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Condition Monitering of Thrust Bearings Based on Machine Learning with Synthetically Generated Data

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Abstract

Different approaches to condition monitoring and failure detection are necessary since rolling element bearing problems are a major contributor to total machine failures. Recent developments in machine learning, which reduce the need for planned maintenance, further quicken the effort to increase defect detection accuracy for financial reasons. Difficult issues remain, such as collecting high-quality data to explicitly train an algorithm, and are made harder by the scarcity of historical data. Furthermore, failure data derived from measurements is usually limited to specific equipment components, like Vernier callipers, which offers only round off thrust bearing values. To overcome this, the study works on deep learning, artificial intelligence & Machine vision technologies are introduced with precise measurement values of thrust bearing.

Keywords: Condition monitoring, Thrust bearing, fault detection, Curve fit Algorithm, Machine vision, Deep learning, Artificial Intelligence [AI], Image processing, Thresholding.

1. Introduction

The most prevalent part of industrial rotating machinery is a thrust bearing. thrust bearing problems can cause machines to malfunction, as well as financial loss and human tragedies. As a result, thrust bearing defect diagnostics are crucial for process automation and machinery maintenance. There are numerous ways to pattern recognition and signal processing that are suggested as diagnostic tools. It is important to remember that faulty frequency features of the vibration signal can be revealed by time-frequency analysis, which includes wavelet analysis and the Hilbert-Huang transform. That being said, a multitude of factors influence the bearing signal's intricacy [1].

Accurately determining the bearing characteristic frequencies is nearly impossible due to variations in bearing geometry and assembly. The transient signal response, which is often obscured by noise and wide band resonance, exhibits distinct behaviours depending on the position of a bearing failure. Thirdly, it is challenging to separate signals with varying severity stages of the same fault type and extract their representative properties. Fourth, how quickly and how much a piece of machinery vibrates depends largely on its operational speed and shaft load, which also affects the vibration signals that are detected. Ultimately, the impracticality of signal processing approaches stems from the inability to gather baseline information on a certain bearing [2].

Artificial intelligence and deep learning techniques are used in AI-based image processing for thrust bearing inner diameter calculation, which automates and enhances measurement accuracy. Artificial Intelligence (AI) can assess photos or video frames of thrust bearings and precisely estimate their inner diameter with the least amount of human involvement by fusing computer vision algorithms with neural networks. In this situation, AI functions provide a number of benefits. It can manage intricate image variations that conventional image processing techniques might find difficult, such as shifting lighting, noise, and perspective distortions. A thorough examination of the inner diameter of thrust bearings is necessary to guarantee the longevity, effectiveness, and safety of the braking system. It ensures standard compliance, even wear of brake components, optimal braking performance, correct fit, and customer satisfaction. Manufacturers can prioritise customer safety and satisfaction by implementing stringent quality inspection procedures that uphold the highest standards of quality control and result in vehicles with dependable and efficient braking systems. Ensuring the safety, functionality, and dependability of a car's braking system requires a quality inspection of the inner diameter of a thrust bearing [3].

When compared to other conventional techniques, image processing for thrust bearing diameter calculation has a number of advantages. The term "image processing" describes the methods and algorithms used by computers to examine, edit, and extract data from digital images. The process entails utilising diverse mathematical functions, filters, and algorithms to augment, modify, or retrieve significant information from the pictures. The two main subcategories of image processing are digital and analog. Analog image processing makes use of electrical or optical methods to alter images, while digital image processing processes images using computer algorithms [4].

2. Literature Survey

The introduction describes how the high temperature, ablation, impact and friction from the pellets, erosion by high-pressure powder gas, and high temperature during firing all lead to cannon barrel wear and tear. One important determinant of the cannon barrels' life is the inside diameter's wear. However, assessing the wear characteristics of the inner diameter of the barrel is challenging due to the deep-hole structure of the barrel and the potential for barrel bore defects. In this paper, a non-contact image-processing based measuring tool for cannon barrel inner diameter is proposed [6].

The paper goes over the fundamental concepts of the overall layout. The suggestion is to use a stationary camera to take pictures of the laser points that are marked on the cannon barrel in wall. The degree of wear can be ascertained by comparing the separations between the laser points in various images. The technique and theory of image processing-based measurement are presented in this paper [7].

A method for precisely measuring the inner diameter of bearings through online subpixel edge detection is presented in this paper. The bearing dimension detection system circumvents the drawbacks of traditional methods by combining computer image processing techniques with machine vision technology. The system's architecture, guiding concepts, and image processing algorithms are all thoroughly described in the paper [8]. High accuracy and dependability can be achieved in industrial settings thanks to the system, as evidenced by the results. The bearing dimension measurement process can be made more precise and efficient with this sub-pixel inspecting technique, which will also revolutionise the inspection process' efficiency [9].

Using OpenCV, an open-source computer vision library, the study suggests a way to measure a workpiece's sub-pixel inner diameter. Accurate measurements without actually touching the workpiece are the aim.

Using OpenCV to measure inner diameter, the researchers created and put into use a visual measurement system. Because the target and noise have very similar grayscale values in the captured image, it is challenging to distinguish between them with a single threshold. A two-step approach with two distinct thresholds is suggested as a solution to this problem. The image's background noise is first eliminated by applying a lower threshold. Next, a higher threshold is utilised to acquire a binary picture that accurately depicts the target's contour. Among the many image processing operations carried out by the system are contour extraction, region of interest extraction, and binarization [10].

In this paper [11], a novel method for high-precision computer vision measurement ellipse detection is presented. The method achieves accuracy at the sub-pixel level by combining spatial moment operators with conventional edge operators. While addressing the shortcomings of current methods, experimental results show its high precision and stability. The suggested method makes use of the Hough transform for ellipse detection, spatial moment-based sub-pixel detection, and the LOG operator for quick edge localization. Along with the randomised Hough transform to lower computational complexity, the paper also introduces a compensation method for better sub-pixel location accuracy. Overall, the method greatly improves computer vision measurement applications' ability to detect ellipses.

3. Proposed Method/Model

This section should provide the full proposed models and architecture for the current research article. The writers' original contributions are presented in this section.

3.1 Camera Calibration

The process of precisely mapping 3D locations in the actual world to the appropriate 2D image coordinates by determining the intrinsic and extrinsic characteristics of a camera is known as camera calibration in image processing and computer vision. It is an important step in many applications, including 3D reconstruction, object tracking, augmented reality, and accurate measurements in computer vision systems. Camera-specific characteristics, or intrinsic parameters, are attributes like focal length, lens distortion coefficients, and principal point, which is the image's optical centre. 3D point projection onto the 2D image plane is influenced by these parameters, which also describe the internal geometry of the camera. To precisely estimate these parameters is the goal of intrinsic calibration. A calibration target, such as a planar pattern with well-known geometric properties (like a checkerboard), is usually photographed in order to accomplish this. Iteratively fine-tuning the intrinsic parameters and modelling the lens distortion effects can be achieved by algorithms through examination of the distortions observed in the calibration target images [12].

The spatial relationship of the camera to the scene it is capturing is defined by extrinsic parameters. In relation to the global coordinate system, they comprise the camera's position

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(translation) and orientation (rotation). The estimation of these parameters is done through extrinsic calibration, which is typically carried out with the use of multi-view geometry or calibration targets with known 3D positions. It is possible to precisely determine the relative pose of the camera by taking pictures of the calibration target from various angles or within predetermined geometric constraints.

3.1.1 Camera Matrix

The camera matrix, also called the intrinsic matrix or the calibration matrix, is a crucial part of camera calibration and is used to simulate image distortion brought on by the lens of the camera. It takes into consideration the inherent camera characteristics and lens distortion and links the 3D world coordinates of a point to the equivalent 2D picture coordinates. Typically, the camera matrix is represented by a 3x3 matrix denoted as K:

$$K = \begin{pmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{pmatrix} \text{.............................} \ (1)$$

where fx and fy are the focal lengths along the x and y picture axes, respectively, and (cx, cy) indicates the primary point or optical center of the image. The principal point is the place where the image plane and the camera's optical axis intersect.

The number 1 in the lower-right corner of the matrix denotes a scaling factor.Use a camera matrix to project 3D points onto the 2D image plane. By multiplying the homogeneous coordinate vector of the 3D point [X, Y, Z, 1] by the camera matrix K, we may obtain the equivalent 2D picture coordinates [u, v, w].

[u, v, w] = K * [X, Y, Z, 1] .... (2)

The normalised image coordinates are then obtained by dividing the resultant image coordinates (u, v) by w.

Lens distortion effects are also incorporated into the camera matrix. Higher-order polynomials, like the Brown-Conrady distortion model, are commonly used to model the distortion coefficients. The distortion coefficients take into consideration two types of distortion: tangential distortion, which results from the lens's misalignment with respect to the image sensor, and radial distortion, which makes straight lines appear curved near the image edges. The distortion coefficients can be used to calculate the distorted image coordinates, which can then be corrected using methods like optimization algorithms or iterative refinement.

To sum up, the intrinsic parameters (fx, fy, cx, cy) that represent the camera matrix are essential for both camera calibration and distortion modelling. It describes the mapping of the camera's focal lengths, main point, and scaling factor from 3D world coordinates to 2D image coordinates. By considering both the camera matrix and the distortion coefficients, an accurate mapping between the distorted image and the real-world scene can be achieved.

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3.1.2 Representing the lens distortion mathematically

When attempting to estimate the 3D points of the real world from an image, several distortion effects need to be considered.. Based on the characteristics of the lens, the distortion effect can be mathematically modelled and combined with the pinhole camera model. Therefore, in addition to intrinsic and extrinsic parameters, it also has additional intrinsic parameters in the form of distortion coefficients, which mathematically represent the lens distortion.

I can modify the Pinhole camera model in the following ways to account for these distortions in the model:

$$\begin{bmatrix} X_c \\ Y_c \\ Z_c \end{bmatrix} = [R|T] \begin{bmatrix} X_w \\ Y_w \\ Z_w \end{bmatrix} \text{.......................} \ (3)$$

K'= Kc …………………… (4)

Zc ' = Zc .... (5)

Zcγ = (1+ K1r 2 + K2r 4 + K3r 6)/(1 + K4r 2 + K5r 4 + K6r6) ………….. (6)

r2 = x'2 + y’2 . . . . (7)

x " = x'(γ)+2P1x'y'+P2(r2 + 2x’2…….. (8)

y"=y'(γ)+P1(r2 + 2y'2) + 2P2x 'y’2....... . (9)

The distCoeffs matrix returned by the calibrateCamera method contains the values of K1, through K6, which stand for the radial distortion, and P1, P2, which stand for the tangential distortion. Since the mathematical model of lens distortion presented above includes radial distortion, decentering distortion, and thin prism distortion, the net radial distortion is represented by coefficients K1 through K6, while the net tangential distortion is represented by P1 and P2.

3.2 Image Acquisition

It is described as the procedure for getting an image for image processing from a source, usually one that is hardware-based. The workflow sequence begins with the image because processing cannot begin without one. The obtained image is not processed in any way. It describes the method of taking digital pictures with imaging equipment like scanners, cameras, and sensors. In a number of areas, such as remote sensing, medical imaging, computer vision, and photography, it is a crucial step. In order for computers or other digital systems to process and analyse an image further, it must first be converted from a physical scene or object into a digital representation [13].

3.3 Image Preprocessing

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Preparing images for subsequent analysis, like feature extraction, image segmentation, or object recognition, is known as image pre-processing [14]. Typical image preprocessing methods consist of the following:

- Image Cleaning
- Denoising
- Artefact removal
- Image Enhancement
- Image Resizing
- Color Space Conversion
- Image Normalisation
- Image Rotation and Alignment
- Image Cropping and Region of Interest (ROI) Extraction
- Image Registration

3.4 Thresholding

One segmentation approach called thresholding produces a binary image by splitting a grayscale image into two regions based on a threshold value (a binary image is one whose pixels have only two values, 0 and 1, and so requires only one bit to encode pixel intensity). Consequently, all other pixels, or 0, will be read as black, or 0, and pixels with intensity levels lower than the designated threshold, or 1, will be understood as white, or 1 in the final image [15].

Assume that the image f(x,y)'s histogram is shown above. At 180 and close to level 40, we can see two peaks. Pixels can be divided into two main groups: pixels with a darker shade in one group and pixels with a lighter shade in the other. Thus, an interesting object may be placed in the background. The entire image will be split into two separate regions if we choose a suitable threshold value, let's say 90.

Stated differently, given a threshold T, the segmented image g(x,y) is calculated as follows:

$G(x,y) = 1$ if $f(x,y) > T$ and $g(x,y) = 0$ if $f(x,y) < T$

The resultant segmented image thus consists of just two classes of pixels, some of which have values of 1 and others of 0. Global thresholding occurs when the threshold T remains constant throughout the processing area of the image. Variable thresholding is when T fluctuates throughout the image region.

The research work used entirely dark and grey pixels, with intensity ranging from a straight 0 for the darker shades to between 120 and 140. We calculated an approximate mean value of approximately 127.

3.5 Edge Detection

To determine an object's boundaries within an image, image processing techniques like edge detection are used. It functions by identifying discontinuities in brightness. Edge detection is used for picture segmentation and data extraction in fields including image processing, computer vision, and machine vision. The image's structure is preserved while extraneous information is reduced thanks to edge detection [16]. By creating a clear separation between two different image variations, it eliminates discontinuities by connecting the neighbouring pixel edges.

3.5.1 Canny edge detection technique

For an ideal edge detector, use the Canny operator. It receives an image in grayscale as input and outputs an image with the locations of tracked intensity discontinuities. Our project makes use of this technique. The Canny operator utilises a multi-step procedure. Gaussian convolution provides overall image smoothing. Next, a simple 2-D first derivative operator is applied to the smoothed image to identify regions with high first spatial derivatives. Ridges emerge from the gradient magnitude image's edges.

In order to create a thin line in the output, the algorithm tracks along the top of these ridges and sets to zero any pixels that are not truly on the ridge top. This technique is known as non-maximal suppression. The hysteresis of the tracking process is managed by two thresholds, T1 and T2, where T1 > T2. Tracking can only begin at a certain location on a ridge above T1. Once over that point, tracking continues in both directions until the ridge's height falls below T2. Such hysteresis aids in preventing the fragmentation of noisy edges into several edge segments.

3.5.2 Contour edge detection

To extract and identify the boundaries of objects or shapes within an image, computer vision professionals use contour edge detection, a fundamental technique. The circular shape of the thrust bearing is located in the context of the problem statement using contour edge detection. The thrust bearing's contour or outline can be recognized, making it easier to evaluate its measurements and take an exact inner diameter measurement. In this problem, contour edge detection works well since it can accurately identify the circular boundary despite changes in lighting or possible noise in the image. This enables the inner diameter of the thrust bearing to be estimated and analysed later on. The solution improves the internal diameter of the thrust bearing with greater efficiency and accuracy by using contour edge detection. This offers an automated and dependable way for quality control procedures in the sector.

3.6 Sub Pixeling

By achieving sub-pixel accuracy in the location of identified edges, a technique known as sub-pixeling is employed to improve the accuracy of edge detection algorithms. Sub Pixeling is used in conjunction with the first edge detection step in the suggested method for determining a thrust bearing's inner diameter. To obtain more accurate and precise edge locations, sub pixeling is done after the edge detection algorithm provides the coarse edge coordinates. This is accomplished by interpolating the precise location of the edge within the pixel boundaries and examining the pixel intensity values surrounding the edges that have been detected [17].

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By giving the more exact coordinates of the detected edges, sub-pixeling improves the accuracy of the inner diameter measurement. This leads to a more accurate measurement of the inner diameter of the thrust bearing and an improvement in the estimation of the circle parameters too. Lower measurement precision is ensured and the possibility of errors and inaccuracies in the final results is decreased by integrating subpixeling into the solution. More accurate and consistent measurements of the inner diameter in industrial settings are made possible by this, improving the quality control process.

3.7 Curve Fit Algorithm

The Circle Fit method, also known as the Direct Circle Fit method, is a fast and efficient way to calculate a circle's diameter from a set of data points. It is minimising the sum of squared residuals to fit a circle directly to the data points [17]. The figure 1 shows the histogram of the image, and a detailed explanation of the Circle Fit method is explained below :

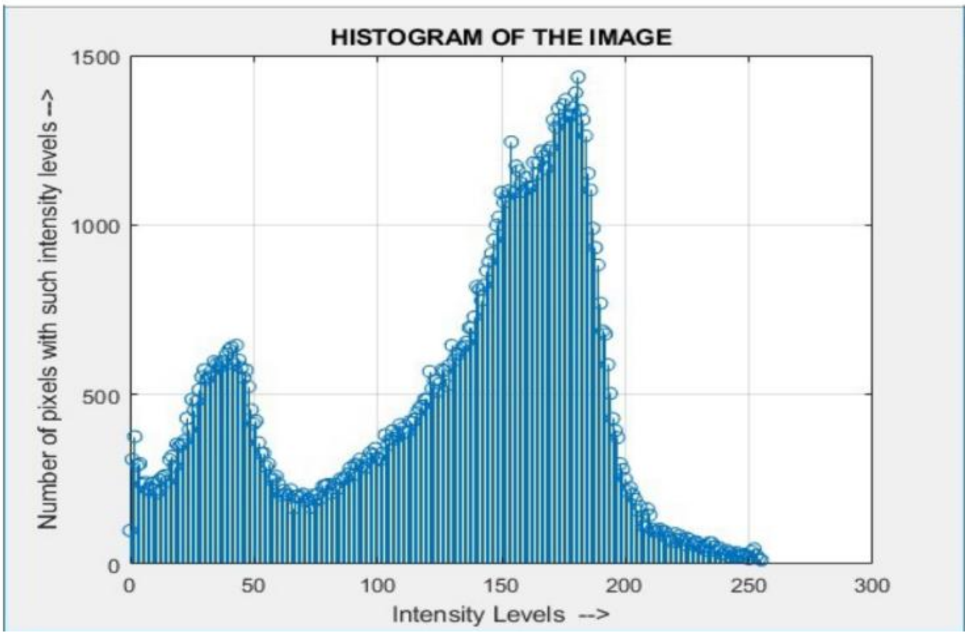

Figure. 1 Histogram of the Image

- Collect the data points: Obtain a set of data points representing the circumference of the circle. Each data point should consist of x and y coordinates.
- Compute the centroid: Calculate the centroid of the data points by taking the mean of the x-coordinates and the mean of the y-coordinates. The centroid serves as the initial estimate for the circle's centre.
- Estimate the radius: Calculate the average distance between the centroid and the data points. This average distance serves as the initial estimate for the circle's radius.
- Iterative fitting: Perform an iterative fitting process to refine the circle's parameters. In each iteration, calculate the squared residuals as the squared difference between the radius and the difference in length from unit data identifies the current estimated circle. Update the estimates of the centre and radius by minimising the sum of the squared residuals.

- Convergence criteria: Repeat the iterative fitting process until convergence is achieved. Convergence can be determined by checking if the change in the estimated centre and radius decreases below a predetermined level or when the allotted number of iterations is reached.
- Calculate the diameter: Once the iterative fitting process converges, the final estimate of the circle's radius can be used to calculate the diameter by multiplying it by 2. The Curve Fit method is relatively fast and robust for estimating the diameter of a circle, especially when the data points are noise-free.

4. Result and Discussion

The images are first converted into grayscale and undergo the image processing methods then the edge detection, contour detection, fit ellipse technique and finally the diameter will be extracted shown in figure 2.

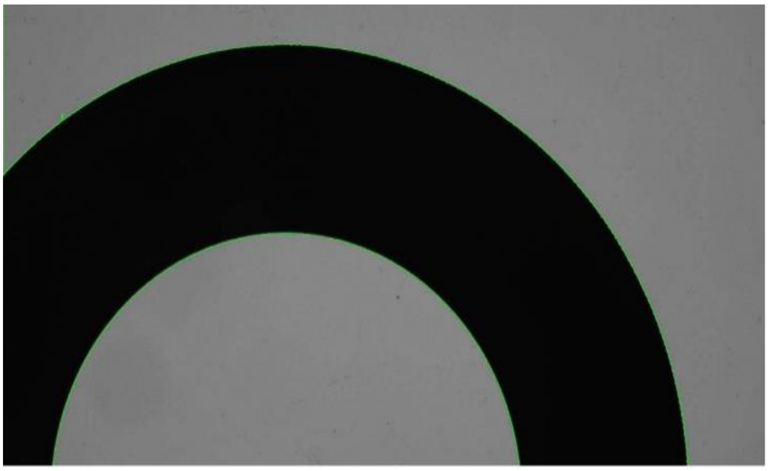

Figure. 2 Grey scale image

These models are trained with several epochs and the detections will provide an accurate result for the thrust bearing.The accuracy is achieved by increasing the intensity of the image model trained with respect to the epochs and the multiple layers.

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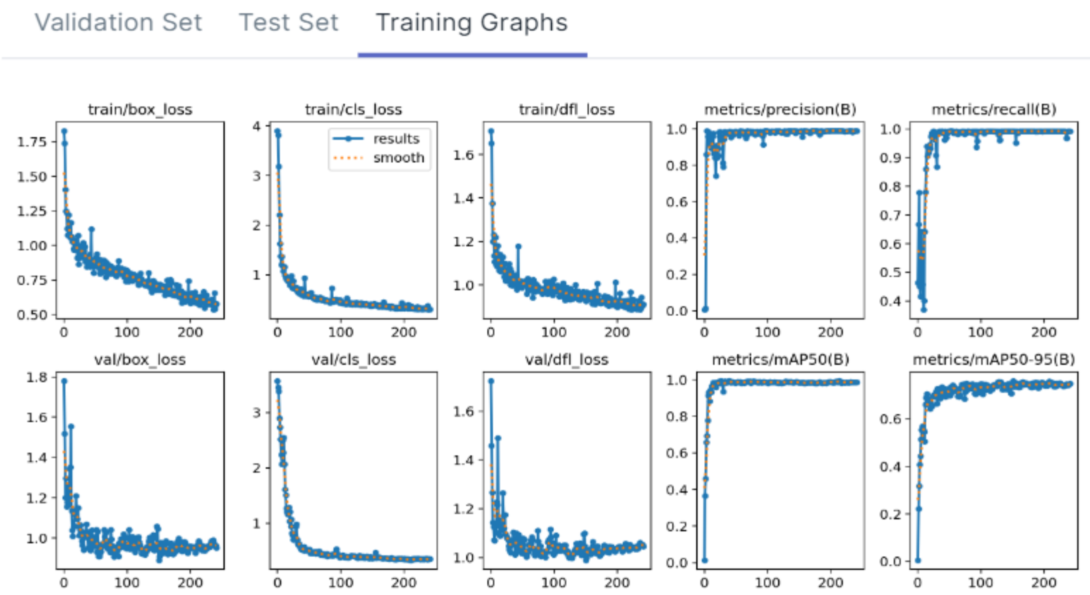

Figure 3 Training Graphs

The figure 3 shows the training models of the given image, futurescope on Condition Monitoring of thrust bearings Based on Machine Learning with Synthetically Generated Data deals with Real-time Implementation: At the moment, the offline analysis of captured images is the main focus of the suggested system. Subsequent investigations may examine real-time implementation, in which the diameter estimation and image processing are done in real-time, enabling prompt adjustments and feedback in industrial environments.

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