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Research article

Unsupervised Optimization of Boundary Information Based on the Coefficient of Variation to Improve Image Segmentation

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ABSTRACT

The automatic retrieval of boundary information from image objects suffers from the problem of under and over-segmentation, where the former leads to missed object detection, while the latter delivers an improper object shape. A method to optimize the automatic retrieval of complete and proper boundary information is proposed in this research based on an unsupervised approach. The strategy is to utilize the trade-off between the coefficient of variation from shape distribution against the mean of entropy contribution from segmented regions. This mechanism relies on the assumption that the segmentation result of a natural image contains a prominent main object representation with its details which are presented as a normal distribution of segmented regions. The research also enhances the entropy-based segmentation evaluation by redefining the computation of image entropy and segmentation entropy. The experiment shows that the proposed approach is capable of reducing over-segmentation by 57.20% compared to the existing algorithm, while at the same time reducing the consumption time by 85.26%. The empirical evaluation shows that the proposed approach delivers the highest accuracy among other evaluated methods. Qualitative validation based on groups of human observers shows that the proposed approach is the most desired algorithm for producing boundary information and measuring segmentation quality. These findings suggest that the trade-off between the mean of entropy contribution from the segmented regions and the coefficient of variation from shape distribution becomes an effective feature for unsupervised retrieval of boundary information.

1. Introduction

Boundary information defines the sharp edge separating an object from other objects or a foreground from the background in an image. The retrieval of this feature is important for various image analysis purposes such as for medical analysis [1], crack detection [2] [3], farming and plantation applications [4], remote sensing [5] [6] [7] and object recognition [6] [8]. However, retrieving a complete boundary information from an image object is not a trivial task. Researchers usually employ image segmentation to obtain the boundary information, based on the rationale that the information can be retrieved by localizing the object regions. In this case, a segmentation algorithm is utilized to localize the pixel groups into a set of regions that represent the image objects equipped with their contents and boundaries. Various methods have been developed under this approach which can be classified into region-based and clustering approaches [9] [10] [11]. This approach is widely known to be prone to produce over-segmentation. Therefore, some supervised metrics have been introduced to evaluate the performance of segmentation algorithms by formulating an objective function that represent the desired segmentation result as the target output [6] [10] [11]. It is worth noting that supervised metrics still suffer from being insensitive to the appearance of either under or over-segmentation [12] [13].

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Moreover, these metrics are also insensitive to the quality of object boundaries, which can lead to missed object detection.

Therefore, the detection of object boundaries has been enriched by the unsupervised approaches. The purpose is to employ certain strategies for boundary optimization without dealing with the predefined target, such as, the measurement of object dimension [14], the convolution operation to optimize edge precision [15], the computation of negative divergence of a normal compressive vector field [16], and the detection of microtype edges [17]. However, these strategies suffer from being insensitive to the delivery of meaningless edge that is caused by the open boundary information [18], and being inefficient due to highly complex algorithm for edge quality measurement [19]. Hence, researchers have enhanced the edge quality measurement by introducing segmentation-based approaches. Some algorithms have been introduced to measure the segmentation quality which include the entropy-based approach [18] [20] [21] [22] and the edge-based approach [3] [19]. It is worth noting that the measurements of segmentation quality simplify the optimization of boundary information by delivering the object boundary as a part of the segmented region. It aims to optimize the production of meaningful shapes by relying on the characteristic of edge-based segmentation to produce the segmented regions based on edge quality. Current unsupervised optimization approaches are built by employing edge-based and region-based feature extraction to select the best edge map, in which the state of the art utilizes either the edge-based measures [3] [19], statistical computation [8] [15][17], or entropy-based measure [18] [20] [21]. Among these approaches, the first two present more complex algorithm than the last, which relies on the entropy measurement. In this case, the entropy has a straightforward optimization mechanism to present the quality of boundary information from the segmented region. However, the available entropy-based features deliver unsatisfactory results due to the appearance of under and over-segmentation [10] [18]. Hence, this research aims to improve the performance of the entropy-based optimization approach.

The rest of this paper is organized as follows. Section 2 presents the conceptual model that contributes to the theoretical development of unsupervised optimization based on entropy measures. Section 2 also elaborates on the data used in this research and the method development that consists of the enhancement of existing evaluation strategies and the development of a new unsupervised optimization based on entropy measures. The experimental results, validation of segmentation quality, and the discussion are presented in Section 3. The study concludes in Section 4.

2. Materials and Methods

2.1. Conceptual Model

This research aims to improve the performance of an unsupervised approach to produce boundary information, i.e., the sharp edge localizing the object with its details from the background scene of a digital image. The strategy is to extend the entropy-based unsupervised segmentation evaluation by introducing a shape distribution as the main instrument to optimize the segmentation quality. The optimization strategy is established by finding the trade-off between the entropy contribution and the coefficient of variation from shape distribution as shown by the conceptual model depicted in Figure 1, in which the proposed approach, as the main contribution of this study, is visualized by the red-colored box. In this case, the optimization objective is to find a high variation of shape distribution to present the existence of image objects. To enable the computation of shape distribution, this study introduces the computation of region entropy with its coefficient of variation and entropy contribution.

Moreover, we also intend to slightly modify the existing approach based on the region feature extraction by supplying the regional shape instead of pixel values to compute the image and region entropy as shown by the red arrow from the red box to the black box in Figure 1. This effort aims to simplify the computation of segmentation entropy and to increase its performance. In this case, the study intends to reduce the algorithm complexity by measuring the information contained in the edge map.

2.2. Dataset Collection

The dataset used in this study was obtained from the USC-SIPI image database [23] and Berkeley image data testing [24]. The former consists of traditional data for image processing while the latter contains image segmentation done by human [25]. Selection criteria were applied to the dataset to include only the image that contains the natural object, and to exclude the texture-only image or the image with

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unclear object presentation or noisy image. A total of 118 images were obtained from this process, in which 19 images are in grayscale and the rest are in full color. The sample images are shown in Figure 2 column A.

2.3. Unsupervised Optimization based on Entropy Measure: The Enhancement of Existing Method

Entropy-based segmentation evaluation (SEG-ENT) has received researchers' attention due to its application mainly in medical image analysis [1] [2] [20]. It is a measure of segmentation quality as computed by Equation 1.

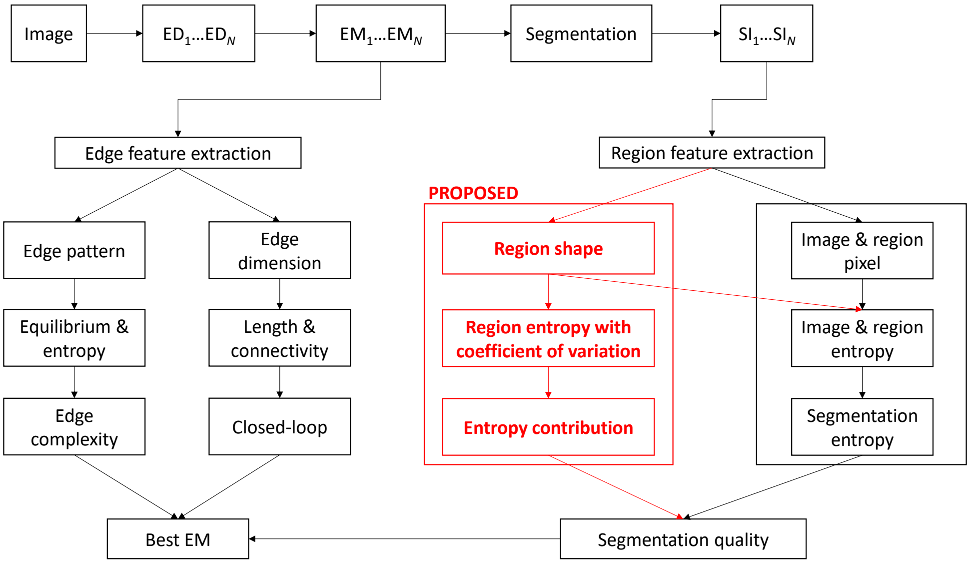

Fig. 1. Conceptual model of unsupervised optimization of boundary information

$$\boldsymbol{E(S)} = \frac{\sum_{i=1}^{m} \boldsymbol{E(r_i)} - \boldsymbol{E(I)}}{\boldsymbol{E(I)}} \tag{1}$$

in which $\boldsymbol{E(S)}$ is the segmentation entropy, $\boldsymbol{E(r_i)}$ is the entropy of region $\boldsymbol{r_i}$ as the result of segmenting image I into a set of regions $\boldsymbol{r_1} \dots \boldsymbol{r_m}$, while $\boldsymbol{E(I)}$ is the image entropy. The mechanism to compute the image entropy is as follows:

$$\boldsymbol{E(I)} = -\sum_{k=0}^{G} \boldsymbol{p_k} \, \boldsymbol{ln} \, \boldsymbol{p_k} \tag{2}$$

with $\boldsymbol{p_k} = \frac{\boldsymbol{n_k}}{\boldsymbol{M \times N}}$, where $\boldsymbol{n_k}$ is the number of pixels with gray level k from an image $\boldsymbol{I} = \boldsymbol{M} \times \boldsymbol{N}$, in which $\boldsymbol{0} \le \boldsymbol{k} \le \boldsymbol{G}$. The mechanism to compute the region entropy is as follows:

$$\boldsymbol{E(r_i)} = -\sum_{k=0}^{G} \boldsymbol{p_{ik}} \, \boldsymbol{ln} \, \boldsymbol{p_{ik}} \tag{3}$$

with $\boldsymbol{p_{ik}} = \frac{\boldsymbol{n_{ik}}}{\boldsymbol{M_i \times N_i}}$, where $\boldsymbol{n_{ik}}$ is the number of pixels with gray level k from a region $\boldsymbol{r_i} = \boldsymbol{M_i} \times \boldsymbol{N_i}$. From a set of edge map $\boldsymbol{EM_1} \dots \boldsymbol{EM_j}$, the best edge map is selected by minimizing $\underset{i=1 \dots j}{\boldsymbol{E_i(S)}}$. The assumption of this approach is that lower segmentation entropy produces a more homogeneous result which leads to a better segmentation. Due to its mechanism, this approach suffers from high computational complexity in computing image and region entropy since it has to deal with the grey levels of multiple regions, i.e., multiple regions with varying pixel values influence the computation iteration and increase the time consumption. Therefore, we propose the simplification of entropy-based segmentation evaluation in order to reduce the algorithm complexity and the time consumption. The improvement is established by replacing the pixel-grain process with the shape-level computation in terms of segmented regions. Two improvement strategies are developed as follows.

Improvement A aims to simplify the pixel-grain process of $\boldsymbol{E(r_i)}$ by removing the grey level of region entropy, resulting in:

$$\boldsymbol{E(r_i)} = -\sum_{i=1}^{m} \boldsymbol{p_i} \, \boldsymbol{ln} \, \boldsymbol{p_i} \tag{4}$$

in which $\boldsymbol{p_i} = \frac{\boldsymbol{n_i}}{\boldsymbol{M \times N}}$, where $\boldsymbol{n_i}$ is the size of a region $\boldsymbol{r_i}$. This strategy still maintains the pixel-grain process by preserving $\boldsymbol{E(S)}$ for the image entropy computation. It is worth noting that image entropy is

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computed only once, i.e., at the beginning of the process. Therefore, the strategy would significantly simplify the algorithm complexity, which leads to reduced time consumption.

Improvement B aims to remove all pixel-grain processes in the computation by simplifying both the segmentation entropy $\boldsymbol{E(S)}$ and the region entropy $\boldsymbol{E(r_i)}$. The modification of segmentation entropy is as follows:

$$\boldsymbol{E(S)} = \frac{\sum_{i=1}^{m} \boldsymbol{E(R) - E(r_i)}}{\boldsymbol{E(r_i)}} \tag{5}$$

with the modification of region entropy $\boldsymbol{E(r_i)}$ defined as Improvement A, and

$$\boldsymbol{E(R)} = -\sum_{i=1}^{m} \boldsymbol{p_i \, ln \, p_i + (1 - p_i) \, ln(1 - p_i)} \tag{6}$$

This strategy replaces all pixel-grain process with the shape-level computation. Both improvement A and B still follow the same mechanism for selecting the best edge map, i.e., by minimizing E(S), since a lower segmentation entropy leads to a better segmentation representing more homogeneous regions.

2.4. The Proposed Unsupervised Measure

The actual distribution of segmented regions is either Poisson due to over-segmentation or categorical due to under-segmentation. In this case, the over-segmentation is characterized by a high variance and a positive skewness, while the under-segmentation presents a low or zero variance. It is important to identify the optimal segmentation having a normal distribution of the segmented region size. This assumption relies on the fact that a natural image normally contains a few objects that are represented by a relatively large-sized regions and their details in smaller regions. In this case, the ratio between the number of regions representing the objects and the details produces varied segmented regions that are distributed normally based on the region size. Hence, the variation of the size of segmented regions becomes a significant information to identify the optimal solution of segmentation result that contains a meaningful object boundary information. It is worth noting that an important object normally has a prominent appearance compared to other objects or its background, in which it is represented by a relatively significant region size of image. A new measure of segmentation quality is developed based on the entropy contribution and the coefficient of variation of object information that is computed by

$$\boldsymbol{C = E\gamma} \tag{7}$$

with E representing the entropy contribution computed by

$$\boldsymbol{E} = \frac{\boldsymbol{H}}{\boldsymbol{m}} \tag{8}$$

in which the computation of H follows the Shannon entropy and the formulation proposed by Bandyopadhyay et al. [20], i.e., $\boldsymbol{H} = \sum_{i=1}^{m} \boldsymbol{p_i \ln p_i}$ with $\boldsymbol{p_i} = \frac{\boldsymbol{n_i}}{\boldsymbol{M \times N}}$ and $\boldsymbol{n_i}$ is the number of pixels from a region $\boldsymbol{r_i}$ as the result of segmenting image $\boldsymbol{I = M \times N}$ into a set of regions $\boldsymbol{r_1} \dots \boldsymbol{r_m} \subseteq \boldsymbol{I}$. Meanwhile, the coefficient of variation $\boldsymbol{\gamma}$ is the measure of dispersion around the mean [26] that is computed as follows:

$$\boldsymbol{\gamma} = \frac{\boldsymbol{\sigma}}{\boldsymbol{\mu}} \tag{9}$$

where $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ are the mean and the standard deviation of the segmented regions in term of the shape size. Here, the coefficient of variation identifies the magnitude of variation among the segmented regions according to the distribution of shape in the segmented image, while the entropy contribution intends to measure the information contribution of each segmented region to build the whole information representing the content of an image. In this case, the desired condition should contain a high variation of segmented shape and a high information contribution to present the existence of image objects. Thus, maximizing Equation 7 becomes the solution to deliver a better segmentation quality and to select the best edge map.

3. Results and Discussion

3.1. Experimental Setting

The experiment is established by conducting a comparison against SEG-ENT [1] [2] [20] as the benchmark to measure the performance of the proposed approach, i.e., improvement A, improvement B, and the proposed method. The rationale behind using the benchmark is the practicality of SEG-ENT

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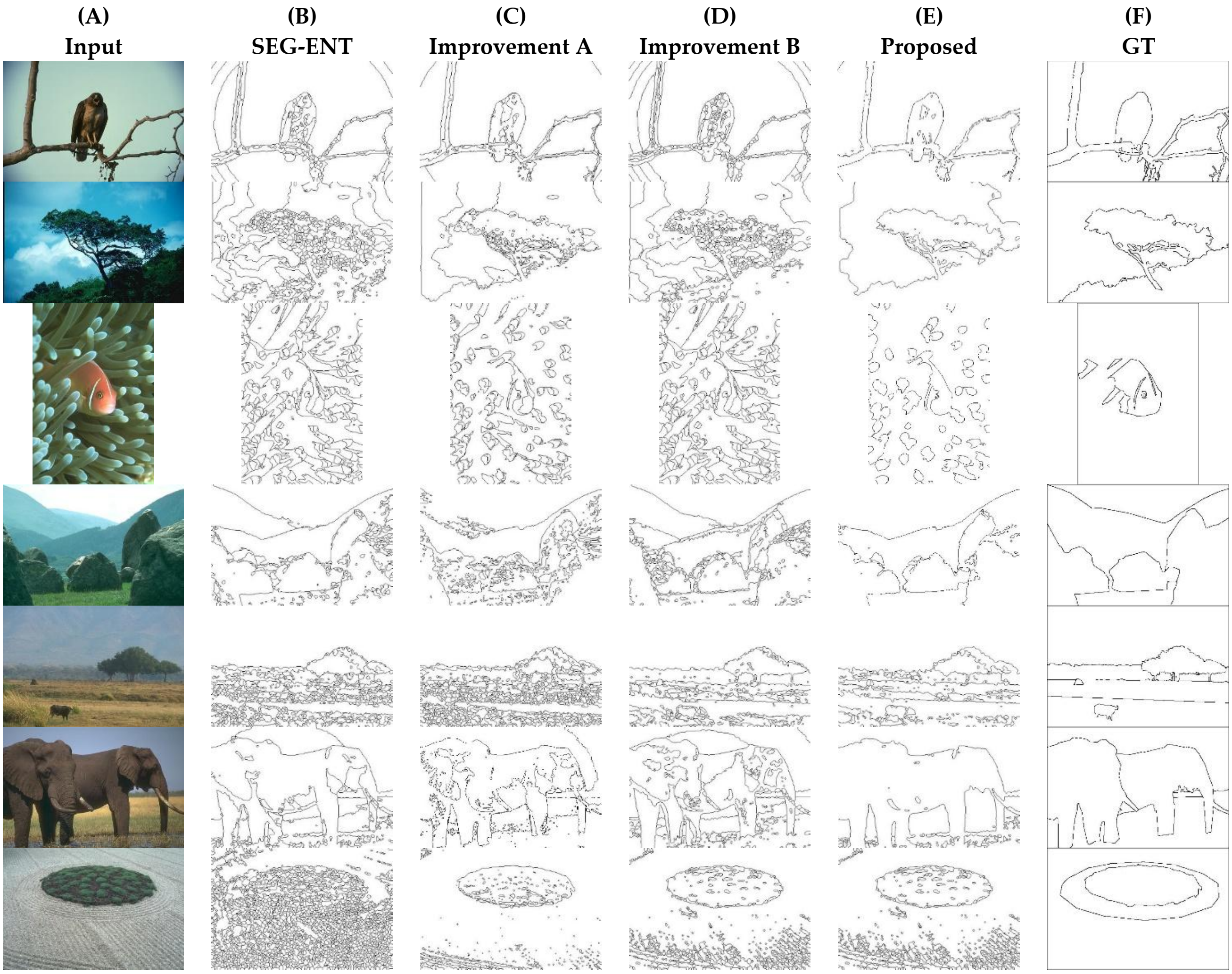
to produce the boundary information based on entropy measurement. The experiment uses 118 test images, as described in the dataset collection section. The experiment is starts by generating a set of edge maps as the representation of boundary information from each test image in the pre-processing stage, in which each edge map presents a unique set of shapes produced by the edge-based segmentation. The developed algorithms then select the best edge map by measuring the segmentation quality of the extracted shape. The best edge map results are then validated using a twofold approach, i.e., the qualitative and quantitative approaches. The qualitative approach analyzes the most desired result from the perspective of human observers. It is achieved by employing some groups of observers to vote the most desired shape among the alternatives obtained from each algorithm. The most dominant shape to be voted by the human observers becomes the most desired shape. In this stage, a point is given to the algorithm whose shape is selected by human observers. In case where human observers select a shape that is assigned by more than a method, the point is equally shared between the methods. Meanwhile, the quantitative approach measures the operational parameters of each method in term of achieving proper segmentation by avoiding under and over-segmentation. It also measures the quantity of over-segmentation reduction and the time consumption to disclose the generic characteristic of each method.

3.2. Experimental Results

The sample of experimental results are shown in Figure 2, which displays the input image and the boundary information obtained by each method in terms of edge maps, i.e., SEG-ENT as the benchmark in column B, improvement A in column C, improvement B in column D, and the proposed method in column E. This figure also presents the ground truth (GT) of the data in column F.



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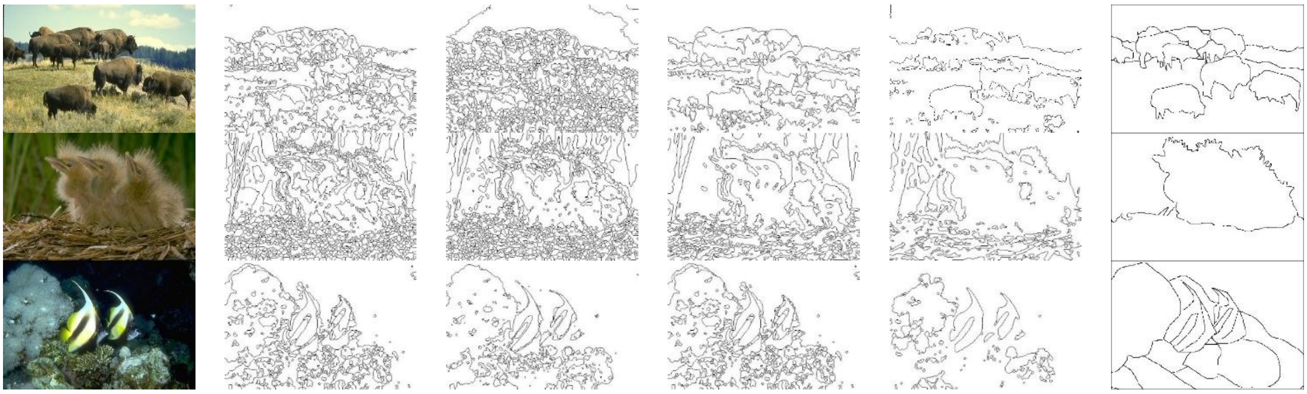


Fig. 2. The sample of experimental results

The result of the human observer votes are given in Figure 3, which contains the observer agreement on each method as presented by the average percentage of points, i.e., 11.61% for SEG-ENT, 23.47% for improvement A, 25.93% for improvement B, and 35.76% for the proposed method. Meanwhile, a quantitative comparison against the ground truth (GT) delivers the average accuracy of 45.23% for SEG-ENT, 50.71% for improvement A, 60.73% for improvement B, and 71.75% for the proposed method.

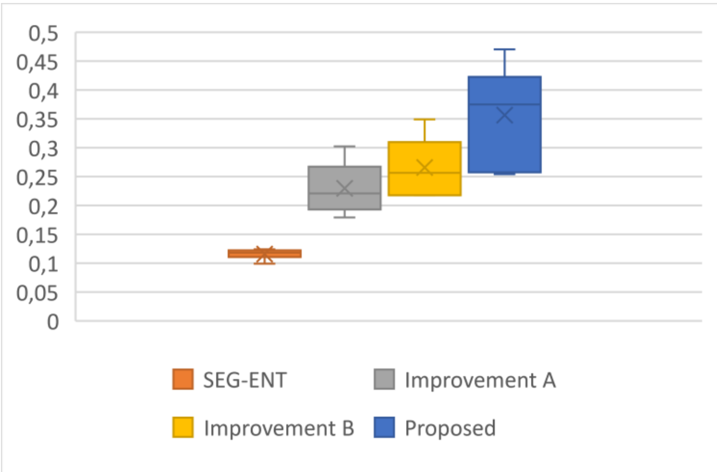


Fig. 3. The result of observer votes

The average time consumption recorded by each algorithm is as follows: 23.03s for SEG-ENT, 3.47s for improvement A, 3.04s for improvement B, and 3.39s for the proposed method, as shown in Figure 4. Hence, the reduction of time consumption is 84.92% for improvement A, 86.72% for improvement B, and 85.26% for the proposed approach compared to SEG-ENT.

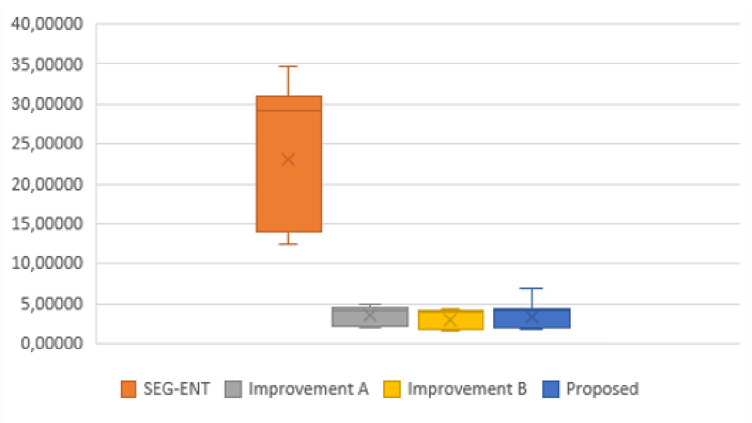


Fig. 4. The time consumption of each method

The experiment also measures the average of the number of segmented regions produced by each method, as shown in Figure 5, i.e., an average of 494.94 segmented regions in the average by SEG-ENT, 544.48 by improvement A, 371.94 by improvement B, and 211.84 by the proposed approach. Hence, the reduction in over-segmentation relative to SEG-ENT is as follows: -10.01% by improvement A, 24.85% by improvement B, and 57.20% by the proposed approach.

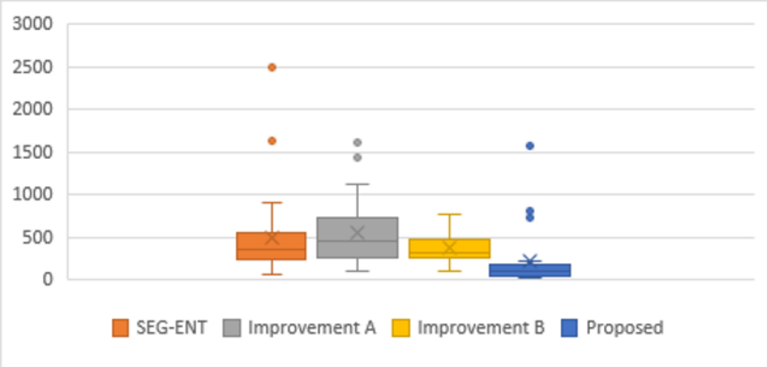
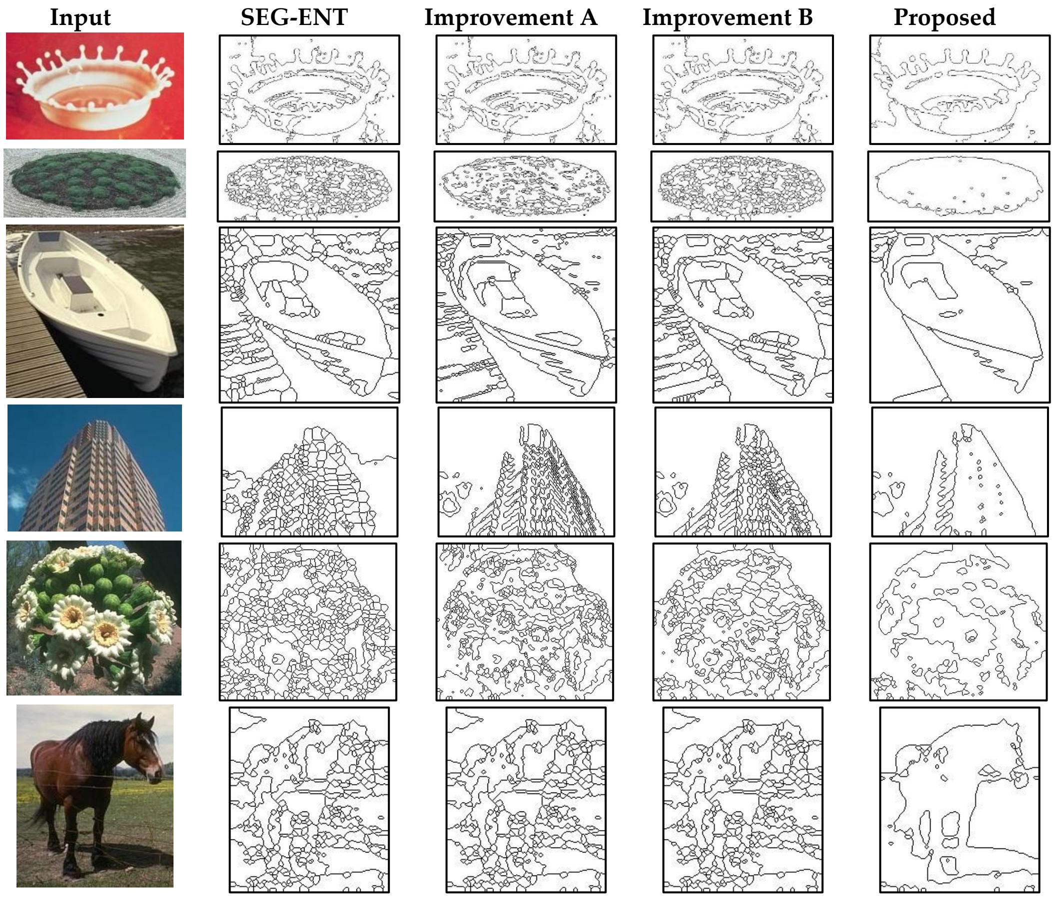


Fig. 5. The number of segmented regions

Further experiments focus only on the object of interest. These experiments are conducted by generating the region of interest (ROI) from the input image, in which 24 ROI images are developed from the test data above. Samples of the ROI and the result produced by each algorithm to assign the best edge map are shown in Figure 6. The same validation process, i.e., employing some groups of human observers as described in the previous experiment is then applied to validate the experimental results. The results of the observer votes based on the ROI present 3.36% for SEG-ENT, 12.38% for improvement A, 12.73% for improvement B, and 71.53% for the proposed approach, as shown in Figure 7. This result demonstrates the improved performance of the proposed approach in delivering boundary information from ROI images.



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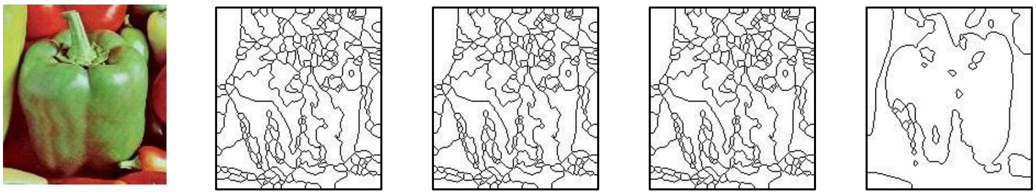

Fig. 6. The experimental result of ROI image

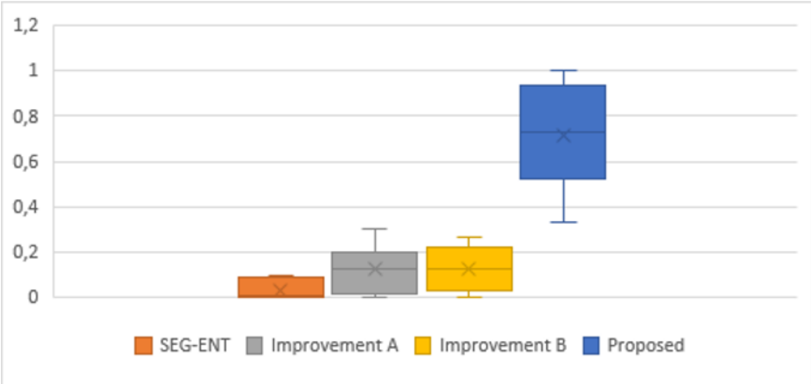

Figure 7. The observer votes of ROI

3.3. Discussion

The experimental results show that SEG-ENT is prone to producing over-segmentation because of its mechanism to assume that more homogeneous partition represents a better segmentation. Therefore, SEG-ENT excels in retrieving objects from complicated scenes, in which the segmentation tends to divide the image into many homogeneous regions. It is worth noting that SEG-ENT shares similar observer appreciation with the improvement B for some input images since they produce similar outputs. However, it received the lowest appreciation from the observers due to over-segmentation.

The enhancement of entropy-based segmentation evaluation, which consists of improvement A and B, obtains higher appreciation from the observer compared to SEG-ENT, as shown in Figure 3. In this case, improvement B records a slightly higher score than improvement A. Here, improvements A and B show successful efforts to reduce over-segmentation by simplifying the computation of segmentation entropy and region entropy. In this case, the complexity of pixel-grain analysis of the original method is replaced by the simpler approach of shape-level analysis to develop entropy measurement for the segmented image.

Meanwhile, the proposed approach obtains the highest score from the observer vote compared to other methods, as shown in Figure 3. The superiority of the proposed approach is driven by the successful reduction of over-segmentation that records 57.20% reduction rate compared to 24.85% for improvement B and -10.01% for improvement A, as shown in Figure 5. In this case, the proposed method suppresses the over-segmentation by maximizing the entropy contribution while at the same time seeking the variation among the segmented regions, which is achieved by maximizing the ratio between the standard deviation and the mean of shape-size distribution. Although over-segmentation still appears in some images, this problem can be reduced significantly by delivering a more compact shape, as shown by the sample of experimental results presented in Figure 2.

Further analysis is applied to the results of the observer votes in order to disclose the significance of the differences in method performance which are defined as H0 and H1 in the first and second columns of Table 1. A two-tailed student's t-distribution test with 0.05 confidence level is employed after running a normality test to prove that the data fit a normal distribution. The result of the analysis in terms of p-value is presented in the third column of Table 1, with the description provided in the fourth column. It proves that all efforts to improve the original entropy-based evaluation deliver a better performance than the original entropy-based evaluation represented by SEG-ENT. The analysis also proves that the improvement A and B perform equally from the perspective of the observer. Moreover, the test also proves that the proposed method performs better than the improvement A but perform equally to the improvement B.

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Table 1: Results of the hypothesis test based on the observer votes

H0	*H1*	*p-value*	Result
SEG-ENT = Improved_A	SEG-ENT ≠ Improved_A	0,00013	H1
SEG-ENT = Improved_B	SEG-ENT ≠ Improved_B	0,00004	H1
Improved_A = Improved_B	Improved_A ≠ Improved_B	0,23328	H0
Improved_A = Proposed	Improved_A ≠ Proposed	0,00963	H1
Improved_B = Proposed	Improved_B ≠ Proposed	0,05205	H0

The experimental results on ROI images shows that simplifying the image data by focusing only on a single object is capable of improving the performance of the proposed method by avoiding over-segmentation. Again, a data analysis based on a two-tailed student's t-distribution with a 0.05 confidence level is applied to the observer vote based on ROI images. The result, as given in Table 2, shows that the original method represented by SEG-ENT and the improved approaches perform equally in delivering boundary information, while the proposed approach performs superiorly compared to the other methods.

Table 2: Results of the hypothesis test on ROI images based on the observer votes

H0	*H1*	*p-value*	Result
SEG-ENT = Improved_A	SEG-ENT ≠ Improved_A	0,09984	*H0*
SEG-ENT = Improved_B	SEG-ENT ≠ Improved_B	0,06672	*H0*
Improved_A = Improved_B	Improved_A ≠ Improved_B	0,95667	*H0*
Improved_A = Proposed	Improved_A ≠ Proposed	0,00034	*H1*
Improved_B = Proposed	Improved_B ≠ Proposed	0,00031	*H1*

4. Conclusion

This research proposes an improvement to the unsupervised optimization of object boundary information by employing the trade-off between the mean entropy of segmented regions and the coefficient of variation from shape distribution. This research also proposes the enhancement of entropy-based segmentation evaluation by simplifying the computation of region entropy and segmentation entropy. A benchmark is employed in the experiment to compare the performance of the proposed and enhanced methods based on quantitative and qualitative approaches. The quantitative approach shows that the enhanced methods deliver higher accuracy than the original, while the proposed method achieves the highest accuracy. This experimental result shows that the proposed method has a greater capability in producing boundary information by avoiding under and over-segmentation compared to other methods. The quantitative approach also shows the highest reduction in over-segmentation by the proposed method while at the same time recording moderate time consumption compared to the enhanced methods. Meanwhile, the qualitative approach shows that the proposed method becomes the most desired algorithm compared to other methods based on the evaluation of some groups of observers. Further experiments focusing on specific regions of interest show an improved performance of the proposed method. It shows that reducing the complexity of image background facilitates the retrieval of image objects.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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