Enhancing Hand Sign Recognition in Challenging Lighting Conditions Through Hybrid Edge Detection

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***Abstract*—Edge detection is essential for image processing and recognition. However, single methods struggle under challenging lighting conditions, limiting the effectiveness of applications like sign language recognition. This study aimed to improve the edge detection method in critical lighting for better sign language interpretation. The experiment compared conventional methods (Prewitt, Canny, Roberts, Sobel) with hybrid ones. Project effectiveness was gauged across multiple evaluations considering dataset characteristics portraying critical lighting conditions tested on English alphabet hand signs and with different threshold values. Evaluation metrics included pixel value improvement, algorithm processing time, and sign language recognition accuracy. The findings of this research demonstrate that combining the Prewitt and Sobel operators, as well as integrating Prewitt with Roberts, yielded superior edge quality and efficient processing times for hand sign recognition. The hybrid method excelled in backlight at 100 thresholds and direct light conditions at a threshold of 150. By employing the hybrid method, hand sign recognition rates saw a notable improvement of the pixel value of more than 100% and hand and sign recognition also improved up to 11.5%. Overall, the study highlighted the hybrid method's efficacy for hand sign recognition, offering a robust solution for lighting challenges. These findings not only advance image processing but also have significant implications for technology reliant on accurate segmentation and recognition, particularly in critical applications like sign language interpretation.**

Keywords—Critical lighting; edge detection; image recognition; image segmentation; sign language

I. Introduction

With the advent of digital devices, there is a growing demand for accurate and efficient sign language recognition systems that can detect and interpret sign language gestures. In developing the devices and applications, image processing technique has become one of the popular methods that have been used upon this issue. However, image processing is a broader term that encompasses a wide range of operations, but for this research the process will be narrowed down into image segmentation. The quality of information obtained from the image or object recognition is influenced by the 'quality' of image segmentation [1]. The quality of image segmentation depends on the manipulation of the methods used by considering the advantages and limitations of the respective methods.

Image segmentation using edge detection is a fundamental step in many computer vision applications, it provides valuable information about the structure and content of images. It serves as a foundation for higher-level tasks such as object recognition on various applications across different industries. It is based on discontinuity in image brightness or contrast. It helps to decrease the unnecessary information in an image while preserving the structure of the image. Edge detection method is one of the most popular image segmentation. The edge detection method helps to find the areas with high-intensity contrasts while preserving the shape of the object. Additional modules such as the edge-detection filter can also be used to help improve the appearance of blurred images by focusing on the corners, curves, and ridges [2]. Edge detection steps include smoothing the image by reducing the noise, improvising by sharpening the edge, determining which edge pixels should be retained and lastly performing localization to determine the exact location of the edge. There are two main types of edge detection methods, namely Gradient or Traditional and Zero-Crossing methods. The magnitude of the gradient is used to identify the edges, as edges correspond to areas where there is a significant change in intensity. For example, Canny [3], Roberts [4], Prewitt [5] and Sobel operators [6] which detect vertical and horizontal edges.

Zero-crossings filtering methods are sensitive to noise, and they help highlight or smooth edges. Some examples of Zero-crossings filtering method are Laplacian of Gaussian [7], and Morphological Operators [8]. In the experiment, a combination of Canny, Prewitt, Roberts, and Sobel edge detection methods was used. These methods were selected for their diverse edge detection capabilities, which are crucial for handling variations in lighting and enhancing the robustness of the algorithm. The combination of these methods helps to ensure that edges are accurately detected under different lighting conditions, thus improving the overall performance and reliability of the algorithm.

Based on the World Health Organization (WHO) statistics, there are over 360 million people with hearing loss disability. This number has increased to 466 million by 2020, and it is estimated that by 2050 over 900 million people will have hearing loss disability [9]. According to the world federation of deaf people, there are about 300 sign languages which is use to bridge communication between deaf and normal people [10].

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Sign language recognition systems play a vital role in facilitating communication for the deaf and hard-of-hearing community, but critical lighting has become one of the barriers for developing accurate hand sign segmentation and recognition. This is due to critical lighting distorting hand sign features, reducing visibility and causing shadows or glare that obscure important details, making accurate recognition difficult. Therefore, developing techniques that can handle critical lighting conditions is crucial for improving the accuracy and robustness of sign language recognition systems [11]. To match with the experiment, the critical lighting is narrowed by focusing on direct light and back light, direct light is where the light directly on the hand sign and it produces shadow. Back light is the lighting that comes from the back of the hand and produces an illuminating scene.

In image processing, segmentation is crucial for effective recognition, with image quality heavily reliant on segmentation quality. Edge detection is a popular segmentation method, however, these methods struggle in critical lighting conditions which impact the accuracy and robustness of sign language recognition systems. Traditional edge detection methods have limitations, such as sensitivity to noise. Lighting conditions significantly affect image quality, making it challenging to identify sign contours accurately [12]. While some research has addressed illumination issues, developing techniques specifically tailored for critical lighting conditions remains essential. Despite traditional edge detection limitations, it also has an advantage that can be applied to detect hand signs. Edge detection methods offer several advantages, such as effectively highlighting object boundaries and enabling feature extraction, which is crucial for tasks like object detection, shape analysis, and pattern recognition [13]. In this study, particular emphasis is placed on direct light and backlight scenarios, to devise an edge detection-based segmentation workflow tailored specifically for hand gesture recognition under these challenging conditions. By tackling the research gap associated with handling critical lighting, the study endeavors to enhance the accuracy and robustness of sign language recognition systems, thereby advancing communication accessibility for individuals in the deaf and hard-of-hearing community.

II. Related Work

Various studies have explored the enhancement of image processing techniques, particularly focusing on edge detection under challenging lighting conditions. Traditional edge detection methods, such as the Canny, Sobel, Prewitt, and Roberts operators, have been widely used due to their simplicity and efficiency in detecting edges based on intensity gradients. However, these methods often fall short in scenarios with uneven lighting, resulting in poor edge quality and recognition accuracy. For instance, Shrivakshan and Chandrasekar [14] highlighted the limitations of these traditional methods in their application to hand sign images captured under direct sunlight, leading to inconsistent edge detection and reduced recognition rates. This underscores the need for more robust solutions that can handle the variability of lighting conditions in real-world applications.

Recent advancements in hybrid edge detection methods have shown promise in addressing these limitations. By combining different edge detection techniques, researchers have demonstrated improved performance through leveraging the strengths of individual methods while mitigating their weaknesses [15]. For example, Abdulrazzaq and Musab [16] developed a hybrid edge detection framework for autonomous vehicles, integrating the Sobel and Canny operators. Their system successfully identified road boundaries and obstacles under varying lighting conditions, showcasing the potential of hybrid methods in enhancing image segmentation reliability. Despite these advances, challenges remain, particularly in achieving real-time processing speeds and maintaining accuracy across diverse lighting environments. The current research aims to address these gaps by comparing conventional methods with novel hybrid approaches tailored specifically for sign language recognition under critical lighting conditions, such as direct light and back light [17]. This study builds on previous work by demonstrating significant improvements in edge quality and processing efficiency, positioning itself as a robust solution for enhancing sign language recognition systems in challenging lighting scenarios.

III. Methodology

A. Data Acquisition

In this experiment, the dataset was carefully categorized and created based on two main critical lighting conditions: direct light and back light. The authors captured sample sets of hand gestures under varied lighting conditions to simulate real-world scenarios as shown in Fig. 1. The hand gestures were used to display the alphabets in sign language for object recognition. A total of 40 datasets were created for this experiment for all 26 English alphabets, with the image dataset captured using a camera in PNG format and a resolution of 922x1224 pixels.

Fig. 1. Example sign language alphabet dataset.

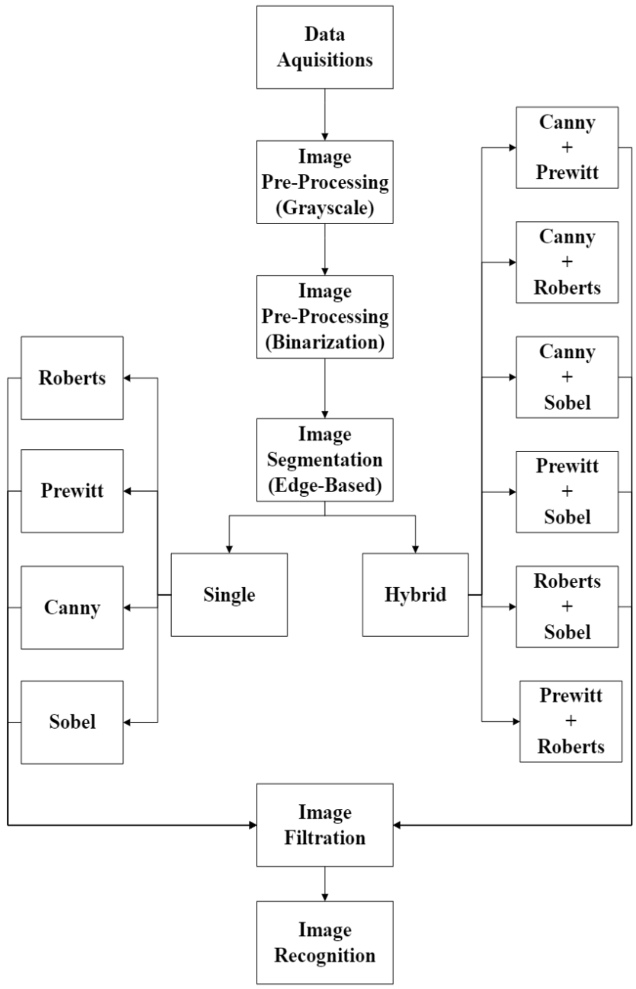

Fig. 2. Single and hybrid method image processing workflow.

B. Image Pre-Processing

Image pre-processing is a crucial step in image analysis and computer vision tasks. For this research, the algorithm was run using MATLAB software. Two values of threshold were used as one of the variables: threshold 100 and 150. The chosen parameter was commonly used in various publications [18, 19]. For binary image alteration, to fill the holes (unwanted gaps) in the binary image, the *imfill()* function with the 'holes' option was used. This ensured that the objects of interest in the binary image were filled. To remove small objects from the binary image, the function *bwareaopen()* function was utilized [20]. The function *imcomplement()* was operated on both single and hybrid edge detection method. Each of the image datasets was tested extensively using the program code in MATLAB. Fig. 2 shows single and hybrid method image processing workflow.

The experiment was done by separating them into two different groups where Group 1 is a single-method test and Group 2 is hybrid method test. The single method test was done with Prewitt, Canny, Sobel, and Roberts edge detection exclusively with different threshold value which then ended with Morphological Operation filtering. On the other hand, Group 2 was also done with the same threshold value and tested with hybrid method as listed in Table I and ended with Morphological Operation filtering.

C. Image Segmentation

The image segmentation was done by separating them into two different groups. Group 1 is a single-method test and Group 2 is hybrid method test. The single method test was done with Prewitt, Canny, Sobel, and Roberts edge detection respectively. For Group 2 is hybrid method, consist of combination methods Canny + Prewitt, Canny + Roberts, Canny + Sobel, Prewitt + Roberts, Prewitt + Sobel and Roberts + Sobel. For hybrid method, the algorithm was different and an additional equal 0.5 weight was assigned to the combine method. The calculation of the kernel matrix for hybrid method can be done by Eq. (1):

$$G_x^{Combined} = w \times A_x + w \times B_x \tag{1}$$

where, G_x is x-axis equation, A represents the first method, B represents second method and w is the weight which constant 0.5 for both methods. The experimental variables are summarized in Table I. However, for the single method, the process flow was standardized according to commonly done by previous research [19, 21].

TABLE I. EXPERIMENTAL VARIABLES

Critical Lighting	Threshold Value	Edge Detection Method
• Direct Light • Back Light	• 100 • 150	• Single ○ Canny ○ Prewitt ○ Roberts ○ Sobel • Hybrid ○ Canny + Prewitt ○ Canny + Roberts ○ Canny + Sobel ○ Prewitt + Roberts ○ Prewitt + Sobel ○ Roberts + Sobel

D. Image Filtration

Both experimental groups were using the same filter. Morphological operations *bwmorph()* function and clean operation was the morphological operation utilized to removes isolated pixels (noise) from the binary image.

E. Image Recognition

For image recognition, the hand sign was uploaded in the simulation software created using MATLAB. The algorithm used for recognition is *centroid [22]*. The centroid coordinates of the detected hand gestures were passed as input to designated functions. This code displayed the original sign language image and overlayed red asterisks at the centroids of the detected hand gestures to visualize where they are located. It was then matched with the alphabet's datasets.

F. Analysis of Results

The next stage involved analyzing the obtained results. Firstly, the visibility and thickness of pixel edges produced during segmentation were analyzed. The calculation of the pixel count of the detected edges was done using Eq. (2).

$$Pixel\ result = \frac{White\ pixel}{Total\ pixel} \times 100\% \tag{2}$$

Secondly, the time taken for successful edge detection and sign language recognition was measured. The accuracy of recognizing the sign language signs was also evaluated to validate the obtained results against the original image. At this stage, the comparison results of the two groups can be analyzed to determine the best hybrid method for edge detection in handling critical lighting conditions for sign language images.

IV. Results and Discussion

A. Appearance of Images

By segmenting the image, the algorithm can focus on specific areas of the image and identify edges more accurately to separate the sign language hand signs from the background. This results in edges that are more defined, with clearer boundaries and connections of the hand signs with the background. The segmented images also make it easier to distinguish between different edges, making them easier to analyze.

In Fig. 3, a detailed comparison of edge detection is presented between the single and hybrid methods. The single method yields disconnected edges, lacking continuity between them. In contrast, the hybrid method generates thicker and finer edges that seamlessly connect, effectively delineating the contours of the hand signs. This cohesive representation enhances the clarity and accuracy of the detected shapes.

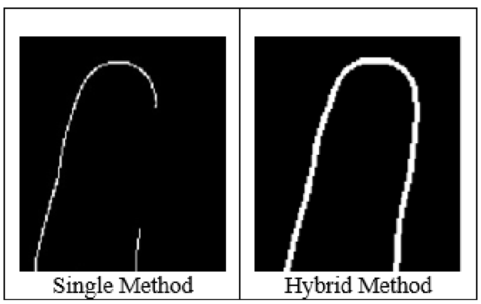

Fig. 3. Zoom in on edge comparison between single and hybrid methods.

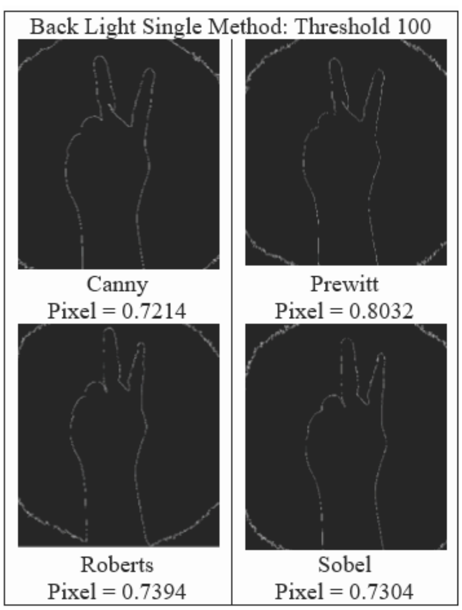

Fig. 4. Appearance of image segmented results for single method with threshold value of 100 in back light condition.

The analysis results shown in Fig. 4 and Fig. 5 reveal that when working with a dataset captured under back light conditions, employing a single method yielded thin edges, often disjointed. Conversely, the adoption of a hybrid approach resulted in thicker edges with clearer connections between them, thus forming well-defined hand shapes conducive to easier detection. Optimal segmentation under back light conditions was achieved with a threshold value of 100, as it generated segmentation outcomes with reduced noise compared to a threshold value of 150. Notably, the hybrid method combining Prewitt and Sobel operators emerged as the standout performer in terms of both image appearance and pixel count analysis, as depicted in Fig. 6 and Fig. 7. This hybrid method produced distinct edges with robust outlines and intricate details, effectively delineating the hand sign shapes.

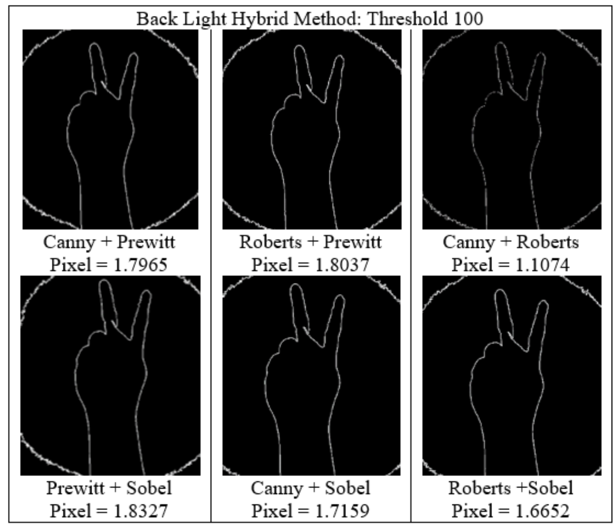

Fig. 5. Appearance of image segmented results for hybrid method with threshold value of 100 in back light condition.

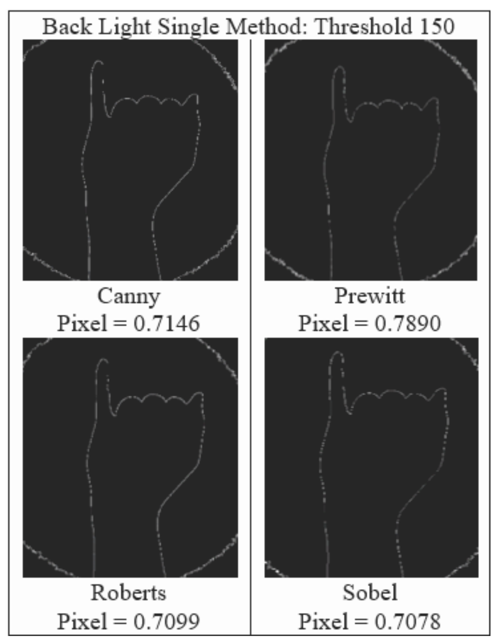

Fig. 6. Appearance of image segmented results for single method with threshold value of 150 in back light condition.

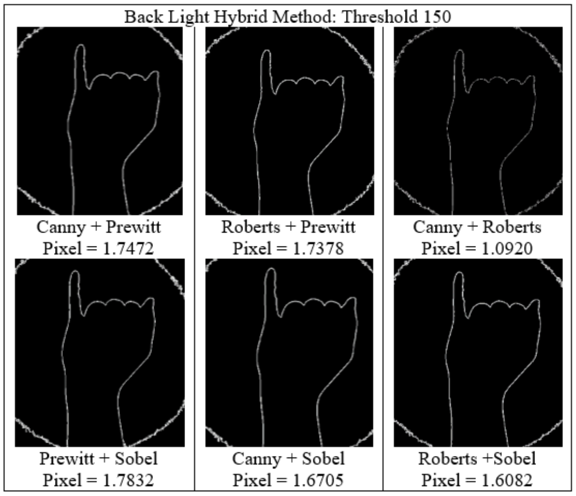

Fig. 7. Appearance of image segmented results for hybrid method with threshold value of 150 in back light condition.

For the data in the direct light condition shown in Fig. 8, single methods produced thin edges and some of them were not connected to each other which loses the shape of hand. This led to difficulties in recognizing the shape of the hand signs and ultimately, recognition failure. However, by utilizing a hybrid method, thicker edges with more visible connections between them were obtained. As a result, a well-defined shape of hands was produced, which facilitated easy detection. For direct light condition, a threshold value of 150 was found to be optimal to the segmentation for this lighting condition. This threshold value resulted in a segmentation output with less noise as compared to a threshold value of 100. In Fig. 9, Fig. 10 and Fig. 11, under direct light conditions, this method yields a segmented image with notably lower noise levels compared to backlit scenarios. The resulting image showcases a cleaner representation, highlighting only the contours of the hand shape with precision. Such refined image information proves invaluable for accurate image recognition tasks.

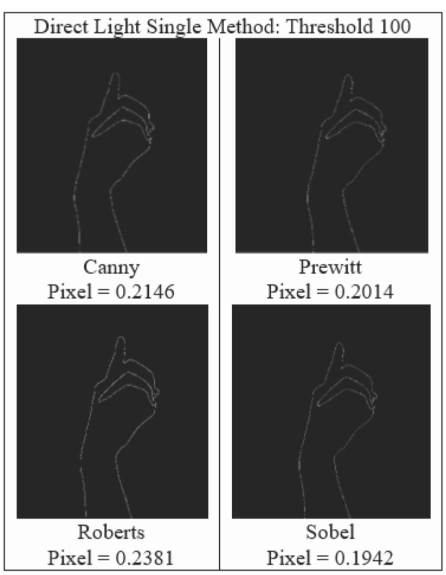

Fig. 8. Appearance of image segmented results for single method with threshold value of 100 in direct light condition.

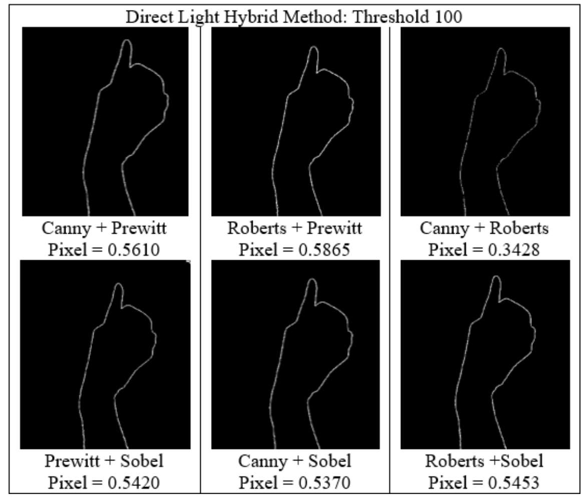

Fig. 9. Appearance of image segmented results for hybrid method with threshold value of 100 in direct light condition.

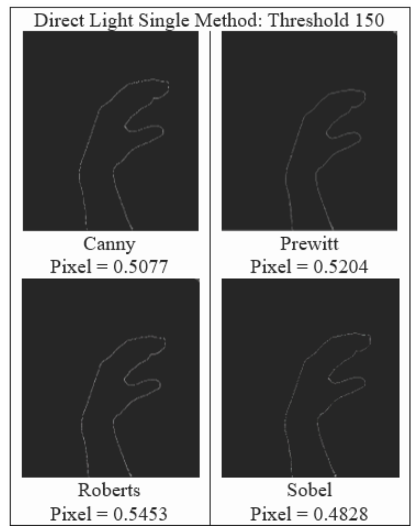

Fig. 10. Appearance of image segmented results for single method with threshold value of 150 in direct light condition.

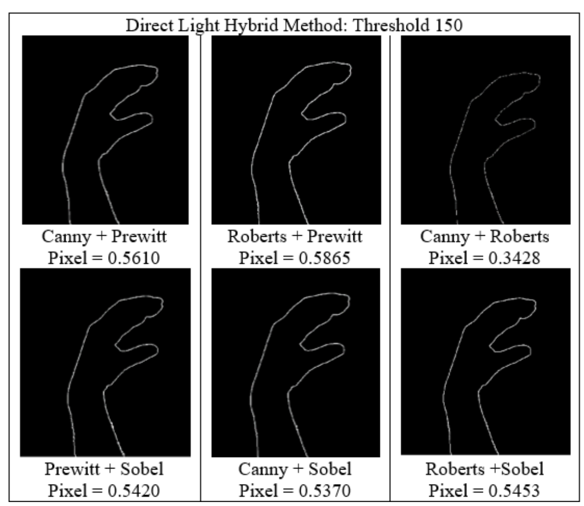

Fig. 11. Appearance of image segmented results for hybrid method with threshold value of 150 in direct light condition.

B. *Pixel Count on Edge*

Pixel count in the context of edge detection refers to the number of pixels in an image that are identified as edges by the edge detection algorithm. Each pixel in the edge-detected image that is part of an edge contributes to the pixel count. Pixel count provides valuable quantitative information about the performance and characteristics of a single and hybrid method of edge detection [23].

1) Single method: The average pixel count for image-segmented results using a single method was displayed in Fig. 12. The error bar was added to indicate the standard deviation of the average pixel count.

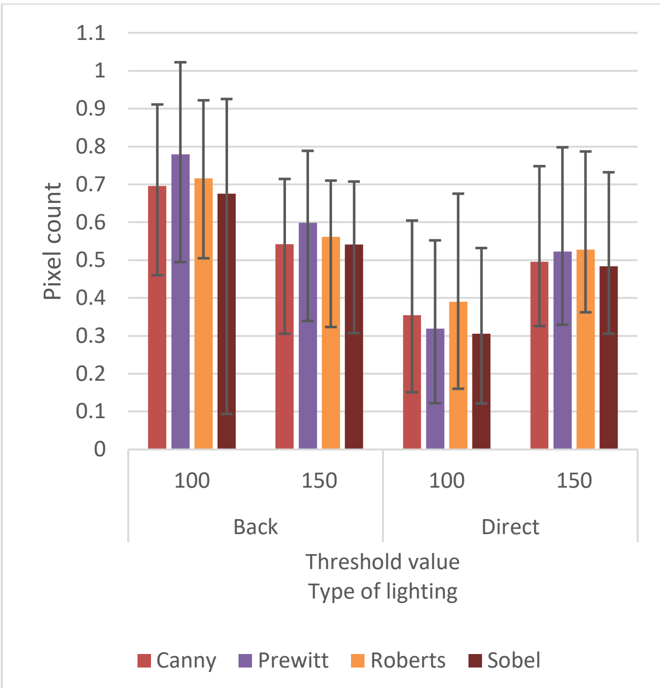

Fig. 12. Pixel count using single method.

The quality of image segmentation is greatly influenced by the lighting conditions, with contrast and brightness playing a key role in distinguishing between the subject and background. In situations with back light condition, the pixel count is a significant factor, although the standard deviation is relatively high due to the variability in the resulting pixel counts. The threshold and weight played a big role, the back light condition was suitable in 100 thresholds, and it produced less noise. However, it is vice versa for direct light. This is because the hand signs and background are equally illuminated, making the edges less distinguishable. With direct lighting, increasing the threshold value enhances the pixel count on the edges. Lower threshold values under direct lighting produce a lower standard deviation, indicating that the pixel counts are closer to each other. It is found that lower threshold values favor back light condition while higher thresholds work better for direct light conditions.

This is aligned with previous research which the choice of the threshold value can critically affect the image segmentation where a value too low may split the regions while too high of a threshold may produce more noise [24]. After comparing the four single methods used, it was found that the Prewitt and Roberts method consistently generated a higher pixel count compared to the other two methods. This can be attributed to the fact that the Prewitt and Roberts operators use a larger kernel size, resulting in a more comprehensive edge detection process [25]. However, it should be noted that although the Prewitt method has a higher average pixel count, its standard deviation is slightly higher than that of the other three methods. On the other hand, the Sobel method produced the highest standard deviation for all lighting conditions and threshold values.

2) Hybrid method: In Fig. 13 shows the mean pixel count for the image segmentation results obtained from hybrid methods. The standard deviation of the mean pixel count is represented by the error bars.

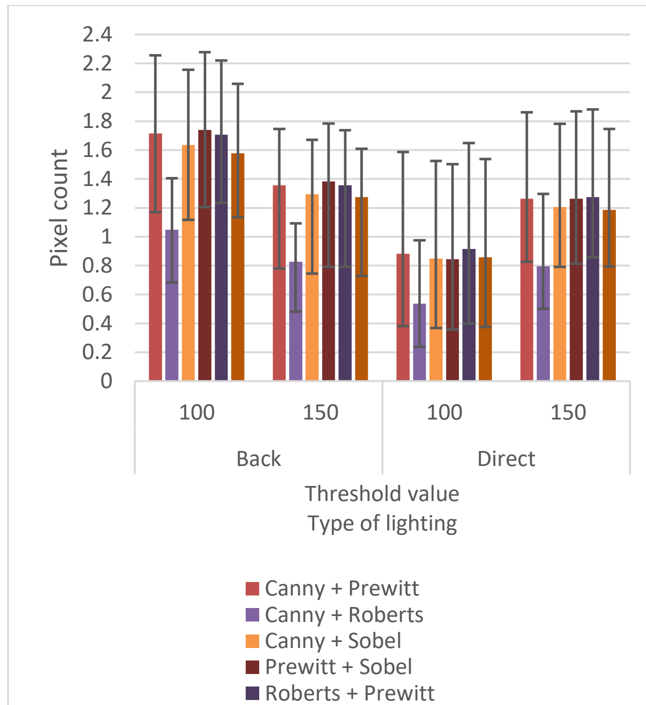

Fig. 13. Pixel count for combined method.

For back light condition, it is better to use lower threshold value since it can preserve more details and information in the hand signs. Meanwhile, for direct lighting, shadows and highlights were stronger, leading to overexposed or underexposed areas in the image which explains the need of higher threshold. This significant increase in pixel value shows that the edges were thicker compared to single method. It is also show a good improvement in pixel count compared to other previous research align to the trend in finding a good pixel edges [26].

After analyzing the results of the hybrid methods for edge detection, it was found that combining Prewitt with the other three methods produced the highest average pixel count for the edges of the hand signs. Specifically, Prewitt+Roberts, Prewitt+Sobel, and Canny+Prewitt consistently obtained the highest pixel count and ranked in the top three, respectively. It is important to note that these three hybrid methods also produced a higher standard deviation, likely due to the wider kernel size used by the Prewitt operator, which can detect edges more comprehensively [27]. On the other hand, Canny+Roberts consistently performed the worst among all the hybrid methods, but the values produced from this method are closer to each other, resulting in a lower standard deviation.

When compared to the results between single and hybrid method, it is seen that there is major enhancement of pixel count through the combination. Most hybrid methods improve the pixel count by more than 100% as compared to its single method. This shows the synergistic and integrative effects of methods with each other. Despite this, only the combination of Canny+Roberts shows an improvement below 100% but the interaction still increases the recognition of hand sign up to 11.5%.

From Eq. (1), the calculation shows the kernels calculation for hybrid method for the best performance hybrid method Prewitt + Sobel and Prewitt + Roberts. It is worth noting that the kernels for Sobel operator along the x-axis and Prewitt operator as S_x, P_x and R_x respectively.

Sobel X-direction kernel:

$$S_x \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

Prewitt X-direction kernel:

$$P_x \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

Combined these two kernels into a single kernel with equal weights by averaging their elements and scaling by the weight. The combined kernel equation can be calculated using Equation 1 where *w* represents the 0.5 weight equally for both methods. This combined kernel will perform edge detection along the x-axis, incorporating features from both the Sobel and Prewitt method as shown in the calculation below.

$$G_x^{Combined} = 0.5 \times \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} + 0.5 \times \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

$$G_x^{Combined} = \begin{bmatrix} -0.5 & 0 & 0.5 \\ -1 & 0 & 1 \\ -0.5 & 0 & 0.5 \end{bmatrix} + \begin{bmatrix} -0.5 & 0 & 0.5 \\ -0.5 & 0 & 0.5 \\ -0.5 & 0 & 0.5 \end{bmatrix}$$

$$G_x^{Combined} = \begin{bmatrix} -1 & 0 & 1 \\ -1.5 & 0 & 1.5 \\ -1 & 0 & 1 \end{bmatrix}$$

Both Sobel and Prewitt operators are effective at detecting edges with high sensitivity, especially in horizontal edges. The combined approach integrates these complementary features, resulting in improved edge detection results along the x-axis. In image processing, the complement of an image refers to the inversion of pixel values, typically achieved by subtracting each pixel value from the maximum value [5]. Complementing an image can be useful for various purposes, such as enhancing contrast or highlighting specific features by inverting the pixel values [28].

Roberts X-direction kernel:

$$R_x = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

Prewitt X-direction kernel:

$$P_x \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

By combining these two kernels into a single kernel with equal weights (0.5) by averaging their elements. The combined kernel calculation can be represented as below:

$$G_x^{Combined} = 0.5 \times \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} + 0.5 \times \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

$$G_x^{Combined} = \begin{bmatrix} 0.5 & 0 \\ 0 & -0.5 \end{bmatrix} + \begin{bmatrix} -0.5 & 0 & 0.5 \\ -0.5 & 0 & 0.5 \\ -0.5 & 0 & 0.5 \end{bmatrix}$$

$$G_x^{Combined} = \begin{bmatrix} 0 & 0 & 0 \\ -0.5 & 0 & -1 \\ -0.5 & 0 & -1 \end{bmatrix}$$

This combined kernel will perform edge detection along the x-axis, incorporating features from both the Roberts and Prewitt operators. By combining the Prewitt and Roberts operators along the x-axis, we can leverage the strengths of both techniques to enhance edge detection performance. The Prewitt operator is effective at detecting edges with high sensitivity, especially in vertical edges, while the Roberts operator can capture diagonal edges more effectively. The combined approach integrates these complementary features, resulting in improved edge detection results along the x-axis.

In mathematics and image processing, the complement of a set or an image refers to the elements or pixel values that are not contained within the set or the original image, respectively. Complementing an image involves inverting the pixel values, such that the maximum pixel value (usually 255 for grayscale images) is subtracted from the original pixel values. This operation can be useful for various image processing tasks, such as enhancing contrast or highlighting specific features by inverting the pixel values.

Pixel count reflects the sensitivity of the edge detection method to variations in the image. A higher pixel count suggests that the method is more sensitive and capable of detecting finer details and subtle variations in intensity, leading to more edge pixels being identified.

C. Time Taken for Edge Detection And Recognition.

1) Single method: The time taken to obtain the edge detection is shown in Fig. 14 with standard deviation indicated as the error bars.

For back light conditions, the time taken by the Canny and Prewitt methods increases with increasing threshold value, while the opposite is true for the Roberts and Sobel methods. The standard deviation for Prewitt, Roberts, and Sobel in back light conditions is almost identical, while Canny produces a high standard deviation, indicating that the Canny method struggles and takes longer to detect the edges of the hand signs. Same goes to direct light condition, increasing the threshold value causes the time taken by all single methods to detect edges increase significantly. Lower threshold values for direct light produce a lower standard deviation compared to higher threshold values. Overall, it is found that Prewitt method works best across lighting condition and threshold value, followed by Sobel, Roberts and lastly Canny.

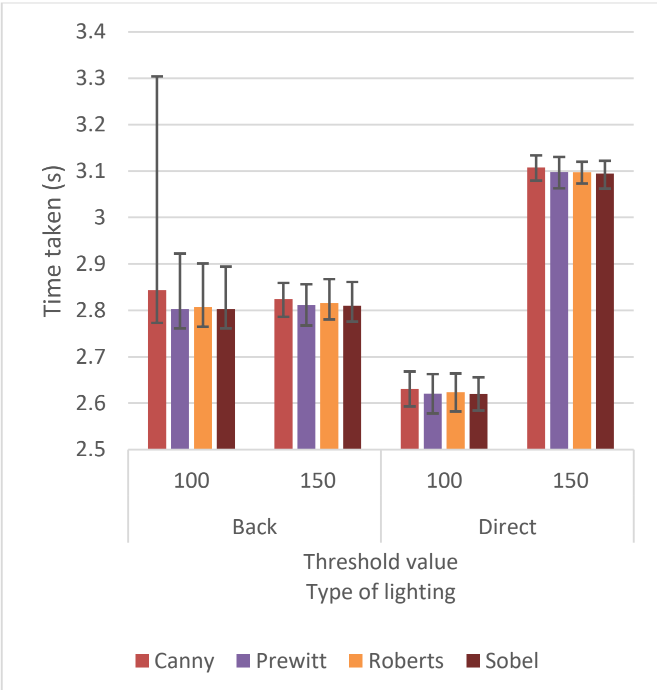

Fig. 14. Time taken for single method.

An analysis of the time taken to generate segmented and recognize image revealed that the Prewitt and Sobel methods consistently performed better than the Roberts and Canny methods. In fact, the Prewitt and Sobel methods consistently placed in the top two positions for producing segmented images in a shorter period. When comparing the standard deviation of these methods, it was found that the Roberts method produced the least standard deviation, followed by the Prewitt, Sobel, and Canny methods. This indicates that the time taken to produce images is more consistent for these methods. The standard deviation between the methods was relatively similar, except for the back light condition where the Canny method produced a wide deviation. Based on the analysis, the Prewitt method was found to be better, as it takes a shorter time in most conditions and has a lower standard deviation with only a slight difference when it loses to the Sobel method [15].

2) Hybrid method: Fig. 15 shows the time taken to obtain edge detection, with the error bars indicating the standard deviation.

The analysis of the time taken for image segmentation and recognition using combined methods reveals less clear trends. In back light conditions, high threshold values struggled to detect edges and required a long time. In direct lighting, both the time taken, and the standard deviation increased with an increase in the threshold value, as a larger contrast between the edges and the background was required for edge detection.

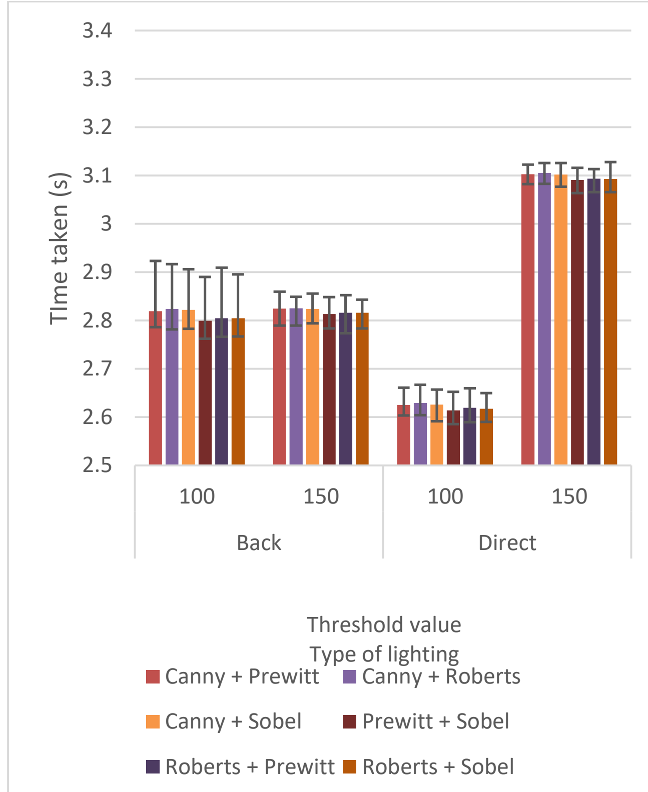

Fig. 15. Time taken for hybrid method.

Upon examining the effect of combined methods, a clear best combination emerges. In most conditions, Prewitt+Sobel and Prewitt+Roberts consistently took the shortest time to perform edge detection and recognition. Between the two, Prewitt+Roberts showed a lower standard deviation, indicating less variation or dispersion among the data points. Conversely, the combinations of Canny with the other three methods performed poorly, taking longer to detect the edges. When compared to single method, combining the methods takes longer time to perform the image segmentation, but since the time taken is still lower than one seconds, it is still adequate to be used in other real-time function [29].

When contrasting the time taken of the hybrid methods versus single methods, it is evident that there is minimal variation in time required to produce the edge detection. All the difference of time between the single and hybrid is fluctuating within a range of ±1% of each other. This proves that, despite the increase in complexity of process, it does not affect computational ability, highlighting the robustness and efficiency of hybrid approaches in edge detection.

D. Recognition of Images

In Fig. 16 shows the image processing interface created in MATLAB to run this experiment. The image processing interface consists of user input 2D alphabet hand sign, image processing and word translation.

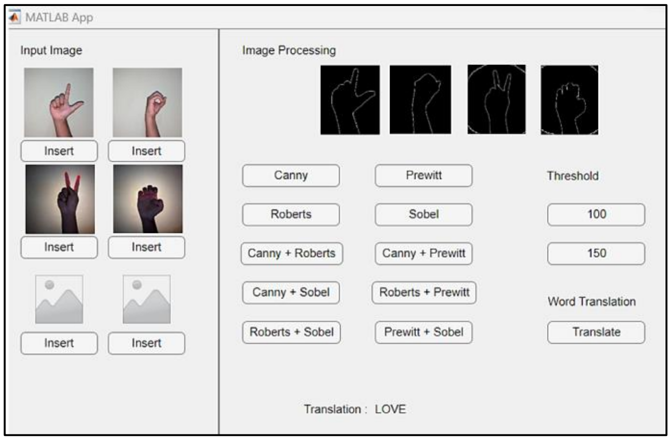

Fig. 16. Image processing interface.

Fig. 17 displays the recognition percentage obtained using all the alphabets with both single and combined methods. It is worth noting that the recognition rate for all single methods is identical; hence, they have been grouped together. The same has been done for combined methods. When comparing the two threshold values, it is observed that the trend is similar to the pixel count. Increasing the threshold value improves recognition in direct light conditions but reduces detectability in back light images. The combined method has been shown to increase the recognition of sign language signs by approximately 7.7- 11.5%. The results suggest that the combined method is more robust and reliable than any of the individual methods alone. The improvement in recognition performance achieved by the combined method can be attributed to its ability to capture complementary information from both methods.

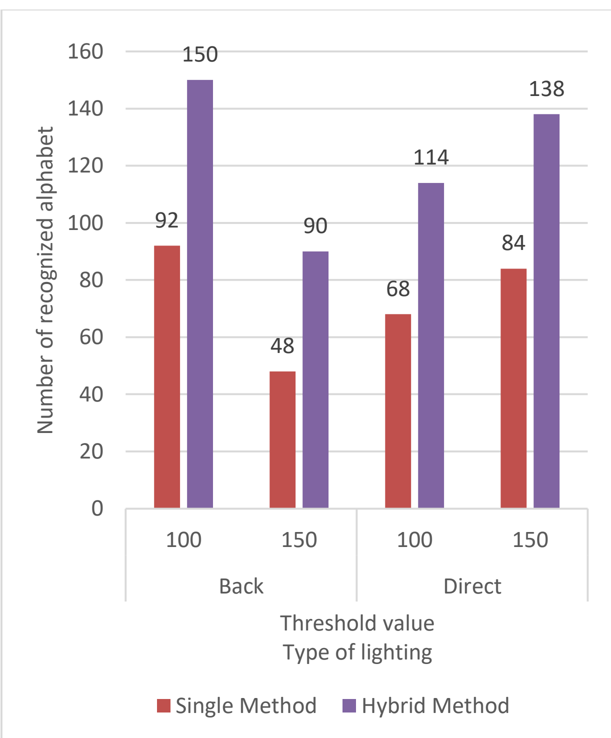

Fig. 17. Total of alphabhet hand signs alphabhet recognition.

E. Optimum Hybrid Method

The Prewitt and Sobel edge detection methods consistently outperformed Roberts and Canny, with Prewitt exhibiting the lowest standard deviation. Prewitt demonstrated superior performance across various lighting conditions and threshold values for edge detection, followed by Sobel, Roberts, and Canny. The Prewitt+Sobel and Prewitt+Roberts combined methods yielded the best results, offering efficient segmentation and hand sign recognition with minimal variation. Furthermore, the experiment revealed that varying the threshold could categorize suitable lighting conditions for critical lighting scenarios. However, increasing the threshold led to longer processing times and higher standard deviations in most conditions.

Overall, it can be concluded that Prewitt+Sobel and Prewitt+Roberts were the best-performing combined methods, enabling the recognition and translation of more alphabets and words compared to single methods. Notably, the combined approach showed a significant improvement of over 100% for pixel edge thickness, and for sign language hand sign recognition, the improvement reached up to 12% compared to individual methods alone, indicating its robustness and reliability in capturing information from both techniques. This efficacy is attributed to the distinct characteristics of Prewitt and Sobel that make them useful in different scenarios.

By combining these two techniques, more robust edge detection results can be achieved, leveraging their complementary properties, increasing robustness, enhancing edge representation, and offering flexibility in various image processing applications. Notably, research by Wanto et al. also corroborates the effectiveness of Prewitt+Sobel as the best combined method [30]. Prewitt and Sobel possess complementary directional sensitivity, with Prewitt emphasizing vertical and horizontal edges, while Sobel emphasizes diagonal edges. Through their combination, edges in various directions can be detected more effectively, enabling the capture of a wider range of edges in an image.

V. CONCLUSION

In conclusion, image segmentation stands as a pivotal process for refining edge detection images, distinguishing them from the background, and highlighting specific areas within the image to accurately identify edges. This refinement results in sharper boundaries and clearer connections, facilitating easier differentiation between different edges. Notably, lighting conditions and threshold values show a significant influence on the quality of image segmentation. While higher thresholds enhance segmentation in direct light conditions, lower thresholds prove more effective for back light images, striking a balance between segmentation accuracy and processing time. However, variations in natural lighting conditions and dynamic environments may pose challenges, impacting the consistency and reliability of edge detection outcomes across different settings. Hybrid edge detection methods surpass single methods, producing thicker, clearer edges under direct lighting and well-defined hand shapes with enhanced visibility in back lighting. Among the hybrid approaches, particularly Prewitt+Sobel and Prewitt+Roberts, demonstrate superior performance with increased pixel count and reduced algorithm processing time, albeit with slightly higher standard deviations. Despite these advantages, the selection and optimization of hybrid methods require careful parameter tuning, which can be resource-intensive and may vary depending on the specific application context and dataset characteristics. The combination of methods yields a notable improvement of 7.7-11.5% in sign language recognition compared to individual methods alone, underscoring their robustness in capturing complementary information. Therefore, careful consideration of the choice of edge detection method, threshold value, and potential use of combined methods is crucial, depending on specific lighting conditions and the desired balance between accuracy, speed, and robustness. In essence, this study underscores the significance of image segmentation in edge detection for sign language hand signs, highlighting the efficacy of combined methods in enhancing recognition accuracy across diverse lighting conditions. These insights not only offer direct applications but also pave the way for integration with Convolutional Neural Networks (CNNs) or Artificial Neural Networks (ANNs) to further enhance the accuracy of hand sign recognition and translation.

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