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INTELLIGENT SEGMENTATION OF FRUIT IMAGES USING AN INTEGRATED THRESHOLDING AND ADAPTIVE K-MEANS METHOD (TSNKM)

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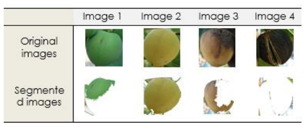
Graphical abstract



Abstract

Recent years, vision-based fruit grading system is gaining importance in fruit classification process. In developing the fruit grading system, image segmentation is required for analyzing the fruit objects automatically. Image segmentation is a process that divides a digital image into separate regions with the aim to obtain only the interest objects and remove the background. Currently, there are several segmentation techniques which have been used in object identification such as thresholding and clustering techniques. However, the conventional techniques have difficulties in segmenting fruit images which captured under natural illumination due to the existence of non-uniform illumination on the object surface. The presence of different illuminations influences the appearance of the interest objects and thus misleads the object analysis. Therefore, this research has produced an innovative segmentation algorithm for fruit images which is able to increase the segmentation accuracy. The developed algorithm is an integration of modified thresholding and adaptive K-means method. The integration of both methods is required to increase the segmentation accuracy for fruits images with different surface colour. The results showed that the innovative method is able to segment the fruits images with high accuracy value,

Keywords: Segmentation, thresholding, K-means, Fuzzy C-means, active contour, natural illumination

1.0 INTRODUCTION

Image segmentation plays important role in computer vision application particularly for fruit grading system. In general, segmentation technique emulates the abilities of humans in recognizing objects. In addition, this technique offers non-destructive method for classifying objects and produces more consistent result than humans. Specifically, the segmentation process divides a digital image into different regions. This process is required to make sure that the interest area could be perfectly and correctly isolated from the background area with the aim to increase the accuracy in object identification phase. An incorrect segmentation degrades the segmentation process and therefore will produce poor result in object analysis. There are several segmentation techniques that can be used to segment digital images. Of all the techniques, thresholding and clustering are extensively used in agricultural area. However, previous studies have shown that these conventional techniques were inadequate for segmenting fruit images captured in natural environment. This is because the images are exposed to the non-uniform illumination, which influences the surface characteristics of the images. The natural lights reflect the object surface and the object will be seen lighter or darker. Therefore, some of the objects were wrongly segmented as shown in the second row in Figure 1. In this study, jatropha fruit images were used for segmenting and analyzing processes.

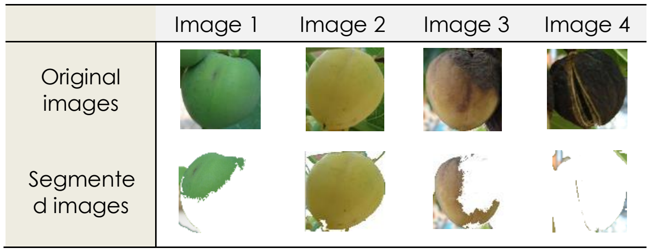


Figure 1 Original and Segmented Images

Jatropha fruit is chosen because it has different surface colour indicating its maturity stages [1][2]. There are four categories of jatropha as presented in Figure 1. The categories are green (Image 1), yellow (Image 2), yellowish-brown (Image 3) and black (Image 4). In the acquisition phase, all the images were captured using a digital camera in a jatropha orchard.

1.1 Thresholding-based Segmentation Technique

Thresholding-based is one the technique that was extensively used for image segmentation. This technique have several advantages such as small storage space, fast processing and easy to manipulate [3]. In addition, it is very simple where it divides the digital image into numerous areas based on the gray levels of the image. The thresholding technique classifies each pixel in the image into two areas. The first is area of interest while the second is area of background. In this case, pixels with different gray level belonged to the class of interest area while pixels with the same gray level belonged to the class of background [4], [5].

Previous researches have shown that thresholding-based technique has been successfully implemented in agricultural application such as in determining tomatoes and oranges [6], date fruit [7] and mangoes [8]. In the research conducted by Haidar *et al*. [8] have developed an adaptive thresholding technique to perform segmentation on date fruit. However, the experiment was conducted in controlled environment. The segmentation process in natural scene becomes more difficult because of the non-uniformity illumination and difference of reflection [9].

For thresholding technique, there are several well-known methods which were extensively used by researchers. One of the methods is Otsu method [10] which utilizes the grayscale image to produce a gray level histogram. The histogram is used to get the optimal threshold value automatically. Threshold value is required to convent the grayscale image into segmented binary image which divides the image into interest area and background. The segmented images are in binary format where value '1' (white pixel) represents interest area and value '0' (black pixel) represents background area.

However, using Otsu method only is not sufficient to properly separate the area of interest from background for images captured under natural environment. This is due to the non-uniform illumination and complex background.

The results in Figure 2 showed that the segmented images were not separated correctly. Therefore, several researchers have developed algorithms that integrated Otsu with other techniques to increase the accuracy of the segmented images. One of technique that get the highest interest from researchers is clustering-based technique.

Haniza *et al.* [11] have developed an improved segmentation method which combined Otsu with FCM and edge detection methods. This algorithm was applied to identify lesions in human retina by extracting edge pixels of the lesions from the background. The performance of the improved method was measured based on true positive fraction (TPF) and true negative fraction (TNF) and the results showed that the method was more accurate than the conventional Otsu and FCM. Krishnaveni & Radha [12] have combined the threholding technique with Particle Swarm Optimization (PSO) method to improve the segmentation method. This proposed method was applied in segmenting sign language images and the results proved that the integrated technique was able to produced higher quality segmented images. J. Wang *et al.* [13] has also proposed an integrated algorithm where it combined Otsu and Canny edge detector to segment a single jujube leaf from leaves images. The results showed that the algorithm has the ability to extract more accurate leaf area even though the jujube leaf was overlapped with other leaves.

1.2 Clustering-based Segmentation Technique

Clustering-based is an unsupervised technique which was extensively used for image segmentation. This technique classifies a set of data into different clusters based on the similarity of features without prior knowledge about the distribution of the data [14]. The clustering technique has been used in many areas such as medical and agriculture. It was applied to find meaningful patterns and to map new data onto identified clusters [15]. Clustering technique can be divided into two types; hard and fuzzy [16].

In hard clustering, the data is divided into two clusters and each data item is assign to only one cluster. While for fuzzy clustering, each data item can be assigned to more than one cluster. The fuzzy technique offers more flexible segmentation process and also able to handle outliers. However, both hard and fuzzy clustering-based techniques have different capabilities in segmenting images. The following sub section reviews the most well-known clustering method for both approaches. The most popular methods for hard and fuzzy clustering techniques are K-means and Fuzzy c-means (FCM), respectively.

K-means method is an unsupervised clustering method which classifies a set of data into multiple (*K*) classes or clusters. This method was recommended by many researchers because it is capable to handle large data sets with straightforward implementation. K-means algorithm classifies each data point to the cluster based on the shortest Euclidean distance to the cluster centers. Although K-means is simple and straightforward, the performance of this algorithm was highly influenced by the initial cluster centre. Previous studies have shown that K-means shows good segmented images only if the cluster centre was initialized correctly. However, the initialization of the cluster centre is more difficult for images captured under non-uniform illumination condition.

FCM is a fuzzy clustering method which allows each data point to be assigned into more than one clusters [17]. The data is assigned to the different clusters based on its membership values. From literature, it showed that FCM method is easy to implement and able to produce good results in segmenting images under controlled environment. However, this method was not comprehensively applied under natural environment. Its sensitivity to the variation of illumination which involves the element of fuzziness and uncertainty lead to the poor segmentation result.

Recently, many researchers have proposed an enhancement of K-means and FCM methods to increase the performance of segmentation process. Siti Noraini & Nor Ashidi [18] have developed an adaptive fuzzy k-means (AFKM) for segmenting indoor and outdoor images. In this research, both K-means and FCM methods were integrated to obtain an optimum cluster center value in order to achieve the best segmented images. Halder *et al.* [19] has also presented an integrated algorithm which combined FCM and genetic algorithm (GA) methods to segment images which captured under natural environment. The advantage of this method was that it did not require the initialization of cluster number. The results showed that the integrated method has the ability to split the images into an optimal number of regions satisfactorily compared to K-means, FCM and fuzzy neural network. Valliammal & Geethalakshmi [20] have also performed a combination of two methods to extract plant leaf image from its background. The researchers have combined K-means and Sobel edge detector because the integration of both methods has successfully produced more accurate results compared to the conventional K-means. Another study on segmenting natural images was conducted by Dante *et al.* [17]. This study has used FCM method to segment the images which adopted from Berkeley data set. However, the used of FCM only is not enough and therefore this research enhanced the method by combining RM-L and L estimators to acquire sufficient spatial information of the images. The estimators were used to detect the presence of impulsive noise with the aim to remove the noise. The improved method was validated on several natural images and the results showed that it was efficient and robust even though the images were exposed to sunlight.

Even though K-means and FCM have been improved by several researchers, these methods have limited capability in segmenting natural images especially for images with different pixel intensity value. The difference of the intensity value was due to the existence of sunlight illumination on the object surface. Therefore, this study has developed a superior segmentation method namely TsNKM to improve the accuracy of the segmented images captured under natural environment.

2.0 AN IMPROVED THRESHOLDING AND ADAPTIVE K-MEANS (TsNKM) METHOD

TsNKM method [22] was developed to overcome the limitations in segmenting natural images. This method integrates two algorithms to allow all fruit images be segmented properly. The two algorithms are improved thresholding [23] and adaptive K-means [24]. The integration of these algorithms was required because the improved thresholding is more suitable for segmenting images with lighter objects such as green, yellow and yellowish-brown, while adaptive K-means is more suitable for images with darker objects. Therefore, the improved thresholding is a complement for the adaptive K-means and thus enables to provide better quality segmented images.

The decision to perform either improved thresholding or adaptive K-means algorithms is based on the object surface colour. In this study, the colour of interest object was measured using LAB colour format. The average of each L*, A* and B* colour element was first measured individually and then added to get the total mean of LAB value. TsNKM is able to provide more intelligent capability because it used IF-THEN rules to select appropriate algorithm for specific images. The selection rules for TsNKM are as follows;

$$\text{Segmentation} \begin{cases} \text{Improved thresholding} & \text{if} \quad 37 <= \text{Mean LAB} <= 68 \\ \text{Adaptive K-means} & \text{if} \quad \text{Mean LAB} < 37 \text{ or Mean LAB} > 68 \end{cases}$$

The complete algorithm of TsNKM method is shown in Figure 2.

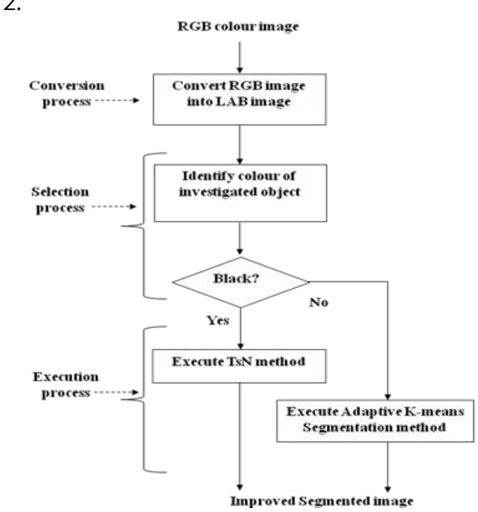


Figure 2 TsNKM Algorithm

TsNKM algorithm consists of three processes; conversion, selection and execution. Conversion process refers to the conversion of image in RGB colour format into LAB format. The LAB format was chosen because it is one of the most suitable colour models for outdoor images [25] and the best match to human perception on colours [26]. The second process which is selection refers to the identification of the interest object in the image. The identification was made based on the LAB colour value which calculated from the object surface colour. The interest object was labelled dark object if the average value of LAB is between 37 and 68, while the object was labelled light object if the value is less than 37 or more than 68. Execution process refers to the implementation of improved thresholding and adaptive K-means methods which depends on the colour identified in the selection process. If the object is dark, the improved thresholding was executed else if the object was light, the adaptive K-means segmentation was executed. Both improved thresholding and adaptive K-means algorithms are presented in Figure 3 and Figure 4, respectively.

The ability of improved thresholding algorithm in segmenting the darker object was contributed by an automatic adjustment of threshold value and inverse algorithm. The adjustment of threshold value is very important to adjust the threshold value automatically until good segmented images were obtained.

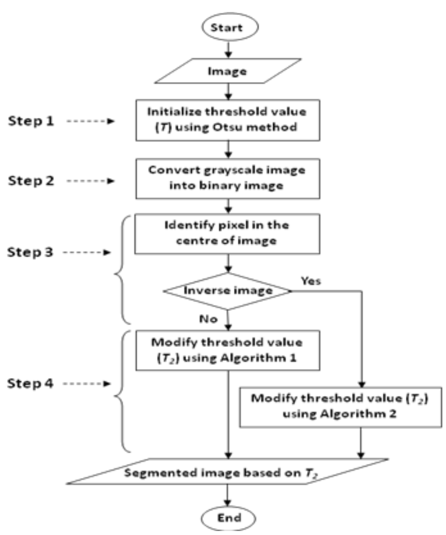


Figure 3 Improved Thresholding Algorithm

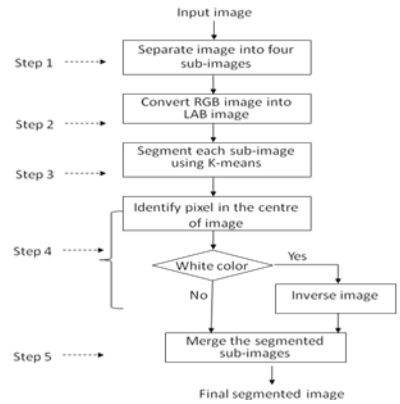


Figure 4 Adaptive K-means Algorithm

The adaptive K-means has the advantage in segmenting lighter objects because it contains two significant processes. The first is separation process which separates an original image into four sub-images. Then, each sub-image was segmented using K-means method. The separation process was required to produce an optimum local intensity value for each sub-image so that the segmentation for the whole original image was more accurate. The segmentation process for each sub-image is shown in Figure 5.

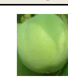
	Image 1	Image 2	Image 3
Original images			
Segmented sub-images			

Figure 5 Segmentation of Sub-images

From the figure, it was observed that some of the segmented areas of sub-images were not correctly classified where the interest areas were wrongly filled with black pixels. Hence, an inverse process was added to solve the limitation. In this process, if the pixel of interest area is black, it was change to white. Next, the sub-images were recombined to generate a segmented image for the entire object. This process is shown in Figure 6.

	Image 1	Image 2	Image 3
Segmented sub-images			
Improved sub-images			
Final segmented images			

Figure 6 Improved Segmented Images using Inverse and Merge Process

3.0 RESULTS AND DISCUSSION

In this section, discussion on the segmentation results produced by Otsu, FCM, K-means and TsNKM is presented. The results are important to measure and compare the performance of all the methods. The comparison is made based on visual evaluation and quantitative evaluation. Both evaluations are discussed in the following sub sections.

3.1 Visual Evaluation of Different Segmentation Methods

Visual evaluation was made based on human perception on the shape of the segmented images. The correct segmented image is denoted by the image with all its pixels which correctly classified as interest area or background area. The correct classified pixels are the pixels which filled with white colour for interest area and black colour for background.

For this research, 100 images of jatropha fruit with four different surface colours were captured and examined. However, for discussion purposes, only four samples are presented in this section. Each sample is used to represent each category of jatropha fruit. The categories are green, yellow, yellowish-brown and black. Figure 7 presents the results of four samples using four segmentation methods. The methods are Otsu, FCM, K-means, and TsNKM. The original images are coded as G1 for green jatropha, Y1 for yellow, Yb1 for yellowish-brown, and B1 for black. All segmented images are represented in binary format with consists of two areas. The areas are interest area (filled with white pixels) and background area (filled with black pixels).

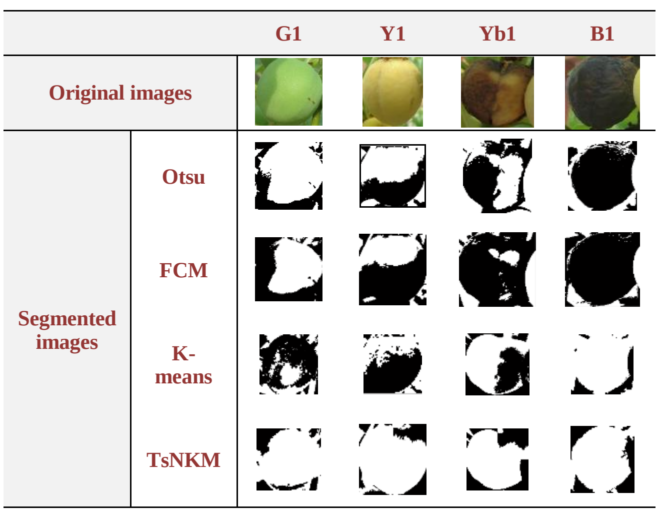


Figure 7 Original and Segmented Images

The observation on the segmented images showed that some of the images were not divided correctly and perfectly by Otsu, K-means and FCM methods. In this experiment, two major problems of the segmented images were observed. The first problem was that the three conventional methods have misclassified some interest area as background where those areas were wrongly filled with black pixels. The images which were wrongly classified are G1, Y1 and Yb1. As a result, the shape of the interest area for these images was not complete, thus reducing the accuracy of the segmented images.

The second problem was that Otsu and FCM have wrongly produced reverse segmented images for image B1. Reverse segmented image refers to the interest area that was reversely classified as background area and vice versa. In this case, the interest area was wrongly filled with black pixels while the background area was wrongly filled with white pixels.

There are two factors that caused the misclassification of the interest area. The first factor was some areas in the original images were seen darker due to the presence of shadow on the object surface as shown in image G1 and Y1. The second factor was the existence of non-uniform natural illumination on the object surface. The presence of illumination on the images produced inappropriate cluster center for FCM and K-means method, and thus leads to inaccurate segmentation results.

In comparison, it was discovered that TsNKM method has successfully produced more accurate segmented images. This is because the interest areas for images G1, Y1, Yb1 and B1 which produced by this method are wider and more perfect. In this case, the interest areas were correctly filled with white pixels and the background areas were correctly filled with black pixels. This results show that TsNKM has the ability to produce good segmented images regardless of objects surface colour. However, visual evaluation is very subjective and arguable because it was measured based on human perception. Therefore quantitative evaluation was then conducted to prove the results and the discussion on this evaluation is presented in the following sub section.

3.2 Quantitative Evaluation of Different Segmentation Methods

Quantitative evaluation was performed by comparing the similarity between segmented images and ground truth. The ground truth refers to a set of ideal images which were created exclusively by human. Each ideal image consists of two correct areas where the first is interest area denoted by white pixels and the second is background area denoted by black pixels. Samples of the ground truth images are shown in Figure 8.

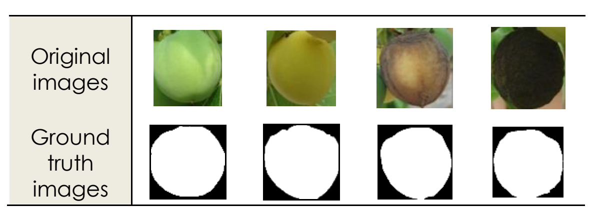


Figure 8 Original and Ground Truth Images

The used of ground truth images is significant in image segmentation to measure how similar is the segmented image to the ideal image. The more similar is the segmented image to the ideal image, the better is the quality of the images. For this study, the similarity of the segmented images was measured by Similarity Index (SI) [27], and Tanimoto Coefficient (TC) [28], [29]. Both SI and TC measure the similarity of the segmented images by calculating the number of foreground pixels that are correctly classified. However, these two measurements have different formulas as shown in Table 1.

Table 1 Formula of Similarity Index (SI) and Tanimoto Coefficient (TC)

	Similarity Index (SI)	Tanimoto Coefficient (TC)
Formula	$2.\frac{n\{A_1 \cap A_2\}}{n\{A_1\}+n\{A_2\}}$	$\frac{n\{A_1 \cap A_2\}}{n\{A_1 \cup A_2\}}$

where;

- A_1 represents ground truth image and A_2 represents segmented image.
- $n\{A_1 \cap A_2\}$ denotes the common area in both set A_1 and A_2 or the number of correctly classified foreground pixels.
- $n\{A_1 \cup A_2\}$ denotes the number of elements either in set A_1 or A_2.
- $n\{A_1\}$ and $n\{A_2\}$ denotes the number in set A_1 and A_2, respectively.

The value of SI and TC varies between 0 and 1. The nearer the value to 1, the higher is the quality of segmented images. Table 2 displays the values of SI and TC for Otsu, FCM, K-means and TsNKM methods. These values are important to evaluate the performance of these methods.

In general, TsNKM has outperformed three other methods in segmenting all the images. This is because all the SI and TPR values produced by TsNKM are higher than the values produced by Otsu, FCM and K-means. The higher values show that the segmented images produced by TsNKM are more similar to the ground truth. Moreover, it indicates that TsNKM is able to segment the images with more perfect shape of the interest area.

Table 2 Similarity Index (SI) and Tanimoto Coefficient (TC) for Otsu, FCM, K-means and TsNKM Methods

		Image 1	Image 2	Image 3	Image 4
Similarity Index (SI)	Otsu	0.826	0.648	0.482	0.104
	FCM	0.778	0.529	0.144	0.016
	K-means	0.296	0.497	0.789	0.894
	TsNKM	0.872	0.904	0.911	0.921
Tanimoto Coefficient (TC)	Otsu	0.757	0.480	0.318	0.055
	FCM	0.637	0.394	0.078	0.008
	K-means	0.174	0.388	0.652	0.808
	TsNKM	0.774	0.917	0.836	0.854

Based on the above table, it demonstrates that TsNKM has consistently produced the highest SI values. In addition, all the values produced by TsNKM are more than 0.81 which indicate that the segmented images have achieved almost perfect similarity [30].

The TC values produced by TsNKM are also the highest compared to those values produced by other three methods. This measurement also shows that the segmented images for TsNKM were more similar to the ground truth.

The good achievement of TsNKM is contributed by two main factors. The first factor is the addition of separation and inverse process in Adaptive K-means algorithm which increase the accuracy in segmenting images of lighter objects. The second factor is the insertion of inverse and adjustment of threshold value process in improved thresholding algorithm. This process allows TsNKM to segment dark images perfectly and accurately. Therefore, it proves that TsNKM has the ability to produce good segmented images for objects with different colours even though the objects were exposed to natural illumination.

The strength of TsNKM was then validated to make sure that this method is competent in segmenting other fruit images. The following section discusses the results from segmentation experiments using different fruits.

3.3 Validation of TsNKM using Other Fruits

The segmented images of different fruits which produced by TsNKM are shown in Figure 9. The SI and TC values for all the segmented images are also presented to prove the ability of TsNKM in producing good results.

	Original images	Segmented images	SI	TC
Green mangoesteen			0.854	0.982
Yellow mango			0.899	0.837
Yellow brown pomegranate			0.921	0.969
Red chilli			0.970	0.968
Purple mangoesteen			0.938	0.978
Black plum			0.772	0.703

Figure 9 Segmented Images of Different Fruits using TsNKM

The results reveal that TsNKM has effectively produced high quality segmented images for all fruits regardless of their surface colour. The segmented images have almost perfect shape of interest area where most of the pixels in the interest area were correctly filled with white pixels. In addition, almost all the SI and TC values produced by TsNKM are more than 0.81. These values indicate that TsNKM is able to segment fruit images with high accuracy value even though the images were captured in natural environment.

4.0 CONCLUSIONS

In conclusion, TsNKM method has a great potential in segmenting all categories of objects even though the objects are varies in terms of colour and illumination exposure. The integration of improved thresholding and adaptive K-means algorithms enables TsNKM to intelligently and correctly select the appropriate process for each image. The developed algorithm shows interesting features where it is able to extract almost perfect shape of interest area from the background. Both visual and quantitative evaluations have verified that TsNKM is able to produce good segmentation results. Thus, it is recommendable for this method to be applied in vision-based application especially in fruit grading system.

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References

[1] Pradhan, R. C., Naik, S. N., Bhatnagar, N., & Vijay, V. K. 2009. Moisture-dependent Physical Properties of Jatropha Fruit. *Journal of Industrial Crops and Products.* 29: 341-347.

[2] Zulham, E., Rizauddin, R., Jaharah, A. G., & Zahira, Y. 2009. Development of Jatropha Curcas Color Grading System for Ripeness Evaluation. *European Journal of Scientific Research*. 30(4): 662-669.

[3] Huang, Q., Gao, W., & Cai, W. 2005. Thresholding Technique with Adaptive Window Selection for Uneven Lighting Image. *Pattern Recognition Letters of Elsevier*. 26: 801-808.

[4] Pal, N. R., & Pal, S. K. 1993. A Review on Image Segmentation Techniques. *Pattern Recognition.* 26(9): 1277-1294.

[5] Sahoo, P. K., Soltani, S., & Wong, A. K. C. 1988. A Survey Of Thresholding Techniques. *Computer Vision, Graphics and Image Processing*. 41: 233-260.

[6] Yin, J.-j., Mao, H.-p., & Zhong, S.-y. 2009. Segmentation Methods of Fruit Image based on Color Difference. *Journal of Communication and Computer.* 6(7): 40-45.

[7] Haidar, A., Dong, H., & Mavridis, N. 2012. Image-based Date Fruit Classification. *Paper presented at the IV International Congress on Ultra Modern Telecommunication and Control Systems* 2012.

[8] Payne, A. B., Walsh, K. B., Subedi, P. P., & Jarvis, D. 2013. Estimation of Mango Crop Yield using Image Analysis - Segmentation Method. *Computers and Electronics in Agriculture.* 91: 57-64.

[9] Dai, M., Baylou, P., Humbert, L., & Najim, M. 1996. Image Segmentation by a Dynamic Thresholding using Edge Detection Based On Cascaded Uniform Filters. *Signal Processing*. 52. 49-63.

[10] Otsu, N. 1979. A Threshold Selection Method from Gray-Level Histograms. *IEEE Transactions on Systems, Man and Cybernetic.* 9(1): 62-66.

[11] Haniza, Y., Hamzah, A., & Hazlita, M. I. 2012. Exudates Segmentation using Inverse Surface Adaptive Thresholding. *Measurement*. 45:1599-1608.

[12] Krishnaveni, M., & Radha, V. 2011. Improved Histogram Based Thresholding Segmentation using PSO For Sign Language Recognition. *International Journal of Engineering Science and Technology (IJEST).* 3(2): 1014-1020.

[13] Wang, J., He, J., Han, Y., Ouyang, C., & Li, D. 2013. An Adaptive Thresholding Algorithm Of Field Leaf Image. *Computers and Electronics in Agriculture*. 96: 23-39.

[14] Jain, A. K. 2010. Data Clustering: 50 Years Beyond K-Means. *Pattern Recognition Letters of Elsevier*. 31: 651-666.

[15] Ghabousian, A., & Shamsi, M. 2012. Segmentation of Apple Color Images Utilizing Fuzzy Clustering Algorithms. *Advances in Digital Multimedia.* 1(1): 59-63.

[16] Brouwer, R. K., & Groenwold, A. 2010. Modified Fuzzy C-Means For Ordinal Valued Attributes with Particle Swarm for Optimization. *Fuzzy Sets and Systems*. 161: 1774-1789.

[17] Dante, M.-V., Franicsco, J. G.-F., & Alberto, J. R.-S. 2013. A Fuzzy Clustering Algorithm with Spatial Robust Estimation Contraint for Noisy Color Image Segmentation. *Pattern Recognition Letters of Elsevier.* 34: 400-413.

[18] Siti Noraini, S., & Nor Ashidi, M. I. 2010. Adaptive Fuzzy-K-Means Clustering Clustering Algorithm for Image Segmentation. *IEEE Transactions of Consumer Electronics*. 56(4): 2661-2668.

[19] Halder, A., Pramanik, S., & Kar, A. 2011. Dynamic Image Segmentation using Fuzzy C-Means Based Genetic Algorithm. *International Journal of Computer Applications*. 28(6): 15-20.

[20] Hamirul'Aini Hambali, Sharifah Lailee Syed Abdullah, Nursuriati Jamil & Hazaruddin Harun 2014. A Rule-based Segmentation Method for Fruit Images Under Natural Illumination. *Proceeding of the 2014 International Conference on Computer, Control, Informatics and Its Applications.* Bandung, Indonesia.

[21] Sharifah Lailee, S. A., Hamirul'Aini, H., & Nursuriati Jamil 2012. Segmentation of Natural Images using An Improved Thresholding-Based Technique. International Symposium on Robotics and Intelligent Sensors IRIS 2012. *Procedia Engineering.*

[22] Sharifah Lailee, S. A., Hamirul'Aini, H., & Nursuriati Jamil 2013. Adaptive K-means Method for Segmenting Images Under Natural Environment. *Proceeding of the 4th International on Computing and Informatics (ICOCI 2013).* Sarawak, Malaysia.

[23] Valliammal, N., & Geethalakshmi, S. N. 2012. Plant Leaf Segmentation using Non Linear K-Means Clustering. *International Journal of Computer Science Issues* (IJCSI). 9(3): 212-218.

[24] Bharati, P. T., & Subashini, P. 2013. Texture Based Color Segmentation For Infrared River Ice Images using K-Means Clustering. *Paper Presented at the International Conference on Signal Processing, Image Processing and Pattern Recognition* (ICSIPR).

[25] Shammala, F. A., & Ashour, W. 2013. Color Based Image Segmentation using Different Versions of K-Means in Two Spaces. *Global Advanced Research Journal of Engineering, Technology and Innovation*. 1(9): 030-041.

[26] Zijdenbos, A. P., Dawant, B. M., Margolin, R. A., & Palmer, A. C. 1994. Morphometric Analysis of Whiite Matter Lessions in MR Images: Method and Validation. *IEEE Transactions on Medical Imaging*. 13(4): 716-724.

[27] Alaniz, J. R. J., Medina-Banuelez, V., & Yanez-Suarez, O. 2006. *Data-Driven Brain MRI Segmentation Supported on Edge Confidence and a Priori Tissue.*

[28] Viera, A. J., & Garrett, J. M. 2005. Understanding Interobserver Agreement: The Kappa Statistic. *Research Series: Family Medicine.* 37(5): 360-363.