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Mechanical Defect Detection of Indonesian Local Citrus Using Fluorescence Image and Discriminant Analysis

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Abstract— The sound and defected citrus should be separated as soon as possible to prevent rotting from occuring early on in the sound citrus. Mechanical defects such as a slit and bruise spread essential oil in citrus peel that glows under UV excitation. The aforementioned defects can be detected using a fluorescence image by digital image analysis based on color and texture features. The aim of this study is to detect the mechanical defects in citrus by classifying the citrus into 3 groups (sound, slit and bruise) using discriminant analysis. Color and texture features were selected as input variables to develop discriminant function. The fluorescence image is captured by the image acquisition system then the digital image analysis algorithm is developed based on color and texture features to classify three groups of treatment for Indonesian local citrus. The results show that fluoresence image features such as hue, saturation, intensity, contrast, correlation, energy and homogenity have a high correlation in group classification. The discriminant function was developed and the classification accuracy for the sound, bruise and slit groups was 73.3% , 96.7% and 70%.

Index Terms— citrus classification, discriminant analysis, fluorescence image, mechanical defect
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1 Introduction

Indonesia has around 19 varieties of local citrus [1] and some of the citrus are exported to East Timor, Malaysia, India, Iran and Singapore. As a fresh agriculture product produced in a tropical country, the citrus is subject to damage during harvesting, handling and transportation. The defected fruits usually become easier to spoil, so it is better to separate them from the rest as soon as possible to prevent further spoilage to other fruits. Separating the defected fruits manually is difficult, especially at early stages of damage, because they do not show any visual change before the defected part changes its color into brown as a browning reaction occurs. However, when citrus experiences injury, small amounts of liquid containing fluorescence substances are released from its peel. The fluorescence substances can facilitate a different approach for early detection of the mechanical defect of citrus, if an appropriate sensor is applied.

Recent study has identified the fluorescence substances in Mandarin citrus [7], and conducted an investigation of wave excitation for fluorescence emission from citrus peel that was exposed to UV light [10]. From this research, it has been known the fluorescence wavelengths of 15 varieties of citrus grown in Japan were 300nm - 700 nm. Furthermore, spectra data was used to support the development of machine vision to detect the defect of fruit. Hyperspectral imaging could be used to detect a bruise in an apple [8], as well as be used for safety inspection of food and agricultural products [3][9]. There are several studies that use machine vision to detect the defect of freeze damage and skin defect [5,12]. Another research studied the pattern of fluorescence associated with citrus peel defects and had separated the citrus defect in some categories [11]. A mechanical defect such as a slit and bruise cannot be detected physically at an earlier stage because there is no variation in color from the defect area in citrus skin versus the fresh area.

Fluorescence imaging can be used as a detection method to evaluate the defected fruit. Fluorescence imaging is supposed to increase the accuracy of mechanical defect detection of citrus. The fluorescence image is captured by an image acquisition system. The mechanical defect in the citrus peel is then detected from the fluorescence imaging. The aim of this study is to detect the mechanical defect of Indonesian local citrus using a fluorescence image and discriminant analysis. This study has developed the image acquisition system with proper light to get the fluorescence image. Furthermore, the image acquisition system can be used to develop a non-destructive evaluation system for defected citrus at the early stage, which is unseen to human eyes.

2 Materials and Methods

2.1 Sample Preparation

This experiment used Garut citrus (Indonesian local citrus variety grown in West Java Province) as a representative of Indonesian local citrus (Fig. 1). Three groups of samples were prepared: a sound group and two mechanical defect groups of slit fruits (caused by swapping a rough surface) and bruised fruits (caused by pressing the citrus with rheometer in 19.61 N.) The three groups of samples were then stored in a room with air conditioning set to 25˚C.

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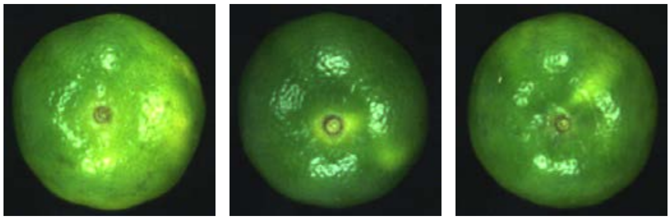


Sound Bruise Slit

Fig. 1. Garut Citrus in 3 treatments

2.2 Fluorescence Image Acquisition

Fluorescence images were captured by an image acquisition system that consisted of 4 UV lamps 15 watt (Sankyo Denky) with a peak in wavelength 352 nm for illuminating the sample and VGA camera (The Image Source) with resolution 744 x 480 pixel. The slope of the lamp was 60^0 to obtain uniform lighting and the distance from object was 10 cm. Figure 2 shows the image acquisition system. This sytem captured image in red, green and blue (RGB) colors. A fluorescence image was captured from two sides of the fruit. 30 set samples of citrus have been taken for each group. In total, 180 pictures were analyzed for all treatments.

Fig. 2. Setting of Image acquisition system

2.3 Feature Extraction

Algorithms were developed in Matlab R2016b to extract the texture and color features of the fluorescence images. Mechanical defects, especially bruises were difficult to detect physiscally by human eyes. In this study, texture and color features were used to be input variabels for classifying the citrus. Texture from the image is information on surface patterns marked by granular detail in the image, as well as information about differences in color or pattern [6]. Contrast, correlation, energy and homogenity are texture features that are analyzed in this study. From the previous study, these four texture features have a relationship with image texture of sample and surface structure of pasta [4]. Texture approach should bring information to identify the mechanical defect in citrus peel by the fluorescence image. The texture features' extraction began by changing the RGB image to grey image using the developed grey level co-occurrence matrix (GLCM). GLCM can explain the differences color or texture of a surface because it calculated by how often two pixels, in the matrix elemen $P_0(i,j)$, with intensity value i and j at particular displacement distance δ from along a given direction θ (horizontally, vertically or diagonally) occur in the image [2]. Texture extraction was done by using following calculations:

$$\text{Contrast (CON)} = \sum_{ij} |i-j|^2 \; p(i,j) \tag{1}$$

$$\text{Correlation (COR)} = \sum_{ij} \frac{(i-\mu i)(j-\mu j)\,p(i,j)}{\sigma i \sigma j} \tag{2}$$

$$\text{Energy (ENR)} = \sum_{ij} p(i,j)^2 \tag{3}$$

$$\text{Homogenity (HOM)} = \sum_{ij} \frac{p(i,j)}{1+|i-j|} \tag{4}$$

The color features used in this study were hue (H), saturation (S) and intensity (I), calculated using the following equations:

$$\mathrm{H} = \arccos\left\{\frac{[(\mathrm{R}-\mathrm{G})+(\mathrm{R}-\mathrm{B})]/2}{[(\mathrm{R}-\mathrm{G})^2+(R-B)(G-B)^{1/2}}\right\}\frac{1}{3}(R+G+B) \tag{5}$$

$$\mathrm{S} = 1-\frac{3}{(R+G+B)}[(R+G+B)] \tag{6}$$

$$\mathrm{I} = \frac{1}{3}(R+G+B) \tag{7}$$

2.4 Discriminant Analysis

There are 7 features (3 color and 4 texture features) used for classification of mechanical defect citrus. All features were analyzed by discriminant power analysis to optimize the number of features that contributed significantly to the classification. The performance of the classifier decreases if there are too many redundant features. Features with high level contribution (determined by value of correlation, wilks lambda, F value and P value) were identified to input variables for developing a discriminant function. Discriminant analysis was developed with software, IBM SPSS Statistic 21. To improve the accuracy in detecting defect fruit, the application of filter for capturing the image and cropping treatment were analyzed. Cropping treatment by decreasing the image size was evaluated to find high correlation in classification.

3 Result and Discussion

3.1 Feature Correlation: Evaluation by Filter and Cropping Treatment

The application of filter for capturing fluorescence images needs to obtain the informative image for classifying the citrus based on mechanical defect. The long pass filter was used to pass the light wavelength from 500 nm. The previous study about fluorescence spectra from Indonesian local citrus showed that the peak of fluorescence spectra from Indonesian local citrus was 500 nm to 555 nm [13]. Figure 3 was the fluorecence image of Garut citrus with and without application of filter.

The image was captured without filter showed he dominance of the blue color from the UV lamp and the fluorescence emission was dim. Fluorescence emission in 500 nm to 555 nm was green in color; this informtion is needed to contribute in classification. The long pass filter was applied to cut the exitation light from the UV lamp so the fluorescence emission could be captured in image. This treatment should increase the correlation of image features to group classification based on defect. Figure 4 shows the different value in correlation between the image captured using filter and without filter. Texture and color features from the image, captured with a filter generally increase the correlation of features to classification. Application of the filter increased the correlation value of all color features, contrast and correlation.

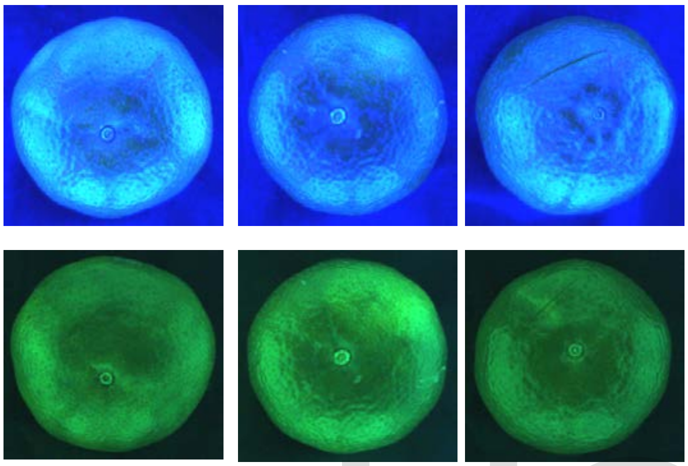
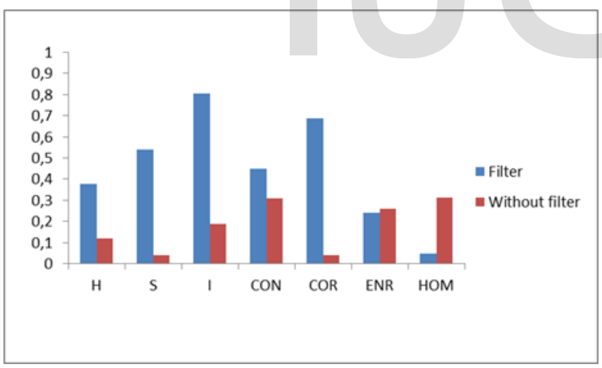
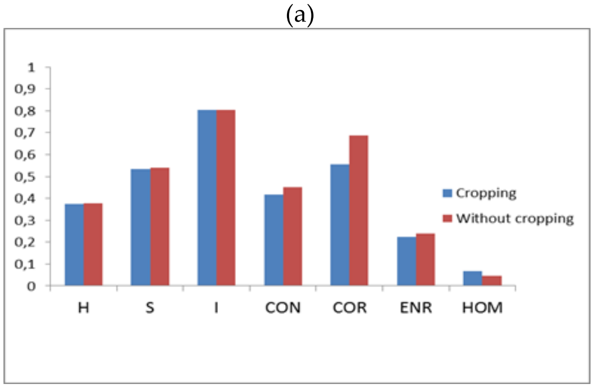


Fig. 3. Fluorescence image of Garut citrus captured without filter (top) and with filter (bottom)



(a)



(b)

Fig. 4. Value of correlation features with classification from fluorescence image of Garut citrus (a) application of filter (b) cropping treatment

The fluorescence image captured in 744 x 480 pixels has a wide enough background section. Treatment of cropping size as input data was expected to make the image more informative for grouped based on defect. The image size was reduced to 320 x 320 pixels by placing the subject in the center and reducing the background area. The correlation value from the image with cropping treatment has generally decreased, but does not occur significantly. It can be concluded that the treatment of image size reduction did not give a significant effect on the correlation between features and classification. The initial image still has a higher correlation value and provided more informative features in classifying the group.

3.2 Feature Selection

Discriminant power analysis has been done to determine the features that strongly correlate to develop the discriminant model. Discriminant power analysis for Garut citrus is shown in Table 1. Correlation values explain the relationship of input variables with each group. A higher correlation value indicates that the variable is closely related to the group. In Garut citrus, the variables of saturation, intensity, contrast and correlation have correlation values above 20%. This value indicated that this variable has the potential to describe groups. Energy variables and homogenity have very low correlation values so it can be concluded that this variable cannot explain the relationship between variables and groups. Furthermore, the value of Wilks Lambda can also explain the differences among groups. The smaller the Wilks Lambda value, the greater the difference between groups. Hue, saturation, intensity, contrast and correlation variables in Garut citrus have Wilks Lambda values below 90% so these factors have the potential to be used as input variables in discriminant analysis. Homogenity does not influence the group's result because P value was more than 5%. The result variables used for developing the discriminant model were hue, saturation, intensity, contrast, correlation and energy.

The highest correlation value in this study was 80% from intensity. Intensity has a high correlation and provides more information for classifying the group. The fluorescence emission from any defect area had a different intensity, which could be information for the defect group. The difference in intensity for each pixel in the image showed the variation in the defect and sound group.

TABLE 1
DISCRIMINANT POWER ANALYSIS OF IMAGE FEATURES

	Correlation	Wilks Lamda	F Value	P Value
H	0,377	0,858	14,698	0,000
S	0,541	0,707	36,609	0,000
I	0,803	0,355	16,852	0,000
CON	0,450	0,798	22,454	0,000
COR	0,687	0,528	79,085	0,000

ENR	0,239	0,943	5,359	0,006
HOM	0,047	0,998	0,195	0,823

3.3 Discriminant Analysis

After variables with a strong correlation had been selected, the variables were used as input to develop the discriminant function (DF). The discriminant functions generated based on the selected input variables were:

$$DF1= -256{,}218+ 1{,}005*H- 0{,}151*S+ 0{,}222*I+ 69{,}532*CON + 158{,}084*COR+ 12{,}907*ENR. \quad (8)$$

$$DF2= -171{,}457+ 0{,}821*H– 0{,}075*S– 0{,}41*I+ 202{,}245*CON +82{,}238*COR+ 29{,}951*ENR. \quad (9)$$

Correlation variable has the largest coefficient in the discriminant function. It mean that this variable has the most influence in the equation for classifying the group. Furthermore, Figure 5 showed the distribution of sample data based on the distance from the center of the group. DF that has been developed can classify bruise with the highest accuracy, where the bruise group occupies the same area and clusters significantly. For the sound group, the distribution data was still overlapping in same area with the slit group, which also reduced the accuracy of DF in classifying sound and slit group.

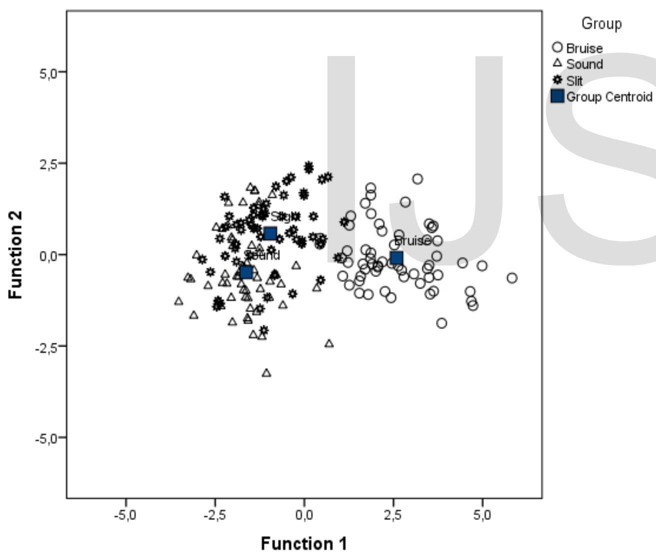


Fig. 5. Distribution of sample data based on the distance from the center of the group

The Eugen value of DF is shown in Table 2. This value shows the magnitude of the diversity of data represented by DF. The value of DF1 was used as a model forming factor representing 94.7%. The DF equation has represented the majority of data because the value was close to 100%. The value of DF1 in Garut citrus was relatively high, was expected to predict the groups accurately and could represent the majority of data.

TABLE 2
EUGEN VALUE OF DISCRIMINANT FUNCTION

Factor	Eigenvalue	Proportion (%)	Accumulation (%)
DF1	3,478	94,7	94,7
DF2	0,194	5,3	100,0

Table 3 was the confusion matrix table in validation the DF for classifying the group.The bruise datas were distributed around the center of the group, so the bruise group had the highest accuracy of 96.7%. This was consistent with the results of the data distribution showed in Figure 5, where bruised data clustered significantly. The accuracy of the sound group and slit group were 73.3% and 70%. The average accuracy of group classification was 80%.

TABLE 3
CONFUSSION MATRIX TO VALIDATE DISCRIMINANT FUNCTION

	Accuracy (%)		
Group	Bruise	Sound	Slit
Bruise	96,7	,0	3,3
Sound	1,7	73,3	25,0
Slit	3,3	26,7	70,0

4 Conclusion

The fluorescence image of Garut citrus was analyzed by digital image analysis and discriminant analysis to classify the citrus, based on the sound and mechanical defect group. The color and texture features were extracted as input variables to develop discriminant function. All colors features, contrasts, correlation and energy were the high correlation variables of the group classification. The discriminant function was tested on dataset and the average accuracy of group classification was 80%. The discriminant function was developed and the classification accuracy for sound, bruise and slit groups were 73.3%, 96.7% and 70%.

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