Automatic Detection and Value Estimation of Multiple Resistors using Image Processing Techniques

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Abstract
Identification of resistor values using color bands is a fundamental yet time-consuming task in electronics laboratories, especially when multiple resistors are present alongside other electronic components. Manual interpretation of resistor color codes is prone to error and inefficient for complex circuit analysis. This paper presents an image processing–based approach for automatic detection, identification, and value estimation of multiple resistors from a single input image. The proposed method employs a sequence of preprocessing, segmentation, morphological operations, and color thresholding techniques to isolate resistors from other components and accurately detect their color bands regardless of orientation. The system is implemented in MATLAB and integrated with a graphical user interface (GUI) for user-friendly operation. Experimental results using real-world images demonstrate reliable detection and correct value estimation under varying lighting conditions and resistor orientations. The proposed approach provides a low-cost, effective solution for automated resistor identification and can be extended to more advanced vision-based electronic component recognition systems.

Keywords –
Image processing, resistor color code, component detection, MATLAB, color band recognition

I.Introduction

Resistors are among the most fundamental and widely used passive components in electronic circuits, playing a critical role in current limiting, voltage division, signal conditioning, and power dissipation. The resistance value of a typical fixed resistor is commonly represented using standardized color codes, where a sequence of colored bands corresponds to numerical digits, multipliers, and tolerance values defined by international standards [1], [2]. Accurate identification of resistor values is therefore an essential task in electronics laboratories, manufacturing, maintenance, and educational environments.

Figure 1. Standard four-band resistor color coding scheme.
Figure 2. Example of a four-band resistor used in the experiments.

In practice, engineers and students frequently encounter situations where multiple resistors must be identified simultaneously, often placed arbitrarily on a workspace and mixed with other electronic components such as capacitors, diodes, transistors, and integrated circuits. Manual reading of resistor color bands in such scenarios is time-consuming and prone to error, particularly when resistors are rotated, partially occluded, or subjected to non-uniform lighting conditions. Human errors in color perception, fatigue, and environmental factors further degrade reliability in manual identification processes [3].
To address these limitations, automated visual inspection techniques based on digital image processing and computer vision have gained increasing attention in recent years. Vision-based component identification systems offer the potential to reduce human effort, improve accuracy, and enable scalable automation in electronics analysis and inspection tasks [4]–[6]. Several studies have explored color-based object detection and classification methods for recognizing electronic components using RGB

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or HSV color spaces [7], [8]. However, many existing approaches focus on controlled environments, single-component detection, or require prior knowledge of component orientation and background conditions.

Commercial and educational software tools for resistor value calculation typically rely on manual input of color sequences, which still requires the user to correctly identify each color band beforehand. Such tools do not eliminate the fundamental challenge of visual interpretation and are unsuitable for automatic processing of images containing multiple resistors [9]. More recent research has investigated machine vision techniques for resistor color band recognition, but many approaches are limited to single-resistor images or fail when resistors are mixed with other components or placed at arbitrary orientations [10]–[12].

In this paper, we propose an automated image-based system for detecting multiple resistors from a single input image, distinguishing them from other electronic components, identifying their color bands, and computing their resistance values without any manual color input. The proposed method employs a sequence of image preprocessing, segmentation, morphological operations, and color thresholding techniques to robustly isolate resistor regions under varying lighting conditions. Orientation-independent band ordering is achieved through spatial analysis of detected color bands, enabling accurate resistance estimation even when resistors are flipped or rotated.

The system is implemented in MATLAB using standard image processing toolbox functions and is integrated with a graphical user interface (GUI) to facilitate ease of use. Experimental results obtained using real-world images demonstrate reliable performance in cluttered environments containing multiple electronic components. While the current implementation relies on rule-based color segmentation, the framework provides a foundation for future extensions incorporating machine learning or deep learning techniques for improved robustness under challenging imaging conditions.

The remainder of this paper is organized as follows. Section II reviews related work on vision-based resistor and component identification. Section III describes the proposed methodology in detail. Section IV presents experimental results and performance evaluation. Section V discusses the limitations of the proposed approach and outlines potential directions for future research, followed by conclusions in Section VI.

II. Related work

Vision-based identification of electronic components has been an active area of research due to its relevance in automated inspection, reverse engineering, and educational applications. Early studies in digital image processing focused on general color-based object detection techniques using RGB and HSV color spaces, where segmentation is performed by thresholding hue and saturation values to isolate target objects under varying illumination conditions [1], [7], [9]. Such techniques have proven effective for basic object recognition tasks but often lack robustness in cluttered environments.

Several researchers have specifically investigated resistor color code recognition using image processing approaches. In [10], a single resistor was detected from a controlled background, and its color bands were extracted using predefined color thresholds. While the method achieved reasonable accuracy, it assumed fixed orientation and uniform lighting, limiting its applicability in real-world scenarios. Similar constraints are observed in other works that rely on isolated component images and minimal background interference [11], [12].

Color segmentation in the HSV color space has been widely adopted for resistor band detection due to its relative invariance to illumination intensity compared to RGB representations [7], [8]. Morphological operations such as erosion, dilation, opening, and closing are commonly applied to refine segmented regions and suppress noise [1], [6]. These methods are effective in enhancing band continuity but often require careful parameter tuning and are sensitive to changes in image quality.

More advanced approaches incorporate feature-based and learning-based methods for electronic component recognition. Shape descriptors, texture features, and region properties have been used to classify components such as resistors, capacitors, and diodes [11], [16]. Recently, machine learning and deep learning techniques, including convolutional neural networks (CNNs), have

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been applied to component classification tasks, demonstrating improved robustness and generalization capabilities [17]–[19]. However, these approaches typically require large labeled datasets and substantial computational resources, which may not be practical for lightweight or educational systems.

Despite these advancements, limited research has addressed the challenge of detecting and identifying multiple resistors simultaneously when they are mixed with heterogeneous electronic components and placed at arbitrary orientations. Many existing systems either assume a single target component or require prior alignment and background separation [10]–[12]. Automatic handling of resistor orientation, particularly distinguishing band order in flipped or rotated configurations, remains an underexplored problem.

The proposed method aims to address these limitations by combining classical image processing techniques, including adaptive preprocessing, morphological filtering, color thresholding, and spatial analysis, to enable robust detection of multiple resistors in a single image. Unlike learning-based approaches, the proposed system does not require training data and is computationally efficient. Furthermore, orientation-independent band sequencing allows accurate resistance estimation even in complex and cluttered environments, providing a practical solution for real-world laboratory applications.

III. Methodolgy

The proposed system follows a structured image processing pipeline designed to detect multiple resistors from a single image, identify their color bands, and compute resistance values accurately under varying environmental conditions. The major stages of the methodology include image acquisition, preprocessing, adaptive structuring, resistor identification, color band detection, orientation handling, and resistance value computation. An overview of the preprocessing stages is illustrated in Fig. 3, while subsequent detection and analysis steps are shown in Figs. 4 and 5.

A. Image Acquisition

RGB images containing resistors and other electronic components are captured using a standard digital camera under real laboratory conditions. The acquired images include a mixture of components such as resistors, capacitors, LEDs, MOSFETs, and integrated devices placed on a uniform background. No constraints are imposed on the orientation or spatial arrangement of the resistors, allowing the system to be evaluated under realistic and unconstrained scenarios. All images used in this work are original and acquired specifically for experimental validation.

B. Preprocessing

The acquired RGB image is initially converted into a grayscale representation to simplify subsequent segmentation operations and reduce computational complexity. Grayscale conversion eliminates color dependency at the early stage while preserving intensity information relevant for component extraction.

A global thresholding technique is then applied to the grayscale image to generate a binary image, separating foreground objects from the background. To enhance segmentation quality, the binary mask is inverted, followed by hole-filling operations to remove internal gaps within detected component regions. Morphological closing using a disk-shaped structuring element is applied to merge fragmented regions and suppress small background artifacts, resulting in well-defined component boundaries.

The complete preprocessing pipeline is illustrated in Fig. 3, showing the transformation from the original RGB image to the final binary masked image.

Figure 3. Preprocessing stages: original RGB image, grayscale conversion, binary masked image.

C. Brightness-Based Structuring

Variations in illumination significantly affect image segmentation performance. To improve robustness under different lighting conditions, the preprocessed image is converted from RGB to HSV color space. The V-channel, representing brightness intensity, is extracted and its average value is computed.

Based on the estimated brightness level, adaptive morphological opening is applied using structuring elements of different sizes. Images with lower brightness levels are processed using larger structuring elements to suppress noise, while images with higher

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brightness require smaller elements to preserve fine details. This adaptive structuring approach ensures consistent segmentation performance across images with uneven lighting and shadow effects.

D. Resistor Indication Among Components

After segmentation, all detected objects are analyzed to identify resistors among other electronic components. Resistors are characterized by a distinctive light brown cylindrical body combined with elongated geometry and colored bands. These features are exploited to distinguish resistors from components such as capacitors, LEDs, and MOSFETs.

Color thresholding is applied to candidate regions to detect the characteristic body color of resistors. Shape-based filtering using region properties further eliminates non-resistor components. Bounding boxes are generated around detected resistor regions and assigned unique identifiers for further processing.

The successful detection of resistors among heterogeneous components is illustrated in Fig. 4.

Figure 4. Detection of resistors among multiple electronic components using color and shape features.

E. Color-Based Detection

Each detected resistor region is cropped from the original image and analyzed independently to detect its color bands. Color masks corresponding to standard resistor band colors (e.g., black, brown, red, orange, yellow, green, blue, violet) are applied sequentially.

For each detected band, spatial features such as centroid location and bounding box dimensions are extracted and stored in a structured data array. This information is later used to determine band order and compute resistance values. Binary masks obtained from different color thresholds enable clear isolation of individual color bands, as shown in Fig. 5.

Figure 5. Color band extraction using individual color masks for resistance calculation.

F. Orientation Handling

Resistors may appear in horizontal, vertical, or arbitrarily rotated orientations, including flipped configurations. To ensure correct band sequencing, the spatial positions of detected color bands are analyzed relative to the resistor body dimensions.

By comparing centroid coordinates and bounding box positions, the algorithm determines the correct reading direction of the color bands. This spatial analysis enables orientation-independent band ordering, ensuring accurate resistance estimation regardless of how the resistor is placed within the image.

G. Resistance Value Calculation

Once the correct order of color bands is established, resistance values are computed according to the standard resistor color code formula. For a four-band resistor, the resistance value is calculated as

$$R = (10D_1 + D_2) * 10^M$$

where D_1 and D_2 represent the numerical values of the first and second significant digit bands, respectively, and M denotes the multiplier band value. The calculated resistance values are expressed in ohms (Ω) and associated with their corresponding resistor identifiers for output visualization.

IV. Experimntal and Performance Evalution

The proposed system was evaluated using a set of test images containing varying numbers of resistors placed among other electronic components such as LEDs, capacitors, transistors, and integrated devices. The images were captured under real laboratory conditions with no constraints on resistor orientation, spacing, or placement. This evaluation setup was chosen to assess the robustness of the proposed approach under practical and unconstrained scenarios.

The system successfully detected resistor regions, distinguished them from non-resistor components, and accurately computed resistance values based on detected color bands. Fig. 6 illustrates a representative output of the system, where detected resistors are automatically identified and their corresponding resistance values are displayed.

Figure 6. Final output showing detected resistors and their computed resistance values.

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H. Accuracy Evaluation

To quantitatively evaluate the performance of the proposed method, the detected resistance values were compared with the actual resistor values determined using standard color code interpretation. Table I presents a comparison between the actual resistance values and those obtained using the proposed image processing approach.

Table I Comparison of Actual and Detected Resistor Values

Resistor No.	Actual Value (Ω)	Detected Value (Ω)	Error (%)
1	1000	1000	0.0
2	220	220	0.0
3	4700	4700	0.0

The experimental results indicate that the proposed system achieved correct resistance estimation for all tested resistors, yielding a percentage error of 0% for the evaluated samples. Accurate results were consistently obtained across different resistor orientations, including horizontal, vertical, and rotated placements, demonstrating the effectiveness of the orientation-handling mechanism.

I. Robustness Analysis

The system demonstrated robustness against moderate variations in illumination and shadow conditions due to the use of adaptive preprocessing and brightness-based structuring. The HSV color space representation and morphological operations contributed to stable color band detection under non-uniform lighting environments.

However, failure cases were observed when images were acquired using low-quality webcam sensors with poor resolution and significant noise. In such cases, color band boundaries became indistinct, leading to incomplete band detection. These limitations highlight the dependency of the proposed approach on input image quality, particularly for accurate color segmentation.

J. Discussion of Results

The obtained results confirm that classical image processing techniques, when properly combined with adaptive preprocessing and spatial analysis, can provide reliable performance for multi-resistor detection without the need for training data. Compared to manual resistor identification, the proposed system significantly reduces human effort while maintaining high accuracy.

Although the experimental dataset was limited in size, the consistency of correct resistance estimation across multiple images demonstrates the feasibility of the proposed approach for practical laboratory applications. The results also establish a baseline for future enhancements using learning-based methods to further improve robustness under challenging imaging conditions.

V. Discussion

The experimental results presented in the previous section demonstrate the effectiveness of the proposed image processing–based approach for automatic detection and resistance value estimation of multiple resistors. The system consistently identified resistors among heterogeneous electronic components and produced accurate resistance values under varying orientations and moderate lighting conditions. These findings validate the design choices made in the preprocessing, segmentation, and color band analysis stages.

One of the key strengths of the proposed method is the use of adaptive morphological processing guided by brightness estimation in the HSV color space. This strategy enables improved robustness against illumination variations and shadow effects, which are common challenges in real-world imaging environments. Unlike fixed-parameter segmentation techniques, the adaptive structuring mechanism allows the system to maintain stable performance across images with different brightness levels.

Orientation-independent band ordering represents another significant advantage of the proposed approach. By analyzing the spatial arrangement of detected color bands rather than assuming a predefined orientation, the system accurately determines band sequences for resistors placed horizontally, vertically, or at arbitrary angles. This capability addresses a major limitation of several existing methods, which often require controlled placement or manual alignment of components prior to analysis.

Despite its advantages, the proposed system exhibits certain limitations. The accuracy of color band detection is inherently dependent

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on input image quality. Images captured using low-resolution or noisy webcam sensors may result in blurred band boundaries, reduced color contrast, and inaccurate segmentation. Extremely poor lighting conditions or severe shadows can also affect the reliability of color thresholding, leading to incomplete or incorrect band detection. These limitations suggest that image acquisition quality remains a critical factor for system performance.

Furthermore, the current implementation relies on rule-based color segmentation and predefined thresholds, which may require fine-tuning when applied to significantly different imaging environments or resistor types. While this approach offers computational efficiency and eliminates the need for training data, it may be less adaptable compared to learning-based techniques when dealing with complex backgrounds or unconventional resistor appearances.

Overall, the discussion highlights that the proposed system provides a practical and efficient solution for automated multi-resistor detection in laboratory and educational settings. The observed limitations also motivate future enhancements, including the integration of machine learning–based color classification, improved noise handling, and real-time image acquisition support, which are discussed in the following section.

VI. Conculesion and Future work

This paper presented an automated image processing–based system for detecting multiple resistors and estimating their resistance values directly from images without requiring manual color input. The proposed approach combines preprocessing, adaptive morphological operations, color-based segmentation, and spatial analysis to robustly identify resistors and their corresponding color bands in images containing heterogeneous electronic components. The system is capable of handling arbitrary resistor orientations, including rotated and flipped configurations, and demonstrates reliable performance under realistic laboratory conditions.

Experimental results obtained using real-world images confirm that the proposed method accurately detects resistor regions and computes resistance values with high precision. The use of brightness-aware preprocessing and orientation-independent band sequencing significantly enhances robustness against illumination variations and placement irregularities. Unlike learning-based approaches, the proposed system does not require training data, making it computationally efficient and well suited for educational and low-resource environments.

Despite its effectiveness, the performance of the system is influenced by input image quality, particularly in scenarios involving low-resolution sensors or severe lighting degradation. These limitations indicate opportunities for further enhancement and motivate future research directions.

Future work will focus on integrating machine learning–based color classification techniques to improve robustness under challenging imaging conditions and reduce dependency on manually defined color thresholds. The incorporation of deep learning models, such as convolutional neural networks, may further enhance component discrimination and color band recognition in complex backgrounds. Additionally, extending the system to support real-time detection using webcam inputs and deploying the framework on mobile or embedded platforms represent promising avenues for practical implementation. Such enhancements would enable broader applicability in automated inspection systems, smart laboratory tools, and assistive educational technologies.

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