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SURFACE DEFECT DETECTION THROUGH COMPUTER VISION

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Abstract: The shape recognition and defect detection of defects at the early stage will helps smooth production process, saves production cost and time. This paper presents a computationally efficient 2D computer vision-based approach to recognize machine parts and detect damaged parts on the assembly line. A contour of the machine parts is extracted and normalized by an equal part area method to describe the shape. The defects in the machine part such as damage, cracks are identified by the similarity measure between model shape and the data extracted from machine part of the assembly line. It gives important clues for machine part shape recognition and defect identification.

Surface defects are a major reason for poor quality of parts for manufacturers. Inspection processes done in industries are mostly manual and time consuming. To reduce error on identifying surface defects requires more automotive and accurate inspection process. Considering this lacking, the recognizer identifies the surface defects within economical cost and produces less error prone inspection system in real time.

This research implements a surface Defect Recognizer which uses computer vision methodology with the combination of local thresholding to identify possible defects. Under the complex background of image acquisition, a new model faster r-CNN with Tensor Flow is proposed for online detection of surface defects. It has better recognition of microdefects under a complex background than some other recognition networks.

Keywords: *Computer Vision, Object Detection, Tensor flow, Faster R-CNN, etc. …*

I. INTRODUCTION

Today streamlined turnout systems are widely used in variegated types of product manufacturing industries and packaging industries with large scale production units. They used mechanized devices such as part feeder, conveyor, image capturing unit, part recognition unit, part selection unit, and intelligent robots that follow stock-still sequence of steps to hoke the product.

There are three classes of turnout systems with respect to productivity namely high, medium, and low volume production units. In upper volume production the turnout systems are fully automated, turnout of parts in other two classes are performed in semi-automated or transmission by hand. The variants of these turnout systems are in-line turnout system, dial indexing system, carousel turnout system, and single station turnout system, which is chosen equal to the manufacturing process, product, and the production quantity required. The initial investment forfeit for establishing such systems is high, but it saves time, money, and labour. The advantages of such system are huge quantity of production, stable product diamond with good quality and reliability.

The machine parts recognition in streamlined turnout systems is entirely variegated from unstipulated object recognition; moreover the worthiness of human to distinguish between healthy and unhealthy machine parts are good but it is a complicated task for a machine. In unstipulated transmission defect detection by human inspectors are impractical with fast moving machine parts on conveyor in wing it is expensive, subjective, inaccurate, eye straining and other health issues to quality tenancy inspectors. By considering these issues, a computer vision based non-contact inspection technique is ripened for defect detection in industrial machine parts by image processing techniques. The present study will help the industrial robot used in turnout process and industrial inspection systems.

The defect detection is performed on machine parts at early stages of the turnout line to ensure product quality. The schematic diagram for defect detection from machine parts is shown in Figure1. The 2D vision of machine parts which are moved withal the conveyor are captured and its purlieus characteristics are analysed to match with its model shape. If there is any deviation in matching result leads to notification of defect which in turn instructs the robot controller to pick up the needing piece from the conveyor and place it in the pallet. [5]

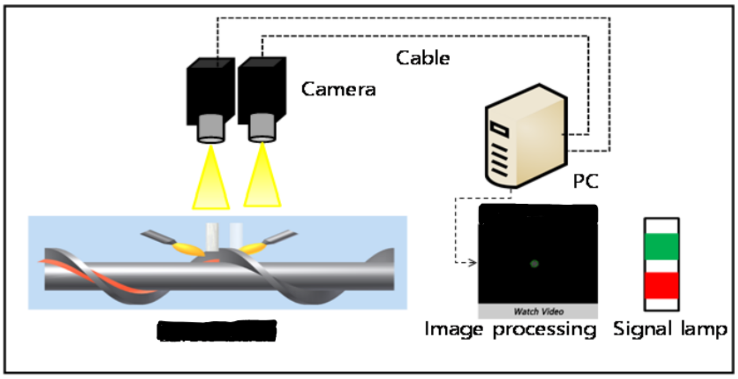

Figure 1. A schematic diagram for machine parts defect detection in model assembly line

In general, defects in machine parts are classified into two types: surface defects and damages. The surface defects are identified by texture and verisimilitude features, but part damages are identified by shape features. In the present study, a shape full-length extraction method is employed which is meaty in nature and it is responsive with the speed of the turnout line. The defect detection is performed with reference to a model shape of the machine part. The shape descriptor uses only the purlieus information to describe the shape of the machine part. The matching of test shape with model shape is performed using correlation coefficient metric. If any deviation found in the test then it is identified as defective. The status of healthy and unhealthy parts is notified to the robot controller for its towardly action. [5]

2. DEFECT DETECTION SYSTEM STRUCTURE

This system mainly includes three modules: parts conveying module, image capturing module and defects detection model. (1) The parts-conveying module is used to realize the movement tenancy and sorting of parts. (2) The image capturing module is well-balanced of a camera, light source and photoelectric sensor, which is used to obtain high-quality images in the process of moving parts. (3) The defects detection module is used to process the placid high-quality images and realize the detection and recognition of the surface defects of parts. The specific process is as follows: the parts is transmitted by the conveyor belt, when it passes through the photoelectric sensor, the signal is transmitted to the console, and the image vanquishment module is controlled by the panel to collect the parts image. Finally, the defect detection module detects and identifies the defect and displays the result in the human–machine interface. [2]

2.1. Surface Defect Detection Algorithm

A non-contact machine vision based defect detection system is proposed in this section. The pursuit assumptions are considered in the present study. The objects moving in the conveyor are captured by vertical direction of the overhead camera in the streamlined turnout lines. The machine parts are placed on the conveyor with predetermined sequence and the timing is synchronized with operation of turnout system. Here the objects on the conveyor are not occluded and they possess rotational orientations. That is, machine part to be captured and the camera are stationary; this simulates the situation in which the camera will periscope the word-for-word shape from the top view and only one part is present per view. The sequence of steps followed in the proposed system is: image capturing, image pre-processing, similarity matching, machine part recognition, and defect detection. These steps are summarized in flow diagram form in Figure 2. [2]

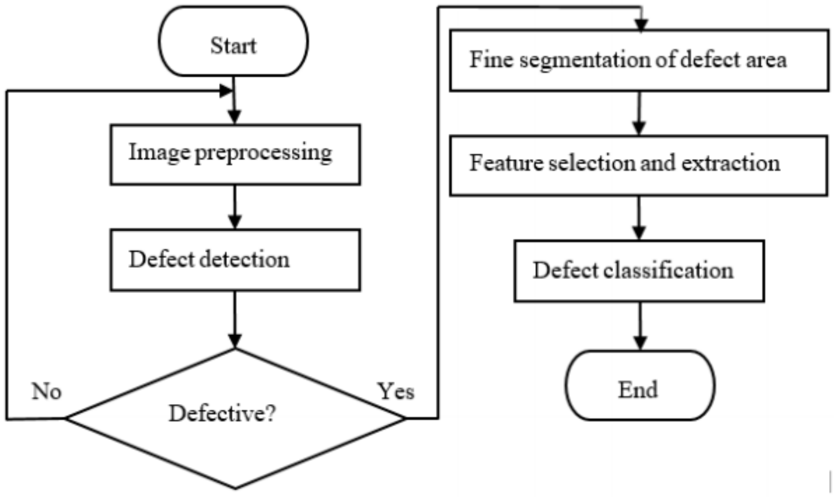

Figure 2. Process followed by model at the time of defect detection

4. SETUP OF TENSOR FLOW WITH FASTER R-CNN PRETRAINED MODEL

The Tensor Flow Object Detection API requires using the specific directory structure provided in its GitHub repository. It also requires several additional Python packages, specific additions to the PATH and PYTHONPATH variables, and a few extra setup commands to get everything set up to run or train an object detection model.

Steps to setup proposed model for surface defect detection-

1] Preparing the workspace –
Installing tensor flow
Installing tensor flow object detection API.
Importing pretrained model for faster r-CNN algorithm.
Install dependencies and compiling package.

2] Preparing the dataset –

2.1 Annotate the dataset
Used labelimg (python based repository) for labelling the dataset.

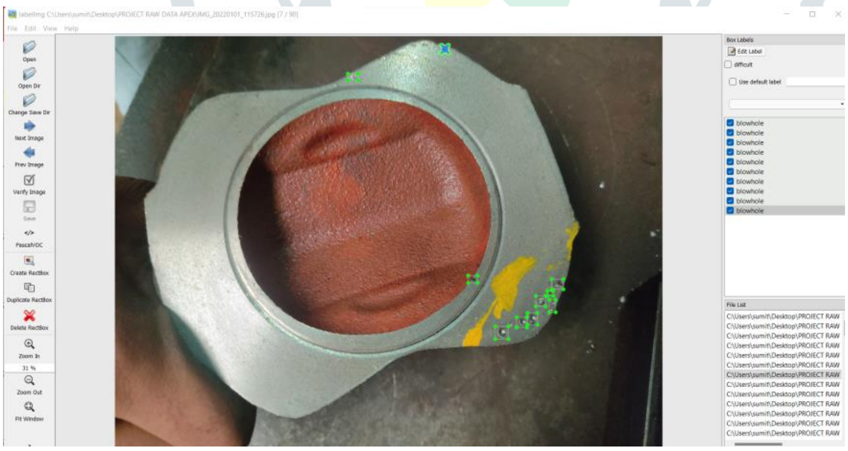

Figure 3 – labelling of the dataset

2.2 Partition the dataset

Dividing the dataset into training and testing datasets with the 80/20 percent. i.e., 80 percent training dataset and remaining into test dataset for validation purpose.

2.3 Create label map –

TensorFlow requires a label map, which namely maps each of the used labels to an integer values. This label map is used both by the training and detection processes.

```
item {
id: 1
name: 'blowhole'
}
```

Figure 4 – label map

2.4 Creating TFRecords –
Now that we have generated our annotations and split our dataset into the desired training and testing subsets, it is time to convert our annotations into the so called TFRecord format.

3] Configuring a training job –

3.1 Download pretrained model –
Here we have taken faster r-cnn as a pretrained model.

3.2 Training the model –
Here we had started training of the model.

If everything has been set up correctly, TensorFlow will initialize the training. The initialization can take up to 30 seconds before the actual training begins.

Each step of training reports the loss. It will start high and get lower and lower as training progresses

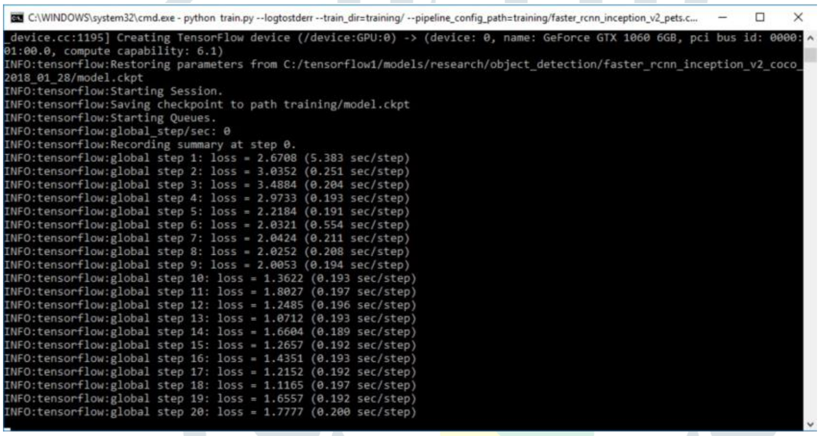

Figure 5 – Training Iterations Of The Model

4] Exporting a trained model –

Once your training job is complete, you need to extract the newly trained inference graph, which will be later used to perform the object detection.

We can use this same inference graph as input to our prediction step with image acquisition system to get direct output within the seconds on production line itself as shown in figure 1 , we will get the signal output for defective parts detection and identification.

5. RESULTS

To see the qualitatively as well as quantitatively performance of the proposed algorithm, some experiments are conducted on several images. The effectiveness of the approach has been justified using different images. The results are computed qualitatively (visually) as well as quantitatively using quality measures.

The figures from Figure 6 to 9 are the screenshots of the proposed work which shows the different images which consists of original images and output defect detected images.

Figure 6. Original image

Figure 7. Defect detected image

Figure 8. Original image

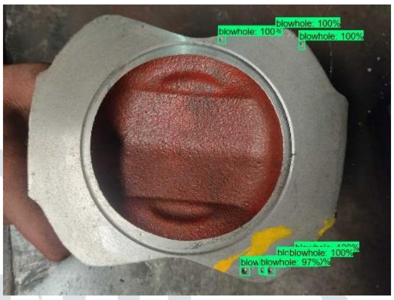

Figure 9. Defect detected image

6. CONCLUSIONS

In this paper, a computer vision based approach to recognize the machine parts and detect damaged parts in automated assembly systems has been presented. The machine part defects in the form of damage, cracks are identified by scanning the shape of the object also we need not need to convert images into gray scale or thresholding of images before training the data , this is one of the advantage of this model.

Here from the point of view of Industry resolution 4.0 where we are moving towards the automated processes, AI ML processes, this method will definitely contribute towards it with some enhancements.

The proposed object recognition system uses colour image directly captured with camera. The colour information in the image can be used for recognition of the object. Color based object recognition plays vital role in Robotics.so it has applications in that field also.

7. ACKNOWLEDGEMENT

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8. REFERENCES

1] Shaoqing Ren, Kaiming He , Ross Girshick , Jian Sun, 2012 Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks

2] Hongzhi Tian, Dongxing Wang *, Jiangang Lin, Qilin Chen and Zhaocai Liu, 2020 Surface Defects Detection of Stamping and Grinding Flat Parts Based on Machine Vision

3] Amandeep Mavi , Mandeep Kaur 2012 Identify Defects in Gears Using Digital Image Processing

4] Liya Yu , Zheng Wang ,and Zhongjing Duan, 2019 Detecting Gear Surface Defects Using Background-Weakening Method and Convolutional Neural Network

5] P. Arjun , T. T. Mirnalinee. 2016 Machine parts recognition and defect detection in automated assembly systems using computer vision techniques

6] S. Satorres Mart´ınez, C. Ortega V´azquez, J.G´amez Garc´ıa and J.G´omez Ortega Quality inspection of machined metal parts using an image fusion technique.

7] Ross Girshick Jeff Donahue Trevor Darrell Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation.

8] Joseph Redmon, Ali Farhadi. Better, Faster, Stronger, real-time detection systems.

9] Q. Guo, C. Zhang, H. Liu, and X. Zhang, "Defect detection in tire X-ray images using weighted texture dissimilarity," Journal of Sensors, vol. 2016, Article ID 4140175, 12 pages, 2016.

10] J. Yuan, Q. Wang, and B. Li, "A flexile and high precision calibration method for binocular structured light scanning system," The Scientific World Journal, vol. 2014, no. 8, Article ID 753932, 8 pages, 2014.

11] J. Yang and G. Yang, "Modified convolutional neural network based on dropout and the stochastic gradient descent optimizer," Algorithms, vol. 11, no. 3, pp. 28–43, 2018.

12] G. Yang, J. Yang, W. Sheng, F. Junior, and S. Li, "Convolutional neural network-based embarrassing situation detection under camera for social robot in smart homes," Sensors, vol. 18, no. 5, pp. 1530–1553, 2018.

13] J. Yang, W. Sheng, and G. Yang, "Dynamic gesture recognition algorithm based on ROI and CNN for social robots," in 2018 13th World Congress on Intelligent Control and Automation (WCICA), pp. 389–394, Changsha, China, China, July 2018.