SMPTS: Segmentation Method for Physically Touching Soybean Images

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***Abstract*—The study mainly aims to develop an image segmentation algorithm named SMPTS for the segmentation of physically touching soybean images in seed testing machines. SMPTS is a classical image-based method. In SMPTS, the binary method with an adaptive mean threshold is to divide the contours of soybeans. The medium filter eliminates salt and pepper noises on the binary image of soybean, which leads to less running time for SMPTS. Otsu with a fixed threshold is to extract the regions of interest of soybean images in physical touching. The minimum bounding rectangle locates individual seeds on the binary image. Individual seed images are cut from the physically contacted soybean images based on location and size. As a result, SMPTS could achieve more than 99% segmentation accuracy, with about 53ms for segmenting a soybean seed on NVIDIA Jetson TX2. Meanwhile, the segmentation accuracy of intact soybeans, immature soybeans, skin-damaged soybeans, spotted soybeans, and broken soybeans is about 100%, 99.66%, 96.56%, 99.44%, and 99.51%, respectively. The code for SMPTS is https://codeocean.com/capsule/9219546/tree/v1 under the MIT license.**

Keywords—image segmentation, image processing, soybean seeds, physically touching seeds, seed testing machine

I. Introduction

Soybean, one of the world's major oilseed crops, is an essential vegetable protein and oil source in people's daily lives. The classical method for evaluating the quality of soybeans is manual counting and classification of soybean seeds by agricultural inspectors. However, the classical method relies heavily on the experience and observation of agricultural inspectors to achieve soybean classification. More importantly, the classical method is time-consuming, heavily subjective, and highly inefficient. Zhang et al. [1] used the signal change caused by seeds impacting the piezoelectric element to achieve soybean counting. However, Zhang's method could not identify different types of soybean seeds based on soybeans' appearances.

With the development of machine vision and image processing techniques, researchers have proposed various image-based recognition methods for agricultural products. Javanmardi et al. [2] used an image segmentation algorithm to separate individual corns and then combined extracted corns' features with a classifier to complete the corn classification. Huang et al. [3] applied Mask R-CNN to perform the segmentation of soybean seeds and then designed a lightweight Convolutional Neural Network (CNN) to achieve 96.2% identification accuracy. To sort high-quality soybean seeds, Zhao et al. [4] developed a deep learning-based sorting system to recognize the full surface of soybean seeds, with a classification accuracy of about 97.84%. Koklu and Ozkan [5] segmented individual dry beans through the classical image processing algorithm and combined 16 bean features with Support Vector Machines (SVM) to classify the beans, with an overall accuracy of 93.13%. Jitanan and Chimlek [6] used features of individual soybeans for classification with an overall accuracy of about 99.2%, but the physical soybean seeds cannot be processed in Jitanan's method. Moreover, the above studies focused more on classifying seeds without physical contact. In general, seeds are often physically touching in the actual detection scenes, which may cause the above studies to have difficulty matching real scenes. It indicates that the image segmentation for physically touching seed is still a challenge.

With the widespread application of CNN for image segmentation, Yang et al. [7] combined Mask R-CNN with transfer learning to achieve individual soybean seeds for touching seed images under the high-throughput soybean seeds phenotyping. Similarly, other researchers, including Liang et al. [8], Toda et al. [9], and Feng et al. [10], have all applied improved CNNs to the segmentation of touching seed images. Although these studies [7-10] could reach better segmentation performance, they are all data-driven and have high requirements for hardware computing power during CNN training. Meanwhile, labelling data is time-consuming and laborious work, the quality of data labelling would directly affect the accuracy of image segmentation. However, classical image processing methods rely more on pixels to process images. Therefore, classical image processing methods are still highly robust and interpretable. Moreover, classical image processing methods require low hardware computing power. Grift et al. [11] designed an image processing algorithm to accomplish maize counting with an error rate of missing seeds ranging from 0 to 4.24%. Tan et al. [12] proposed an algorithm for touch seed counting of hybrid rice, and the average accuracy reached 94.63%. Liu et al. [13] improved the watershed algorithm to achieve segmentation of touching beans with better segmentation performance. To count soybean seeds and recognize broken seeds, Chen et al. [14] proposed a clustering algorithm based on SVM and K-Means for segmenting touch bean seeds. Although the researchers have paid more attention to image segmentation of physically touching seeds, touching seeds on the images is rare. Lin et al. [15] proposed an image segmentation algorithm for physically touching soybean images based on Multi-scale Retinex with Color Restoration (MSRCR), which segments a seed in approximately 104ms on NVIDIA Jetson TX2 with a segmentation accuracy of over 99%. While Lin's algorithm can reach better segmentation results, the algorithm may need help to fully segment seeds covered with grey-black or purple spots on the surface [16]. The above studies can achieve good segmentation accuracy for physically contacted seeds, but the part of the research [11-14] do not exhibit their real-time performance.

Based on the above analyses, we aim to develop an image segmentation algorithm applied to seed testing machine, which can completely segment seeds regardless of how the soybean seed surface is covered with any classification features of soybeans. More importantly, the image segmentation algorithm should facilitate real-time segmentation of physically touching seeds while operating on a resource-constrained platform.

II. Materials and Methods

A. Image Acquisition System

The image acquisition system contains an industrial camera (MV-CA060-11GM, HIKVISION Co., Ltd., Hangzhou, China), light source, NVIDIA Jetson TX2, power supply, and display, as shown in Fig. 1. The soybean images (3072×2048 pixels) were saved in JPG format. Meanwhile, the image acquisition system collected 38 images of physically touching soybean seeds to validate the performance of SMPTS.

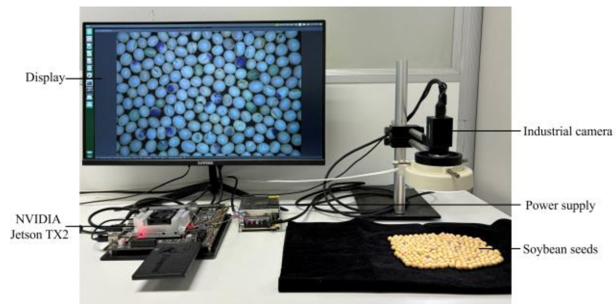


Fig. 1. Image acquisition system.

B. Image Segmentation Algorithm

Fig. 2 shows the flowchart of SMPTS. The Binary Method with Adaptive Mean Threshold (BM-AMT) is applied to extract the contours of soybeans. Then, a medium filter is used to eliminate salt and pepper noises on the binary image of BM-AMT. Then, Otsu with a Fixed Threshold (Otsu-FT) is applied to segment the background and foreground of the original images, but all seeds on binary images are physically in contact. To extract the interest regions, the binary image of Otsu-FT multiplies the binary image of BM-AMT, the result is named the binary image of interest regions (Image-IR). The Minimum Bounding Rectangle (MBR) locates individual seeds on Image-IR. The size of MBR was used to judge whether seeds were in physical contact. If the seeds were non-physically touching, those individual seed images were cropped out from the original images after masking. If the seeds were physically touching, the erosion operation with the 13×13 kernel was applied to eliminate some tiny contact between seeds on the binary image of interest regions after masking. Then, those seeds were relocated by MBR. Finally, those individual seed images were cropped out.

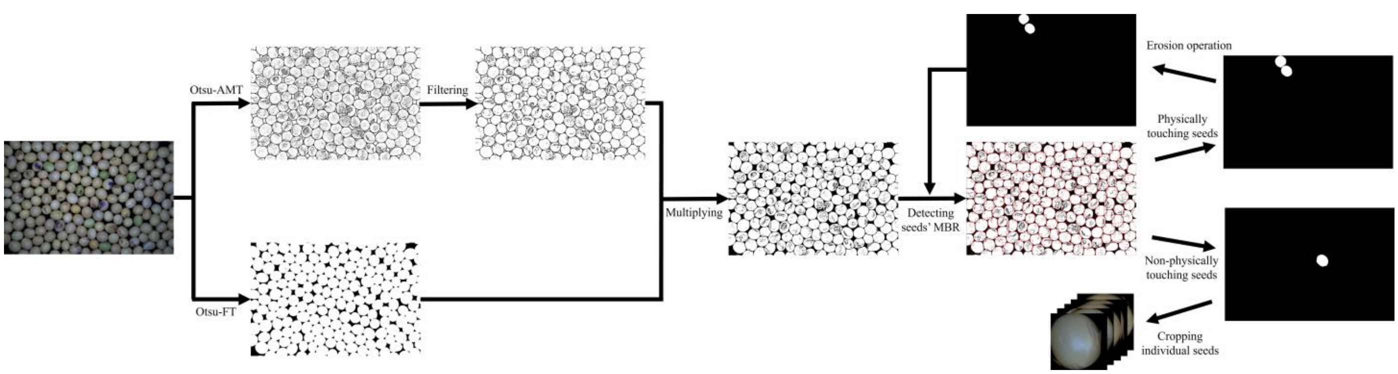


Fig. 2. The flowchart of image processing.

III. Experiments and Analysis

A. Experiment Environments

SMPTS was constructed in C/C++ with OpenCV 3.4.8. SMPTS performed various experiments on the desktop computer with an Inter(R) Core(TM) i7-13700 2.10GHz CPU and 32GB RAM. Finally, SMPTS was run and tested on the NVIDIA Jetson TX2.

B. Evaluation Metrics

There are three evaluation metrics to evaluate SMPTS, including the Rate of Intact Seeds (RIS), the Rate of Physically Touching Seeds (RPT), and the Rate of Over-segmented Seeds (ROS).

$$RIS = \frac{Total\ number\ of\ \ intact\ segmented\ individual\ seeds}{Total\ number\ of\ \ individual\ seeds\ on\ the\ original\ image} \tag{1}$$

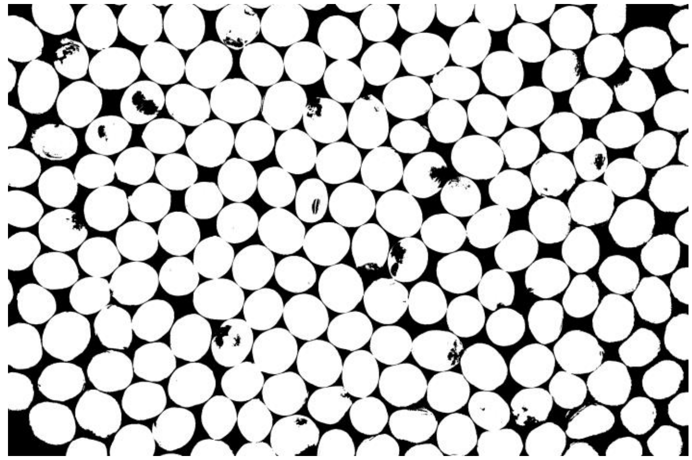
$$RPT = \frac{Total\ number\ of\ \ physically\ touching\ seeds}{Total\ number\ of\ \ individual\ seeds\ on\ the\ original\ image} \tag{2}$$

$$ROS = \frac{Total\ number\ of\ over-segmented\ seeds}{Total\ number\ of\ \ individual\ seeds\ on\ the\ original\ image} \tag{3}$$

C. Binary Method Selection

Fig. 3 shows the results of segmenting seed images with physical contact using Otsu with Adaptive Thresholding (Otsu-AT). In the binary image, there are many tiny contacts between seeds, which causes a smaller number of individual seed images to be segmented from soybean images with physical contacts. Meanwhile, Otsu-AT cannot entirely segment individual seeds located in the corners of the image into the foreground of the binary image due to uneven illumination. More importantly, Otsu-AT is more likely to misclassify some typical features of soybeans (e.g., spotted or broken features) into the background of binary images, which could contribute to the incompleteness of individual soybean seeds cropped from the original images. There are various thresholds in different regions of the physically touched soybean image, preventing Otsu-AT for global image segmentation using one threshold from achieving better segmentation.

(a) Original image.

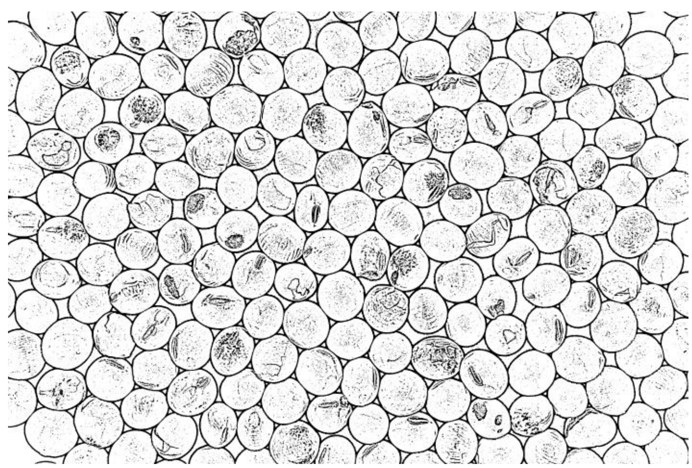


(b) Binary image.

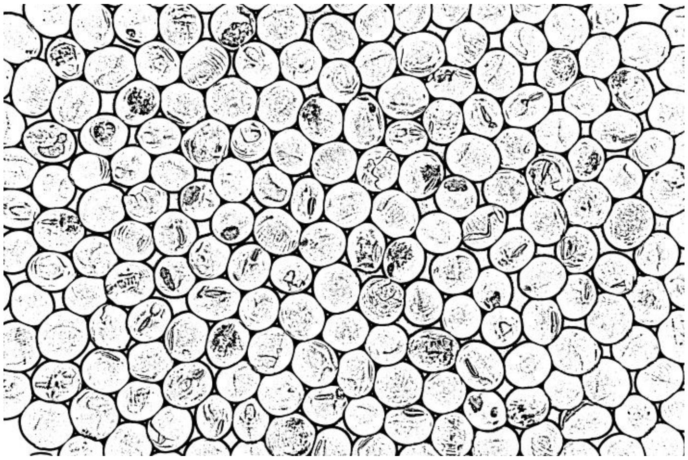
Fig. 3 The result of Otsu-AT.

The Binary Method with Adaptive Thresholds (BM-AT) is a multi-threshold image segmentation algorithm. The core of BM-AT is to split the image into various regions, and then calculate the individual thresholds for each region. Finally, BM-AT divides images' foreground and background based on the thresholds of each region. Therefore, BM-AT can mitigate the effect of illumination on image segment results.

There are two methods for threshold calculation in BM-AT: the adaptive gaussian threshold and the adaptive mean threshold. Since BM-AT uses different thresholds for image segmentation in various image regions, BM-AT can only perform foreground and background segmentation for grey-scale discontinuous areas, unlike Otsu-AT, which uses a threshold for global image segmentation. Fig.4 shows the binary image of the Binary Method with Adaptive Gaussian Threshold (BM-AGT) and BM-AMT, respectively. To extract the interest regions of soybean images, the binary images of BM-AGT and BM-AMT were multiplied by the binary image of the binary method with a fixed threshold (BM-FT), respectively, as shown in Fig. 5.

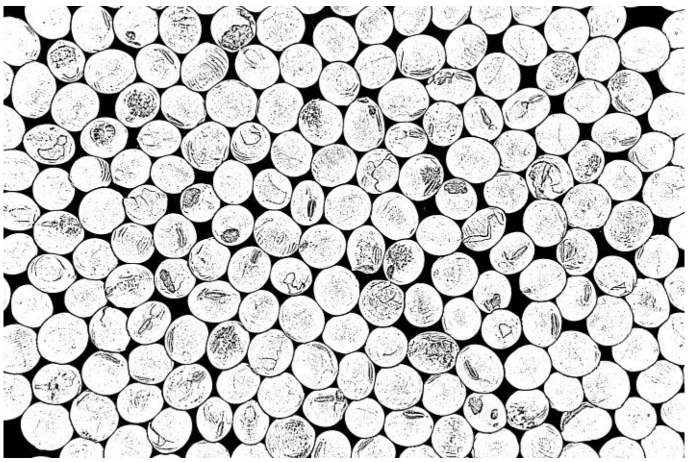


(a) The binary image of BM-AGT.

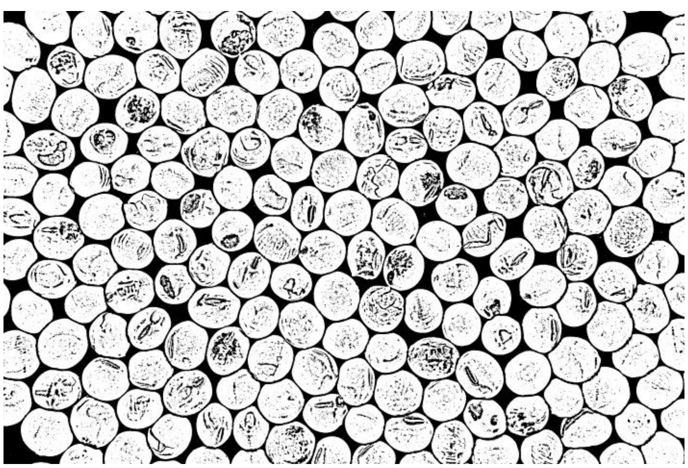


(b) The binary image of BM-AMT.

Fig. 4 The binary images of BM-AGT and BM-AMT.



(a) The result of multiplying the binary image of BM-AGT with the binary image of BM-FT.



(b) The result of multiplying the binary image of BM-AMT with the binary image of BM-FT.

Fig. 5 The binary image of interest regions of soybean images.

Table I shows the results of different adaptive methods. BM-AMT achieves about 99.17% of RIS, while BM-AGT only reaches 93.83% of RIS. Meanwhile, the average segmentation time of BM-AGT (approximately 145ms) for a seed is about 1.27 times higher than that of BM-AMT (about 114ms). In RPT, BM-AGT is considerably lower than BM-AMT.

TABLE I. THE SEGMENTATION ACCURACY OF DIFFERENT BINARY METHODS

Methods	**Evaluation Metrics**			
	RIS	***RPT***	***ROS***	***Average segmentation time/ms***
BM-AMT	99.17%	0.83%	0.39%	114
BM-AGT	93.83%	6.17%	0.09%	145

D. Parameter Selection of BM-AT

In BM-AT, the block size means the size of a pixel neighborhood, which is used to calculate a threshold of the pixels in the pixel neighborhood. Table II shows the results using different block sizes in BM-AMT. As the block size increases, the average segmentation time of a seed decreases from 183ms to 105ms. When the block size was set to 25, RIS was the highest, and RPT was the lowest.

TABLE II. THE EFFECT OF BLOCK SIZES ON BM-AMT FOR SMPT

Block size	**Evaluation Metrics**			
	RIS	***RPT***	***ROS***	***Average segmentation time/ms***
19	98.66%	1.34%	0.72%	183
21	98.75%	1.25%	0.66%	167
23	98.95%	1.05%	0.39%	153
25	**99.17%**	**0.83%**	**0.39%**	**114**
27	99.05%	0.95%	0.39%	110
29	98.93%	1.07%	0.45%	105

E. Parameter Selection of Medium Filter

After BM-AMT, there are many salt and pepper noises on the binary image, resulting in longer average segmentation times for a seed. The medium filter can eliminate salt and pepper noises because MBR would locate all tiny objects on the binary image. Table III shows the results of removing salt and pepper noises using medium filters with different kernel sizes. The average seed segmentation time of the image processing algorithm without a medium filter (about 3,052ms) is considerably higher than that of the image processing algorithm with medium filters (all less than 300ms). Remarkably, the larger the kernel size of the medium filter, the faster the average segmentation time of a seed. The average seed segmentation time of the image segmentation algorithm with a 5×5 kernel size of medium filter is 114ms, but its RIS and RPT are pretty good among others.

TABLE III. THE EFFECT OF MEDIUM FILTERS WITH DIFFERENT KERNEL SIZES FOR SMPT

Kernel size	**Evaluation Metrics**			
	RIS	***RPT***	***ROS***	***Average segmentation time/ms***
-	99.14%	0.86%	0.45%	3,052

Kernel size	Evaluation Metrics			
	RIS	***RPT***	***ROS***	***Average segmentation time/ms***
3×3	99.05%	0.95%	0.45%	294
5×5	**99.17%**	**0.83%**	**0.39%**	**114**
7×7	98.75%	1.28%	0.26%	83
9×9	97.77%	2.23%	0.28	65

F. *Method Selection for Seperating Tiny Contact Seeds*

The image processing algorithm that does not process the contact seeds achieves about 92.74% of the RIS, but some tiny contact seeds can still be further segmented on the binary image. Table IV shows that Erosion Operation (KEOP) and Watershed Algorithm (WA) are used to process the tiny contact seeds. The image processing algorithm with 13×13 kernel erosion operation has excellent segmentation accuracy (about 99.17%), and the average segmentation time of seeds is about 114ms. In comparison, the image processing algorithm with the Watershed Algorithm (IMGP-WA) is approximately 98.63% of RIS, and the average segmentation time for a seed is about 136ms. More importantly, the ROS of IMGP-WA (about 1.02%) is significantly higher than that of the image processing algorithm with KEOP (all less than 0.55%), which indicates that IMGP-WA causes over-segmentation of seeds. Meanwhile, the average segmentation time of seeds with IMGP-WA is about 136ms, significantly higher than that of the image processing algorithm with KEOP (all less than 115ms).

TABLE IV. DIFFERENT METHODS OF ELIMINATING SOME TINY CONTACT BETWEEN SEEDS

Methods	Evaluation Metrics				
	Kernel size	***RIS***	***RPT***	***ROS***	***Average segmentation time/ms***
-	-	92.74%	7.26%	0.47%	121
KEOP	7×7	98.07%	1.93%	0.50%	115
	9×9	98.72%	1.28%	0.45%	115
	11×11	98.98%	1.02%	0.44%	115
	13×13	**99.17%**	**0.83%**	**0.39%**	**114**
	15×15	98.91%	1.09%	0.54%	115
WA	-	98.63%	1.37%	1.02%	136

G. *Comparison and Discussion*

Yang et al. [7] utilized Mask R-CNN and transfer learning to segment individual soybean seeds from physically touched soybean seed images. Yang's method has an RIS of over 99% and takes about 104ms to segment individual seeds. In comparison, SMPTS takes about 53ms to segment individual seeds on NVIDIA Jetson TX2 and achieves an RIS of approximately 99.17%. Although Yang's method achieves a RIS of more than 99% for images of physically touched soybean seeds, Yang's method aims at segmenting intact soybeans that are complete and shiny; they do not consider other types of soybean seed segmentation, which may make Yang 's method unable to serve the image segmentation of soybean seed classification tasks. However, the SMPTS can realize five kinds of soybean seed segmentation: intact soybeans, immature soybeans, skin-damaged soybeans, spotted soybeans, and broken soybeans [17].

Lin et al. [15] designed an MSRCR-based image segmentation algorithm for physically contacted soybean images; the results of Lin's algorithm realize about 98.75% RIS with 104ms for segmenting a seed in our soybean images on NVIDIA Jetson TX2. However, the RPT and ROS of Lin's algorithm (about 0.99% and 1.58%, respectively) are higher than those of the SMPTS (about 0.83% and 0.39%, respectively). The ROS of Lin's algorithm (about 1.58%) is nearly four times that of the SMPTS (about 0.39%). More importantly, the average segmentation time of a seed of the SMPTS (about 53ms) is significantly lower than that of Lin's algorithm (about 202ms). Because there are a lot of salt and pepper noises in our soybean images, the average seed segmentation time of Lin's algorithm is considerably longer than SMPTS. Table V shows the comparison experiments.

Table VI and Table VII show the segmentation results of Lin's and our algorithms, respectively. The largest RIS of Lin's algorithm is immature soybeans, and the second largest RIS is intact soybeans, while the largest RIS of SMPTS is intact soybeans, and the second biggest RIS is immature soybeans. In Table VI, the highest RPT and ROS are broken soybeans (approximately 3.27% and 4.80%, respectively), and the lowest RIS for broken soybeans is about 96.73%. Table VII shows similar results: the RPT of broken soybeans is significantly larger than that of other soybeans, and the RIS of broken soybeans is the lowest. The RPT of Lin's algorithm (about 3.27%) is slightly lower than that of SMPTS (about 3.44%), but the ROS of Lin's algorithm (about 4.80%) is almost five times higher than that of SMPTS (about 0.97%). The ROS of Lin's algorithm for spotted soybeans has similar results. The ROS of Lin's algorithm for spotted soybeans (about 1.95%) is over three times higher than that of SMPTS (about 0.64%). The main reason is that Lin's algorithm adopts MSRCR to enhance the contrast between seeds and the background on soybean images. Therefore, some spotted or broken features on the soybeans would be over-enhanced by MSRCR, which makes those classification features on the soybeans' surface similar to the background on the image. When Otsu-AT was used to produce binary images, these features were classified into the background of the binary image. Finally, a completely broken or spotted soybean may be divided into many parts, leading to a completely broken or spotted soybean with many MBRs on binary images.

TABLE V. METHOD COMPARISONS

Methods	Evaluation Metrics			
	RIS	***RPT***	***ROS***	***Average segmentation time/ms***
Yang et al., 2021 [7]	>99.00%	-	-	104
Lin et al., 2023 [15]	99.01%	0.99%	1.58%	202
SMPTS (Ours)	99.17%	0.83%	0.39%	53

TABLE VI. DETAIL RESULTS OF LIN'S ALGORITHM

Methods	*Soybean types*	Evaluation Metrics		
		RIS	***RPT***	***ROS***
Lin et al., 2023 [15]	Intact	99.55%	0.45%	0
	Immature	100%	0	0
	Skin-damaged	99.05%	0.95%	1.89%
	Spotted	99.58%	0.42%	1.95%
	Broken	96.73%	3.27%	4.80%

TABLE VII. DETAIL RESULTS OF SMPTS

Methods	*Soybean types*	Evaluation Metrics		
		RIS	***RPT***	***ROS***
SMPTS (Ours)	Intact	100%	0	0
	Immature	99.66%	0.34%	0
	Skin-damaged	99.52%	0.48%	1.57%
	Spotted	99.44%	0.56%	0.64%
	Broken	96.56%	3.44%	0.97%

IV. CONCLUSION

This study mainly is to construct the SMPTS for segmenting physically touching soybean images in seed testing machines. In SMPTS, BM-AMT is vital in to extract the contours of soybeans. A medium filter serves to eliminate salt and pepper noises on the binary images of BM-AMT, resulting in a significant reduction in the average time to segment the seeds. The erosion operation with the 13×13 kernel was used to process those soybean seeds in tiny contact with other soybean seeds, which increases the SMPTS's RIS significantly. As a result, the RIS of the SMPTS can achieve about 99.17% with approximately 53ms for segmenting a soybean seed on NVIDIA Jetson TX2, which could meet the online requirement of image segmentation of physically touching soybean seeds. Meanwhile, the RIS of intact soybeans, immature soybeans, skin-damaged soybeans, spotted soybeans, and broken soybeans is about 100%, 99.66%, 96.56%, 99.44%, and 99.51%, respectively.

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