A Modified Otsu-based Image Segmentation Algorithm (OBISA)

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***Abstract*— Image thresholding is usually a preprocessing step in a number of image processing algorithms. The segmented images are input for image analyses, computer vision, and visualizations and object representation. Otsu thresholding method is a widely used image thresholding technique. It provides fairly accurate results for segmenting a gray level image with only one modal distribution in a gray level histogram. However, one of the drawbacks is high computational cost and noise that are mostly contributed by inappropriate expression of class statistical distributions. This paper presents an improved Otsu-based image segmentation algorithm to enhance the performance of the Otsu method. Standard deviation is used in the computation of the optimal threshold instead of using variance. A reasonable threshold range is computed to lower the computational cost. Testing results showed that the improved method is more satisfactory than the original Otsu thresholding algorithm.**

***Index Terms*—image analysis, segmentation, statistical distribution, thresholding**

I. Introduction

COMPUTER vision has unique characteristics making it distinct from other fields [1]. The author further states that it is a broad interdisciplinary area where both computer and human vision systems share the same objective that is to convert light into useful signals. Despite this significant progress, there is no further development in this basic theory [2]. Furthermore, [3] added that one of the areas of computer vision is image processing and researchers are now exploring more objective methods, such as image analysis, to replace the subjective and laborious manual methods in agricultural applications.

These image processing methods can be applied to field-scale applications that include plant diseases [4], pests [5], [6], plant row count [7] and even for variety identification [8]. These are but some of the many applications of information technology in the field of precision agriculture.

In image processing, segmentation is an essential basic operation for meaningful analysis and interpretation of an acquired image. It is one of the main steps in image processing where an image is subdivided into segments [9]. It has been subject to considerable research activity, and segmentation plays a vital role in image understanding, image analysis and image processing [10].

Thresholding is a commonly used method that improves the image segmentation effect. It is simple and easy to implement. The widely used thresholding technique is the Otsu thresholding technique [8], [11]. It is proposed by [12] as a method for choosing the optimal threshold to minimize the within-class.

Authors [13] concluded in their study that inappropriate expression of class distribution contributes to most of the noise in the different improvements of the Otsu method. Otsu uses variance to represent the dispersion of each class based on distance square from the mean to any data. Computing the variance cannot denote the real statistical distribution since the optimal threshold is biased towards a larger variance among two class variance, thus, minimizing the between-class standard deviation, as a criterion for optimal threshold selection, expresses a more accurate statistical distribution.

Since computing standard deviation incurs higher computing time as compared with simple variance computation, this study proposes to optimize the algorithm. Setting a reasonable threshold range so as to lower the computational cost is done by removing outliers in the form of the gray value which is either too low or too high [14].

II. Otsu Method

Otsu is originally proposed by [12] and is further studied by [15] as a dynamic threshold selection method that suggests maximizing the weighted sum of between-class variances of foreground and background pixels to establish optimum threshold. This is done by partitioning the image into two classes *W1* and *W2* at gray threshold *T*. Such that *W1 = {0, 1, 2 … , T}* and *W2 ={T + 1, T + 2, … L-1}* where L is the total number of gray levels of the image.

Let the number the number of pixels at i gray level be n_i and $N = \sum_{i=0}^{L-1} n_i$ be the total number of pixels at a given image.

The probability of occurrence of gray level i is defined in equation 1.

$$P_i = \frac{n_i}{N}, P_i \geq 0, \sum_{i=0}^{L-1} P_i = 1 \tag{1}$$

W1 and *W2* are normally corresponding to the object of interest and the background. For the background, the probabilities of the two classes is shown in equation 2.

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$$P_{w1} = \sum_{i=0}^{T} p_i \text{ and } P_{w2} = \sum p_i = 1 - P_{w1} \tag{2}$$

The means of the classes *W1* and *W2* can be computed as shown in equations 3 and 4.

$$\mu_{w1} = \sum_{i=0}^{T} \frac{i * p_i}{P_{w1}} \tag{3}$$

$$\mu_{w2} = \sum_{i=T+1}^{L-1} \frac{i * p_i}{P_{w2}} \tag{4}$$

The following formula depicted as equation 5 is the derived formula based on equations 3 and 4:

$$\sigma^2(T) = P_{w1}P_{w2}(\mu_{w1} - \mu_{w2})^2 \tag{5}$$

The optimal threshold T^* can be obtained by maximizing the within-class variance.

$$T^* = Arg \max_{0<T<L-1} \sigma^2(T) \tag{6}$$

The Otsu method is simple and thus used widely in image segmentation. According to [8] and [11], the advantages and simplicity of Otsu thresholding technique is what makes this algorithm popular to a large number of proposed improvements and research studies including this study as well.

III. The Proposed Improvement of Otsu Method

Otsu looks at the histogram of the image, the pixel values, and property that where you can see the uniformity of the pixel values better segment out the object by minimizing the weighted within-class variance.

This study will come up with an improved Otsu-based image segmentation method based on between- class variance standard deviation.

A. Initial threshold segmentation

Partition the image into two classes *W1* and *W2* with the image mean grey value T_0 such that $W_1 = \{0,1,2,\ldots T\}$ and $W_2 = \{T+1, T+2, \ldots L-1\}$, where *L* is the total number of gray levels of the image.

$$T_0 = \sum_{i=0}^{L-1} i * p_i \tag{7}$$

$$\text{Where } p_i = \frac{n_i}{N}, p_i \geq 0, \sum_{i=0}^{L-1} p_i = 1 \tag{8}$$

B. Calculate lower threshold.

The means of W_1 can be computed (shown in equation 9) where P_{w1} is previously defined in equation 2.

$$T_1 = \sum_{i=0}^{T_0} \frac{i * p_1}{P_{w1}} \tag{9}$$

C. Calculate high threshold.

The mean value of the class W_2 will be calculated to get the high threshold T_2.

$$T_2 = \sum_{i=T_0+1}^{L-1} \frac{i * p_i}{P_{w2}} \tag{10}$$

Where P_{w2} is previously defined in equation 2.

D. Set the threshold selection range.

The selection of the threshold range will optimize the algorithm by removing the gray values that are too low or too high. This way, noise of the image will be reduced as well as the time complexity of the algorithm. Equation 11 shows the computation for the median of the histogram for the foreground and equation 12 is for the background.

$$\lambda_1 = \frac{\tilde{x} + 0}{2} \tag{11}$$

$$\lambda_2 = \frac{\tilde{x} + 255}{2} \tag{12}$$

Where λ_1 is the computation for the mean between 0 and the median $\tilde{x}$ and λ_2 is the mean from median to 255.

E. Calculate the between-class variance using standard deviation. The standard deviation for W_1 and W_2 are defined as follows:

$$\sigma_{w1} = \sqrt{\sum_{i=\lambda_1}^{T} \frac{(i-\mu_{w1})^2 * p_1}{P_{w1}}} \tag{13}$$

$$\sigma_{w2} = \sqrt{\sum_{i=T+1}^{\lambda_2} \frac{(i-\mu_{w2})^2 * p_1}{P_{w2}}} \tag{14}$$

where $T \epsilon [\lambda_1, \lambda_2]$.

The between-class variance can now be computed using the between-class variance with standard deviation as shown in equation 15.

$$\sigma_i = \sqrt{P_{w1}P_{w2}(\mu_{w1} - \mu_{w2})^2} \tag{15}$$

F. Segment the image based on the threshold value computed.

The biggest limitation with Otsu is its assumption of binary classes: It partitions the grayscale histogram to two classes. However in real-world segmentation problems we images have more than two class of segments and that is why, this preprocessing step of Otsu will include the converting of image into grayscale if the image being feed for segmentation is still in the RGB color space.

IV. Analysis of the Simulation Experiment

Images of a man (481 * 321) and coins (301 * 246) have been tested to evaluate the performance of the proposed improvement of the Otsu algorithm. Table 1 shows the basic information of the test images.

TABLE I. PROPERTIES OF THE IMAGES

	Man	*Coins*
Pixel number	154401	74046
Maximum gray value	255	233
Minimum gray value	0	7
Average gray values	103.8172	86.9496

Fig.1 shows the original images (man and coins) while Fig.2 shows the histogram of the test objects.

Fig. 1. Original images (a-man and b-coins)

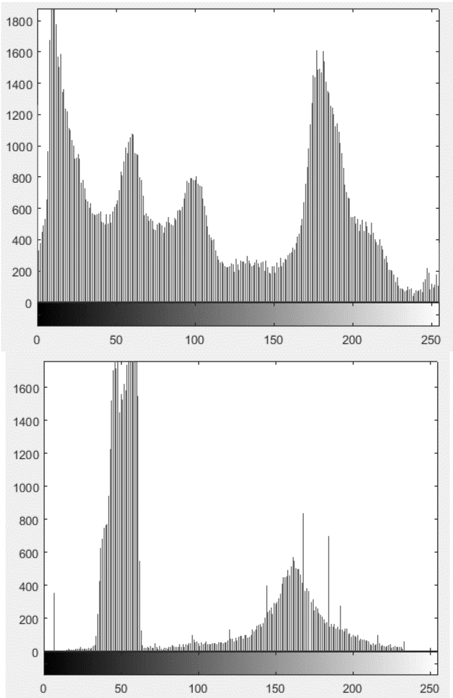

Fig. 2. Histogram of the images (a-man and b-coins)

It can be seen in the images that follow that the proposed study is able to segment the images better than the original Otsu algorithm. Fig. 3a and Fig. 3b show the segmentation result by the Otsu method while Fig. 4a and Fig. 4b show the segmentation result of the proposed method OBISA.

Fig. 3a. Otsu method segmentation result for man

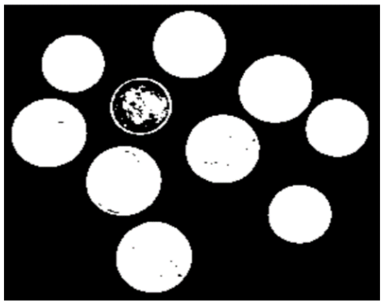

Fig. 4b. Otsu method segmentation result for coins

Fig. 5a. Result of the segmentation using OBISA for man

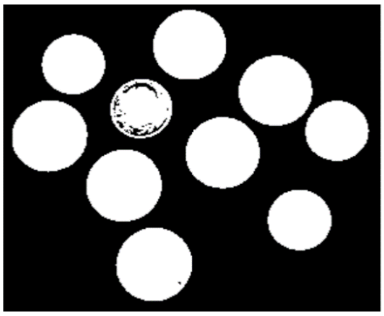

Fig. 6b. Result of the segmentation using OBISA for coins

In comparing the proposed method OBISA with the original Otsu method, Table 2 shows the optimal threshold and the average computing time (in milliseconds). The test images are tested in a 100 times repeat process.

TABLE II. OPTIMAL THRESHOLD AND COMPUTING TIME

		Man	*Coin*
Otsu method	Optimal threshold	115	128
	Average time /ms	12.97000	25.83000
Proposed method	Optimal threshold	115	109
	Average time /ms	12.32000	12.09000

V. CONCLUSIONS

In this paper, an Otsu-based image segmentation algorithm for thresholding images is proposed. The original Otsu method segmented a gray-level image with a bimodal distributed histogram. Unfortunately, in the computation of the optimal threshold, the variance formula does not completely represent the statistical distribution, thus, the reason for the presence of noise in the segmented images. It is in this motivation to replace the variance formula with standard deviation for the computation of the between-classes for the optimal threshold. However, standard-deviation computation is more computationally-expensive compared with using the variance formula only. This drawback in the form of computational cost is addressed with the setting of a reasonable threshold range and removing the outliers in the form of the gray values. Compared with the original Otsu algorithm, this proposed Otsu method can obtain a more satisfactory thresholding results.

VI. Future Work

This study is a preprocessing step for cassava variety recognition. The segmented image of a cassava leaf using OBISA will be the input image to the cassava variety recognizer using Artificial Neural Network with backpropagation. Experiment result will compare the accuracy of the recognizer using OBISA, ANN and Backpropagation and recognizer using original Otsu method, ANN and backpropagation.

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