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COMBINATION OF FIRST AND SECOND ORDER STATISTICAL FEATURES OF BULK GRAIN IMAGE FOR QUALITY GRADE ESTIMATION OF GREEN COFFEE BEAN

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ABSTRACT

This study evaluated the use of image features for estimating the quality of green coffee beans in bulk. These features are extracted from green bean image obtained with a camera installed inside in a closed chamber equipped with varied light sources. Image data acquisition was done by preparing green coffee beans on a sample board, leveling the surface, and then putting inside the chamber. This experiment used three sets of sample consisting of two sets of Robusta coffee (eight categories) and a set of Arabica coffee (seven categories). Each sample was captured thirty times with randomization prior measurement to various illuminations. The image data of each set were randomly divided into training and testing data set. Statistical features including first and second order statistical features were then extracted and concatenated as a feature set. The feature set extracted from the training data set was learned to a classifier being used to identify the testing data set. Recognition accuracy of the classifier was used to determine an appropriate combination of features applying for quality estimation system based on statistical features for the bulk coffee grains. The result indicates that the illumination influences on the classification accuracy in which the optimum rate is obtained at the range of 100-200 lux. The highest accuracy is obtained at 100 lux in which the use of either second order statistical features or combination of selected first and second order features reach the average recognition level of 80%. Therefore, these features can be recommended as meaningful feature for estimating the coffee grains quality in bulk required on the industry of secondary coffee processing.

Keywords: coffee grain quality, statistical feature, estimation system, accuracy.

INTRODUCTION

Coffee grain commonly known as green bean in trading is peeled coffee grain as final product of the primary coffee processing as well as raw material for the industry of secondary coffee processing. As a commercial commodity and raw materials of industry, grade is a standard criterion used to assess the quality of the coffee grains. Quality standard of domestic coffee grains refers to the Indonesian National Standard (SNI) no. 01-2907-1999 governing definition, classification, quality requirement, sampling method, test method, labelling requirement, packaging method and recommendation (Mulato *et al*., 2010). The SNI is explicitly classifying the quality of the coffee grains into six grades determined by the number of weighed defects found in the sample. There are some defect types usually contained in coffee grains, not only due to various levels of grain defect but also because of the number of such potential foreign objects presented in the sample (soil, gravel, or twigs of coffee tree, and so on). Each of them has different weighed score used for counting the defect number.

Although quality grading of green bean is needed for trading as well as for secondary processing, both have different prominence. Market usually requires defined labelling of the grain quality because it corresponds to the product price. In this case, determining the grade of the coffee grains should be done carefully by observing and counting the number of defects precisely. In other case for such coffee processing industry, the quality classification is required to determine an appropriate treatment for the grains in order to obtain an optimal coffee flavour. Because coffee grains in adjacent grade have almost similar chemical compositions, processing of the materials needs same appropriate treatments. Therefore, the processing in secondary coffee industry requires more quality estimation system rather than precisely grade classification. Nevertheless, the industry needs a fast and reliable quality estimation system in order to follow the process in continuously and periodically. As it is known that defects have different visual perception compared to the good grains, a computer vision system can be recommended for designing a fast and reliable quality estimator of the green coffee bean.

Research on grading of coffee grain in bulk using image parameters has been done previously by Faridah *et al*. (2011). The study used seven image features, namely mean of R, G, B, and four features of gray level co-occurrence matrix (energy, entropy, contrast, and homogeneity) for grading of Robusta coffee. Realizing to the grain as such biological material influenced by some external factors, the use of the true colour (RGB) for such identification system may has disadvantages due to the heterogeneity of the colour grains. For example, different climate and growing conditions can produce grains with different colours though it is classified on the same grade and varieties. This condition can affect to the value of the RGB features which may also influence to the performance of the identification system. In addition, the use of such limited number of features may not enough to represent all important features necessarily used to characterize the grain image. Therefore, observing the main features which may able to be used as meaningful feature of the coffee grain image is still necessary. Haralick *et al*. (1973) explained that determining of the essential features to describe an image can be done naturally by looking back to the types of features used by human senses for collecting information from the image. In connection with various features perceived by humans in particular regard to image classification of bulk coffee grains, it is necessary to finding an optimal combination of features which may reliable to produce a high classification level and be able to overcome the heterogeneity of the studied material.

This study aimed to find and evaluate a combination of image features required to build a machine vision as a quality estimator of green coffee bean in bulk. Basically, humans perceive characters of an image visually based on spectral, textural, and contextual features. The average level variations of the various visible bands of an electromagnetic spectrum on an image is represented as spectral features, spatial distribution level on the color image is described as texture features, while information on the level of colour pixel groups in an image region is defined as contextual features (Haralick *et al*., 1973). These features are more easily recognizable as colour, texture, and shape features in which researchers thoroughly investigate for such feature extraction algorithms (Liu and Yang, 2008).

As main element of image, pixel contains two information, namely as brightness value (colour intensity) and pixel location in coordinates in the image (Zheng *et al*., 2006). Since the features are extracted from the pixel element, they are also known as statistical features. There are three methods for extracting the features from an image namely with first, second, and high order statistical approaches corresponding to spectral, textural, and contextual features. Spectral features are obtained directly from the spectrum distribution of the colour intensity on the image that is also known as first order statistical (FOS) features, while textural features are obtained by modification of the image colour intensity that can be used to describe the relationship between pairs of pixels known as second order statistical (SOS) features, whereas contextual feature known as a high-order statistical features (HOS) that is used to quantify the size of the region in the image through the pixels that have the relation brightness. Considering on the character of image of a homogeneous across the surface that represents the quality of the coffee grains, the study was focused on the FOS features and SOS features particularly extracted by using gray level co-occurrence matrix (GLCM).

The use of image features for various applications especially in the field of food and agriculture has been studied by researchers. Research on the use of visual features to identify wheat grain varieties have been done by Pourreza *et al*. (2012) and Zapotoczny (2011), identification of wheat quality classes (Manickavasagan *et al*., 2008), classifying cereal grains (Choudhary *et al.*, 2008), and its application to the evaluation of food quality has been reviewed by Zheng *et al.* (2006) such as for classification of commercial potato chips (Mendoza *et al*., 2007), predicting the texture quality parameters of potato chips (Thybo *et al*., 2004), for distinguishing between organic and non-organic bread loaves (Gonzales-Barron and Butler, 2008). Among them, the SOS features mostly dominate the analysis specially extracted by using GLCM approaches. The proposed method by combining the first and second order statistical features was expected to obtain a good accuracy for estimating the grade of green coffee bean in bulk.

MATERIAL AND METHOD

Green coffee sample

This study used three sets of samples consisting of a set of Arabica Coffee and two sets of Robusta coffee. Each sample set consisted of all grade samples in accordance with SNI standard. Specification of the sample sets is presented in Table-1.

Table-1. Specification of the sample set.

Grade	Defect number		
	Sample 1 (Arabica)	**Sample 2** (Robusta)	**Sample 3** (Robusta)
I	9	5	10
II	14	17	28
III	27	34	42
IVA	53	53	58
IVB		69	79
V	92	103	146
VI	153	185	210
OG	NA	NA	NA

Imaging system

A closed sampling chamber with size of 60x60x60 cm equipped with a camera and light sources was designed for this research. The light sources consisted of 4 lamps installed on the four top corner of the chamber equipped with lighting driver for regulating the illumination level. A camera webcam (Logitech HD C920) mounted on the centre-top of the chamber with a round of 20 cm distance to the placed sample. Sample board was designed with size of 40x30x1 cm. Because the camera was the main device, its setting should be fixed; all automatic features were disabled and replaced with manual mode. In addition, a set of lux-meter was also necessary to

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ARPN Journal of Engineering and Applied Sciences

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measure the sampling room lighting. The hardware design of this study is presented in Figure-1.

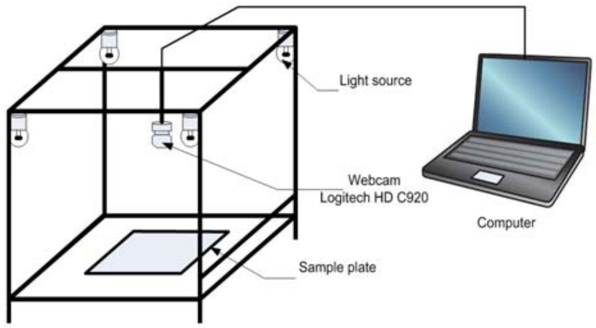

Figure-1. Experimental setup.

Image acquisition

Capturing image from the sample was done with fixed-manual mode of the camera for all measurement. This experiment varied the sampling room lighting with illumination of 40, 100, 200, 300, 400 and 500 Lux. After setting the lighting, each sample was poured in the sample board. The grains surface was then flattened to achieve a homogeneous profile and minimize the appearance of the background on the obtained image before it was placed into the sampling chamber. This arrangement was expected to represent the real raw material appearance on sample preparation stage in the secondary coffee industry. Each sample was captured thirty times with randomization before measurement (each sample set consists of 240 images for Robusta and 210 images for Arabica). All image samples were true color bitmap with size of 640x480 pixels.

Data analysis

The data sets consisting of all categories for each sample set were analyzed for each variation of illumination. The analysis was started by dividing the data into training and testing data set. The training data set was used to train an artificial neural network applied as classifier and identifier, while the testing data set was prepared to evaluate performance of the trained classifier. Training convergence (speed and error) and accuracy of the classifier were analyzed to select an appropriate feature set for this case. Schematically, the data processing of this experiment is presented in Figure-2, which can be explained as follows.

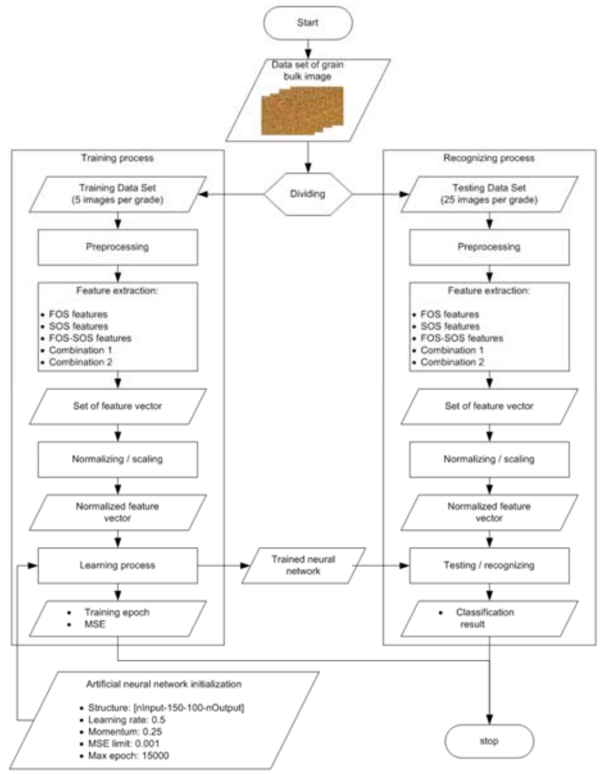

Figure-2. Data analysis flowchart.

Preprocessing

Prior to be analyzed, the image sample should be prepared with pre-processing stage. This process began with determining the region of interest (ROI) of the image being analyzed. The ROI was obtained by cropping out 10 pixels in width of the image sample outside. Thus, the ROI had size of 620x460 pixels. The ROI was then converted into gray scale image and normalized in the range of [0,255] before its features were extracted.

Feature extraction

This study focused on evaluating the use of FOS and SOS features. The FOS and SOS features extracted from normalized gray scale image with gray level of G and size of MXN, A [x, y] (x = 0,1, .., M-1; y = 0,1, .., N-1), are defined as follows.

FOS features extraction

FOS analysis is used to obtain features derived directly from the spectral distribution of color intensity. This analysis started to count an image histogram p[i] (i = 0, 1, .., G-1) containing of the distribution of color intensity i obtained from A [x, y]. The histogram was then normalized as the following equation.

$$P[i] = \frac{p[i]}{\sum_{i=0}^{G-1} p[i]} = \frac{p[i]}{M \times N} \quad (1)$$

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There are 9 FOS features extracted from the normalized histogram P[i], namely feature of energy (F1), entropy (F2), mean (F3), variance (F4), skewness (F5), kurtosis (F6), smoothness (F7), standard deviation (F8), and spot (F9). The feature of entropy describes normality distribution of the colour intensity, while the energy feature shows how much variation on the brightness level. The mean describes the average colour of the image, the variance describes the colour intensity variation, the skewness describes the intensity of a darker or lighter colour compared to the mean, the kurtosis provides uniformity information of the intensity distribution, the smoothness describes the image surface smoothness, and the spot feature informs the region of image which too deviate from the mean. These features are defined as follows.

$$F1 = \sum_{i=0}^{G-1} (P[i])^2 \tag{2}$$

$$F2 = -\sum_{i=0}^{G-1} P[i] \log_2 P[i] \tag{3}$$

$$F3 = \frac{\sum_{i=0}^{G-1} ip[i]}{\sum_{i=0}^{G-1} p[i]} = \frac{\sum_{i=0}^{G-1} ip[i]}{M \times N} = \sum_{i=0}^{G-1} iP[i] \tag{4}$$

$$F4 = \sum_{i=0}^{G-1} (1 - F3)^2 P[i] \tag{5}$$

$$F5 = \sum_{i=0}^{G-1} (1 - F3)^3 P[i] \tag{6}$$

$$F6 = \sum_{i=0}^{G-1} (1 - F3)^4 P[i] \tag{7}$$

$$F7 = 1 - \frac{1}{1 + F4} \tag{8}$$

$$F8 = \sqrt{\frac{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (A[i,j] - F3)^2}{M \times N - 1}} \tag{9}$$

$$F9 = \frac{\sum_{i=0}^{F3-Th} P[i] + \sum_{i=F3+Th}^{G-1} P[i]}{\sum_{i=0}^{G-1} P[i]} \tag{10}$$

With Th is a given threshold.

SOS features extraction

SOS analysis describes the relationship between pairs of pixel intensity in the image, in which the GLCM analysis plays as the popular method successfully applied for representing the textural features. The GLCM analysis for textural feature extraction can be explained as follows. Co-occurrence matrix CM [i, j] of the image of A [x, y] is defined as a matrix whose elements are the relative pair number of colour intensity in the image with particular distance of d and direction of ɵ. An image with gray levels of G provides a GxG of the CM matrix size. Since the matrix is considered too large and complex for analysis, the original image with gray level of G needs to be converted into a new image A '[x, y] with smaller gray level of H, defined as follows.

$$A'[x,y] = \frac{A[x,y]}{G/H} \tag{11}$$

Generally, the use of gray level of 16 [0.15] is sufficient for this analysis. The co-occurrence matrix of the new image A'[i, j] is defined as follows.

$$CM[k,l \mid d,\theta] = Z_{[k,l|d,\theta]} \tag{12}$$

Where Z is the pair number of the colour intensity of k and l with analysis distance of d and direction angle of ɵ. k and l is the gray level of A', so that the value of k and l is between 0 to H-1. The CM matrix should be normalized as follows.

$$Q[k,l] = \frac{CM[k,l]}{\sum_{k=0}^{H-1} \sum_{l=0}^{H-1} CM[k,l]} \tag{13}$$

GLCM features that can be extracted from the Q [k, l] are vary but this study only focused on 17 features as combination of GLCM features explained by Haralick *et al.* (1973) and by Soh and Tsatsoulis (1999). The features include energy (angular second moment, F10), entropy (F11), contrast (F12), inverse difference moment (homogeneity, F13), autocorrelation (F14), dissimilarity (F15), sum of average (F16), the sum of entropy (F17), sum of variance (F18), difference of entropy (F19), information measures of correlation (F20, F21), difference variance (F22), correlation (F23), sum of square (F24), cluster shade (F25) and cluster prominence (F26). These textural features are defined as follows.

$$F10 = \sum_{k=0}^{H-1} \sum_{l=0}^{G-1} (Q[k,l])^2 \tag{14}$$

$$F11 = -\sum_{k=0}^{H-1} \sum_{l=0}^{G-1} Q[k,l] \times \log(Q[k,l]) \tag{15}$$

ARPN Journal of Engineering and Applied Sciences

$$F12 = \sum_{k=0}^{H-1}\sum_{l=0}^{G-1}(k-l)^2 \times Q[k,l] \tag{16}$$

$$F13 = \sum_{k=0}^{H-1}\sum_{l=0}^{G-1}\frac{Q[k,l]}{1+(k-l)^2} \tag{17}$$

$$F14 = \sum_{k=0}^{H-1}\sum_{l=0}^{G-1} k \times l \times Q[k,l] \tag{18}$$

$$F15 = \sum_{k=0}^{H-1}\sum_{l=0}^{G-1} |k-l| \times Q[k,l] \tag{19}$$

$$F16 = \sum_{i=0}^{2H-2} i \times Q_{x+y}[i] \tag{20}$$

$$F17 = -\sum_{i=0}^{2H-2} Q_{x+y}[i] \times \log(Q_{x+y}[i]) \tag{21}$$

$$F18 = \sum_{i=0}^{2H-2}(1-F17)^2 \times Q_{x+y}[i] \tag{22}$$

$$F19 = -\sum_{i=0}^{H-1} Q_{x-y}[i] \times \log(Q_{x-y}[i]) \tag{23}$$

$$F20 = \frac{F11 - C1}{\max\{BX, BY\}} \tag{24}$$

$$F21 = \sqrt{(1-\exp[-2(C2-F11)])} \tag{25}$$

$$F22 = \sqrt{\frac{\sum_{i=0}^{H-1}(Q_{x-y}[i] - \overline{Q_{x-y}})^2}{H-1}} \tag{26}$$

$$F23 = \frac{\sum_{k=0}^{H-1}\sum_{l=0}^{H-1} k \times l \times Q[k,l] - \mu_x \times \mu_y}{\sigma_x \times \sigma_y} \tag{27}$$

$$F24 = \sum_{k=0}^{H-1}\sum_{l=0}^{H-1}(k-\mu_x) \times (k-\mu_y) \times Q[k,l] \tag{28}$$

$$F25 = \sum_{k=0}^{H-1}\sum_{l=0}^{H-1}(k+l-\mu_x-\mu_y)^3 \times Q[k,l] \tag{29}$$

$$F25 = \sum_{k=0}^{H-1}\sum_{l=0}^{H-1}(k+l-\mu_x-\mu_y)^4 \times Q[k,l] \tag{30}$$

with

$$p_{x[k]} = \sum_{l=0}^{H-1} Q[k,l] \tag{31}$$

$$p_{y[l]} = \sum_{k=0}^{H-1} Q[k,l] \tag{32}$$

$$\mu_x = \sum_{k=0}^{H-1}\sum_{l=0}^{H-1} k \times Q[k,l] \tag{33}$$

$$\mu_y = \sum_{k=0}^{H-1}\sum_{l=0}^{H-1} l \times Q[k,l] \tag{34}$$

$$\sigma_x = \sum_{k=0}^{H-1}\sum_{l=0}^{H-1}(k-\mu_x)^2 \times Q[k,l] \tag{35}$$

$$\sigma_y = \sum_{k=0}^{H-1}\sum_{l=0}^{H-1}(l-\mu_y)^2 \times Q[k,l] \tag{36}$$

$$Q_{x+y}[i] = \sum_{k=0}^{H-1}\sum_{l=0}^{H-1} Q[k,l], \qquad i = k+l \tag{37}$$

$$Q_{x-y}[i] = \sum_{k=0}^{H-1}\sum_{l=0}^{H-1} Q[k,l], \qquad i = |k-l| \tag{38}$$

$$C1 = -\sum_{k=0}^{H-1}\sum_{l=0}^{H-1} Q[k,l] \times \log(p_{x[k]} p_{y[k]}) \tag{39}$$

$$C2 = -\sum_{k=0}^{H-1}\sum_{l=0}^{H-1} p_{x[k]} p_{y[k]} \times \log(p_{x[k]} p_{y[k]}) \tag{40}$$

$$BX = \text{entropy of } p_x \tag{41}$$

$$BY = \text{entropy of } p_y \tag{42}$$

Selecting a feature set

Feature selection plays as a major role on this experiment. Selected feature set determines the performance of the classifier. Selecting the feature is done by analyzing the relationship between each response to the grade of the classified sample. Difference in response of

ARPN Journal of Engineering and Applied Sciences

each feature per grade sample has likely to be meaningful features on this case. This study examines five sets of features formed from FOS and SOS features as presented in Table-2. Before trained on the classifier, each feature set is normalized in order to obtain a homogeneous range of values.

Table-2. Examined feature set.

Name of set	Feature
Feature set 1	26 features of FOS and SOS: F1 up to F26
Feature set 2	9 features of FOS: F1 up to F9
Feature set 3	17 features of SOS: F10 up to F26
Feature set 4	7 features: mean of R, mean of G, mean of B, F10, F11, F12, and F13
Feature set 5	17 features of FOS and SOS: F1, F2, F4, F7, F8, F9, F10, F11, F12, F15, F16, F17, F20, F23, F24, F25, F26

Learning process

An artificial neural network was selected as classifier for evaluating and selecting feature sets for estimating the grade of green coffee bean in bulk. The normalized feature set was then trained on the classifier defined as multilayer perceptron with structure of [nInput-150-100-nOutput]. The neural network was trained by the error back propagation method with learning rate and momentum of 0.5, 0.25 respectively, error limit of 0.001, and maximum iteration of 15000. Once training was finished, the final weight of the network along with the training result (sse and epoch) were recorded. The trained network was then applied to identify the corresponding testing data set.

Testing process

Each image sample on the testing data sets was analyzed in the same manner as the training data set. After determining and normalizing the ROI, a feature set was extracted from the image sample. The feature set was then scaled by the dividing it with a constant number obtained from the training data set. Then, the feature set was identified by the trained classifier. Outcomes of the neural network were then compared with the actual grade of sample. Classification accuracy was defined as ratio between the numbers of correctly identified samples to the number of the testing data set. The level was then used to select an optimum feature set corresponding to the highest accuracy of identification.

Determining of the distance d and direction θ for GLCM analysis

Calculating the CM matrix in GLCM analysis requires a particular distance and a direction angle. So far, there are no definitive guidelines for determining an optimum number of the both parameters. In this study, the optimum distance was determined by simulating the features at various numbers of both parameters. Simulation of some features at varied distance of 1 to 100 pixels extracted from randomized image sample is presented in Figure-3. The graph shows that the features are influenced by the distance parameter if it is less than 10 pixels and relatively stable longer distance. Therefore, the distance d for this analysis was determined at 10 pixels. As for the angle, some references recommend to select one or more of four different angles of 0°, 45°, 90°, and 135° (Liu and Yang, 2008). For obtaining an optimum feature, this research applied the all recommended directions.

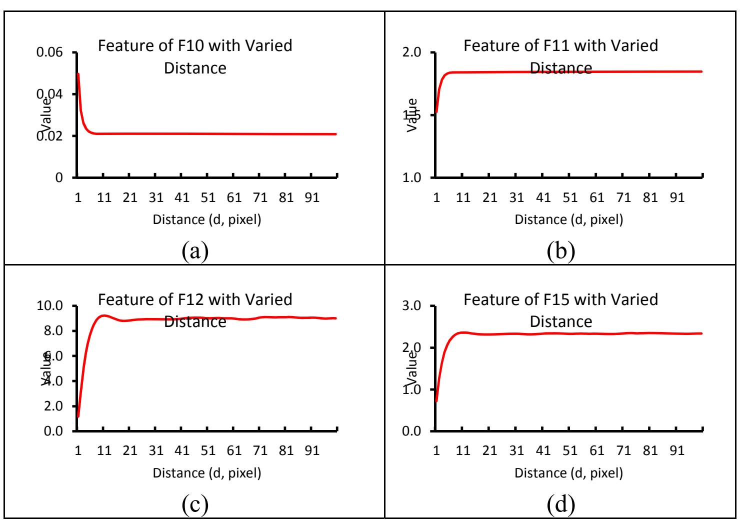

Figure-3. Feature values with varied distance: (a) F10, (b) F11, (c) F12, and (d) F15.

ARPN Journal of Engineering and Applied Sciences

RESULT AND DISCUSSIONS

Data set from the three sample sets were divided into two, namely with training and testing data set. Training data set consists five images for each grade sample or approximately 16% data from the total number of the data set, while testing the data set includes twenty five other data from each grade that were not selected as the training data set. There were five pairs of randomized training and testing data set per each sample set and illumination which was expected to represent all variations in the real application. Feature set was extracted from each training data set and then trained to the classifier. The trained classifier was then tested to the corresponding testing data set. The specificity of each feature set (feature vector) is reflected on the classifier ability to learn the patterns. It can be viewed from the number of iteration and the classifier error while training. Iteration number of the classifier for each matching feature set and illumination level is presented in Figure-4, while the corresponding error (sum of square error, SSE) of the classifier for the data set is presented in Figure-5. Both parameters illustrate the influence of illumination and feature set on the convergence speed of the classifier.

Lighting effect on the convergence of classifier can be viewed from the iteration number and the SSE value. In general, the epoch required by classifier to train the pattern sets tends to rise in line to the entire feature sets. For the five feature sets tested, the iteration tends to be lower for the illumination level of 40, 100, and 200 lux; while it increases significantly for the lighter illumination. Some feature sets approach to the limit of iteration provided in the training set. Figure-5 provides a similar trend of SSE corresponding to the various illumination levels. The SSE tends to rise in line to the increase of the lighting level especially provided by feature sets 3, 4 and 5. The three sets perform low SSE at 40 and 100 lux. At illumination of 300 lux, all feature sets can be trained with relatively similar value of SSE. They show to increase at 400 lux and then decrease at 500 lux. Since both iteration and SSE number reflect on the easiness of the classifier for mapping the trained data patterns, by considering to both variables, it can be inferred that a meaningful feature may be obtained at the low range of illumination (40, 100, 200, and 300 lux).

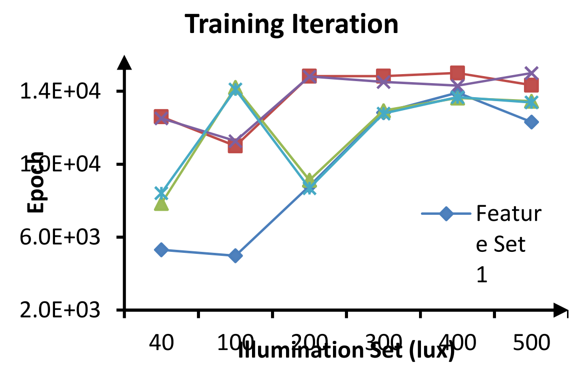

Figure-4. Average of iteration number for all feature sets and illumination levels.

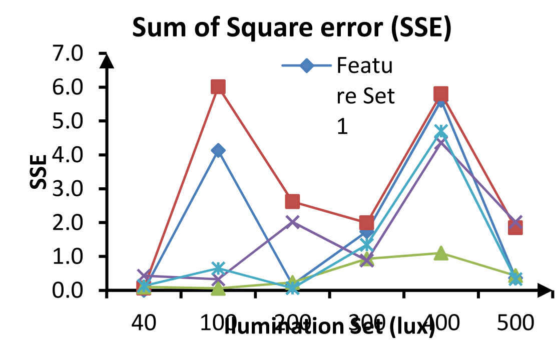

Figure-5. Average of SSE for all feature sets and illumination levels.

Beside to describe the influence of illumination on the convergence of the classifier, the trend of iteration and SSE can be used also to represent the distinctiveness of patterns between grades of sample. The small SSE provided at 40 lux of illumination shows that the classifier can learn the patterns easily; it indicates that the entire feature sets are able to result a unique pattern for each sample grade. However, viewing on Figure-5, different epochs presented by the feature sets can be grouped as follow, from the lowest into the highest value, feature set 1, feature set 3 and 5, and feature set 2 and 4 respectively. Since the SSE is relatively equal, it can be inferred that the most distinctiveness pattern are obtained by applying the feature set 1 consisting of all first and second order statistical features. A different result is provided at 200 lux of illumination, in which a lowest SSE and iteration number are presented by feature set 1, 3, and 5. While at 100 lux, only the feature set 1 provides lowest iteration in contrast to the value of SSE. At 300 and 400 lux, all evaluated feature sets perform with high iteration and SSE. Considering on the lighting levels, it can be obtained that feature set 3 and 5 have similar trend for both SSE and iteration number. Smaller SSE performed by feature set 5 at all lightings indicates that the feature set provides

VOL. 10, NO. 18, OCTOBER 2015 ISSN 1819-6608

ARPN Journal of Engineering and Applied Sciences

meaningful feature of the sample. Besides, it also tolerate to the illumination.

In addition, Figures 4 and 5 also explains the potency of either FOS or SOS features corresponding to their ability to characterize the grades of green coffee bean. It can be viewed on the convergence of the three feature sets (feature set 1, 2, and 3). The feature set 3 provides SSE less than two other feature sets for all lighting levels. This trend indicates that the classifier can learn patterns obtained from feature set 3 fast than both other sets. This also means that the feature set 3 consisting of SOS features is more able to represent each sample grade rather than the feature set 2 which only contains of FOS features. Thus, it can be inferred that the second order statistical features is more dominant for classifying grades of green coffee bean than the first statistical feature.

The trained classifier was then tested to identify the corresponding testing data set. The recognition result for the entire data and sample sets is presented in Table-3. Table-3 also illustrates the vigor of illumination and feature set on the level of identification. The entire feature sets provide a similar trend of identification level which can be characterized as follow. The low accuracy is obtained at 40 lux of lighting. In line to the higher lighting level from 100 to 200 lux, all feature sets obtain higher recognition levels. The rate tends to decrease at lighter illuminations (300, 400, and 500 lux). Considering on the five feature sets, the best accuracy is presented at the level of 100 and 200 lux. This result indicates an opportunity to obtain optimum features for this application at the lighting range of 100 to 200 lux.

Table-3. Average of the classification result for all testing data sets at all varied illuminations and examined feature sets.

Illumi-nation	**Identification result** (%)					
	Feature Set 1	**Feature Set 2**	**Feature Set 3**	**Feature Set 4**	**Feature Set 5**	**Average**
40	76.07	62.72	73.51	59.54	75.70	69.51
100	68.48	56.99	80.60	70.85	80.50	71.48
200	77.70	62.93	76.90	62.20	76.92	71.33
300	68.76	59.88	70.86	68.94	71.86	68.06
400	50.93	52.40	56.48	58.61	53.06	54.30
500	59.42	58.28	59.59	64.54	58.56	60.08
Average	66.89	58.87	69.66	64.12	69.43	65.79

In terms of feature sets, the average level of identification from the lowest to the highest for all variations of illumination are presented by the feature set 2, 4, 1, 5 and 3 respectively. The difference in the level between feature sets 2 and 3 may also indicate the domination of both sets as meaning features. The feature set 2 with pure FOS features produces 58% of accuracy. It is much lower than the use of SOS features accommodated in the feature set of 3 (69%). This difference concludes that the potency of the second-order features as meaningful feature of bulk coffee grain is greater than the first order features. Nevertheless, the learning ability viewed by feature set 2 indicates that the role this feature set cannot be ignored. In addition, ability of the feature set 5 for distinguishing the sample grade also strengthens the role of the first-order features.

Considering on the variation of lighting, it can be inferred that the range of 100 to 200 lux provides the best opportunity to extract meaningful features of the coffee grain image. The better performances corresponding to convergence of training and level of identification are presented by the application of feature set 3 and 5. For seeing the reliability of each feature set, Table-4 presents the identification level of the entire data sets for each sample set were tested on the best illumination (100 lux). The highest level of identification (80%) is obtained by applying the feature set 3 and 5. Comparing to the identification level provided by applying of the feature set 4, the use of the feature set 3 and 5 gives better results. It means that the use of more completed features (feature set 3) or combined features (feature set 5) can improve the accuracy of such estimation system proposed by Faridah *et al.* (2011). In addition, the classification level which is almost equal to the three sample sets for both varieties of sample (Arabica and Robusta) indicates that the feature set 3 and 5 can be used for general classification of grains particularly for such similar character material. Thus, both feature set 3 consisting of 17 second order features (energy/ angular second moment, entropy contrast, inverse difference moment/homogeneity, autocorrelation, dissimilarity, sum of average, sum of entropy, sum of variance, difference of entropy, two features of information measures of correlation, difference variance, correlation, sum of square, cluster shade and cluster prominence) and feature set 5 consisting of 6 first order features (energy, entropy, variance, smoothness, standard deviation, and spot) and 11 second order features (energy/ angular second moment, entropy, contrast, dissimilarity, sum of average, sum of entropy, information measures of correlation, correlation, sum of square, cluster shade, and cluster prominence) have the same opportunities to estimate the coffee grain quality in bulk. Nevertheless, the use of feature set 5 has more benefit since it accommodates both features (first and second order statistical features).

Table-4. Classification result for all sample sets at 100 lux of illumination.

Sample set	Number of image			Identification result (%)				
	Trai-ning	Tes-ting	Data number	Feature Set 1	Feature Set 2	Feature Set 3	Feature Set 4	Feature Set 5
Sample 1	35	175	210	84.34	76.46	84.00	67.66	85.71
Sample 2	40	200	240	81.40	60.90	78.50	75.80	77.10
Sample 3	40	200	240	39.70	33.60	79.30	69.10	78.70
Average				68.48	56.99	80.60	70.85	80.50

CONCLUSIONS

Evaluation of the use of FOS and SOS features as feature input for such quality estimation system of green coffee bean in bulk has been conducted. In general, the result shows that there was an opportunity to use a combination of those features for characterizing the bulk coffee grains. Based on training and testing, the role of SOS features looks more dominant than the features of FOS. The result also shows the influence of illumination on the accuracy of this estimation system in which that a high classification level can be obtained at the illumination range of 100 and 200 lux. In this lighting condition, the use of FOS and SOS features, either in separately or in combination, provides good identification accuracy. The best classification is achieved in the illumination of 100 lux where the accuracies of the feature set 1 to 5 are 68%, 56%, 80%, 70%, and 80% respectively. Thus, the use of the feature set 3 (17 features of SOS) or feature set 5 (17 combination features) have a greater chance than any other feature sets. Besides, both the feature sets also show their reliability from two different varieties of sample (Arabica and Robusta). Although both have equal accuracy, we consider using the feature set 5 because it combines the first and second order features. Based on the type of feature, feature set 5 consisting of 17 features may correspond to the meaningful feature of the sample grades. The features are 6 first order features (energy, entropy, variance, smoothness, standard deviation, and spot) and 11 second order features (energy/ angular second moment, entropy, contrast, dissimilarity, sum of average, sum of entropy, information measures of correlation, correlation, sum of square, cluster shade, and cluster prominence).

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