Indonesian Journal of Electrical Engineering and Computer Science
Vol. 36, No. 3, December 2024, pp. 1807~1815
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v36.i3.pp1807-1815

Colour sorting ROS-based robot evaluation under different lights and camera angles

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Article Info

Article history:

Received Jan 3, 2024
Revised Aug 23, 2024
Accepted Aug 31, 2024

Keywords:

Colour sorting
Diameter estimation
Image processing
Mobile robot
Welzl's algorithm

ABSTRACT

Automated colour sorting, aided by mobile robots, is widely prevalent in the current manufacturing industry. Obstacles, such as fluctuating light conditions and camera angles, frequently hinder this procedure. Creating a colour sorting robot is a complex and time-consuming task, especially due to the vulnerability of the RGB colour space to detection errors in extreme brightness or darkness. In response to these concerns, we introduce a mobile robot that operates on the robot operating system (ROS) platform and incorporates OpenCV. This robot employs the hue, saturation, and value (HSV) colour space model for its image processing capabilities in recognising the colours and Welzl's algorithm for the ball's diameter estimation. The robot's performance was assessed across various luminous fluxes and camera tilt angles. It demonstrated exceptional performance at 64 lm and a tilt angle of 40 degrees, achieving an average accuracy of 87.5% for detecting the colour of the ball, and 81.25% for determining its location based on colour. For the ball's diameter estimation, it was found that the best estimation was received at 64 lm and 30 degrees, with both 96.32%.

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1. INTRODUCTION

Colour-coding is hard and it is a lengthy process that is prone to human mistakes, lowering product quality and efficiency [1]. Automatic colour sorting boosts efficiency and accuracy [2]. Excellent colour sensors and algorithms reduce human error [3], and strong colour sensors let the robots detect colours [4] in various applications. These sensors filter data instantly utilising strong real-time analysis [5]. Hand sorting is slower and less accurate than computers. New automated sorting algorithms enhance accuracy and enable new applications. Automation makes colour sorting harder but faster and more precise. Lighting [6] and camera position on sorted items [7] affect colour detection. Both impact sorting reliability and efficiency by affecting colour recognition accuracy. Camera colour interpretation changes with light [8], [9]. Harsh illumination can fade or intensify colours [10]. Moreover, poor lighting causes the colour to darken. Sorting and camera angle also affect the light source during colour detection. Furthermore, camera colour can change with surface reflections [11] from the angles of incidence and reflection [12]. In addition, the position of the camera also affects the shadow of the colour [13]. Camera angles that collect shadows from surrounding objects or structures may make darker areas appear distinct or unevenly coloured.

Most colour identification systems employ RGB, which most automatic colour sorting cannot handle the assisted problems. Light affects RGB digital photography and its processing [14], which misinterprets the difference between light and dark colour perception [15]. RGB measures colour intensity, but not its brightness [16]. Unfortunately, environmental lighting misidentifies the items' colour and inaccurately sorts them. On the bright side, the hue, saturation, and value (HSV) distinguishes hue from illumination intensity [17] in colour operating systems. This separation recognises colours without light and shadow in uneven lighting. HSV adapts better to changing illumination since hue provides colour type, saturation, and value brightness [18]. On another note, the colour spaces can alter the size estimation of an object. The RGB paradigm does not discriminate colour from brightness, making object edges hard to see in different lighting. In Industrial quality control and agriculture grading, edge detection and size estimation are affected by light. Transitioning from RGB to HSV for size estimation is not difficult. Calibrating the colour detector and converting the RGB to HSV colour space without losing detail in calculating the object size. HSV identifies edges in different lighting, although direct sunlight or darkness may distort hue and saturation. HSV separates colour from illumination intensity, however, its application in extreme conditions is uncertain. Unknown room-light HSV performance without artificial lighting. Like colour identification, formation detection fails. Colour space selection affects shape correctness in colour-and-form sorting algorithms.

Therefore, research on how colour spaces affect object edge and contour identification in different lighting conditions could improve object classification. Ambient lighting and camera position in automatic colour sorters were examined. This examined how these components affect colour identification and object size estimates, critical to colour sorting robot performance. We tested the HSV colour space's fundamental constraints in diverse lighting. For accuracy, the HSV colour sorting was used in this work.

2. PREVIOUS WORK ON COLOUR SORTING ROBOT

Innovative automatic colour sorting uses multiple approaches and technologies. Comparisons provide colour sorting system precision, efficiency, and applicability improvements. Arduino UNO supports colour-based control system development with TCS3200D and TCS34725 [19]-[21]. For reliable colour identification, the TCS34725 colour sensor has an IR blocking filter [22]. The complete process included robotic system setup and debugging, although robotic arms were effective for colour-based sorting [23]. This comparison highlights the monitored object to contrast broad system development with smart, sensor-based sorting. Another novel colour sorting system uses an Arduino Uno and colour sensor. The 16.7 million-colour sensor outputs 8-bit RGB data for each basic colour. Decomposing colours into RGB sorts them [24].

MATLAB colour-codes conveyor belt images from webcams [25] with the issue between HSV and RGB colour processing. They successfully claim that HSV is better at detecting colours under changing lighting, however a more extensive investigation comparing HSV to RGB in diverse industrial scenarios would strengthen this case. The HSV model's enhanced colour description at varying brightness levels converts RGB photos to HSV, which erosion and dilution improve the HSV threshold colour identification. Image processing with a pick-and-place robotic gripper enables colour and shape-based industrial sorting [26]. To improve image colour and brightness in agriculture machine vision systems with variable outdoor lighting, overcurrent-driven LEDs have been tested [27]. The authors propose an active illumination camera system for sunlight, vehicle motion blur, and ground vibrations. Six times their usual LEDs provide a bright flash synced with a camera to improve daylight photos. LED strobes improve apple orchard shots under shifting lighting. HSV channel standard deviation is 85% lower with LED flashes than with auto-exposure settings, enhancing colour uniformity and brightness. Finally, sensor integration, real-time picture processing, and inventive environmental lighting solutions enable automatic colour sorting. These findings demonstrate that existing technologies can enhance industrial sorting and expand research.

3. METHOD

3.1. ROS nodes for colour processing operation

This work uses ROS packages cv_bridge, usb_cam, and ros_arduino_python on a Bveeta mini mobile robot as shown in Figure 1. The cv_bridge connects ROS with OpenCV, allowing easy switching [28]. Alternatively, the usb_cam package is used to link a web camera to a ROS-based mobile robot to capture and publish images as ROS image topics, /usb_cam/image_raw. ROS's ros_arduino_python module facilitates Python-based Arduino-ROS communication. Through the /cmd_vel topic, users can link Arduino-based hardware to ROS, making it easy to integrate robotic systems or sensors like the DC Motor in this project [29].

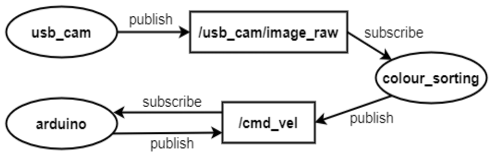


Figure 1. Relationship between ROS nodes and topic for colour processing operation

3.2. Ball's colour detection and diameter estimation techniques

Colour thresholding calculates image frame track area % for ball and track colours. RGB-to-HSV conversion in this work. HSV thresholds distinguish yellow, blue, red, and green. To compute robot forward speed, use the ball centroid. Image-coloured ball percentage changes with binary conversion. Use the same method to calculate the drop position and area after colour determination. The robot moves unless that area is 50% of the frame, then the ball is released. Edge detection in image processing determines ball diameter. Identifies the image's ball perimeter. Pre-edge detection HSV is binary. Contrasting ball and backdrop colours help spot edges. Figure 2 shows how canny edge detection extracts the spherical border. Making all perimeter points a continuous line generates a circular shape that improves edge recognition. Welzl's algorithm finds the ball's diameter by randomly selecting contour points recursively. These points determine the circle's center and radius based on the triangle formed. In (1) calculates the triangle's radius using the lengths of its sides, represented by |AB|, |BC|, and |CA|.

$$radius = \frac{(|AB| x\ |BC| x\ |CA|)}{4\ x\ (Area\ triangle)} \quad (1)$$

In (2) calculates the ball diameter. However, this method determines the ball's diameter in pixels. To calculate the diameter in centimeters, multiply the diameter in pixels by 0.0264583333, as each pixel equals 0.0264583333 centimeters.

$$diameter\ (pixels) = radius\ x\ 2 \quad (2)$$

$$diameter\ (cm) = radius\ x\ 0.0264583333 \quad (3)$$

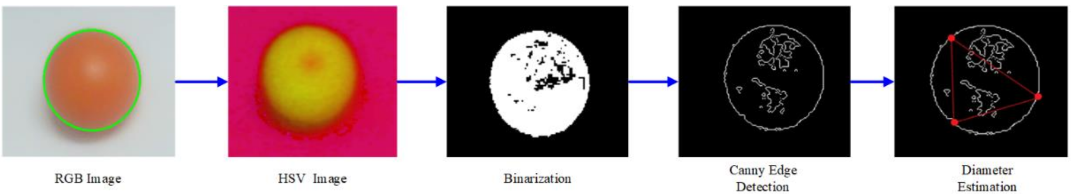
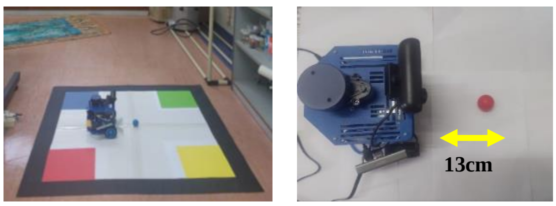


Figure 2. The ball diameter estimation based on the triangle method from the extracted edge of it in an image

3.3. Experimental setup

This study's experimental setup is shown in Figure 3. The study has a 105 cm×105 cm colour sorting track as shown in Figure 3(a). Yellow, blue, red, and green 25 cm×25 cm square boxes are attached to track corners. A 247cm-away ceiling light illuminates. The webcam's depth measuring constraints force a 13 cm spacing between the ball and robot in Figure 3(b). Two experiments test the mobile robot's colour sorting. The first tests colour detection at 43, 51, and 64 lm. Figure 4 shows the robot's webcam tilt angles of 30, 40, and 60 degrees. This study uses 307,200 pixels in each video frame.



(a) (b)

Figure 3. The experimental setup is (a) colour recognition was done on track and (b) a fixed 13 cm distance from the Bveeta mini mobile robot for diameter

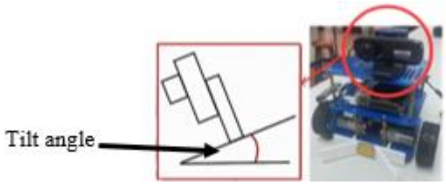


Figure 4. The tilt angle of the web camera that is attached to the mobile robot

4. RESULTS

The information presented in Table 1 demonstrates the complex relationship that exists between light flux and the colour sorting mobile robot’s capabilities in three different areas: colour identification, track boundary identification, and final location determination. The diversity in performance measures among various levels of luminous flux (43 lm, 51 lm, and 64 lm) and varied colours (red, yellow, blue, and green) offers a comprehensive dataset for analysis.

Table 1. Performance of the sorting colour mobile robot under different luminous flux effects

Luminous flux (lm)	Colour	Determine the ball’s colour (%)	Recognize the track’s border (%)	Determine the correct final location (%)
43	Red	100	75	75
	Yellow	100	100	100
	Blue	75	25	25
	Green	100	75	75
51	Red	100	100	75
	Yellow	100	100	50
	Blue	75	75	50
	Green	75	75	75
64	Red	100	100	100
	Yellow	75	100	75
	Blue	100	75	75
	Green	75	100	75

The robot detects red and yellow balls 100% at 43 lm light flux. However, its blue detection drops to 75%, showing that distinguishing hues with decreasing light intensity may be difficult. Only 25% of blue balls are on the track. Blue objects may need more light to classify. It can better recognize the track border and forecast the end position for most colours at 51 lm, with few exceptions. It recognizes red and yellow 100% of the time, but blue at 75%. Colour accuracy lowers to 75% for green drops, while end location accuracy improves. More light enhances performance, however, colour sensitivity and calibration need work. At 64 light meters, the red object final location detection is 100%. Unlike typical, yellow colour identification accuracy declines to 75% under lower light flux. This may suggest oversaturation or computational constraints for high-brightness colour.

Robotic colour sorting requires proper illumination because luminous flux influences robot sorting. variable colours, jobs, and lighting conditions have variable success rates, showing a complicated interaction between light output, sensor calibration, and algorithms. The system needs algorithmic or sensor sensitivity changes to recognize and categorize blue colours in all lighting conditions. Rising bright flux reduces yellow balls’ colour determination success rate, which helps improve lighting adaption. Dynamic sorting can fix these issues. The mechanism adapts to the current luminous flux. Results suggest mobile robots may automatically categorize colours in varied circumstances. But thriving across colours and careers is hard. Mobile robots’ colour perception with different light fluxes is shown in Table 2. Examine 43, 51, and 64 lm light flux. The average destination pixel count and percentages for red, yellow, blue, and green are analyzed. This study exposes the system’s colour sorting and light responsiveness.

Colour detection rates fluctuate a little at 43 lm, indicating the system can differentiate colours in weak circumstances. Low lighting degrades the system’s colour identification and processing, as demonstrated by lower destination pixel percentages. Green is seen more often, suggesting system bias or low-light green spectrum sensitivity. The 51 lm light flux helps all colour identification, especially blue and green. This improvement emphasizes colour data collecting and analysis illumination. Moderate lighting improves the system’s sensors and algorithms’ detection rates. All colours look better at 64 lm, but green stands out. This illustrates that appropriate lighting enhances system performance and colour processing. Colour identification increases with luminous flux, underscoring lighting’s role in automatic sorting. Table 3 illustrates webcam tilt effects photos. Table 3 shows the camera tilt angle for 64 lm of luminous flux. This table shows colour recognition accuracy is best at 40–60 degrees. At 40 degrees, the robot detects red, blue, and yellow/green balls 100% and 75% accurately. The technique finds red balls 100% and yellow, green, and blue 75%.

Table 2. Performance of the detected pixels by the mobile robot under different luminous flux effects

Luminous flux (lm)	Colour	Average destination pixels detected	Average destination pixels percentage (%)
43	Red	98500	32.06
	Yellow	101087	32.91
	Blue	98286	31.99
	Green	106335	34.61
51	Red	111800	36.39
	Yellow	105069	34.20
	Blue	113079	36.81
	Green	108924	35.46
64	Red	148906	48.47
	Yellow	149725	48.74
	Blue	139869	45.53
	Green	157376	51.23

Table 3. The performance of the sorting colour mobile robot under different camera's tilt angle

Camera's tilt angle (°)	Colour	Determine the ball's colour (%)	Recognize the track's border (%)	Determine the correct ball's location (%)
30	Red	100	100	50
	Yellow	100	100	50
	Blue	75	0	0
	Green	100	75	75
40	Red	100	100	100
	Yellow	75	100	75
	Blue	100	75	75
	Green	75	100	75
60	Red	100	100	100
	Yellow	75	100	75
	Blue	100	25	25
	Green	100	100	100

At 60 degrees, the robot identifies red, green, and blue balls 100% but only 75% of yellow balls. Red and green balls are completely aligned, however yellow and blue are 75% and 25% off. At 30 degrees, the robot recognizes red, yellow, and green balls 100% but only 75% blue balls. Green ball location accuracy drops to 75%, red and yellow to 50%, and blue to 0%. These data demonstrate how camera angle affects robot sorting colour recognition. Sorting requires camera colour recognition, which is affected by observation angle. Colours can be distorted by severe camera tilt. Occlusion is reduced by camera angle, enhancing sorting. Successful colour-sorting robots need the best camera angle to detect colours properly and reduce errors. Shadows from excessive camera tilt affect image capture and colour sensitivity. Low tilts cast shadows, darkening the image, while small tilts reduce the detected item to fewer pixels. Camera tilt angles affect mobile robot colour identification in automatic sorting as shown in Table 4. A comprehensive analysis of colour identification efficiency at 30°, 40°, and 60° tilt angles optimizes camera location for sorting accuracy. These findings matter because a 40° camera tilt increases colour detection. Correct angles eliminate shadows, increase lighting, and capture object colours. Automatic sorters must balance camera angle, lighting, and item visibility.

Table 4 Total number of pixels successfully detected by the mobile robot under different camera tilt angles

Camera's tilt angle (°)	Colour	Average destination pixels	Average destination pixels percentage (%)
30	Red	100601	32.75
	Yellow	115779	37.69
	Blue	109887	35.77
	Green	116331	37.87
40	Red	148906	48.47
	Yellow	149725	48.74
	Blue	139869	45.53
	Green	157376	51.23
60	Red	124407	40.50
	Yellow	113999	37.11
	Blue	133373	43.42
	Green	109097	35.51

Data indicate camera tilt. More shadows and a less direct line of sight to objects may affect 30° tilt colour identification. The 60° tilt angle increases vision but distorts colours and dims objects. Angles of camera tilt alter colour perception. Because colours interact with light and shadow at different angles, statistics imply colour matters for detection. The camera's green pixel identification rises at 30°-40° and drops at 60°. The angle of the camera affects colour recognition. Results indicate key automated sorting system design and implementation variables. Different operational conditions require dynamics system camera angle modification for accuracy. Angle-induced colour detection variability reduction approaches are promising and warrant study. Changing detection parameters using real-time camera orientation analysis may help. Uncertain industrial conditions hurt automated sorting. Camera tilt angles must be precise for colour detection. Real-world robotic systems use colour interpretation lamps, adjustable camera mounts, and several cameras at appropriate angles. Colour recognition and automated sorting system reliability depend on camera tilt angles. Industrial automated item sorting uses clever algorithms and systems. Tables 5 and 6 estimate ball diameter at different light flux and camera tilt angles. These tables demonstrate that the system can reliably estimate object sizes, a crucial feature of automated sorting applications, and suggest future development.

Table 5. The ball's diameter estimation under different luminous flux

Luminous flux (lm)	Colour	Average estimated diameter (cm)	Absolute average error (cm)	Absolute average error percentage (%)
43	Red	3.44	0.06	1.77
	Yellow	3.53	0.03	0.77
	Blue	3.69	0.19	5.43
	Green	4.02	0.52	14.86
51	Red	3.54	0.04	1.03
	Yellow	3.59	0.09	2.43
	Blue	3.70	0.20	5.77
	Green	3.96	0.46	13.20
64	Red	3.60	0.10	2.97
	Yellow	3.58	0.08	2.20
	Blue	3.69	0.19	5.51
	Green	3.64	0.14	4.06

Table 6. The ball's diameter estimation under different camera tilt angles

Camera's tilt angle (°)	Colour	Average estimated diameter (cm)	Absolute average error (cm)	Absolute average error percentage (%)
30	Red	3.22	0.28	8.03
	Yellow	3.33	0.17	4.80
	Blue	3.67	-0.17	4.74
	Green	3.38	0.12	3.51
40	Red	3.60	-0.10	2.97
	Yellow	3.58	-0.08	2.20
	Blue	3.69	-0.19	5.51
	Green	3.64	-0.14	4.06
60	Red	4.23	-0.73	20.80
	Yellow	4.44	-0.94	26.77
	Blue	3.38	0.12	3.54
	Green	4.06	-0.56	15.91

The system lighting sensitivity is verified by ball diameter estimate under different luminous flux levels. Both blue and green balls make 5.43% and 14.86% errors at 43 lm. Size estimate mistakes occur when the system cannot distinguish object edges at low light intensity. Red and yellow ball error percentages decrease with 64 lm light flux, improving the diameter estimate. Blue and green balls make more mistakes in low light. The technology is sensitive to hues in the same lighting and needs optimal illumination to measure item size. Camera tilts complicate diameter estimation and system operation. Negative errors show 30° angles underestimate red balls and overestimate blue balls, showing image capture angle impacts item sizes. A 40° tilt reduces errors across all hues, validating prior findings that this angle balances colour identification and size estimate. At 60°, red and yellow balls exhibited 20.80% and 26.77% larger absolute average mistakes. Size estimate is hindered by large tilt degrees from distortion and object visibility shifts.

Many important automated sorting system development variables are highlighted by these studies. First, adaptive algorithms are needed to estimate size accurately due to system performance variance under varied lighting and colours. 2, Camera placement is crucial in automated item recognition and measuring systems due to high tilt angle error rate disparity. Determine the camera tilt angle to reduce errors and regulate item sizes and colours to extend system utilization. Consistent size estimation errors, especially in suboptimal settings, indicate object measurement method difficulties. Researchers must research image processing or sensor technologies that provide more accurate size and form data. The system's object size estimation accuracy is promising, but its unpredictability under diverse ambient conditions and object properties could be improved. Fixing these issues will improve the industrial system's dependability and efficiency.

5. DISCUSSION

Industrial robotics and image processing benefit from automated object sorting. Mobile colour sorters are tested for light flow, camera tilt angles, colour identification, object localization, and size estimate. Ideal illumination (43 and 64 lm) makes some colours 100% visible. Blue ball success rates drop at 43 lm, questioning the system's wavelength, shadow, and light fluctuation sensitivity. The difference helps eco-friendly colour recognition systems. The directed light source and sorting control may limit use. Colour perception is difficult to translate into robotic gripper coordination due to track border identification and object positioning issues. Visual input and dynamic mechanical movements are difficult to synchronize for blue objects. System performance, camera tilt, and luminous flux appear connected. More light improves colour and object recognition. Its exact illumination settings under unexpected industrial lights may limit its utility. The best camera tilt angle for colour and object localization is 40 degrees. Automatic colour sorting is affected by image angle. Automatic sorting is complicated by diameter estimation. High light flux and a 40-degree camera tilt angle yield the most accurate size estimates, but deviations generate substantial errors. These errors, especially at 60° camera tilts, show the difficulty of converting two-dimensional visual data into three-dimensional object properties. Lighting, camera location, and image processing object dimension limits are continuously monitored in this system performance component.

Trials say light flux and camera tilt angles determine system success. Better illumination and camera alignment improve colour, position, and sorting. In unexpected industrial situations, illumination and camera angle limit system adaptability. Under ideal conditions, the system can estimate item diameter, but illumination and camera angles limit it, showing the challenge of converting two-dimensional image processing into three-dimensional object characterization. Making progress, but implementation uncertain. Light and shade can confuse system and item colours. Dim lab light hinders colour detection. Another issue is dimensionally correct item size estimation. Size estimation errors, especially under large camera tilts, demonstrate the challenges of transforming two-dimensional visual data into three-dimensional object attributes. Size estimation requires better or new sensing technologies because image processing cannot quantify physical dimensions. Automatic sorting algorithms distinguish colours and find items, researchers found. Computing, environmental adaptation, and better detection and sorting are needed to overcome restrictions. Addressing these difficulties will improve automated sorting technologies' precision, durability, and industrial application.

6. CONCLUSION

This article analyzes and experiments with automated object-sorting systems in industry to demonstrate their potential. Industrial sorting has advanced using image processing algorithms and robotic systems that distinguish and sort by colour under varying illumination and camera angles. The studies demonstrate the system's accurate item size estimation and efficient colour detection, especially in good illumination. However, sensitivity to particular colour wavelengths, shadows and illumination variations, and item placement precision make such systems difficult to use in dynamic industrial settings. Future studies should improve colour identification algorithms to adapt to lighting variations without compromising accuracy. This includes studying advanced machine learning models that adapt to different settings and boost colour wavelength sensitivity.

ACKNOWLEDGEMENTS

The authors would like to sincerely thank the School of Electrical Engineering at the College of Engineering, Universiti Teknologi MARA, for their invaluable support in terms of specialist knowledge, facilities, and financial assistance.

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