I.J. Image, Graphics and Signal Processing, 2024, 4, 1-14
Published Online on August 8, 2024 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijigsp.2024.04.01

Image Analysis of Impurity in Machine-harvested Cotton Based Machine Vision

Mingjie LI*
College of Computing and Information Technologies, National University, Philippines
Management Science and Engineering, Anhui University of Finance and Economics, Bengbu, Anhui 233030, PR China
Email: 120082120@aufe.edu.cn
ORCID iD: https://orcid.org/0009-0001-6209-0668
*Corresponding Author

Vladimir Y. Mariano
College of Computing and Information Technologies, National University, Philippines
Email: vymariano@national-u.edu.ph

Received: 08 December, 2023; Revised: 17 February, 2024; Accepted: 10 March, 2024; Published: 08 August, 2024

Abstract: The mechanization rate of cotton picking continues to increase with the continuous improvement and development of China's agricultural modernization level. However, when picking cotton, the machine cannot distinguish between cotton fibers and impurities well, resulting in a certain gap in impurity content compared to manually picked cotton. This paper combines machine vision and image processing technology to adopt an improved Canny-based impurity image processing algorithm. By performing light processing, selecting a color space, filtering images, and removing noise from machine-harvested cotton images, the suppression of virtual edges on impurity images allows for more accurate identification of impurities on the cotton surface. Finally, experimental details and results conclusively demonstrate the effectiveness of this method, providing a basis for detecting and classifying cotton impurities.

Index Terms: Machine Vision, filtering, impurity, machine-harvested cotton

1. Introduction

Cotton plays a pivotal role as a primary raw material in the textile industry and carries strategic significance owing to its diverse applications in textiles, medical products, and military equipment. China stands prominently as a leading nation in cotton production, consistently maintaining a position among the foremost global producers. [1].

With the continuous improvement and development of China's agricultural modernization and the escalating labor costs, the conventional methods of manual planting, irrigation, and cotton picking are no longer aligned with the fundamental requirements of China's cotton development. To ensure the long-term stability and increased production of China's cotton products, it is imperative to enhance the level of cotton mechanization, whereby the comprehensive mechanization and automation of cotton production emerge as the prevailing trend in the cotton planting industry. Facilitated by pertinent policies, the degree of cotton mechanization in China has witnessed a significant upsurge. According to data from the Chinese Ministry of Agriculture and Rural Affairs in 2022, the mechanization rates reached 99.5% for cotton machine plowing, 92.06% for machine sowing, and 76.8% for machine picking. The comprehensive mechanization rate encompassing cultivation, seeding, and harvesting reached 90.46%, with the machine picking rate exhibiting a notable year-on-year increase of 8.78% [2].

Machine-picking technology has substantially enhanced the efficiency and cost-effectiveness of cotton harvesting. Nevertheless, in comparison to hand-picked cotton, there remains a disparity in the quality of machine-harvested cotton. Particularly noteworthy is the significantly higher trash rate associated with machine-picked cotton, typically ranging from 9% to 18% [3](as shown in Figure 1).


a. machine-harvested cotton


b. Hand-picked cotton

Fig. 1. Comparison of hand-picked cotton and machine-harvested cotton

During the picking process, machine-harvested cotton struggles to effectively distinguish between cotton fibers and impurities. Consequently, immature cotton peaches, cotton shells, cotton sticks, and various impurities may be inadvertently collected alongside the cotton. This leads to heightened impurity content in the harvested cotton, thereby intensifying the subsequent task of purging impurities from the cotton. Table 1 illustrates a comparison of the impurity content between the two cotton picking methods.

Table 1. Comparison of Impurities in Cotton Picking by Machine and By Hand

Impurity type	Impurity content of hand-picked cotton (%)	Impurity content of machine-harvested cotton (%)
Cotton boll	0	3.0-4.0
Cotton stalk	0	3.0-4.5
Leaf chip	1.0-3.0	2.0-3.5
Stiff valves and sterile seeds	1.0-1.5	4.5-6.5
Total cotton impurity content	2.0-4.5	9.0-12.0

Presently, the determination of cotton impurity content primarily relies on impurity analysis machines coupled with manual sorting. This method is time-consuming and exhibits low detection efficiency. High-Volume Instrument (HVI) is predominantly utilized to assess the number and area ratio of impurities on the cotton surface. However, this equipment is cost-prohibitive and lacks the capability to categorize impurities comprehensively. In light of these challenges, this paper proposes an image recognition method for detecting cotton surface impurities based on the Canny algorithm. This approach offers foundational technical support for impurity detection and classification, holding significant potential for broad application and practical significance.

2. Literature Review

Digital image processing constitutes a pivotal component of machine vision, playing a crucial role in determining its specific efficacy. The digital image processing techniques developed thus far can be broadly classified into two primary categories: analog signal image processing and digital signal image processing[4]. Within the domain of machine vision, the predominant focus of research centers on digital image processing, wherein captured image information is converted into matrix signals suitable for computerized analysis. By harnessing the computer's high-speed, stability, and precision capabilities, digital image processing is employed to manipulate the substantive content of images.

In the Python programming language environment, the OpenCV library is utilized to implement diverse image processing methods for the identification and classification of impurities in cotton. This process predominantly encompasses acquiring cotton images, enhancing and refining target images, image segmentation, and the separation of impurities. The specific framework diagram is depicted in Figure 2.

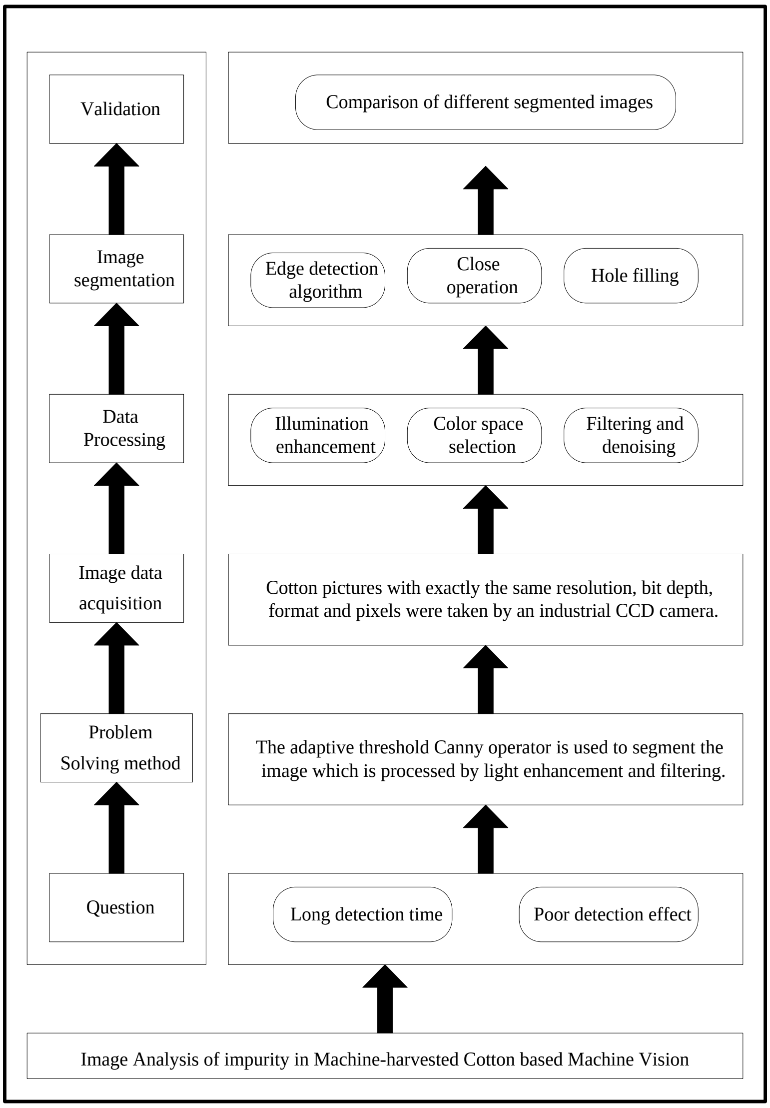

Fig. 2. The main technical roadmap

3. Methodology

3.1 Cotton raw image acquisition

According to the overall requirements for the detection of impurities in machine-harvested cotton, a machine vision test bench was designed, and the components of the test bench were briefly introduced. The selection and design of the light source were carried out, and the relevant parameters of the test bench were determined.

The acquisition of raw images constitutes the initial and indispensable step in the processing pipeline, serving as a prerequisite for all subsequent processing steps. All ensuing processing procedures rely fundamentally on the collected raw images. Consequently, the acquisition and retrieval of raw images are pivotal and essential components of the overall process.

Numerous factors contribute to the determination of the quality of the final captured images, with lighting conditions emerging as one of the most pivotal elements among them. In the process of image acquisition, the judicious selection of appropriate lighting conditions can significantly mitigate the adverse effects of shadows or reflections on image quality. This not only markedly enhances the accuracy of algorithmic detection results but also expedites computations, thereby conserving processing time. In the context of manual visual inspection methods employed to identify impurities in cotton, the ideal lighting environment entails the utilization of natural light during sunny mornings. Consequently, in this study, the D65 mode (International Standard Artificial Daylight) in a standard light source box is chosen to simulate optimal lighting conditions for manual visual inspection. The lamp's color temperature is set to 6500K, and the working power is 18W, effectively replicating the ideal lighting environment.

Following the establishment of the lighting environment, the additional hardware devices required for image acquisition include the camera and optical lens. In machine vision systems dedicated to related inspections, CCD cameras are the preferred choice for image capture by most manufacturers. Consistent with the design of cotton impurity detection and recognition methods discussed in this paper, a CCD camera is selected as the image acquisition device. The camera utilized in the experiment is the RY-800 line scan CCD industrial camera, manufactured by IDS, a German company, as depicted in Figure 3. The camera lens boasts automatic zoom control with 5 groups of 16 lenses. It exhibits a compact size and offers rapid and stable transmission speeds. The camera and optical lens are seamlessly integrated, and once assembled, they are connected to the computer with the corresponding software installed. Additionally, the light source box with the pre-set lighting mode facilitates the commencement of image acquisition.

Fig. 3. Test scheme frame diagram

The cotton samples are uniformly arranged within the light source box under the predetermined lighting conditions. Subsequently, various types of impurities are randomly positioned on the distributed cotton samples. Utilizing the standardized D65 lighting environment, a line scan CCD camera is employed to capture images of the samples. The resultant raw images are then stored on the computer. Figure 4 depicts a selection of cotton images featuring impurities obtained during the experimental process in this study. Table 2 provides an overview of the properties associated with the captured cotton images.

Fig. 4. Some pictures of raw cotton containing impurities collected

Table 2. Cotton Data Set Attributes

Source	Bit depth	Resolution	Image format
Taken with a CCD camera	24	1201×851	JPG

3.2 Image preprocessing

Typically, subsequent to the image acquisition stage, it becomes imperative to execute preprocessing on the images before direct utilization. This necessity arises due to the challenging task of circumventing the influence of various external factors encountered during the image acquisition process, including the acquisition environment, lighting conditions, acquisition devices, transmission devices, and others. These factors have the potential to introduce diverse interferences and effects on the images. For instance, noise may manifest in the images owing to the transmission process, and uneven lighting may impede the accurate reflection of information within the captured images. Consequently, image preprocessing emerges as a crucial and requisite step, given that appropriately executed preprocessing measures can significantly enhance image readability and algorithm processing speed, concurrently mitigating challenges in subsequent image segmentation and feature extraction.

In general, the preprocessing steps serve the subsequent processing tasks. In this paper, a series of preprocessing steps, such as adjusting uneven lighting, selecting color space and channels, image enhancement, and noise reduction through filtering, are performed to preliminarily process the acquired raw images.

1) Uneven lighting adjustment processing

Uneven lighting represents a significant challenge that necessitates consideration in the formulation of cotton impurity detection algorithms. CCD cameras operate on the principle of light reflection for image capture. However, the cotton layer under observation is not a straightforward planar two-dimensional structure. Owing to its inherent structural characteristics, such as unevenness, varied elevations, and minute pores, even in meticulously designed and optimal lighting environments, the acquired images may still manifest conspicuous uneven lighting. Certain regions within these images may exhibit high light intensity, such as concentrated reflections on the cotton layer's surface, while other areas may register low light intensity, exemplified by the pores within the cotton layer. In regions characterized by high light intensity, the local brightness exceeds that of the overall image, potentially resulting in the loss of fine details. Conversely, in regions marked by low light intensity, the extraction of pertinent information during subsequent processing becomes challenging, leading to incomplete analysis and potential misjudgments, consequently yielding inaccurate results. Consequently, addressing the issue of uneven lighting is imperative to mitigate its impact on the accuracy of impurity detection and attain more reliable judgment results.

This paper primarily tackles the challenge of uneven lighting in images of machine-harvested cotton impurities through the implementation of homomorphic filtering. An image $f(x,y)$ can be represented as a combination of two parts: the illumination distribution function $f_m(x,y)$ and the reflectance function of the objects $f_n(x,y)$. Therefore, the image can be expressed as Equation 1[5]:

$$f(x,y) = f_m(x,y) \times f_n(x,y) \tag{1}$$

These two components exhibit significant disparities in their frequency domain distributions. The illumination component predominantly occupies the low-frequency region, characterized by gradual and uniform variations, whereas the reflectance component primarily resides in the high-frequency region. To disentangle the illumination and reflectance components, a straightforward approach involves transforming the image into the frequency domain. To achieve enhancement, the emphasis is placed on fortifying the high-frequency component (i.e., the reflectance component) to enhance image details, while mitigating the low-frequency component (i.e., the illumination component) to diminish the impact of lighting on the image. This objective is accomplished by employing an appropriate homomorphic filtering function $H(u,v)$. The specific steps of the operation are expounded as follows:

Firstly, conduct the logarithmic operation to convert the multiplication operation into an addition operation. Equation 3.1 is thus transformed into Equation 2:

$$lnf(x,y) = lnf_m(x,y) + lnf_n(x,y) \tag{2}$$

Subsequently, execute the Fourier transform to convert the spatial domain expression 3.2 into the frequency domain expression 3:

$$R(u,v) = R_m(u,v) + R_n(u,v) \tag{3}$$

Conduct homomorphic filtering on $R_m(u,v)$ for enhancement, augmenting the reflection component while diminishing the illumination component. This yields Equation 4:

$$F(u,v) = H(u,v)R_m(u,v) + H(u,v)R_n(u,v) \tag{4}$$

Subsequently, execute an inverse Fourier transform ($IFFT$) on the enhanced $F(u,v)$to revert the frequency domain representation back to the spatial domain representation. This yields Equation 5:

$$IFFT[F(u,v)] = IFFT[H(u,v)R_m(u,v)] + IFFT[H(u,v)R_n(u,v)] \tag{5}$$

Finally, execute the reverse operation of the logarithm, namely the exponential operation, to derive the ultimate adjusted image expression, as illustrated in Equation 6:

$$f(x,y)' = e^{IFFT[F(u,v)]} \tag{6}$$

Homomorphic filtering is employed on the grayscale cotton impurity image to rectify its uneven illumination and mitigate the influence of uneven lighting on the image. The processing outcome is depicted in Figure 5. It is discernible that the overall brightness of the image is adjusted and evenly distributed. The occurrence of several gray blocks in the original image before adjustment is largely eradicated, and the details of the image are effectively preserved.

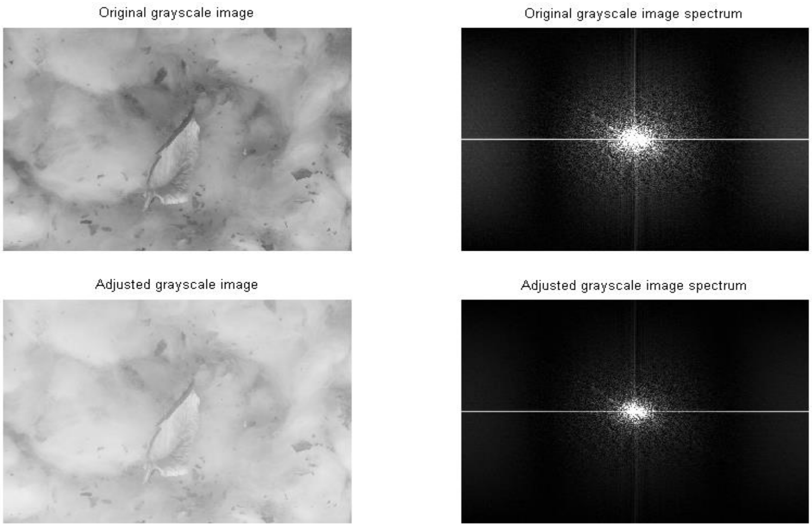

Fig. 5. Effect drawing of uneven light adjustment

2) Color space selection

Color space is defined by establishing distinct descriptive scales for color [6]. Depending on specific requirements, various descriptive scales can be employed to define color in diverse manners, with each color space featuring distinct representations of grayscale values [7]. Consequently, it is feasible to select an appropriate color space that aligns with the detection requirements.

Machine-harvested cotton images manifest variations when presented in different color spaces. To attain improved segmentation of impurities in these images, the selection of an appropriate color space becomes imperative. Widely utilized color spaces encompass BGR, RGB, GRAY, HSV, YCrCb, HLS, XYZ, Lab, YUV, among others. Figure 6 illustrates the display results of machine-harvested cotton images in different color spaces [8].

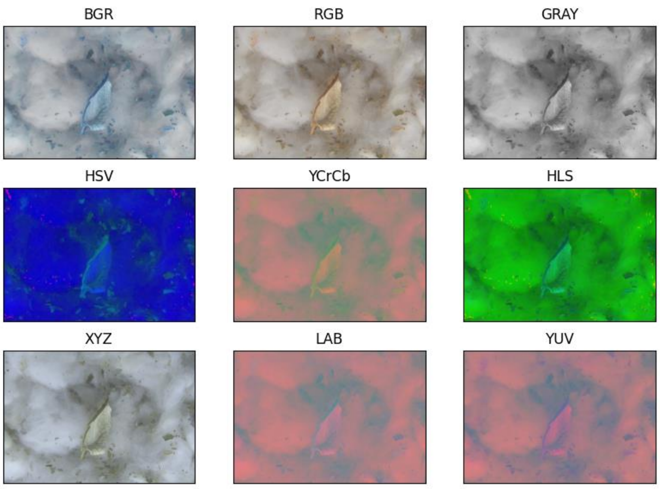

Fig. 6. Machine-harvested cotton images in different color Spaces

To choose color spaces and channels exhibiting distinct differentiation between machine-harvested cotton impurities and the background, grayscale histogram analysis is conducted on the individual channels of various color spaces. The analysis outcomes are depicted in Figures 7 to 9.

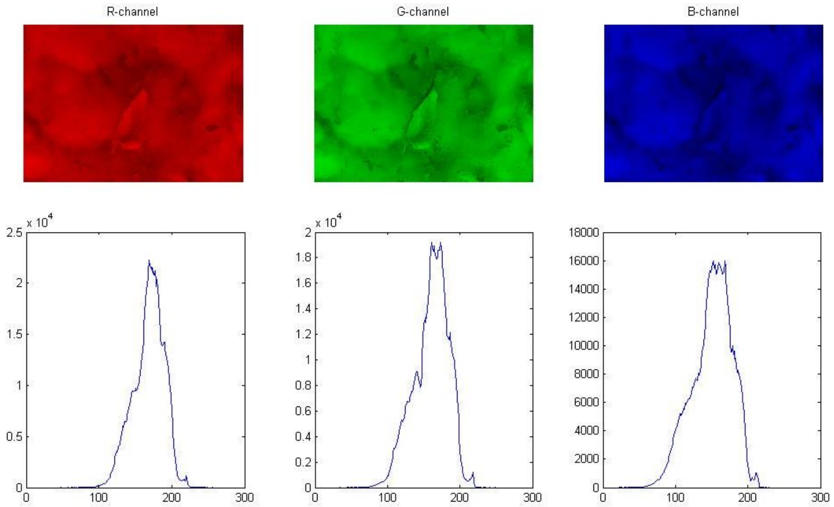

Fig. 7. Analysis of each channel in RGB color space

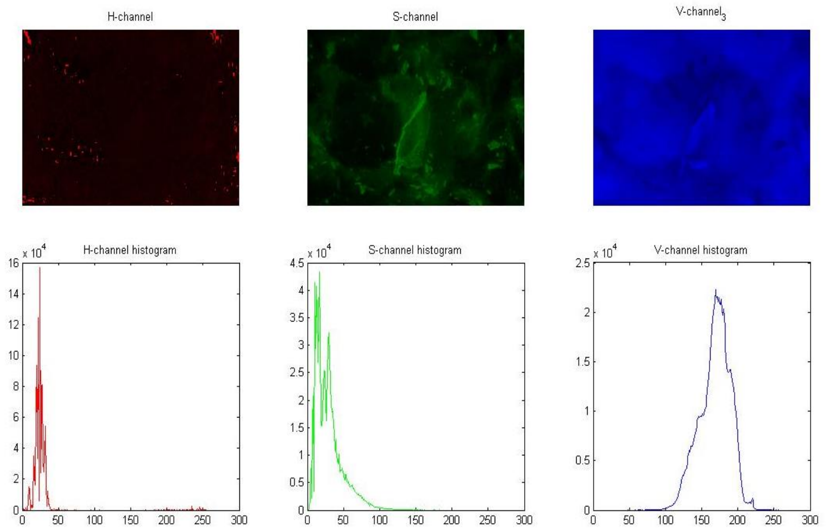

Fig. 8. Analysis of each channel in HSV color space

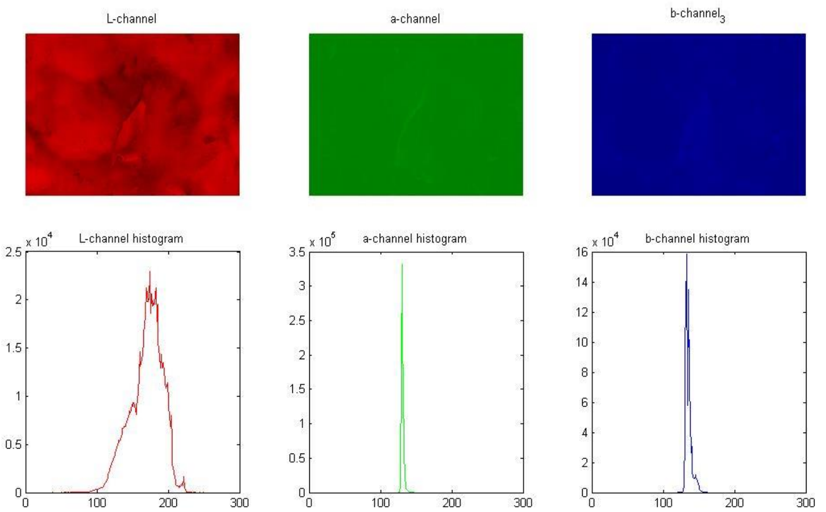

Fig. 9. Analysis of each channel in Lab color space

Upon scrutinizing the three color spaces, it is evident that the grayscale histograms of the RGB color space channels display similarity, portraying a broad range of grayscale values that pose challenges in distinguishing impurities from the background. In contrast, within the HSV color space, the H channel exhibits an uneven distribution of grayscale values, resulting in poor differentiation of impurities. However, the S channel manifests a concentrated distribution of grayscale values with fewer interference points and a segmentation threshold between 20 and 30. This indicates clear differentiation between impurities and the cotton background in the image.

On the other hand, akin to the RGB color space, the Lab color space also presents ineffective differentiation through its L channel's grayscale value distribution. The a and b channels demonstrate relatively similar distributions with concentrated grayscale values around specific points, highlighting certain colors in impurities but failing to effectively distinguish them from the cotton background. Consequently, for machine-harvested cotton impurity segmentation purposes, the utilization of the S channel within the HSV color space is recommended.

3) Image filtering and denoising processing

Any interference affecting an image can be denoted as noise. Throughout the acquisition and transmission processes of an image, various types of noise can easily impede its quality. The causes of noise are diverse, encompassing factors such as electromagnetic waves, device performance, sensor temperature, among others[9]. The presence of noise markedly impacts image quality, increasing the complexity of image interpretation and potentially resulting in misinterpretation of the final detection results. The generation and distribution of noise lack regularity, and its magnitude, type, and distribution are random[10]. Despite enhancement processing, a substantial amount of noise persists in the image. The presence of this noise heightens the challenge of algorithm implementation, diminishes the accuracy of detection results, and exerts a considerable negative impact on subsequent processing steps and detection outcomes[11]. Therefore, performing denoising processing on the image becomes imperative.

The Non-local Means (NLM) algorithm, introduced by Buades et al [12], posits that noise patches in an image exhibit similarity. In the context of machine-harvested cotton images, noise points frequently originate from small holes created by interwoven cotton fibers, presenting as noise points in the image. Through the application of a weighted average of structures resembling noise points in the machine-harvested cotton image, the algorithm accomplishes denoising.

The filtered grayscale value $\hat{f}(i)$ at any pixel point i in the noisy image $f = \{f(i)|i \in I\}$ is given by:

$$\hat{f}(i) = \sum_{j \in I} W(i,j)\, f(i) \tag{7}$$

$$W = \frac{1}{Z(i)} e^{-\left\| f\left(N_i - f(N_j)\right)\right\|_{2,\alpha}^{2} / h^2} \tag{8}$$

Where, $W(i,j)$ represents the weight, $\|\bullet\|_{2,\alpha}^{2}$ is the Gaussian-weighted Euclidean distance that measures the similarity between pixels i and j, α is the standard deviation of the Gaussian kernel, $\alpha > 0$, h is the filtering parameter, and N_k is the square neighborhood centered at point k. The normalization constant $Z(i)$ is given by:

$$Z(i) = \sum_{j \in I} e^{-\left\| f\left(N_i - f(N_j)\right)\right\|_{2,\alpha}^{2} / h^2} \tag{9}$$

To avoid over-weighting, when $i = j$, the weight $W(i,j)$ is given by:

$$W(i,j) = max\left(W(i,j)\right), i \neq j \tag{10}$$

Following the application of median filtering for denoising on the machine-harvested cotton image, additional denoising is undertaken using the NLM algorithm, as illustrated in Figure 10. It is discernible that the impurity regions exhibit increased smoothness, contributing to improved identification of impurity areas.

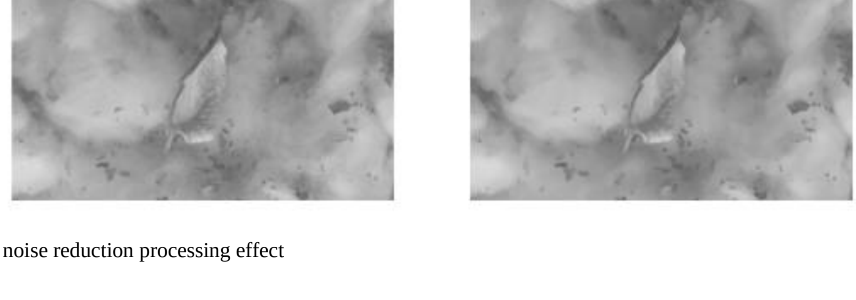

Fig. 10. NLM algorithm noise reduction processing effect

3.3 Cotton image segmentation

The process of image segmentation entails the extraction and separation of regions of interest from an image. In the context of machine-harvested cotton images, this study endeavors to classify, recognize, and detect impurities in the cotton. Consequently, the regions of interest are defined as areas containing impurities, and the objective is to accurately segment these areas from the cotton background [13,14]. For practical segmentation performance, the identification of edges, representing boundary lines between target areas and backgrounds, is crucial. Effective edge detection serves as a pivotal initial step for accurate segmentation of target areas. Therefore, the selection of a suitable edge detector [15] is of paramount importance as it directly influences subsequent processing steps.

Presently, diverse edge detectors have been developed, including the Roberts operator, Sobel operator, Prewitt operator, Laplacian operator, Canny operator, etc., which are commonly utilized for the detection of impurities in machine-harvested cotton images (as depicted in Figure 11).

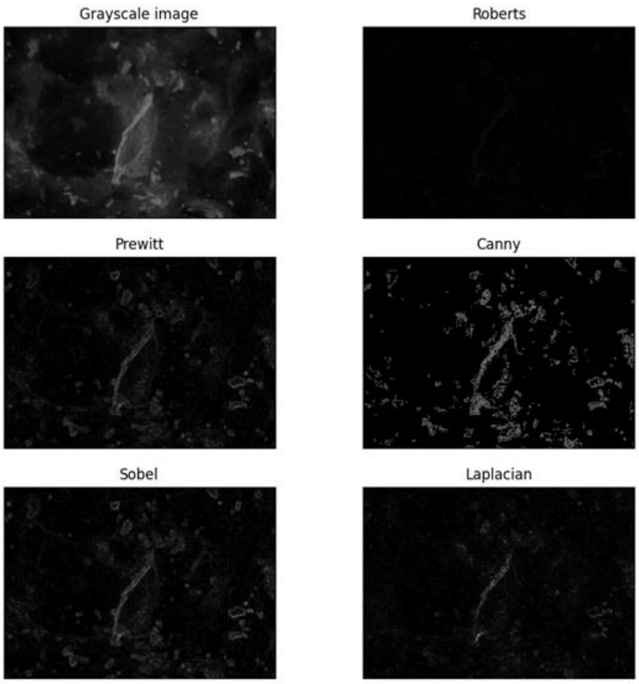

Fig. 11. Comparison of edge detection of impurities in machine-harvested cotton

As evident from the above figure, edge detection is conducted following the grayscale transformation of machine-harvested cotton images. The edges detected by Laplacian and Roberts operators appear discontinuous and contain less edge information, which is not conducive to subsequent segmentation operations. Although the Sobel operator and the Prewitt operator exhibit good recognition of impurity edges, they are susceptible to interference from background information, leading to the presence of smoky interference information. On the other hand, the Canny operator can clearly detect edges, capturing detailed information with effective detection capabilities. Despite the uneven surface of the impurity, the Canny operator identifies the internal texture of the impurity surface as an edge, without detrimentally impacting subsequent processing. Therefore, the Canny operator adeptly discerns the contour information of impurities, but optimization and refinement are still deemed necessary needed.

The threshold size in the Canny algorithm requires manual configuration, and the threshold selection is a highly intricate process. It necessitates prior experience to determine a general value interval, and extensive experimentation within the chosen interval is essential to ascertain the appropriate threshold. The algorithm employs a fixed multiple relationship between high and low thresholds. In the process of manually selecting thresholds, a high threshold may result in broken and incomplete extracted edges, while a low threshold may lead to extensive misjudgments, even extracting noisy pixels as edge pixels, thereby altering the outer contour of the target area completely. Furthermore, the application of the same set of thresholds across different images may not be universally applicable during processing[16]. A set of thresholds that effectively extracts edges in one image might not perform optimally in another image, thereby necessitating additional unnecessary work. Figure 12 illustrates the segmentation effect of the traditional Canny algorithm with different values for the high threshold, where the low threshold is set to 0.5 times the high threshold.

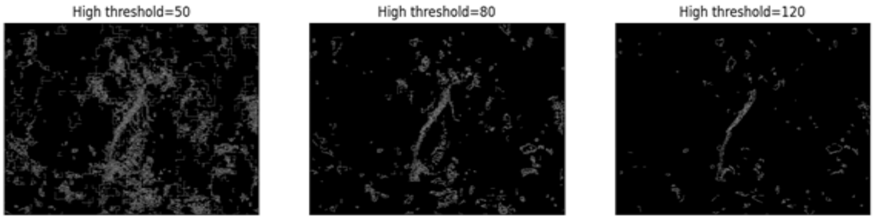

Fig. 12. Effect chart by Canny algorithm of different threshold

To address this challenge, this paper integrates the OTSU algorithm with the Canny algorithm and introduces the concept of maximum inter-class variance from the OTSU algorithm to enhance the Canny algorithm. The pixels in the image, after non-maximum suppression in the Canny algorithm, can be categorized into three groups, denoted as E_1, E_2, and E_3, respectively. Where E1 represents non-edge pixels in the original image, and the gradient amplitude interval is set as $[t_1, t_2]$, in which the gradient amplitude of all pixels is less than the low threshold. E2 represents the pixels to be confirmed in the original image, including gradient amplitude interval $[t_{x+1}, t_k]$. All gradient amplitudes in this interval are between high and low thresholds, and it is necessary to further determine whether they are edge points. E3 represents the edge point determined in the original image, containing the gradient amplitude interval $[t_{x+1}, t_z]$, where all gradient amplitudes are greater than the high threshold. If the total number of pixels in the original image is denoted as N, and the number of pixels corresponding to the gray gradient value is $t_i$is denoted as n_i, its probability can be expressed as:

$$p_i = {}^{n_i}/_{N} \; (i = 1,2,\ldots,Z) \tag{11}$$

Subsequently, the expected value of the gradient amplitude of the original graph is calculated as follows:

$$E_t = \sum_{i=1}^{z} t_i \times p_i \tag{12}$$

The expected gradient amplitudes forE_1, E_2, and E_3 are:

$$\begin{cases} e_1 = \dfrac{\sum_{i=1}^{x} t_i \times p_i}{\sum_{i=1}^{x} p_i} \\ e_2 = \dfrac{\sum_{i=x+1}^{k} t_i \times p_i}{\sum_{i=x+1}^{k} p_i} \\ e_3 = \dfrac{\sum_{i=k+1}^{z} t_i \times p_i}{\sum_{i=k+1}^{z} p_i} \end{cases} \tag{13}$$

Also define:

$$\begin{cases} p_1 = \sum_{i=1}^{x} p_i \\ p_2 = \sum_{i=x+1}^{k} p_i \\ p_3 = \sum_{i=k+1}^{z} p_i \end{cases} \tag{14}$$

Then the evaluation function can be expressed as:

$$\sigma^2 = \left(\sum_{h=1}^{3} \left(e_h - E_t\right)^2 \times p_h\right) \tag{15}$$

The value of the maximum value of the evaluation function σ^2 is calculated through search. t_k and p_k corresponding to the maximum value are set as the high and low thresholds of the improved Canny algorithm respectively for segmentation. The improved Canny algorithm makes up for the shortcomings of the traditional Canny algorithm, which requires artificial presetting of high and low thresholds and a large number of repeated tests, and the relationship between high and low thresholds is no longer fixed, which improves its practicability. The improved Canny algorithm is used to extract the edge of the impurity image of raw cotton. The effect is shown in Figure 13, and the extracted contour is continuous and complete.

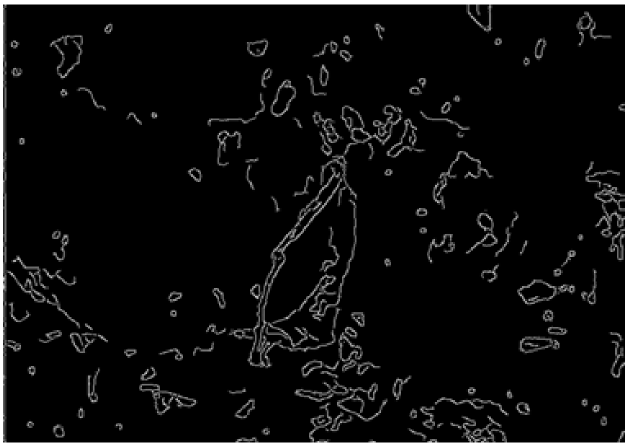

Fig. 13. Effect chart by improved Canny algorithm

During the edge detection process, all detected edges correspond to impurities. Consequently, the area enclosed by these edges can be filled to obtain the impurities. For open edges, a morphological dilation operation is employed to connect them, followed by an erosion operation to restore the edge width, as illustrated in Figure 14. The edges forming closed loops represent impurity regions, necessitating filling to constitute complete impurity regions, as depicted in Figure 15.

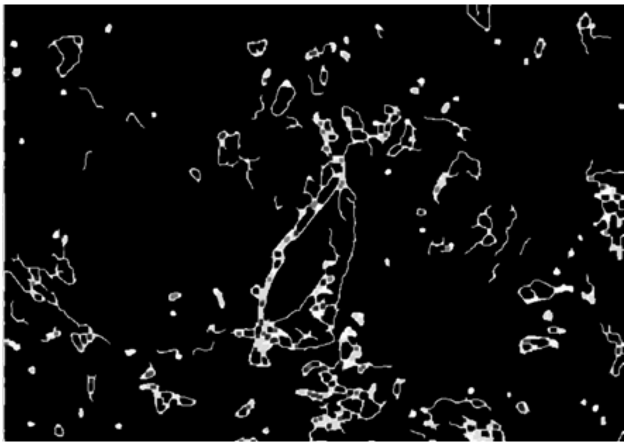

Fig. 14. Close operation

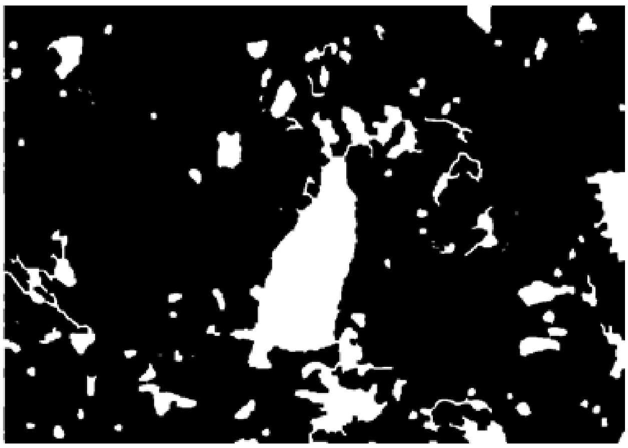

Fig. 15. Hole filling

To facilitate observation, the output image serves as a template for operations with the original input photograph, highlighting the impurity section in the color photo while rendering the rest in black, as illustrated in Figure 16.

Fig. 16. Impurity color image after segmentation

4. Proof of Concept

In practical detection, the speed, accuracy, and robust performance of an algorithm are also crucial factors in determining its suitability. Therefore, by collecting multiple images of machine-harvested cotton seeds and processing them, we compare the segmentation results of different algorithms for machine-harvested cotton, observing the differences among them.

Eight sets of randomly selected machine-picked seed cotton images, each containing impurities, were employed to assess the segmentation effectiveness and processing speed of the enhanced Canny operator segmentation algorithm, traditional Canny operator segmentation algorithm, SVM algorithm, and K-means clustering algorithm. The results are depicted in Figure 17 to Figure 20.

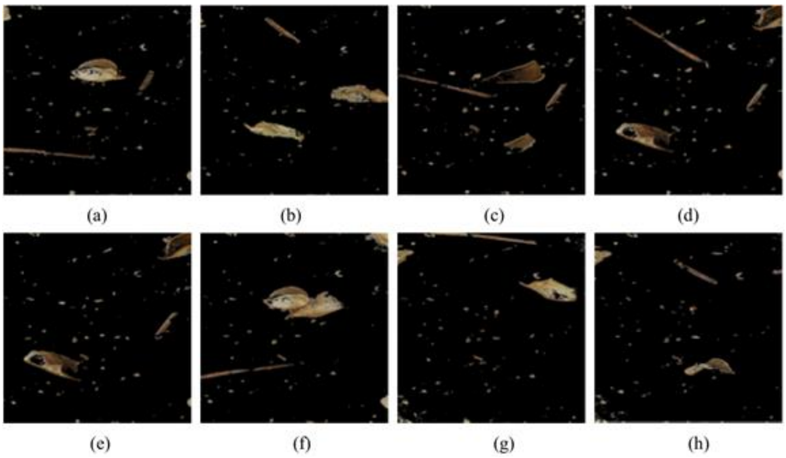

Fig. 17. SVM of image segmentation

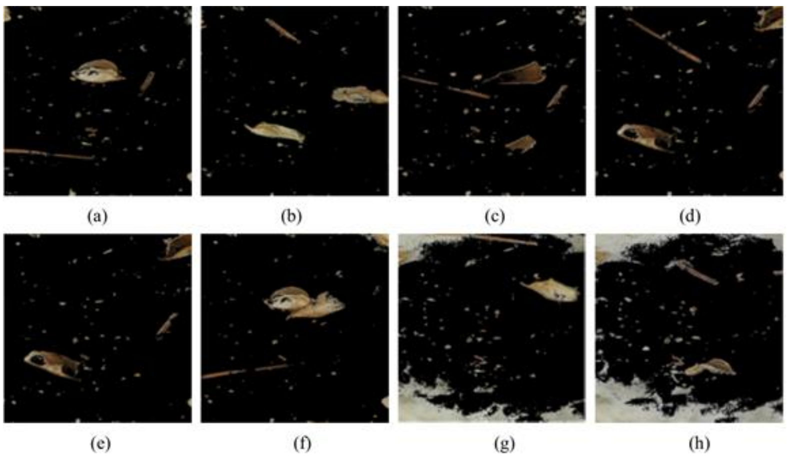

Fig. 18. K-means clustering of image segmentation

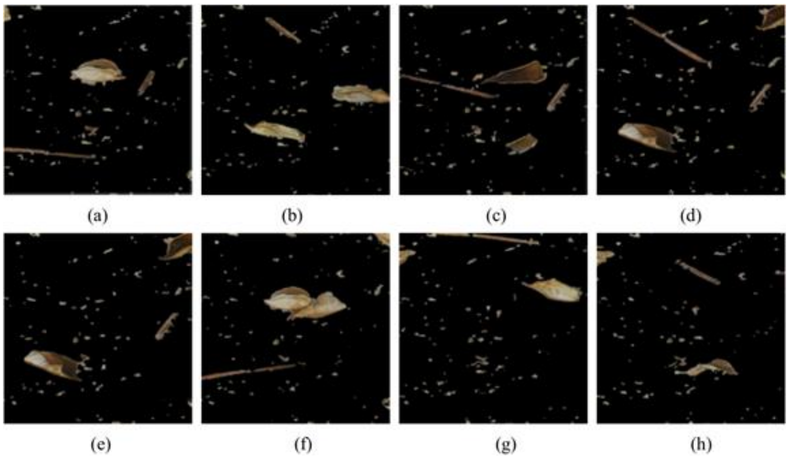

Fig. 19. Traditional Canny of image segmentation

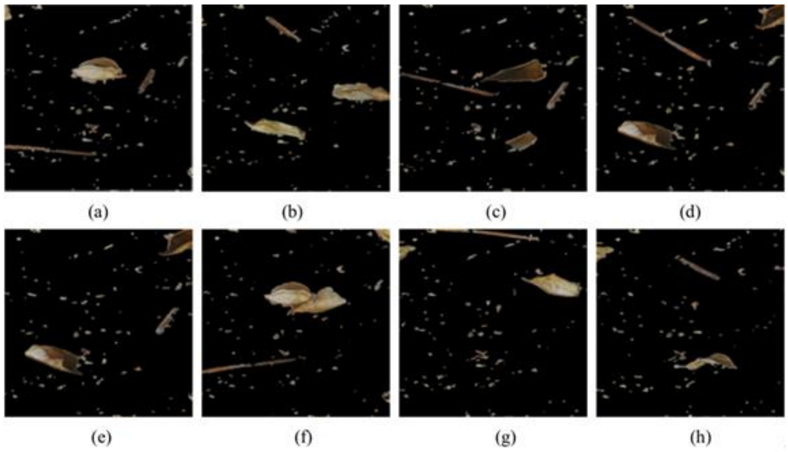

Fig. 20. The proposed algorithm of image segmentation

It is evident from the above figures that the proposed algorithm attains a more precise segmentation effect compared to the other operators. This enhancement aids in avoiding any influence from cotton backgrounds while also reducing instances of false segmentations. However, K-means clustering segmentation is susceptible to the background color of an image, negatively impacting its robustness and potentially resulting in false segmentations in larger cotton areas.

Among the aforementioned algorithms, both the proposed impurity rate detection algorithm and the traditional Canny operator's impurity rate detection algorithm demonstrate an average processing time of 0.5 seconds per image, enabling real-time detection. In contrast, K-means clustering necessitates an average processing time of 12.632 seconds per image, while SVM segmentation is unsuitable for real-time detection due to the requirement for manual background and foreground selection.

5. Conclusion

This paper introduces an enhanced and practical methodology for recognizing cotton impurity images, leveraging machine vision technology to execute a sequence of image processing tasks on cotton images. Ultimately, an improved Canny algorithm is applied to segment cotton impurity images, facilitating swift and accurate recognition of these images from magazines. The innovation of this method lies in combining the OTSU algorithm with the Canny algorithm, incorporating the idea of maximizing inter-class variance from the OTSU algorithm into the Canny algorithm for improvement. This addresses the drawback of the Canny algorithm requiring manual threshold setting. Compared to alternative methods, this approach demonstrates rapid recognition speed, straightforward operation, and outstanding recognition effectiveness. This technology can provide technical support for the optimization of the mechanical cotton cleaning system, enabling the rapid detection of impurities in machine-harvested cotton. It allows real-time monitoring of impurities, quickly acquiring data to assist in the timely removal of impurities.

References

[1] Dong Quancheng, “Research on Key Technologies of Cotton Glint and lint cleaning”. Shandong University, 2016.
[2] Cao Jiqiang, Cheng Lu, ZHANG Chunyu, “Research status and countermeasures of machine-picked cotton primary processing in Xinjiang”, Cotton Textile Technology ,vol.49, no.02, pp75-79, 2021
[3] Zhang Ming, “Countermeasures to improve the mechanization level of cotton production in Aksu Region”, Xinjiang Agricultural Mechanization, no.1, pp41-42, 2021.
[4] Wu Tingrong,Chen Yajun,Yang Shuhan, “Detection and experiment of seed cotton impurity content based on image analysis”, Journal of Xi 'an University of Technology, vol.37, no.02, pp235-241, 2021.
[5] Sun Zhaolin, “MATLAB Application of Image Processing”, Tsinghua University Press, no.5, pp231-232, 2002.
[6] Zhang Hui, “A review of theoretical and empirical research on color space conversion”, Packaging Engineering, vol.32, no.13, pp102-107, 2011.
[7] Guo LI, “Research on grayscale algorithm of color image in color space”, Shaanxi Normal University, 2017.
[8] Xie Y T, “Cotton heterofiber detection method based on RGB space model”, Modern Industrial Economy and Information Technology, vol.9, no.01, pp67-68, 2019.
[9] Qing Xiangyun, Duan Hong, Wei Junmin, “Research on fabric defect detection and recognition based on local entropy”, Textile journal, vol.25, no5, pp57-58, 2004.
[10] Zhang Xin, LI Daoliang, Yang Wenzhu, WANG Jinxing, LIU Shuangxi, “Fast segmentation of high resolution color images of cotton fibers”, Chinese Journal of Agricultural Machinery, vol.42,no.1, pp159-164, 2011.
[11] Chen Yan, “Research on image denoising method”, Digital Technology and Application, no.05, pp131-132, 2017.
[12] A Buades, B Coll , J M Morel, “Image denoising by non-local averaging”, IEEE International Conference on Acoustics, Speech, and Signal Processing(ICASSP), 2005.
[13] Qi Yinglan, “Visual detection method of raw cotton impurities using adaptive filtering and threshold iteration”, Woolen Textile Science and Technology, vol.48, no. 02, pp73-77, 2019.
[14] Liu Shikai, Zhou Zhiyuan, Shi Baosen, “Research progress of optical image edge detection”, Laser and Optoelectronics Progress, vol.58, no.10, pp193-204, 2021.
[15] Zhao Linjun, Zhu Ruisha, “Research on Image Contour Edge Analysis Based on Canny Edge Detector”, Academic Journal of Computing & Information Science,vol.50, no.01, pp10-15, 2022.
[16] Li Baozhi, Ni Hongqi, Lin Siyu, “Axial dimension detection method of ripple compensator based on image recognition”, Journal of engineering design, vol. 29, no.01, pp10-19, 2022.

Authors' Profiles

Mingjie LI is a PhD scholar in College of Computing and Information Technologies National University, Philippines. Before coming into PhD, he had worked as Experimentalist fellow in Management Science and Engineering, Anhui University of Finance and Economics, China. He has total of 15 years of experience in teaching and Research. His main interest includes Machine learning, data analysis and Image/Video Processing.

Vladimir Y. Mariano is currently working as a professor of faculty of Computing and Information Technologies at National University in Philippines. He received the B.S. degree in statistics and the M.S. degree in computer science from the University of the Philippines Los Banos, and the Ph.D. degree in computer science and engineering from The Pennsylvania State University. His research interests include computer vision, digital image processing, and machine learning.

How to cite this paper: Mingjie LI, Vladimir Y. Mariano, "Image Analysis of Impurity in Machine-harvested Cotton Based Machine Vision", International Journal of Image, Graphics and Signal Processing(IJIGSP), Vol.16, No.4, pp. 1-14, 2024. DOI:10.5815/ijigsp.2024.04.01