Proceedings of the 2nd International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/96/20241240

Enhancing Object Sorting Under Low-Light Conditions with CLAHE, Gaussian Blur, ROI, and Custom PID on a Raspberry Pi Robotic Arm

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Abstract. This paper addresses the significant challenge faced by robotic vision systems in detecting and sorting objects accurately under varying lighting conditions. Such variations in light can lead to decreased detection accuracy and inefficiencies in automated sorting processes. The paper employs a combination of literature review and experimental validation to investigate the effectiveness of advanced image processing techniques and control algorithms. Specifically, it explores the application of CLAHE adaptive compensation, Gaussian Blur, custom ROI, and PID controllers within a visual object sorting system to improve its robustness under diverse lighting conditions. The use of CLAHE and Gaussian Blur effectively compensates for uneven lighting, while custom ROI and PID controllers further optimize the system's response to fluctuating conditions.

Keywords: Object Sorting, Image Processing, ROS, CLAHE, PID Control.

1. Introduction

Object sorting in automated systems has gained increasing importance across various industrial sectors. The ability to accurately detect and classify objects under varying lighting conditions is crucial for the efficiency and reliability of these systems. However, fluctuating light conditions pose significant challenges to the accuracy and stability of object detection systems, necessitating the development of more robust image processing techniques. Therefore, ongoing research has focused on optimizing these systems to better handle such challenges, and one promising approach involves the application of Contrast-Limited Adaptive Histogram Equalization (CLAHE), which has been shown to significantly enhance image contrast and improve detection accuracy under inconsistent lighting conditions [1-2].

The integration of sensor-based technologies has revolutionized material classification processes, making them more accurate and efficient. Studies indicate that sensor-based sorting, widely adopted in industries such as agriculture and recycling [3]. Additionally, innovations in image processing techniques, such as grayscale conversion and edge detection, have significantly enhanced the precision of robotic systems in identifying and sorting objects, even in complex industrial environments [4]. These developments not only address current challenges but also lay the foundation for further improvements, particularly in optimizing systems to perform reliably under varying lighting conditions and incorporating advanced control algorithms for enhanced performance.

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This study employs a combination of image processing techniques and ROS-based robotic systems to tackle the challenges posed by varying lighting conditions in object detection and sorting. The research focuses on optimizing sorting performance through the use of OpenCV for image processing and ROS for robotic control, aiming to enhance system stability and accuracy under different lighting conditions [5-6]. The significance of this research lies in its potential to contribute to the development of more reliable and efficient computer vision systems. By applying adaptive algorithms like CLAHE and integrating sensor data, this study provides practical solutions to improve detection stability, which could be beneficial for various fields that face similar challenges, thereby offering a foundation for future advancements in this domain [7].

2. Literature review

In the context of improving object detection and sorting under varying lighting conditions, several image processing techniques and control algorithms have been explored. These include CLAHE, Gaussian Blur, Region of Interest (ROI) segmentation, and PID controllers. Each of these techniques has its own advantages in enhancing the performance of robotic vision systems in challenging environments.

CLAHE improves image contrast under varying lighting conditions. Unlike traditional histogram equalization, CLAHE limits contrast enhancement to prevent over-amplification. Studies have shown that CLAHE significantly enhances the visibility of details in images, making it particularly useful in environments with inconsistent lighting [1].

Gaussian Blur is another applied image processing technique used to reduce image noise and fine detail. It smooths the image by averaging pixel values with a Gaussian kernel, effectively reducing high-frequency noise. Gaussian Blur improves the performance of vision-based systems [8].

The use of ROI segmentation in image processing allows for focusing computational resources on specific areas of an image that are more likely to contain relevant information. ROI segmentation has been particularly effective in applications where the objects of interest are consistently located within certain regions of the image. By narrowing the focus, ROI can significantly reduce the processing time and increase the stability of object detection systems, even in challenging conditions such as low light or cluttered backgrounds [2].

Custom PID controllers are essential in fine-tuning the control of robotic systems, especially in dynamic environments with varying external conditions. Traditional PID controllers may struggle in environments with inconsistent lighting, where standard parameters may not suffice for optimal control. Custom PID controllers, however, can be adjusted to better respond to specific environmental factors, thereby improving the stability and accuracy of robotic arm movements during object sorting tasks. Custom PID controllers are particularly effective in reducing the time required for pose adjustments and improving sorting accuracy [9].

In summary, the integration of these techniques—CLAHE for contrast enhancement, Gaussian Blur for noise reduction, ROI segmentation for focused detection, and custom PID controllers for precise control—forms a comprehensive approach to improving the performance of object sorting systems under varying lighting conditions [10]. Each technique addresses specific challenges within the object detection process, and their combined application leads to significant improvements in accuracy, stability, and efficiency in robotic vision systems. These advancements not only enhance the current capabilities of automated systems but also provide a foundation for future research and development in this field.

3. Methodology and Results

The experiments were conducted using a robotic arm powered by a Raspberry Pi 5, running within a Docker container on a Raspberry Pi OS environment. The test objects consisted of three colored blocks (red, blue, and green), and the experiments aimed to evaluate the system's performance under varying lighting conditions.

3.1. Impact of Low Lighting Conditions on Object Sorting without Enhancements

Under low lighting conditions, the detection time for color blocks significantly increased when using the Raspberry Pi vision-based robotic arm. Specifically, the Average Recognition Time for red, blue, and green blocks increased from approximately 8 seconds in normal brightness conditions to over 20 seconds in low brightness, as shown in Figure 1. Similarly, the Pose Adjustment Time also increased considerably, averaging around 17 seconds in low light compared to about 6 seconds in normal conditions, as shown in Table 2. This increase reflects the system's struggle to accurately detect and adjust to the objects' positions in a poorly lit environment [7]. The reduced contrast and visibility under low light not only extended processing times but also led to instability and inaccuracies in the detection process, causing the bounding boxes to fluctuate, which ultimately compromised sorting reliability [3].

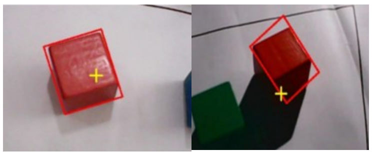

Figure 1. Comparison of Normal and Low Brightness

Table 1. normal brightness

Block Color	Average Recognition Speed (s)	Pose Adjustment Speed (s)
Red	8.3	6.3
Blue	8.2	6.1
Green	8.4	6.6

Table 2. low brightness

Block Color	Average Recognition Speed (s)	Pose Adjustment Speed (s)
Red	22.5	17.2
Blue	20.3	16.2
Green	23.8	19.9

3.2. CLAHE

In the second step, adaptive lighting compensation using CLAHE was applied, resulting in significant improvements. The Average Recognition Time was optimized by approximately 5 seconds, and the Pose Adjustment Time improved by around 1 second. In the color detection algorithm, the original image was first converted into the LAB color space, where the L (lightness) channel was isolated. CLAHE was then applied to the L channel to enhance the local contrast, particularly in regions with uneven lighting. After this enhancement, the L channel was merged back with the A and B channels, and the image was converted back to BGR format. This process significantly improved the effectiveness of color segmentation under challenging lighting conditions, making color detection more stable and reliable across different scenarios. As a result, the average recognition speed improved to approximately 17.5 seconds, while the average pose adjustment speed improved to around 16.4 seconds (Table 3) [1].

```
# Convert the image to LAB color space
lab = cv2.cvtColor(img, cv2.COLOR_BGR2LAB)
l, a, b = cv2.split(lab)
# Apply CLAHE to the L channel
clahe = cv2.createCLAHE(clipLimit=1.5, tileGridSize=(8, 8))
cl = clahe.apply(l)
# Merge the enhanced L channel with the original A and B channels
limg = cv2.merge((cl, a, b))
# Convert the LAB color space back to BGR format
```

```
img_clahe = cv2.cvtColor(limg, cv2.COLOR_LAB2BGR)
```

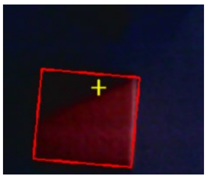

Figure 2. Low brightness using CLAHE

Table 3. Low brightness using CLAHE

Block Color	Average Recognition Speed (s)	Pose Adjustment Speed (s)
Red	17.6	16.3
Blue	16.7	15.1
Green	18.3	17.9

3.3. Gaussian Blur

In the third step, Gaussian Blur was applied following the CLAHE enhancement. The inclusion of Gaussian Blur slightly increased the average recognition time by approximately 0.2 seconds, resulting in an overall average of 17.8 seconds. However, the average pose adjustment time saw a significant reduction of about 2 seconds, bringing it to an average of 14.5 seconds (Table 4). Consequently, the robotic system was able to perform more precise adjustments, minimizing errors in positioning and enhancing overall performance.

```
# Apply Gaussian Blur - Added section
img_clahe = cv2.GaussianBlur(img_clahe, (5, 5), 1)
```

Table 4. Low brightness using CLAHE, guass

Block Color	Average Recognition Speed (s)	Pose Adjustment Speed (s)
Red	17.8	14.6
Blue	17.0	13.3
Green	18.5	15.5

3.4. ROI

In the fourth step, incorporating the Region of Interest (ROI) method into the experiment led to a reduction in the average recognition time to approximately 13.2 seconds and the average pose adjustment time to around 10.6 seconds (Table 5). The ROI method effectively leveraged its strengths by focusing computational resources on relevant areas of the image, leading to a significant enhancement in detection efficiency. In the code implementation, the ROI function was used to define a specific region of interest based on the rotation angle, allowing the system to focus on areas where objects were most likely to appear.

Table 5. low brightness using CLAHE, guass, ROI

Block Color	Average Recognition Speed (s)	Pose Adjustment Speed (s)
Red	12.7	10.5
Blue	12.9	9.8
Green	14.1	11.4

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3.5. Custom PID

In the final stage of improvement, the implementation of a Custom PID controller led to significant enhancements in sorting accuracy, particularly under varying brightness conditions. Under normal brightness, the accuracy increased to an average of 89%, while under low brightness, the accuracy improved drastically from 35-41% to an average of 87% (Table 6). This improvement is attributed to the Custom PID's ability to dynamically adjust control parameters in response to fluctuating lighting conditions, thereby stabilizing the sorting process and reducing errors. The Custom PID controller was implemented using a Python class to fine-tune control over robotic movements. The PID algorithm calculates the difference between the desired setpoint and the measured value, generating an error signal. The controller then adjusts the output to minimize this error using proportional, integral, and derivative terms [9].

Table 6. Impact of Custom PID on Sorting Accuracy Under Different Lighting Conditions

sorting accuracy	Normal brightness	low brightness	Normal brightness with Custom PID	low brightness with Custom PID
Red	72%	35%	88%	84%
Blue	75%	41%	92%	90%
Green	71%	34%	87%	86%

```
class PID:
    def __init__(self, p, i, d):
        self.p, self.i, self.d = p, i, d; self.prev_err = 0; self.integral = 0
    def update(self, setpoint, value):
        err = setpoint - value; self.integral += err
        return self.p * err + self.i * self.integral + self.d * (err - self.prev_err)
pid = PID(1.0, 0.1, 0.01); print("Control Signal:", pid.update(100, 90))
```

4. Discussion

The implementation of image processing techniques such as CLAHE, Gaussian blur, and custom ROI has significantly improved the system's performance under varying lighting conditions. After applying CLAHE, the average recognition time was reduced to 17.6 seconds, and the pose adjustment time decreased to 16.3 seconds. This demonstrates CLAHE's effectiveness in enhancing local contrast and improving detection accuracy in low-light environments [3].

Introducing Gaussian Blur further improved the system's stability by smoothing out image noise. Although the recognition time increased slightly to 17.8 seconds, the pose adjustment time improved significantly, dropping to 14.6 seconds. The reduction in noise allowed for more precise and reliable pose estimation, showcasing Gaussian blur's impact on stability and accuracy [8].

The application of the custom ROI method resulted in further improvements. By focusing computational resources on key areas of the image, the recognition time dropped to 13.2 seconds, and the pose adjustment time reduced to 10.6 seconds. This method, combined with Gaussian blur, helped mitigate inaccuracies in ROI placement, stabilizing detection boxes and improving the system's overall performance under low-light conditions [2].

Lastly, the custom PID controller had a substantial impact on sorting accuracy. Under low-brightness conditions, the sorting accuracy increased dramatically, from 35-41% to 84-90%, highlighting the controller's ability to dynamically adjust to fluctuating lighting conditions and stabilize the sorting process. Though the improvement in recognition and pose times was modest, the PID controller significantly boosted overall system reliability and sorting accuracy [7].

5. Conclusion

This study explores the optimization of object sorting systems under varying lighting conditions by integrating advanced image processing techniques such as CLAHE, Gaussian blur, and custom ROI,

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along with a tailored PID controller. The results demonstrate significant improvements in recognition time, pose adjustment time, and sorting accuracy, particularly in low-light environments.

However, this research has its limitations. The study primarily focuses on the technical aspects of system optimization and does not explore potential variations in real-world applications, such as different object shapes, sizes, or materials. Additionally, the long-term impact of these optimizations on system wear and tear was not considered.

Looking forward, the findings of this study pave the way for further advancements in the field of automated sorting systems. As technology continues to evolve, there is potential for even greater integration of AI-driven algorithms, real-time adaptive controls, and more sophisticated sensor technologies.

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