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The Machine Vision Approach as a Poka-Yoke System in Conrod Bearing Assembly Station of Engine Production Line

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ABSTRACT

This paper presents a machine vision approach to detect the installation error of conrod bearing in four-cylinder engines. Since there are always human errors in engine production lines that would reduce the quality of the final product, it is vital to establish the intelligent machine vision systems in order to track the process of assembling parts and prevent installation errors. The proposed method is such that by taking an engine block image, it produces a binary image that the whole image is black and only the places where conrod bearings exist are white, and also it announces which bearings are present and which ones are not installed. To this end, firstly the images of 16 different bearing installation cases were captured by camera. Then, all images were analyzed with a combination of image processing methods including Gaussian filtering, image thresholding and segmentation, and morphological techniques including erosion and dilation. Finally, with applying if-then rules on the characteristics of the objects created in the image, its condition was decided. The results showed that the best threshold range for separating the bearing from other parts of image was between 110 and 245. Also a disk-shaped structuring element with the radius of 60 provided the best morphological tool to detect the bearings. In addition, the results demonstrated that the regions belonged to conrod bearings had an area between 30,000 and about 80,000 pixels. With using if-then rule, the different bearing installation cases in all images were successfully detected with 100% accuracy. The total time for analyzing each image was about 1 s. So the results showed that the proposed machine vision system provided a non-error and fast tool for detecting the existence of conrod bearings which can be served as a Poka-Yoke system in the engine production line.

1) Introduction

Todays, internal combustion engines (ICEs) have numerous applications in human life. One of these applications is to produce mechanical power for any types of vehicles. ICEs are constructed with different parts and mechanisms which should be designed well to achieve desired performance. Lots of parts used in ICEs causes the assembly process to be difficult in the production line. The human resource is usually employed as operator in engine production line, which can cause the human error to take place during the work. The error during the assembly process will diminish the quality of final product and consequently customer satisfaction [1]. If an error occurs in assembling one of the main and key engine parts, it can jeopardize the reputation of a manufacturer. So according to the existence of human errors in production lines and their negative and harmful effects in final products, it is essential to establish systems for detection of such errors and prevention of their occurrence so that their effect will reduce to zero. It can be seen in famous engine and automotive companies that such detector systems are being used. These systems are so-called poka-yoke means inadvertent error prevention or anti-error systems. A poka-yoke is a preventing, correcting, or drawing attention system to human errors that helps an equipment operator avoid mistakes and defects caused during an assembly process [2]. As it is obvious from its name, the system must not allow even an error to occur within the assembly line. Since the assembly process for engine parts is different from each other, it is necessary to establish the poka-yoke for each assembly stations separately [3-6]. There are various methods to detect defects during assembly process which should be employed according to the part type and its function. For example, functional evaluation, nondestructive tests and visual inspections are some of these methods.

As the automation of visual inspection is becoming more and more important in modern industry [7], one of the recent and capable approaches for automatic inspection of parts and objects is the use of machine vision (MV) systems which perform the detection operation through the process of seeing [8]. Accordingly, the primary requirement of MV systems is digital images which have to be captured by camera. Afterward, using image processing methods the images are analyzed in order to simplification, noise reduction, elimination of undesired sections, correction and generally preparation for extracting the desired features and final decision on it. Thus the MV systems are mainly based on image processing, features extraction and decision making methods such as if-then rules, fuzzy rules, neural networks, support vector machines and other machine learning techniques. Nowadays, the MV systems are widely used for inspection, control, detection and tracking objects and processes in different applications such as automotive [9], agriculture [10], energy [11], aerospace [12], medicine [13], chemistry [14], etc. Moreover, the MV systems currently allocate effective applications in engine and automotive industries; of course there are still a few researches in this area. For example, Deepak and Balakrishnan (2011) developed a machine vision method to assess honing angle of cylinder liners by extracting the frequency domain characteristics of cylinder liner images. They employed Fourier transform and Hough transform methods for processing the images containing the honing texture patterns. For collecting database, the images of 14 different cylinder liners manufactured with varying honing angles were captured [15].

Rajesh Kanna et al. (2012) developed a machine vision system to inspect the holes of engine cylinder block [16]. Lawrence et al. (2014) tried to characterize cylinder bore surface topography by using machine vision approach [17]. Costa et al. (2015) used image processing methodologies for characterizing early flame of combustion in a single cylinder 4-stroke GDI engine. They could evaluate local and integral luminous intensity, and flame morphology parameters by image processing [18].

Chen et al. (2019) used flame image processing technique to obtain the characterization of in-cylinder combustion temperatures. To capture the in-cylinder combustion images, a high-speed charge-coupled device (CCD) camera was utilized [19]. Xuyun et al. (2019) presented a machine vision system based on convolutional neural network (CNN) for fault detection of aircraft engines [20]. Capela et al. (2020) proposed a method for smart quality inspection of the engine labels using machine vision and CNN. Experiments and analysis were performed on two brands of Citroën and Peugeot [21].

Angermann et al. (2021) developed a method based on machine learning to assess quantitatively wear on cylinder liner surfaces for large IC engines. To this end, the bearing load curves were computed from reflection RGB images of the liner surface [22]. Moosavian et al. (2022) developed a non-contact method to measure transverse vibration of engine accessory belt based on machine vision approach and deep leaning technique [23].

In this regard, according to the necessity of existence of poka-yoke to prevent the errors in the production line which causes significant reduction in the quality of final product, the present paper as a novel work, focuses on development of an intelligent poka-yoke to detect the assembly error of conrod bearing in its assembly station. It is emphasized that despite of practicality of this research, it possesses highlight originalities in case study and analysis approach. This paper used a combination of image processing, feature extraction and decision making methods. Figure 1 shows the flowchart of the present work. In the following, imaging setup is firstly described, then a brief explanation about the theory of the used analysis methods are given, afterward the obtained results are presented and discussed and finally the conclusions are given.

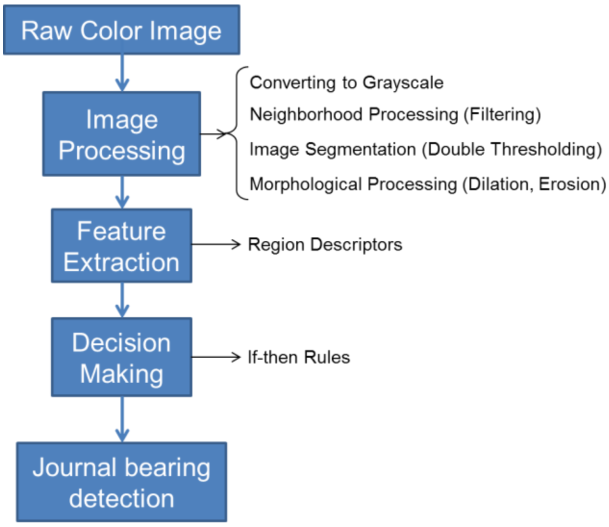

Figure 1: Flowchart of the present work

2) Materials and Methods

2.1) The Imaging Test Setup

In the experiments, a four-cylinder engine block containing pistons, rings and connecting rods was used. The used condition was exactly the same as the engine condition in the conrod bearing assembly station in the production line. In the assembly station of conrod bearing, the engine body is laid upside down on the pallet due to the accessibility of the operator to the connecting rods for assembling the conrod bearing. Therefore in the experiments, the engine block was placed upside down on the bed, and all pistons were taken to their BDC (Bottom Dead Center) position as shown in Figure 2.

In order to take photos, a Canon G12 10MP Digital Camera installed on its base in a completely stable position was used. The distance and angle of the camera was adjusted so that full size of the engine block was in the photo frame.

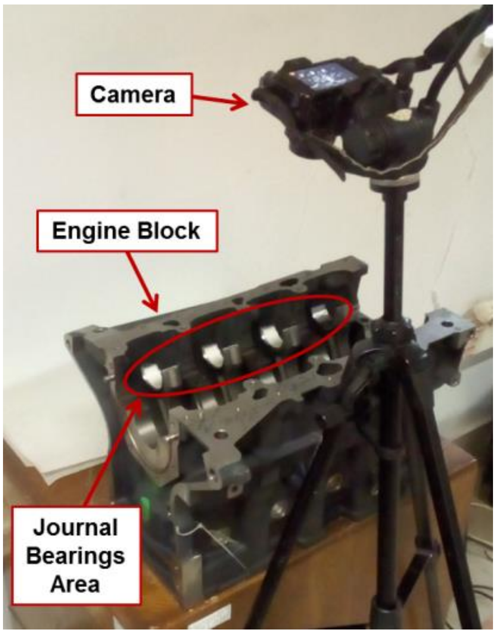

Figure 2: Configuration of imaging setup

As it can be seen from Figure 2, the engine under study possesses four cylinders that one conrod bearing should be installed on each one. So the number of events (conrod bearing existence) occurring in the production line is 2^4, because there are two outcomes for bearing existence, namely present and absent. Accordingly, with various combination of conrod bearing installation, all 16 possible events were generated as shown in Figure 3.

As shown in Figure 3, the following fifteen different possible errors which can be occurred in the production line, were studied in this research:

- No conrod bearings are installed
- All conrod bearings are installed except No#1
- All conrod bearings are installed except No#2
- All conrod bearings are installed except No#3
- All conrod bearings are installed except No#4

Figure 3: 16 different cases of conrod bearing installation captured by camera

- Conrod bearings No#1 and 2 are not installed
- Conrod bearings No#3 and 4 are not installed
- Conrod bearings No#1 and 4 are not installed
- Conrod bearings No#2 and 3 are not installed
- Conrod bearings No#1 and 3 are not installed
- Conrod bearings No#2 and 4 are not installed
- Only conrod bearing No#1 is installed
- Only conrod bearing No#2 is installed
- Only conrod bearing No#3 is installed
- Only conrod bearing No#4 is installed

For each conrod bearing installation cases, 30 images with dimensions of 3648×2736 Pixels were captured. It is noted that new conrod bearings were used for photography because the bearings assembled in the engine production line are new. Since the machine vision systems are sensitive to lighting, the images were captured under the same lighting conditions. The best photography condition, including a right angle, middle position and use of camera flash without any external light, was achieved by trial and error. One of the criteria considered for selecting the best lighting condition, was the light reflection which is among the issues in any machine vision system especially for shiny objects such as metals. After trial and error in determination of the best lighting condition, it was found that the reflection could not be removed from the images. But it also turned out that due to the opaque color of bearing top surface, of course only for new bearings, the reflection was less visible where there is a bearing and completely visible where there is no bearing. This characteristic could be used for detection of bearing existence but a more advanced method has been developed in this research.

2.2) Image Processing

In order to process the images, different image processing methods described in below, were employed. To this end, MATLAB R2016a software was used.

2.2.1) Smoothing

Image smoothing is used to suppress noise usually by some form of averaging of brightness values in some neighborhood. Smoothing may cause sharp edges to be blurred, and so those smoothing methods are proper to preserve the edges. One of the effective image smoothing methods is the use of Gaussian filter. The Gaussian filter is one of the low-pass filters, which tries to reduce the effect of high frequencies in an image by bringing the brightness distribution in a neighborhood to the normal (Gaussian) distribution [24, 25]. The result of this filter, like other low-pass filters, is to obtain a smoother image than the original image. The equation of a Gaussian distribution for one dimensional function is as follows:

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \quad (1)$$

where σ is the standard deviation of the distribution. In this equation, it is assumed that the average is zero [24].

2.2.2) Segmentation

Image segmentation is among the most important stages leading to the analysis of processed image data. Its main goal is to split an image into parts that have a strong correlation with objects or areas of the real world contained in the image. If the aim is complete segmentation, it will result in a set of disjoint regions corresponding uniquely with objects in the input image, or for partial segmentation, in which regions do not correspond directly with image objects [24].

Segmentation methods comprise of three groups according to the dominant features they employ; first is global knowledge about an image or its part; this is usually represented by a histogram of image features. Edge-based segmentations form the second group, and region-based segmentations the third. Many different characteristics may be used in edge detection or region growing, for example, brightness, texture, velocity field, etc [24].

The simplest segmentation process is Gray-level thresholding. Many objects or image regions are characterized by constant reflectivity or light absorption of their surfaces; then a brightness constant or threshold can be determined to segment objects and background. Thresholding is computationally inexpensive and fast. It is the oldest segmentation method and is still widely used in simple applications; it can easily be performed in real time applications. Thresholding is the transformation of an input image f to an output (segmented) binary image g [24]:

$$g(x, y) = \begin{cases} 1 & \text{for } f(x, y) > T \\ 0 & \text{for } f(x, y) \le T \end{cases} \quad (2)$$

where T is the threshold, $g(x, y) = 1$ for image elements of objects, and $g(x, y) = 0$ for image elements of the background (or vice versa).

If objects do not touch each other, and if their gray-levels are clearly distinct from background gray levels, thresholding is a suitable segmentation method. Correct threshold selection is crucial for successful segmentation; this selection can be determined interactively or it can be the result of some threshold detection method. Only under very unusual circumstances will a single threshold for the whole image (global thresholding) be successful: even in very simple images there are likely to be gray-level variations in objects and background; this variation may be due to non-uniform lighting, non-uniform input device parameters or a number of other factors [24].

Basic thresholding as defined by Eq. (2) has many modifications. One possibility is to segment an image by two upper and lower thresholds, which is called double thresholding [26]:

$$g(x, y) = \begin{cases} 1 & \text{for } T1 < f(x, y) \le T2 \\ 0 & \text{for } f(x, y) \le T1 \ \ or \ \ f(x, y) > T2 \end{cases} \quad (3)$$

2.2.3) Morphology

Mathematical morphology is a well-established area of image processing. It is based on the algebra of non-linear operators operating on object shape and in many respects supersedes the linear algebraic system of convolution. Morphology can be employed in many tasks such as pre-processing, segmentation using object shape and object quantification which provides a better and faster method than the standard approaches [25]. Morphological tools are often used in most image processing tasks, especially where the shape of objects and speed is an issue like industrial inspection, optical character recognition, analysis of microscopic images and document analysis. Mathematical morphology is on the basis of using non-linear algebra and operating with point sets, their connectivity and shape, which simplify images, and quantify and preserve the main shape features of objects. Some of the purposes of the morphological operations are noise filtering, shape simplification, skeletonizing, segmenting objects, and obtaining quantitative characteristics of objects like area and

perimeter [24].
Dilation and erosion are among the primary morphological operations. Dilation, also known as Minkowski addition operator, is an operation that increases the dimensions of the components inside the image by one or more pixels. Erosion operation as clear as its name implies, causes objects to shrink or thin in binary images. For more information about their theory, please see [24].

3) Results and Discussion

As mentioned previous, the image processing, feature extraction and decision making methods were used in this paper to detect the presence or absence of conrod bearing. The entire analysis stages is illustrated in Figure 4 in the form of step-by-step results on one of the 16 different cases of conrod bearing installation, namely conrod bearings 2 and 4 are present and conrod bearings 1 and 4 are not installed.
As it can be seen from Figure 4, the analysis stages were as follows:
1) Garyscaling: The RGB image captured by the camera (Figure 4(a)), were firstly converted to gray image.
2) Filtering: Gaussian filter was then used to remove the sharp pixels and minimize their effects in the image (Figure 4(b)). In this research, since it was aimed to discover the existence of not a small object, filtering not only does not interfere, but also gives a smoother image that helps object detection. It should be noted that the standard deviation of the filter should not be so high that the conrod bearings and their boundary will be unclear or displaced. Therefore, a standard deviation that prevents sharpness and slightly flattens large changes in the pixel values, is desirable. To this end, the standard deviation of 4 was employed for Gaussian filter.
3) Cropping: To focus on the region of conrods, the image was cropped to remove the extra parts of the engine block and to create the frame in which the bearings are available with a higher magnification (Figure 4(c)).
4) Segmentation: By double thresholding method, the image was segmented in order to separate the pixels related to the conrod bearings from other areas (Figure 4(d)). To this end, the lower threshold of 110 and the upper threshold of 245 were considered. The threshold values were obtained by examining the brightness of the pixels of the areas containing the conrod bearing and the areas without the conrod bearing.
5) Filling: As it can be seen from Figure 4(d) which is the consequence of the segmentation stage, the pixels related to the conrod bearing, was completely separated. But for the conrod bearing#2, it can be seen that the surface of this bearing was not separated continuously, and there was a black region in the middle of the bearing area. To overcome this problem, all of the holes in the binary image of Figure 4(d) were filled, so an integrated white area was created for the conrod bearing#2 (Figure 4(e)).
6) Erosion: In Figure 4(e), apart from the bearing areas which were separated well, some extra white areas were created at the locations where no bearing existed. This was due to that their pixel values were placed in the applied thresholding range. Because these pixels are not related to the conrod bearings, they should be removed from the binary image. To this end, the erosion technique with a disk-shaped structuring element was used. According to the size of the white areas belonged to the bearings, the value of 60 was chosen for the radius of this structuring element. The result of the erosion technique is shown in Figure 4(f). As it can be seen, all white areas in Figure 4(e) except the areas related to the bearings, were eroded and removed.
7) Dilation: In Figure 4(f), the areas related to the bearings was shrunk after the erosion process. In order to return these areas to their primary size (before erosion), the dilation technique was used by the same disk-shaped structuring element with 60 radius. The final processed image is illustrated in Figure 4(g). As shown, only white areas related to two conrod bearings#2 and 4 remained and the other objects of the image including non-bearing connecting rods and the engine block parts were masked. This image is called final binary image.
After the above mentioned analysis stages, a decision making must be done in order to determine the number of present conrod bearings. At the first stage of decision making, the area feature of the white regions was used. In order to obtain the correct range of the area, after analyzing all of the images related to 16 different conrod bearing installation cases, the area of the white regions belonged to the bearings in the final binary images were calculated. Figure 5 shows the histogram of

these area values. As it can be seen, the white regions related to the conrod bearings for all images of this research, had an area between 30,000 and about 80,000 pixels. Therefore, in the final binary image, any white region whose area is within this range indicates the presence of the bearing, and any white region whose area is outside this range is not a bearing.

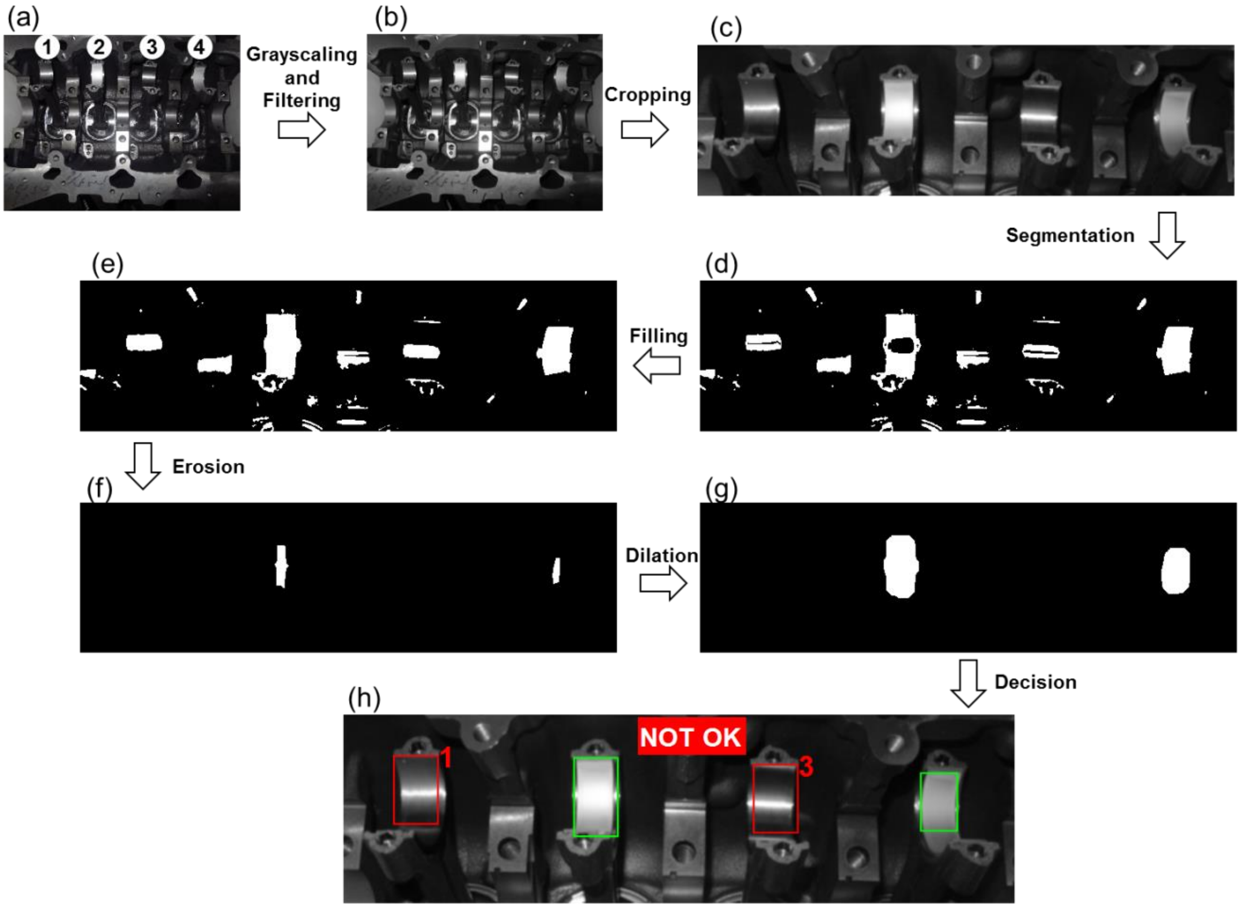

Figure 4: Step by step analysis results for one of the bearing installation cases: (a) raw color image (b) gray filtered image (c) cropped image (d) filled binary image (e) binary image (f) eroded image (g) dilated image (h) final image

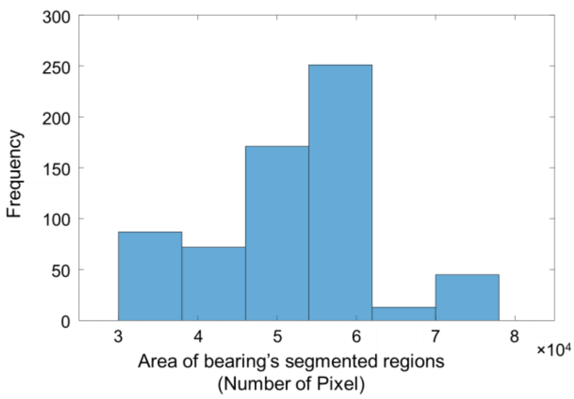

Figure 5: Histogram of the separated white color regions belonged to bearing

After detection of the bearing existence, it must be identified the number of present bearings. To this end, the feature of the white region center position was used. By examining the position of the bearings center in all images, it was found that the horizontal position of the conrod bearings#1, 2, 3 and 4 was placed in the range of 300 and 400, 1100 and 1200, 1910 and 2010, 2680 and 2780, respectively. Any region outside of the mentioned ranges is not related to the conrod bearing. Accordingly, by adapting the center of the detected bearing regions to the above ranges, the number of the bearings available can be identified. For example, if there is only one white region in the final binary image with an area between 30,000 and 80,000, and the horizontal position of its center is 1170, it is found that there is just conrod bearing#2, and the conrod bearings#1, 3 and 4 are absence means have not been installed. Or as another example, if there are two white regions in the final binary image with an area between 30,000 and 80,000, and the horizontal position of their center are 1146 and 2709, it can be found that the conrod bearings#2 and 4 are present, so the conrod bearings#1 and 3 have not been installed. Figure 6 indicated the flowchart of the decision making on the final binary images to detect the conrod bearing existence.

Finally, after performing all analysis stages, the result of final decision of this intelligent system, can be shown to the operator of the production line in the form of Figure 4(h). In Figure 4(h), because two conrod bearings#1 and 3 are not installed, the message of "NOT OK" is issued, which means that the bearing installation condition is unacceptable. Also, if not even a bearing is installed, the system issues "NOT OK" message because, as mentioned earlier, this system is a poka-yoke and must not allow an engine without even a bearing to reach the crankshaft installation station.

In the next step, the mentioned analysis was performed for all different cases of bearing installation so that the performance of the proposed method to be evaluated for other cases. Figure 7 shows the final output of the used analysis for each of the different bearing installation cases. The output is shown as an image in which the green and red boxes indicate the existence and non-existence of the bearings, respectively, with the corresponding cylinder number. As shown in Figure 7, the presence and absence of bearings was correctly identified for all bearing installation cases. It is noted that in the output image, the "OK" message is shown means acceptable condition, only when all bearings are installed.

To quantify the overall accuracy of the system, all images were analyzed. The results showed that the proposed method detected the bearing installation cases in all images with 100% accuracy. The initial expectation was to provide a method that would have no errors, because a system is referred to as Poka-Yoke when its accuracy is 100% and its error is zero. It is emphasized that another advantage of the proposed method was the correct combination of not so complex methods in image processing, feature extraction and decision making stages, which caused the total analysis time to be about 1 sec. According to the results, it can be said that the present research was able to create an accurate and fast intelligent Poka-Yoke system for detection of conrod bearing installation condition that could effectively be used in the engine production line.

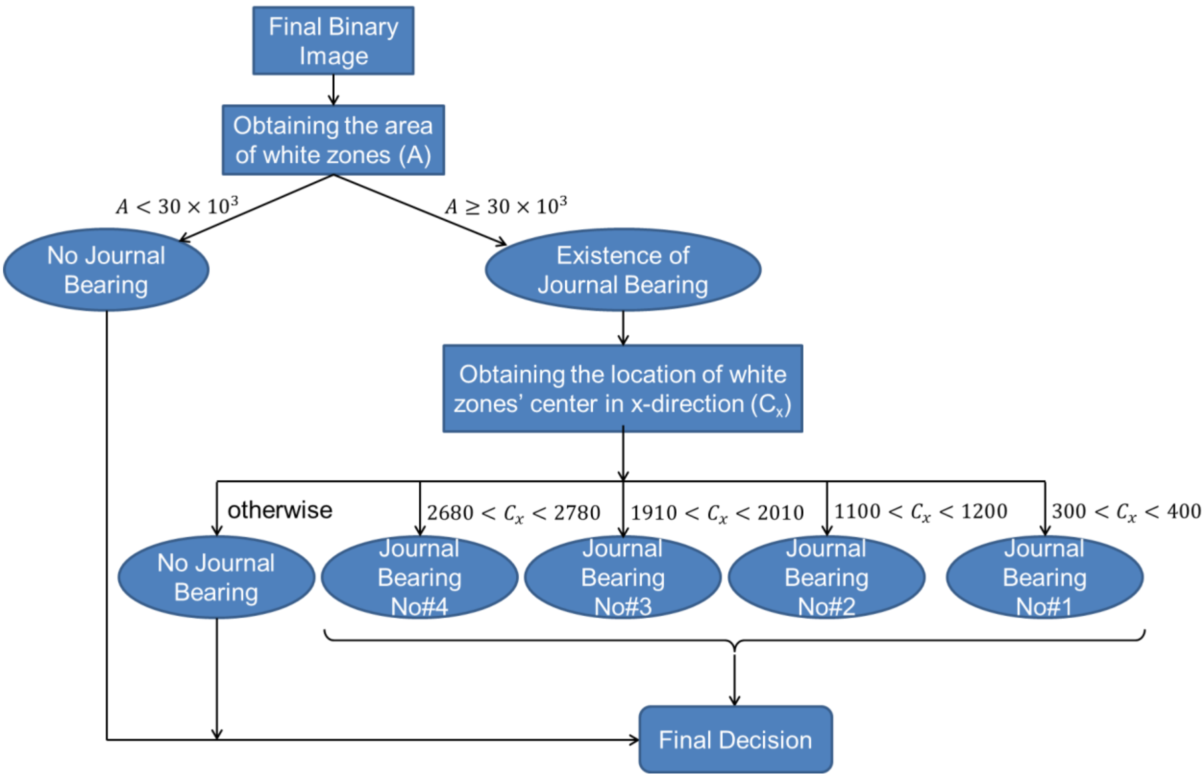

Figure 6: Flowchart of the decision making on the final binary images

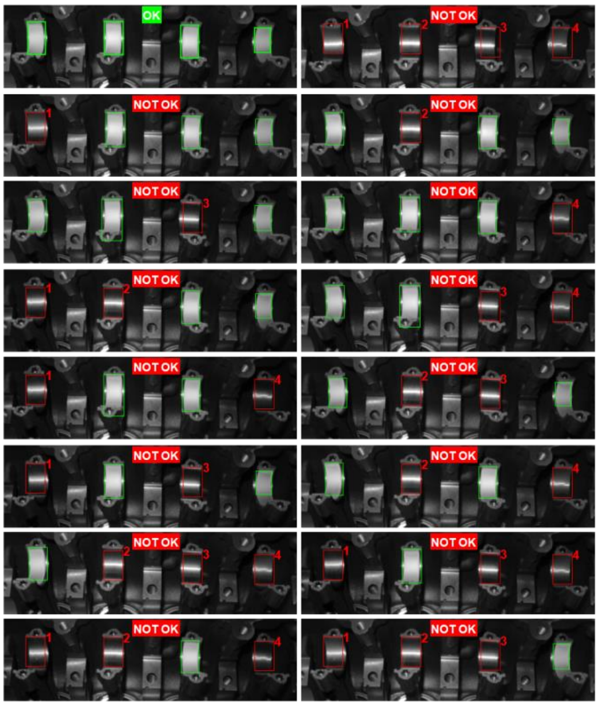

Figure 7: Final output of the proposed method for all 16 different conrod bearing installation cases

It is emphasized that this research did not study the effect of the position of the connecting rod, for example, changes in its height, its rotation around the axis of the piston pin or around the cylinder axis. In order to establish a comprehensive multi-task Poka-Yoke system for bearing installation station, it is suggested to improve its capabilities by adding more features like bearing fault detection, detection of bad installation means the conrod bearing is not placed correctly in the bearing cap, insensitivity to lightning conditions, etc. Hence, it is recommended the above features are surveyed in future research.

For real application, it is enough to establish a software communication between production line automation and the proposed machine vision system. Electronic board as hardware interface like Raspberry Pi and Arduino which can receive/send the pulses from/to the production line controller should be used. To this end, it is necessary to connect two pins of the board called input and output, to the production line controller which is usually programmable logic controller (PLC). When the engine body reaches the imaging station by the automatic guide rail of the production line, an electric voltage pulse is sent to the input pin of the board by the PLC, so that the camera takes automatically a picture of the engine body. Of course, there should be an online connection between the camera and board. For this purpose, industrial cameras such as Basler and Raspberry Pi Camera Module is recommended. After imaging, the system starts to process the captured image until the final result is obtained in the form of OK or NOT OK message. Then, the board outputs a voltage pulse corresponding to the final result to the PLC. If the pulse corresponding to the OK result is delivered, the automation of the line allows the engine body to be moved to the next station, i.e. crankshaft installation. But if the pulse corresponding to the NOT OK result is delivered, it alerts the production line technician to check and fix the conrod bearing error.

6) Conclusions

Existence of Poka-Yoke systems in engine production lines is necessary in order to prevent human and non-human errors in the process of assembling parts and to increase the quality of the final product. Accordingly, the current paper presents an accurate and rapid intelligent method as a Poka-Yoke system to detect the non-installation error in conrod bearings of a four-cylinder IC engine. It means that this method is able to detect the absence of conrod bearings along with the number of cylinders whose connecting rod does not have bearing, and display them to the operator visually. For this purpose, at first, the images of all possible cases of the bearing installation were captured by a camera. Then, all images were analyzed with image processing techniques such as Gaussian filtering, image thresholding and segmentation, and morphological techniques including erosion and dilation. Then, the characteristics of the area and position of the objects created after processing were extracted from the images. Finally, with the if-then rules, the condition of the images was decided. The results showed that according to the lighting conditions used in this study, which was the use of camera flash, the best threshold range for separating the bearing part from other parts of the engine block was between 110 and 245. Also, in order to remove the extra portions from the processed binary image, a disk-shaped structuring element with the radius of 60 provided the best result. In addition, according to the dimensions of the images, the results showed that the separated regions in the binary image belonged to conrod bearings had an area between 30,000 and about 80,000 pixels. To evaluate the performance of the proposed method, all images were analyzed. The evaluation results showed that the accuracy of this method in detecting all different bearing installation cases was 100%. Also, the total time for analyzing each image was about 1 sec. High accuracy and high speed are the features that are vital for real and online industrial applications of Poka-Yoke systems, and the proposed method has both of these features. Therefore, it can be said that the developed machine vision system has the necessary and sufficient merit to be used in the production line of the studied engine as a Poka-Yoke system of the conrod bearing installation. To this end, it is enough to establish an online connection between the proposed method and the control equipment of conrod bearing station of production line.

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رویکرد بینایی ماشین به‌عنوان یک سامانۀ ضدخطا در ایستگاه هم‌بندی یاتاقان متحرک خط تولید موتور

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چکیده

این مقاله به ارائۀ یک روش بینایی ماشین برای تشخیص خطای نصب یاتاقان شاتون (متحرک) در موتورهای چهار سیلندر می‌پردازد. از آنجایی که همواره خطاهای انسانی در خطوط تولید موتور وجود دارد که باعث کاهش کیفیت محصول نهایی می‌شود، راه اندازی سیستم‌های بینایی ماشین هوشمند به منظور رصد فرایند هم‌بندی قطعات و جلوگیری از خطاهای نصب بسیار لازم است. روش پیشنهادی به این صورت است که با گرفتن تصویر بدنۀ موتور، یک تصویر دودویی ایجاد می‌کند که کل تصویر سیاه بوده و فقط محل‌هایی که یاتاقان‌های متحرک وجود دارد سفید است، و همچنین اعلام می‌کند که کدام یاتاقان‌ها وجود دارند و کدام‌ها نصب نشده‌اند. بدین منظور ابتدا تصاویر ۱۶ حالت مختلف از نصب یاتاقان توسط دوربین گرفته شد. سپس تمام تصاویر با ترکیبی از روش‌های پردازش تصویر شامل فیلتر گاوسی، آستانه‌گذاری و بخش‌بندی تصویر، و تکنیک‌های ریخت‌شناسی از جمله فرسایش و گسترش تجزیه و تحلیل شدند. در نهایت، با اعمال قواعد اگر-آنگاه در مورد ویژگی‌های اشیاء ایجاد شده در تصویر، وضعیت آن تصمیم‌گیری شد. نتایج نشان داد که بهترین محدوده آستانه برای جداسازی یاتاقان از سایر قسمت‌های تصویر بین ۱۱۰ تا ۲۴۵ است. همچنین یک المان ساختاری دیسکی شکل با شعاع ۶۰ بهترین ابزار ریخت‌شناسی برای تشخیص یاتاقان‌ها را ارائه داد. علاوه بر این، نتایج نشان داد که نواحی متعلق به یاتاقان‌های متحرک مساحتی بین ۳۰ تا حدود ۸۰ هزار پیکسل داشتند. با استفاده از قواعد اگر-آنگاه، حالات مختلف نصب یاتاقان در تمام تصاویر، به طور موفقیت آمیز با دقت ۱۰۰ درصد تشخیص داده شد. کل زمان تجزیه و تحلیل هر تصویر حدود ۱ ثانیه بود. بنابراین نتایج نشان داد که سامانۀ بینایی ماشین پیشنهادی، ابزاری بدون خطا و سریع برای تشخیص وجود یاتاقان‌های متحرک را فراهم می‌کند که می‌تواند به عنوان یک سامانۀ ضدخطا در خط تولید موتور مورد استفاده قرار گیرد.

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