A Novel Fast Otsu Digital Image Segmentation Method

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Abstract: Digital image segmentation based on Otsu’s method is one of the most widely used technique for threshold selection. With Otsu’s method, an optimum threshold is found by maximizing the between-class variance and the algorithm assumes that the image contains two classes of pixels or bi-modal histogram (e.g., foreground and background). It then calculates the optimal threshold value separating these two classes so that, their between class variance is maximal. The optimum threshold value is found by an exhaustive search among the full range of gray levels (e.g., 256 levels of intensity). The objective of this paper is to develop a fast algorithm for the Otsu method that reduces the number of search iterations. A new search technique is developed and compared with the original Otsu method. Experiments on several images show that the proposed Otsu-Checkpoints fast method give the same estimated threshold value with less number of iterations thus resulting in a much less computational complexity.

Keywords: Image thresholding, otsu method, optimized search technique.

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1. Introduction

Digital image segmentation is a fundamental step in many image analysis applications and is a very critical task. One can define image segmentation as a partitioning or clustering technique used for image analysis. In another words, it is a process of subdividing an image into its constituent regions or objects as part of the analysis process \cite{4, 7, 15}. Image segmentation algorithms are generally based on one of two basic properties of intensity values: Discontinuity and similarity. In the first type, an image is partitioned based on sudden changes in intensity (e.g., gray level), while in the other type, an image is partitioned into regions that are considered to be similar based on certain criteria \cite{7, 15}. Otsu method is one of the well-known thresholding methods and involves an iterating process through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e., the pixels that fall in either foreground or background. The aim is to determine the threshold value where the sum of the foreground and background spreads is at its minimum since the threshold value having a maximum between-class variance has also a minimum within-class variance. Therefore, it is a good alternative to use the between-class variance for finding optimum threshold since it requires less computational complexity \cite{15, 16, 18}. In addition, there does not exist a single image segmentation algorithm, which can give the best result for every digital image. Depending on to the type of the given image application the most appropriate approach is to be chosen to achieve the best segmentation result. In some applications, the processing time (or computational complexity) is an essential issue. For example, in biometric authentication and verification systems this is a typical constraint in addition to an efficient segmentation.

The method proposed in this paper is aimed to develop a faster method for estimating the optimal threshold value in Otsu method by minimizing the number of search iterations along possible threshold values. This is achieved by selecting a sub-range of gray levels around an initial estimated threshold value while still keeping the keeping the quality of the segmentation process intact.

The paper is organized as follows: Section 2 introduces the segmentation process in general and thresholding technique in particular. Section 3 presents a brief introduction on Otsu method of thresholding. The proposed technique is explained in section 4 while section 5 is concerned with the experimental results carried out. Section 6 concludes the paper.

2. Image Thresholding

Digital image segmentation has been a major research topic in digital image processing resulting a variety of methods and algorithms developed and improved for image segmentation ranging from general segmentation methods to tailored for certain image type or a certain application \cite{2, 17}. Each method has a different approach in defining what characterizes a good segmentation and uses a different technique to find the optimal segmentation \cite{13, 14}. Image thresholding is one of the main approaches of
segmentation and Otsu thresholding method is one well-known thresholding technique.

Image thresholding is considered the easiest way to segment an image. Although, it seems simple the problem of choosing a good and an accurate threshold value is a difficult task. Thresholding is most commonly used for separating objects from the background [3, 9, 10, 11, 15]. The most widely used thresholding technique uses the gray level histogram. When an image, \( f(x, y) \) is composed of dark objects on a light background, then the foreground is clearly distinguishable from the background. In this case, the image histogram will be bimodal so that, the threshold value will lie in the valley of the histogram ensuring that the objects can be extracted by comparing pixel values with a threshold \( T \). If any pixel \((x, y)\) for which \( f(x, y) \geq T \) is considered as belonging to the object class, otherwise, it belongs to the background class [7, 8]. Unfortunately, this is not the case in most images. In addition to histogram based thresholding techniques, several techniques have been proposed, trying to find a way of choosing the best value of threshold \( T \) that will result in an accurate segmentation. Otsu method is one of the widely used thresholding methods; Otsu’s method involves iterating through all possible threshold values and calculating the weighted sum of within-class variances of the foreground and background pixels. The aim is to find the threshold value where the sum of within-class variances is at its minimum.

### 3. The Otsu’s Method

Let the pixels of a given picture 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 \( N = n_1 + n_2 + ... + n_L \). The probability distribution \([8, 12, 16]\):

\[
p_i = \frac{n_i}{N}, \quad p_i \geq 0, \quad \sum_{i=1}^{L} p_i = 1
\]

Now, when we classify the pixels into two classes \( C_0 \) and \( C_1 \) (background and objects) by a threshold at level \( t \), \( C_0 \) denotes pixels with gray levels \([1, 2, ..., t]\) and \( C_1 \) denotes pixels with levels \([t+1, ..., L]\). Then, the probability of class occurrence and class mean respectively are \([1, 12]\):

\[
o_0 = P_r(C_0) = \sum_{i=1}^{t} p_i = \omega(t)
\]

\[
o_1 = P_r(C_1) = \sum_{i=t+1}^{L} p_i = 1 - \omega(t)
\]

And

\[
\mu_0 = \sum_{i=1}^{t} i p_r(i) = \frac{1}{o_0} \sum_{i=1}^{t} \frac{p_i}{\omega(t)} \mu(t)
\]

\[
\mu_1 = \sum_{i=t+1}^{L} i p_r(i) = \frac{1}{o_1} \sum_{i=t+1}^{L} \frac{p_i}{1 - \omega(t)} (\mu(t) - \mu(t))
\]

Where \( o_0 \) and \( \mu_0 \) are the 0th and 1st order cumulative moments of the histogram up to \( t \) level and are defined as follow:

\[
\omega(t) = \sum_{i=1}^{t} p_i
\]

And

\[
\mu(t) = \sum_{i=1}^{t} ip_i
\]

And \( \mu_1 \) is the total mean level of the original image which is computed as:

\[
\mu_1 = \sum_{i=1}^{L} ip_i
\]

For any \( t \), the following relation is valid:

\[
o_0 \mu_0 + o_1 \mu_1 = \mu_1, \quad o_0 + o_1 = 1
\]

The class variances and total variance are given by:

\[
\sigma^2_{o} = \sum_{i=1}^{t} (i - \mu_0)^2 p_i (i \in C_0) = \frac{1}{o_0} \sum_{i=1}^{t} (i - \mu_0)^2 \frac{p_i}{\omega(t)}
\]

\[
\sigma^2_{1} = \sum_{i=t+1}^{L} (i - \mu_1)^2 p_i (i \in C_1) = \frac{1}{o_1} \sum_{i=t+1}^{L} (i - \mu_1)^2 \frac{p_i}{1 - \omega(t)}
\]

In order to evaluate the goodness of the threshold (at level \( t \)), within-class variance and between-class variance are used as measures of class separability. They are defined, respectively as follows:

\[
\sigma_{o}^2 = o_0 \sigma_0^2 + o_1 \sigma_1^2
\]

\[
\sigma_{o}^2 = o_0 (\mu_0 - \mu)^2 + o_1 (\mu_1 - \mu)^2 = o_0 \sigma_0 (\mu_0 - \mu)^2
\]

And the following relations hold:

\[
\eta = \frac{\sigma_{o}^2}{\sigma^2_T}
\]

\[
\eta = \sigma_0^2 + \omega_0^2
\]

The problem is then reduced to maximize one of these criterion measures. It is noticed that \( \sigma_{o}^2 \) is dependent on 1st order statistics while \( \sigma_{o}^2 \) depends on 2nd order statistics. Therefore, \( \sigma_{o}^2 \) is the simplest measure with respect to \( t \). Thus, \( \eta(t) \) is adopted as the criterion measure to select the best threshold value \( t \) which is determined by a sequential search by using the following functions \([12]\):

\[
\eta(t) = \frac{\sigma_{o}^2(t)}{\sigma^2_T}
\]

\[
\sigma_{o}^2(t) = \frac{[\mu_0 \omega(t) - \mu(t)]}{\omega(t)} [1 - \omega(t)]
\]

Since, \( \sigma^2_T \) is not a function of threshold \( t \), then the optimal threshold should be the value which maximizes \( \sigma_{o}^2(t) \). Thus the optimal value threshold \( t \) is computed with the following equation \([12]\):

\[
\sigma^2_{o} = \max \sigma^2_{o} (t), 1 \leq t \leq L
\]

### 4. Proposed New Fast-Otsu Methods (Otsu-Checks-points)

In Otsu method the value of \( \sigma^2_{o} (t) \) is computed for each \( t, 0 \leq t \leq L \). Once this done, the minimal value of
\[ \sigma_B^2(t), \text{ say } \sigma_B^2(t^*) \text{ is selected from these } L \text{ values and } t^* \text{ is then considered as the optimal threshold value} \ [12]. \]

By using Equation 18, for each \( t \) the computational effort for calculating \( \sigma_B^2(t) \) is bounded by \( cL \), where \( c \) is constant. By considering the time complexity notation [6], let \( f(t) \) be the time complexity for \( t \) to calculate \( \sigma_B^2(t) \), therefore, \( f(t) \leq cL \), i.e., \( f(t) = O(L) \). For \( 0 \leq t \leq L \), it requires \( O(L^2) \) cycles to calculate all \( \sigma_B^2(t)^2 \) [5]. Our aim is to speed up the process of Otsu thresholding by developing a fast iterative Otsu thresholding algorithm. We speed up the process by iteratively minimizing the range of possible threshold values until the range reaches its minimum length, which is 3 gray level.

For a bimodal histogram, in most of the cases the optimal threshold estimated by Otsu method should not be far from image global mean \( m_{gt} \). Figures 1 and 2 show examples of an image and its histogram. Considering this, we can narrow the search range to a certain distance around the local mean. However, since this is not the case in all images, instead of building the search range only around the global mean; we propose to set our initial search range to the full gray level range. In that range we then set three checkpoints, choose the one with the maximum Between Class Variance (BCV) \( \sigma_B^2 \), then set it as the initial estimated threshold \( T_{init} \). Around this estimated threshold value, we will build the new search range and repeat the same process of setting checkpoints and narrowing the search range until we reach one of our stopping conditions:

1. The BCV at the selected initial threshold \( T_{init} \) has BCV larger than the two gray levels around it \( (T_{init} = 1, T_{init}+1) \), in this case we will set optimal threshold to \( T_{init} \) and exit our search process.
2. The range become only three gray levels length, at this point we will set the optimal threshold to the one of the 3 gray levels that has the maximum between class variance BCV and exit our search process.

![Image 1](original histogram and segmented image of skin cancer 5)

![Image 2](original, Otsu-T=91, histogram)

Figure 1. Original, histogram and segmented image of skin cancer 5.

![Image 3](original, Otsu-T=90, histogram)

Figure 2. Original, histogram and segmented image of einstein.

Figure 3 depicts an example of an image and its histogram showing the phases of our search process.

Now, in our initial stage we set the initial checkpoints to the global mean of the full histogram as the mid-checkpoint \( icp_2 \) and two local means of the two parts of the histogram after splitting it into two parts on each side of this mid-checkpoint. This results in 3 initial checkpoints \( (icp_1, icp_2, icp_3) \) for which we compute \( (\sigma_B^2(icp_1), \sigma_B^2(icp_2), \sigma_B^2(icp_3)) \), respectively. The three initial checkpoints are defined, respectively as:

\[
\text{icp}_1 = \mu_{f} = \sum_{j=1}^{L}j p_j \\
\text{icp}_2 = \mu_{f} = \sum_{j=icp_1}^{icp_2}j p_j \\
\text{icp}_3 = \frac{L}{icp_3} \sum_{j=icp_3+1}^{L}j p_j 
\]

These checkpoints divide the image histogram of an image, \( f(x, y) \) into four initial sub-ranges, as follows:

\[
i\text{range}_1 = \min(f(x, y), \ldots, icp_1) \\
i\text{range}_2 = \text{icp}_1, \ldots, icp_2 \\
i\text{range}_3 = icp_2, \ldots, icp_3 \\
i\text{range}_4 = icp_3, \ldots, \max(f(x, y))
\]

In our proposed optimized search techniques, we will choose the checkpoint with the maximum \( \sigma_B^2(t) \) and set it as the initial estimated threshold \( T_{age} \). Next, we will narrow the search range for the next stage to one of the two initial sub-ranges bounded by this checkpoint (initial estimated threshold \( T_{init} \)). To select the sub-range, we will do the following:

1. Check BCV for the two gray levels around it \( (T_{init}-1, T_{init}+1) \) and compare it to BCV at this checkpoint.
2. If \( \text{max BCV} \) is at \( T_{init} \) we select the sub-range that ends at this checkpoint.
3. If \( T_{init} \) has max BCV, we select the sub-range that starts at this checkpoint.
4. On the other hand, if \( T_{init} \) itself has max BCV, we then will stop our search process and set the optimal threshold to \( T_{init} \).

Now, in the following stages and in case we didn’t exit the search process, we will set our checkpoints

\[
\text{icp}_1 = \mu_{f} = \sum_{j=1}^{L}j p_j \\
\text{icp}_2 = \mu_{f} = \sum_{j=icp_1}^{icp_2}j p_j \\
\text{icp}_3 = \frac{L}{icp_3} \sum_{j=icp_3+1}^{L}j p_j 
\]
differently. For the current sub-range $R_i = [r_1, r_2]$, the three check points $(cp_1, cp_2, cp_3)$ are set as follows:

$$
cp_2 = r_1 + \frac{(r_2 - r_1)}{2} \tag{26}
$$
$$
cp_1 = r_1 + \frac{cp_2 - r_1}{2} \tag{27}
$$
$$
cp_3 = cp_1 + \frac{r_2 - cp_2}{2} \tag{28}
$$

These check points will again divide the current histogram range into four new sub-ranges, as follows:

$$
Range_1 = r_1, \ldots, cp_1 \tag{29}
$$
$$
Range_2 = cp_1, \ldots, cp_2 \tag{30}
$$
$$
Range_3 = cp_2, \ldots, cp_3 \tag{31}
$$
$$
Range_4 = cp_3, \ldots, r_2 \tag{32}
$$

Once again, we will choose the checkpoint with the maximum $\sigma_2^2 (i')$, then we narrow the search range in the same way done in the initial stage; This process will keep repeated until the optimal threshold is found or the selected sub-range is small enough that is when the range is made of only 3 gray levels.

The proposed search algorithm can be summarized in the following steps:

1. Compute image histogram $hist(f(x, y))$ and probabilities of each intensity level $Prop(f(x, y))$.
2. Find $icp_2$, $P_1$ and $icp_3$ using Equations 19, 20, 21 respectively.
3. Compute $(\sigma_2^2 (icp_1), \sigma_2^2 (icp_2), \sigma_2^2 (icp_3))$, using Equation 17.
4. Find $Max_{i=1:3} \sigma_2^2 (icp_i)$.
5. Set initial threshold $T_{init}$ equals to selected checkpoint $icp$.
6. Using one of the ranges defined in Equations 22, 23, 24, 25 set next search range $R_i = [r_1, r_2]$ as follows:
   a. Check BCV for the two gray levels around it $(T_{init}-1, T_{init}+1)$ and compare it to BCV at this checkpoint.
   b. If max BCV is at $(T_{init}-1)$ we select the sub-range that ends at this checkpoint.
   c. If has max BCV, we select the sub-range that starts at this checkpoint.
   d. On the other hand, if $T_{init}$ has max BCV, then optimal threshold $t'$ is found and set to $T_{init}$ and we stop our search process.
7. While (size(Sub-range)< 3) and (optimal threshold is not found) do:
   a. Find $P_2$, $cp_1$ and $cp_3$ using Equations 26, 27, 28 respectively.
   b. Compute $(\sigma_2^2 (cp_1), \sigma_2^2 (cp_2), \sigma_2^2 (cp_3))$, using Equation 17.
   c. $Max_{i=1:3} \sigma_2^2 (cp_i)$.
   d. Using one of the ranges defined in Equations 29, 30, 31 and 32, we check and set next search range $R_i = [r_1, r_2]$ in the same manner described in step 6.
8. If size(Sub-range)= 3, then $\forall t \in$ current sub-range $R_i$, Compute $\sigma_2^2 (t)$, using Equation 18.
9. Set optimal threshold $t'$ to $t$ with $Max \sigma_2^2 (t)$.

Table 1 compares the pseudo code and performance for original Otsu and proposed Otsu-checkpoints on a sample test image.

### Experimental Results

The proposed method has been implemented and evaluated using 80 real images with different dimensions and gray levels. Those test images are from Gonzalez [4], which are widely used in research papers related to image segmentation with different types of methods and techniques. First the original Otsu method (Otsu) is applied on these 80 test images; then the same images are segmented using our proposed fast Otsu method (Otsu-checkpoints) and the results are shown in Tables 2 and 3. For evaluating the performance of the proposed method against original Otsu, we have used three measures: Number of iterations, computational complexity and the estimation of accuracy. With number of iterations, we refer to the size of gray level range, which has been tested for maximum between class variance. In the conventional Otsu, this is equal to the full gray level range. The second measure is the computational complexity and it is related to the number of iterations calculating $\sigma_2^2 (t)$. Considering the time complexity notation [3], in the conventional Otsu method, for the full range of gray levels $[0, ..., L]$, it requires $O(L^2)$ cycles to calculate all $\sigma_2^2 (t)$ [2]. In our optimized Otsu method, we do not calculate $\sigma_2^2 (t)$ for the full range of gray levels but rather this is done for a subset of gray levels. The size of this subset, denoted as $L_s$, is not fixed and in the worst case it will be $L_s < L/3$, thus the computational complexity will be $O(L_s^2)$. We can clearly see that the computational complexity is related to the size of the tested gray levels, which is equivalent to number of
iterations. For the third measure, we have computed the accuracy of our method by estimating the threshold values by comparing the estimated threshold to that found by the original Otsu and then compute the percentage of exact matches. We have evaluated the performance of our method in enhancing the conventional Otsu by the percentages of reduction in iterations and computational complexity. The percentage of computational complexity is computed based on the assumption that for each \( t \) the computational effort for calculating \( \sigma^2(t) \) is bounded by \( cL \), where \( c \) is constant. Since, \( c \) is a constant for any value \( t \) and the computational effort is affected by the number of iterations (value of \( L \)), then the percentage of reduction can be calculated as:

\[
\frac{1}{n} \sum (L^2 - L_i^2)
\]

\[
(33)
\]

Where \( n \) is the number of test images.

Table 2. Estimated thresholds and evaluation for methods: Otsu, proposed otsu-checkpoints (part-1).

<table>
<thead>
<tr>
<th>Image</th>
<th>Threshold Proposed</th>
<th>Global Mean</th>
<th>Compute</th>
<th>Selected</th>
<th>Cp</th>
<th>Cp</th>
<th>Cp</th>
<th>Cp</th>
<th>No. of Ips</th>
<th>% Errd</th>
<th>% Empired</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skin Cancer 1</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>94.14</td>
<td>99.66</td>
</tr>
<tr>
<td>Skin Cancer 2</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>94.14</td>
<td>99.66</td>
</tr>
<tr>
<td>Skin Cancer 3</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>94.14</td>
<td>99.66</td>
</tr>
<tr>
<td>Skin Cancer 4</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>94.14</td>
<td>99.66</td>
</tr>
<tr>
<td>Skin Cancer 5</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>1</td>
<td>1</td>
<td>1</td>
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<td>1</td>
<td>94.14</td>
<td>99.66</td>
</tr>
<tr>
<td>Skin Cancer 6</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>94.14</td>
<td>99.66</td>
</tr>
<tr>
<td>Skin Cancer 7</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>94.14</td>
<td>99.66</td>
</tr>
<tr>
<td>Skin Cancer 8</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>143</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>94.14</td>
<td>99.66</td>
</tr>
</tbody>
</table>

As shown in Tables 2 and 3, our method yields excellent results, this is demonstrated by the fact that we succeeded in estimating the same threshold value found by the original Otsu method with 100% estimation accuracy, while reducing the computational complexity by an average of 99.10% and with 90.83% average reduction of the number of search iterations as shown in Table 3. As described earlier, the optimal threshold value does not always lie around the global mean, this can be clearly seen in Tables 2 and 3. For example, in 15% of the images the optimal threshold value does not occur in the area centered around the global mean. Our proposed technique has succeeded in selecting the correct area within which the exact threshold value is estimated by Otsu method. Theretofore, the results clearly show that our proposed method yields a high accuracy of threshold estimation with a significant reduction of the computational complexity when compared to original Otsu counterpart.

6. Conclusions

Digital image segmentation is an essential task in many digital image-processing applications. Obtaining better and more efficient image segmentation is a critical issue in these applications while still reducing the computational complexity. This paper has proposed a fast Otsu thresholding technique. From the evaluation of the accuracy of threshold estimation, the reduction of the computational complexity, it can be concluded that our proposed method (Otsu-checkpoints) is able to produce the same threshold value compared to the original Otsu method but with a significant reduction of the computational complexity. Thus, making it...
useful in many applications where real (near) real time is required.

References

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