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Enhancing Image Thresholding with Masi Entropy: An Empirical Approach to Parameter Selection

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ABSTRACT

Image multilevel thresholding is used as a preprocessing step in computer vision or image processing applications. In recent years, various methods and criteria have been tested to improve thresholding performance and efficiency. State-of-the-art methods combine a metaheuristic optimization algorithm to optimize some objective function. Commonly used objective functions include Otsu criterion and entropy-based methods. Masi entropy is one of the objective functions that recently showed significant potential in image thresholding. It can deal with additivity and non expandability of information. However, in order for applying Masi entropy, there is a parameter r that needs to be tuned. Different works proposed different values and methods to determine the value of r. Nevertheless, there is a lack of validation and comparisons between these methods. This work is an experimental study validating a previously introduced method for selecting r. We compare the performance over two datasets including 700 various images while varying the number of thresholds from 1 to 15. Structural similarity index (SSIM) and peak signal-to-noise ratio (PSNR) metrics are used to evaluate the performance. The collective and individual performance improvements are elaborated. It is shown that the tested method achieves a significant improvement in segmentation quality over all tested numbers of thresholds. Higher numbers of thresholds showed greater improvement than smaller numbers. These results demonstrate the practical utility of the tested method in entropy-based image multilevel thresholding.

Keywords

Multilevel Thresholding, Image Segmentation, Masi entropy, Parameter selection, Unsupervised Classification

1 INTRODUCTION

Image thresholding is common task in gray-level image processing applications pipelines. In particular, multi-level thresholding is used as a preprocessing step in analysis of medical images, satellite images and defects in crop images [DDR+20]. Over the years, various image segmentation techniques have emerged, each balancing different trade-offs. One widely used approach is image thresholding, which classifies pixels based on intensity thresholds. Pixels with values below a threshold belong to one category, while those above it belong to another. Despite its efficiency and simplicity, thresholding has a major drawback: it disregards spatial relationships between pixels, considering only intensity values. Additionally, its effectiveness diminishes in images with uneven lighting conditions. Due to these limitations, thresholding is often employed as a preliminary step in image processing workflows [ARM24].

Image thresholding can be categorized into bi-level and multi-level methods. Bi-level thresholding divides an image into two segments, typically foreground and background, whereas multi-level thresholding partitions an image into multiple segments. Over time, various thresholding techniques have been introduced, with many bi-level approaches being extended to multi-level segmentation. Most of these methods rely on an objective function that evaluates candidate thresholds and selects the optimal set by maximizing or minimizing a given criterion. Commonly used objective functions include Otsu's between-class variance [Ots79], Kapur's entropy [KSW85], Tsallis entropy [Tsa88], Renyi entropy [SWY97], Masi entropy [Mas05] and fuzzy entropy [DRD+19]. As a result, multi-level thresholding is formulated as an optimization problem. However, as the number of thresholds increases, the computational complexity grows exponentially, making exact optimization impractical [Tub14].

To address this challenge, metaheuristic optimization algorithms have gained popularity in recent years for multi-level thresholding. While these algorithms do not guarantee a globally optimal solution, they strike a balance between computational efficiency and segmentation quality. Unlike exact methods, which require extensive computation to achieve optimal results, metaheuristics produce near-optimal solutions in significantly less time [VTM23].

A growing trend in segmentation research is the integration of different metaheuristic algorithms with various objective functions to enhance performance while reducing computational cost. Several optimization algorithms have been applied to multi-level thresholding, including variations of the Whale Optimization Algorithm (WOA) [MY22, ABMAA22], Battle Royale optimizer [AOFD+24], improved African vultures optimization algorithm [GI24], enhanced chameleon swarm algorithm [MHH+24], the Coronavirus Optimization Algorithm [AEMH23, HKHM23], the Chimp Optimization Algorithm [EHR+23], and Particle Swarm Optimization (PSO) [GZB+20, NLZ24]. These approaches aim to accelerate the segmentation process while maintaining high-quality results.

Out of these approaches, using Masi entropy as an objective function has shown an improvement in segmentation quality results [NZLD17, SB19]. However, on using Masi entropy, there is a parameter r that needs to be set for thresholding an image. Traditionally, the parameter r should be proportional to the degree of additivity and/or nonextensivity of data. On experimentation on a set compromising non-destructive testing images, infrared images, and some standard benchmark images, Nie *et al.* [NZLD17] found out that tuning r led to values lying in the interval $[0.5, 1.5]$. Moreover, they pointed out that images from the same application or the same imaging device and environment can use the same value for r after tuning. Shubham and Bindary used the specific value of 1.2 in their experiments to threshold a set of natural and satellite images. This choice gave the optimal results in their experiments [SB19]. Khairuzzaman *et al.* performed a comparison to determine a suitable value of r [KC19]. They found that the values of $r < 1$ give better performance. However, their experiment was performed on only a single image using only two thresholds. Mousavirad *et al.* incorporated the parameter r into the optimization process [MOC+22]. Later on, Lei *et al.* proposed an adaptive technique to calculate the value of r based on the histogram of the image [LLWY24]. The effectiveness of this method was illustrated on only one image using one threshold.

Therefore, there isn't an agreed-upon way to select the value of the parameter r. Moreover, there is a lack of experimentation on each selection method. These methods need to be tested using a bigger number of pictures, from different types or modalities. Furthermore, the robustness of each selection method need to be tested under different numbers of thresholds. This can lead to better understanding of the interaction of the value of r and the quality of thresholds found. Hence, multilevel thresholding methods can be improved when the parameter r is selected optimally. This paper performs a comparison between these existing methods to select the value of r. The performance of these methods are compared together.

The remaining parts of this paper are structured as follows. Section 2 illustrates Masi entropy based image thresholding and the role of parameter r, whereas Section 3 presents the experimental results and discussion. Section 4 concludes the paper and suggests possible directions for future research.

2 METHODS

In this section, Masi entropy is reviewed where emphasis is given on the parameter r and its contribution to the overall Masi entropy.

2.1 Masi Entropy

For multilevel image thresholding, Masi entropy is used as an objective function to be maximized. The objective function takes as input n thresholds to segment the image into $n+1$ classes. Let the n thresholds be $0 < T_1 < T_2 < ... < T_n < L-1$ where L is the number of gray intensity levels in the image. For simplicity, we assume $T_0 = 0$ and $T_{n+1} = L$. Moreover, we assume that the class i for $1 \leq i \leq n+1$ consists of all pixels with intensity levels in the interval $[T_{i-1}, T_i)$. We also let p_i be the probability of a pixel having intensity i in the image. For $0 \leq i \leq L-1$, p_i is calculated by Equation (1) where $h(i)$ is the number of pixels in the image that has intensity level i and M is the total number of pixels in that image. The Masi entropy objective function for multilevel thresholding is then given by Eq. (2).

$$p_i = \frac{h(i)}{M} \tag{1}$$

$$J(T_1, ..., T_m, ..., T_n) = \sum_{i=1}^{n+1} H_i \tag{2}$$

where

$$H_m = \frac{1}{1-r} \cdot \log(1-(1-r) \cdot \sum_{i=T_{m-1}}^{T_m - 1} \frac{p_i}{w_m} \cdot log(\frac{p_i}{w_m})) \tag{3}$$

$$w_m = \sum_{i=T_{m-1}}^{T_m - 1} p_i \tag{4}$$

2.2 Adaptive method for selecting r

In the work of Lei *et al.* [LLWY24], an adaptive method to set the value of the parameter r was proposed . This method relies on the image itself and its histogram. The value of r is set according to the following equation.

$$r = \frac{i_{max}}{f_{max}} \tag{5}$$

where

$$i_{\max} = \arg \max_{0 \le i < L} p_i \tag{6}$$

and

$$f_{\max} = \arg\max\left(\{i \mid p_i > 0\}\right) \tag{7}$$

Here, i_{max} is the most frequent gray level in the image (the gray level that is highest in the image histogram). $f_{\max}$ is the brightest gray level in the image. $f_{\max} \le L-1$ since an image might have some gray levels missing.

Theoretically, it can be seen that $f_{\max}$ takes values in the interval $[0, L-1]$, while $i_{\max}$ takes values in the interval $[0, f_{\max}]$. Hence, r values should range between 0 and 1 inclusively. However, Equation (3) wouldn't be computable for values of $r = 0$ and $r = 1$. Also, when $f_{\max} = i_{\max} = 0$, the parameter r is undefined. Accordingly, the adaptive method sets r to 1.2 instead. In such cases, it is obvious that the adaptive method would not change the segmentation quality.

3 RESULTS

This section presents the experimental setup and the obtained results. We begin by analyzing the average improvements achieved by the adaptive method. Following that, we examine cases where the adaptive method led to performance degradation and conduct a visual analysis of such cases for further insight. Finally, we explore the correlation between the amount of improvement and the number of thresholds used.

3.1 Setup

The tested algorithms were implemented in Python 3. The experimental setup was an i7-10750H CPU and 16GB of RAM on a Microsoft Windows 10 operating system.

The experiment was carried out on the Berkeley Segmentation Data Set BSDS500 [AMFM11] and Weizmann segmentation evaluation database [AGBB07]. BSDS500 dataset contains 500 natural images, while Weizmann database contains 200 images. For each image, mutlilevel thresholding using Masi entropy is performed with number of thresholds ranging from 1 to 15. The search is carried out using the dynamic programming technique proposed by Lei *et al.* [LLWY24] as it was shown to give optimal result in a practical timeframe for high numbers of thresholds. The experiment was repeated for $r = 1.2$ and $r = i_{max}/f_{max}$.

The segmentation quality is assessed using structural similarity index (SSIM), and peak signal-to-noise ratio (PSNR).

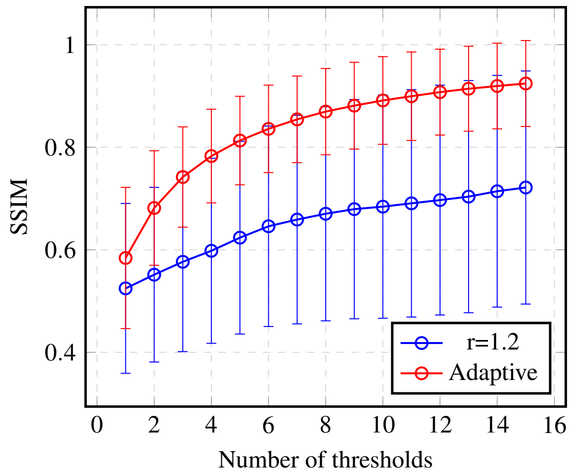


Figure 1: Mean and standard deviation (error bars) SSIM values for each number of thresholds for $r = 1.2$ and the adaptive method

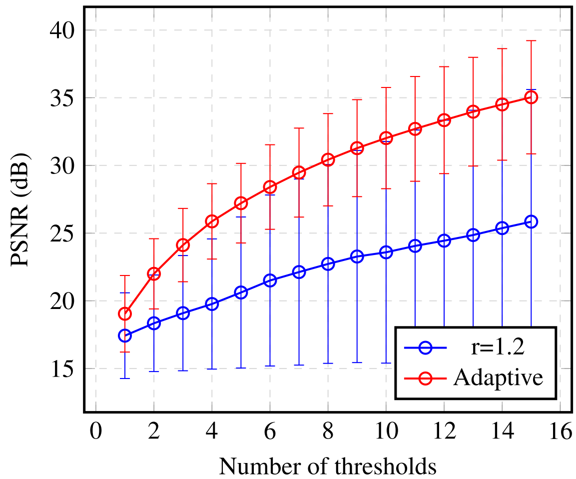


Figure 2: Mean and standard deviation (error bars) PSNR values for each number of thresholds for $r = 1.2$ and the adaptive method

3.2 Average Improvement of SSIM and PSNR

Figure 1 shows for each number of thresholds the mean SSIM value for all 700 images tested when using the adaptive method $r = i_{\max}/f_{\max}$ and when using the fixed value $r = 1.2$. The standard deviations are also shown in the figures for reference. The figure demonstrates that the adaptive method consistently achieves higher SSIM values across all threshold numbers, indicating an improvement in segmentation quality. Notably, the difference between the two methods was

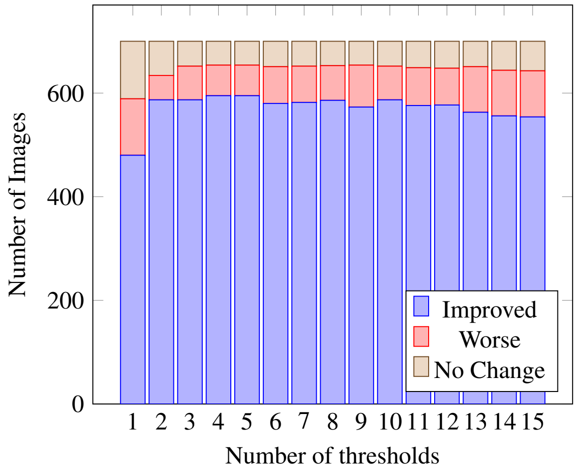


Figure 3: Number of images where SSIM increased, didn't change or decreased by the adaptive method with respect to $r = 1.2$

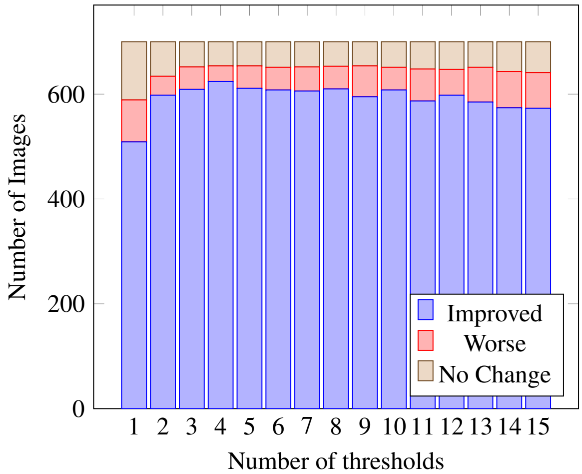


Figure 4: Number of images where PSNR increased, didn't change or decreased by the adaptive method with respect to $r = 1.2$

less apparent when using a single threshold but became increasingly pronounced as the number of thresholds increased. This suggests that the adaptive method achieves higher improvement with higher numbers of thresholds. Furthermore, the standard deviation of the SSIM values in the original method was relatively high, indicating a lack of robustness between different images. In contrast, the adaptive method exhibited a lower standard deviation, indicating a more consistent performance across the data set. This implies that the adaptive approach is better suited to varying image conditions, and more adaptable to different subject images.

Figure 2 shows the corresponding mean values of PSNR together with standard deviation for each number of thresholds. Similar observations can be made. The adaptive method resulted in higher PSNR mean values than the original method $r = 1.2$. The adaptive method have smaller variance indicating more consistency over tested images.

3.3 Individual Analysis of images

As computing the mean average over multiple images may overlook important variations, we analyze how many images improved, remained unchanged, or worsened with the adaptive method. Figures 3 and 4 present stacked bar charts visualizing this distribution for both SSIM and PSNR respectively. It can be observed that for each threshold count, the majority of images show improvement.

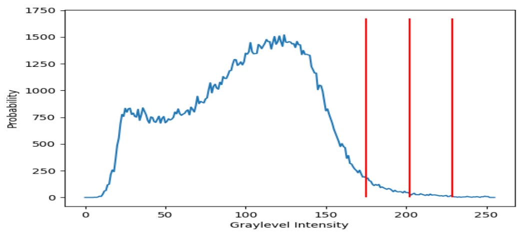
For SSIM values, the highest number of improved images was at 4 and 5 thresholds (595 images, 85%), while the lowest improvement was at 1 threshold (480 images, 68.57%). Similarly, for PSNR values, the highest improvement occurred at 4 thresholds (611 images, 87.29%), followed by 5 thresholds (608 images, 86.86%), while the lowest was at 1 threshold (509 images, 72.71%). Notably, the highest number of worsened images for both SSIM and PSNR occurred at 1 threshold (111 images, 15.86%), indicating that lower threshold counts led to less consistent segmentation performance.

Figures 5 and 6 visualize the difference between the original method and the adaptive method on two images from BSDS500 dataset, where one of them got improved and the other got worse. Each of the two figures contain the original image, and the thresholding results using $r = 1.2$ and using the adaptive method. These results are represented by the segmented image, where each segment has all its pixels colored by the same color and by the histogram of the image where vertical red lines indicate the thresholds found by the thresholding algorithm. In Fig. 5, we can see how the adaptive method improved the thresholded (segmented) image significantly with respect to the output from the original method. Many details of the image are maintained. This can also be seen on the placement of thresholds from both methods on the histogram. However, in Fig. 6, it can be seen that the adaptive method weakened some of the features of the wolf in picture. Some facial features can be recognized in the image thresholded by $r = 1.2$ whereby they are unrecognizable in the output of the adaptive method.

3.4 Comparison of performance in terms of the number of thresholds

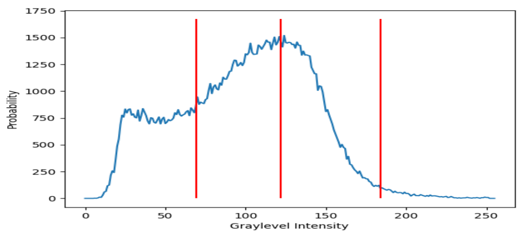
Figure 7 illustrates the average difference in SSIM between the adaptive and original methods. At $n = 1$, the improvement is relatively small, then gradually increases until $n = 4$, where it begins to stabilize with minor fluctuations. The highest improvement occurs at $n = 12$ and $n = 13$, followed by a slight decrease at $n = 14$ and $n = 15$.

(a) Original Image (b) Segmented ($r = 1.2$)



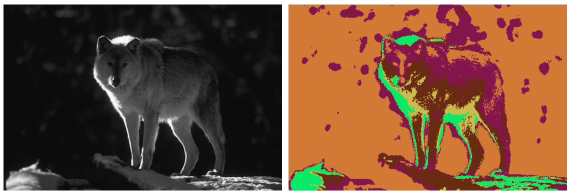
(c) Histogram with thresholds for $r = 1.2$

(d) Original Image (e) Segmented ($r_{adaptive}$)

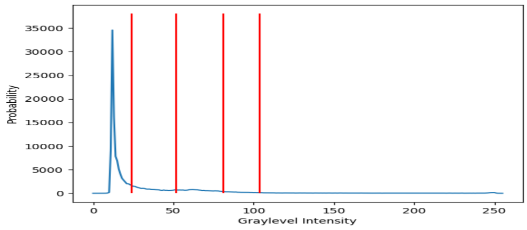


(f) Histogram with thresholds for $r = i_{\max}/f_{\max}$

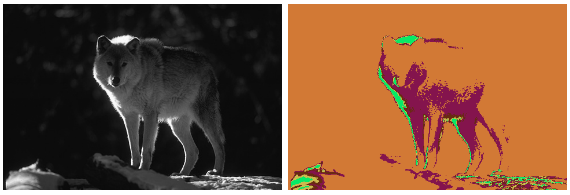
Figure 5: Comparison on image bsds500_175032 with 3 thresholds.



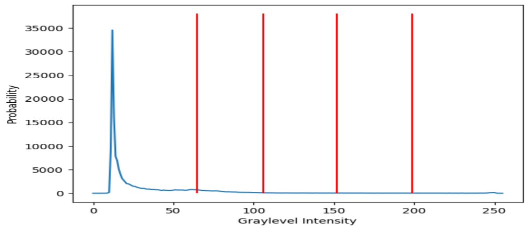
(a) Original Image (b) Segmented ($r = 1.2$)



(c) Histogram with thresholds for $r = 1.2$



(d) Original Image (e) Segmented ($r_{adaptive}$)



(f) Histogram with thresholds for $r_{adaptive} = i_{\max}/f_{\max}$

Figure 6: Comparison on image bsds500_42078 with 4 thresholds.

Figure 8 presents the same analysis for PSNR. Similar to SSIM, the improvement is smallest at $n = 1$ and increases progressively, eventually saturating at higher threshold values. However, the increase in PSNR improvement is more gradual compared to SSIM, suggesting a less abrupt enhancement pattern.

4 CONCLUSION

In this paper, we examined the impact of an adaptive selection method for the parameter r in Masi entropy-based multilevel thresholding. By comparing the adaptive method $r = i_{\max}/f_{\max}$ with the fixed value $r =$

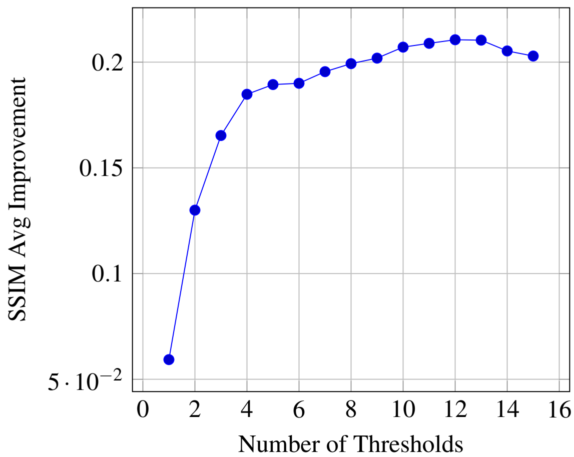


Figure 7: SSIM Average Improvement per number of thresholds

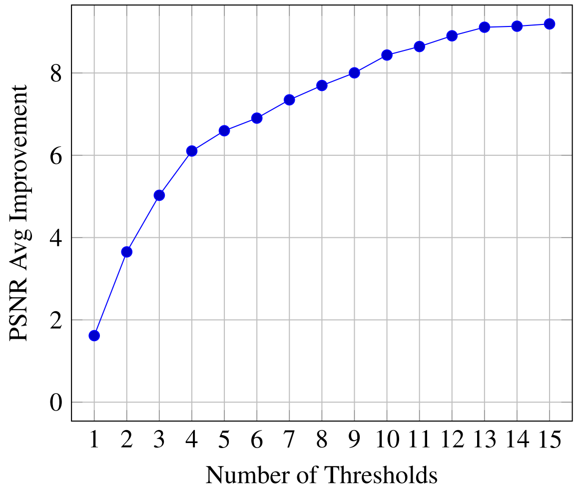


Figure 8: PSNR Average Improvement per number of Thresholds

1.2, we assessed segmentation quality using SSIM and PSNR across 700 images from the BSDS500 and Weizmann datasets.

Results showed that the adaptive method consistently outperformed the fixed approach, achieving higher mean SSIM and PSNR values while maintaining lower variance, indicating greater robustness across different images. The performance gain became more pronounced with increasing numbers of thresholds, particularly beyond $n = 3$. Furthermore, an individual image analysis confirmed that the adaptive method improved segmentation quality in the majority of cases, with the most significant improvements occurring at $n = 4$ and $n = 5$.

These findings highlight the importance of adapting r based on image characteristics rather than relying on a fixed value. Future works include more thorough analysis on cases where the adaptive formula failed to improve or maintain the segmentation quality. Also, performance on other image modalities and other datasets can be explored. Furthermore, refinements to the adaptive formula could be explored. Better alternatives may be derived after a thorough analysis of Masi entropy equation and its different terms. Additionally, optimization of SSIM and PSNR with respect to the parameter r may be performed to reach optimal values of r. Performing that over a large number of images could help find a general formula for computing r.

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