Using Machine Vision To Inspect Oil Palm And White Powder Starch

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Abstract: - Color and size are two important attributes for quality evaluation of most food and bioproducts. Many of the quality factors affecting oil palm and white powder starch are determined primarily by visual inspection. Such inspections determined market price and to a certain extent consumers' preferences. However, the inspection of oil palm and white powder starch is a very repetitive and tedious task which is also subjective in nature. This paper describe techniques and methods developed for starch and oil palm imaging using machine vision technology. The system was able to correctly classify 91.2% of oil palm for color, and 91.1% of starch for size. Classification scores located near the separation boundaries were the major source of misclassification error.

Key-Words: - Machine vision, Automated inspection, Color analysis, Stepwise discriminant, Quality evaluation.

1 Introduction

Color and size are two important attributes of visual information. Despite this, color images have not been widely used due to a large storage and high computational requirements. With the advent of microprocessor technology and information system, both the computing and storage costs are rapidly decreasing. The work reported here has been motivated by the need to develop efficient machine vision inspection system for automated control of fruit and food processing, namely, the oil palm and starch production sectors. Technically there is a great potential for automation of oil palm and starch inspection since, since crude palm oil and sago starch are being produced everyday throughout the year. In 1997, this country produced more than 9 million tones or about 60% of the total production, reaching more than 4 billion people worldwide and contributing USD 3,4 billion to the country's export earning [1].

Among the many tests that need to be carried out on oil palm fruits during processing is the measurement of color for color determines product quality and defect..The Palm Oil Research Institute of Malaysia (PORIM) established four classes of ordinary oil palm *Elaeis guineesis* which is used in this study [2]. The classes, unripe, underripe, ripe and overripe are determined qualitatively by human expert.

Grading and sorting are two important operation performed routinely during starch refining process. Some starch granules come in various color, size, shape and defect, often attributable to adverse growing conditions, such as too little or too much moisture or frost damage to the plant [3]. Grading is performed primarily by trained human inspectors who assess starch granules and make quality judgement microscopically.

In both cases, there are some disadvantages to using human inspectors, including inconsistency, short supply of labor, extensive time required due to huge production volumes. More importantly, a significant proportion of the local productions are destined for overseas market which demand good quality and highly consistent products. Hence, there is genuine need to focus research and development related to oil palm and starch automation.

2 Problem Formulation

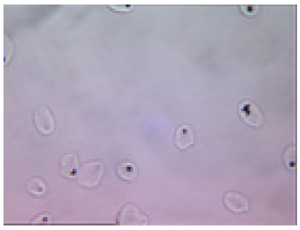
Fig. 1 shows color image captured from a group of oil palm fruits serving as references of 4 different degrees of ripeness or classes. It can be seen from this image that the color of each fruit is highly non-uniform, changing appreciably as one moves from the apex to the base of the fruit.

Fig.1 Oil palm fruits' image showing four different classes or ripeness: top left is unripe, top right is underripe, button left is ripe and button right is overripe.

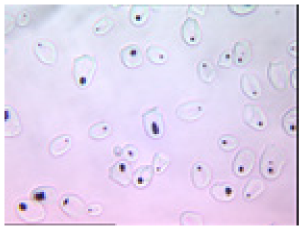
Unlike oil palms, the size and shape of starch granules are important for quality indicator of sago starch. The size of common white *Metroxylon sagu* starch, which is used this study, is averaged around 30µm. However, the presence of other contaminants such the fiber and cell-wall granules generally lowers the grade of starch. The size of these contaminants are relatively smaller compared to starch granules. Hence, a good quality starch contains a larger proportion of the larger granules and very little proportion of smaller granules.

The Malaysia Crop Research and Application Unit (CRAUN) divides white powder starch into three categories based on average granules size. The diameter for super grade starch ranges from 25 to 35µm, the industrial grade is from 15 to 25µm and, the defect grade starch ranges from 5 to 15µm [3]. Figs. 2(a) –(c) illustrate images of starch granules when viewed under microscope under the magnification scale of 40.

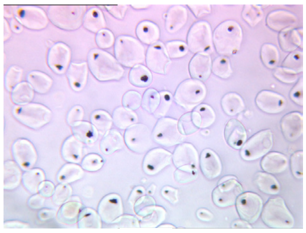
In practice, these guidelines are not strictly adhered because of the difficulty in measuring the distribution of the granules and establishing the cut-off points that would help grade discrimination.



(a)



(b)



(c)

Fig.2 Examples of starch granules corresponding to (a) super, (b) industrial and (c) defect grade categories

2.1 Color inspection

The classification of the image into groups belonging to various grades was based on the color of the object. In color image processing, the color of a pixel is usually given as three values corresponding to the tristimulli of red (R), green (G), and blue (B). Although RGB data are useful for color inspection but it does not describes color the way that human perceives color. Various representation schemes have been developed to solve this. On of them is the hue (h), the saturation (S) and, the intensity (I) which approximately model human perception of color [4]. This model was therefore used in this application. The first step in machine vision inspection was to transform the RGB to HSI values. For 8-bit machine vision system, such transformations are as follows (only h component is given here)

If $B \geq G$

$$h^{o} = \left\{ 360^{o} - \cos^{-1}\left(\frac{-0.5[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}} \right) \right\} \times \frac{255}{360} \tag{1}$$

If $B < G$

$$h^{o} = \cos^{-1}\left(\frac{-0.5[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}} \right) \times \frac{255}{360} \tag{2}$$

The above transformations were performed on image shown in Fig. 1 resulting the hue distributions which are shown graphically in Fig.3. 3.

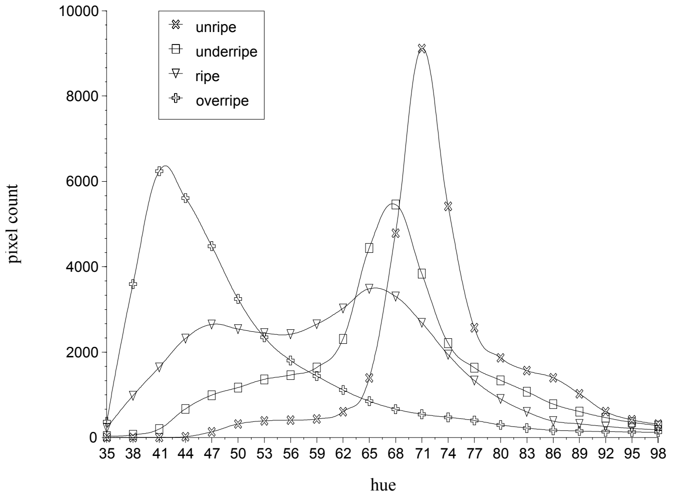


Fig. 3 Hue distributions computed from oil palm image shown in Fig. 1.

In digitised hue scale, yellow has a value of 42, green 85 and cyan 127. It can be seen from this figure, hue values for all classes of oil palm fall in the range between 35 (yellowish red) to 100 (greenish yellow). Evidently, the distributions are skewed towards yellow as the rate of ripening increases. It was heuristically discovered that cyan background provided high contrast between oil palm colours and the background. Furthermore the background is essentially constant, providing no additional information on oil palm. Hence, it was necessary to remove the cyan background colour, leaving only hue values belonging to oil palm. Low pass filter with cut-off point set to 100 was implemented to do this.A close inspection of Fig. 3 reveals that there is no single threshold point exists since hue values of all classes lie in the range between 36 and 98. Therefore, direct thresholding will result in a large number of oil palms being misclassified. Hence, a different approach is needed to classify oil palms based strictly on their hue values.

2.2 Size inspection

The shape and size of an object is usually described from the boundary information. Shape perception generally involves converting the boundary information to certain defined known categories such as circle or square [5]. This method are quite mathematical intensive since it requires the computation of curve coefficients infinitely. Furthermore, the object boundary must firstly be located to enable object descriptors be accurately established. Referring to Figs. 2, the starch images exhibited high degree of complexity in that the number of granules which overlapped is significantly large. This caused the difficulty in tracing the boundary points of all overlapped cases. The method used to solve this problem was to treat each granule as a blob and calculate the ratio between the number of blobs to the image size. Since the latter is fixed, in this way, the granule size can approximately be estimated.

3 Problem Solution

One effective way for solving this type of color classification was to treat hue values as features and apply stepwise discriminant analysis to establish classification criterion from training test samples. The details have been published elsewhere and interested readers are referred to this reference [6]. Here a summarized version of this analysis is given only to facilitate discussions on machine vision vision application. The basic idea is to generate the discriminant functions, transforming multivariate h^{o} to univariate *y* such that *y's* from population G_i for $i = 1,2,3,\cdots,g$ were separated as much as possible. The results can be interpreted in terms of the sample Mahalanobis' distance such as

$$D_i^2 = \left(h^o - \bar{h}_i^o\right)^{\mathrm{T}} S_{\text{pooled}}^{-1} \left(h^o - \bar{h}_i^o\right) \tag{3}$$

where,

h^{o} = hue vector of object under test,

$\bar{h}_i^{\mathrm{o}}$ = average hue vector for *i*th group, and,

S_{pooled} = pooled covariance matrix.

In this case it is always desirable to form h^{o} from a best subset of dependent hue variables before performing discriminant analysis. The Wilk's Λ method was implement to do this. In operation this method computes discriminant power of each variable in terms of *F*-statistic. Mathematically, this is given by [7]

$$F = \frac{n-g-p}{g-1}\frac{1-\Lambda}{\Lambda} \tag{4}$$

where n is the number of observation, g is the number of group, p is the length of vector h^{o} and Λ is the Wilk's statistics. This equation provides a stepwise analysis procedure serving as F-to-enter and F-to-remove. At each stage h^{o} with the largest F-to-enter is added to the set if its F-value is larger than the specified threshold, F_{in}. After this variable has been entered, all h^{o}s in the set were reexamined and the one with the smallest F-to-remove was deleted if the F-value was less than a second threshold value, F_{out}. In this way a set subset containing a best h^{o}s were produced from the full available of h^{o}s.

The above algorithm was tested using a training test set comprising of 25 samples of each grade. A total of 71 variables ranging from hue 30 to hue 100 were analyzed using Wilk's Λ analysis. The algorithm took 5 steps to converge producing 11 principle hues. They are 39, 43, 49, 55, 58, 65, 70, 73, 80, 87 and 88 corresponding to a loss of 84.5% in variation. The discrimination powers of these hues are demonstrated canonically in Fig. 4.

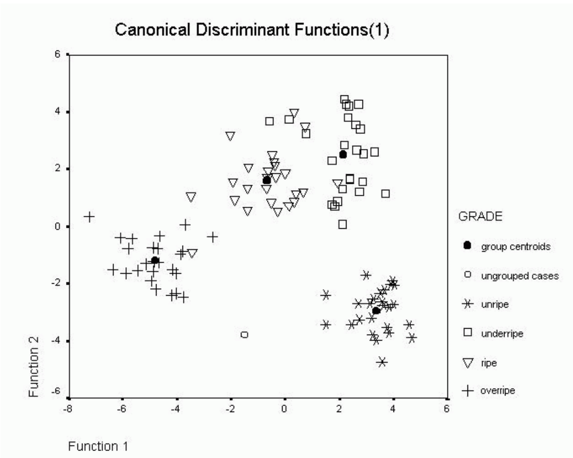


Fig.4 Canonical plot using 11 principles hues

Clearly for Fig. 4, four groups are formed representing the oil palm classes of unripe, underripe, ripe and overripe. A difficulty in discriminating underripe from the ripe samples is clearly evident in this plot. Results from discriminant analysis on the 11 principle hues using independent test samples are tabulated in Table 1. The overall 91% correct classification rate by sample class has been achieved, with low of 84% for underripe, and a perfect 100% for unripe. The data represents, therefore, general classification rate by oil palm class. Generally, there are some differences in classes classification rates between machine vision and inspectors. This variation indicates some inconsistency in machine vision inspection.

Classificat-ion		Human grading			
		Overripe	Ripe	Underripe	Unripe
Machine vision grading	Overripe	93	7	-	-
	Ripe	2	88	10	-
	Underripe	-	-	95	5
	Unripe	-	-	10	90

Table 1 Color classifications using 11 principle hues.

As previously mentioned, one of the sign that the starch is degrading is when the ratio between larger to smaller size granules decreases. If the image size is fixed, then, a better grade starch has fewer granule since each granule occupies a relatively larger image space. Alternatively, a lower grade starch has more granules because of its lower size-to-space ratio. Hence the number of count in the image space gives a rough estimation on the size of starch granules, and hence, its quality criteria. Using these guidelines, an algorithm was developed to count the number of granules that are presence on the starch image. Classification was achieved using a direct thresholding technique. The algorithm was tested using 45 starch images comprising of 15 samples of each grade. In this example, two threshold values were empirically chosen. They are 19 and 51 corresponding to a lower and higher threshold points respectively. Fig. 5 shows the results from machine vision classifications.

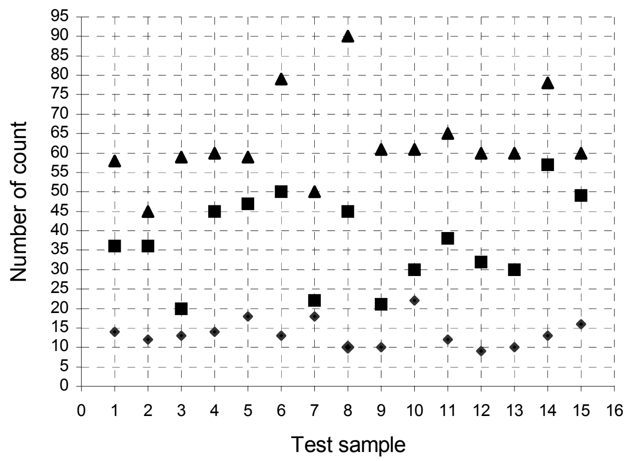


Fig.5 Number of count versus sample number for

grade determination: ♦ good grade, ■ industrial grade and ▲ reject grade.

It can be seen from Fig. 5 the classification is better for super and industrial grade samples. In both cases only 1 of 15 samples have was misclassified. However, similar result was not observed when discriminating reject grade samples. The disagreement between computer and inspector occurred when the number of count lie near the separating region, with 13 of 15 samples correctly classified. The average classification accuracy for three categories is nearly 90%. In order to improve classification accuracy other starch features such as the shape must be fully accounted. This requires further studies.

4 Conclusion

A working machine vision system has been developed for oil palm and starch imaging. The machine is useful not only for reducing the amount of manual labor in grading, but more importantly, it helps promoting grading consistency and standardization. Commercial oil palm and starch producers are presently considering establishing a new grading standard that would help include more grades. The work presented here could be used to set quantitative standard for the proposed quality schemes of these agricultural products.

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