©2021 Published in 9th International Symposium on Innovative Technologies in Engineering and Science 15-17 October 2021 (ISITES2021 Sakarya - Turkey)
https://doi.org/10.33793/acperpro.04.01.33

A Model Proposal for the Adaptation of a System That Can Detect Cataphoresis Coating Defects with a Deep Learning Based Image Processing Technology to Automotive Quality Process

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Abstract

Just as in all sectors, the quality control process affects the concepts of quality, cost and customer satisfaction directly or indirectly in the automotive sector. Recently, detecting defects with image processing technology in quality control has found a wide application area. One of the manufacturing methods required in the production of some metal parts in the automotive industry is the cataphoresis coating process. Many and various types of visual defects occur at this stage. In order to notice these defects, there is a need to switch to a human-independent and technological quality control process. There are studies on how image processing technology will detect the visual defects on the part and how it will affect quality and customer satisfaction. This project aims to offer a model that defines how digital image processing with software and hardware systems will be adapted, become suitable for mass production, transportation of the parts and design the layout to cataphoresis coating process using artificial intelligence. Thus, with the adaptation of the system to the quality control process, an improvement in cost, delivery time and work efficiency will be achieved, the Industry 4.0 journey will go one step further.

Key words: Artificial Intelligence, Image Processing, Cataphoresis Coating, Deep Learning

1. Introduction

Cataphoresis coating is one of the key processes for the automotive industry to ensure that the components of the final products are high quality. These parts, which will come together to form automotive, go through many processes while being produced. Cataphoresis coating is one of the last phases of the flowchart at automotive parts manufacturing and parts need to inspect after that. It should be aimed to complete the delivery cycle of each product without defects. Following this purpose, companies continue to work to improve quality control processes, which play a major role in catching defects. For instance, during the quality control process, detecting the defects in the product before the product reaches the customer will provide a significant benefit to the company in terms of customer satisfaction. As a result of increased satisfaction, the continuity and loyalty of customers will also increase. In addition, the expenses related to resending the product to the customer will also be eliminated.

Checking of these parts is executed manually characteristically because they have complicated 3D curved shapes and black color of the coating [1]. Manual checking protracts the process over and

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the total manufacturing time of parts rises. This increase and developing technology have encouraged organizations to benefit from deep learning in the quality control process. Deep learning is a sub-branch of artificial intelligence used to make correct data-based decisions and build neural network models [2]. Deep learning needs unquantified big data to make these decisions. However, the greater the number of these data, the more reliable decision of artificial intelligence will be. Deep learning, which helps to reduce the time of processes, can be used in many organizations, whether in manufacturing or service. In addition, an important benefit of deep learning is the prevention of human originated defects. Based on this information, it can be predicted that deep learning will significantly increase the efficiency of processes.

Detecting the defects that occurred while the cataphoresis coating process, utilizing deep learning, decreases the total cost. But the main subject that must have been investigated is how the camera will integrate into the system. The dusty environment of the cataphoresis coating process may affect capturing of the camera a clear image. On the other hand, if the camera is too far from the system may introduce new costs and risks as parts have to be transported. In this article, these problems related to the adaptation of the camera to the quality control process are researched. Firstly, there will be some technical information about the deep learning and quality control process in section of materials and methods. Then, in the proposed methodology section, a framework is presented explaining how the system works. In Case Study section, information is given about the company where the study will be conducted, the application of our methodology. Suggestions are presented on how to adapt the materials to use for deep learning to the quality control process and how deep learning will provide inspection.

2. Materials and Method

2.1. Definition of Cataphoresis Process

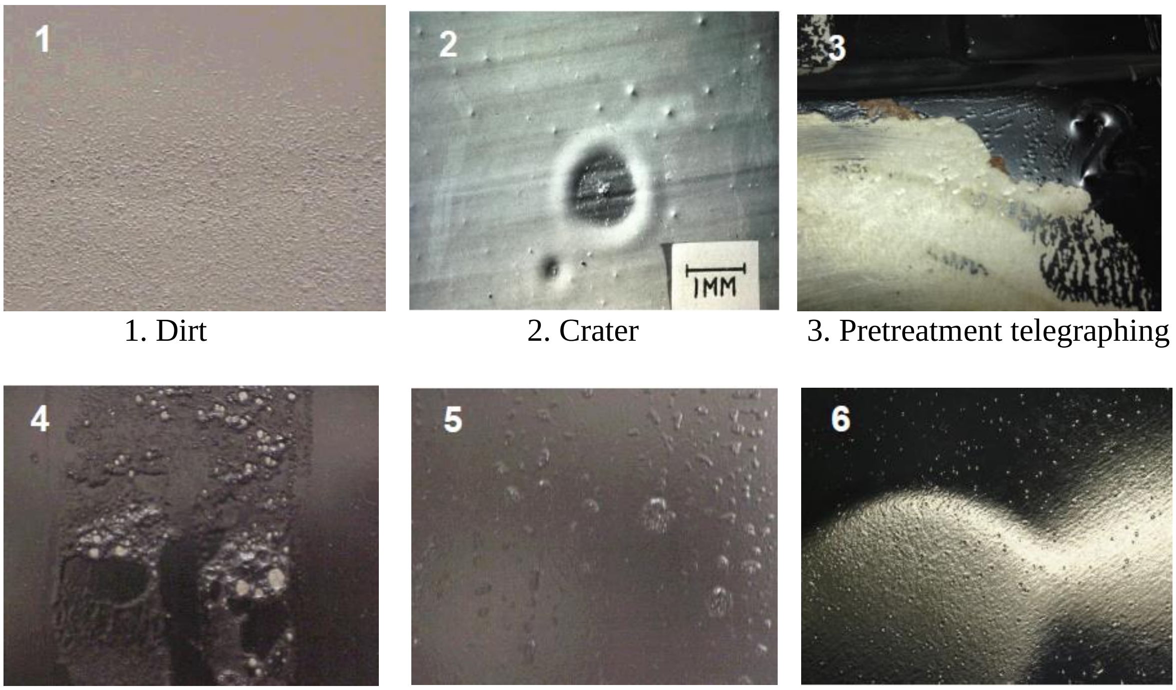
Cataphoresis is an electrochemical method of painting that uses electrical current to deposit the paint particles to a conductive metal surface. Cataphoresis (cathodic electrodeposition or cataphoretic painting) is an automated process of painting by immersion, which is based on the movement of charged particles in an electric field (paint) towards an oppositely charged pole (metallic surface to be painted). The work piece is negatively charged, the paint-ions are positively charged. The fundamental physical principle of electrocoating is that materials with opposite electrical charges attract each other. An electrocoat system applies a Direct Current charge to a metal part immersed in a bath of oppositely charged paint particles. The paint particles are drawn to the metal part and paint is deposited on the part, forming an even, continuous film over every surface, in every slot and corner, until the coating reaches the desired thickness. At that thickness, the film insulates the part, so attraction stops and electrocoating is complete. A part can be painted both inside and out, wherever the liquid can reach a metal surface.

The coating thickness is limited by the applied voltage. Generally, 18-30 microns of film thickness is desired to achieve 1008 hours of salt spray corrosion resistance for the parts made by the steel sheet material.

The cataphoresis process is composed of main following steps and baths:

1. Hanging the parts
2. Cleaning and pretreatment
3. Cataphoresis paint application and rinsing
4. Curing oven

Quality Control and Process Flow



1. Dirt | 2. Crater | 3. Pretreatment telegraphing

4.Pretreatment carryover | 5. Rinsing | 6. Pinholes / Gassing

Figure 1. Some images of defects in cataphoresis process

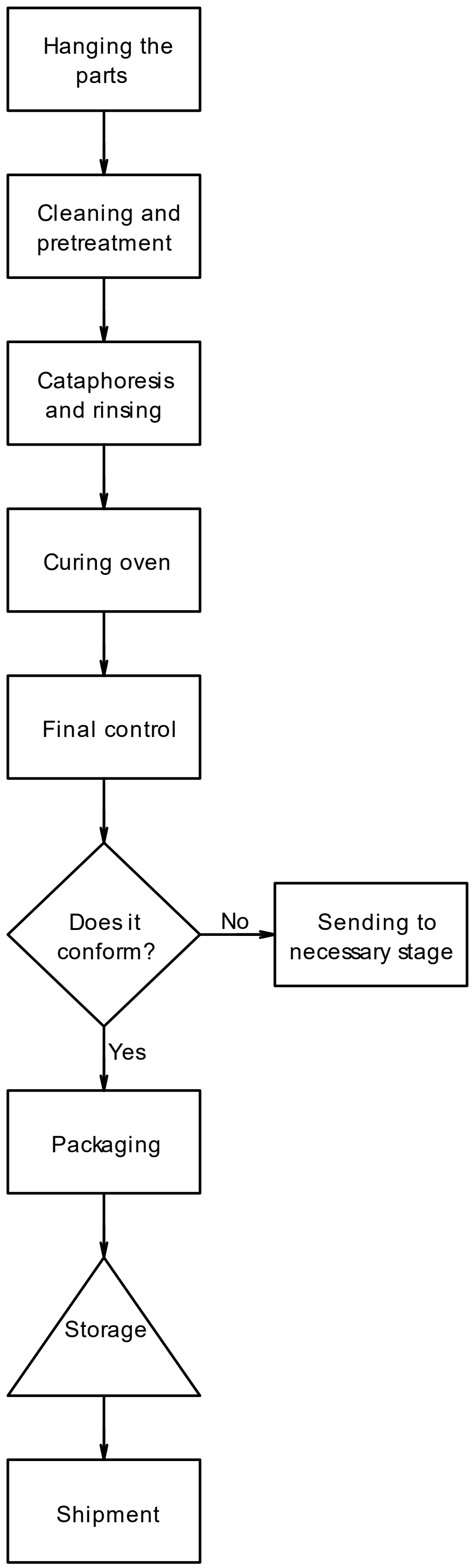


Figure 2. Cataphoresis process and control flow chart

2.2. Deep Learning

Artificial neural networks are used as an inevitable method in the development of many innovative technologies with the adequate performance of applications in the field of computer vision, progress in computer science, the development of optimization techniques, the abundance of data. These applications have produced solutions to many problems in various sectors ranging from health to textile. Within the framework of this study, today, Convolutional Neural Network (CNN) based computer vision applications are at a point where they can provide an alternative to legacy quality control applications. Le Cun et al. solve the large-scale real-world problem with CNN structure by performing handwritten digits identification [3]. After this important work, deeper models were developed with larger data sets, and state of art models such as AlexNet [4], VGGNet [5], GoogleNet [6], ResNet [7] emerged and object detection evolved to a further stage. With the development of the region proposal structure with R-CNN, a pre-training for auxiliary tasks in the scarcity of labeled data has significantly improved performance while localization and segmentation can be applied to high-capacity CNN structures [8]. With the work of Girshick et al., a significant performance leap has been seen to perform real-time object recognition and segmentation with high accuracy. With the Region Proposal Network (RPN) structure introduced in the work of Ren et al., real-time frame rates became operable in real-world applications.[9]

3. Proposed Methodology and Its Industrial Application

There are two main stages to be considered for a complete end-to-end visual defect detection model to be developed for industrial use. They are hardware structure consisting of a camera, illumination, and object and software that will process the resulting image and detect and segmentation the defect are two fundamental stages. The method to be proposed within the framework of this study is discussed from different aspects of these two stages according to an object with a cataphoresis coating therewithal the desired output. When examining the quality control of cataphoresis-coated objects, it is obvious that the reflective surface of the object as a result of this process and the complex topological surface structure of the parts to which the coating process will be applied are among the obstacles encountered. In addition to all these, there is an inverse relationship between the computational cost and performing the segmentation and classification with high accuracy and robustness, while selecting a real-time quality control model.

3.1. About The Firm

Karakaya 86 is a commercial coating & painting company, established in 1986 in Kartal-İstanbul, serving mainly automotive, defense, machine manufacturing industries by adopting customer satisfaction as a principle. The company has more than 350 employees, 1 central factory, 3 branches, and a Research & Development Center certified by the Ministry of Industry and Technology. The processes of cataphoresis, powder painting, alkaline zinc, alkaline zinc-nickel, blackening, zinc phosphating, Oxsilan (silane coating), passivation have been managing with a great deal of experience. With the R&D Center, the company focuses on state-of-the-art processes, research on artificial intelligence, industrialized information on coating &painting.

3.2. Image Acquisition

The first thing to be contemplated will be the illumination of the highly reflective surface formed after the cataphoresis coating. Deciding on the appropriate lighting will minimize the noise in the image acquisition stage so that more meaningful results can be obtained from the model input structure and will reduce the workload in the preprocessing stage. Reflections caused by improper illumination can cause type 1 error in the detection of defects that may occur on the surface. However, it can also create distortion and faulty images due to lighting in parts with complex geometric superficies. In order to avoid this problem, the use of coaxial forward lighting method has been considered. According to Ren et al. coaxial forward lighting is advantageous over traditional lighting mode in terms of preventing object reflection and providing consistent lighting [10]. In this way, the light source is used by reflecting it from another surface without falling directly on the object in order to prevent errors that may occur on a very smooth and reflective surface.

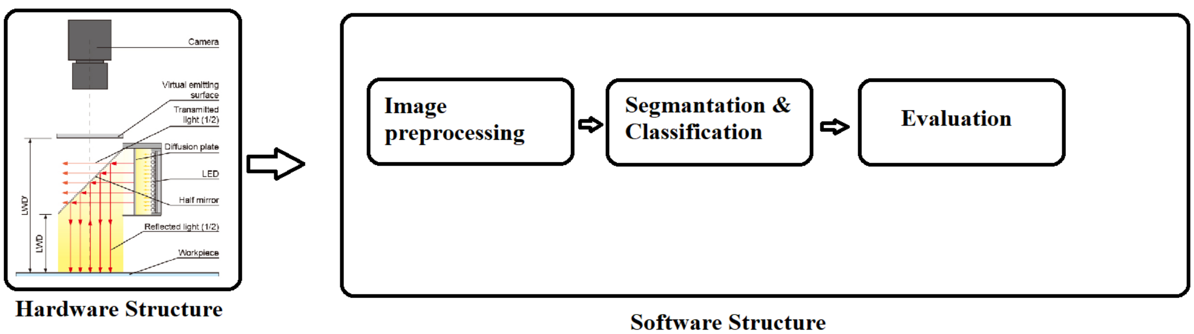


Figure 3. Coaxial forward lighting [11]

3.3. Image Preprocessing

With image processing, the desired output is to remove noise from the input image used in the detection process, thus aiming for higher accuracy in the classification and segmentation process of the deep learning model. The image preprocessing methods to be used within the framework of the study have been determined as multiresolution analysis and wavelet transform candidate methods, focusing on reducing the noise that may inevitably occur during the visual data acquisition phase, and also considering the time and computational cost since a real-time quality control process is planned. Multiresolution analysis results in a resolution determined by a threshold value where all details have vanished, and a result in which different resolution values are expressed simultaneously, taking into account the differences in its adjacent resolution value [12]. Besides, in research from Xue-wu et al., It has been shown that with Multi-resolution wavelet transforms, the computational cost is cut down along with noise is decomposed effectively during wavelet smoothing by reducing certain detail coefficients to zero [13]. The image preprocessing stages in this study carried out by Xue-wu et al. for a surface with high reflectivity are suggested to be used in a cataphoresis-coated part, considering its reflective surface. In addition to all these, various filters can be applied in order to increase the generalization ability of the model.

3.4. Model Selection and Building Model Pipeline

The proposed model is shown in Figure 4.

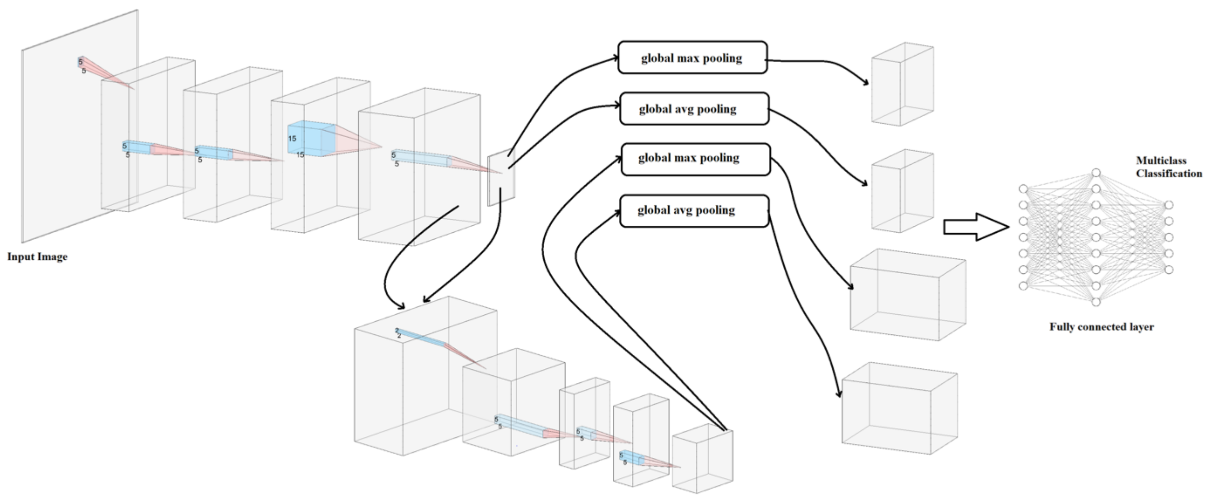


Figure 4. The proposed framework

The prominent elements in planning a real-time deep learning-based surface quality control method are the balance achieved between two desirable but incompatible features from time to time. The trade-off that stands out is the computational cost between detection and accuracy of classification for online quality control. A pixel-level classification and localization for surface defect detection can only be a candidate to replace manual quality control practices if sufficiently accurate and highly automated. In addition, the model needs to be able to distinguish between the defect types and the defect-free image because the separation of defect types provides a crucial foresight about the performance and operation in the production process. In the review by Zhao et al., generic object detection models are covered under two main headings: Region Proposal-Based and Framework and Regression/Classification-Based Framework [14]. The difference between the two basic frameworks is the increase in computational cost with the bottleneck created by the necessity of training each stage separately, since the Region Proposal-Based and Framework consists of stages that are correlated with each other, on the other hand, Regression/Classification-Based Framework takes the problem as a whole and tries to perform the same task as a regression [15]. This fundamental difference becomes important when presenting a model that can operate in real-time, but recent developments in hardware can make a difference at this point, and time constraints can be overcome with very high-performance hardware. In the study of Tabernik et al., a two-stage structure is established for surface defect detection. In the first phase, pixel-wise localization of the surface defect is performed by a dedicated network to the segmentation of the defect detection, thus overfitting is prevented by increasing the number of learning inputs. In the second stage, binary classification is made by feeding with the output of the first stage [16]. Based on this model, in the proposed model, it is planned to expand the pixel-wise segmentation in the first stage and make a wider scan on individual inputs, while at the same time increasing the number of inputs for the first network, in addition to this, multiple classifications instead of binary classification in the decision model are considered in order to examine various defect types. The problem that may arise with our proposed model is that the computational cost of the model increases slightly, but today's computers are very capable to run our algorithm.

Conclusions

Companies in the manufacturing sector usually target zero defects in all processes. Nevertheless, defects occur even at a low rate. The main issue is that do not send to customers incorrect products. At this point, the importance of the quality control process emerges. This process is the last chance not to lose customer satisfaction.

Deep learning techniques offer effective alternatives in detecting defects in the quality control process. In this study, a framework is proposed to carry out the quality control phase at the end of the cataphoresis coating process and used the data from Karakaya 86 company with the help of deep learning. Information is given about Karakaya 86 company and the cataphoresis coating process. It is investigated which of the deep learning technique would be more effective. At the end of the study, to distinguish various types of defects, to detect faulty parts with high accuracy, and to implement a real-time quality control application, the correct illumination method is determined, the relationship between the calculation cost and the accuracy of the model is examined, and the method that would be suitable for the part geometry and the coating feature is proposed. The proposed two-stage model performs the segmentation of the image in the first stage and uses the segmented image as input to classify the error type in the second stage. We found 2 studies about cataphoresis coating process, but they can decide only the part is defective or not. Whereas our model may explain the types of defects in the same part.

Acknowledgements

The study is conducted in and supported by Karakaya 86. We thank to Top Management and R&D Center Team Members for their contributions.

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