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Research Article

An Improved Otsu-Based Image Segmentation Approach for Accurate and Efficient Target Identification

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ABSTRACT

Image processing plays a vital role in enhancing understanding and interpretation, both for humans and computer-based systems. Among its various techniques, segmentation, thresholding, and edge detection are fundamental components in computer vision and image analysis. This paper presents an improved Otsu method for effective segmentation of objects from their image backgrounds. The conventional Otsu method divides an image into background and foreground regions based on a global threshold value. However, it performs poorly for images with a unimodal histogram distribution, as the computed threshold corresponds to the average of the mean intensities of the two classes separated by the threshold value. To overcome this limitation, the proposed improved Otsu method introduces a modification based on weighted background variance. In this approach, the weighting parameter 'ω' (ranging from 0 to 1) adjusts the between-class variance, allowing the algorithm to achieve an optimal threshold determined primarily by the variance of the target object. For precise boundary detection of the target, the Laplacian of Gaussian (LoG) operator is applied. The effectiveness of the proposed method is validated through experimental results and compared with other thresholding techniques, including the basic Otsu, Gaussian Otsu, Weighted Object Variance (WOV), and Recursive Otsu methods. The proposed method demonstrates superior performance, achieving an accuracy of 95.46\% for target object detection. It also exhibits faster processing, with an elapsed time of 0.0139 seconds, which is 0.2623 seconds faster than the WOV method and 0.768 seconds faster than the Gaussian Otsu method. Additionally, tests under salt-and-pepper noise (variance = 9) confirm the robustness and reliability of the improved approach for accurate image segmentation.

Keywords: Image segmentation, weighted background variance, OTSU Thresholding, Object detection, Laplacian of Gaussian, Machine vision

Introduction

Image segmentation is a fundamental technique employed to partition an image into its constituent parts, allowing for the extraction of pertinent information from the image [1].OTSU method is an exceptionally simple histogram-based thresholding technique created for the purpose of automating image thresholding [2]. Various image segmentation techniques leverage specific features within image data, and their effectiveness is inherently constrained. Consequently, it becomes essential to tailor the selection of methods to cater to the diverse requirements of practical applications. In this article, we conduct a comparative analysis of multiple threshold segmentation and edge detection algorithms. Our emphasis is on scrutinizing the maximum between-class variance algorithm and enhancing its performance [3]. In image processing, OTSU the method named after Nobuyuki Otsu is used to perform image thresholding. OTSU algorithm computes a single intensity threshold, this threshold breaks up pixels into two classes, namely foreground and background. The threshold is defined by maximizing the matrix called inter-class variance or minimizing the matrix intra class variance [4]. OTSU method is implemented differently such as utilizing only zero and the first order cumulative moments of the grey level histogram, the method is characterized by its non-parametric and unsupervised nature of threshold selection [5]. The thresholding methods are categorized according to the information they exploit, such as histogram shape, measurement space clustering, entropy, object attributes, spatial correlation, and local grey

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surface [6]. The two-dimensional OTSU thresholding algorithm looked like an effective improvement of the original OTSU. The 2D histogram is projected onto a diagonal, which forms a 1D histogram with obvious peak and valley distribution. The method is applied on a vertical line to the diagonal to find the optimal threshold value [7]. Introducing recursive OTSU thresholding method where the set of background pixels is determined by standard OTSU thresholding and re- threshold these pixels alone to extract more. This could continue until the resulting set of foreground or background pixels is empty [8]. A vision-based thresholding system requires image acquisition, image processing, and binarization [9]. It gives a satisfactory result when the image histogram is bimodal but fails when the image histogram is unimodal or close to unimodal. OTSU method can obtain a satisfied segmentation when the object and image background have similar variance, however, the method fails if the sizes of the object and image background are of greater difference. The shuffled frog-leaping algorithm (SFLA) is a newly developed memetic meta-heuristic algorithm with good global search capability, the updating rule is carefully designedto extend the length of each frog's jump by emulating the frog's perception and action uncertainties [8]. However, the three-dimensional (3-D) OTSU is very time-consuming and cannot be used for real-time application. Gaussian OTSU's method is an extension of OTSU's method and it uses maximum between-class variance as an optimal threshold, the experimental study on OTSU and Gaussian OTSU thresholding algorithm can root out in literature [10]. Image segmentation algorithm by narrowing the selection range of threshold and searching the minimum variance ratio, the algorithm selects the optimal threshold [11]. The weighted object variance method is used forinspecting the defects, a parameter is weighted on the object variance keeping back-ground variance unchanged to overcome the problem of false defect detection [11]. The modified two-stage multi-threshold OTSU (TSMO) yields the same set of thresholdsas those obtained by using conventional OTSU, in addition, effective histogram-based valley estimations are developed for determining an appropriate number of clusters for an image [12]. An exhaustive survey of image thresholding methods, their formulasunder uniform notation, and the performance comparison is performed in the literature [13]. The OTSU method fails to segment the images with the histogram unimodaldistribution because the OTSU threshold is equal to the average of the mean levelsof two classes portioned by this threshold [14]. A new unsupervised method for the detection of cracks with grey color-based histogram and OTSU's thresholding methodon 2D pavement image. At first, the method divides the input image into four inde-pendent equally sized sub-images. Then, the search for cracks is based on the ratiobetween Ostu's threshold and the maximum histogram value for every sub-image [15].By scrutinizing the difficulties in OTSU and the improved OTSU methods, this paper formulates an effective thresholding method, called weighted background variance (WBV).

The contributions of this research are encapsulated as follows:

1. An Improved OTSU method is formulated, in which a parameter is compounded on the background between-class variance.
2. On recursive testing and experimentation, the value of the parameter is found tobe 0.5572 multiplied by background between-class variance. It safeguards that the value of the threshold must be calculated mainly by the object variance.
3. NLoG (negative Laplacian of Gaussian) is used to detect the object's boundaries and features for the detection.
4. The results are tested by adding salt and paper noise to the image.
5. The cogency of the method is endorsed by various image results. The results areverified and compared with the Gaussian OTSU and the WOV method.

The remaining section of the paper is organized as follows: in section 2, the Gaussian OTSU and the WOV methods are explained. Section 3 throws light upon the mathematical model of the proposed improved OTSU. The experimental results and the comparison of these three methods are shown in section 4. Conclusion and future research are described in section 5.

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Methods and Materials

1.1 Gaussian OTSU Technique

OTSU method converts the image into the background and the foreground based on the threshold value. It gives a satisfactory result when the image histogram is bimodal but fails when the image histogram closes to unimodal. The Gaussian OTSU method processes the input image, obtains the image histogram (distribution of pixels), com- putes the threshold value, and segments the image into a binary image using the calculated threshold. OTSU proposed a dynamic threshold selection method in the year 1979 [5]. This method suggests maximizing the weighted sum of between-class variances of foreground and background pixels to establish an optimum threshold. We can partition the image into two classes w_1 and w_2 at grey T. such that, $w_1 = \{0,1,2,. . . , T\}$ and $w_2 = \{T +1, T + 2, . . . , L-1\}$, where L is the total number of the gray levels of the image. The pixel at the i grey level is n_i, and N is the total number of pixels in a given image defined by Eq(1)

$$N = \sum_{i=0}^{n} ni \qquad 1$$

The probability of occurrence of grey level i is defined by Eq(2)

$$pi = \frac{ni}{N} \qquad 2$$

Where,

$$pi \geq 0, \sum_{i=0}^{n} pi = 1 \qquad 3$$

The above two classes are normally corresponding to the object of interest and the background. The probabilities of the two classes are defined by Eq(4)

$$Pw1 = \sum_{i=0}^{T} pi \text{ and } Pw2 = \sum_{i=T+1}^{L-1} pi = 1 - Pw1 \qquad 4$$

The means of the classes w1 and w2 are µw1 , µw2 respectively which is define by Eq(5) and Eq(6)

$$\mu_{w1} = \sum_{i=0}^{T} \frac{i * p_i}{P_{w1}} \qquad 5$$

$$\mu_{w2} = \sum_{i=T+1}^{L-1} \frac{i * p_i}{P_{w2}} \qquad 6$$

So we can get the equivalent variance represented by Eq(7)

$$\sigma^2(T) = Pw1\, Pw2(\mu_{w2} - \mu_{w1})^2 \qquad 7$$

The optimal threshold T^* can be obtained by maximizing between–class and classvariance given by Eq(8)

$$T^* = Arg_{max}\sigma^2(T) \qquad 8$$

The OTSU method fails to segment the images with the histogram unimodal dis-tribution because the OTSU threshold is equal to the average of the mean levels of two classes portioned by this threshold [14]. The OTSU thresholding method is explainedin Fig(1).

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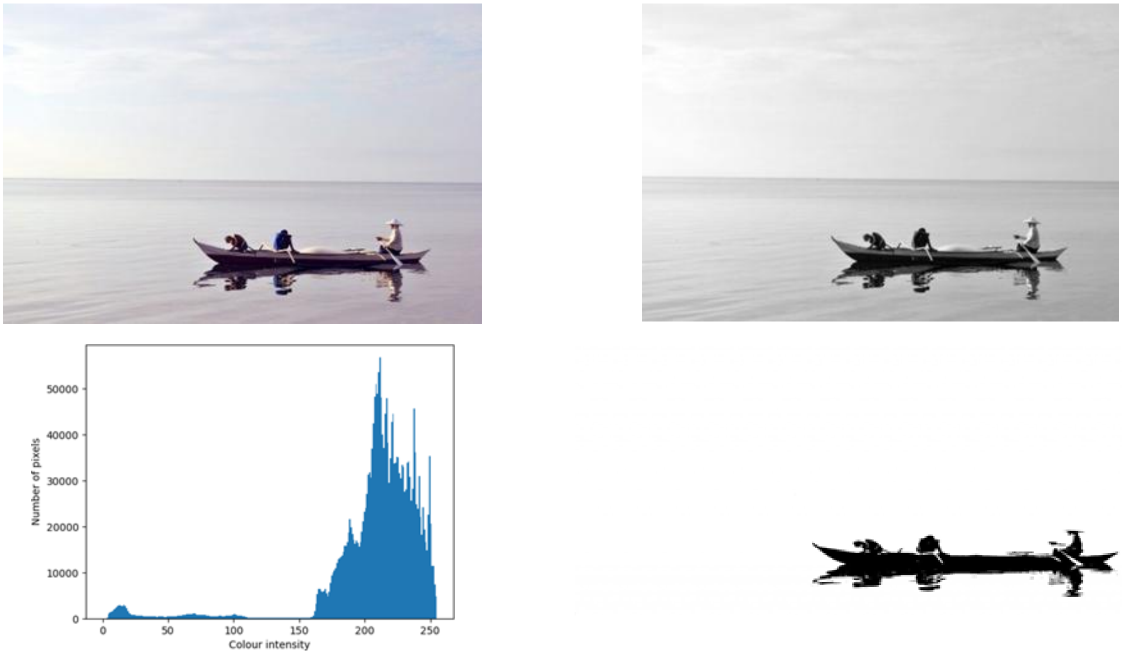

Figure 1 from left to right, Original Image; Pre-processed Image; Histogram of the Input Image; Image after Thresholding

1.2 Weighted Object Variance Method

In the OTSU method, the defect-free image segmentation is neglected. Most thresh- olding methods can correctly separate defects from their background, but wrongly conclude a defect-free image into the detective image. The object area is normally much smaller than the background area. Therefore, the desired threshold should be close to a low grey level compared with the threshold generated by the OTSU threshold. The OTSU threshold is given by Eq(9)

$$T_h = \frac{(u_0(t) + u_1(t))}{2} \tag{9}$$

This OTSU threshold makes the object and background have a similar size. The desired threshold should keep the probability of the object at a small value or even equal to 0. To get the desired threshold, the first term i.e. the object variance of between-class variance showed by Eq(10), should contribute less to the and the thresh- old should be mainly decided by the second term of between-class variance i.e. the background variance.

$$Y_b(t) = wP_0(t)\big(u_0(t)\big)^2 + P_1(t)(u_1(t))^2 \tag{10}$$

The first term in between-class variance, given by Eq(10), is defined as the object variance and the second term is the background variance [11]. A parameter ω ranging from 0 to 1 is weighted with first term and keeping the second term unchanged. The weighted object variance is ω times the original object variance.

A weighted parameter equal to the cumulative probability of the defect occurrence is a better selection for defect detection [11]. To avoid false detection, the object variance should contribute less. The problem with using this method is that the defects are very small as compared to the background. This method is valid when the object is small compared to the background, but when the object and background are similar or bigger than that of the background, this method fails to give the desired threshold. Generally, the main criteria are converting an image into a binary image and selecting the best threshold. The OTSU method is based on a pixel intensity distribution histogram. The color images contain a lot of information. Three matrices are allocated for the colored images named red channel, green channel, and blue channel, which require a high amount of computational power and computation time. To reduce the computational time, the first image is converted into the grey level. The objects

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can be detected according to their grey-level information. Although, it is tricky to select an optimal threshold to separate an object from the image background because of the following factors:

1. Because of illumination inequalities and low contrast between the object and the background
2. Sometimes the object is much smaller than that of the background and vice-versa, it is difficult to locate the object as the size of the object in the frame is not the same. Thus, the image histogram is not always bimodal.
3. Using the 2D or 3D OTSU method may not work. As the complexity increases the computation time also increases, so it cannot be used in real-time applications.

By scrutinizing the problems in the existing thresholding methods for object detection, we formulate an Improved Thresholding method for object detection. The method is an improved version of Gaussian OTSU and Weighted object variance OTSU. The threshold value obtained by the proposed OTSU method gives better results and an optimal threshold value.

Proposed method

1.3 Dataset

The dataset is compiled from images obtained from Pixabay, a popular online platform for free images [16]. The dataset consists of 110 images, each categorized and labeled for specific use cases. The data is widely available on Pixabay site. The dataset also consists of 50 images taken by the camera having the following specifications:

- T12-megapixel Wide Camera: Aperture: f/1.8, Optical Image Stabilization (OIS): Yes, Focus: Phase Detection Autofocus (PDAF), HDR: Smart HDR
- 12-megapixel Ultra-Wide Camera: Aperture: f/2.4, Field of View: 120 degrees, Focus: Fixed focus, HDR: Smart HDR

1.4 Methodology

If the object is much smaller than that of the background, the histogram is unimodal or close to unimodal, so the optimal threshold must lie on the left rim of the unimodal histogram. If the object size and the background-size is comparable we will get a bimodal histogram, the optimal threshold must lie on the valley between two peaks (the first peak is smaller than the other). In both cases, the object variance is close to zero and the background variance is maximum. As we go on increasing the threshold value, the background variance decreases, and the object variance increases. The between-class variance reaches it's maximum when the grey level value equals to aver- age of two class variances. The results show that OTSU always gives a higher threshold value than desired. This is because the OTSU method gives equal weightage to both object and background variances.

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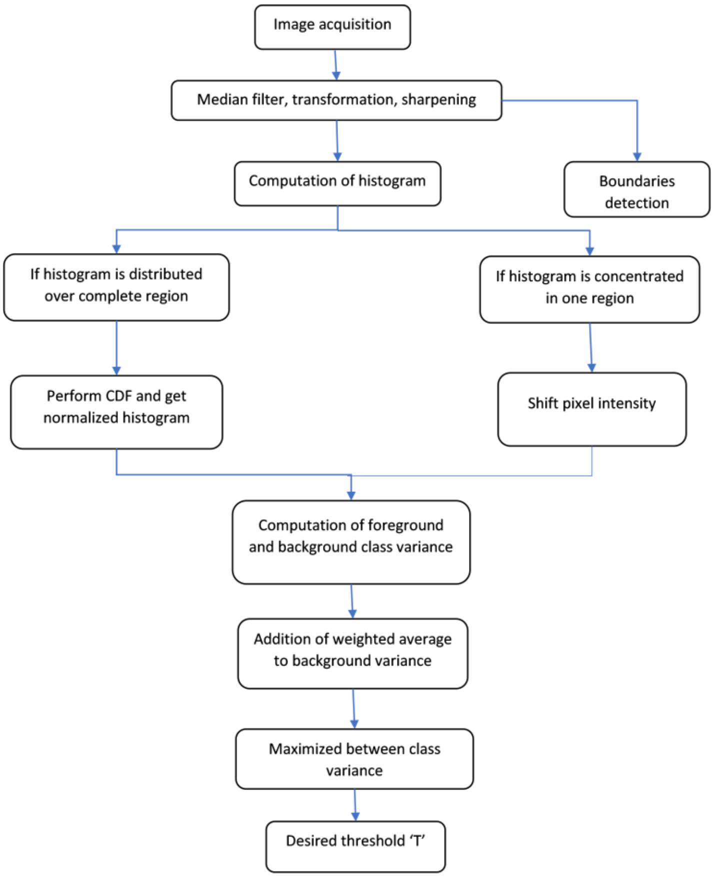

Figure 2 Flow chart of the proposed method

In this paper, the area with a grey level lower than the threshold is defined as objects or defects (black pixels), and grey levels of pixels that are higher than the threshold are defined as the background (white pixels). OTSU method works on the histogram distribution. The proposed method is formulated on the experiments based on the histogram of the different images. The methodology of the proposed paper is shown in Fig (2).

The target object is much smaller than that of the background area, due to which the histogram of the image is unimodally distributed. Fig (3) shows the image and its unimodal distribution. The most frequent value in an image is called mode.

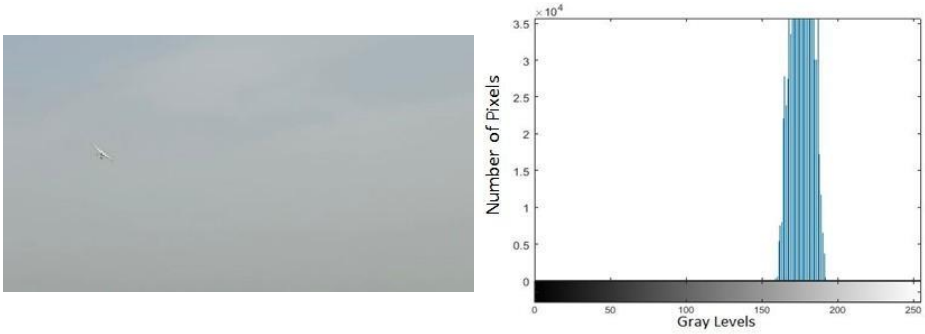

Figure 3 From left to right image is a Flight test of a fixed-wing UAV, and Pixel Intensity Distribution of the same Flight test of a fixed-wing UAV Image

The OTSU method fails when there is a unimodal histogram is present. The primary focus is to convert unimodal distribution. The threshold must occur in between two valleys. Intensity can be better distributed on histogram if we allow areas of lower local contrast to gain higher. The intensity should be distributed over a range and not

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concentrate on a particular area. Grey level values in an image range from 0 to 255 (L). The pixel at the ith grey level is ni, and N is the total number of pixels in a given image. The probability of occurrence of grey level ith is defined by pi Eq(2). The Cumulative distribution function (CDF) can be defined by Eq(11)

$$CDF = \emptyset = \sum_{i=0}^{l} pi \qquad 11$$

$$j = grayvalue_{(max)} * CDF \qquad 12$$

Where j is the equalized intensity value for the pixel at the ith grey level up to intensity value l . If the histogram is concentrated on one area only, the modified histogram distribution does not work. We shift darker pixels to the lower rim and brighter ones to the higher rim to overcome this. In the above example, Fig (3) the intensity values value are concentrated over a region of 160 to 180. But our area of interest is between 160 to 180, so in the modified distribution, we take 160 as 0 (zero) and 180 as 255 (max) and redistribute the intensity histogram. Fig (4) shows theoriginal pixel intensity distribution and the modified pixel intensity distribution.

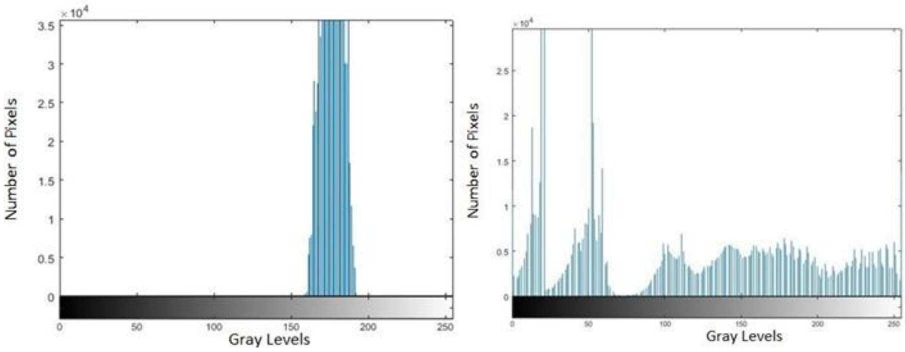

Figure 4 From left to right, Original Pixel Intensity Distribution, Modified Pixel Intensity Distribution of the image after the Pixel-Shifting Operation

1.5 Boundaries detection

Edges are the discontinuities that bring change in pixel intensity which define the boundaries of an object. Edge is a line having larger gradients. For edge detection in an image, the Laplacian operator is widely used. The Laplacian operator provides the location of the edge using the second derivative. A 9-pixel sliding window is used to extract the neighboring information. The edge detection is based on zero-crossing, i.e the point at which the Laplacian function changes its sign from positive to negativeor vice-versa. It is a linear operation so it requires only one convolution. However the drawback of the Laplacian operator is that it does not provide the magnitude as well asthe direction on the edge. The Laplacian filter is also very sensitive to the noise presentin the image [17], henceforth a Gaussian low pass filter is utilized to eliminate the noisepresent in the image [18]. Variances are The Laplacian of an image that highlights a region of rapid intensity change. To reduce its sensitivity, a Gaussian smoothing filteris used. The mathematical representation of Laplacian of Gaussian(LoG) is given by Eq(13)

$$LoG = \frac{x^2 + y^2 - 2\sigma}{2\pi\sigma} * exp\,(-\frac{x^2 + y^2}{2\sigma^2}) \qquad 13$$

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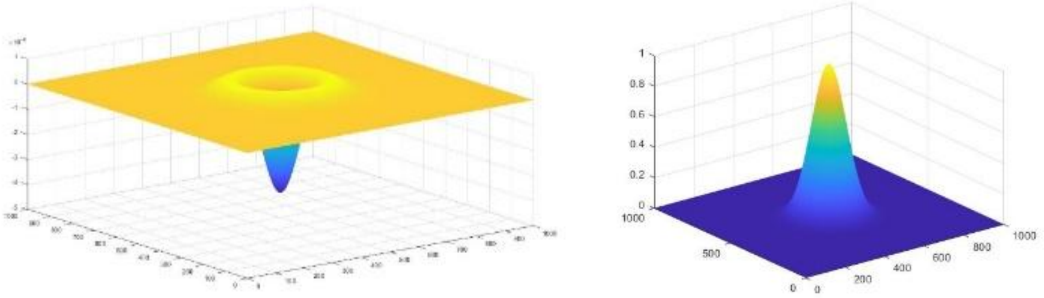

Figure 5 Left image is a Laplacian filter and the right low pass Gaussian filter

Fig (5) shows the NLOG (Negative Laplacian of Gaussian) operator. The NLOG operator is normalized by the negative LoG operator, whose expression is Eq(13). Fig (6), Fig (7) shows the results of the image captured during the flight test for this experiment, the successive images in Fig (7) show the target UAV has been identified and detected. The flight test is carried out in ambient conditions.

Figure 6 Image is captured during the flight test

Figure 8 from left to right, Flight test of fixed-wing UAV, the successive images show the UAV isidentified in and detected

Figure 7 from left to right, the image source is pixabay, the successive images show the Quadcopter, as well as the background edge features, are identified and detected.

1.6 Increased Object Variance

If the area of the target object is smaller than that of the area of the background in an image, then the intensity

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histogram approaches unimodal distribution. The weight of the object variance and the background variance is the same in the OTSU algorithm which makes it calculate a higher threshold than the optimized threshold value. The resulting threshold must be decided by object variance, which means more weight must be given to object variance. To overcome this we multiply the term ϵ with background variance. The value of ϵ lies between 0 to 1. So that we can get the following equivalent formula Eq(14)

$$\sigma^2(T) = P_{w1}P_{w2}(\epsilon * \mu_{w2} - \mu_{w1})^2 \qquad 14$$

The optimal threshold T* defined by Eq(7), can be obtained by maximizing the between-class variance. As ϵ ranges from 0 to 1, the background variance is low andthe threshold is mainly decided by the object variance. ϵ should be optimal, if we select ϵ close to zero most of the image features are considered in the foreground andif we select ϵ close to 1 it is similar to OTSU when object size and background size are the same.

Experimental Results

1.7 Experimental Setup

In order to verify the potency of the proposed algorithm, MTALB2021a software is used to simulate the results and test the algorithm. The experimental platform is shown in the following (Table 1)

Table 1 Experimental Platform

Platforms	Description
Experimental Platform	Intel i7-10700 CPU
Network Training Platform	Intel R UHD Graphics 630
Operating System	Windows 10
Language	Matlab 2021a

1.8 Result

As the object is of primary concern the object variance should contribute and the optimal threshold must be decided by object variance. The value of ϵ lies between 0 to 1. By experimentation, we found that the optimum value of ϵ is 0.577. Substituting ϵ equal to 0.577 in Eq(14) the desired value of the threshold is obtained. The results are compared with the Gaussian OTSU method and the weighted object variance method. To test the methods with the noise, salt and paper noise with variance 9 is added to the input image. This means that 9% of the pixels change into black or white. Fig (10) shows the threshold value obtained by Gaussian OTSU, the weighted Object variance method, and the proposed method.

Figure 9 Picture is taken from Pixabay for the experiment purpose

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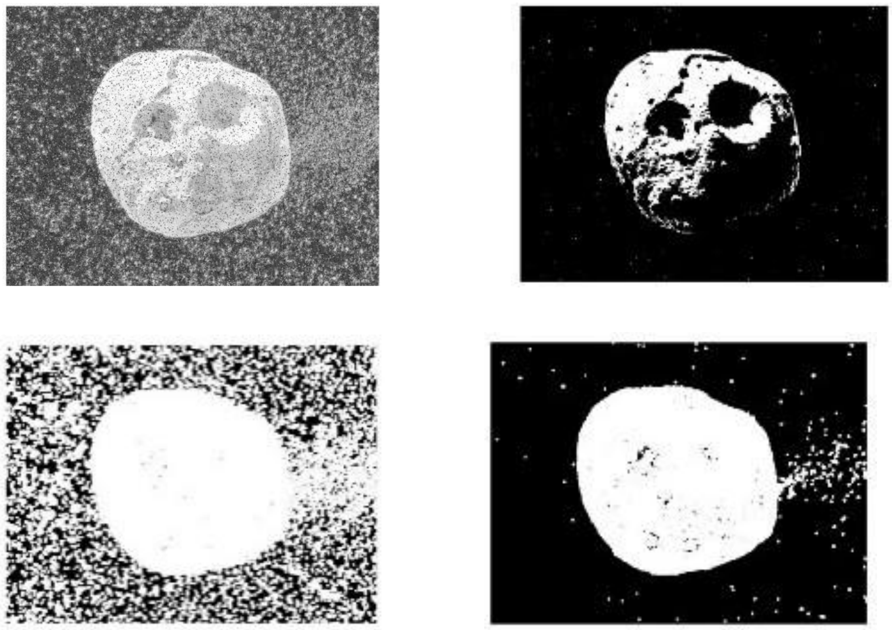

Figure 10 from left to right, the image source is pixabay, the successive images show the Quadcopter, as well as the background edge features, are identified and detected

From Fig (10), the object detected by the Gaussian OTSU method is almost correct at the boundaries but the internal features of the object are missing. The Gaussian OTSU method fails to detect the internal features of the object. The WOV method predicts a threshold with lots of noise. The internal features of the object are detected but a high level of noise is present in the equivalent binary image. The threshold value obtained by the proposed method is close to desired. The object boundaries withthe internal features are detected and the noise present in the WOV method is also removed. The object can be differentiated from the background.

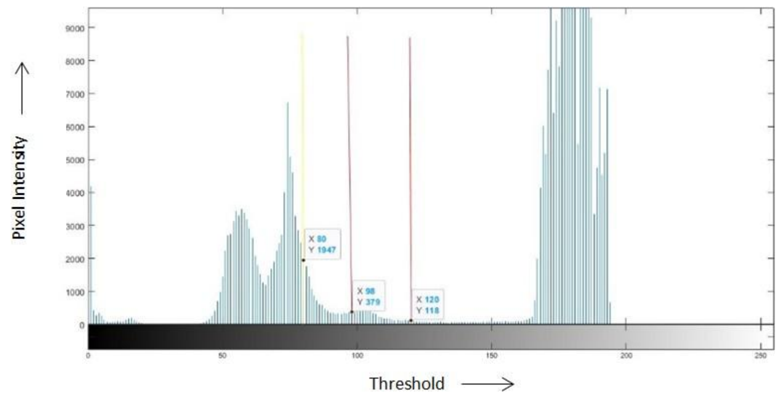

Figure 11 Histogram intensity distribution of Figure(6) showing the threshold value of the OTSU method (T_h=120), weighted variance method (T_h=98), proposed method (T_h=80)

Fig (11) shows the histogram of the pixel intensity distribution. Here the object is black (foreground) and the background is white in the equivalent binary image. The

threshold value obtained by the OTSU method is 120 which is higher than that of desire. This is because OTSU assumes the object variance and background variance of the same size. The threshold obtained by the WOV method is 98, which is lower than the OTSU threshold as the parameter equal to the cumulative probability of the occurrence of the object is weighted to the object variance. The threshold calculated by the proposed method is lower than the WOV method and is close to desired. The threshold calculated by the proposed method is 80.

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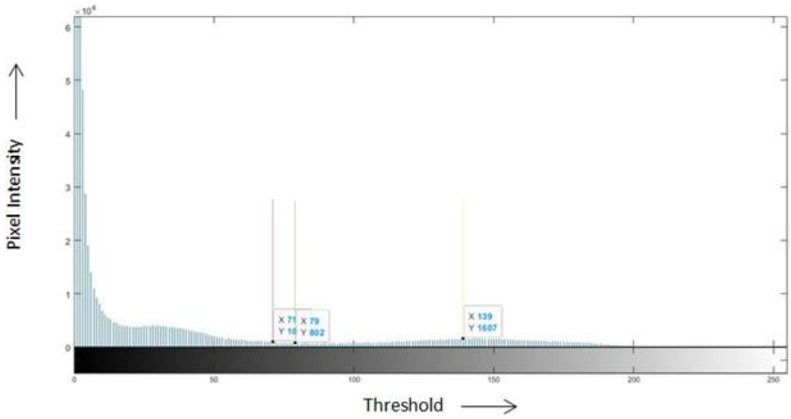
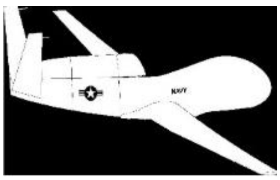
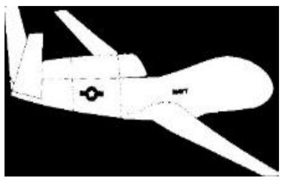


Figure 12 histogram intensity distribution of fig(7) showing the threshold value of the OTSU method (T_h=71), weighted variance method (T_h=79), proposed method (T_h=139)

Fig (12) shows the histogram of the pixel intensity distribution. Here the object is white (foreground) and the background is black in the equivalent binary image.The threshold value obtained by the OTSU method is 71 which is lower than that of desire. Due to this internal feature of the target objects are not scanned up as a complete target. The threshold obtained by the WOV method is 79, which is higher than the OTSU threshold as the parameter equal to the cumulative probability of the occurrence of the object is weighted to the object variance. The threshold calculated by the proposed method is higher than the WOV method and is close to desired. The threshold calculated by the proposed method is 139.

Table 2 Image and its binary image after thresholding using Gaussian OTSU, the WOV method, and the proposed method with respective thresholding values (T_h)

Original Image	Otsu Method	WOV Method	Proposed Method
 Multirotor UAV	 Th= 91	 Th = 72	 Th = 68
 Source- Pixabay	 Th = 155	 Th = 73	 Th = 163

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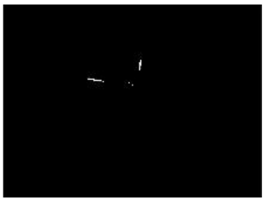
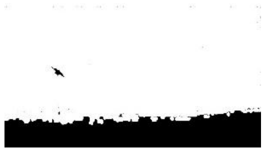
 Fixed-wing uav	 Th = 68	 Th = 45	 Th = 119
 Source- Pixabay	 Th = 115	 Th = 175	 Th = 67
 Fixed-wing uav	 Th = 176	 Th = 88	 Th = 61
 Fixed-wing uav	 Th = 120	 Th = 98	 Th = 80

Table 2 Image and its binary image after thresholding using Gaussian OTSU, the WOV method, and the proposed method with respective thresholding values (Th) shows the image and its binary image after thresholding using Gaussian OTSU, the WOV method and the proposed method with respective thresholding values (T_h) From the above table, when the object size is much smaller than that of the background the weighted object variance method and the proposed method give satisfactory results as seen in rows 1,5 and 6. The threshold value obtained by the weighted variance method is lesser than the OTSU method but higher than that ofthe proposed method. As the size of the object increases the OTSU method gives better results but the WOV method fails to deliver the desired results as seen in rows 2,3 and 4. Though OTSU predicts a threshold close to desire but fails to detect a complete object and misses internal features of the object. The threshold obtained by the proposed method is less than that of the OTSU and WOV methods considering the target object is dark and the background is white, as shown in rows 1,4,5 and 6. Similarly, the threshold obtained by the proposed method is more than that of the OTSU and WOV method considering the target object is dark and the background is white, as shown in rows 2,3.

The proposed method calculates the threshold value in both cases close to desired i.e. when the target object is

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smaller compared to the background as well as when the target object is of similar size to the background. Table 2 shows the threshold value calculated by the proposed method gives satisfactory results and detects compared with the OTSU method and WOV method.

The method is simulated on the Matlab R2021a explained in Table 1. The Elapsed time is the time required to detect the target object in an image. The Elapsed timefor the Gaussian OTSU method is 0.7823 seconds. The elapsed time for the Weighted object variance method is 0.2762 seconds. Whereas the elapsed time of the proposed method is 0.0139 seconds. This shows that the computational time of the proposed methods is lesser than that of the Gaussian OTSU and WOV methods.

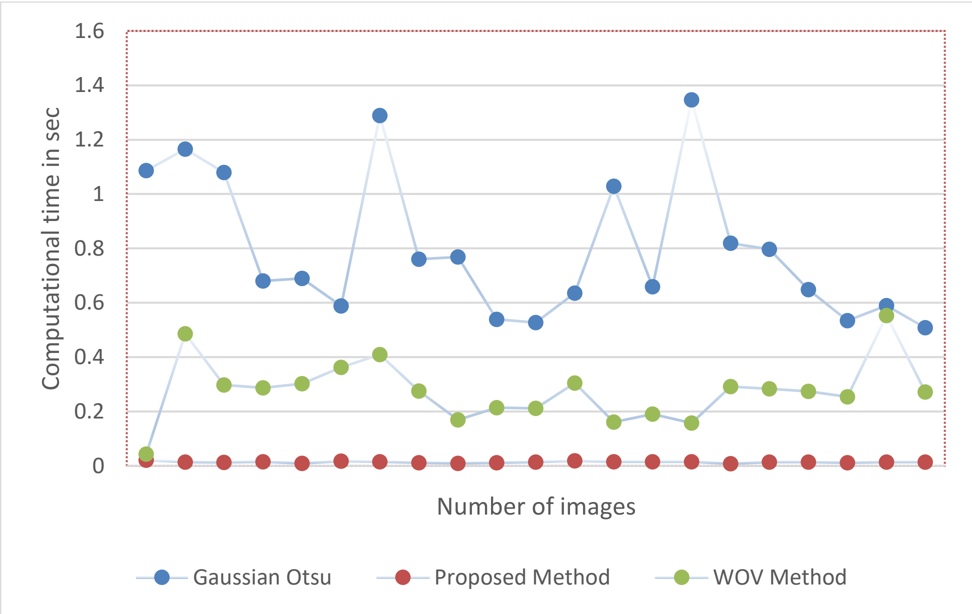

Figure 13 Plot of computational time for Gaussian method, WOV method, and the proposed method. On the x-axis, the sample image number is labeled and on the y-axis, the computational time is labeled in seconds

In order to verify the proposed algorithm different types of images with different types of backgrounds are tested. This includes images from the tests conducted in the outside environment, objects placed in indoor conditions, and some images from the internet. To verify the adaptability of the proposed method images with different resolutions such as 400x400 pixels, 1600x1600 pixels, 480x850 pixels, and 640x1024 pixels with horizontal and vertical resolution 96dpi, are selected. The mean computationtime for the Gaussian method results as 0.7823 seconds with a maximum of 1.3465 seconds and a minimum of 0.057 seconds, whereas the mean computation time for the WOV method is 0.2762 seconds with a maximum and minimum of 0.4863 seconds and 0.0434 seconds respectively. The mean computational time for the proposed method is 0.0139 seconds with a maximum of 0.0212 seconds and a minimum of 0.009886 seconds. From Fig (13), it is verified that the elapsed time of the proposed method is less than that of Gaussian OTSU as well as the WOV method.

Conclusion

This paper presents an improved OTSU method to detect the object by selecting the Optimal threshold value. A parameter equal to 0.577 is accumulated with the background variance for better selection of the threshold value. The methodology involves the negative LoG operator to detect the boundaries of an object and the pixel shifting algorithm to enhance the histogram of the pixel distribution of an image. Comparing the proposed method with the OTSU method, Gaussian OTSU method, and weighted object variance method, the proposed method accurately differentiates the object and the background. When the object is much smaller than that of the background, the OTSU method always concludes higher threshold value, whereas the weighted variance and proposed method give the threshold value lower than that of OTSU and nearer to the desired. T_h(otsu) > T_h(wov) > T_h(proposed) when the object is black and the background is white and vice-versa.

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When the object is equal toor bigger than that of the background, the weighted variance method always gives a much lower value than the desired threshold. The OTSU method predicts a higher value than the WOV method but fails to separate objects, the Proposed method givesa value near the desired threshold.

Declarations

1.9 Conflict of interest

None

1.10 Funding

None

Data Availability

Data is available in popular online platformof free images [16] and dataset generated by camera mention in section 3.1 will get available as per the request.

References

[1] Siddique MAB, Arif RB, Khan MMR (2018) Digital image segmentation in matlab: A brief study on otsu's image thresholding. 2018 International Con- ference on Innovation in Engineering and Technology (ICIET) pp 1–5. URLhttps://api.semanticscholar.org/CorpusID:54023148

[2] Bangare S, Dubal AA, Bangare P, et al (2015) Reviewing Otsu's method for image thresholding. International Journal of Applied Engineering Research 10:21777– 21783. https://doi.org/10.37622/IJAER/10.9.2015.21777-21783

[3] Qu Z, Zhang L (2010) Research on image segmentation based on the improvedotsu algorithm. 2010 Second International Conference on Intelligent Human- Machine Systems and Cybernetics 2:228–231. URL https://api.semanticscholar. org/CorpusID:18956764

[4] Qiao Y, Hu Q, Qian G, et al (2007) Thresholding based on variance and intensitycontrast. Pattern Recognition 40(2):596–608. https://doi.org/https://doi.org/10. 1016/j.patcog.2006.04.027, URL https://www.sciencedirect.com/science/article/ pii/S0031320306001841

[5] Otsu N (1979) A threshold selection method from gray-level histograms. IEEE Transactions on Systems, Man, and Cybernetics 9(1):62–66. https://doi.org/10. 1109/TSMC.1979.4310076

[6] Sezgin M, Sankur B (2004) Survey over image thresholding techniques and quan- titative performance evaluation. Journal of Electronic Imaging 13(1):146 – 165. https://doi.org/10.1117/1.1631315, URL https://doi.org/10.1117/1.1631315

[7] Zhu N, Wang G, Yang G, et al (2009) A fast 2d otsu thresholding algorithm based on improved histogram. 2009 Chinese Conference on Pattern Recognition pp 1–5. URL https://api.semanticscholar.org/CorpusID:43917857

[8] Wang N, Li X, Chen Xh (2010) Fast three-dimensional otsu thresholding with shuffled frog-leaping algorithm. Pattern Recogn Lett 31(13):1809–1815. https: //doi.org/10.1016/j.patrec.2010.06.002, URL https://doi.org/10.1016/j.patrec.2010.06.002

[9] Sharp C, Shakernia O, Sastry S (2001) A vision system for landing an unmannedaerial vehicle. In: Proceedings 2001 ICRA. IEEE International Conference on Robotics and Automation (Cat. No.01CH37164). IEEE, Seoul, Korea, p 1720– 1727 vol.2

[10] Yousefi J (2011) Image binarization using otsu thresholding algorithm Ontario,Canada: University of Guelph 10

[11] Yuan X, Lushen W, Peng Q (2015) An improved Otsu method using the weighted object variance for defect detection. Applied Surface Science 349:472–484

[12] Huang M, Yu W, Zhu D (2012) An improved image segmentation algorithm based on the otsu method. In: Teruhisa Hochin RL (ed) 2012 13th ACIS Inter- national Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing. IEEE, Kyoto, Japan, p 135–139

[13] Sezgin M, Sankur B (2004) Survey over image thresholding techniques and quantitative performance

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evaluation. Journal of Electronic Imaging 13(1):146–165

[14] Xu X, Xu S, Jin L, et al (2011) Characteristic analysis of Otsu threshold and its applications. Pattern Recognition Letters 32(8):956–961

[15] Akagic A, Buza E, Omanovic S, et al (2018) Pavement crack detection using otsuthresholding for image segmentation. In: 2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO). IEEE, Opatija Croatia, p 1092–1097

[16] dataset [Online]. P (2022) Pixabay free image dataset available. Https://pixabay.com/datasets/free-images

[17] Stankovi; I, Brajovi; M, Stankovi; L, et al (2021) Laplacian filter in reconstruc- tion of images using gradient-based algorithm. In: 2021 29th Telecommunications Forum (TELFOR). IEEE, Belgrade Serbia, p 1–4

[18] Rawat P, Sawale MD (2017) Gaussian kernel filtering for video stabilization.In: 2017 International Conference on Recent Innovations in Signal processing and Embedded Systems (RISE), pp 142–147, https://doi.org/10.1109/RISE.2017. 8378142

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