DIRT IN AUTOMOTIVE PAINTING: AN APPROACH SUPPORTED BY CYBER-PHYSICAL SYSTEMS FOR PROCESS AUTOMATION

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Abstract: Dirt in vehicle paint impacts the final quality and appearance even when it is small. Controlling dirt in painting systems requires considerable work due to the number of variables that can generate defects. In the automotive industry, a dirt specialist is responsible for collecting dirt on vehicles, analyzing, identifying and directing actions for process control. As there is dirt which is similar but not the same, the process requires the great experience of an expert. The goal of this paper is to identify technologies and appropriated neural networking as a solution path to support the development of a digital approach to automate the painting quality control improving decision-making. Research has shown many available technologies, however with limitations to implement.
Keywords: Dirt in paint; Paint defect; Automation on dirt analysis; Image classification; Convolutional neural networks

SUJIDADE NA PINTURA AUTOMOTIVA: UMA ABORDAGEM APOIADA POR SISTEMAS CIBERFÍSICOS PARA AUTOMAÇÃO DO PROCESSO

Resumo: Sujidade na pintura afeta a qualidade final do veículo, mesmo quando pequena. Controlar a sujeira na pintura exige forte trabalho devido ao número de variáveis que geram defeito. Nesse cenário, o especialista de sujidade é responsável por coletar sujidade no veículo, analisar e direcionar ações para controle de processos. Como existem sujeiras semelhantes, ter experiência é necessário para definir assertivamente o tipo de sujidade. O objetivo deste artigo é, a título de estado da arte, identificar tecnologias e rede neural apropriada como caminho de solução para apoiar o desenvolvimento de uma abordagem para automatizar e melhorar a tomada de decisão no processo de identificação de sujidade. Pesquisas mostraram tecnologias disponíveis, mas que apresentam limitações para sua implementação.

Palavras chaves: Sujidade em Pintura automotiva; Defeito de pintura; Automação em análise de sujidade; Classificação de Imagem; Rede neural convolucional;

1. INTRODUCTION

Painting is one of more complex processes in the automotive industry. Several layers must be applied until reaching the required technical specifications, color and final appearance before being delivered to the consumer [1]. Imperfections in each of the previous processes impact the quality of the painting and they are difficult to characterize but they directly impact the final vehicle paint quality.

The layers are applied separately, but they must work together in order to protect the vehicle providing protection against corrosion, durability, color and appearance. Each of these layers has special performance requirements and must be prepared to join the next layer, forming a durable cover that should not flake nor peel [2].

The layers of paint have the purpose of protecting the surface of the car as well as being essential for appearance and color as they are the first characteristics generally observed by the consumer. The color enhances the visual attraction of the vehicle, an important criterion of purchase. According to surveys carried out by the industry, almost 60% of consumers identified color as an important factor in their decisions when purchasing vehicles [3].

Painting is complex because it is a multi-stage process [3]. Defects in the surface of the cured layers are a major problem in the automotive industry. This is because although these defects are often very small, the human eye can detect them [4].

Defects can occur due to more than twenty types of dirt (Figure 1). Dirt is characterized as any particle of material that is generated during the production process of the body. It can appear in a liquid, solid or flexible form, adhering to the paint layer, causing unwanted imperfections.

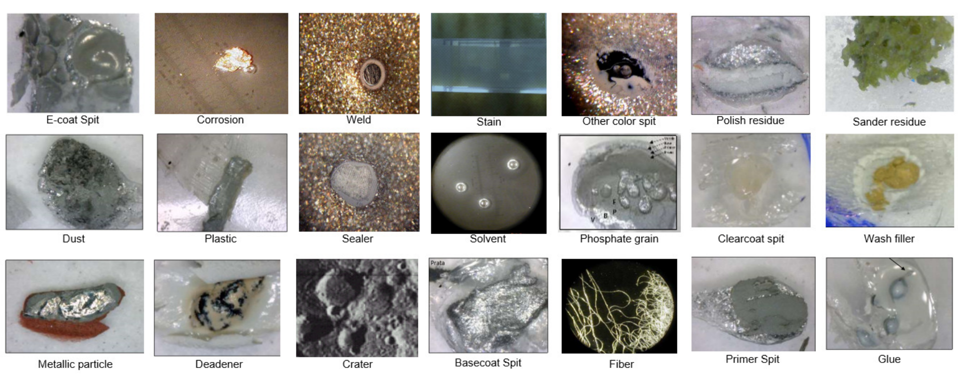

Figure 1 – Example of types of dirt.

Data from one particular automotive industry reveals that dirt is currently the main quality problem, equivalent to 36% of the number of defects found in produced units.

An effective analysis is required to control painting processes in order to ensure quality for the final consumer and to assure the paint quality of the vehicles produced, quality indicators are required to explain the number of vehicles that go to the end of the process with repair or without.

Controlling dirt in a painting system requires considerable effort to control process engineering due to the number of variables that can generate defects. A dirt specialist is required to collect dirt from vehicles and analyzing it to identify the type of defect and define controls for the processes through this information.

To collect the dirt, the specialist needs to go through several manual steps to identify the defect. As there are many similar defects, the professional requires expertise in order to assertively define the type of defect. These manual steps are time-consuming and can generate erroneous conclusions for the necessary adjustments in the process to be carried out. Furthermore, it is often a destructive process that generates unnecessary repairs.

This paper goes to the state of art to identify available technologies that may support the development of a cyber-physical digital approach capable of analyzing dirt and treating the problem of dirt in painting in an agile, automated and accessible way, improving the decision-making process on body painting processes.

2. METHODOLOGY

Figure 2 presents the method used in this study to carry out each step of the dirt analysis process.

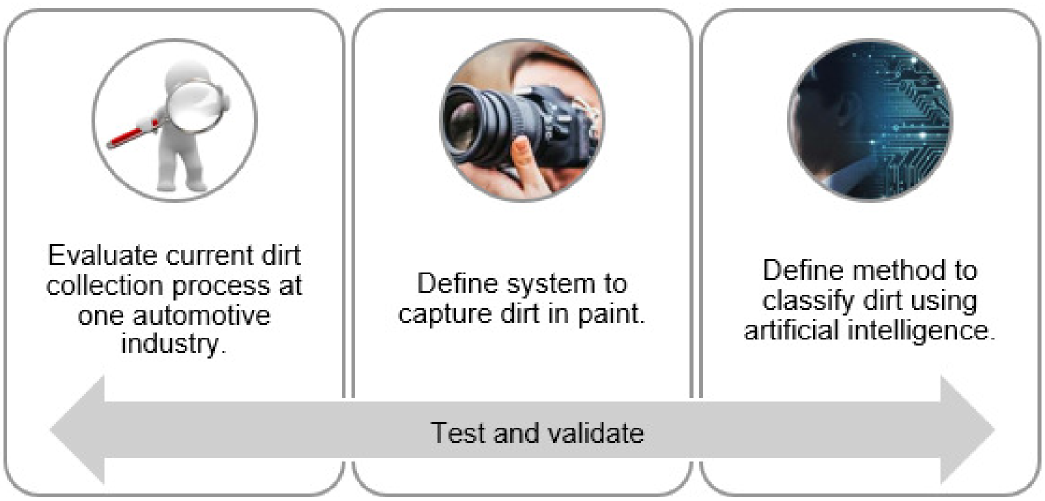

Figure 2 – Project objective.

One benchmark made with ten productive plants in one automotive manufacturing company to evaluate their current dirt collection and analysis process in order to understand the types of dirt, occurrence and causes, equipment and quantity of works involved, time spent and sample size of this process.

A systematic review has done at Science Direct, IEEE and Google Scholar with the support of Mendeley app in order to identify current technologies already researched and used to detect defects with nondestructive process on surfaces and the more appropriate data analytics approach used to classify and treat information.

3. RESULTS AND DISCUSSION

Benchmark with plants of one company revealed that dirt collection process and analysis is very similar across the plants and that the process is very manual with some steps that are time-consuming (approximately five hours), with high probably to errors and with low sampling size. It shows also that normally the data collection is done by using of portable microscope [5]. This device is only able to capture the image and requires someone with expertise to categorize defects. Moreover, defects are generally covered with a layer of paint, not allowing measurement directly on surface so it is necessary to remove it for proper analysis.

The use of mass spectrometry method is also common to analyze paint defect in automotive industry. Its unique advantage is related to ability to define where the defect was generated through categorization of its organic composition [6],however, like the microscope, it still requires someone with expertise to complete whole process of dirt data collection.

Image acquisition is also used in the industry focusing on quality improvement for cars completely painted or cars in sheet metal. The technology used is based on a machine vision system to capture an image combined with a classifier to identify defects. [7] was developed from a visual inspection system and the corresponding algorithm for the detection of paint defects in the automotive industry; [8] studied the defect inspection of coated automobile roofs using a single camera; [9] investigated a machine vision detection method for surface defects of automobile stamping parts; [6] implemented a system to detect defects at one paint shop with artificial vision. Other areas of industry have also developed quality monitoring systems based on a similar principle: [10] proposed an automatic section system based on vision machine for bearing surface and [11] developed a defect detection method for a rail surface based on line-structured light.

Image classification is another critical step in development of an on-line machine vision based control system [12]. Convolutional neural networking is the most used method to extract information from image using an appropriate classifier: [13] proposed method to classify medical image using convolutional neural networks. [14] applies the same approach to classify satellite multispectral image, [15] applied in vegetation species classification with hyperspectral images, [16] used tomography image classification. Approximately 20000 articles over the last three years were found using as keyword ‘convolutional networks for image classification’, showing what is most applied nowadays.

Regarding defects that appear at the paint shop, some examples can be found in the literature related to inspection process after the application of the last paint layer. Those solutions are able to identify defects to produce cars on line. [17] developed a process able to identify defects with a cycle time of 70 seconds, showing that it is possible to increase the sample size of the current process due to time spent. [18] showed a solution able to detect 100% of paint defects that are observed through human inspection at paint shop (i.e. orange peel, overspray, crater, solvent, bubbles), while [17] identifies craters, dirt, stripes, humidity marks, hair, and drops of various types on non-flat surface. [8,10,17] These articles make it clear that it is very difficult to obtain adequate responses between dark and metallic colors, as well as the influence of lighting in obtaining the image and the generation of pseudo-defects.

The research has shown that the effects of illumination and different types of colors have to be taken into consideration during the definition of best method of image acquisition. Articles [8,10,17,18] also showed that there already is technology able to identify many types of paint defects using non-destructive processes using neural networks. However, these solutions focused on helping operators to improve the accuracy of inspection of vehicles at final stages of the paint process, operating online and with huge frames. The studies developed so far have failed to focus on improving the quality of monitoring within the paint process. Dirt analyses considering detection in different paint layers and illumination for troubleshooting is the investigation theme of this article. The use of special systems for image acquisition, associated with convolutional neural networks is a possible solution path for this specific case.

4. CONCLUSION

This article has attempted to demonstrate that the current process of collecting and analyzing dirt in an automotive paint can be automated using existing technologies and that tools that already exist can obtain answers within a cycle of 70 seconds.

Some technologies have already been adopted in the paint shop such as the microscope and spectrophotometer for analyzing paint defects to ascertain possible causes of faults in order to support quality monitoring. Other systems developed for automotive industry for paint shops focus on improvements in the quality of operator inspection at polish lines, final stage of paint process with the car completely painted with all the layers. Vision machine technology was used on these systems which captures information through one image.

It is also concluded that a convolutional network is more suitable and easier to implement to get the information from one image in order to classify it, eliminating the need for a specialist in dirt collection and analysis.

Further investigation will determine the best configuration using current technologies which can support the development of a portable cyber-physical digital approach capable of analyzing dirt and treating the problem of dirt in painting, which can operate with different layers and environments. This is an agile and accessible way to improve the decision-making process in automotive painting processes, supporting quality monitoring.

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