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Image Convolution to Obtain Color ROI after Segmentation Process with Fuzzy Cmeans

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Abstract

Image segmentation is still an important concern in terms of digital image processing. Segmentation refers to dividing an image into several parts based on similar characteristics or uniformity. Its use is quite important, especially related to the analysis and application of digital image processing. The challenge faced is separating the object image from its background in images with complex backgrounds. The aim of this research is to separate tomatoes from simple to complex backgrounds. This paper proposes a convolution method of segmented binary images and RBG images all based on contours using Fuzzy C-means and reconstruction operations to obtain the foreground from an image with a complex background. This method has been tested on ripe tomatoes with various backgrounds. This method has Indicated Performance Achievement Sc = 99.2%, Fpe = 0.6% and FNe = 0.4%. This shows that the method is suitable and robust for the dataset used in this study, especially if it will be continued for further work related to the classification of tomato maturity assessment.

Keywords: background, foreground, fuzzy cmean, convolution, segmentation

1. Introduction

Image segmentation is still an important concern in terms of digital image processing. Segmentation refers to the partition [1] of an image into several parts based on the similarity of features [2] or the uniformity possessed [3]. Its usefulness is quite important, especially related to the analysis and application of digital image processing. The challenge faced is that there is no single segmentation method that can be used for all cases. This is because the image has differences in color, texture, illumination level and different noise. Usually segmentation uses local information in digital images to calculate the best segmentation, such as color information used to create a histogram or information that shows edge, border, or texture information [4][5]. Meanwhile [6] uses pixel range values or global and local threshold values to classify. The global thresholding method only chooses one threshold value for the entire image. Local Thresholding selects different threshold values for different regions.

Obtaining color images [7] as a result of segmentation from an image with a complex background is quite a challenge for researchers, especially when applied to images with natural backgrounds. Complex backgrounds in rice fields, plantations allow objects to mix with other objects such as stems, leaves, soil, rocks or sky. There is some literature on segmentation developed for images with complex backgrounds such as oil palm [8], blueberry fruit [9], apple harvesting [10], the Fruit-trees in Multi-stage Outdoors Orchard under Natural Conditions[11], threshold, clustering, area and model image segmentation methods [12]. Meanwhile segmentation with thresholding histograms [13] has been used in image analysis, especially data analysis based on two main reasons: being able to show solidly for large enough data and allowing it to be used to infer the characteristics of data behavior in histograms. In addition, information obtained from the statistical aspects of this approach makes it strong against quantization noise. A feature can be described well in a one-dimensional field [14] in a fairly simple way. Each feature has a value interval that is different from one another. This is indicated by each feature having a different peak value and at a certain distance. Segmentation using color thresholding [15] writes that segmentation based on color is very effective for determining the maturity level of fruits and vegetables without difficulty by changing some of the parameter values. [16] Presented an analysis of the skin segmentation approach using color pixel classification, because color is something that is visually visible for the first time when an object is successfully captured by a camera. In addition, color has important information

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to represent the quality of an image [5]. These various methods are attempted to obtain good segmentation results. However, the main problem with some color image segmentation results with complex backgrounds is that the segmented image is not clean from the background.

The aim of this research is to increase the ROI of color images resulting from image segmentation with complex backgrounds. This paper proposes a convolution method for segmented binary images and color images based on post-segmentation image contours with Fuzzy Cmeans.

2. Research Methods

The proposed method for automatically segmenting tomato images with complex backgrounds is divided into three stages: (1) Image localization, (2) Pre-processing and (3) Segmentation. Each stage has several processes, Figure 1. Shows the details of the process stages to get segmentation results. In this study the total amount of data was 10 (simple (5)), and complex (5), the main data was obtained by acquisition using the Galaxy A5+ smartphone camera and some data downloaded from the internet. The acquisition was carried out in an open area at 11 o'clock in the afternoon. The image format used is JPEG.

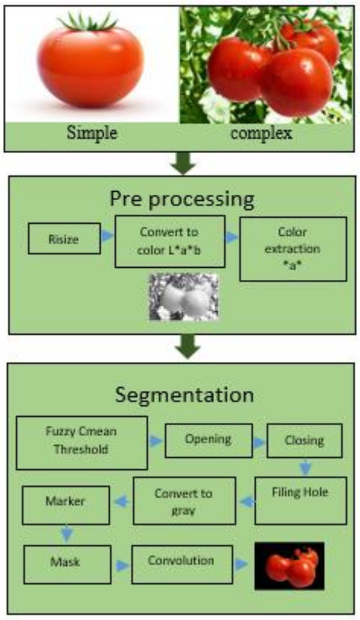


Figure 1. Overview of the automatic segmentation process of tomatoes: (a) image localization, (b) *a* image, and (c) segmented image

2.1 Localization of the image

Image localization in this study uses conventional techniques, namely by cropping the image from the top left to the bottom right which contains all the desired images.

2.2 Pre processing

This process aims to get a part of the image with a focus area close to the object image. This section is called the region of interest (ROI) of the image. ROI has various sizes as shown in Figure 2 (Figure 2(a) and (c) the original size image, Figure 2(b) and (d) the resized result). The size of the image is smaller than the original image because it has been cropped. Resize the original image with various resolutions to 500 x 500 pixels. This measure is expected for the time efficiency [17] of the ROI selection process. The original image is in RGB format and for process optimization it is converted to L*a*b image. From the L*a*b color, the *a* component was selected to obtain potential tomato fruit from a complex background [18] [19]. Convert RGB color to L*a*b using equation (1) [8]

$$
\begin{aligned}
L &= 0.2126R + 0.7152G + 0.9722B \\
a &= 1.4749(0.2213R - .339G + 0.1177B) + 128 \\
b &= 0.6245(0.1949R + 0.6057G - 0.8006B) + 128
\end{aligned} \tag{1}
$$

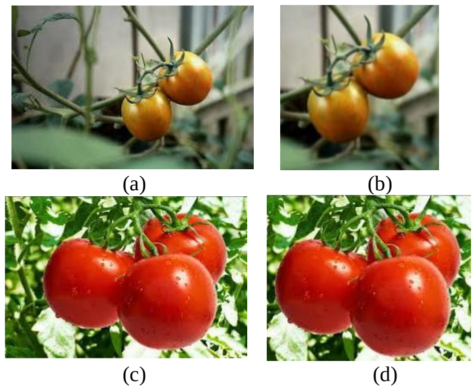
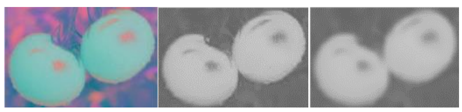


Figure 2. Resizing resolution, (a), (c) image with original size, (b) (d) resized result

Segmentation is often faced with image quality which experiences color gradations and can affect the final result. In this study, Gaussian filtering is used to smooth the gradations that occur at the edges of the image against the background. Gaussian filtering is a process to reduce noise in images in order to obtain images that are ready for processing. The performance of the Gaussian filter is shown in figure 3. In the Lab image, figure 3(a) shows noise on ROI (tomatoes). While the Lab component, namely image *a* image 4(b) is the image before filtering. The effect of the gauss filter is that the existing noise becomes slightly faded, figure 3(c).



(a) (b) (c)

Figure 3. The performance of the Gaussian filter: (a) the noise on ROI (tomatoes), (b) the image before filtering, (c) the existing noise becomes slightly faded

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2.3 Segmentation

The process of partitioning a digital image into several segments is defined as image segmentation. Segmentation aims to divide the image into regions that are more representative and easy to analyze. The region may correspond to an individual surface, object, or a natural part of the object. Usually image segmentation is a process used to find objects and boundaries (for example, lines or curves) in an image. Furthermore, it can be defined as the process of labeling each pixel in an image, where all pixels that have the same label have certain visual characteristics [5]-[13].

In this research, segmentation is designed using fuzzy cmean. Fuzzy cmean, is a Fuzzy C-means (FCM) clustering algorithm that allows one part of the data to be in more than one cluster based on the membership function [20]. FCM is a popular segmentation technique used in the field of segmentation [21],[22],[3]. The basic theory of FCM is partitioning of data. If $X = (x_1, x_2, \ldots x_n)$ is a set of numeric data in Rd and c be integers between 1 and n. Given X, we say that c fuzzy subset $\{uk : X \rightarrow [0, 1]\}$ is the c-partition of X if the following conditions (2), (3) and (4) are met [21]:

$$0 \leq u_{k,i} \leq 1 \qquad \forall_{k,i} \tag{2}$$

$$0 \leq \sum_{k=1}^{c} u_{k,i} = 1 \qquad \forall_{k,i} \tag{3}$$

$$0 < \sum_{i=1}^{n} u_{k,i} < n \qquad \forall_{k} \tag{4}$$

Where uk, $i = uk\ (xj)$, $1 \leq k \leq c$ and $1 \leq i \leq n$. Suppose uk, i fulfills the conditions above represented by the matrix $c \times n\ U = [u\ k,\ i]$. FCM aims to determine the cluster center vk (k = 1; 2;; c) and the fuzzy partition matrix U by minimizing the objective function J defined as equation (5)

$$J(U,V,X) = \sum_{K=1}^{C} \sum_{I=1}^{N} u_{k,i}^{m}\, d_{k,i}^{2} \tag{5}$$

Where di, j is the Euclidean distance from sample xj to the cluster center vi defined in equation (6):

$$d_{k,i} = \sqrt{\sum_{j=1}^{d} (v_{k,j} - x_{i,j})^2} \tag{6}$$

Exponent m in Eq. (5) is the level of fuzziness associated with the partition matrix (m> 1). If m = 1 then soft clustering will be changed to hard case. The commonly used standard is m = 2.

FCM Algorithm [21] : Choose an integer c and a threshold value. For example $m\ to\ be\ equal\ to$ 2. Fix and initialize the fuzzy partition matrix U with random values so that it satisfies the conditions in equations (1), (2) and (3); Calculate the value of vj as the fuzzy center using equation (7)

$$v_k = \frac{\sum_{i=1}^{n} (u_{k,i})^m\, x_i}{\sum_{i=1}^{n} (u_{k,i})^m}\ \forall k1, \ldots c \tag{7}$$

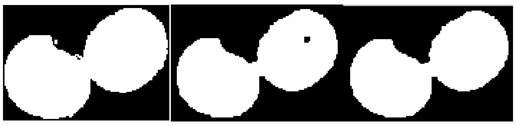
changing the fuzzy matrix partition for variable U with equation (8)

$$u_{k,i} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{k,i}}{d_{k,k}}\right)^{\frac{2}{m-1}}} \tag{8}$$

Meanwhile, the value of dk is calculated according to equation (6); Calculate the objective function J using equation (5). If the convergence or difference between two adjacent computational values of the objective function J is less than a given threshold then stop. Otherwise, go to step 2.

The FCM application in this study uses the default settings, namely: matrix partition = 2, number of iterations = 100, repair value = 0.0005.

Morphology operation, popularly used to reduce noise after segmentation operations [23] edge detection or image color conversion to binary. One part of the morphology method is edge erosion. Edge Erose, is a popular process used to remove segmentation noise that is predicted as the desired object. In this research applied edge erosion using disc type element structure. Figure 4 shows the edge detection performance, Figure 5(a) is the original image resulting from the segmentation process, and Figure 4(b) is the result of the noise removal operation with a strel disk and Figure 4(c) Hole closure in the image by operating the hole filter model.



(a) (b) (c)

Figure 4. Erosion and Hole Performance, (a) original image, (b) erosion with disk, and (c) hole

Convolution is a way to obtain a new image by adding two U matrices. In this study, convolution was carried out to obtain the ROI of color images as a result of segmentation. The process is carried out by adding each RGB image component with binary image *f(x,y)* equation (9) from the FCM segmentation results (figure 5 (c)). *r(xi,yj)*, *g(xi,yj)*, and *b(xi,yj)* respectively are images with R color component, images with G color component, and images with B color component. The matrix of components R, G, and B each has a pixel value of 0 to 255. While f(xi,yj) is a binary image value [0 1]. R_f, G_f and B_f are the results of adding RGB image components and binary images.

$$\begin{aligned} Rf(xi,yj) &= r\,(xi,yj) * f\,(xi,yj) \\ Gf(xi,yj) &= g\,(xi,yj) * f\,(xi,yj) \\ Bf(xi,yj) &= b\,(xi,yj) * f\,(xi,yj) \end{aligned} \tag{9}$$

Image Construction, construction is the process of rearranging the components (R_f, G_f and B_f) resulting from the convolution into one RGB unit. This process combines R_f, G_f and B_f (equation (9)) into a segmented image (figure 5 (f)). Image construction performance is shown in Figure 5.

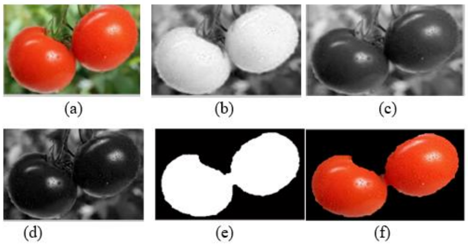


Figure 5. R, G, B component construction and segmentation results, (a) input image, (b) R component, (c) G component, (d) B component, (e) binary image and (f) construction results

3. Results and Discussions

The image data used for the performance evaluation of the proposed method is divided into two categories of background images: simple (figure 6(a) and 6(b), and complex (figure 6(c))). The total amount of data is 10 with each image category consisting of 50% simple images and 50% complex images. All data in color image mode is in the RGB spectrum.

(a) (b) (c)

Figure 6. Dataset types, (a) simple, (b) moderate, and (c) complex

The performance of the proposed method is compared with the ground truth as a reference to determine the success of the process. Ground truth is a selection method in a conventional way. The ground truth image is processed using photopea online. Besides that, this research also shows the selection using Otsu threshold. To get a comparison of the performance of the proposed method with the Otsu and Ground Truth methods, the performance results are shown as shown in table .

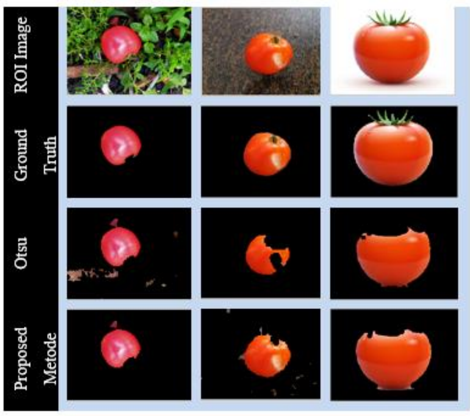


Figure 7. Results of tomato fruit segmentation using ground truth, otsu and proposed method

As a comparison of the performance of the proposed method from the success of detecting ROI from object pixels using ground truth, the Otsu method, and the proposed method obtained the average accuracy for Otsu is 99.91% and the proposed method is 99.93% as shown in Table 1.

Table 1. The results of object segmentation calculations

Test Image	Segmentation yield (%)		
	Groundtruth	Otsu	Proposed method
Tomat20.jpg	31731	99,99	99,91
Tomat26.jpg	14836	99.98	99,95
Tomat31.jpg	14838	99,91	99,99
Tomat30.jpg	22919	99,93	99,97
Tomat38.jpg	25176	99,84	99,86
Tomat39.jpg	80318	99,91	99,91
Tomat40.jpg	27187	99,87	99,97
Tomat42.jpg	17309	99,85	99,83
Tomat43.jpg	22408	99,88	99,91
Tomat44 .jpg	29626	99,98	99,96

Evaluation of the proposed segmentation method is reviewed in three performance categories, namely segmentation accuracy (Sc), positive error (FPe), negative error (FNe). Sc is used to evaluate the overlapping area of tomato fruit segmentation results from the proposed method and groundtruth.

FPe is used to evaluate the average background segmentation fault identified as the tomato fruit area of the proposed method. FNe is used to evaluate the average segmentation fault of tomatoes identified as the background area of the proposed method. Sc, FPe, and FNe values were obtained by calculating the binary value [0 1] of the segmented image. The Sc value should have a high score for the accurate category. While FPe and FNe on the other hand must have a low value. Meanwhile the equations used to evaluate performance are written in equations 10, 11 and 12.

$$S_c = (A_p \cap A_g)/(A_p \cup A_g) \times 100\% \quad (10)$$

$$FP_e = |A_p - (A_p \cap A_g)|/\overline{A_g} \times 100\% \quad (11)$$

$$FN_e = |A_g - (A_p \cap A_g)|/A_g \times 100\% \quad (12)$$

A_p notation is the segmented area of tomato fruit using the proposed method. The notation Ag is the fruit area of a tomato based on groundtruth. Meanwhile the notation (A_g)¯(complement of A_g) is the number of pixels detected as background.

Evaluation of the proposed method for the results parameters Sc, Fpe and FNe based on equations 10, 11 and 12 from the results in Table 1 obtained the value of Indication of Performance Achievements as written in Table 2. The implementation of the proposed method is presented in Table 2. The average yield for each parameter obtained by Sc data is 99.92%. Meanwhile, the FPE or background value that is recognized as an object is 0.06%, this achievement is no better than the

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Otsu method. Whereas the FNE value, which is an image object recognized as a background, is 0.04% better than the Otsu method.

Table 2. Comparison of segmentation performance

Method	Indication of average performance achievement		
	Sc	FPe	FNe
Otsu	99,90%	0.01%	0.10%
Proposed Method	99,92%	0.06%	0.04%

This method is linear with research conducted [8] by segmenting oil palm fruit. Convolution between the segmented mask image on the binary spectrum and the original image on the RBG spectrum is a new method for obtaining segmentation results in color image mode.

4. Conclusion

Segmentation of colored objects from the proposed method and has been tested on tomatoes with successive processes of resizing, color conversion, color extraction, gaussian filter and hole filter, then selection using FCM, morphological operations, convolution and finally the construction is quite successful. The average performance of the proposed method for segmentation of simple, moderate and complex backgrounds is Sc = 99%, Fpe = 0.06%, and FNe = 0.04% The proposed method can be applied to foreground and background segmentation in other cases.

References

[1] Y. Zou, J. Zhao, Y. Wu, and B. Wang, "Segmenting star images with complex backgrounds based on correlation between objects and 1D Gaussian morphology," *Appl. Sci.*, vol. 11, no. 9, pp. 1–12, 2021, doi: 10.3390/app11093763.

[2] K. Anwar, M. Yunus, and Sujito, "Segmentasi Citra Warna Otomatis Rambu Lalu Lintas dengan Penerapan Mask Thresholder," *J. Edukasi dan Penelit. Inform.*, vol. 7, no. 3, pp. 481–487, 2021, doi: 10.26418/jp.v7i3.49969.

[3] S. Arumugadevi, "Color Image Segmentation Using Feedforward Neural Networks with FCM," vol. 13, no. October, pp. 491–500, 2016, doi: 10.1007/s11633-016-0975-5.

[4] R. Selection, "EDTRS : A Superpixel Generation Method for SAR Images Segmentation Based on Edge Detection and Texture Region Selection," 2022.

[5] D. Khattab, H. M. Ebied, A. S. Hussein, and M. F. Tolba, "Color image segmentation based on different color space models using automatic GrabCut," *Sci. World J.*, vol. 2014, 2014, doi: 10.1155/2014/126025.

[6] H. A. Hambali, S. Lailee, S. Abdullah, and H. Harun, "Jurnal Teknologi An I Ntegrated T Hresholding And A Daptive K-," no. April 2017, 2016, doi: 10.11113/jt.v78.8993.

[7] T. Tabassum, "Detection of Fruits Defects Using Colour Segmentation Technique," no. June, 2018.

[8] A. Septiarini, H. Hamdani, H. R. Hatta, and K. Anwar, "Automatic image segmentation of oil palm fruits by applying the contour-based approach," *Sci. Hortic. (Amsterdam).*, vol. 261, no. October 2019, p. 108939, 2020, doi: 10.1016/j.scienta.2019.108939.

[9] X. Ni, C. Li, H. Jiang, and F. Takeda, "Deep learning image segmentation and extraction of blueberry fruit traits associated with harvestability and yield," *Hortic. Res.*, vol. 7, no. 1, 2020, doi: 10.1038/s41438-020-0323-3.

[10] H. Kang, "Fruit Detection and Segmentation for Apple," 2019, doi: 10.3390/s19204599.

[11] Y. Abbaspour-gilandeh, "A Video Image Segmentation System for the Fruit-trees in Multi-stage Outdoors Orchard under Natural Conditions," 2018, doi: 10.15832/ankutbd.434137.

[12] Q. Hu, J. Tian, and D. He, "Wheat leaf lesion color image segmentation with improved multichannel selection based on the Chan – Vese model," *Comput. Electron. Agric.*, vol. 135, pp. 260–268, 2017, doi: 10.1016/j.compag.2017.01.016.

[13] J. Delon, A. Desolneux, J. Lisani, and A. B. Petro, "A Nonparametric Approach for Histogram Segmentation," no. February 2007, 2014, doi: 10.1109/TIP.2006.884951.

[14] J. Delon, A. Desolneux, J. L. Lisani, and A. B. Petro, "Color Image Segmentation Using Acceptable Histogram Segmentation," pp. 239–246, 2005.

[15] M. Dadwal and V. K. Banga, "Color Image Segmentation for Fruit Ripeness Detection : A Review," pp. 190–193, 2012.

[16] S. L. Phung, "Skin segmentation using color pixel classification : analysis and comparison," vol. 27, no. January, pp. 148–154, 2005.

[17] S. Lailee, S. Abdullah, H. Aini, and N. Jamil, "Segmentation of Natural Images Using an Improved Thresholding-based Technique," vol. 41, no. Iris, pp. 938–944, 2012, doi: 10.1016/j.proeng.2012.07.266.

[18] Z. Wang and S. Zhang, "Segmentation of Corn Leaf Disease Based on Fully Convolution Neural Network," vol. 1, no. 1, pp. 9–18, doi: 10.25236/AJCIS.010002.

[19] G. Sun, X. Jia, and T. Geng, "Plant Diseases Recognition Based on Image Processing Technology," vol. 2018, pp. 1–8, 2018.

[20] M. Nazari, "Improve Semi-Supervised Fuzzy C-means Clustering Based On Feature Improve Semi-Supervised Fuzzy C-means Clustering Based On Feature Weighting," no. January 2013, 2016.

[21] A. Hamad, S. Aminifar, and M. Daneshwar, "An interval type-2 FCM for color image segmentation," vol. 10, no. 46, 2020.

[22] M. Akbar *et al.*, "Gpu Accelerated Fuzzy C-Means (Fcm) Color Image," vol. 3839, pp. 165–174.

[23] A. O. Chime, R. O. Aiwansoba, M. E. Osawaru, and M. C. Ogwu, "Morphological Evaluation of Tomato (Solanum lycopersicum Linn .) Cultivars," vol. 21, no. 2, pp. 97–106, 2017, doi: 10.7454/mss.v21i2.7421.

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