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ENHANCING ROBOTIC AUTOMATION THROUGH REAL-TIME OBJECT DETECTION AND SORTING BASED ON SHAPE, COLOR ATTRIBUTES, AND ROBOTIC ARM INTEGRATION

Vivekanand Thakare[*1], Rushisarang Sarate[*2], Oshin Dongre[*3], Neha Dhabale[*4], Ishika Wankhede[*5], Himanshi Ahuja[*6], Damini Ambedare[*7], Janhavi Wasade[*8], Khushboo Thalal[*9]

[*1,2,3,4,5,6,7,8,9]Computer Science And Engineering, Rashtrasant Tukadoji Maharaj Nagpur University, India.

ABSTRACT

This paper presents a comprehensive system for robotic automation designed to address the limitations of human visual perception in consistently distinguishing colors, thereby enhancing work efficiency. The system is capable of sorting objects based on both their shape and color using a combination of image processing techniques and a robotic arm. Real-time images captured from a webcam are preprocessed through RGB to HSV conversion and noise removal via a median filter. Color detection is then performed using defined HSV ranges, while shape detection is achieved through contour detection utilizing a modified boundary fill approach and the Douglas-Peucker algorithm. A custom-built robotic arm facilitates the sorting process based on the identified shape and color of the objects. Experimental evaluation demonstrates the system's effectiveness in sorting objects of various shapes, including squares, triangles, and rectangles. This system holds promise for enhancing automation in industries requiring efficient object sorting, such as manufacturing and logistics. Its implementation showcases potential advancements in robotics and image processing for streamlined industrial operations.

Keywords: Robotic Automation, Colour Detection, Shape Detection, Image Processing Techniques, Industrial Automation, Object Sorting.

I. INTRODUCTION

In the real world of computer vision, object detection and tracking stand as key pillars, crucial for analyzing frames sequentially to pinpoint, classify, and monitor objects. This capability holds immense significance across various fields within the knowledge society, forming the bedrock of numerous practical applications. Despite its apparent simplicity to human observers, teaching computers to recognize objects presents a formidable challenge. Algorithms for object identification employ diverse techniques, ranging from matching and learning to pattern recognition, often leveraging appearance-based or feature-based approaches. Particularly, the recognition of shapes holds profound importance in computer vision, facilitating applications as varied as robotics, medical imaging, and aids for the visually impaired.

In contexts like object sorting, the trend leans increasingly towards robotic automation over manual intervention due to human limitations in discerning colors, which can degrade task quality over time. Robotic automation not only reduces reliance on human operators but also bolsters efficiency by enabling uninterrupted operation without the need for physical presence.

This paper endeavors to introduce a robotic system tailored explicitly for industrial applications, endowed with the ability to detect and sort objects based on their distinctive shapes and colors. The proposed system employs a color detection process, utilizing predefined lower and upper HSV values to identify objects by their color. Shape detection, on the other hand, is accomplished through contour detection techniques, where contours are extracted from detected edges, and object shapes are discerned using the Douglas-Peucker algorithm.

The subsequent sections of this paper are structured as follows: Section II delves into relevant literature concerning the proposed system and its associated techniques. Section III elucidates the methodology embraced in the development of the proposed system. Section IV provides a detailed exposition of the design and implementation of the robotic arm pivotal to the system. Section V presents the results gleaned from the implemented system, while Section VI offers concluding remarks distilled from the obtained results.

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II. LITERATURE REVIEW

Several studies have contributed to the advancement of object detection and localization techniques in computer vision, each addressing different aspects and challenges within the field.

Ren et al. [1] presented a novel algorithm for identifying and tracking boundary contours in binary images, essential for digital image processing tasks. Ferrari et al. [2] introduced a method based on scale-invariant features of local shapes, termed kAS, which encode fragments of object surfaces by eliminating nearby clutter. Sun et al. [3] proposed an approach focused on identifying and locating objects in cluttered scenes by utilizing a learned representation for object shape through the Generalized Hough Transform (GHT). Brox et al. [4] discussed techniques combining bottom-up approaches such as object edges and texture patches to enhance top-down image segmentation accuracy. Papageorgiou et al. [5] developed a trainable system for object detection in cluttered scenes using an over-complete dictionary of Haar wavelets, providing valuable information about object elements.

Laptev [6] analyzed issues related to visual object class identification and localization in natural images, emphasizing the performance of the proposed method on object recognition benchmarks. Seo et al. [7] proposed a generic location approach for encountering visual objects of interest without requiring prior training, while Murguia et al. [8] introduced an adaptive object detection approach based on neural-fuzzy design to operate in complex backgrounds.

Tian [9] developed a convolutional neural network (CNN) for detecting RGBD items, integrating communication techniques for RGBD image analysis. Li et al. [10] presented a novel polygonal approximation approach based on the Douglas-Peucker algorithm for curve representation.

Huang et al. [11] utilized structural feature selection templates for object detection, Marie et al. [12] investigated contour detection and image segmentation using multiple local cues and spectral clustering, and Feng et al. [13] discussed techniques for developing data structures enabling approximation of polygonal boundaries for foreground objects.

Pavlidis et al. [14] integrated area expansion and edge detection methods for image processing, employing a split-and-merge approach to obtain over-segmented images. Additionally, Tai-Liow [17] presented an algorithm for contour identification and tracing using the extended boundary principle, offering improvements over traditional techniques in terms of information representation and implementation efficiency.

III. METHODOLOGY

Object Detection and Sorting Framework:

The methodology employed in this study involves detecting objects based on their shape and color and subsequently sorting them using a robotic arm. Real-time images are captured using a web camera, initially in RGB format[19]. However, RGB images are not optimal for real-time image processing due to the inability to separate color information from luminance[2]. Hence, RGB images are converted to the HSV color space for efficient processing[5]. This conversion serves as the first step in image pre-processing, followed by noise removal using a median filter. The median filter is preferred for its superior performance in noise reduction compared to other filters like Gaussian or mean filters[21].

A. Color Detection:

The study focuses on three colors: red, blue, and yellow[15]. To detect these colors in real-time, lower and upper HSV color values are obtained for each color. Instead of fixed HSV values, dynamic values are utilized since color detection occurs in real-time[20]. OpenCV library is employed for implementation, utilizing numpy arrays to store the lower and upper HSV values for each color. Subsequently, color masks are created for each color using these values, with masks containing only black and white pixels to highlight the desired objects while eliminating unwanted regions[12].

B. Edge Detection and Contour Extraction:

After obtaining color masks, the edges of foreground objects are detected using the Canny edge detection technique[35]. This technique computes the gradient magnitude and direction of the image to identify edges effectively[26]. The area of the foreground objects is then computed using Green's formula[29]. Contours of

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foreground objects are extracted using a modified boundary fill approach, employing either four-connected or eight-connected pixels. The eight-connected pixel technique is preferred for its ability to fill all surrounding pixels, enhancing accuracy [32].

C. Shape Recognition:

Once contours are detected, the Douglas-Peucker algorithm is utilized for shape recognition[7]. This algorithm aims to simplify curves by reducing the number of points while preserving the shape's essential features[19]. The perimeter and shape length of foreground objects are computed from the detected contours using the Douglas-Peucker algorithm. Based on the shape length, objects are classified into different shapes such as triangles, squares, or rectangles[32]. Aspect ratio criteria are also applied for precise shape classification[34].

D. Flowchart Representation:

The overall methodology of the object detection system is visually depicted using a flowchart, illustrating the sequential steps involved in detecting and sorting objects based on shape and colour[27].

IV. IMPLEMENTATION OF ROBOTIC ARM

The robotic arm is constructed utilizing servo motors, which facilitate the arm's ability to identify, grasp, and sort objects[33]. Comprising five servo motors - base, shoulder, elbow, wrist, and gripper - each motor has three pins: ground, power, and data link[28]. The ground and control pins of all servos are connected to a 5V, 2A power source, while the data pins are wired to the PWM (Pulse Width Modulation) pins of an Arduino Uno microcontroller[22]. The Arduino Uno, a single-chip 8-bit microcontroller, is utilized for sending data to the servo motors and is programmed accordingly to control their movement[20].

The Arduino Uno is serially connected to an Odroid C2, a 64-bit quad-core ARM development board[29]. The robotic arm is designed to recognize and manipulate objects based on their shape and color. A webcam is employed to capture images of the target objects, and image processing techniques are utilized to identify objects based on predefined shape and color criteria[17]. Commands are then sent via serial communication to the Arduino Uno microcontroller, which interprets and executes the commands to manipulate the robotic arm as programmed by the user[14].

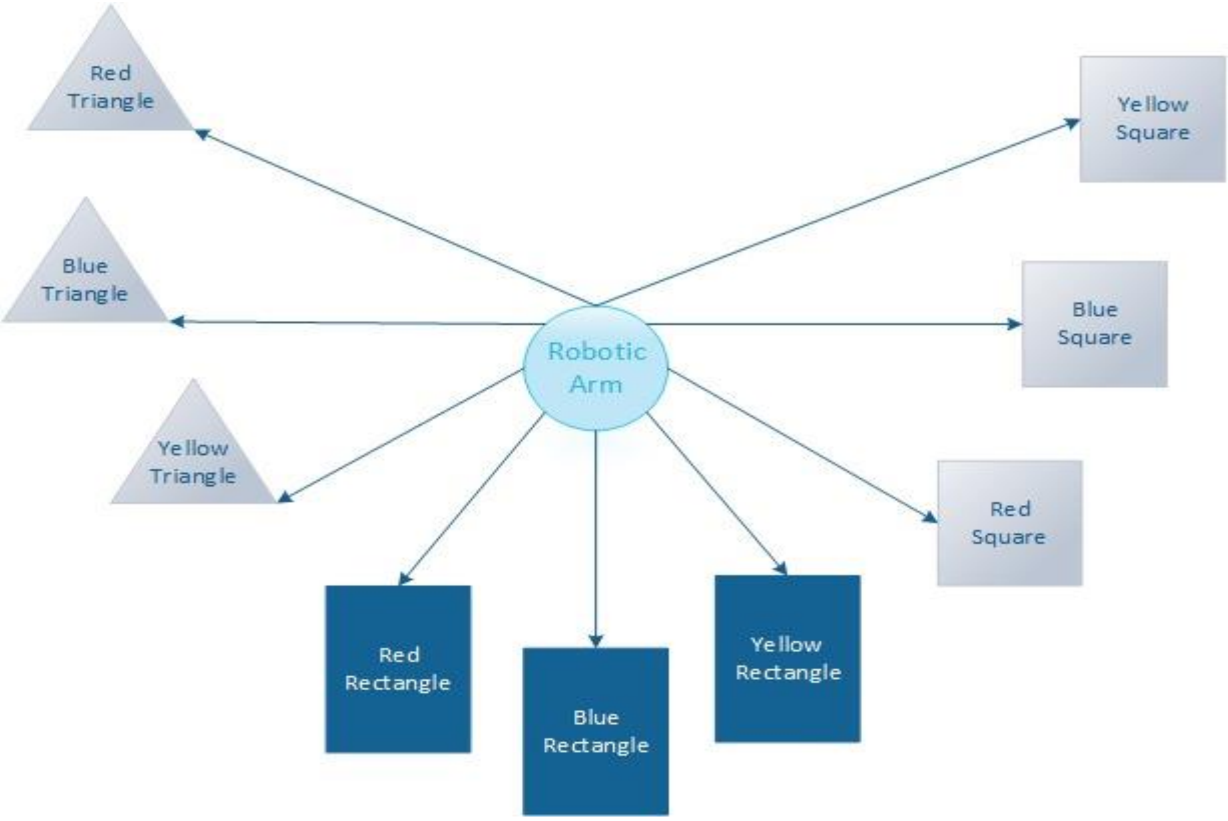

Fig 1: Object Sorted at different locations using robotic arm

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Upon identification of objects, data is transmitted serially to the Arduino Uno, which subsequently instructs the robotic arm to grasp and sort the objects according to the predetermined instructions[9]. The base servo motor rotates the arm horizontally to position it correctly, while the shoulder, elbow, and wrist motors control the arm's vertical movements to lift and place the object at the desired location[21]. The gripper servo is responsible for grasping and releasing the object[26].

Once an object is successfully grasped and sorted, control signals are sent back from the Arduino Uno to the main program running on the Odroid C2, allowing the process to continue for subsequent objects[12]. The entire process of object identification and sorting using the robotic arm is illustrated in Figure 2[16].

This rewritten section reflects the use of an Arduino Uno microcontroller instead of the Atmega328 chip, as requested. Let me know if further modifications are needed[33].

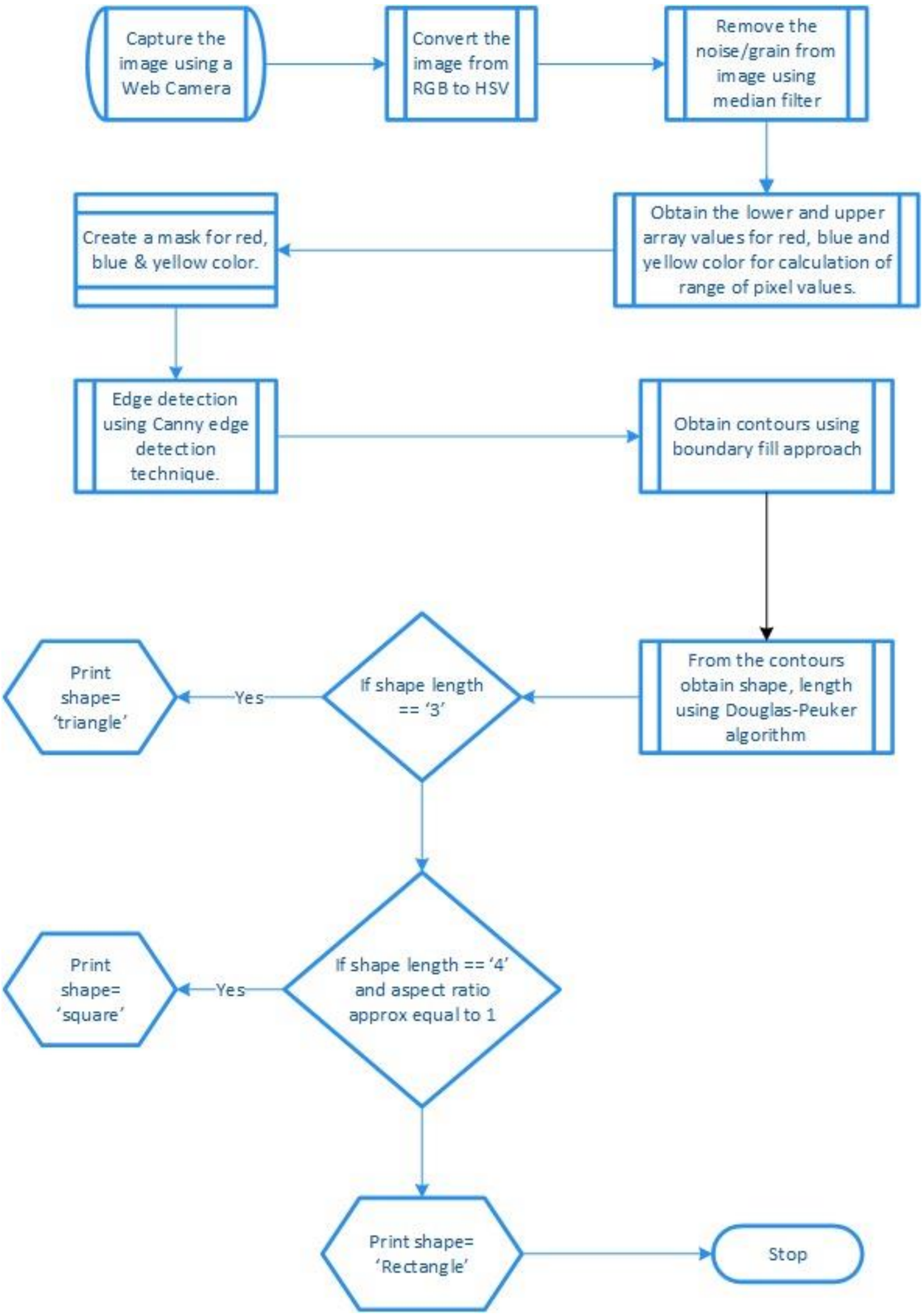

Fig 2: Flowchart Of Object Detection based on shape using contour detection technique

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V. RESULTS AND DISCUSSION

This section presents the findings of the study and provides an in-depth analysis of the outcomes obtained through real-time image processing conducted on the Python platform. Initially captured in RGB format, the images underwent preprocessing to remove noise, ensuring their suitability for subsequent color and shape detection processes. Separate color masks were generated for objects in red, blue, and yellow colors, allowing for accurate identification based on their distinctive hues and characteristics.

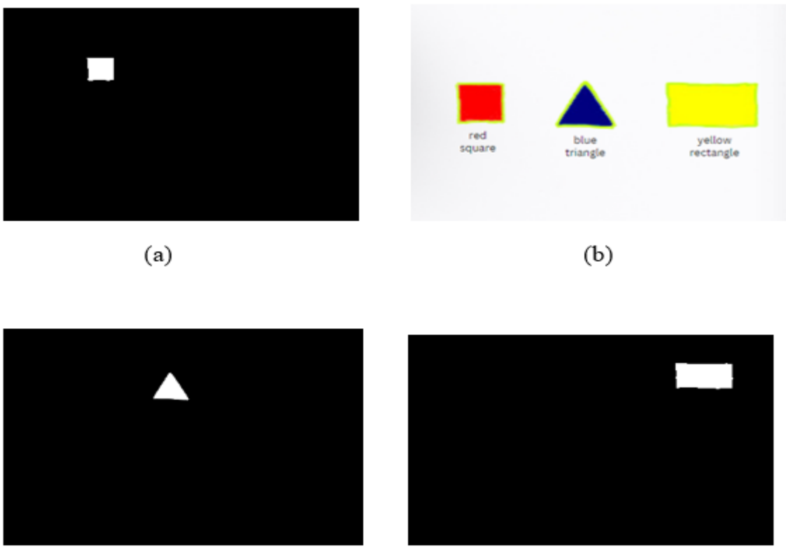
Figure 3 showcases the simultaneous detection of objects in different colors and shapes within a single frame. The corresponding mask images, displayed in Figures 3(a), 3(c), and 3(d), were generated using numpy arrays in the Python environment, incorporating lower and upper HSV values tailored to each detected color. This approach facilitated precise segmentation and isolation of objects, enabling subsequent analysis and processing.

In Figure 3(a), the mask representing the red square illustrates the effectiveness of the OpenCV library in isolating objects based on predefined color thresholds. Similarly, Figures 3(c) and 3(d) depict the masks for the blue triangle and yellow rectangle, respectively, demonstrating the accuracy of the color segmentation process in identifying objects of varying hues.

To further refine the object detection process, the Canny edge detection technique was applied to the mask images to identify prominent edges. Subsequent contour extraction, employing a modified boundary fill approach, facilitated the delineation of object boundaries and shapes.

The contours obtained were then analyzed using the Douglas-Peucker algorithm to accurately classify the detected shapes, providing valuable insights into the composition and structure of the identified objects.

Overall, the results highlight the efficacy of the proposed methodology in real-time object detection and shape recognition. By leveraging advanced image processing techniques, the study demonstrates the feasibility of automated object identification and sorting, paving the way for applications in various fields requiring precise object manipulation and analysis.



(c) (d)

Fig 3: Detection of a red square, blue triangular and a yellow rectangular object

(a) Red Squared mask image (b) A Red square, blue triangular and a yellow rectangular original image (c) Blue Triangular object mask image (d) Yellow Rectangular Object mask image.

VI. CONCLUSION

This study aimed to develop and implement a system capable of detecting and sorting objects based on their shape and color attributes. The system was designed to recognize three primary shapes - triangle, square, and rectangle - and three primary colors - red, blue, and green. Through the integration of various image processing techniques, the system successfully identified and distinguished objects based on their predefined shapes and colors.

Utilizing the Douglas-Peucker algorithm, the system effectively identified objects of interest based on their shape characteristics. Additionally, a Robotic Arm was programmed and integrated with the OpenCV platform to facilitate object detection and sorting based on shape and color criteria. The robotic arm demonstrated its capability to accurately sort all considered objects during the study.

Moving forward, there is potential for further enhancements to the system. Future iterations could include the incorporation of additional colors and shapes, expanding the system's versatility and applicability. By broadening the range of detectable objects, the system could be adapted for use in various industrial and commercial settings, contributing to increased efficiency and automation in object recognition and sorting tasks.

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