2003), categorized application of the automated visual inspection in the industry as: Dimensional, Structural (correct assembling), Surface and Operational.

TABLE I. TYPE OF AVI APPLICATION

Dimensional	Dimensions, shape, positioning, orientation, alignment, roundness, corners	
Structural	Assembly	Holes, slots, rivets, screws, clamps
	Foreign objects	Dust, bur, swarm
Surface	Pits, scratches, cracks, wear, finish, roughness, texture, seams-folds-laps, continuity	
Operational	Incompatibility of operation to standards and specifications	

According to the authors in (Malamas et al., 2003) our model can be categorized as a Structural type of the Automated Visual Inspection. Key research contribution presented in this paper is an implementation of the image template matching Normalized Cross-Correlation (NCC) method for the real-time screw detection on a moving object in the real-life industrial environment. The advantage of using the model proposed in this paper is a high accuracy, low cost of implementation, and low hardware requirements. We will identify the main challenges and, give guidelines for the successful implementation of the AVI models in the industrial environment with a focus on the moving objects. We will show that the accuracy of the presented model can outperform human results in the visual quality control process. The Template Matching technique is an algorithm used to find areas of a source image that match or that are similar to a template image (Heipke, 1996). To be able to utilize a template matching approach we need two main components: Source image and template image (Perveen, Kumar, & Bhardwaj, 2013). Normalized Cross-Correlation (NCC) is a method for image similarity measurement. This method is invariant to linear brightness and contrast variations, and according to the authors from (Perveenet al., 2013), easy hardware implementation makes it useful for real-life applications. NCC method will be explained in more detail below.

In this paper, authors will present the results of the experiment which is conducted in the real industry environment, discuss the results and give suggestions for future work. Accuracy evaluation of the normalized cross-correlation algorithm for the image matching that is applied for the real-time screw detection on the moving object will be presented. The remainder of this paper is organized as follows: Section two will discus related work. In the Section three experiment setup and implementation, procedure will be presented, Section four will provide experiment result. Section five will discuss results. Finally, the research conclusion is provided by highlighting the main research contribution in Section six.

II. RELATED WORK

There are a lot of researches that are related to template matching problems and the implementation of the computer

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vision in the industry. Authors in (Cruz-Ramirez, Mae, Takubo, & Arai, 2008) proposed a methodology to achieve Light Gauge Steel detection in order to detect screws that held ceiling boards the Light Gauge Steel. Reaching up to the ceiling to detach screws without damaging the materials can be a dangerous task to the workers. It is also important to carefully remove the screws in order to reuse the materials. Hence this research aimed to teach robot arm to reach targets remotely for the safety of the operator without damaging the materials during the dismantling process. However, the small size of the screws contributes to the difficulties of vision-based detection. Therefore the use of the robotic arm for the detection process of the screw on LGS is essential in helping humans to complete the tasks with less effort by allowing humans to control the robot using an interface. This research proposed a method for metal-ceiling structures screws removal. The system starts by utilizing information sent by stereo camera which serves as an 'eye-in-hand' system to measure the pose of linear structures of LGS. The trajectory near LGS is then defined by the control program in order to obtain closer observation of the screws attached to it. To extract more details of both the LGS and screws attached to it, the robot utilizes the lighting system attached to it. Under the structure during the motion, multi-template matching algorithm technique will then be applied to detect the screws for every caught image. A multi-frame integration will then be used to analyze the results of all the processed images along the trajectory in order to increase efficiency in screw detection

task. The 3D position of each screw measured is also done by multi-frame integration. The robotic arm then places its tool's tip to that position automatically once the 3D position is recognized as a target. In our approach, we use NCC image matching algorithm to detect screws on the moving objects.

Industries are incentivized to automate visual inspection of polished wafer surfaces in order to lower inspection costs as well as human errors.

The fuzzy logic algorithm is utilized by authors in (Li & Lin, 1994) for automated visual inspection system as a method for detection of dimple defects on polished wafer surfaces. Preprocessing is first performed by authors in (Li & Lin, 1994) in order to eliminate noise and lower potential dimple defects. Four pattern features are then defined based on the scale, position, and orientation-invariant. A wide range of different variations in shapes of dimple defects are then solved by the Fuzzy membership function, as Fuzzy logic acts as a powerful tool to manage uncertainty and imprecision of the possible defects. Development of a decision-making mechanism to detect dimple defects is then achieved based on the value of membership function. This is made possible because the value of membership function is able to describe a pattern's closeness to dimple, hence making the algorithm distortion-invariant.

Inspection of surface quality is often utilized in industry to automate quality control. (Bhandarkar, Faust, & Tang, 1999) CATALOG is a system based on Computer Axial Tomography (CT) for the detection of internal wood log defects. Slices of CT images are extracted and each individual slice is then segmented into two-dimensional regions. These segmented image slices are then analyzed and characterized as defect-free or defect-like individually. Correlation of defect-like areas across the CT sequence enables reconstruction of log defects in three dimensions.

Color characterization of an imaging system is an essential step for color measurements on food products. Food quality controls, based on products appearance properties, require accurate color measurements to adequately detect defects and/or products classification. Automatic visual inspection systems are also applied in automating fruit harvesting systems. In order to solve the 'line of sight' issue encountered by MAGALI (Grand d'Esnon, 1987) project, where there is an obscure between the vision and the target at picking state, (Harrell, Adsit, Munilla, & Slaughter, 1990) encountered this problem by using an 'eye-in-hand' approach by attaching color video at the end of effector on spherical manipulator with an ultrasonic transducer to compensate the distance to the fruit (Harrell, Slaughter, & Adsit, 1989). This method manipulated the contrast color between the fruit and the background to track the fruit. (Rabatel, Bourely, Sevila, & Juste, 1995)(Juste & Sevila, 1992), demonstrated a citrus fruits harvesting technique by using a gripper that is a spherical manipulator with hydraulic power and a camera positioned in the center of the manipulator. It uses a single B/W camera in vision detection that is of the gray level scheme using 635nm

wavelength filter and 560nm wavelength filter with a supporting flashing light. The color image of the mature fruit detection was then used with Bayesian classifier as a discrimination function. It was found that the color scheme performed better than the monochromatic scheme. The main difference in our research from the survey presented in (Cruz-Ramirez et al., 2008), is that we used a single template approach and Kalman filtering algorithm to minimize errors during the industry implementation.

III. MODEL CREATION

III.I Problem statement

In order to maximize the quality of visual control and minimize the effect of the AVI model error on the final result of quality control, goal of proposed AVI model is to identify two screws (marked as PASS) on the surface of the product instead of a hole without screw which indicating there is no screw (FAIL). Following the adopted approach, the main task of the AVI model for the real-time screw detection is to identify two screws on the product surface. The screw position on the product that is a subject of the visual quality control is shown in Fig.1.

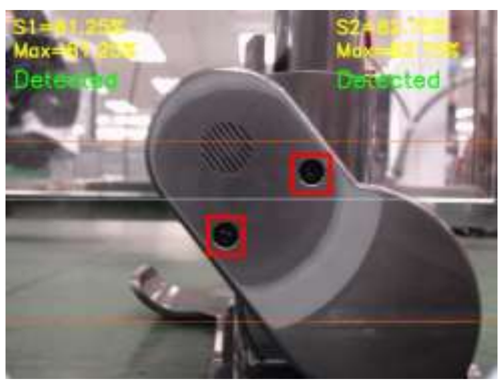

Fig. 1. Screw position on the product surface

The real-life industry conditions are as follows: Workers place products on the conveyor belt without a special care about technical limitations of the model (angle and direction). The products are moving on a conveyor belt with a testing surface facing the camera as is shown on Fig.2.

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Fig. 2. Product on the conveyor belt

In order to perform visual quality control of a product in the industry conditions, the proposed AVI model should satisfy the following requirements:

- Recognize new product for control on the conveyor belt
- Detect two screws on the product
- Categorize product as pass or fail

III.II Matching algorithm

For the object detection and object recognition tasks we use image template matching algorithm. According to the authors in (Kuruppu, Manoj, Kodituwakku, & Pinidiyaarachchi, 2013), there are six most used template matching algorithms: Squared difference and Normalized squared difference matching algorithms are given in equations (1) and (2) match the squared difference. A good match will give a value of zero and a bad match will give a larger value. Where, (x, y) is the search block pixel position and (x', y') is the macro block pixel positions. T is the macro block (template) and I is the search block (image). w and h are the width and height of the image. Cross Correlation and Normalized Cross Correlation (NCC) matching algorithms are given in equations (3) and (4) respectively. Matches the template against an image generating a good match with a larger value and a bad match with a smaller value or a zero. Correlation coefficient and Normalized correlation coefficient matching algorithms are given in equations (5) and (6). These algorithms match a template relative to its mean against an image, a good match will provide a value of 1 and a mismatch will provide a value of -1. Value 0 indicate no-correlation.

$$R_{sqdiff}(x,y) = \sum_{x',y'} (T(x',y') - I(x+x',y+y'))^2 \quad (1)$$

$$R_{Norsqdiff}(x,y) = \frac{\sum_{x',y'} [T(x',y') - I(x+x',y+y')]^2}{\sqrt{\sum_{x',y'} (T(x',y')^2 - \sum_{x',y'} I(x+x',y+y')^2}} \quad (2)$$

$$R_{CrossCorr}(x,y) = \sum_{x',y'} (T(x',y') \cdot I(x+x',y+y')) \quad (3)$$

$$R_{NorCrossCorr}(x,y) = \frac{\sum_{x',y'} (T(x',y') \cdot I(x+x',y+y'))}{\sqrt{\sum_{x',y'} (T(x',y')^2 \cdot \sum_{x',y'} I(x+x',y+y')^2}} \quad (4)$$

$$R_{CorrCoef}(x,y) = \sum_{x',y'} (T'(x',y') \cdot I'(x+x',y+y')) \quad (5)$$

$$R_{NorCorrCoef}(x,y) = \frac{\sum_{x',y'} (T'(x',y') \cdot I'(x+x',y+y'))}{\sqrt{\sum_{x',y'} (T'(x',y')^2 \sum_{x',y'} I'(x+x',y+y')^2}} \quad (6)$$

Where:

$$T'(x'y') = T(x'y') - \frac{1}{wh} \sum_{x''y''} T(x''y'') \quad (7)$$

and

$$I'(x+x',y+y') = I(x+x',y+y') - \frac{1}{wh} \sum_{x'',y''} I(x+x'',y+y'') \quad (8)$$

According to the authors in (Kuruppu et al., 2013), there is no statistically significant differences found between the

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six template matching algorithms. Authors (Kuruppu et al., 2013) stated that Normalized based template matching algorithms and squared difference algorithms give more accurate results. According to the stated findings we decide to use NCC image template matching algorithm. The first step in the implementation procedure is a template preparation.

III.III Template images creation

To implement a template matching algorithm according to defined model requirements, we use two template images (product and screw template image). Product template image is used to detect new product on the conveyor belt and second template image is used to detect screws on the product surface. According to the authors in (Zhao, Huang, & Gao, 2006), template matching methods based on normalized cross-correlation can give good results for translation, small rotation and, scale changes between the two images. To avoid this limitation of normalized cross-correlation algorithms we measure distance and the angle of the product in relation to the camera during the template images creation (we create a template in the real-life industrial environment). Distance and angle values will be later used to control the distance between camera and product in the implementation and application phase. Authors in (Zhao et al., 2006) stated that NCC method is invariant to linear brightness and contrast variations. In real life implementation, we experimentally determined that level of light and camera focus can significantly affect to the quality of matching results. We can conclude that in the process of the template generation in real-life implementation it is necessary to carefully define nominal parameters:

- Camera resolution
- Illumination of the object
- Distance between object and camera
- Angle of the object relative to the camera

Since proposed AVI model need to detect a template on the moving object and NCC algorithm search source image pixel by pixel, it is important to determine camera resolution to minimize model response time and ensure satisfactory quality of the captured frame. In our implementation we decide to use resolution 640x480 pixels. Illumination of the object during a template generation is another aspect that need attention during a real-life factory implementation. In the real factory implementation, shadows and changes in the level of the light in the production hall can reduce model accuracy. We decide to use additional light source and direct illuminate testing surface with 250 lux. In the template generation process it is necessary to define nominal distance between camera and object and use same distance during implementation. Same like for the distance, angle of the object relative to camera should be same during template creation and model utilization. In our experiment we use different parameters settings and measure accuracy of the proposed AVI model. We analyses results and determine best combination of the parameters. Product template image is shown in Fig. 3. The screw template image is shown in Fig. 4. Light source, camera and distance and angle control are shown on Fig. 5.

III.IV Model implementation

After template preparation, we implement the proposed AVI model for real-time screw detection. We build software model using Open Source Computer Vision Library (OpenCV). OpenCV is an open source computer vision and machine learning software library (Bradski & Kaehler, 2000). Pseudocode is given in Table II.

Fig. 3. Product template image

Fig. 4. Screw template image

Proposed AVI model for real-time screw detection on a moving object, analyze every frame taken from the camera. The camera is fixed on the edge of the conveyor belt. In order to ensure the same distance from the camera and the angle of the controlled products used for creating a template image, we use guideline mounted on the conveyor belt as shown on Fig. 5.

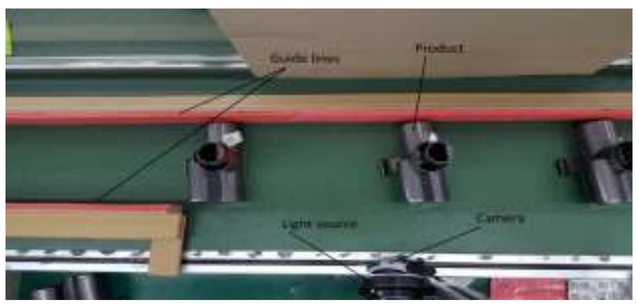

Fig. 5. AVI NCC model, industry implementation

During a model testing we detect significant differences between result in the testing environment and real-life industry implementation. We discover that vibrations of the conveyor belt in real-life industry implementation causes extremely high inaccuracy of the results. In the next section we will analyze different settings parameters and introduce solution for the vibrations problem.

TABLE II. MODEL PSEUDO CODE

```
INPUT: Prepared template images
OUTPUT: Inspection results

Procedure NCCdetect()
InitializeParameters()

Readtempaltes(product,screw)

While(True)
detectProduct(usingNCC)
if product detected = True
results = detectScrew(usingNCC)
increment Passparam()
else
if passparam >1
if result <2
```

```
showInspection = Fail
else
showInspection =Pass
endif
reset passparam()
endif
endif
End While
End proc
```

IV. EXPERIMENT

NCC algorithm slide template image across the captured frame image one pixel at a represents a similarity between the template image and location in the captured frame image. Since the AVI model based on the NCC algorithm is very sensitive to the translation, small rotation and, scale changes between the two images, we conducted an experiment to determine the best settings parameters for the proposed model. In our experiment, we change AVI model settings parameters (distance from the camera, rotation changes and, illumination) and measure the correlation value and Y position of the detected pattern. In the presented case as we mentioned before, proposed AVI model has the best response time with the resolutions 640x480 pixel. We tested 26,680 products and save results with the time stamp to the log file

In order to determine the best settings, we analyze results. Fig. 6. shows the correlation between the settings parameters.

As we can see from the heat map, shown on Fig. 6., the greatest impact on correlation value has small product rotations as well as distance from the camera lens. Fig.7. shows the measured upper left pixel position of the detected pattern on the search image. During real-life industrial implementation we detect high number of the false negative results. Fig. 8. shows a measured correlation value in the defined time interval. As we can see from the diagram that is shown in Fig. 8., there are significant differences of the measured correlation value in the time interval. These oscillations in the reading are caused by vibrations of the conveyor belt. A clearer view of vibration effects can be seen in the diagram shown in Fig. 7. where top left pixel position, of the detected pattern on the search image is changing in the time interval.

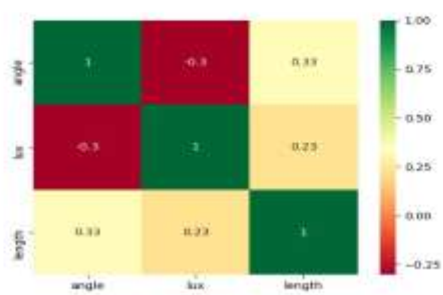

Fig. 6. Variable correlation map

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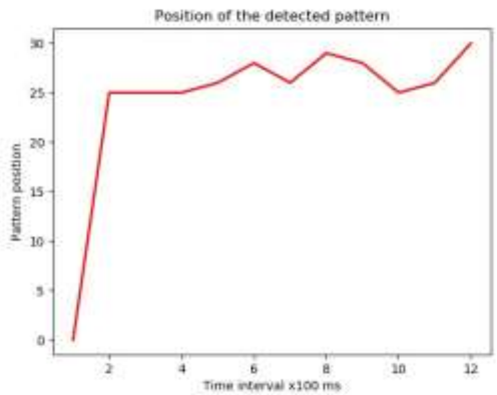

Fig. 7. Detected pattern position

The presence of the conveyor belt vibrations in the real-life implementation of the proposed model causes different system readings and can be defined as noisy system. In order to overcome those errors, we apply Kalman filtering method on to measured values (Welch & Bishop, 2004). The Kalman filter is a mathematical algorithm that provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error. As is shown on Fig. 9., after applying Kalman filtering method, readings of the system become stable and ensure satisfying accuracy of the model.

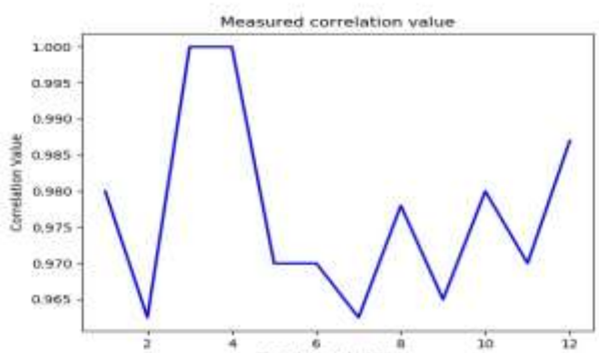

Fig. 8. Correlation value measured in the time interval while product passing camera

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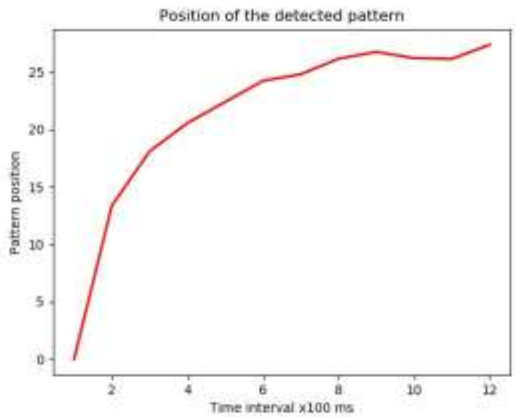

Fig. 9. Measured pattern position after Kalman filtering

We also analyzed experiment results in order to determine the best distance between camera and product. We apply different distances and measure correlation value. After experiment we visualize and analyses data (Fig. 10.). As we can see on Fig. 10., the highest measured correlation value is for the 90 mm distance between product and camera. Fig. 10. also shows a large dispersion of the measured correlation value caused by vibration of the conveyor belt.

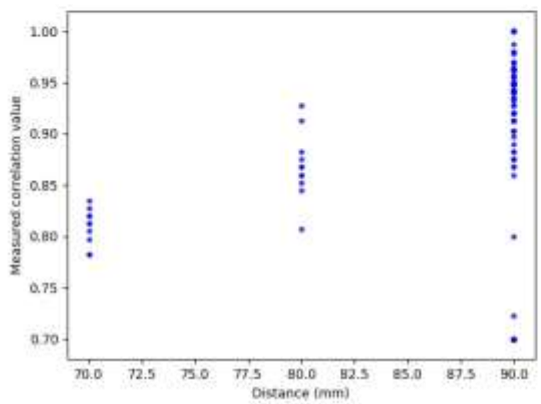

Fig. 10. Measured Correlation value to determine optimal distance between camera and product

After analysis of the data from our experiment, we define nominal settings for our model implementation. Illumination is 250 Lux, Distance from the camera is a 90mm and the angle of the product is a 0. Also we change model algorithm and apply Kalman filtering method. After applying new settings we have evaluated accuracy of the model.

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Fig. 11. Implementation of the AVI in the industry environment

V. Evaluation and discussion

As we stated in the introduction part of this paper, the authors in (Drury, 1992) indicate that human experts can find only 80% of the defects. We conclude the experiment and test accuracy of the presented AVI NCC based model for real-time

screw detection on a moving object (Fig. 11.). The baseline for our experiment was a result of the human visual quality control. Every product was controlled in parallel by humans and with our model. An independent human inspector (evaluator) was involved to check results of the human and our model quality control results.

We tested the accuracy of a sample of 40 000 products. According to the evaluator, human quality control has 47 false inspection result and our model has only 19 false inspection results. According to the presented results, the accuracy of the presented model for the real-time screw detection on a moving object is a 99,95 % and human control has accuracy 99,88%. Based on the results of model evaluation, we can conclude that the proposed AVI model using Kalman filter method can be used with high precision in real industrial environments to detect screws on the moving object. The measured high accuracy of the model confirms the proposed approach in the process of setting the model parameters.

VI. Conclusion

In this paper, we present AVI model based on the NCC template matching algorithm for real-time screw detection on a moving object applied in the industrial quality control. Presented model, using NCC algorithm, recognize new product for the control, detect screws on the product and categorize inspection result as pass or fail.

We present AVI approach based on image template matching Normalized Cross-Correlation algorithm for the real-time screw detection on a moving object in the real-life industrial environment. We present the main implementation challenges and provide guidelines for the successful AVI model implementation in the industrial environment. During the experiment, we determine AVI model settings parameters (distance from the camera, rotation changes and, illumination). Finally, we prove that the level of vibrations in real life industrial environment significantly affects to model accuracy.

In order to overcome noisy real-life implementation results, we use Kalman filtering method to make estimations of the current state of the system. We show that the accuracy of the presented model can outperform human results in the industrial visual quality control process. In the future work, the focus of our research will be Deep learning models for object detection and new approaches for the appropriate dataset generation.

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