RESEARCH PROPOSAL

TITLE: 3D DEEP LEARNING FOR AUTOMOTIVE BUMPER INSPECTION

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TABLE OF CONTENTS

1.Abstract

In addition to the fact that the inspection of car parts is very crucial today, users want their cars to have a smooth body. This changing demand has greatly increased production sensitivities. Therefore, automotive companies had decreased the acceptable error limit on the supplied parts. This pushes suppliers to increase their R&D projects. With this project, we aim to reduce the error rates of car bumpers to zero with computer vision and optical methods, and also to reduce the inspection cycle time for a bumper. We propose a combined 3D deep learning solution for this problem, since depth is important in defects and measurements. Moreover, we plan to avoid human error and reduce inspection times by proposing an end-to-end inspection system.

2.Introduction

In the context of the developing industry 4.0, automotive companies have turned to robots and sensors with low risk of error instead of solving problems in production lines with old traditional expensive methods or using human. Following this, it turns these technologies into the developing artificial intelligence and deep learning application facilities which are cheaper, visual, understandable and human-oriented, in order to solve the problems on the production line and quality control.

Competition in the ecosystem of the automotive industry is becoming increasingly fierce, so inevitably the involved firms cannot endure unless they are distinguished by quality, efficiency, adaptability and flexibility. Moreover, today's automobile purchasers are entitled to request high quality products, which are fully tailored to their needs and continuously adaptable to their daily habits.[1] For this reason, the quality control methods are significant for producing automotive parts. Visual inspection is one of the most primitive and successful control methods that has been used for centuries. Visual inspection was essentially human-led but has recently been supplemented by the artificial perception provided by computer vision systems (CVSs).[2]

The developments gained in the field of CVSs have already started to be used as 2D pictures and videos in the industry and we are seeing the progress of the models for anomaly detection. As the accuracy rates and gains of the projects increase, solutions are tried to be produced for other problems that are not in 2 dimensions.The increased availability and precision of modern 3D sensors has led to significant advances in the field of 3D CVSs.[3] 3D CVSs techniques and models have begun to be developed in search of detections to anomalies or defective parts in 3 dimensions.

In the field of anomaly detection, although many two-dimensional model types have been tried, some methods have not been tried in newly developing three-dimensional methods. In this research project, we want to explore and develop a new combined model. This combined model will perform 3D Supervised Learning defect(anomaly) detection, and 3D unsupervised learning for classification to find defected bumper or not.

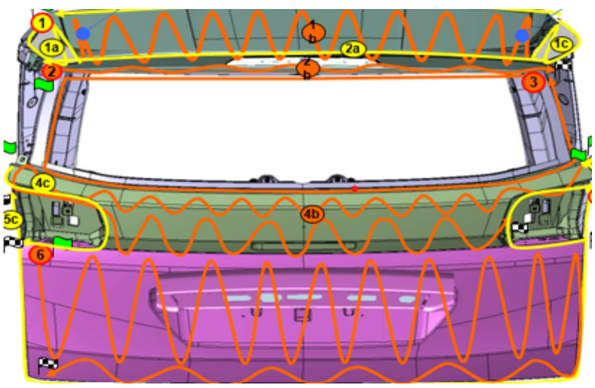

Figure1 : A sample of manual(hand-eye) inspection

3.Engineering Research Question

Main question

Can/How the use of 3D deep learning methods improve the accuracy in defect(anomaly) detection on the automotive bumpers?

Sub Questions

1. What extent will the new type of combined model (that will be presented as a hypothesis) increase the sensitivity accuracy?
2. How can the model test time (for a bumper) be reduced below the available manual eye test time?

Hypothesis

If we can combine 3D model anomaly detection and localization and classification systems as one model, we can accurately pick out and classify deformed bumpers in one time. And it will reduce test time.

4.Literature Review

Although we found more than ten articles on our subject, we wanted to review the most recent three here. However, after examining all other articles, we reached our research gap.

4.1.Summarize available literature

Although there are many different publications and articles so far, we wanted to analyze only 3 of the most recent ones here.

A mobile vision inspection system for tiny defect detection on smooth car-body surfaces based on deep ensemble learning(2019) [4]

In their system, a dedicated image acquisition module (IAM) with a high-resolution camera, plane light-emitting diode light source and laser rangefinder is designed to capture surface images over bright field illumination. A specific deep ensemble learning algorithm, named TinyDefectNet, is proposed to identify tiny defects in large images acquired from the IAM online. The experiment results indicate their inspection system is on par with the average performance of experienced inspectors but it is much faster than artificial visuals.The experimental results show that their inspection system achieves detection recall of 93% and detection precision of 88%. Its performance exceeds the average of senior inspectors, but its speed is 20× faster than artificial visual detection. They have saved 30 min for every car body inspection. They decreased this time from 40min to 10 min.

An Efficient Automotive Paint Defect Detection System(2019) [5]

They present an efficient *deflectometry* based detection system developed for semi-specular/painted surface defect detection. This system consists of a robotic arm that carries a screen/camera setup and can detect defects on large surfaces with different topologies, such as a car bumper, by traversing its profil.

While finding the defects on the surface, they create an error pool using the deflectometry method described above. They detect the error from this error pool according to the threshold level specified and at the same time eliminate the noise from being an error.

Fourteen different error types were sampled and controlled. These ; Dirt,Cold Slug ,Spits ,Fish Eye ,Flash ,Blister,TPO,Protrusion,OverSanded,Hot Pre-paint ,Overflame Torch,Water Spots,TPO Residue,Popping ,HD Post Paint. He tested it by taking 3 samples from each of them. And as a result, it detected 100% error in the others except cold slung and pupping. However, cold slung: 75% pupping was detected with 50% accuracy. Later, he wanted to evaluate the system by taking samples from bumpers in different segments. And you can see the value parameters below.

An improved MobileNet-SSD algorithm for automatic defect detection on vehicle body paint(2021)[6]

They are proposing an improved MobileNet-SSD algorithm for defect detection of car body paint. The process consists of two parts, the data enhancement algorithm extended data set and the improved MobileNet-SSD algorithm to detect the defect location. A new image data enhancement algorithm is proposed to enhance the data set by making the corresponding cutting strategy and sampling position for the defective paint image, which realizes multi-direction and multi-angle cutting for the defective paint image. Combining MobileNet with the SSD network and improving its network structure layer, a matching strategy for aspect ratio of paint image is proposed to realize automatic detection and classification method based on car body paint defects.

They worked on 6 different defects and the total amount of 2D images was 500. That is shown below. They had %95 accuracy with the MobileNet-SSD model. Moreover they have really good testing time compared to the other models.

4.1.2. Analyze the limitations and difficulties inference previous studies

A mobile vision inspection system for tiny defect detection on smooth car-body surfaces based on deep ensemble learning(2019)

They have made two categories as convex defect or concave defect, although there are many types of defect. Different experiments were carried out by taking high-resolution images and reducing them to small sizes. However, the detected defects are limited and although they state that they can detect less than 4.5 mm2, it has not been explained how many mm2 they can detect. In our study, we need to detect as much as 1mm2. The ensemble method used here is a 2D deep learning example. Since they did not use any other auxiliary optical devices, their accuracy remained at 88%.

An Efficient Automotive Paint Defect Detection System

Since various different scenarios have not been tested, it cannot be considered as a definitive solution. The system could not achieve the same effective result in a few different errors. Moreover, the detection method used is not based on artificial intelligence.The system made is not user friendly and does not make localizations of the defect. And this is weak in terms of data retention in order to get down to the root cause of the defect.

An improved MobileNet-SSD algorithm for automatic defect detection on vehicle body paint

In the article, they tried to find defects in two dimensions and three dimensions with the examples taken from the two-dimensional plane, and although the established model gave very good results, it is very difficult to test the recessed regions in which we consider a bumper as a whole. And the defects found are limited in number and do not have the function of defining or debugging other types of defects that may come.

4.2. Identify research gap in the field

The main objects of 2D image surface defect-detection technology are surface scratches and abrasions. Obtaining in-depth information about the defects is limited. However, in the actual production process, the defect information of the product is not only displayed on the surface of the manufactured product but also requires the use of 3D defect-detection methods to detect the 3D surface characteristics of the test sample.[7] 3D defect(anomaly) detection ,localization and classification on the automotive bumpers is our research gap. We want to create a new combined model that can do these tasks at one time. Since 3D deep learning methods have not been used in the studies until now, we want to analyze with this study whether this method can improve the existing results. We want to shed light on the studies in the field of three-dimensional deep learning with the models we will develop in accordance with the problem.

5.Research Aims and Objectives

5.1.Overall Aim

1. Develop a 3D defect(anomaly) detection ,localization and classification deep learning combined model.

2. Creating end to end detection and classification systems.

5.2.Specific Objectives

1. We want to develop a new combined 3D deep learning model that finds the defect(anomaly) on the painted automotive bumper. After finding defects, we will classify and locate them to find the root cause of defects. Specifically, we want to detect the following defects; deposit on or under lacquer, grains, punctures,drip, paint smudge,deformation, ripple, hollow, shrink marks, defective plastic trimming,paint scratches,imprint on/under lacquer,scratch on paint,traces of polishing, halos,flaking,crack, deterioration and other defects with not labeled.

2. We would like to develop an end-to-end software model. The car bumpers will start their journey with the deflectometry tunnel method after that we need to take various images from multiple cameras, then these images implement and run in the AI model to achieve the solution. As a final the model will be working with the cloud computing system to be established. With this way, We want to reduce this inspection cycle time to less than 50 seconds. Finally, we will be creating an interface for the end user to use.

5.3.Methodology

Aim 1 : 3D image training data will be collected by multi-view cameras and a deflectometry tunnel and it will be one shot taking images and reconstructing these images into the 3 dimension. Anomaly data will be labeled with known defects to enable 3D supervised object detection. On the other hand, non-anomaly data will be trained in the 3D unsupervised model to learn accurate data. The final combined model will be working as shown on Figure2.

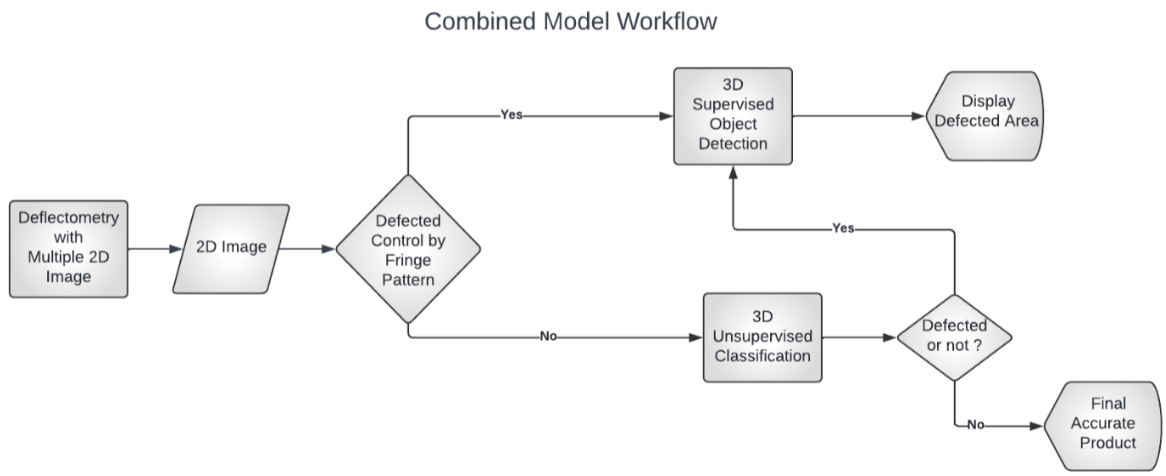

Figure2: Model Workflow

It will be checked with the fringe pattern, and the resulting defected or non-defective products will be reinserted into 2 different models, detecting and classifying the defected area, and then making the sizing calculation. Acceptable length, width and depth values of each error rate have been determined by the company. The products that are checked and passed according to these values will be sent to the customer as the final product.

Aim 2: Dataset samples will be collected with Flex&Gate, the car bumpers manufacturer. This company will help us obtain and analyze data from different angles. Data will be collected from distorted images of a calibrated scene and many cameras in it with the help of a deflectometry tunnel, the shape of mirror objects. It will be ensured that the bumpers entering the tunnel are placed on a mechanism that will ensure their stability.

Our dataset will be stored using the S3 bucket cloud system. Since we will be using multiview data representation in our AI model, we need a lot of data storage. Therefore, we need to use cloud computing. An automated pipeline will then be achieved using the Kubeflow MLOps system. Our data will be tested with the model we have created. All errors will be classified and recorded. The model will then be retrained with this data and will also provide support for the circus to reach the root cause. Finally, a convenient interface will be made for the end user to use the model easily.

5.3.3. Limitations of the project

Before inserting the bumpers into the deflectometry tunnel, we need to adjust its position very well. We also need to calculate how many cameras should be used in the tunnel. If we cannot adjust the camera angles and the surface to be photographed well, the data we will collect will not be suitable for our modem. For this reason, we have some calculation constraints regarding the location of the bumpers and the cameras in the tunnel. Also, the person responsible for the deflectometry tunnel during data collection will need to be trained. It is necessary to check the continuous tunnel to make sure that it works smoothly.The training time of the 3D model will be very long. Because the type of dataset we use and our 3D model are very complex.

6.Expected Results

We expect to do an end-to-end software project. In other words, it will be a project that integrates everything from the beginning of the project to the last stage. In our project, we want to calculate the depths of some of our defect types by using a 3D model. In this way, we will help to determine in detail what the errors that occur in the production line are caused by. After evaluating our project with a minimum 99% accuracy rate, we aim to create a user interface where our model can be used by everyone. By establishing an automation system, we aim to use it in fault detection and classification of the buffer. In addition, reducing the detection time of our model to less than 50 seconds is among our biggest goals. Finally, we aim to detect all defects and achieve high accuracy rates by using 3D models for the first time in bumpers inspection research projects so far.

7.Timetable

	S1	S2	S3	S4	S5	S6
Literature Review						
Analytic understanding & Data Collection						
Data Preparation & Analysis						
Modelling						
Evaluation & Feedback						
Model Development						
Deployment						
Thesis Writing						

8.References

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The MVTec 3D-AD Dataset for Unsupervised 3D Anomaly Detection and Localization

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A Mobile Vision Inspection System for Tiny Defect Detection on Smooth car-body Surfaces based on Deep Ensemble Learning

[5] Sohail Akhtar, Adarsh Tandiya, Medhat Moussa, Cole Tarry.2019.

An Efficient Automotive Paint Defect Detection System

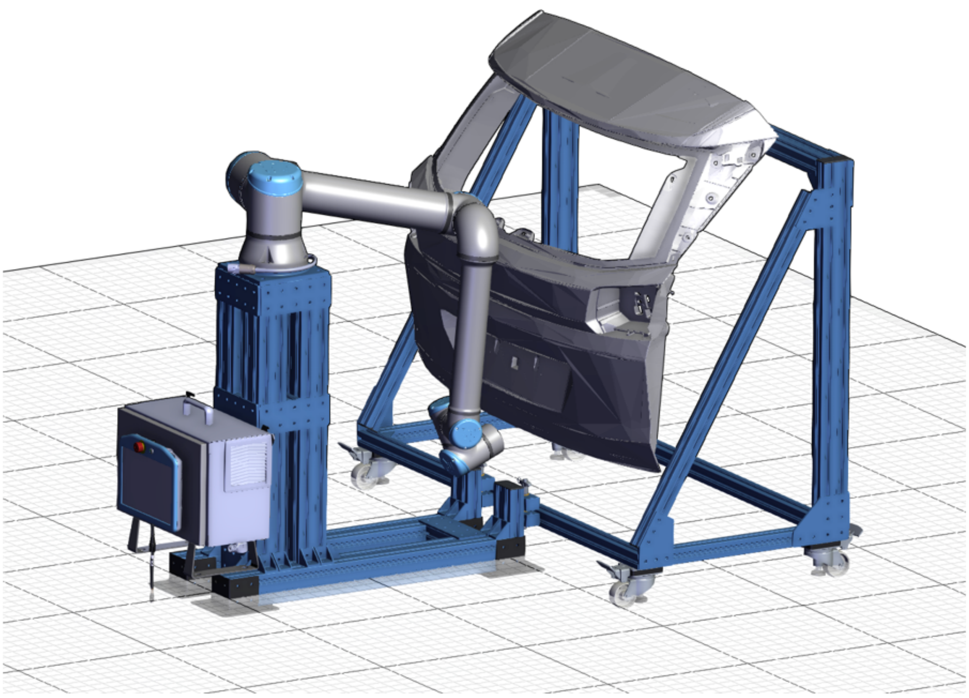
[6]Jindong Zhang, Jiabin Xu, Kunpeng Zhang, Tong Liu, Donghui Wang, Xue Wang.2021

An improved MobileNet-SSD Algorithm for Automatic Defect Detection on Vehicle Body Paint

[7] Jing Yang Shaobo Li Zheng Wang , Hao Dong , Jun Wang and Shihao Tang.2020.

Using Deep Learning to Detect Defects in Manufacturing: A Comprehensive Survey and Current Challenges

First Prototype(For Scanning Arm)



Second Prototype(Still Developing for Deflectometry Tunnel)