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Performance analysis of image thresholding: Otsu technique

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ABSTRACT

Image thresholding is usually applied as an initial step in many algorithms for image analysis, object representation and visualization. Although many image thresholding techniques were proposed in the literature and their usage is well understood, their performance analyses are relatively limited. We critically analysed the feasibility of successful image thresholding under a variation of all scene parameters. The focus is based on Otsu method image thresholding technique since it is widely used in many computer vision applications. Our analysis based on Monte Carlo statistical method shows that the success of image segmentation depends on object-background intensity difference, object size and noise measurement, however is unaffected by location of the object on that image. We have also proposed a set of conditions to guarantee a successful image segmentation. Experiment using real-image data was set up to verify the validity of those conditions. The result demonstrates the capability of the proposed conditions to correctly predict the outcome of image thresholding using Otsu technique. In practice, the success of image thresholding could be predicted beforehand with the aid of obtainable scene parameters.

1. Introduction

Image segmentation is the process or technique of partitioning a digital image into several sets of pixels [1]. This segmentation process is the fundamental step for image analysis, object representation, visualization and other image processing tasks that is applied in various field of applications [2]. The main purpose of image segmentation is to simplify and/or change the respective image sample into an easily analysed image [3]. Thresholding method is the simplest and one of the most widely used techniques for image segmentation due to its simplicity [4]. The basic approach is to select an appropriate threshold value from a gray scale image. The purpose of thresholding is to separate the foreground of an image from its background [5–7]. Any pixel with an intensity value lower than the selected threshold value is considered to be region black part and vice versa [8]. Thus, thresholding is important in many applications such as industrial inspection, tracking, classification and detection [9].

Generally, thresholding techniques can be categorised into two classes which are global thresholding and local thresholding [10]. In global thresholding, a single threshold value is used to separate the foreground and the background of an image. While in local thresholding, a threshold value is assigned to each pixel to determine whether it is a foreground or background pixel using local information from the image [11]. Additionally, there is a number of thresholding algorithms already appeared in the literatures, and they can be broadly classified based on the information that they manipulate [25] – Histogram [38], clustering [39], entropy [14], object attribute [40], spatial [41] and local [42]. Even though the use as image thresholding is well understood and widely applied, their performance analyses are largely unaddressed. Thresholding performance also depends on a number of scene parameters, namely object-background intensity difference, noise measurement, size and position of the object.

For example, Fig. 1 shows the results of image thresholding using five different techniques [4]. Fig. 1(a) is the original grayscale image before undergoing image segmentation. Fig. 1(b) and (c) represent the successful cases of image segmentation while Fig. 1(d), (e) and (f) represent the unsuccessful cases of image segmentation using different thresholding techniques namely Otsu's, Hou's, Kapur's, minimum error and ground truth techniques [4]. It would be better if one is able to understand and analyse the parameters affecting the success of image thresholding. Then the success of image thresholding could be guaranteed and predicted beforehand based on those understanding.

The novelty of this paper mainly lies in the developing the conditions for successful thresholding using Otsu technique. The developed conditions enable one to predict the outcome of thresholding. Generally, in practice, we have a rough idea of the object-background

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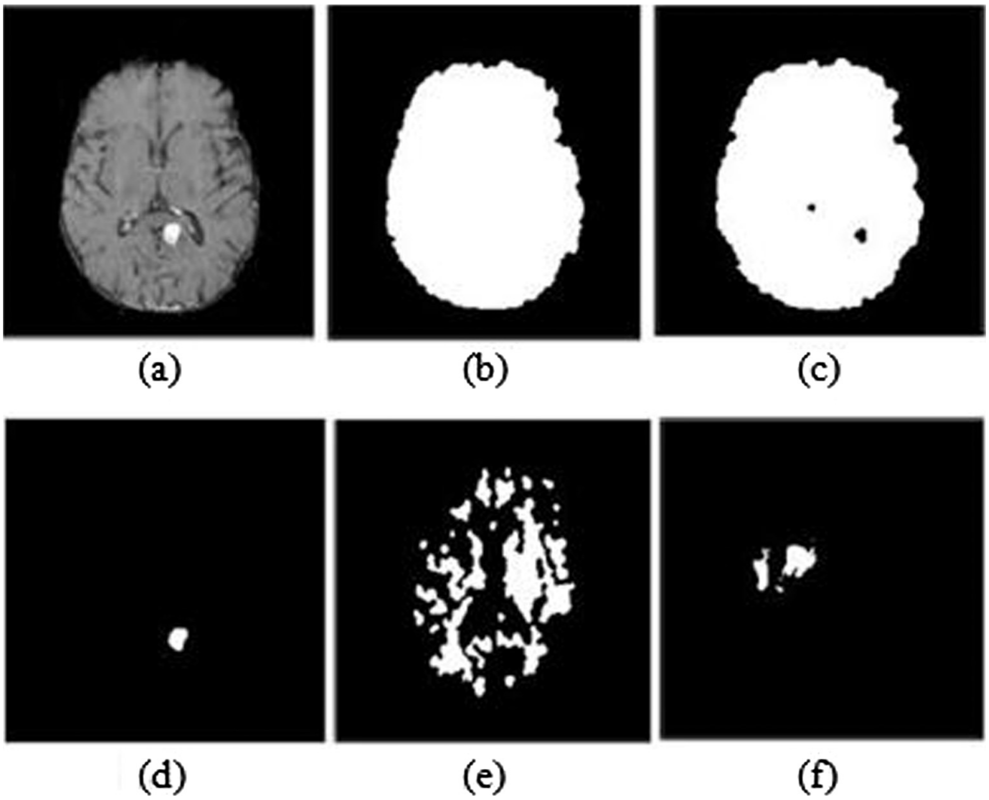

Fig. 1. Successfulness of the segmentation using different thresholding techniques. (a) Original grayscale image, (b) Otsu's techniques based threshold image, (c) Hou's techniques based threshold image, (d) Kapur's entropy techniques based threshold image, (e) Minimum error thresholding techniques based threshold image, (f) Ground truth techniques based threshold image.

intensity difference and object size which are the priori parameters associated with the performance of Otsu technique, thus we can predict the thresholding outcome beforehand. Therefore, these conditions serve as a guideline for practitioner in applying thresholding using Otsu technique.

2. Backgrounds and related works

Image thresholding is widely applied as an initial process in many computer vision algorithms. Even then, image thresholding is unable to exploit specific information or characteristics of the image. While human can easily differentiate an object from a complex background, it is somehow a difficult task for image thresholding to separate them [33]. Generally, thresholding techniques can be categorised into global thresholding and local thresholding. For global thresholding, a single stage threshold value is produced to separate an object from its background in an image. Meanwhile in local thresholding, thresholding is performed in one pass using local information obtained from the image [11]. However, global thresholding and local thresholding have its own weakness in certain image processing due to their inability to exploit information on the characteristics of their threshold images. In some cases, traditional technique is sufficient to segment the images as it treats all images in the same way.

In addition, Abutaleb [5], Brink & Pendock [13], Kapur et al. [14] and Pal & Pal [15] have proposed thresholding techniques based on entropy while Liang & Mao [7] and Pal & Rosenfeld [16] have proposed thresholding techniques using fuzzy approach. All of these methods are categorised as global thresholding technique.

There are also a number of techniques being proposed to solve local thresholding. Among the proposed techniques are intensity histogram of pixels in rectangular windows (proposed by Chow & Kaneko [17], Eilvil et al. [18] and Taxt et al. [19]), maximum and minimum intensities of pixels in rectangular windows (proposed by Bernsen [20]), mean and standard deviation of pixels in rectangular windows (proposed by Niblack [21]) and edge information (proposed by Parker [22] and Yanowitz & Bruckstein [23]).

The focus of this study is on Otsu thresholding techniques due to its simplicity, robustness and adaptability and one of the most applied thresholding algorithm is Otsu thresholding [12]. Otsu thresholding technique was proposed by Kittler and Illingworth (minimum error techniques) [6] and Nobuyuki Otsu [12]. Otsu thresholding techniques choose the optimal threshold by maximizing the between class variance of the gray levels in the object and background portions while Kittler and Illingworth minimum error technique approximates the histogram by a mixture of normal distributions and minimizes the classification of error probability [6,12]. These two methods have received compliments in many studies because of good performance on real images segmentation. Additionally, Otsu can be used and functions very well for thresholding if the implementation of noise removal and character recognition are properly done [11]. The advantage is the simplicity in calculating the threshold since the calculation involves 1D intensity data and this helps to reduce the computational processing time in real life application. Due to these advantages, a large number of methods have been proposed to improve the original Otsu's method, including [43,44]. However, these methods are usually unable to produce satisfying segmented results in case those images are riddled by noise.

Kalathiya and Patel had proposed the Otsu method with two different approaches which are iteration approach and custom approach [24]. During implementation, they had successfully showed that both of these approaches have given almost the same threshold value for segmenting image. The maximum result for between class variance of gray levels is defined as custom approach while the minimum result within class variance is defined as iterative approach [25].

The equation for within class variance (iterative approach) is shown in Eq. (1). Let σ_W^2 indicates the mathematical expression for within class variance, σ_b^2 is for the variance of the background pixels and σ_f^2 is for the variance of the foreground pixels. Additionally, W_b and W_f indicate mathematical symbols for weight of background and foreground, respectively.

$$\sigma_W^2 = W_b\sigma_b^2 + W_f\sigma_f^2 \quad (1)$$

The equation for between class variance (custom approach) is shown in Eq. (2). Let σ_B^2 indicates the mathematical expression for between class variance, μ_b represents the mean value of the background pixels while μ_f is the mean value of the foreground pixels. Meanwhile, W_b and W_f indicate mathematical symbols for weight of background and foreground, respectively.

$$\sigma_B^2 = W_b W_f (\mu_b - \mu_f)^2 \tag{2}$$

Otsu thresholding technique is useful in performing image segmentation as it requires less computational time compared to other techniques. This is because Otsu thresholding involves simple mathematical expression in its algorithm when determining or calculating the best threshold value.

Jose Sigut, Francisco Fumero and Omar Nunez have proposed the measurement of segmentation that includes evaluations of the over-segmentation and under-segmentation [26]. They mentioned that segmentation that involves measurement has been proven by others to be a good choice for evaluating segmentation performance [27,28]. The proposed evaluation method was derived and successfully implemented in the image segmentation to examine the segmentation performance. They have proposed the formulae for over-segmentation and under-segmentation by using segmentation covering measures. The relative measures for the proposed evaluation during segmentation are given in Eqs. (3) and (4).

$$SC_{ovrel} = SC_{ov}/SC \tag{3}$$

$$SC_{unrel} = SC_{un}/SC \tag{4}$$

The mathematical expression SC_{ovrel} indicates the relative segmentation covering for over-segmentation while SC_{unrel} is for the relative segmentation covering for under-segmentation. The SC_{ov} and SC_{un} mathematical symbols indicate segmentation covering measurement for over-segmentation and under-segmentation, respectively. The mathematical symbol SC indicates the segmentation covering measurement for the image. These mathematical expressions introduced by them are useful in determining the segmentation performance. A relative segmentation result is obtained by taking a number of segmented points (under-segmented points, over-segmented points or good-segmented points) divided by a number of true points (original gray scale points). This expression can easily obtain the results of the segmentation performance.

Even though the use of Otsu techniques for thresholding is well understood and widely applied, their performance analyses are still relatively limited. Most of the thresholding performance analysis focused on comparison between techniques – quantitative [25,34] and qualitative [35] – and did not emphasise on analysis of the condition that would guarantee a successful thresholding. This condition is very important as it will allow practitioners to correctly predict their outcome, beforehand. Currently, related study on performance analysis is limited to range segmentation [36], motion segmentation [29–32] and volumetric images [37]. Our aim is to critically analyse the feasibility of successful Otsu thresholding technique under variation of all scene parameters that include object-background intensity difference, object size and its location and measurement. Then a set of conditions that guarantee successful image segmentation was proposed. These conditions could then be used to predetermine the outcome of Otsu thresholding and able to provide early guidance to algorithm developers.

3. Performance analysis of Otsu thresholding technique

Otsu technique works based on thresholding one-dimensional intensity data extracted from two-dimensional image [43–44]. This setup results in a simple computation, robust and adaptable to many computer vision applications [12]. In order to analyse the performance of Otsu thresholding technique, we considered a practical case where 2D images consist of two pixel groups corresponding to object to be segmented and background. In this study, our concentration is on Otsu technique performance analysis of four parameters which understandably affect Otsu thresholding [45–47] and are usually encountered in the scene:

(a) object-background intensity difference representing the lighting condition of the scene
(b) object size and location representing the location and distance of object with respect to camera
(c) noise measurement representing the quality of images and camera hardware

Since Otsu technique performs thresholding based on data intensity, other parameters such as shape or geometric characteristic of object are expected to have no effect to the thresholding performance.

A publicly available implementation of Otsu thresholding technique was used [12] in the analysis. Otsu thresholding technique is implemented as a measure to compare two images (original grayscale image and segmented image). This is because Otsu thresholding technique performs nonparametric and unsupervised image thresholding during image segmentation process. It determines an optimal threshold of an image by minimizing the within class variance using only the gray level histogram of the image and its performance should be able to represent performance of other lower level thresholding algorithm. An image is modelled as:

$$\mathrm{I} = f(\mathrm{I}^o) = f(\mathrm{I}_b^o + \mathrm{I}_f^o) \tag{5}$$

where I^o is the original image, I_b^o is the (original) background image, I_f^o is the (original) foreground/object image, and function f(.) represents the acquisition transformation. Noise may be present within an image and can be described as:

$$\mathrm{I(x,y)} = f(\mathrm{I}^o\mathrm{(x,y)}) = Ns\mathrm{(x,y)}[(\mathrm{I}_b^o\mathrm{(x,y)} + I_f^o\mathrm{(x,y)})] \tag{6}$$

$$= Ns\mathrm{(x,y)}(\mathrm{I}_b^o\mathrm{(x,y)}) + Ns\mathrm{(x,y)}(\mathrm{I}_f^o\mathrm{(x,y)}) \tag{7}$$

where Ns (x,y) is the noise within the image at coordinate (x,y).

Let the pixels of a given image (I) be represented in L gray levels [1, 2, …, L]. The number of pixels at level i is denoted by n_i and the total number of pixels by $N = n_1 + n_2 + \dots n_L$. A probability distribution is obtained;

$$p_i = \frac{n_i}{N}; \quad p_i \geqslant 0\,; \quad \sum_{i=1}^{L} p_i = 1 \tag{8}$$

The pixel is divided into 2 classes C_0 and C_1 (background and object or vice versa) by a threshold at level k. The C_0 indicates pixels at level [1…k] and C_1 denotes pixels at level [k + 1….L].

The probabilities of class occurrence are determined using

$$w_0 = \sum_{i=1}^{k} p_i = \omega(k) \tag{9}$$

$$w_1 = \sum_{i=k+1}^{L} p_i = 1 - \omega(k) \tag{10}$$

where

w_0 = probability of C_0 occurrence
w_1 = probability of C_1 occurrence

The class mean levels are given by

$$\mu_0 = \sum_{i=1}^{k} \frac{ip_i}{\omega_0} \tag{11}$$

$$\mu_1 = \sum_{i=k+1}^{L} \frac{ip_i}{\omega_1} \tag{12}$$

where

$$\mu_0 = \text{mean } C_0$$
$$\mu_1 = \text{mean } C_1$$

$$\omega(k) = \sum_{i=1}^{k} p_i \tag{13}$$

$$\mu(k) = \sum_{i=1}^{k} ip_i \tag{14}$$

are the zeroth and first order cumulative moments of the histogram is up to the kth level. The total mean level k of the original image is given by Eq. (12)

$$\mu_T = \sum_{i=1}^{L} ip_i \tag{15}$$

The class variance are based on Eqs. (13) and (14)

$$\sigma_0^2 = \sum_{i=1}^{k} (1-\mu_0)^2 \frac{p_i}{\omega_0} \tag{16}$$

$$\sigma_1^2 = \sum_{i=k+1}^{L} (1-\mu_1)^2 \frac{p_i}{\omega_1} \tag{17}$$

The discriminant criterion measure is used to evaluate the threshold.

$$\lambda = \frac{\sigma_B^2}{\sigma_\omega^2}; \kappa = \frac{\sigma_T^2}{\sigma_\omega^2}; \eta = \frac{\sigma_B^2}{\sigma_T^2} \tag{18}$$

where

$$\sigma_\omega^2 = \omega_0\sigma_0^2 + \omega_1\sigma_1^2 \tag{19}$$

$$\sigma_B^2 = \omega_0\omega_1(\mu_1-\mu_0)^2 \tag{20}$$

$$\sigma_T^2 = \sum_{i=1}^{L} (1-\mu_T)^2 p_i \tag{21}$$

are within-class variance, between-class variance, and total variance of levels, respectively. As η is the simplest measure with respect to k, thus, η is adopted to measure the threshold at level k.

Sets of synthetic images were developed to represent a scene with an object and background and serve as an input to the Otsu thresholding technique. The scene and measurement parameters were varied during the experiment by altering the characteristics of the synthetic images such as:

(a) Intensity difference between pixels corresponding to object and background, denoted by I. $I = 100\%$ indicates a black background and white object or vice versa, while $I = 0\%$ is when pixels corresponding to object and background have similar intensity values.
(b) Object size appeared on image plane, denoted by the width and length of object denoted by $S = lxl$. We used a square image of 50×50 pixels for ease of analysis. Object Size, $S = 100\%$ indicates $l \times l$ is 50×50 pixels which exactly covers the whole image. While $S = 20\%$ indicates the object size $l \times l$ is 10×10 pixels out of 50×50 square image.
(c) Object location appeared on image plane, is denoted by P. We varied the location of the object at different parts of the synthetic image. These object will be located at first quadrant, second quadrant, third quadrant, forth quadrant and at the centre of the image plane.
(d) Noise measurement as denoted by σ^2. A standard normal distribution noise will add to the 50×50 pixels image plane. All points or pixels in the input image plane contaminated by noise are assumed to be independently and identically distributed with mean, $\tilde{x} = 0$ and variance, $\sigma^2 = 1$. The noise is controlled by varying $\sigma^2 = 0.5$ to 4.

Then the synthetic image was fed into the thresholding using the Otsu. Thresholding performance was then measured using the segmentation ratio, ζ.

$$\zeta = no.\ of\ segmented\ points\ /\ no.\ of\ true\ points \tag{22}$$

Ideally a good segmentation is achieved when segmentation ratio ζ is equal to 1 indicating all pixels associated to the object are successfully segmented. Meanwhile, the value of ζ less than 1 or greater than 1 shows under-segmentation or over-segmentation case, respectively. Under-segmentation indicates that some pixels corresponding to object was not segmented, while over-segmentation indicates that some pixels associated to the background were segmented as object.

$$Segmentation\ ratio\ \zeta = \begin{cases} \zeta < 1,\ under\ segmentation \\ \zeta = 1,\ good\ segmentation \\ \zeta > 1,\ over\ segmentation \end{cases} \tag{23}$$

To examine Otsu thresholding performance, the analysis is divided into three parts which are feasibility analysis of thresholding, consistency analysis of thresholding, verification and demonstration using real image data.

3.1. Feasibility analysis of the Otsu thresholding

For Part 1 of the threshold segmentation analysis, this research focuses on the background intensity, object size, object position and noise. These parameters are proposed because these are the basic parameters that would affect the segmentation performance. For background intensity parameter, I is varying from value bit 0 to value bit 1 with an increment of 20%. For object size parameter, S is initially fixed at 10×10 pixels and then varied to 50×50 pixels with an increment of 20%. For object position parameter, P is initially fixed at the centre of the image and then the object is varied at different quadrants of the image. A normal distributed noise is added to the synthetic images to investigate the condition for successful image segmentation in noise parameter. The noise density is varied from $\sigma^2 = 0.5$ to 4 with intent to determine the limitation of these proposed parameters at different noise levels. These are the synthetic images that will be implemented in the theoretical experiments.

Without loss of generality, these four parameters will be tested with Otsu thresholding algorithm for the purpose of robust estimation for real image application. It is assumed that the object at each image samples is considered as the target and is visualized to be the inliers in which we aim to segment from the background that is known as outliers. The analysis aims to investigate the theoretical limit of the Otsu thresholding applicable to image segmentation in term of known scenes and fixed parameters.

The result for the feasibility of each proposed parameters (background intensity, object size, object position and noise) are provided as below.

Fig. 2 shows the synthetic reference image for background intensity parameter, image before thresholding and its thresholding result (including segmentation ratio, noise, intensity, object size and location). Theoretically, the image will become easier to segment when the intensity difference greater. It was observed from results in Fig. 2 that noise is controlled at $\sigma^2 = 0.5$, it can be noticed that when the background intensity (I) is less than 40%, the percentage of the segmentation becomes higher as it undergoes over-segmentation. This indicates that the segmentation is inaccurate for the inlier and outlier to be successfully segmented as object and background. Some of the outlier points might accidentally be reduced to inlier points after Otsu segmentation. Similarly, the percentage for segmentation experiencing under-segmentation will be higher when background intensity (I) is more than 40%. This is due to some outlier points at background

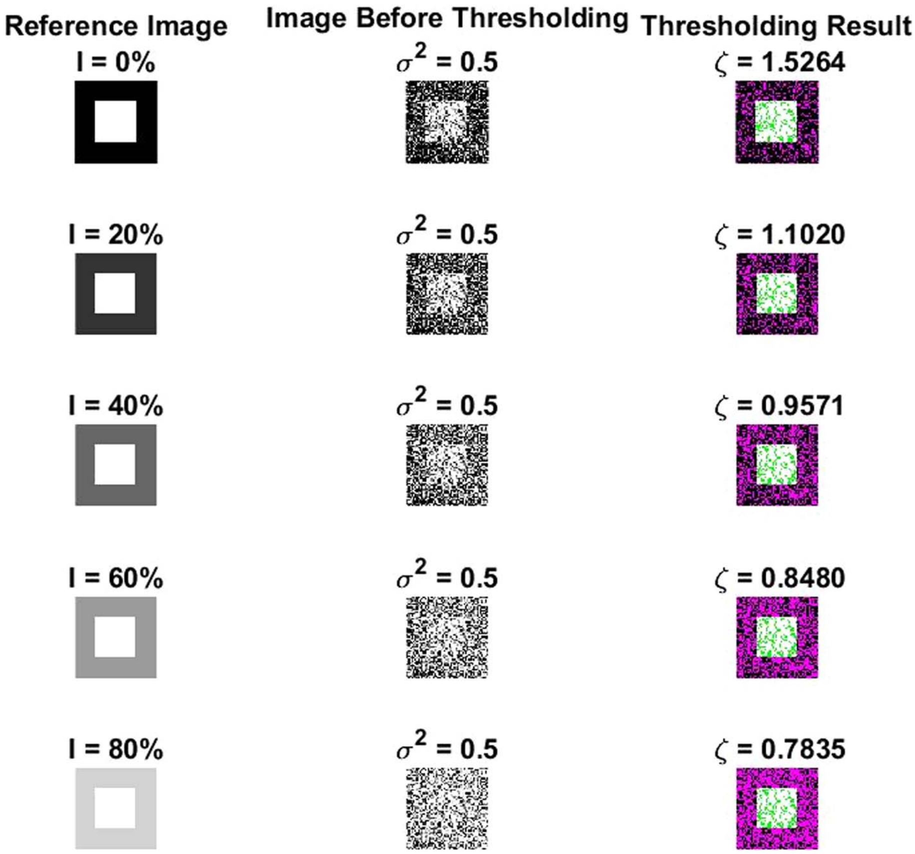

Fig. 2. Synthetic reference images for intensity parameter, image before thresholding, and thresholding result (include segmentation ratio ζ, noise σ^2, intensity I, object size S and location P).

intensity post 40% might recognize them as inlier points as their intensity or brightness become more akin to the inlier pixels. Additionally, it could be noted that, segmentation or thresholding becomes relatively easier when the intensity difference between object and background is higher.

Fig. 3 shows the synthetic reference image for object size parameter, image before thresholding and its thresholding result (including segmentation ratio, noise, intensity, object size and location). From the observation through results in Fig. 3, noise is controlled at $\sigma^2 = 0.5$ and it can be scrutinized that when the object size (S) is less than 40 × 40 pixels, the percentage of the segmentation undergoing over-segmentation becomes higher. This implied that the segmentation is inaccurate for the inlier and outlier to be successfully segmented as object and background. This shows that, when the object appearing in the image plane is smaller, it is generally becoming more difficult to be appropriately segmented. This might generate over-segmentation as some of the outlier points might be reduced to inlier points after Otsu segmentation. Similarly, the percentage for segmentation experiencing under-segmentation will be higher when the size of object (S) is more than 40 × 40 pixels. This is due to the object points are increased and snowballed compared to background points. Or in other word, the probability of the object points to perform image segmentation after mixing with normal noise is higher as the object size is increased. Thus, probability for inlier points at size of object post 40 × 40 pixels will increase as the points might accidentally be reduced to outlier points due to incorrect segmentation.

Fig. 4 shows the synthetic reference image for object position parameter, image before thresholding and its thresholding result (including segmentation ratio, noise, intensity, object size and location). Theoretically, the object position in a particular image does not affect the performance of thresholding unless the position of the current object has different levels of light intensity. From the observation through results in Fig. 4, noise is controlled at $\sigma^2 = 0.5$, it can be seen that the result for object size (S) is equal to 10 × 10 pixels has consistent results for different object positions. Similarly, for object size (S) is equal to 20 × 20 pixels, 30 × 30 pixels and 40 × 40 pixels, the segmentation ratio results are consistent at different object position parameters varied at first quadrant ($\zeta = 7.4800$), second quadrant ($\zeta = 7.4600$), third quadrant ($\zeta = 7.6100$), forth quadrant ($\zeta = 7.4800$) and centre ($\zeta = 7.4900$) of the synthetic images.

3.2. Consistency analysis of the Otsu thresholding

Consistency analysis is performed to examine the validity of feasibility analysis. The experiment was designed based on Monte Carlo statistical approaches. In each analysis, 100 cases of randomly generated synthetic images were fed into Otsu thresholding. After thresholding were performed, 100 values of ζ were recorded and the consistency was measured by mean and standard deviation of ζ denoted by $\widetilde{\zeta}$ and σ_ζ, respectively. The image segmentation from Otsu thresholding will be considered good and consistent if and only if the $\widetilde{\zeta} \approx 1$ and $\sigma_\zeta \approx 0.01$ throughout the experiments. Consistency analysis was then repeated for all the parameters. A pseudocode to summarise the analysis setup is included in Fig. 5.

The results for the consistency analysis under variation of all scene parameters (background intensity, object size, object position and noise) using synthetic images are provided in Fig. 6. Fig. 6 shows some broad pictures of the required condition for the proposed parameter (background intensity, object size and object position to their respective noise) to guarantee a successful image segmentation. From the graphs, the optimum conditions for each parameter are determined.

Fig. 6(a) is the segmentation performance for background intensity parameter varied at different noise level parameters. From the graphical result, at $\sigma^2 = 1.0$ and background intensity $I = 40\%$, segmentation is the most accurate as it resulted in segmentation ratio $\widetilde{\zeta} \approx 1$ and $\sigma_\zeta \approx 0.01$. This indicates that image undergoes good segmentation at

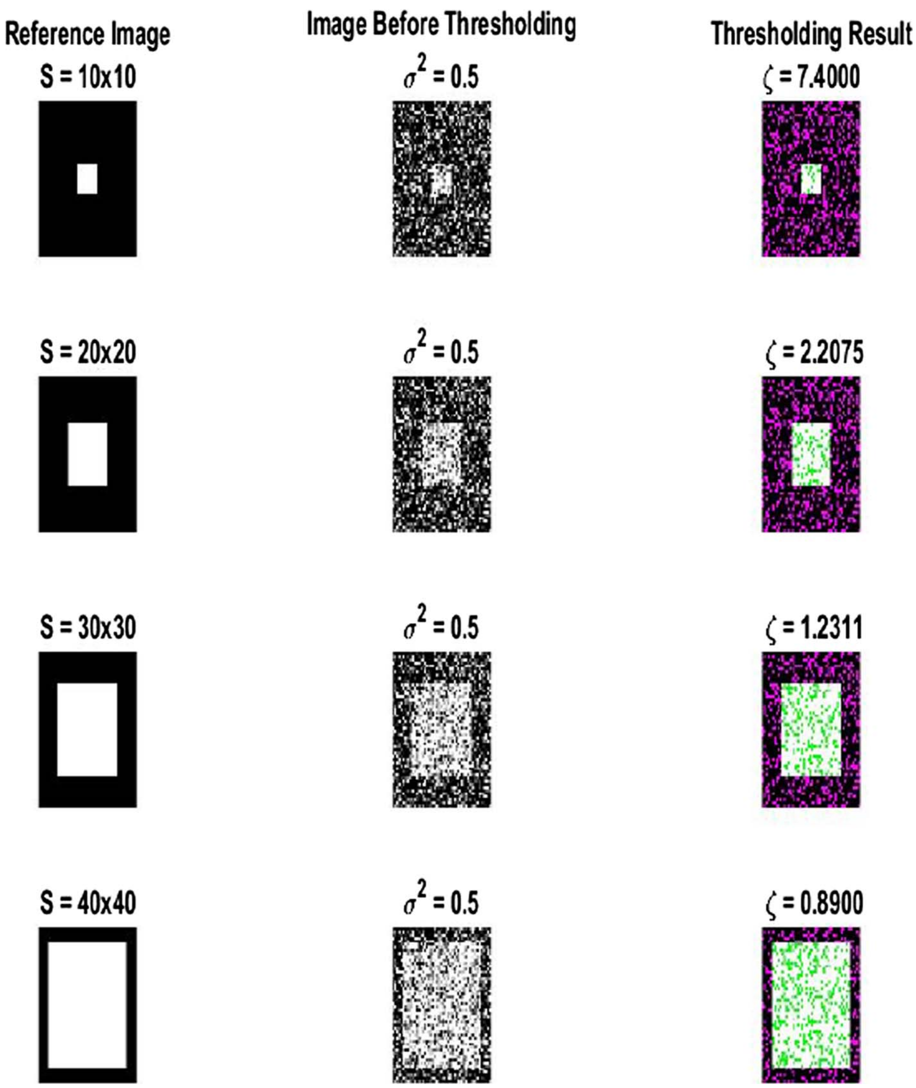

Fig. 3. Synthetic reference images for object size parameter, image before thresholding, and thresholding result (include segmentation ratio ζ, noise σ^2, intensity I, object size S and location P).

background intensity is approximately 40%. Moreover, from Fig. 6(a), it can be observed that the segmentation is incorrect for all background intensity variation from 0 to 1 with an increment of 20% except for $I = 40\%$ as this region is the correct segmentation. Next, we examined the effect of noise variance to the image segmentation with intensity parameter. From the graphical results in Fig. 6(a), at $I = 40\%$, it showed that all segmentation is in correct segmentation as their mean segmentation ratio value is closer to one compared to other noise variances. From the analysis, we can conclude that the intensity has influenced target segmentation since their intensity values are independent of object size, image size and object position.

Fig. 6(b) is the segmentation performance for object size parameter varied at different noise level parameter. From the graphical results, at noise variance is equal to one and object size $S = 40 \times 40$ pixels, segmentation is the most accurate as it has segmentation ratio $\tilde{\zeta} \approx 1$ and $\sigma_\zeta \approx 0.01$. This indicates that image undergoes good segmentation at object size is approximately 40×40 pixels. It can be observed from Fig. 6(b) that the segmentation is incorrect for all object size variation from 10×10 pixels to 50×50 pixels with an increment of 20% except for $S = 40 \times 40$ pixels as this region is the correct segmentation. Next, we examined the effect of noise variance to the image segmentation with object size parameter. From the graphical results in Fig. 6(b), at $S = 40 \times 40$ pixels, it shows that all segmentation is in correct segmentation as their mean segmentation ratio value is closer to one compared to other noise variances. From the analysis, we can conclude that object size has influenced target segmentation since their object sizes are independent of intensity, image size and object position.

The condition of the segmentation performance for object position parameter is observed through Fig. 6(c). From the graphical results, at noise variance equal to one, the result of the segmentation with object position parameter does not influence the mean of segmentation ratio for various object sizes. Besides, we can observe and note that the data results (mean of segmentation ratio for various object sizes) is consistent and almost constant throughout the experiment by varying the positions of the object (first quadrant, second quadrant, third quadrant, forth quadrant and centre). In summary, as a preliminary theoretical analysis, we can conclude that the object position parameter does not influence the performance of the segmentation.

From the graphical results obtained in Fig. 6(a)–(c), segmentation ratio is equal to 1 indicates a good segmentation whereby the foreground and background are successfully distinguished from each other. These optimum values serve as the conditions for each parameter in order to achieve good segmentation.

Fig. 7 shows the conditions to guarantee successful thresholding using Otsu with $\tilde{\zeta} \approx 1$ and $\sigma_\zeta \approx 0.01$, and was interpolated based on Fig. 6. It is observed from Fig. 7 that intensity parameter and object size parameter are approximately at 35% and 72%, respectively, for different noise levels to guarantee successful thresholding. Additionally, from Fig. 6(c), the object position parameter does not influence the segmentation performance. Thus, the data interpolation is

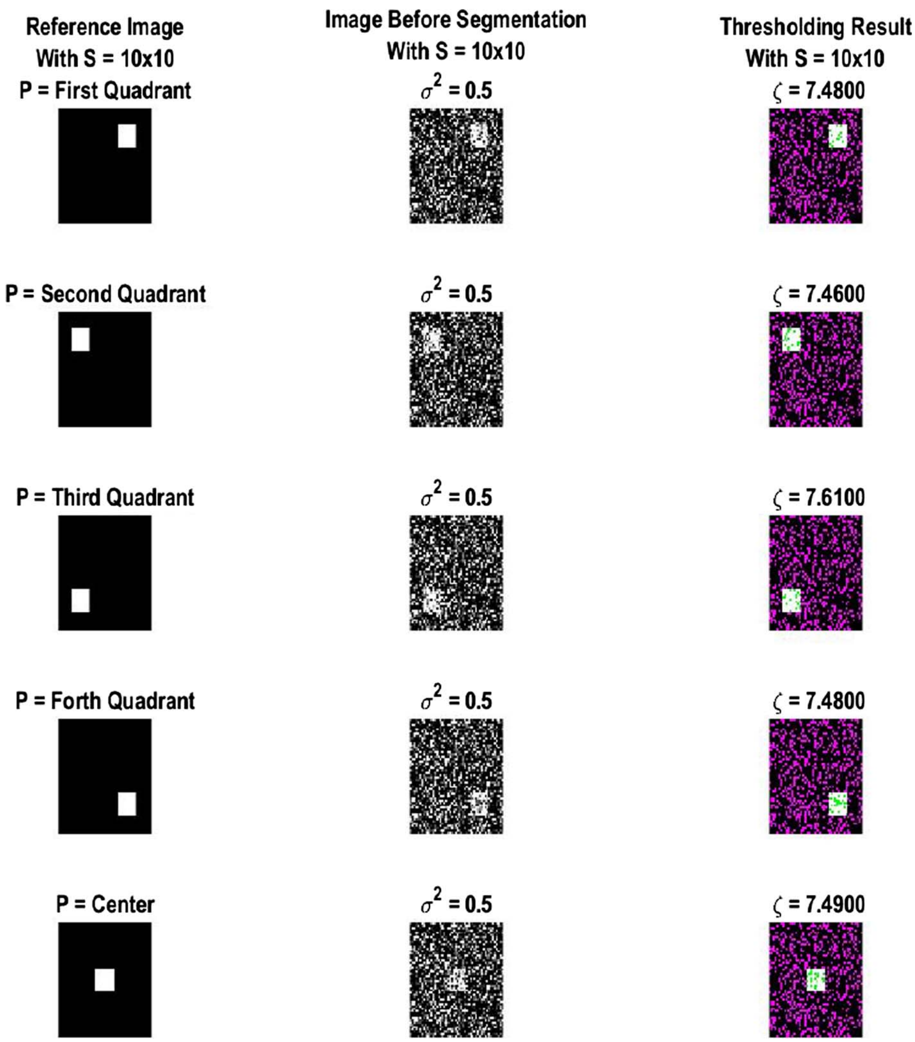

Fig. 4. Synthetic reference images for object position parameter, image before thresholding, and thresholding result (include segmentation ratio ζ, noise σ^2, intensity I, object size S and location P).

Repeat ($noise\ variance, \sigma^2 = 0.5\ to\ 4$).
Repeat ($Intensity, I = 0\ to\ 1\ with\ increment\ 20\%$).
Repeat ($Object\ Size, S = 10x10\ pixels\ to\ 50x50\ pixels\ with\ increment\ 20\%$).
Repeat
($Object\ Position, P\ placed\ at\ center\ and\ then\ varied\ at\ different\ quadrant$)

i. Repeat ($j = 1\ to\ 100$).
   1. Generate synthetic image according to each parameters that described above.
   2. Calculate true points of the inlier (before adding noise and segmentation).
   3. All image points is contaminated with normal distributed noise $N(0, \sigma^2)$.
   4. Perform segmentation using Otsu algorithm.
   5. Calculate segmented points of the inlier (after adding noise and segmentation).
   6. Record segmentation performance, segmentation ratio, ζ (number of segmented points over number of true points).

ii. End

iii. Calculate and record mean and standard deviation of 100 ratios ζ.

End, End, End, End

Fig. 5. Pseudocode for consistency analysis.

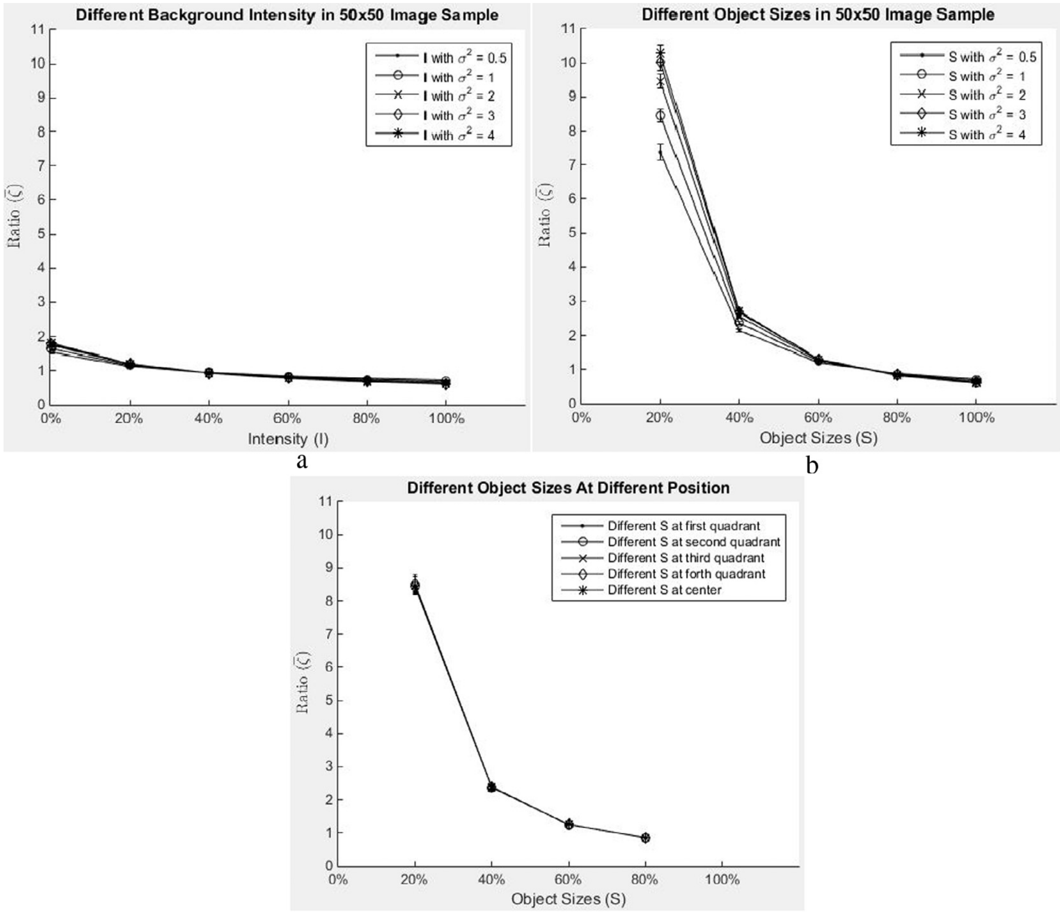

Fig. 6. Segmentation performance for all proposed parameters. (a) Segmentation performance ($\tilde{\zeta}$ and σ_{ζ}) for background intensity parameter at different noise level (from $\sigma^2 = 0.5$ to $\sigma^2 = 4$), (b) Segmentation performance ($\tilde{\zeta}$ and σ_{ζ}) for object size parameter at different noise level (from $\sigma^2 = 0.5$ to $\sigma^2 = 4$), (c) Segmentation performance ($\tilde{\zeta}$ and σ_{ζ}) for object position parameter at different object size (from $S = 20\%$ to $S = 80\%$).

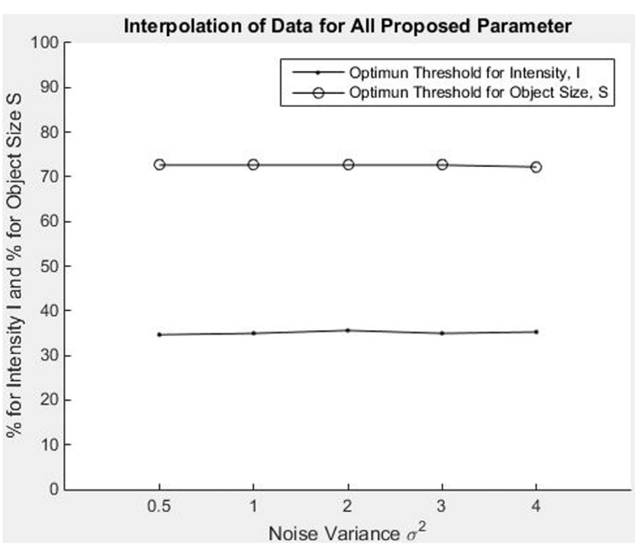

Fig. 7. Interpolation of data for all proposed parameters.

involved the other three parameters (background intensity, object size and noise) since the object position parameter does not influence the overall performance of the segmentation. Fig. 7 can be used as a guideline to guarantee a successful and the optimum Otsu thresholding.

3.3. Verification using real images application

The third part of the experiment is aimed to examine the validity of the proposed conditions for thresholding in Fig.7. Additionally, our intention is to demonstrate the capability of the proposed conditions in practical application by correctly predict the outcome of thresholding beforehand.

Four images of a spoon were acquired using a standard commercially available phone camera and used with the following estimated parameters:

Sample 1: The sample is controlled at the background intensity level of around 35% to examine the effect of intensity parameter to the Otsu threshold segmentation. The main object position is located at second quadrant with level of object intensity at around 100%.

Sample 2: The sample is controlled at the background intensity same as in Sample 1 and the main object position is located in the first quadrant to examine the effect of the object position parameter to the Otsu threshold segmentation.

Sample 3: The sample is controlled at the object size at a level of around 70% to examine the effect of the object size parameter to the Otsu threshold segmentation. The main object is located at the centre of the image with object intensity level of around 100%.

Sample 4: The sample is controlled at the background intensity level of around 70% with object intensity level of around 100%

Based on the estimated parameters, we predicted that Otsu method should be able to successfully segment the Image 1, 2 and 3 since the estimated values of I and S are controlled at 35% and 70%, respectively. Similarly, Image 4 is predicted to produce unsuccessful

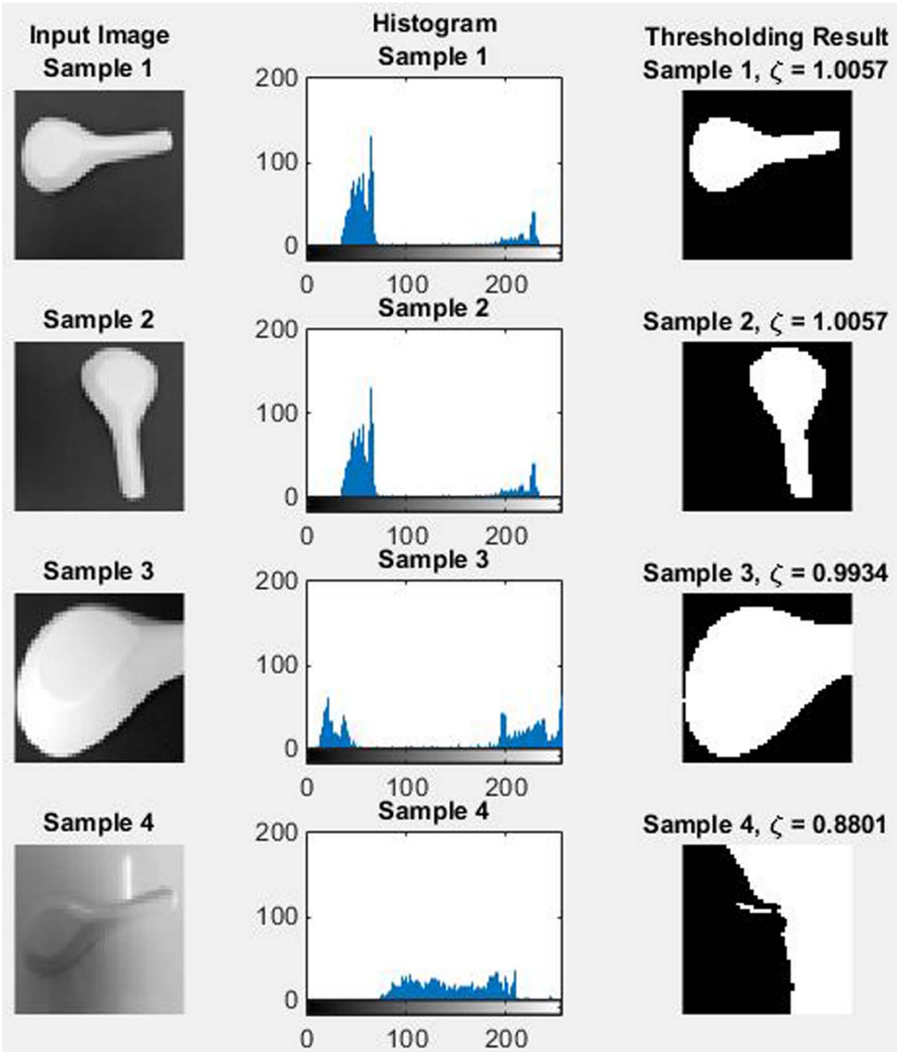

Fig. 8. Real images captured at known parameters before segmentation, histogram and thresholding result.

thresholding result as the estimated values of I and S are controlled at 70% and 30%, respectively. All images were then fed into the Otsu thresholding and their results and histograms were recorded.

From experimental thresholding results as shown in Fig. 8, it is proven and verified that the Sample 1, Sample 2 and Sample 3 performed correct segmentation with known scene parameters (estimated values of I and S are controlled at 35% and 70%, respectively). Their segmentation ratio results ζ are approximately to 1 which indicated correct segmentation. Additionally, based on the histogram results, Sample 1, Sample 2 and Sample 3 can be threshold successfully as the histograms clearly follow a bi-modal distribution, or in other word, their pixel grayscale levels are distributed over two classes of the histogram. One class represents the spoon object itself while other class represents its corresponding background. Thus, these three samples can be threshold successfully as indicated by good serration in the histogram. For Sample 4, it is controlled at the background intensity level of around 70% and the result shows under-segmentation. The segmentation ratio ζ for Sample 4 is largely different from the ideal segmentation ratio in order to have a correct segmentation. The reason for Sample 4 could not undergo successful segmentation is its histogram is a well-mixed histogram. There are no clearly distinguishable classes for Sample 4 as the pixels grayscale levels are in a flat histogram shape or in a uniform value along the pixels axis.

The real image experimental results obtained are closely coherent with the conditions in Fig. 7. The results also show that the conditions in Fig. 7 are exactly relevant for real image application. Thus the conditions could serve as a guideline for thresholding applications and enable one to predict the success of Otsu thresholding.

4. Conclusion

In this study, the feasibility, consistence and performance analysis of image thresholding using Otsu algorithm were analysed. Our analysis showed that image parameters such as intensity level between object and background, object size, object position and noise would affect the performance of Otsu thresholding. Additionally, the location of objects on image plane do not influence Otsu thresholding results. We also proposed the optimum conditions to guarantee successful Otsu thresholding in terms of object background intensity parameter and object size parameter which are around 35% and 72%, respectively, for all noise levels. We also showed the validity of the proposed conditions by correctly predict the outcome of Otsu thresholding using real image data. In practice, the conditions for image thresholding to be successful can be predicted using the proposed conditions. These conditions serve as a guideline for Otsu thresholding.

References

[1] F. Patricia, R. Joao Manuel, Computational Vision and Medical Image Processing, Taylor & Francis Group, London, 2012, pp. 88–90.
[2] G. Evelin Suji, Y.V.S. Lakshmi, G. Wiselin Jiji, MRI brain image segmentation based on thresholding, Int. J. Adv. Comput. Res. 3 (l) (2013) 97–101.
[3] K. Satish, S. Raghavendra, A study on image segmentation and its methods, Int. J.

Adv. Res. Comput. Sci. Software Eng. 3 (9(2277 128X)) (2013) 1112–1114.
[4] P.K. Sahoo, S. Soltani, A.K.C. Wong, A survey of thresholding techniques, Comput. Vision Graph. Image Process. 41 (1988) 233–260.
[5] A.S. Abutaleb, Automatic thresholding of gray-level pictures using two dimensional entropy, Comput. Vision Graph. Image Process. 47 (1989) 22–32.
[6] J. Kittler, J. Illingworth, Minimum error thresholding, Pattern Recogn. 19 (1) (1986) 41–47.
[7] K.H. Liang, J.J.W. Mao, Image thresholding by minimizing the measures of fuzziness, Pattern Recogn. 28 (1) (1995) 41–51.
[8] A. Sheeba, S. Manikandan, Image Segmentation Using Bi-level Thresholding, in: International Conference on Electronics and Communication System, 2014.
[9] J. Sullivan, S. Carlsson, Recognizing and tracking human action, ECCV (2002).
[10] H. Devi, Thresholding: a pixel-level image processing methodology preprocessing technique for an OCR system for the Brahmi script, AA 1 (2006) 161.
[11] Yan Solihin, C. G. Leedham, The multi-stage approach to grey-scale image thresholding for specific applications, Nanyang Technological University, School of Computer Engineering, Nanyang Avenue, Republic of Singapore, 2000, pp. 1–27.
[12] N. Otsu, A threshold selection method from gray-level histogram, IEEE Trans. Syst. Man Cybern. 9 (1979) 62–66.
[13] A.D. Brink, N.E. Pendock, Minimum cross-entropy threshold selection, Pattern Recogn. 29 (1) (1996) 179–188.
[14] J.N. Kapur, P.K. Sahoo, A.K.C. Wong, A new method for gray-level picture thresholding using the entropy of the histogram, Comput. Vision Grap. Image Process. 29 (1985) 273–285.
[15] N.R. Pal, S.K. Pal, Entropic thresholding, Signal Process. 16 (1989) 97–108.
[16] S.K. Pal, A. Rosenfeld, Image enhancement and thresholding by optimization of fuzzy compactness, Pattern Recogn. Lett. 7 (1988) 77–86.
[17] C.K. Chow, T. Kaneko, Automatic detection of the left ventricle from cineangiograms, Comput. Biomed. Res. 5 (1972) 388–410.
[18] L. Eikvil, T. Taxt, K. Moen, A Fast Adaptive Method for Binarization of Document Images, in: Proceedings the 1st International Conference on Document Analysis and Recognition, Saint-Malo, France, 1991, pp.453–443.
[19] T. Taxt, P.J. Flynn, A.K. Jain, Segmentation of document images, IEEE Trans. Pattern Anal. Mach. Intell. 11 (12) (1989) 1322–1329.
[20] Bernsen J. Dynamic thresholding of grey-level images, in: Proceedings 8th International Conference on Pattern Recognition, Paris, 1986, pp.1251–1255.
[21] W. Niblack, An Introduction to Digital Image Processing, Prentice Hall, Englewood Cliffs, N.J., 1986, pp. 115–116.
[22] J.R. Parker, Gray level thresholding in badly illuminated images, IEEE Trans. Pattern Anal. Mach. Intell. 13 (8) (1991) 813–819.
[23] S.D. Yanowitz, A.M. Bruckstein, A new method for image segmentation, Comput. Vision Graph. Image Process. 46 (1) (1989) 82–95.
[24] S. Kalathiya, P. Patel, Implementation of Otsu method with two different approaches, Int. J. Softw. Hardware Res. Eng. 2 (2014) 2347–4890.
[25] M. Sezgin, B. Sankur, Survey over image thresholding techniques and quantitative performance evaluation, J. Electron. Imaging 13 (1) (2004) 146–165.
[26] S. Jose, F. Francisco, N. Omar, Over- and under-segmentation evaluation based on the segmentation covering measure, in: Conference on Computer Graphics, Visualization and Computer Vision, 2015, ISBN 978-80-86943-66-4.
[27] P. Arbelaez, M. Maire, C. Fowlkes, et al., From contours to regions: an empirical evaluation, in: IEEE Conference on Computer Vision and Pattern Recognition. CVPR 2009, 2009, pp. 2294–2301.
[28] P. Arbelaez, M. Maire, C. Fowlkes, et al., Contour detection and hierarchical image segmentation, IEEE Trans. Pattern Anal. Mach. Intell. 33 (5) (2011) 898–916.
[29] S. Basah, A. Bab-Hadiashar, R. Hoseinnezhad, Conditions for motion-background segmentation using fundamental matrix, IET Comput. Vis. 3 (4) (2009) 189.
[30] S. Basah, R. Hoseinnezhad, A. Bab-Hadiashar, Analysis of planar-motion segmentation using affine fundamental matrix, IET Comput. Vision 8 (6) (2014) 658–669.
[31] S. Basah, A. Bab-Hadiashar, R. Hoseinnezhad, Conditions for segmentation of 2D translations of 3D objects, in: Image Analysis and Processing – ICIAP 2009, 2009, pp. 82–91.
[32] S. Basah, R. Hoseinnezhad, A. Bab-Hadiashar, Limits of motion-background segmentation using fundamental matrix estimation, in: 2008 Digital Image Computing: Techniques and Applications, 2008.
[33] M.H.J. Vala, A. Baxi, A review on Otsu image segmentation algorithm, Int. J. Adv. Res. Comput. Eng. Technol. 2 (2) (2013) 387–389.
[34] I.E. Abdou, W.K. Pratt, Quantitative design and evaluation of enhancement or thresholding edge detectors, Proc. IEEE 67 (5) (1979) 753–763.
[35] T. Celik, Unsupervised change detection in satellite images using principal component analysis and means clustering, IEEE Geosci. Remote Sens. Lett. 6 (4) (2009) 772–776.
[36] R. Hoseinnezhad, A. Bab-Hadiashar, D. Suter, Finite sample bias of robust estimators in segmentation of closely spaced structures: a comparative study, J. Math. Imaging Vision 37 (1) (2010) 66–84.
[37] M. Hadian Jazi, A. Bab-Hadiashar, R. Hoseinnezhad, Statistical analysis of three dimensional optical flow separability in volumetric images, IET Comput. Vision 9 (6) (2015) 895–902.
[38] M.I. Sezan, A peak detection algorithm and its application to histogram-based image data reduction, Graph Models Image Process. 29 (1985) 47–59.
[39] C.K. Leung, F.K. Lam, Performance analysis of a class of iterative image thresholding algorithms, Pattern Recogn. 29 (9) (1996) 1523–1530.
[40] W.H. Tsai, Moment-preserving thresholding: a new approach, Graph Models Image Process. 19 (1985) 377–393.
[41] R. L. Kirby, A. Rosenfeld, A note on the use of (gray level, local average gray level) space as an aid in threshold selection, IEEE Trans. Syst. Man Cybern. SMC-9, 1979, pp. 860–864.
[42] W. Niblack, An Introduction to Image Processing, Prentice-Hall, Englewood Cliffs, NJ, 1986, pp. 115–116.
[43] H. Cai, Z. Yang, X. Cao, W. Xia, X. Xu, A new iterative triclass thresholding technique in image segmentation, IEEE Trans. Image Process. 23 (3) (2014) 1038–1046.
[44] J.H. Xue, D.M. Titterington, t-Test, F-tests and Otsu's methods for image thresholding, IEEE Trans. Image Process. 20 (2011) 2392–2396.
[45] P. Ranefall, C. Wählby, Global gray-level thresholding based on object size, Cytometry Part A (2016).
[46] H. Cai, Z. Yang, X. Cao, W. Xia, X. Xu, A new iterative triclass thresholding technique in image segmentation, IEEE Trans. Image Process. 23 (3) (2014) 1038–1046.
[47] Y. Zou, F. Dong, B. Lei, S. Sun, T. Jiang, P. Chen, Maximum similarity thresholding, Digital Signal Processing 28 (2014) 120–135.