Real-Time Visual Quality Inspection System for Automotive Cable Manufacturing*

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***Abstract*—In both society and industry, electric cables are used for various purposes. Companies often use different colors and materials to distinguish their properties. Quality control in cable manufacturing involves checking that colors meet specifications and that stripe widths (if present) are within the required range. Manual quality inspection methods are typically inefficient, time-consuming and error-proned, leading to uncaught defects. This paper introduces an automatic real-time visual inspection system that monitors the cable quality during its manufacturing process. The system employs image processing routines and four industrial Flir Blackfly S USB3 cameras to capture and analyze the entire cable perimeter in real-time. It evaluates the colors and thickness of the stripes to ensure they meet the predefined standards. The proposed solution aims to improve inspection accuracy and reduce the number of unnoticed defective cables that passes through the quality control. Experimental results show high precision and recall rates in segmentation, color verification and stripe evaluation tasks. The cable segmentation routine achieved a precision of 99.96%, while the stripe segmentation routine achieved 90.25%. The color verification routines for cables and stripes achieved precisions of 86.30% and 90.00%, respectively. The system stripe evaluation task achieved a precision rate of 79.74%. All image processing routines run in under 30 ms on a mid-tier performance workstation, demonstrating the system's practical applicability and effectiveness in modern cable manufacturing lines.**

***Index Terms*—Industrial cable inspection, real-time inspection, electric cable verification, quality control, image processing, industrial cameras, cable manufacturing, segmentation, color verification, automated inspection systems, industrial quality control, artificial intelligence**

I. Introduction

Automatic vision inspection systems have been widely used in industry [1]–[4]. Some industrial contexts, such as companies that manufacture electric cables, can be challenging for vision inspection systems due to the variety of colors and materials used to differentiate their specifications. In addition to the challenges posed by color standards, the electrical cable extrusion process is typically very fast. Small issues can affect large portions of the cable during production, requiring manual inspection and causing financial loss. A recurring problem is the color fading caused by pigment dilution during the manufacturing. To address this issue, the quality control departments typically define a tolerance range for the color, between a more intense pigment (maximum) and a more faded pigment (minimum). The ideal pigment falls somewhere between the maximum and minimum of the specified range. The electric cable cover can also contain two stripes which are colored with a different pigmentation that follows the same standards. Similarly to the color, the stripe thickness has an acceptable operating range relative to the cable's total perimeter. A common problem, related to stripes, is when their count is different from the expected.

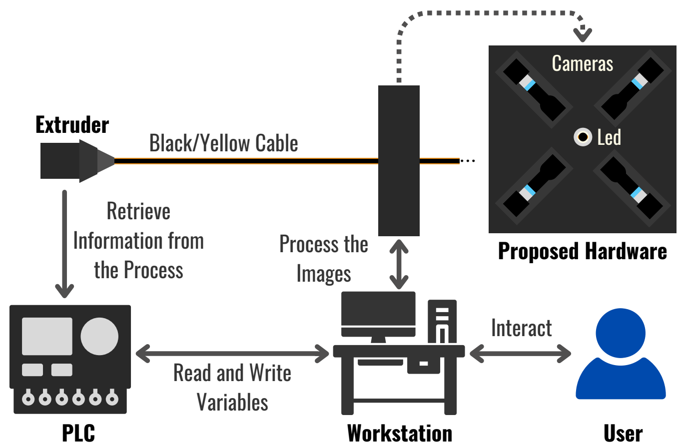

Fig. 1. Overview of the proposed system architecture, highlighting the main components. The pipeline includes a cable extruder attached to a Programmable Logic Controller (PLC). The extruded cable passes throgh an enclosure designed to feature four industrial cameras. Captured images are sent to a workstation that runs routines in order to verify cable compliance in real-time during production.

This work introduces a system for real-time inspection of automotive electric cables during their manufacturing process, as shown in Figure 1. The system inspects the full perimeter of the cable, checks its colors to verify compliance with predefined industrial standards. If stripes are present, it also checks their count and thickness. To do so, the solution employs four Flir Blackfly S USB3 cameras with 0.30X SilverTL Telecentric lenses to capture all sides of the cable, which are then combined into a panoramic view for evaluation. A custom enclosure was designed to reduce external interference and dust, improving the system's reliability.

The remainder of the paper is structured as follows: Section II provides a review of literature. Section III describes the development and operation of the system. Section IV showcases achieved results. Finally, Section V summarizes and discusses the findings and proposes directions for future research.

II. Related Works

Image processing and machine learning techniques are revolutionizing automatic inspection and quality control across various industries. For electrical component inspection, studies have explored automated optical systems for verifying wire sequences in cables using color recognition and image alignment [4]–[6]. Deep learning, particularly CNNs, has enhanced defect detection in cable manufacturing and other areas [7]–[9]. Beyond defect detection, machine learning facilitates anomaly detection in high-voltage equipment and other critical systems, leveraging techniques like support vector machines and Gaussian Mixture Models [10], [11]. Other domains benefit from multichannel analysis and alternative color spaces for improved detection in tasks like weed identification and facial emotion recognition [12], [13].

This work stands out by introducing a real-time automotive electric cable manufacturing inspection system that verifies produced cable quality with regard to multiple aspects. It analyzes cable and stripe colors, counts the number of stripes, and checks their thickness to ensure compliance with required standards. Additionally, the combination of efficient image processing routines along with industrial cameras and a custom enclosure ensured accurate and reliable inspections.

III. Methodology

This section outlines the steps involved in developing the proposed solution. It includes solution's operation scenario, hardware used for inspection, cable inspection routines for quality assessment, and the experimental setup used for solution evaluation.

A. Operation Scenario

The solution inspects cables with diameters between 1.2 mm and 4.2 mm, which may or not feature two stripes with thicknesses between 7% and 17% of the cable's perimeter. As shown in Figure 1, the cable passes through an extrusion process at up to 800 m/min, requiring real-time inspection. Since the process involves melting PVC particles, any color nonconformity can affect at least 20 meters of cable due to the high extrusion speed. Lastly, the system checks if the cable color falls within the calibration tolerance. If stripes are present, it also verifies their color, count and thickness meet the required standards.

B. Hardware for Inspection

Applied hardware setup consists of four Flir Blackfly S USB3 industrial cameras with 0.30X SilverTL Telecentric Lenses connected to a workstation via USB. These cameras provide high image quality with 12-bit color depth for accurate color verification. They were housed within a custom-designed square enclosure (Figure 1) that minimizes external noise, dust, and interference. This enclosure features a central, ceramic-lined aperture ring for cable passage, a lid for safety and dust prevention, and an LED ring for illumination. To stabilize the cable and reduce vibrations, a ceramic ring is applied to the aperture. Furthermore, the chosen camera model features configurable parameters like exposure time and frame rate, minimizing blurring in acquired images caused by high speed and vibration. The computation is handled by a workstation equipped with an Intel Core i7-10700 processor and 32GB of RAM, sufficient for running image processing routines and machine learning algorithms without a GPU.

C. Cable Inspection Process

As shown in Figure 1, images captured by the enclosure cameras are sent to the workstation via serial communication and undergo a five-step inspection process. First, the cable is segmented from the background for each image. Then, the images are combined into a panorama representing the full cable perimeter. The system checks for stripes, extracting and measuring them as a percentage of the panorama's width if present. Finally, the cable (and stripe, if applicable) color is compared to the reference. After these steps, the system determines if the cable meets the standards, requiring approval in all verifications to be considered compliant.

1) Cable Segmentation: The routine starts by resizing the captured image to a 500×694 format and cropping it to 5% of its original size. The cropped frame is then converted to YCrCb color format and a mask is generated using the Y channel. Contrast in this channel is adjusted using histogram equalization, followed by a hit-and-miss morphological operation. Additional morphological and thresholding operations eliminate small noise. Finally, a flood fill operation is conducted on both sides of the cable to ensure all noise is removed, preserving only the cable mask. Once the mask is properly defined, it is analyzed to determine if any rotation is required to ensure the cable is completely vertical. Lastly, the generated mask is applied to the camera frame, isolating the cable and removing the background.

2) Panorama construction: Standard image stitching techniques often fail on featureless surfaces like thin cables. Therefore, a geometric model was used to generate a panoramic view of a striped cable. Multiple cameras were positioned at fixed distances around the cable with slightly overlapping fields of view, capturing different portions. These portions were combined to form a complete 360-degree panoramic image. The final system utilized four cameras to capture the visible extent of the cable in the resulting panorama.

3) Stripe Segmentation: To identify and segment stripes from the panorama, some features are manually defined. These features consist of statistical metrics of individual channels from HSV, YCrCb, RGB, Lab, and grayscale color spaces. The metrics used are mean, standard deviation, and difference between maximum and minimum values of each channel. These informations describe the colors in the panorama. A Random Forest (RF) [14] model was trained using these features to determine which HSV channel best separates cable color from stripe color. With these three channels, we find that it is possible to segment any color combination. After selecting the optimal channel, segmentation is performed, followed by a small noise removal step. Finally, the stripe segmentation routine returns a binary mask, where white pixels represent stripes and black pixels represent the main body of the cable.

4) Stripe Verification: Once the stripe segmentation mask is accurately estimated, their count and individual thickness relative to the cable's perimeter can be evaluated. This verification applies only to striped cables. If no stripes or only one stripe is detected, the system reports non-conformity due to an insufficient number of stripes. If two stripes are identified, the system confirms compliance based on the number of stripes and proceeds to verify their thickness. If three stripes are detected, an analysis is conducted to determine if the second stripe is split at the borders of the panorama. This involves shifting the panorama until the space between the stripes is centered. If, after shifting, the panorama contains only two stripes, the system confirms compliance and checks their thickness. If more than two stripes are still present, non-compliance is reported. Lastly, if four or more stripes are detected, non-compliance is also reported. The thickness verification checks whether each stripe falls within the tolerance range of 7% to 17% of the total panorama width.

5) Color Verification: The color verification process collects points from the generated panorama and compares them to reference (calibration) colors, checking if they fall within the specified difference thresholds in the HSV color space. Points outside the compliant range are marked as incorrect. The number of color points collected can be set as a system parameter. If stripes are present, the same process applies to them. The system also allows users to define the expected percentage of correct points needed to determine color compliance, with a default value of 60%. If the percentage of correct points is lower than expected for either the cable or the stripe, the color verification indicates non-conformity.

D. Experimental Setup

Three experiments were designed to evaluate the performance of the proposed system using data from a real manufacturing process. The dataset consists of 804 collections, each containing four images (one from each camera), totaling 3216 images. A more detailed annotation was performed on a subset of 164 collections, specifying color conformity, stripe thickness (measured in millimeters using a precision tool), and color calibrations. This detailed annotation was limited to the subset due to the time-consuming nature of the process. The experiments were designed as follows:

- **Cable/Stripe Segmentation:** Evaluated across the entire dataset by comparing generated masks with manual annotations. Precision, recall, and execution time were measured.
- **Color Verification:** Evaluated on 164 collections. Precision and recall were used to compare automated results with manual annotations.
- **Stripe Estimation/Verification:** Evaluated on 164 collections. Stripe thickness was estimated (in pixels, percentage, and millimeters) and compared to the annotations. Absolute error (mm) was calculated, and stripe conformity was assessed using precision.

IV. Results

This section presents an evaluation of the proposed system along with results from conducted experiments.

A. Cable and Stripe Segmentation Assessment

Performance metrics for cable and stripe segmentation routines, as shown in Table I, indicate that cable segmentation achieves high precision (99.96%) and recall (99.32%), demonstrating its effectiveness in accurately identifying cable pixels and segmenting them from the background. Stripe segmentation also achieved high precision (90.25%) and recall (94.07%) values, indicating a strong performance in detecting most stripe pixels. Regarding execution times, the cable routine completes in 0.71 ms while the stripe routine in 10.14 ms, both being efficient and suitable for real-time applications. Although the cable routine has a lower execution time, it is run for each camera image, whereas the stripe routine is executed once per processing loop.

TABLE I
PERFORMANCE METRICS CONCERNING BACKGROUND AND STRIPE SEGMENTATION ROUTINES.

Segmentation Routine	Precision	Recall	Execution Time
Cable	99.96%	99.32%	0.71 ms
Stripe	90.25%	94.07%	10.14 ms

B. Color Verification Evaluation

The cable color verification routine achieved a precision of 86.30% and a recall of 91.30% (Table II), demonstrating high accuracy in correctly identifying compliant cable colors with a balanced trade-off between false positives and true positives. Similarly, the stripe color verification routine exhibited a high precision of 90.00%, indicating better accuracy in identifying compliant stripe colors, though with a slightly lower recall of 80.00%, suggesting a higher rate of false negatives. Overall, both cable and stripe color routines show balanced performance. Figure 2 illustrates examples of non-conformity in stripe and cable colors properly identified by the system.

TABLE II
PERFORMANCE METRICS FOR COLOR VERIFICATION ROUTINES.

	Precision	Recall
Cable color	86.30%	91.30%
Stripe color	90.00%	80.00%

C. Stripe Estimation and Verification

Performance metrics for the stripe estimation and verification routines, as exposed in Table III, indicate that the system achieved an absolute error of 0.33 mm in estimating stripe thickness, which may be attributed to thinner cables. Despite this, the system maintains a high precision rate of

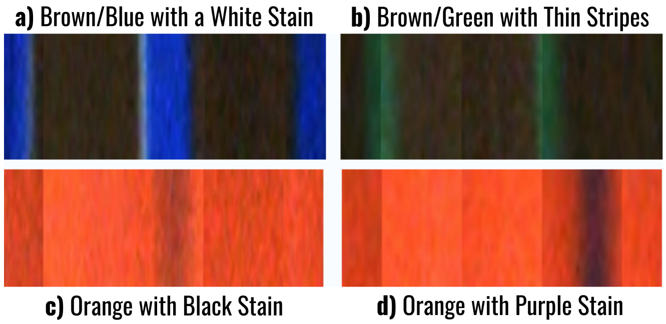

Fig. 2. Examples of nonconformities successfully identified by the system: a) and b) cables with stripes contaminated by different colors, while c) and d) cables without stripes stained during production.

79.74%, demonstrating that it can still accurately determine stripe conformity. This step has an execution time os 1.65 ms, proving system's capability for real-time processing.

TABLE III
PERFORMANCE METRICS CONCERNING STRIPE ESTIMATION ROUTINE.

	Error	Precision	Execution Time
Stripe	0.33 mm	79.74%	1.65 ms

V. CONCLUSIONS

This work presented a system designed to inspect automotive eletric cables in real-time during their manufacturing process, addressing industrial quality control challenges. It utilizes image processing techniques, machine learning models, and high-resolution industrial cameras to provide a comprehensive analysis of cable and stripe colors, along with stripe thickness verification, ensuring the cables meet predefined quality standards. The solution overcomes the limitations of traditional manual inspections by providing continuous, accurate, and consistent evaluation of the entire production, eliminating the need to inspect only a fraction of the batch post-production. The system's performance was validated through an experimental setup, showing high precision rate in segmentation, stripe evaluation and color verification tasks. The complete processing loop, integrating all routines, runs in under 30 ms. Future research will focus on exploring alternative techniques to further improve precision while maintaining efficiency. Large-scale field trials will be conducted to validate system performance in broader operational environments with samples from various cables and materials.

VI. ACKNOWLEDGMENTS

This project was supported by the Science, Technology and Innovations Ministry of Brazil, with resources from law nº 8.2428 of October 23, 1991 within the Softex[1] National Innovation Priority program, coordinated by Softex and EDGE[2]/Vertex[3] Innovation Center and published by [RESIDENCIA EM TIC-09 (process[01245.005714/2022-18])].

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