Detection of Irregularities on Automotive Semiproducts

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ABSTRACT: *The use of applications for automated inspection of semiproducts is increasing in various industries, including the automotive industry. This paper presents the development of an application for automated visual detection of irregularities on commutators that are parts of vehicle's fuel pumps. Each type of irregularity is detected on a partition of the commutator image. The initial results show that such an automated inspection is able to reliably detect irregularities on commutators. In addition, the results confirm that the set of attributes used to build the classifiers for detecting individual types of irregularities and the priority of these classifiers significantly influence the classification accuracy.*

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1. Introduction

Information technology (IT) is replacing human work in numerous domains. Such a technology is especially suitable for repetitive non-creative procedures where high accuracy is required. Automotive industry is introducing IT in various segments, for example in storage management and automated inspection of semiproducts.

Automated inspection of semiproducts can be done by analyzing data from several sources, such as sensors, lasers and cameras. Utilization of cameras for this purpose has several advantages, e.g., it is fast, thus not slowing down the production line, it is cheaper in comparison to highly specialized sensors, and the same hardware can be used for inspection of heterogeneous semiproducts.

This paper presents the development of an application for automated visual inspection of commutators as semiproducts for automotive industry. This application processes images of commutators with computer vision algorithms to obtain the attributes describing visual properties of the commutator. These attributes are then used by machine learning algorithms to classify the commutators, i.e., to determine whether or not they contain irregularities and, in the case they do, what is the type of irregularities.

Experimental detection of irregularities was performed using various sets of attributes and various classification modes, including the detection of individual types of irregularities with binary classifiers and the classification of all types of irregularities with a single classifier.

The paper is further organized as follows. The problem of detecting irregularities on commutators is presented in Section 2. Section 3 describes the application for detecting irregularities that was designed and implemented in a prototype form for a specific production line. The experiments and results from the development process are presented and discussed in Section 4. Finally, Section 5 concludes the paper with some ideas for future work.

2. Problem Description

Commutators are parts of electric motors that periodically reverse the current direction between the rotor and the external circuit. If the electric motor is installed in the vehicle's fuel pump, it has to withstand the chemical stress, which is usually not the case for other types of electric motors. Therefore, special graphite-copper commutators are produced for this purpose.

The production of graphite-copper commutators involves several stages. Among them the most critical one is soldering of graphite and copper parts of the commutator. The quality of the soldered joint is crucial for the quality of the commutator since even the smallest joint irregularity is unacceptable. During the soldering phase, four types of irregularities may occur:

1. Metalization defect, i.e., there are visible defects on the metalization layer,

2. Excess of solder, i.e., more solder is applied than feasible,

3. Deficit of solder, i.e., less solder is applied than feasible, and

4. Disoriented, i.e., the copper part is not appropriately oriented with respect to the graphite part.

The analysis of these irregularities showed that each type occurs only on a specific part of the commutator. Consequently, when visually inspecting the commutator, its image can be partitioned into four segments, each showing the presence or the absence of an individual type of irregularity, and into the rest of the image that can be disregarded since it contains no information about the irregularities. Currently, these irregularities are detected through manual inspection of the commutators. This approach is time-consuming and its results may be subjective. The goal of this research is to design and implement an automated visual inspection of commutators that would overcome the weaknesses of the manual inspection.

3. Automated Visual Inspection of Graphite-copper Commutators

The idea for the automated visual inspection of graphitecopper commutators is to consist of three phases. Firstly, a digital image of the commutator is obtained. Secondly, this image is processed using computer vision algorithms that extract informative attributes. Finally, these attributes are used by classifiers to determine whether the irregularities are present on the commutator and identify their type in the case of their presence. Before applying this inspection procedure on the production line, the classifiers need to be built with machine learning algorithms.

3.1 Processing Commutator Images with Computer Vision Algorithms

Commutator images are processed in several steps. Since the commutators are not properly aligned, their rotation angle and position in the image have to be determined first. The center of the commutator is detected by matching the image with the template image of the center. Next, the position of the commutator's pin is found. The line between between the center of the commutator and the pin is used to determine the rotation angle.

The next step of image processing consists of determining four regions of interest (ROIs), one for each type of irregularities. Each ROI is obtained by applying the corresponding binary mask to the image. Before applying the binary mask, the mask has to be properly positioned and rotated. To that end, the information about the center of the commutator and its rotation angle (obtained in the previous step) is used. As a result, four ROIs are obtained. They are further processed with the same sequence of computer vision algorithms, where only the input parameter values of these algorithms are specific for each ROI.

At this stage, ROIs are in RGB format. However, preliminary tests showed that in order to reliably detect the irregularities, only one color plane should be used. Moreover, these tests also showed, that the most appropriate color plane is the red one, with the exception of the excess of solder irregularity for which the best color plane is the blue one. Consequently, the most appropriate color plane is extracted from each ROI with respect to the observed irregularity. This extraction results in gray-scale ROIs.

Gray-scale ROIs are then filtered with the median filter to reduce noise from the images. For this purpose a 2D median filter is used, where the size of the median window is an input parameter.

In the next step, a threshold function is used to eliminate pixels that are not relevant for detecting the irregularities. Each ROI is processed with a specific value of the binary threshold. This step results in a black (background) and white (relevant regions) image.

Connected pixels are then grouped together with the connected-component labeling algorithm [5] in order to detect the connected regions. This enables to process relevant regions, i.e., particles, rather than single pixels.

In the last image processing step, a particle filter is used to remove small particles that can be present in the image due to noise. The size of the particles to be filtered is an additional input parameter.

After the image is processed with the computer vision algorithms, the following six attributes are calculated for each ROI, i.e., for each type of irregularity:

- The number of particles,
- The cumulative size of particles in pixels,
- The maximal size of particles in pixels,
- The minimal size of particles in pixels,
- The gross/net ratio of the largest particle, and
- The gross/net ratio of all particles.

These attributes are then used to build the classifiers and classify the commutator images.

3.2 Learning Classifiers with Machine Learning Algorithms

The goal of the classifiers is to determine whether a commutator contains any irregularities. Two approaches were applied to solve this classification problem:

1. All the attributes were included in a single set of attributes and a single classifier was built to classify the commutators into one out of five possible classes (either one of the four types of irregularities or no irregularity),

2. Each type of irregularity was detected with a binary classifier, where the binary classifiers were prioritized to determine the irregularity when irregularities of several types were detected.

The classification approach using four binary classifiers was further structured based on the attributes and learning instances used when building the binary classifiers. Specifically, when building a binary classifier for detecting irregularities of a particular type, four learning modes were tested:

1. Only attributes of the corresponding ROI and only commutators that are either without irregularities or contain irregularities of this particular type are used,

2. All attributes, but only commutators that are either without irregularities or contain irregularities of this particular type are used,

3. Only attributes of the corresponding ROI, but all commutators including irregularities of all types are used, and 4. all attributes

Class	Number of images
Without irregularities	212
Metalization defect	35
Excess of solder	35
Deficit of solder	49
Disoriented	32

Table 1. Distribution of test images

Class	Median window size	Threshold value	Particle size
Metalization defect	3	54	13
Excess of solder	3	5	2
Deficit of solder	5	78	760
Disoriented	1	81	184

Table 2. Input parameter values for the computer vision algorithms

and all commutators including irregularities of all types are used.

4. Experiments and Results

The proposed method for detecting irregularities was tested on a set of images of commutators without irregularities and the ones containing irregularities. The distribution of the test images among the irregularity classes is shown in Table 1.

The applied computer vision algorithms were implemented in Open Computing Language (OpenCL) [3] that is suitable for deploying on embedded many-core platforms and installing in the production environments. More precisely, we used the OCL programming package [2], which is an implementation of OpenCL functions in the Open Computer Vision (OpenCV) library [4]. The connected-component labeling algorithm was implemented based on description from [5]. The input parameter values of computer vision algorithms were determined using a tuning procedure described in [1] and are shown in Table 2. The classifiers were built using the Weka machine learning environment [7]. In particular, the J48 algorithm, the Weka's implementation of the C4.5 algorithm for building decision trees [6], was used for this purpose.

Learning mode	Best priority	Max. accuracy [%]
1	C_1, C_3, C_2, C_4	81.8
2	C_3, C_2, C_1, C_4	77.1
3	C_2, C_3, C_1, C_4	81.5
4	C_1, C_3, C_4, C_2	83.5

Table 3. The best binary classifier priorities and classification accuracies of learning modes

Figure 1 shows the classification accuracies obtained with the tested classifiers and learning modes. When binary classifiers are applied, all the permutations of priorities are tested, therefore a distribution of classification accuracy is shown. The results indicate that the highest classification accuracy is obtained using learning mode 4, i.e., when the attributes describing all types of irregularities and the images of all commutators are used to build the binary classifiers. This enables to, for example, correctly classify a commutator with irregularity x_1 when the binary classifier

Highest priority	**Best learning mode**	**Max. accuracy [%]**
C_1	4	83.5
C_2	4	83.2
C_3	4	83.5
C_4	4	83.5

Table 4.The best learning modes and classification accuracies of binary classifier priorities

for irregularity x_1 is used. Such performance is not guaranteed when building the binary classifiers for irregularity x_i without taking into account the images of irregularities x_j, $i \neq j$ (learning modes 1 and 2). Consequently, when classifying the commutators with previously unseen irregularities (learning modes 1 and 2), the classification accuracy varies significantly with respect to the priority of classifiers as shown in Figure 1. These results also confirm that partitioning the classification problem into four subproblems, one for each irregularity type, results in higher classification accuracy, but only if all attributes and commutators with all irregularities are used when building the binary classifiers (see the classification accuracy of learning mode 4 in comparison to classification accuracy of the single classifier in Figure 1). On the other hand, when building the binary classifiers from the reduced set of attributes or the reduced set of irregularities, the obtained classification accuracy is lower than the classification accuracy of the single classifier. Finally, these results show that the priority of classifiers influences the classification accuracy. The priority is especially important when using learning modes 1 and 2.

The results were further analyzed with respect to various priorities of binary classifiers and learning modes (see Tables 3 and 4). For this purpose, the binary classifiers were abbreviated as follows:

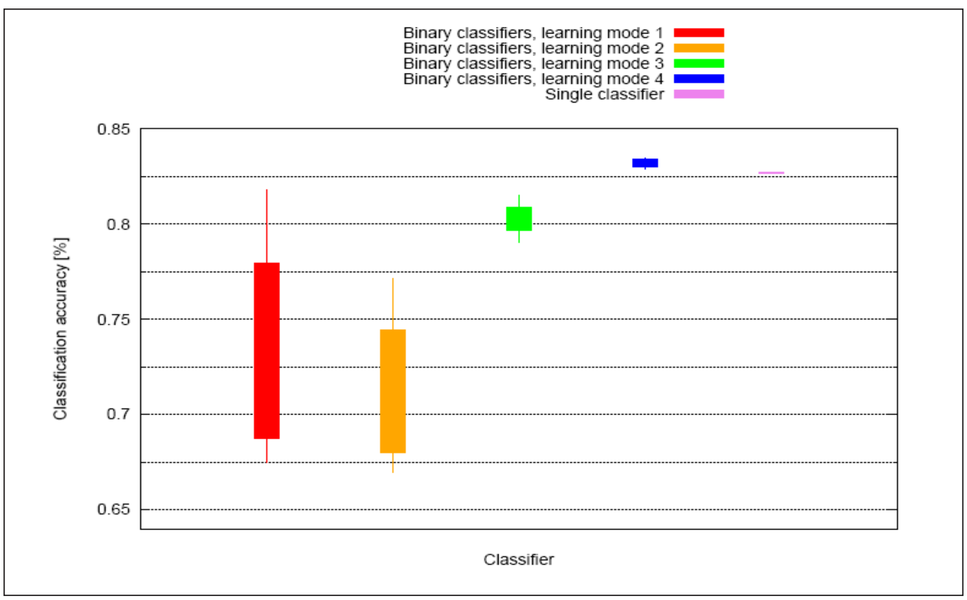

Figure 1. Classification accuracies of the tested classifiers and learning modes

C_1 – The binary classifier for detecting metalization defects,

C_2 – The binary classifier for detecting the excess of solder,

C_3 – The binary classifier for detecting the deficit of solder, and

C_4 – The binary classifier for detecting disoriented commutators.

Table 3 shows the best priorities of binary classifiers and the corresponding classification accuracy for each learning mode. This table shows that the most important binary classifier is C1 since it has the highest priority in two cases. In addition, the highest classification accuracy is obtained when this classifier has the highest priority. The second most important classifier is C3 since it has the highest priority once and the second-highest priority three times.

Table 4 shows the best learning mode and the corresponding classification accuracy when the binary classifiers have the highest priority. These results show that the learning mode 4 is the best one irrespectively of the binary classifier that has the highest priority. Nevertheless, when classifier C2 has the highest priority, a lower classification accuracy is achieved than in other cases.

5. Conclusions

This paper presented the development of an automated procedure for visual detection of irregularities on graphite-copper commutators after the soldering of graphite and copper in the production process. Four types of irregularities were detected a) with a single classifier and b) by partitioning the problem into four subproblems, learning the binary classifiers for each irregularity type and assigning priorities to the classifiers. The results show that the highest classification accuracy is achieved when the binary classifiers are used that are trained on the data of all types of irregularities. The results also indicate that the priority of classifiers significantly influences the classification accuracy and therefore needs to be taken into account.

In the future work we will test additional machine learning algorithms for potential improvement of the classification accuracy. Additional attributes could be extracted from the images with machine vision algorithms. It would be also interesting to compare our results with the results produced by the existing methods for detecting irregularities on semiproducts. The ultimate goal of this work is to put the automated inspection procedure into regular use on the production line.

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