THE MACHINE VISION IN WIRE HARNESS INDUSTRY FOR FUSE BOX INSPECTION

Milan Nikolić*
[0009-0004-0716-9586]

Singidunum University,
Belgrade, Serbia

Abstract:

The application of technological innovation has the ability to greatly enhance the efficiency and accuracy of quality control in industrial tasks. Machine vision (MV), a key innovative technology used in industrial inspection, allows for reliable and swift inspections, providing the advantage of improved quality and business productivity. This paper presents traditional machine vision in the wire harness industry, with a focus on its application in Fuse Box inspection using a camera, data collection sensors and image processing software. Through this analysis, the aim is to offer a comprehensive overview of the potential of traditional machine vision on Vision Inspector, analyses the advantages, the causes of the problems and propose improvement by integrating the Faster R-CNN model into an existing machine vision.

Keywords:

Machine Vision, Fuse Box, Wire Harness, Quality Control, Faster R-CNN.

INTRODUCTION

A wire harness [1] is a set of wires or cables that enable the transmission of electrical signals and information between different devices and systems inside the vehicle, ensuring their functionality. The Fuse Box, which contains fuses and relays, is an integral part of the wire harness and protects the vehicle from excessive currents and short circuits, which is why its correctness is important. Identification of irregularities by quality control is of great importance as it ensures quality and compliance with required specifications. Traditional visual inspection is usually performed manually by the operator in order to visually determine the condition and their conformity, which can result in errors and inefficiencies, which depend on the operator's attention, level of training and the length of the process itself. As an alternative for quick and precise inspection, machine vision is used, where the process of identifying malfunctions is performed on the basis of predefined parameters in order to reduce errors and interventions by the operator. In this paper, the process of inspecting the Fuse Box on machine vision will be presented in order to improve it, increase efficiency by using the integration of deep learning with Faster R-CNN model with existing machine vision.

Correspondence:
Milan Nikolić

e-mail:
misa_aum@hotmail.com

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2. APPLICATION OF MACHINE VISION

Machine vision [2] is a technology that enables machines (usually computers) to see, make decision and extract information from digital images or videos captured by cameras. Machine vision can be applied in a wide range of industries and fields: industrial quality control industry, agriculture industry, automotive industry, textile industry, printing industry, security industry, medical diagnostics industry, robotics industry, logistics and warehousing industry, food and beverage industry, pharmaceuticals industry and more.

In general, the basic components used in machine vision systems for image capture and processing are common across a wide range of applications. Components that machine vision includes are camera, sensor, lens, light source, image processing software and communication interfaces [3]. The camera captures static images of the object for inspection and analysis, with a sensor converting light into digital images for computer processing. A lens mounted in the camera provides the necessary magnification, working distance, and image resolution. The camera captures static images of the object for inspection and analysis, with a sensor converting light into digital images for computer processing. Illumination is used to illuminate the image scene, improving the quality of the captured image by maximizing contrast and emphasizing the features to be analysed. For further analysis, the camera's captured image is saved on the computer via the frame grabber. Communication entails establishing a connection between the camera, which captures the images, and the image processor.

The processed data is then relayed to the components for further use. Image analysis relies on computers equipped with various software programs designed to assist with and enhance image processing tasks.

3. THE PROCESS OF FUSE BOX INSPECTION

For better understanding the Fuse Box process in the wire harness industry requires an analysis, documentation, evaluation of activities within the organization, and identification of improvement opportunities. To initiate this understanding, it is necessary to show the process of traditional machine vision.

Based on the specifications received from the customers, the engineers prepare a master sample for a specific model (a sample covering all possible combinations for the model), which is used to adjust the machine itself, as shown in Figure 1.

Depending on the specifications and needs, the number of models that can be adjusted and checked is not limited. Once the master sample preparation is finished, the image is captured and stored for a particular model. This model is then transformed from the RGB (Red, Green, Blue) colour space to the HSI colour space [4], facilitating and simplifying the extraction of colour information. The HSI (Hue, Saturation, Intensity) model is used because it provides better performance compared to the standard RGB model. Hue is the colour used to distinguish between fuses and relays, Saturation represents the colour intensity for better detection of details, and Intensity represents distinguishing between fuses and relays based on brightness. Shown in Figure 2. HSI Inspection Areas are defined and manually marked inspection areas of fuse, relays and after that all marked areas are individually adjusted based on the HSI model, in order to separate inspection areas from the background through segmentation using the threshold. This technique involves setting a pixel intensity threshold over the marked areas in the image and in case the pixel intensity values are above the defined threshold (Pass Range), they are considered part of the object, and if they are below the defined threshold, they are not considered

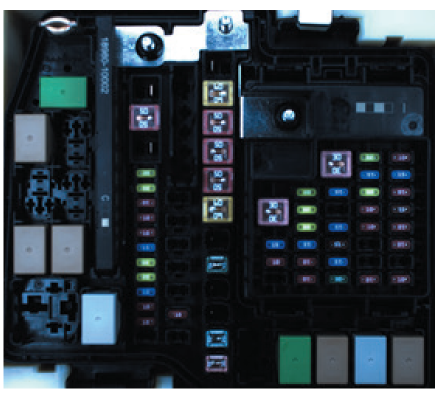

Figure 1. Picture of master sample for specific model.

part of the object, but part of the background. To achieve the separation of objects with different colours, a thorough analysis is performed to evaluate the precision of detection and recognize potential instances of either true positives or false negatives. This is accomplished by establishing the range of values based on HSI and successfully defined pass range, as shown in Figure 3. After the settings are made, analysis, testing, and final optimization of the model are performed in order to achieve the best detection accuracy and successful verification by quality control.

The inspection process involves comparing a captured image of a Fuse Box marked inspection areas and configuration files stored in the machine vision system. This comparison allows for the identification of fuses and relays in the image based on the colour difference. Figure 4 shows where fuses or relays are misplaced or false negatives are detected. All images are captured during the inspection, regardless of their accuracy, stored and archived.

Figure 2. HSI Inspection colour areas setting.

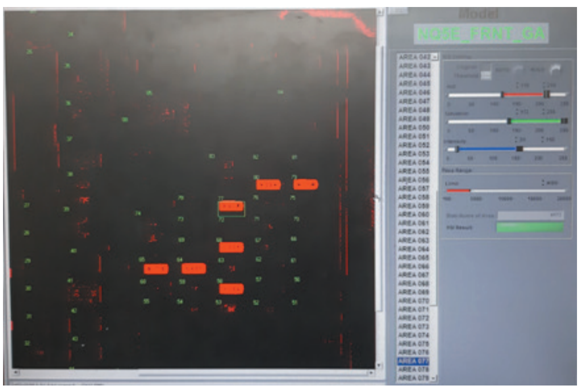

Figure 3. HSI colour setting areas in threshold.

Figure 4. An example of inspection result.

4. PROPOSED APPROACH FOR IMPROVEMENT

Machine vision, based on traditional image processing principles, has proven to be a very effective tool for a Fuse Box inspection. It stands out for its high precision requirements and serves as a reliable inspection method as long as the parameters remain within certain limits. However, challenges arise when dealing with material discoloration and glare, which can cause identical parts to look different on camera and thus increase the number of false negative inspection results. Based on these, frequent intervention by engineers and quality control is required to re-modify, adjust parameters and verify machine vision, which causes delays in the inspection process, especially if several different models are tested on the same machine.

Based on the described traditional machine vision and challenges, a proposal for improving the inspection process is using deep learning and archived images with Faster R-CNN [5] (Region-based Convolutional Neural Network) to allow enhanced accuracy while reducing the probability of false negatives inspections. This network generates region suggestions that are then used by the detection network to classify objects and determine their locations. Faster R-CNN architecture is shown in Figure 5.

Faster R-CNN architecture include:

- Convolutional Layers: Images are first processed by convolutional layers to extract feature maps which serve as a basis for detecting objects [6] [7];
- Region Proposal Network (RPN): The feature maps are used by the RPN to identify region proposals that are likely to contain objects [8];
- Region of Interest (ROI) Pooling: These region proposals are normalized through ROI Pooling to a uniform size to be processed by the subsequent layers [9] [10]; and
- Classification and Regression: The pooled features are then passed to fully connected layers to classify the objects and refine their locations within the image [11] [12].

Here is an overview of how to integrate Faster R-CNN with an existing machine vision system:

- Data Preparation: Adapting techniques from the paper [13] approach the complexities of material discoloration and glare that can challenge the uniformity of appearance in identical Fuse Box parts. A diverse set of archived images is extracted to capture a wide range of environmental and lighting conditions that affect the visual presentation. Each image is then subjected to detailed annotation, with the annotation work not only including the identification of each fuse or relay, but also extending to an in-depth representation of their condition, including the effect of discoloration and glare. The marking process emphasizes the accuracy of the condition and the need to distinguish between different types of defects, regardless of material or image variations. This is ensured by specifically marking out colour change, positional inaccuracies, providing the

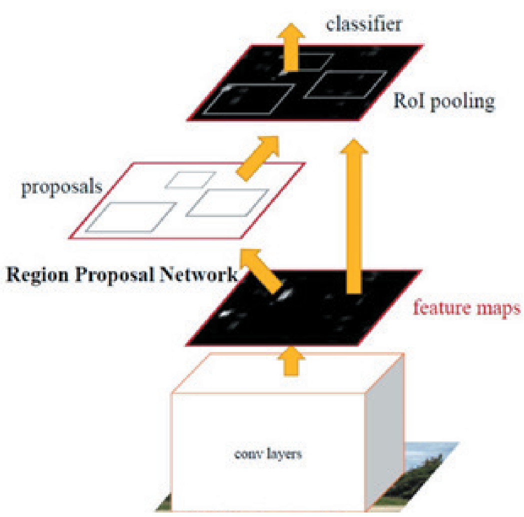

Figure 5. Faster R-CNN architecture [5].

model with plenty of examples of both normal variances and actual failures. These steps would allow a model to be trained for robust detection and estimation of the Fuse Box condition;

- Data Augmentation: Since luminance and colour variations are important, applying a data augmentation technique to the training set would create more diverse conditions, such as luminance and colour variations. By synthetically changing the training images to simulate different lighting conditions [14] the capacity of the model to recognize defects under different conditions can be improved. This would include applying changes such as simulating shadows, adjusting brightness levels, and creating halos of varying intensity on the dataset images. Augmentation techniques [14] can be adapted to enrich the training set, which should create a model that is more robust to changes in illumination with the aim of improving detection accuracy under different illumination conditions. Using the fast colour averaging technique [15] images can be pre-processed to have consistent colour values in similar areas. This involves averaging the colour values of all pixels within the contours of each object to their mean value. This preprocessing method will help reduce colour variability due to lighting differences and improve the system's ability to accurately recognize and inspect Fuse Boxes. Applying this technique to the pre-training data set would improve model's robustness to colour and illumination variations;
- Feature Extraction: After the data preparation and augmentation phase, the machine vision system would use the feature extraction component of Faster R-CNN [5] to distinguish objects within the Fuse Box images. The deep convolutional network [8] systematically extracts a hierarchical set of features from the images, capturing essential visual attributes such as textures, edges, and colours. These characteristics are pivotal in enabling the model to distinguish between different visual elements within Fuse Box images. In parallel, the Region Proposal Network (RPN) [5] leverages these extracted features. It accurately predicts potential object boundaries and generates region proposals, earmarking where components such as fuses and relays are potentially located within the image. As posited in [16] each region proposal is accompanied by an objectness score. This would indicate the probability that the suggested region actually contains the object, increasing the discrimination between relevant components and irrelevant background information;
- Training the RPN: Training of the Region Proposal Network by integrating sophisticated deep learning techniques from [17]. By training the RPN with a rich dataset that includes varied images of Fuse Boxes, the network is adept at identifying nuances that distinguish potential regions where fuses and relays are situated. This training regimen equips the RPN with the agility to accurately forecast prospective regions for detailed analysis, taking into account the complexity of background clutter and the diversity of fuse and relay appearances. The depth and breadth of feature learning ensure that the RPN develops a keen sensitivity to the intricacies of the target objects, thereby enhancing the reliability and efficiency of the region proposal mechanism;
- Region of Interest (ROI) Pooling: Region of Interest Pooling is a crucial component that synergizes with the training of the Region Proposal Network. Based on [16] this process acts as a crucial intermediary, transforming variable-sized RPN outputs into a uniform format required for the high-precision object detection phase. During the RPN training phase, ROI Pooling standardizes the size of the proposed regions, ensuring the consistency of feature maps fed into further detection layers. This uniformity facilitates accurate and robust predictions by the trained RPN, enabling it to propose candidate regions in Fuse Box images with a high degree of precision, and thus fortifying the efficacy and reliability of the entire detection operation. Integrating ROI Pooling as part of the RPN training process is a move that would boost machine vision performance;
- Object detection: Building on the trained region proposal network and ROI Pooling process, the next step would involve actual object detection. Using techniques from [17] this phase would use the consistency achieved through ROI Pooling to thoroughly analyse standard size feature maps for potential defects. During object detection, there is a focus on component colour variations, which is critical due to the nature of fuses and relays in color-coded wire harnesses. An object detection model, trained on different data sets, would identify and classify components by recognizing their

specific colour codes, enabling the detection of errors based on incorrect colour or misplacement that could indicate a defect. This recognition of colour variations would not only be essential for identifying the correct parts, but also for verifying their suitability for specific positions within the Fuse Box. Consequently, this focus on colour variation would improve the accuracy of object detection thereby enhancing the overall accuracy and reliability of machine vision systems; and

- Integration: By communicating between the traditional machine vision system and the Faster R-CNN model using an interface would ensure that the images captured by the machine vision system can be efficiently transferred to the Faster R-CNN model without any compatibility issues. In the event that an image does not meet predefined criteria or thresholds during initial inspection by traditional machine vision techniques, it would be forwarded to the Faster R-CNN component for further analysis, as shown in Figure 6. This sequential approach would ensure that the images are subjected to more computationally intensive screening of the Faster R-CNN only, when necessary, which would optimize processing time and resources.

The expectation for the proposed integration of a Faster R-CNN model with the existing machine vision system for Fuse Box inspection is that it will substantially improve the ability to identify and classify defects in various lighting and colour conditions. The deep learning model is anticipated to provide enhanced accuracy in object detection tasks due to its advanced feature learning capabilities. Moreover, the use of a vast, well-labelled archive of images for training should enable the system to recognize a wide range of potential defects, reducing false negatives and increasing the reliability of the inspection process. The Faster R-CNN's ability to learn from complex patterns within the data is expected to result in a more adaptive and robust system. Ultimately, the model is expected to lead to higher efficiency in the production line by decreasing the inspection time and improving the overall quality control of the wire harness manufacturing process.

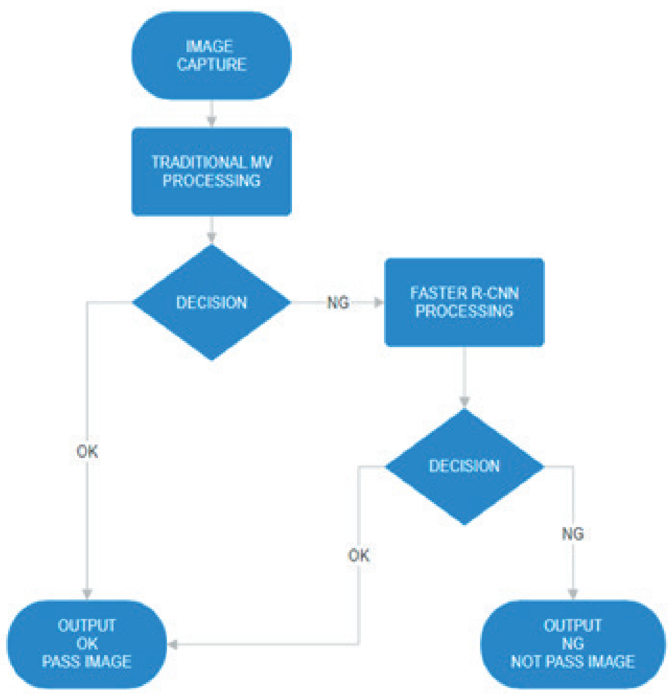

Figure 6. Simple flow chart for new integrated model.

5. CONCLUSION

In conclusion, integrating a Faster R-CNN deep learning model into an existing traditional machine vision system holds great promise for increasing the quality and accuracy of Fuse Box inspections in the wire harness industry. Although challenges related to model integration and continuous model training exist, the potential benefits in terms of increased inspection accuracy and reduced need for manual intervention could significantly overcome these obstacles. With rigorous training, validation, and continuous improvement through feedback loops, the proposed model would be poised to become an indispensable tool in the inspection process, further optimizing production flow and reducing the likelihood of errors-defects reaching the end user.

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