AN IMPROVEMENT OF CROSS ENTROPY THRESHOLDING FOR SKIN CANCER

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Recommended Citation
DOI: https://doi.org/10.54729/2706-784X.1029

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1. INTRODUCTION

Skin cancer is the most common type of cancers in humans [11]. Five main ABCDE properties (Asymmetry, Border, Color, Diameter, and Evolving) in the lesion are examined to rule out skin cancer [12]. Diagnosis by physicians is helped by several image analysis techniques to measure these properties [9]. Accurate analysis of the lesion in the image should be distinguished from the background and its boundaries. This is done by several image segmentation techniques that identify the boundaries of a lesion, by exploiting the color and the texture characteristics in an image [13]. A fundamental step in image analysis is image segmentation that precedes feature extraction, selection and classification. Broadly, there are four classes of segmentation methods, including edge-based methods, region-based methods, thresholding-based methods, and hybrid methods [20,21]. Edge-based methods spotlight around contour detection. Segmentation is performed by finding contour of each object within an image. In region-based methods, the main idea is to estimate for each pixel which classes it belongs to. Thresholding-based methods are well-known and most popular for image segmentation. Thresholding consists in converting a multi-level image into a binary image. It is based on the assumption that the foreground and the background in the image have two distinct gray level distributions [2]. Segmentation is performed by finding threshold values, which are separating between gray level distributions of foreground and its background. The regions having gray levels below the threshold are assigned to the background and the regions having gray levels above the threshold are assigned to the objects, or vice versa [10]. Hybrid methods offer a solution to the problems of the previous methods by combining two or more of these methods to complement weaknesses in each other [24]. It yields high precision, accuracy and efficiency of segmented images.

For image segmentation, thresholding is related to thresholds estimation problem [1]. Finding a threshold value that partitions or clusters the gray-level values of the image into two classes, one representing the object while the other representing the background, is one of the aims of thresholding techniques.

Section 2 explains the cross entropy thresholding. In section 3, we introduced the four statistical distributions, their chart and their properties. Section 4 describes our proposed improvement Method of PAL and its algorithm. Section 5 explains the performance measures. Section 6 includes experimental results of the applying method. Finally, we stated our conclusion.

2. ENTROPY BASED THRESHOLDING

Kullback has proposed the Cross Entropy, to measure the theoretic information distance between two distributions. The minimization of the cross entropy forces the total intensity in the thresholded image to be identical to that of the original image in both the object and the background regions. The more similar the distribution of two variables, the smaller cross entropy is, and vice versa.

The cross entropy is defined as [4]:

\[ D(F,G) = \sum_{i=0}^{L} f_i \log \frac{f_i}{g_i} \]  

where, \( F \) and \( G \) are two different sources of information, \( f_i \) and \( g_i \) are the two statistical distributions of the two sources while \( L \) refers to the number of information values.

To determine the optimal threshold \( \hat{t} \) of an image \( I \), Minimum Cross Entropy Thresholding technique (MCET) minimizes the cross entropy between original image \( I \) and the resulting thresholded image \( I_t \). Once the optimal threshold is determined, pixels are classified into two classes: \( C_1 = \{0, 1, \ldots, t-1\} \) and \( C_2 = \{t, t+1, \ldots, L-1\} \) where \( C_1 \) is the class of pixels which fall below the optimal threshold, and \( C_2 \) is the class of pixels which are equal or exceed the optimal threshold. \( C_1 \) represents the object class and \( C_2 \) represents the background class. Given the threshold \( t \) of an image \( I \) whose pixels are represented by the function \( I(x,y) \), the resulting thresholded image \( I_t \) is defined as:

\[
I_t(x,y) = \begin{cases} 
0, & I(x,y) < t \\
1, & I(x,y) \geq t 
\end{cases}
\]  

Entropy based thresholding considers an image histogram as a probability distribution and then selects an optimal threshold value to separate object from the background [8]. Figure 1 shows an example of a histogram with the threshold line separating the object class from the background class.
Li and Lee estimate the threshold by using the cross entropy defined by Kullback. According to Entropy-Li and Lee, the cross entropy \( D(I, I_t) \) between the original image \( I \) and the thresholded image \( I_t \) is defined as:

\[
D(I, I_t) = \sum_{i=0}^{t} i . h(i). \log \frac{i}{\mu_O} + \sum_{i=t+1}^{L} i . h(i). \log \frac{i}{\mu_B} \quad (3)
\]

Where \( i \) counts from 1 till \( L \), \( h(i) \) is the histogram of the original image, \( t \) is the threshold of the image, and \( \mu_O \) and \( \mu_B \) are the mean value of object and background regions in the original image.

However, the objective function of Kullback is a non-symmetric function therefore, it cannot be called divergence. To overcome this problem, Brink and Pendock proposed a new method based on a true symmetric cross entropy and they redefined the information theoretic distance as:

\[
D(F, G) = \sum_{i=0}^{L} f_i . \log \frac{f_i}{g_i} + \sum_{i=0}^{L} g_i . \log \frac{g_i}{f_i} \quad (4)
\]

Exhaustively, the cross entropy for the object and background regions are respectively \( D_O(t) \) and \( D_B(t) \):

\[
D_O(t) = D(F_O, G_O) = \sum_{i=0}^{t} f^O_i . \log \left( \frac{f^O_i}{g^O_i} \right) + \sum_{i=0}^{t} g^O_i . \log \left( \frac{g^O_i}{f^O_i} \right) \quad (5)
\]

\[
D_B(t) = D(F_B, G_B) = \sum_{i=t+1}^{L-1} f^B_i . \log \left( \frac{f^B_i}{g^B_i} \right) + \sum_{i=t+1}^{L-1} g^B_i . \log \left( \frac{g^B_i}{f^B_i} \right) \quad (6)
\]

Thus, the total cross entropy is:

\[
D(t) = D_O(t) + D_B(t) \quad (7)
\]

and the cross entropy \( D(I, I_t) \) between the original image \( I \) and the thresholded image \( I_t \) becomes:

\[
D(I, I_t) = \sum_{i=0}^{t} i . h(i). \log \frac{i}{\mu_O} + \sum_{i=t+1}^{L} i . h(i). \log \frac{i}{\mu_B} + \sum_{i=0}^{t} \mu_O . h(i). \log \frac{\mu_O}{i} + \sum_{i=t+1}^{L} \mu_B . h(i). \log \frac{\mu_B}{i} \quad (8)
\]

Both Lee and Brink assumed that each pixel in the object and the background of the thresholded image should be equal to the average of pixels' value respectively in the corresponding partition of the original image. Wherever, Pal assumed that each pixel in the segmented image is modeled by a statistical distribution [9]. In his view, the gray values in the object region and the background region follow the Poisson distribution (respectively \( g^O_i = \frac{e^{-\mu_O} \mu_O^i}{i!} \) and \( g^B_i = \frac{e^{-\mu_B} \mu_B^i}{i!} \)), and he used the symmetric version of distance defined by Brink and Pendock in the equations (5), (6) and (7), to develop a cross entropy method that is more general than Li and Brink [11]. To improve the work of Pal, we propose in this paper to use others statistical distributions that are more general than Poisson distribution, therefore, we estimate the optimal threshold by using Pal-MCET method with separately Gaussian, Lognormal and Gamma distributions.
3. STATISTICAL DISTRIBUTIONS

A histogram represents statistical information for image pixels. In a histogram, the number of pixels at each gray level or color intensity level (pixels intensity distribution), are graphed. Essentially, there are two types of distributions of gray level (mode): symmetric and non-symmetric. Poisson and Gaussian can approximate only a symmetric shape of histogram whereas Log Normal and Gamma distributions represent both symmetric and non-symmetric modes. Next, we introduce a general description of the statistical distributions used in our literature.

3.1. Poisson Distribution

In probability theory, a Poisson distribution is a discrete probability distribution that is used for discrete data. Poisson can only approximate a symmetric shape of the histogram. The probability density function of the Poisson distribution is:

\[ f = \frac{e^{-\mu}}{i!} \mu^i \] (9)

Where \( \mu \) is the mean value of the image, and is computed as [9]:

\[ \mu = \frac{\sum_{i=0}^{L} h(i) L}{\sum_{i=0}^{L} h(i)} \] (10)

Figure 2 shows the Poisson distribution with different means. It is clear that Poisson can approximate only a symmetric data.

![Fig.2: Poisson Distribution with different means](image)

Reference: N. Zreika.

3.2. Gaussian Distribution

In probability theory, Gaussian distribution is a continuous probability distribution and has a bell-shaped probability density function, known as the Gaussian function [16]:

\[ f(x, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \] (11)

Where \( x \) is the pixel’s intensity level; \( \sigma \) is the standard deviation and \( \mu \) is the mean.

Gaussian distribution can only approximate a symmetric shape of the histogram. Figure 2 shows a Gaussian Distribution with same value of mean \( \mu \) and different standard deviation \( \sigma \). Therefore, the mean \( \mu \) and the standard deviation \( \sigma \) can be estimated as following [9]:

\[ \mu = \frac{\sum_{i=0}^{L} i h(i)}{\sum_{i=0}^{L} h(i)} \] (12)

\[ \sigma^2 = \frac{\sum_{i=0}^{L} (i-\mu)^2 h(i)}{\sum_{i=0}^{L} h(i)} \] (13)
Figure 3 shows the Gaussian distribution with same value of mean $\mu$ and different value of standard deviation $\sigma$. It is clear that Gaussian distribution can approximate only a symmetric shape of histogram.

![Gaussian Distribution]

Reference: N. Zreika.

3.3. Log Normal Distribution

Log-normal distribution is a continuous probability distribution of a random variable whose logarithm is normally distributed [9,10]. Log-Normal distribution is used to model symmetric and moderate positively skewed data. The probability density function of the Lognormal distribution is defined as [15]:

$$f(x, \mu, \sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{\ln x - \mu}{\sigma} \right)^2}$$ (14)

Where $x$ is the pixel’s intensity level; $\mu$ is the mean and $\sigma$ is the standard deviation. $\mu$ and $\sigma$ are estimated as following:

$$\mu = \frac{\sum_{i=0}^{L} \ln(i)h(i)}{\sum_{i=0}^{L} h(i)}$$ (15)

$$\sigma^2 = \frac{\sum_{i=0}^{L} (\ln(i) - \mu)^2 h(i)}{\sum_{i=0}^{L} h(i)}$$ (16)

Figure 4 shows the Lognormal distribution with same value of mean $\mu$ and different value of standard deviation $\sigma$. we can see that if $\sigma=0.1$, the distribution is symmetric. As $\sigma$ increases, the distribution tends to be skewed to right.

![Log Normal Distribution]

Reference: N. Zreika.
3.4. Gamma Distribution

Gamma Distribution is a two parameter family of continuous probability distributions in probability theory and statistics. It is a general type of statistical distribution. When simplicity and capability to provide symmetric and non-symmetric histograms are sought, Gamma distribution is used [20]. By changing the parameter shape N, the shape of Gamma distribution function can be altered from symmetric to asymmetric. The probability density function of the Gamma distribution in homogenous area is given by [6,7]:

\[ f(x, \mu, N) = \frac{2q^{N} N^{N} x^{N-1} e^{-\frac{q}{\mu} x^{2}}}{\mu N \Gamma(N)} \]  

(17)

Where \( q = \frac{\Gamma(N+0.5)}{\sqrt{N \Gamma(N)}} \), \( x \) is the intensity of the pixel, \( \mu \) is the mean value of the distribution and \( N \) is the shape of distribution. The mean \( \mu \) is estimated as following:

\[ \mu^{2} = \frac{\sum_{i=0}^{T} h(i) i^{2} q^{2}}{\sum_{i=0}^{T} h(i)} \]  

(18)

Figure 5 shows the Gamma distribution for one mode and with different shape parameter \( N \) and same mean \( \mu = 10 \). In this Figure, we can see that if \( N =1 \), the distribution is skewed to right. As \( N \) increases, the distribution tends to be symmetric.

Many algorithms have been proposed for cross entropy thresholding. Li and Lee (1993) have introduced the minimum cross entropy thresholding algorithm that selects the threshold, which minimizes the cross entropy between the segmented image and the original image [1]. They used the kullback’s information theoretic distance \( D \) between two probability distributions [3,4], and they proposed a sequential method based on Gaussian distribution [6].

An iterative method derived from Li and Lee [5] has been developed by Li and Tam (1998). These authors find the threshold value by minimizing the cross entropy using Gaussian distribution [5]. Also, they found the optimal threshold value by minimizing cross entropy using Gamma distribution [7].

4. THE PROPOSED IMPROVEMENT OF PAL METHOD

As stated before, Pal assumed that image histograms are modeled by a Poisson distribution [9]. He used the probability density function of Poisson distribution to estimate the distribution of gray level in the object and the background of the thresholded image (respectively $g^O = \frac{e^{-\mu_O}}{t!} \cdot \mu_O^t$ and $g^B = \frac{e^{-\mu_B}}{t!} \cdot \mu_B^t$), as well he estimated the mean value of object and background regions (respectively $\mu_O$ and $\mu_B$) based on Gaussian distribution.

However, the data in an image does not always follow Poisson distribution. In general, Poisson distribution can only approximate a symmetric shape of the histogram but sometimes the histogram of an image is not symmetric, or it could be positively skewed. In this case, a more general distribution to represent the data of the image is required. In this paper, our goal is to propose an improvement of Pal method and El-Zaart method by using statistical distributions other than Poisson and comparing them with Pal Poisson. We used Gaussian distribution [7] which can model only symmetric data. We also used Gamma distribution [7] which can model symmetric and skewed to the right data, as well as Lognormal distribution which can model moderate positively skewed data and symmetric data.

Figure 7 shows the evolution of Pal Method and the proposed improvement made by N. Zreika & El-Zaart.

The sequential algorithm for our proposed improvement method of Pal using separately the 4 described statistical distributions is described as follows:

1. Input: image $I(x, y)$
2. Compute histogram $h(i)$ of the input image, where $i=0\ldots255$.
3. For each value of threshold $t=1, \ldots, 255$
   3.1 Compute $\mu_O(t)$ and $\mu_B(t)$ using one of the statistical distributions above.
   3.2 Compute the probability distributions of the object and background regions in the segmented image $g^O_i$ and $g^B_i$.
   3.3 Compute $D_O(t)$ and $D_B(t)$ using equations (5) and (6).
   3.4 Compute the total cross entropy using equation (7). $D(t) = D_O(t) + D_B(t)$.
   3.5 Compute the minimum distance and the corresponding threshold
      If ($\min > D(t)$)
      
      \[
      \{ \begin{align*}
      \min &= D(t) ;
      \end{align*} \}
      \]
4. Output: optimal threshold: \( t^* \)

- Pal used Poisson distribution in order to estimate the distribution of gray level in the object and the background of the thresholded image
  \[ g^O = e^{\mu^O h(i)} \] and \( g^B = e^{\mu^B h(i)} \)
  He estimated \( \mu \) based on Gaussian distribution where \( \mu = \frac{\sum h(i) l(i)}{\sum h(i)} \)

- El-Zaat used Poisson distribution in order to select the optimal threshold
  \[ g^O = e^{\mu^O h(i)} \] and \( g^B = e^{\mu^B h(i)} \)
  He estimated \( \mu \) based on Gamma distribution where \( \mu^2 = \frac{\sum h(i) l(i) i^2 a^2}{\sum h(i)} \)

- N. Zreika & El-Zaat use Gaussian distribution in order to select the optimal threshold
  \[ g^O(x, \mu_O, \sigma_O) = \frac{1}{\sigma_O \sqrt{2\pi}} e^{-\frac{1}{2}(x - \mu_O)^2} \]
  and \( g^B(x, \mu_B, \sigma_B) = \frac{1}{\sigma_B \sqrt{2\pi}} e^{-\frac{1}{2}(x - \mu_B)^2} \)
  \( \mu \) is estimated based on Gaussian distribution where \( \mu = \frac{\sum h(i) l(i)}{\sum h(i)} \)

- N. Zreika & El-Zaat uses Lognormal distribution in order to select the optimal threshold
  \[ g^O(x, \mu_O, \sigma_O) = \frac{1}{x \sigma_O \sqrt{2\pi}} e^{-\frac{1}{2} \ln x - \mu_O)^2} \]
  and \( g^B(x, \mu_B, \sigma_B) = \frac{1}{x \sigma_B \sqrt{2\pi}} e^{-\frac{1}{2} \ln x - \mu_B)^2} \)
  \( \mu \) is estimated based on Lognormal distribution where \( \mu = \frac{\sum h(i) l(i)}{\sum h(i)} \)

- N. Zreika & El-Zaat use Gamma distribution in order to select the optimal threshold
  \[ g^O(x, \mu_O, N) = \frac{2^N N^N}{\mu_O G(N)} \left( \frac{ax}{\mu_O} \right)^{2N-1} e^{-N \left( \frac{ax}{\mu_O} \right)^2} \]
  and \( g^B(x, \mu_B, N) = \frac{2^N N^N}{\mu_B G(N)} \left( \frac{ax}{\mu_B} \right)^{2N-1} e^{-N \left( \frac{ax}{\mu_B} \right)^2} \)
  \( \mu \) is estimated based on Gamma distribution \( \mu^2 = \frac{\sum h(i) l(i) i^2 a^2}{\sum h(i)} \)

Fig.7: Evolution of Pal Method

5. PERFORMANCE MEASURES

The quality of the segmentation result is quantitatively evaluated based on two performance measures: Image Uniformity (UN) and Region Contrast (RC) [10]. We have also calculated the arithmetic average of the normalized score of UN and RC represented by AVG.

Image Uniformity is generally used to describe region homogeneity in an image. It is proportional to the variances of the two classes (foreground and background). It is based on the assumption that a good threshold value will classify pixels in an image to foreground and background classes where variances in both classes are minimized. For a given threshold \( t \), image uniformity is defined by [10]:

\[ UN(t) = 1 - \frac{\sigma^2_B(t) + \sigma^2_O(t)}{c} \]  \hspace{1cm} (19)

where \( \sigma^2_B(t) \) and \( \sigma^2_O(t) \) represent respectively the variance of the foreground and background regions, and
6. EXPERIMENTAL RESULTS AND DISCUSSION

An algorithm was implemented based on our new proposed distributions (Gaussian, Log Normal and Gamma), and tested on a set of 200 images. The images were taken from patients with potential skin cancer [22]. In addition, we implemented the original Pal’s Poisson method for comparison purposes. Our objective was to prove which distribution yields better segmentation for skin cancer images.

Table 1 shows the results of images after applying the 3 proposed improvement methods on our dataset. We selected the images where all the methods give a good segmentation. The table lists the threshold found as well as the 3 performance measures UN, RC, and AVG with their rank. For each image, the methods were then ranked according to their performance. Promising results and a better estimation of the optimal threshold value have been obtained from MCET-Gamma (Table 2). Thus, 80% of tested images had better segmentation results with Gamma method. This was based on the average performance metric of uniformity and inter-region contrast. In 85% of the cases inter-region contrast was higher with MCET-Gamma thresholding results while for uniformity measure, MCET-Poisson was ranked 1st in 69% of the images.

In conclusion, we propose that using MCET-Gamma results in better segmentation of skin cancer images than using the other methods. Doing this, skin cancer images follow a gamma distribution rather than Poisson, Gaussian or Lognormal distribution.

The following figures (Figure 8, Figure 9, Figure 10 and Figure 11) show a sample of the testing results. Each figure contains the original image (a), its grayscale version (b), the thresholded images respectively resulting from MCET-Poission (c), MCET-Gaussian (d), MCET- Log Normal (e), and MCET- Gamma (f). The graph (g) shows the histogram of the image with 4 vertical lines representing the value of thresholds found in each method. Each figure also lists, for each method, the corresponding UN, RC and AVG values.

In Figure 8, according to UN measure, MCET-Poisson shows best segmentation results (UN = 0.9532), whereas according to RC and AVG measures, MCET-Gamma shows best segmentation results (RC = 0.4154, AVG = 0.6834).

In Figure 9, according to UN, RC and AVG measures, MCET-Poisson shows best segmentation results (UN = 0.9651, RC = 0.4065, AVG = 0.6799).

In Figure 10, according to UN measure, MCET-Poisson shows best segmentation results (UN = 0.9710), whereas according to RC and AVG measures, MCET-Gamma shows best segmentation results (RC = 0.4660, AVG = 0.7159).

In Figure 11, according to UN and AVG measures, MCET-Lognormal shows best segmentation results (UN = 0.9759, AVG=0.7045), whereas according to RC measure, MCET-Poisson shows best segmentation results (RC = 0.4338).

\[
C = \frac{(g_{\text{max}} - g_{\text{min}})^2}{2}
\]

Where \( g_{\text{max}} \) and \( g_{\text{min}} \) are respectively the maximum and minimum grey levels values in the original image.

\( g_{\text{max}} \) and \( g_{\text{min}} \) ranges between \([0, L]\).

The value of UN ranges between \([0,1]\), where a value of 1 means that the segmentation is perfect while a value of 0 means that the segmentation is bad.

Region Contrast (RC) is used to detect if the segmented image has high contrast across adjacent regions. The higher the contrast across adjacent regions, the better the quality of the segmented image. For a given threshold \( t \), the region contrast is defined as [10]:

\[
RC(t) = \frac{\left|\mu_O(t) - \mu_B(t)\right|}{\mu_O(t) + \mu_B(t)}
\]

Where \( \mu_O(t) \) and \( \mu_B(t) \) are respectively the average of the gray level values of the object and the background classes. Similar to UN, the value of RC ranges between \([0,1]\), where a value of 1 means that the segmentation is perfect while a value of 0 means that the segmentation is bad.
Fig. 8: (a) Original Image (IMD004). (b) Grayscale version. (c) Segmented Image using MCET-Poisson. (d) Segmented Image using MCET-Gaussian. (e) Segmented Image using MCET-Log Normal. (f) Segmented Image using MCET-Gamma. (g) Histogram of IMD004 image.

Fig. 9: (a) Original Image (IMD016). (b) Grayscale version. (c) Segmented Image using MCET-Poisson. (d) Segmented Image using MCET-Gaussian. (e) Segmented Image using MCET-Log Normal. (f) Segmented Image using MCET-Gamma. (g) Histogram of IMD016 image. Reference: N. Zreika.
Fig. 10: (a) Original Image (IMD065). (b) Grayscale version. (c) Segmented Image using MCET-Poisson. (d) Segmented Image using MCET-Gaussian. (e) Segmented Image using MCET-Log Normal. (f) Segmented Image using MCET-Gamma. (g) Histogram of IMD065 image.

Fig. 11: (a) Original Image (IMD348). (b) Grayscale version. (c) Segmented Image using MCET-Poisson. (d) Segmented Image using MCET-Gaussian. (e) Segmented Image using MCET-Log Normal. (f) Segmented Image using MCET-Gamma. (g) Histogram of IMD348 image. Reference: N. Zreika.
Table 1: Comparison of Performance Measures (UN, RC, and AVR) between MCET-Poisson, MCET-Gaussian, MCET-Lognormal and MCET-Gamma. Reference: N. Zreika.

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<th>Distribution</th>
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<th>UN</th>
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<th>RC</th>
<th>RC/Rank</th>
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Table 2: Evaluation Of Performance Measures For The 4 Methods, Reference: N. Zreika.

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7. CONCLUSION AND FUTURE WORK

We have compared three new variants MCET-Gamma, MCET-Lognormal, and MCET-Gaussian, with MCET-Poisson. The methods were tested on a dataset of skin cancer images [22]. Our experiments revealed that the optimal threshold can be found by using the Gamma Pal method rather than the traditional Poisson Pal method. In this regard, Gamma distribution is more general, and solves the problem of non-symmetric histograms in images.

In future work, we will apply our proposed methods on other datasets, and we will focus on extending these methods to a multi-level thresholding and heterogeneous thresholding.

REFERENCES