MEDIAN FILTER FOR TRANSITION REGION REFINEMENT IN IMAGE SEGMENTATION

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ABSTRAK

Segmentasi citra berbasis transition region adalah salah satu metode segmentasi citra yang sederhana dan efektif. Metode ini mampu mensegmentasi citra yang mengandung objek tunggal atau banyak. Namun, metode ini bergantung pada latar belakang. Metode ini dapat memberikan hasil segmentasi yang buruk jika varians tingkat keabuan pada background cukup tinggi atau background bertekstur. Jadi metode untuk memperbaiki transition region sangatlah diperlukan. Pada penelitian ini diusulkan sebuah metode baru untuk memperbaiki transition region dengan median filter berdasarkan persentase transitional pixels yang saling berdekatan. Transition region diekstraksi dari citra grayscale. Perbaikan pada transition region dilakukan berdasarkan persentase transitional pixels yang saling berdekatan. Beberapa operasi morfologi kemudian dilakukan pada transition region. Setelah itu, proses edge linking digunakan untuk menghubungkan ujung transition region yang putus. Region filling dilakukan untuk mendapatkan area foreground. Akhirnya, citra hasil segmentasi diperoleh dengan menampilkan piksel citra grayscale yang terletak di area foreground. Nilai misclassification error (ME), false negative rate (FNR), dan false positive rate (FPR) dari hasil segmentasi dihitung untuk mengukur kinerja metode yang diusulkan. Kinerja metode yang diusulkan dibandingkan dengan kinerja metode lainnya. Hasil eksperimen menunjukkan bahwa metode yang diusulkan memiliki nilai rata-rata ME, FPR, dan FNR: 0.0297, 0.0209, dan 0.0828 yang menunjukkan bahwa metode yang diusulkan memiliki kinerja yang lebih baik daripada metode-metode lain. Terlebih lagi, metode yang diusulkan bekerja dengan baik pada citra dengan berbagai macam background, terutama pada citra dengan background bertekstur.

***Kata Kunci**: false negative rate, false positive rate, median filter, misclassification error, transition region.*

ABSTRACT

Transition region-based image segmentation is one of the simple and effective image segmentation methods. This method is capable to segment image contains single or multiple objects. However, this method depends on the background. It may produce a bad segmentation result if the grey level variance is high or the background is textured. So a method to repair the transition region is needed. In this study, a new method to repair the transition region with median filter based on the percentage of the adjacent transitional pixels is proposed. Transition region is extracted from the grayscale image. Transition region refinement is conducted based on the percentage of the adjacent transitional pixels. Then, several morphological operations and the edge linking process are conducted to the transition region. Afterwards, region filling is used to get the foreground area. Finally, image of segmentation result is obtained by showing the pixels of grayscale image that are located in the foreground area. The value of misclassification error (ME), false negative rate (FNR), and false positive rate (FPR) of the segmentation result are calculated to measure the proposed method performance. Performance of the proposed method is compared with the other method. The experimental results show that the proposed method has average value of ME, FPR, and FNR: 0.0297, 0.0209, and 0.0828 respectively. It defines that the proposed method has better performance than the other methods. Furthermore, the proposed method works well on the image with a variety of background, especially on image with textured background.

***Keywords**: false negative rate, false positive rate, median filter, misclassification error, transition region.*

I. INTRODUCTION

IMAGE segmentation is one kind of very fundamental process in digital image processing and computer vision. Image segmentation aims to get objects from an image using image characteristics such as grey level, colour, and texture. It is usually used for further processing such as biomedical image analysis, character identification and object recognition[1]. In general, the method of image segmentation can be categorized into several types of approaches: thresholding based approach [2–5], boundary based approach [6], region-based approach[7] and hybrid approach [8–11].

In thresholding based image segmentation, objects and backgrounds are considered to have different grey-level distributions. It means that there are two or more peaks on the image histogram that can be separated by the threshold. Thus, the segmentation process in this approach is done by determining the pixels that have a grey level above the threshold value as the object while the pixels that have the grey level below the threshold value as the background, or vice versa. Boundary-based approaches generate transition zones, edges or boundaries in images that separate objects and backgrounds.

Region-based image segmentation is done by grouping pixels with their neighboring pixels which have similar values [12], separating pixels that have different values into other groups, or a combination of both ways [13]. Hybrid based image segmentation can be done by combining two or more approaches in order to produce better segmentation.

Image segmentation with thresholding to determine the transition region is a hybrid method that combines region-based and thresholding approaches [1, 14]. In this segmentation method, pixels that have values above the threshold are considered as transitional pixels which then form a transition region. Region filling is performed at the transition region to produce a binary image containing area or region of the object. Then, the segmentation process is performed by displaying the pixels within the region of the binary image. All pixels in the grayscale image that have the same position as the object position in the binary image will be displayed as an object.

Zhang and Gerbrands (1991) proposed a transition region-based image segmentation method using the effective average gradient (EAG) as a transition region descriptor [15]. This method can only be used in an image that has a drastic grey level change so it is not suitable for complex images that have a high variance of grey levels. To overcome these weaknesses, Yan et al. proposed transition region extraction based on local entropy (LE) [16]. However, this method still lacks if there are many grey level variations in the neighborhood that will increase the local entropy value of a pixel and making the pixel a transitional pixel even though it is a foreground or background. Then, Li & Liu proposed a new method of local grey level difference (LGLD) based transition region extraction method [17]. This method considers the change in grey levels and the number of changes. Furthermore, a method of a modified local entropy method (MLE) is proposed by Li et al. [18]. This method takes into account the frequency and degree of grey level changes for transition region extraction. This method can produce a better transition region than LE. But this method still needs the user to determine values to balance the contribution of local complexity and local variance, and values to control the number of pixels in the transition region.

Then Li et al. (2016) proposed a new method for image segmentation that contains a single object using the salient transition region [14]. The research proved effective in terms of image segmentation with a single object. Then, Parida and Bhoi proposed a novel method to segment a grayscale image containing single and multiple objects based on the transition region [1]. This method uses the local variance value of each pixel as the basis for determining the transition region. This method can produce a good segmentation result on an image containing single or multiple objects. However, this method still has a shortcoming that will generate false transitional pixels in the background area if the background is too complicated. False transitional pixels may make the segmentation result worse because the system will show some background pixels as objects. So a method that can repair the transition region by reducing the generated false transitional pixels is needed.

In this paper, we propose a new method to repair the transition region with a median filter based on the percentage of the adjacent transitional pixels. Repaired transition region can make a better segmentation result because it can reduce the appearance of background pixels in the resulting image. The rest of this paper is divided into 3 sections: section II-IV. The proposed method is described in section II. Experimental results and analysis is displayed in Section III, and conclusions are described in Section IV.

II. PROPOSED METHOD

Image segmentation based on the transition region can be used to define the object of an image by showing only pixels that are considered objects. In this study, there are several steps that are conducted to segment the image as shown in Fig. 1. The transition region is extracted from the grayscale image using local variance. Then, transition region refinement is conducted based on the percentage of the adjacent transitional pixels to repair the transition region. Several morphological operations are processed to the transition region to obtain the cleaner transition region with a single pixel width. Then, the edge linking process is used to connect the edge of the transition region to obtain the intact transition region. Region filling is then conducted to the intact transition region to produce the area of a foreground. Finally, the image of segmentation result is obtained by showing the pixels of the grayscale image that are located in the area of the foreground. The proposed method is tested on some images from MSRA dataset, Weizmann dataset, and input images from [1] as shown in Fig. 2 and the ground truth as shown in Fig 3.

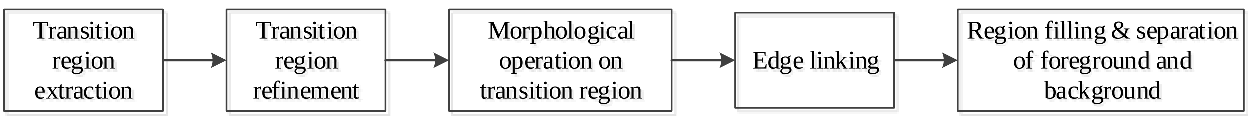


Fig. 1. System design.

Fig. 2. Some input images from [1].

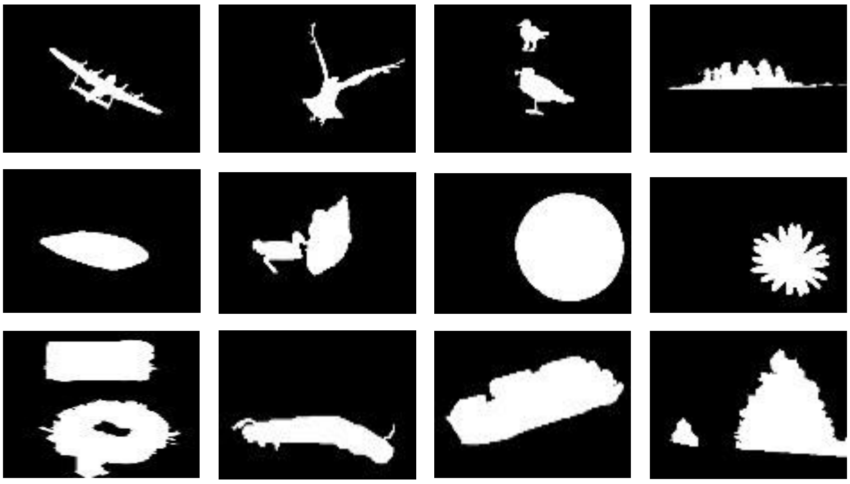


Fig. 3. Ground truths of input images from [1]

A. Transition region extraction

The transition region is a structure in an image similar to the edge. Transition region has three characteristics: transition region usually has a width of several pixels near the edge, it surrounds the object and should lie between the object and the background, there is a grey level change in the pixels in the transition region. Information for transition region extraction can be obtained from transitional pixels that have larger size and frequency of grey level changes than non-transitional pixels [19]. The transition region extraction process aims to obtain a transition zone close to the outline of the object [14].

There are many descriptors for transition region extraction [15–17]. In this study, the local variance is used for transition region extraction. Local variance can distinguish areas that contain edges or not [1]. Edges usually exist in areas with high variance values. For central pixels *p(i, j)* of *m x m* local neighborhood window, local variance LV can be calculated using Equation (1).

$$LV(i,j) = \frac{1}{m^2 - 1} \sum_{x=1}^{m} \sum_{y=1}^{m} (f(x,y) - \bar{f})^2 \tag{1}$$

f(x, y) denotes the local pixel grey level value in the local neighborhood window and $\bar{f}$ represents the average grey level of the local neighborhood window.

By moving the window from left to right and top to bottom, the local variance calculation is run across the image to obtain the local variance value matrix as shown in Equation (2).

$$LV = \begin{bmatrix} LV(1,1) & LV(1,2) & \dots & LV(1,N) \\ LV(2,1) & LV(2,2) & \dots & LV(2,N) \\ \dots & \dots & \dots & \dots \\ LV(M,1) & LV(M,1) & \dots & LV(M,N) \end{bmatrix} \tag{2}$$

M denotes the height of the image and N represents the width of the image.

The values in the matrix will be compared with global threshold Tg. Global threshold value can be calculated using Equation (3).

$$T_g = \frac{1}{M \times N} \sum_{k=1}^{M} \sum_{l=1}^{N} f(k,l) \tag{3}$$

where $f(k, l)$ is the grey level of a pixel (k, l) in the input image. Pixels that have local variance values greater than or equal to Tg will be considered as transitional pixels as shown in Equation (4).

$$\Omega_R(i,j) = \begin{cases} 1 & \text{if } LV(i,j) \geq T_g \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The transition region is organized by grouping the connected transitional pixels Ω_R and making each group into a different transition region as shown in Fig. 4.

B. Transition region refinement

The transition region is highly dependent on the background of the image. Transition region will be generated nicely in images with a simple background. However, some false transitional pixels may be generated in the background area if the images contain backgrounds with high variations of grey levels, a drastic change in grey levels, or textured backgrounds. False transitional pixels usually have a fairly close distance to other transitional pixels but not attached.

The appearance of false transitional pixels in the background area is expected to be solved using smoothing or filtering techniques, such as a median filter. However, the use of filtering techniques can also aggravate the transition region in images with a good background (slight grey level variation or no drastic grey level change). Thus, this study proposes a new technique that can determine automatically whether filtering techniques need to be used to repair the transition region or not.

Transition region is expected to be intact and appear in the edge of the object as shown in Fig. 5 (b), so that the transition region can be filled by region filling and the system can produce a good segmentation result [1]. Transitional pixels attached to each other are considered normal because it is assumed to be a transition region. However, transitional pixels that are close to others but not attached can be considered as false transitional pixels because it often appears in the center of foreground or background as shown in Fig. 5 (c). False transitional pixels can make the segmentation result worse because the system will show some background pixels as objects. So the appearance of false transitional pixels is expected to be reduced by transition region refinement process using median filter.

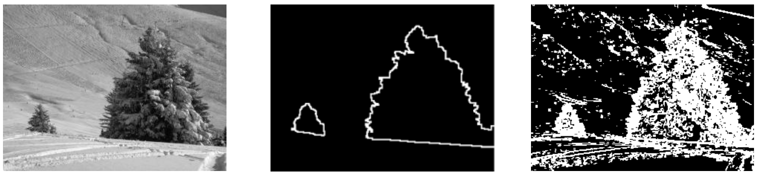
The decision of using filtering is made based on the testing on several images that have been categorized: 1) simple background & simple foreground, 2) textured background & simple foreground, 3) simple background & textured foreground, and 4) textured foreground & textured background from [1] as shown in Fig. 2. The results of testing are shown in Table I. The use of filtering on image type 1 and type 2 yields better average value of ME, FPR, and FNR than without using filtering. The use of filtering on this type of image can generate fewer transition regions in the background area while still maintaining the appearance of transition regions on the edges of objects.

TABLE I
PERFORMANCE MEASURES (ME, FPR, FNR) FOR VARIOUS TYPES OF IMAGES WITH OR WITHOUT FILTERING

Image Types	Images	ME		FPR		FNR	
		Filter	No filter	Filter	No filter	Filter	No filter
Type-1 images (simple background & simple foreground)	airplane	**0.012**	0.0166	**0.0032**	0.0089	0.1594	**0.1457**
	eagle	**0.0064**	0.0065	0.0053	**0.0047**	**0.0259**	0.0376
	bird	**0.0226**	0.0278	**0.0144**	0.0194	**0.1625**	0.1708
Average of Type-1		**0.0137**	0.0170	**0.0076**	0.0110	**0.1159**	0.1180

(a) (b)

Fig. 4. Image (a) grayscale, (b) transition region.



(a) (b) (c)

Fig. 5. Image (a) grayscale, (b) expected transition region, (c) generated transition region that contains many false transition regions.

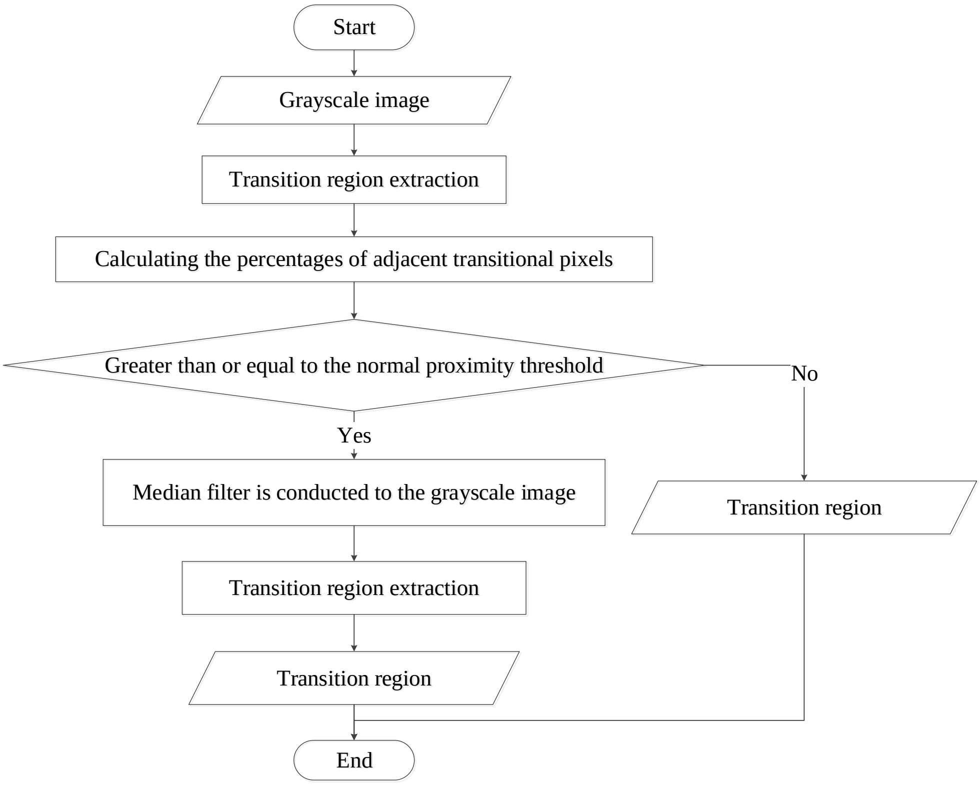
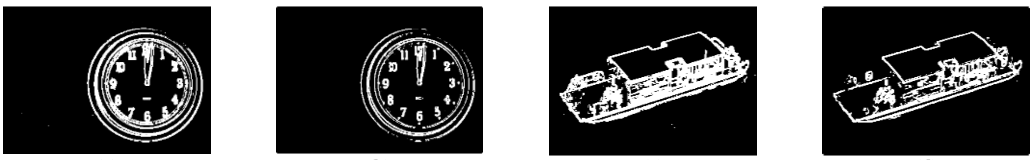


Fig. 6. Flowchart of transition region refinement.

(a) (b) (c) (d)

Fig. 7. Transition region (a) & (c) before filtering, (b) & (d) after filtering.



(a) (b) (c) (d)

Fig. 8. Transition region (a) & (c) before filtering, (b) & (d) after filtering.

Moreover, the use of filtering on image type 4 which has a very textured foreground and background like mountain trees and yack image is very effective as shown in Fig. 7. However, the use of filtering on image type 3 produces worse misclassification error and false negative rate values. This happens because the use of filtering makes the textures of foreground softer that causes the edges of objects being difficult to be detected and connected as shown in Fig. 8. This case also occurs in the boat image that the foreground is more textured than the background. This type of image does not require filtering because the transition region can already be produced properly without filtering.

Filtering can make the textured background smoother and simpler that will be able to reduce the appearance of false transitional pixels. However filtering can make the edge of foreground worse because it smooths every pixel in the image. It means that filtering is not suitable for all image conditions. So a technique that can determine the use of filtering is proposed. This technique defines that filtering will be conducted if the percentages of adjacent transitional pixels is greater or equal to normal proximity threshold *nt*. Adjacent transitional pixel is a pixel that has distance less than or equal to the maximum distance *dt* from another transitional pixel as shown in Fig. 9. Number of adjacent transitional pixels *ft*, number of transitional pixels attached to each other *fm* and percentages of adjacent transitional pixels *pa* are counted to determine whether the filtering is used or not. The value of *ft* is obtained by summing the number of adjacent transitional pixels horizontally of each row in image. The value of *ft* is then compared with the value of *fm* to determine the value of *pa* using Equation (5). Median filter process will be performed to the image if the value of *pa* is greater than or equal to the normal proximity threshold *nt*. Flowchart of transition region refinement can be seen in Fig. 6.

$$pa = \left(\frac{ft}{fm}\right) * 100 \qquad (5)$$

C. *Morphological operation on transition region*

Morphological operation is done to the transition region to produce a better transition region that surrounds the whole object and slightly appears in the background. Morphological operation that is used in this study based on

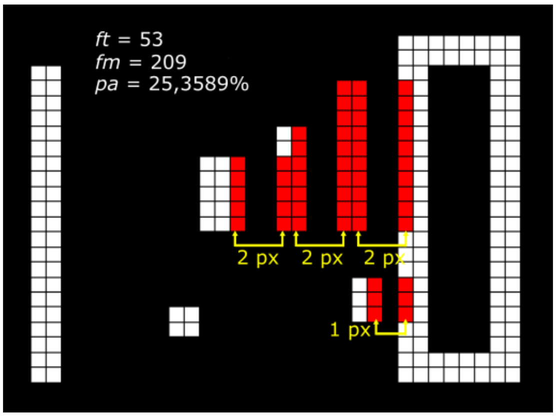
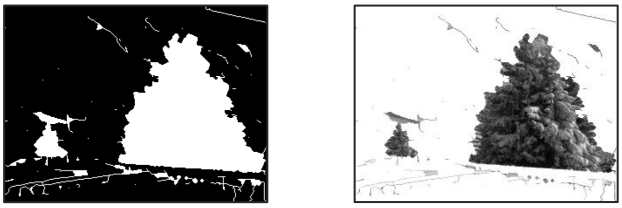


Fig. 9. Transition region with *dt*=2: red box is considered as an adjacent transitional pixel.

(a) (b) (c) (d)

Fig. 10. Image (a) H-connected foreground pixel, (b) spurious pixel, result of (c) H-break removal, (d) Spurious removal.



(a) (b)

Fig. 11. Image (a) binary, (b) segmentation result of the proposed method.

[1]. Thinning operation is conducted to have edges of single pixel width. Many isolated foreground pixels are distributed throughout the image by this operation. A foreground pixel that is located between two short edges or between a short edge and the long edge is considered as H-connected foreground pixel as shown in Fig. 10 (a). Another type of foreground pixel that is expected to be deleted is spurious pixel. Spurious pixel is a foreground pixel that is attached to the edge. It is shown in Fig. 10 (b). There are some morphological operations that are conducted to remove these pixel types: i) cleaning, this process is conducted to remove many isolated foreground pixels. ii) H-break removal is used to remove H-connected foreground pixel. iii) Spurious removal is executed to remove spurious pixels. The output image of these morphological operations is expected to be cleaner as shown in Fig. 10 (c) and (d).

D. Edge linking

The generated edge image from the previous step is not always fully connected. To solve this problem, the edge linking is conducted to the generated edge image. In this study, the edge linking process is adapted from [1]. If an endpoint of foreground edge (discontinuous edge pixel) has not been assigned to another foreground edges, the edge linking process is conducted to the pixel. This pixel will be considered as start pixel. The city block distance from the start pixel to another endpoint of another foreground edge is calculated. Another endpoint that has the smallest city block distance is used as target pixel. The start pixel will be linked to the target pixel if their city block distance is equal or less than 10. The result edge image of this process is expected to be continuous.

E. Region filling & separation of foreground and background

The edge image then undergoes the process of region filling to fill the hole or area in order to obtain a binary image that contains foreground and background as shown in Fig. 11 (a). The binary image is used for the process of separating objects from the background. Pixels of the grayscale image that intersect with foreground pixels in binary image will be displayed. While the background pixels are not displayed. The results of this process can be seen in Fig. 11 (b).

III. EXPERIMENTAL RESULTS AND ANALYSIS

This study used some images from MSRA dataset, Weizmann dataset, and input images from [1]. Some tests were performed to determine the use of filtering and to find the appropriate parameter values for the proposed method. There are several stages that are conducted to test this system. First, the grayscale image is inserted into the system. The image is then segmented by system to obtain a segmented image containing single or multiple objects. The misclassification error (ME), false positive rate (FPR), and false negative rate (FNR) values of segmentation results are then calculated based on ground truth. ME is used to calculate the rate of classification errors in pixels (foreground classified as background or vice versa) using Equation (6).

$$ME = 1 - \frac{|B_o \cap B_t| + |Fr_o \cap Fr_t|}{|B_o| + |Fr_o|} \tag{6}$$

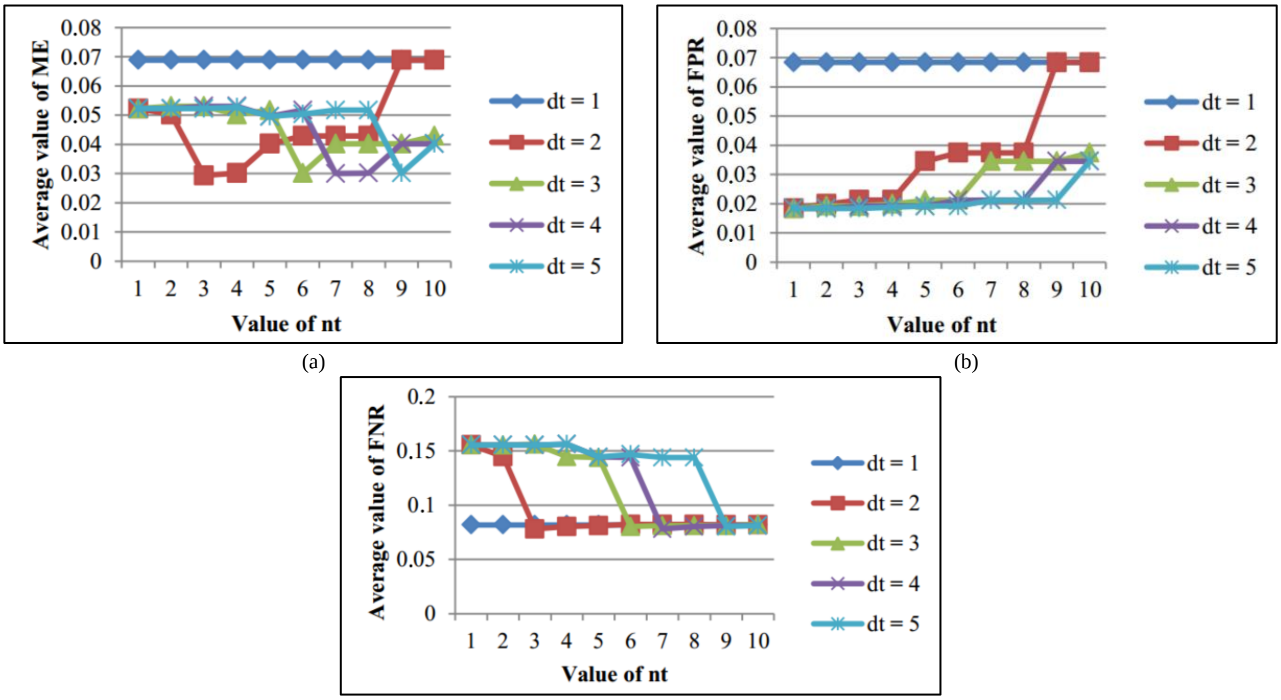
where B_o is the set of background pixel in ground truth image and Fr_o is the set of foreground pixel in ground truth image, while Fr_t and B_t define the set of foreground pixel and the set of background pixel in segmented image. FPR is the rate of background pixels classified as foreground as shown in Equation (7). FNR defines the rate of foreground pixels classified as background using Equation (8). Segmented image that has smaller value of ME, FPR, and FNR is better.

$$FPR = \frac{|B_o \cap Fr_t|}{|B_o|} \tag{7}$$

$$FNR = \frac{|Fr_o \cap B_t|}{|Fr_o|} \tag{8}$$

There are two parameters that are needed by this method to determine whether filtering is used or not: the furthest distance of adjacent transitional pixels *dt* and normal proximity threshold *nt*. Testing is conducted by segmenting the images using *dt* with value 1 to 5 and *nt* with value 1% to 10% to obtain the optimal value of *dt* and *nt*. The results of each parameter combination are shown in Fig. 12. Then, 5 best combinations and the results are shown in Table II.

The ME value is chosen as the basis for determining the optimal value for all parameters required by this system



(a) (b) (c)

Fig. 12. Average value of (a) ME, (b) FPR, and (c) FNR.

because it shows a misclassification on background and foreground. The combination of *dt* and *nt* that produce the best ME value are 2 and 3 as shown in Table II. It shows that the transitional pixels considered adjacent are at a maximum distance of 2 pixels from the other transitional pixels. The more adjacent transitional pixels allow more false transitional pixels to appear. If the number of adjacent transitional pixels is greater than or equal to 3% of the number of attached transitional pixels then the filtering will be performed. Because if too many false transitional pixels appear, it may result in merging the background with foreground that makes the segmentation results worse.

Performance of the proposed method is compared with the other transition region-based image segmentation

TABLE II

THE BEST RESULTS OF COMBINATION OF *DT* AND *NT*

dt	*nt*	Average value of ME	Average value of FPR	Average value of FNR
2	3	**0.0293**	**0.0213**	**0.0779**
4	7	0.0300	0.0213	0.0780
2	4	0.0302	0.0213	0.0803
3	6	0.0302	0.0213	0.0803
4	8	0.0302	0.0213	0.0803

TABLE III

PERFORMANCE MEASURES FOR IMAGE SEGMENTATION BY SEVERAL METHODS

Image type	Image	ME			FPR			FNR		
		MLE	Parida & Bhoi	Proposed	MLE	Parida & Bhoi	Proposed	MLE	Parida & Bhoi	Proposed
1) Simple background & simple foreground	Airplane	0.0263	0.0179	**0.0166**	0.0248	**0.0089**	**0.0089**	**0.0507**	0.1670	0.1457
	Eagle	0.0534	**0.0065**	**0.0065**	0.0308	**0.0047**	**0.0047**	0.4460	0.0378	**0.0376**
	Bird	0.0654	**0.0274**	0.0278	0.0414	**0.0192**	0.0194	0.4808	**0.1684**	0.1708
2) Textured background & simple foreground	Island	0.0435	**0.0106**	0.0142	0.0379	**0.0068**	0.0077	0.1406	0.1168	**0.0979**
	Iceberg	0.1046	**0.0091**	0.0167	0.0456	**0.0036**	0.0126	0.6575	0.0600	**0.0550**
	Duck	0.1756	0.0327	**0.0202**	0.0957	0.0239	**0.0097**	0.7555	0.0957	**0.0950**
3) Simple background & textured foreground	Clock	0.2474	0.0615	**0.0082**	0.0333	**0.0025**	0.0035	0.6819	0.1809	**0.0177**
	Flower	0.1571	**0.0078**	0.0080	0.0678	**0.0072**	0.0075	0.7633	**0.0118**	**0.0118**
	Wall décor	0.0719	0.0628	**0.0584**	0.0475	**0.0208**	0.0210	**0.1163**	0.1389	0.1261
4) Textured foreground & textured background	Caterpillar	**0.0740**	0.1052	0.1168	**0.0707**	0.0974	0.1181	0.1560	**0.0948**	0.1082
	Boat	0.1871	0.0622	**0.0169**	0.0436	0.0017	**0.0011**	0.5243	0.2023	**0.0537**
	Mountain-tree	0.1271	0.0726	**0.0459**	0.1258	0.0721	**0.0364**	0.1308	0.0741	**0.0735**
Average		0.1111	0.0397	**0.0297**	0.0554	0.0224	**0.0209**	0.4086	0.1124	**0.0828**

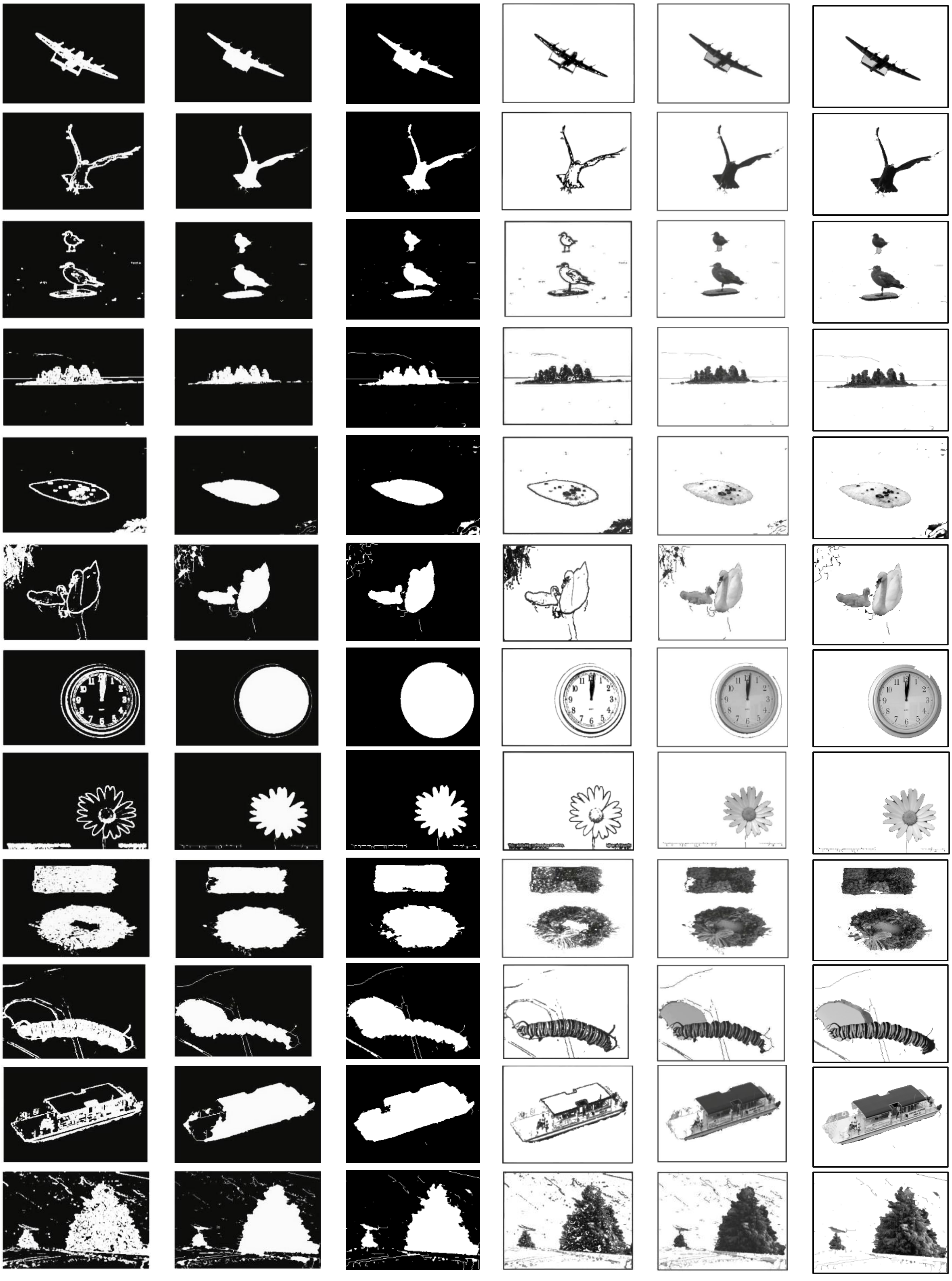
methods: Method by Parida & Bhoi [1] and MLE [18]. The quality of segmentation results by several different methods can only be assessed through visual perception. Fig. 13 shows some results of segmentation obtained by various methods. Table III shows some test results on several types of images. In images with type 1, the proposed method has similar results to the method of Parida & Bhoi. This happens because in this type of image, transition region can be produced well, so filtering process is not done on this type. Furthermore, in the image with type 2, the proposed method has worse ME and FPR values than the result of Parida & Bhoi for island and iceberg image because filtering process is not performed on both images and the edge linking of the proposed method still connects some unnecessary transition region. But the proposed method produces the best result for the duck image because filtering process is done in this image. The use of filtering can make background smoother and make fewer transition regions appear in the background. The proposed method also has the best FNR value indicating that the proposed method can display object better in this type of image.

For segmentation of images with type 3, the proposed method has better ME and FNR values than MLE and Parida & Bhoi methods because the edge linking of the proposed method can connect the transition region that is broken on the clock image. This can happen because the filtering is not done on this image, so there are still many transition regions appear at the edge of the object that facilitate the process of edge linking.

In the image with type 4, the proposed method has the best result for all values on the boat and mountain trees images. Both images get different handling by the proposed method, i.e. without filtering on the boat image and the use of filtering on the mountain trees image. The use of filtering on mountain trees image can reduce the false transition region that appears in the background area while maintaining the transition region's appearance in the object area to facilitate the edge linking process. However, the proposed method has worse ME and FPR values than MLE for caterpillar image.

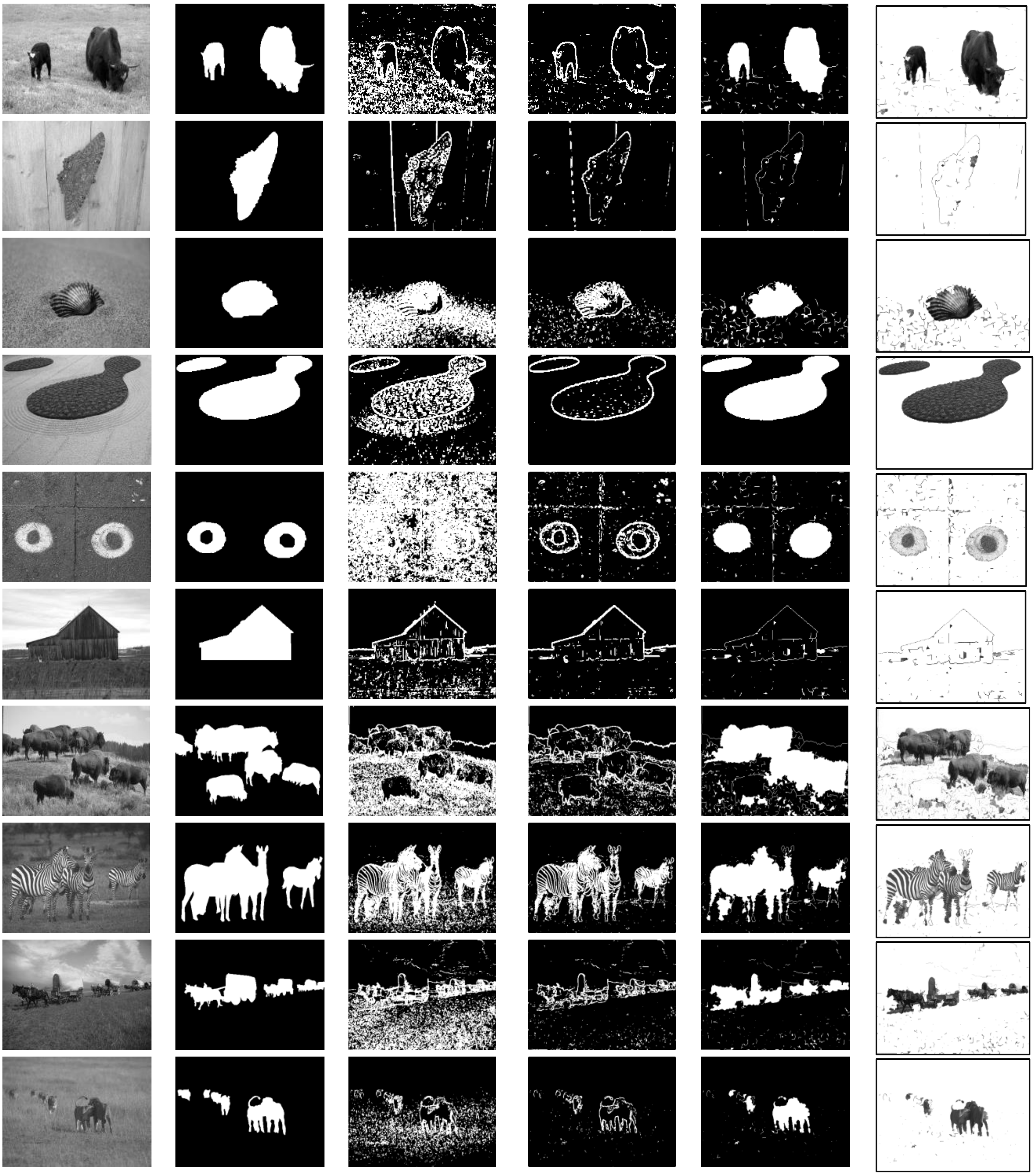
In addition, the proposed method is also tested for some additional images as shown in Fig. 14 and Fig. 15. Fig. 14 shows some images with textured backgrounds while Fig. 15 shows some images with simple backgrounds. Fig. 14 (c) displays the transition region before filtering that contains many false transitional pixels appearing in the background area of the image. The false transitional pixels will increase the number of misclassification error because there are many pixels of background become foreground on the image of segmentation result. This problem can be solved by the proposed method as shown in Fig. 14 (d) that shows the results of transition region refinement with median filter. Fig. 14 (d) shows that many false transitional pixels have been removed so that the segmentation results are better as shown in Fig. 14 (e-f). However, Sometimes the filtering process can lead to deletion of the transition region in the edge of foreground area such as the butterfly and the hut image in Fig. 14 (d). It happens because the foreground and background have similar gray levels like the hut image or the foreground is more textured than the background like the butterfly image. If the number of removed transition regions in the edge of foreground area is quite a lot, it can worsen the results of the edge linking process because the edge linking in this study can only be done on two endpoints of the transition region that has a city block distance of 10. So the foreground on the butterfly and the hut images fails to be segmented intact. Not all images are processed by filtering because they do not meet the criteria for filtering as shown in Fig. 15 (a). The transition region of the image that does not meet the criteria for filtering will pass through the process of transition region refinement without going through the filtering, so there is no change in the transition region after the transition region refinement process.

The use of filtering in the image can reduce the rise of the transition region in both the background and foreground areas. The reduction of the transition region in the background area is very useful because it reduces the occurrence of false transitional pixels in the background area. By reducing the occurrence of false transitional pixels in the background area, the system is easier to determine which objects exist in the image that will make the segmentation errorless. While the reduction of transition region in the foreground area sometimes produces bad results because the transition region that is on the edge of the object may be reduced which can make the transition region is not intact or interrupt the edge linking process. So the determination of when the filtering is used is very important with the aim of maintaining the texture of the object. The proposed method has the ability to determine when the filtering will be used and when the filtering is not used, only images that meet the criteria will be processed by filtering. With the ability of the proposed method, both images with simple or textured backgrounds are successfully segmented with good results and can satisfy the user.



(a) (b) (c) (d) (e) (f)

Fig. 13. Segmentation mask of (a) MLE, (b) Parida & Bhoi, (c) proposed method, segmentation result of (d) MLE, (e) Parida & Bhoi, (f) proposed method.

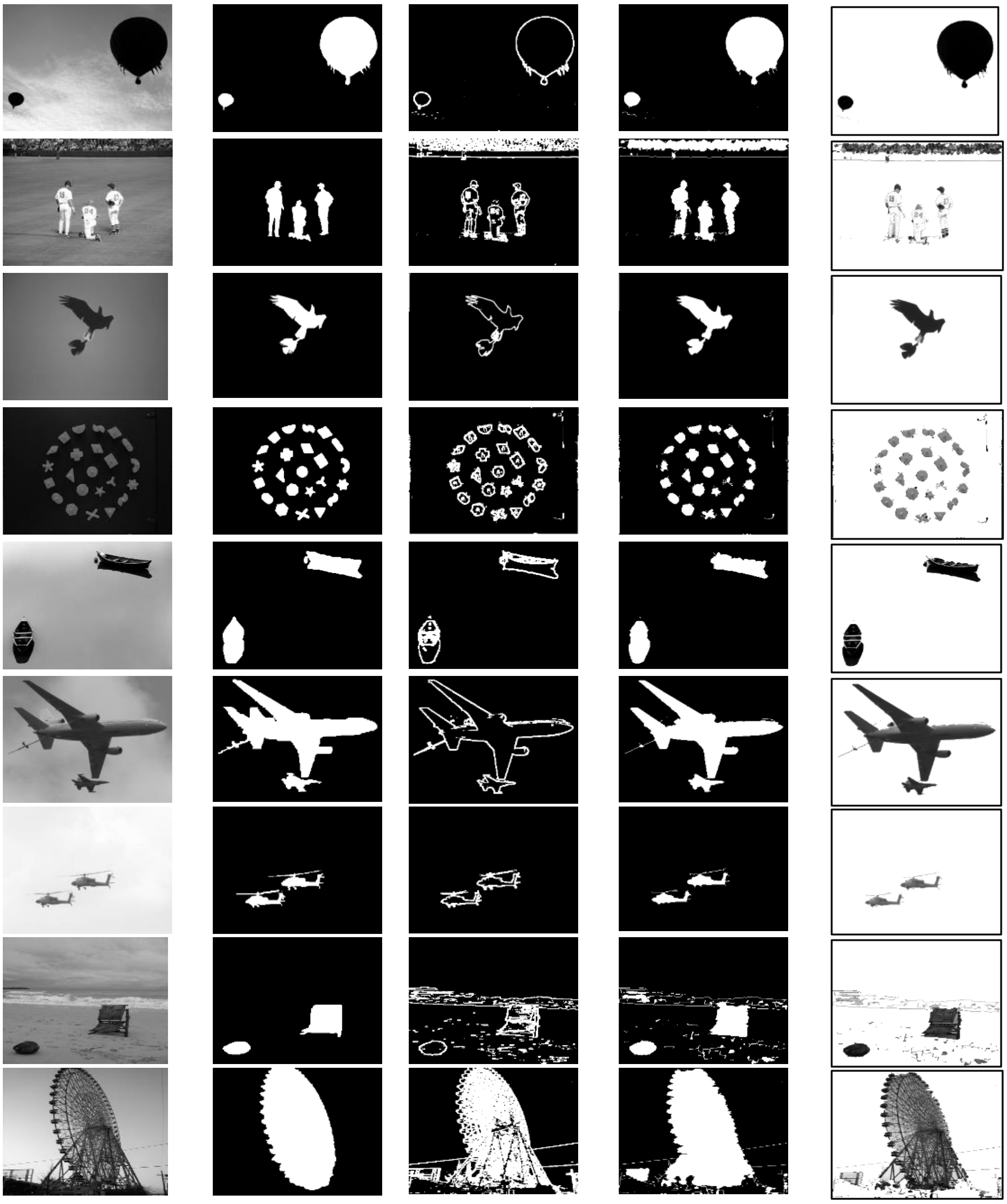


(a) (b) (c) (d) (e) (f)

Fig. 14. Image (a) Input, (b) Ground truth, (c) transition region based on local variance, (d) transition region after refinement by the proposed method, (e) Segmentation mask of the proposed method, (f) Segmentation result of the proposed method.

IV. CONCLUSION

In this paper, a novel method to repair the transition region with median filter based on the percentage of the adjacent transitional pixels has been presented for image segmentation. The proposed method has the best average value of ME, FPR, and FNR than MLE method [18] and the method of Parida & Bhoi [1]. It indicates that the proposed method has better performance of image segmentation than these two method. Moreover, The proposed method works efficiently on the image with a variety of background, especially on image with textured background. However, sometimes the proposed method is difficult to produce a full foreground if the distance between the broken transition region is far.



(a) (b) (c) (d) (e)

Fig. 15. Image (a) Input, (b) Ground truth, (c) transition region based on local variance, (d) Segmentation mask of the proposed method, (e) Segmentation result of the proposed method.

REFERENCES

[1] P. Parida and N. Bhoi, "Transition region based single and multiple object segmentation of grayscale images," *Eng. Sci. Technol. an Int. J.*, vol. 19, no. 3, pp. 1206–1215, 2016.

[2] J. Kittler and J. Illingworth, “Minimum error thresholding,” *Pattern Recognit.*, vol. 19, no. 1, pp. 41–47, 1986.

[3] G. Qorik *et al.*, “SEGMENTASI CITRA PANORAMIK GIGI MENGGUNAKAN SIMILARITAS ANTAR GRAY LEVEL BERDASARKAN INDEX OF FUZZINESS,” *JUTI J. Ilm. Teknol. Inf.*, vol. 14, pp. 83–90, 2016.

[4] B. M. K. Dan, P. Citra, and L. Myeloid, “Segmentasi dan pemisahan sel darah putih bersentuhan menggunakan k-means dan hierarchical clustering analysis pada citra leukemia myeloid akut,” *JUTI J. Ilm. Teknol. Inf.*, vol. 15, pp. 140–151, 2017.

[5] F. A. Hermawati, H. Tjandrasa, and N. Suciati, “Hybrid Speckle Noise Reduction Method for Abdominal Circumference Segmentation of Fetal Ultrasound Images,” *Int. J. Electr. Comput. Eng.*, vol. 8, no. 3, pp. 1747–1757, 2018.

[6] M. E. Nilsback and A. Zisserman, “Automated flower classification over a large number of classes,” *Proc. - 6th Indian Conf. Comput. Vision, Graph. Image Process. ICVGIP 2008*, pp. 722–729, 2008.

[7] Y. Y. Boykov and M.-P. Jolly, “Interactive graph cuts for optimal boundary & region segmentation of objects in N-D images,” *Proc. Eighth IEEE Int. Conf. Comput. Vision. ICCV 2001*, vol. 1, no. July, pp. 105–112, 2001.

[8] S. Yousefi, R. Azmi, and M. Zahedi, “Brain tissue segmentation in MR images based on a hybrid of MRF and social algorithms,” *Med. Image Anal.*, vol. 16, no. 4, pp. 840–848, 2012.

[9] M. Lee, W. Cho, S. Kim, S. Park, and J. H. Kim, “Segmentation of interest region in medical volume images using geometric deformable model,” *Comput. Biol. Med.*, vol. 42, no. 5, pp. 523–537, 2012.

[10] T. a. Ta, T. H. Cao, and T. V. Nguyen, “The Hybrid Approach of Image Segmentation Using MeanShift and Saliency Maps,” *2012 Fourth Int. Conf. Knowl. Syst. Eng.*, pp. 11–17, 2012.

[11] A. Nyma, M. Kang, Y.-K. Kwon, C.-H. Kim, and J.-M. Kim, "A Hybrid Technique for Medical Image Segmentation," *J. Biomed. Biotechnol.*, vol. 2012, pp. 1–7, 2012.

[12] C. C. Kang, W. J. Wang, and C. H. Kang, "Image segmentation with complicated background by using seeded region growing," *AEU - Int. J. Electron. Commun.*, vol. 66, no. 9, pp. 767–771, 2012.

[13] K. Strasters and J. Gerbrands, "Three-dimensional image segmentation using a split, merge and group approach," *Pattern Recognit. Lett.*, vol. 12, no. May, pp. 307–325, 1991.

[14] Z. Li, G. Liu, D. Zhang, and Y. Xu, "Robust single-object image segmentation based on salient transition region," *Pattern Recognit.*, vol. 52, pp. 317–331, 2016.

[15] Y. J. Zhang and J. J. Gerbrands, "Transition region determination based thresholding," *Pattern Recognit. Lett.*, vol. 12, no. 1, pp. 13–23, 1991.

[16] C. Yan, N. Sang, and T. Zhang, "Local entropy-based transition region extraction and thresholding," *Pattern Recognit. Lett.*, vol. 24, no. 16, pp. 2935–2941, 2003.

[17] Z. Li and C. Liu, "Gray level difference-based transition region extraction and thresholding," *Comput. Electr. Eng.*, vol. 35, no. 5, pp. 696–704, 2009.

[18] Z. Li, D. Zhang, Y. Xu, and C. Liu, "Modified local entropy-based transition region extraction and thresholding," *Appl. Soft Comput. J.*, vol. 11, no. 8, pp. 5630–5638, 2011.

[19] A. W. Rosyadi, R. Danardono, S. S. Manek, and A. Z. Arifin, "A Flexible Sub-Block In Region Based Image Retrieval Based On Transition Region," *J. Ilmu Komput. dan Inf.*, vol. 11, no. 1, pp. 42–51, 2018.