Journal of Oil Palm Research Vol. 22 August 2010 p. 765-773

FEATURE EXTRACTION FROM OIL PALM *in vitro* SHOOT IMAGES

ABDUL HALIM ISMAIL*; MOHAMMAD HAMIRUCE MARHABAN*; SAMSUL BAHARI MOHD NOOR* and AHMAD TARMIZI HASHIM**

ABSTRACT

The feature extraction techniques are discussed in this article. The algorithms and methods developed are robust and advanced enough to be used in combination with a machine vision algorithm and automation system. The subject under study is oil palm in vitro *shoot images. The potential features extracted from the images could be used as a vision sensor to replace human expertise via an automation system. Two main categories of the* in vitro *shoots could be visually identified, namely the normal and abnormal groups. Image interpretation can categorize the* in vitro *shoot automatically in its group. The techniques proposed are not influenced by the shape or orientation of the* in vitro *shoot. The feature vector is plotted to prove the separability of both normal and abnormal* in vitro *shoots.*

Keywords: oil palm *in vitro* shoots, machine vision, feature extraction, thresholding, image processing.

Date received: 20 May 2009; **Sent for revision:** 30 June 2009; **Received in final form:** 3 February 2010; **Accepted:** 6 April 2010.

INTRODUCTION

Machine vision has become an ideal part in an automation system. This element provides intelligent sensory information for automation and a non-destructive method to analyse the subject. In this article, the subject is oil palm tissue cultures. The current manual protocol in selecting oil palm tissue cultures requires a great deal of time, human expertise and involves a great amount of cost. These three factors pose an engineering problem. The use of machine vision and an automation system has long solved these problems in other fields, such as in microchip and electronics manufacturing, but not many attempts have been made to automate the *in vitro* processes via robotics. Sogeke (1998) explains that the stages in oil palm tissue culture include callus initiation, embryoid formation and proliferation, shoot development, and pre-nursery and field planting. Abdullah *et al.* (2005) illustrated the oil palm tissue culture at every stage in proficient details. In this article, the research focuses on *in vitro* shoot development and selection. The current manual job is tedious at this stage and needs human expertise.

The key for a vision sensor to work successfully in an automation system lies in the features extracted from the subject's images. It is crucial to extract the most discriminant features between the classes studied, namely, the normal and abnormal *in vitro* shoots. These discriminant features can be classified afterwards using the pattern recognition method to group them automatically in their dedicated class.

There have been a small number of researches using machine vision for plant tissue culture process recognition. The closest references are the research on potato plantlet segments by Achanatis *et al.* (1993) and Peleg *et al.* (1993). The research concentrated on separating the manually pre-cut potato segments by the recognition of buds, leaves and stems using computer vision. Complex image processing and feature extraction methods were utilized in order to recognize the potato tissue culture through the classification approach. The threshold value for image segmentation was experimentally chosen by Peleg *et al.* (1993) before applying the contour detection method. This method, however, is not suitable for industrial application as the different lighting control may affect the experimental

* Department of Electrical and Electronics Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia.
E-mail: halimismail@ieee.org

** Malaysian Palm Oil Board, P. O. Box 10620, 50720 Kuala Lumpur, Malaysia.

threshold value. The blobs in the segmented image were segregated into curvatures that were likely to describe the shapes of the plantlets. Taking into consideration the time and the complexity of the mathematical operation to calculate the curvatures and also the dynamic shape of the plantlets, it is difficult to extract discriminant features and to complete the processing in near real-time. Thus, it would not be practical for industrial application.

Colour features were used by Achanatis *et al.* (1993) to analyse the potato plantlets class. A 'good' plantlet is defined as a plantlet segment containing at least one leaf attached to a piece of stem, and 'bad' is otherwise. In order to identify them using colour information, 0.25 ppm ancymidol is added to the nutrient medium in order to increase the colour difference, *i.e.* the leaves are dark green while the stems are light yellow. This approach is not suitable for oil palm *in vitro* shoots because they are not separated into leaves and stems. Furthermore, chemical addition is strongly discouraged because it may affect the efficiency of the oil palm tissue culture mass propagation process.

IMAGE PROCESSING APPROACH

Figure 1 shows the flow chart of steps in extracting the features from oil palm tissue culture images. The images were initially taken in a three-dimensional colour space, but only one-dimensional grey scale images were used for processing. Thresholding algorithm was then applied to the grey scale images for segmentation before exploring the methods for feature extraction based on thinning and convexity algorithm.

Image identification can be used for future automation in the oil palm clonal propagation process. Therefore, the camera used for image digitization was of industrial standard, *i.e.* the ImagingSource DFK-310BF03 Firewire colour camera with manual shutter and illumination control. The viewing mode is in the RGB colour model, while the YCBCr model was used when capturing the images. For speedy processing, the luminance space, *Y*, was used because it is similar to the grey scale representation of an image. Thus, the camera in question was best suited for this application. To create a versatile dataset for analysis, 20 samples were digitized using this camera. As a result, 100 images per sample were successfully digitized under various lighting conditions and geometrical orientation. *Figure 2* shows an example of normal and abnormal grey scale images, ranging from typical acceptable shoots to various kinds of shoots with abnormalities in different orientations. The thresholding method was later used to contrast the *in vitro* shoot from the background.

Thresholding is vital in order to extract useful information from the image. Thresholding is noted as a simple approach but is an effective tool to separate objects from the background (Gonzalez and Woods, 2002). Automatic thresholding was used by means of adaptive threshold values according to the image. Many automatic thresholding algorithms have been developed (Sahoo *et al.*, 1988; Guo and Pandit, 1998; Segzin and Sankur, 2004). The method described by Otsu (1979) for automatic thresholding was used in this work. The weighted sum of within-class variances of the foreground and background pixels was calculated to establish an optimum threshold, x_{th}. The optimum threshold value was later used as

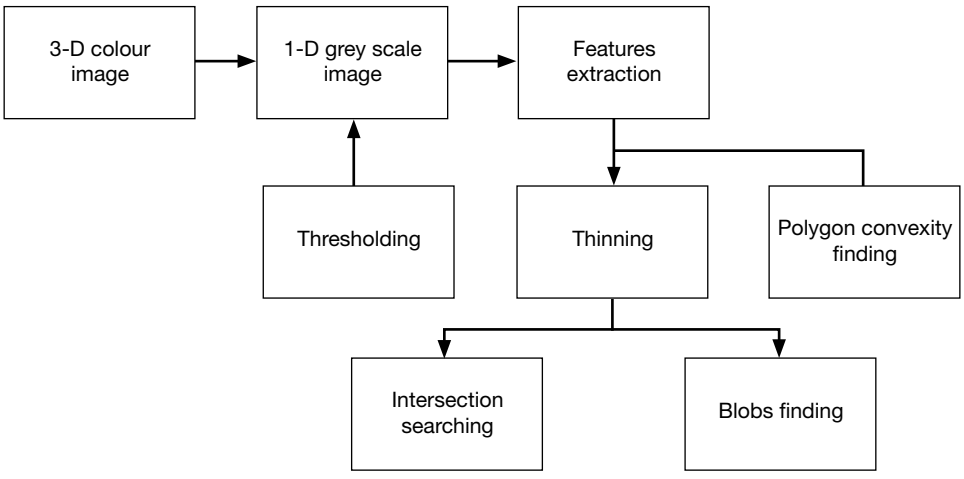

Figure 1. Flow chart of feature extraction of oil palm in vitro *shoot images.*

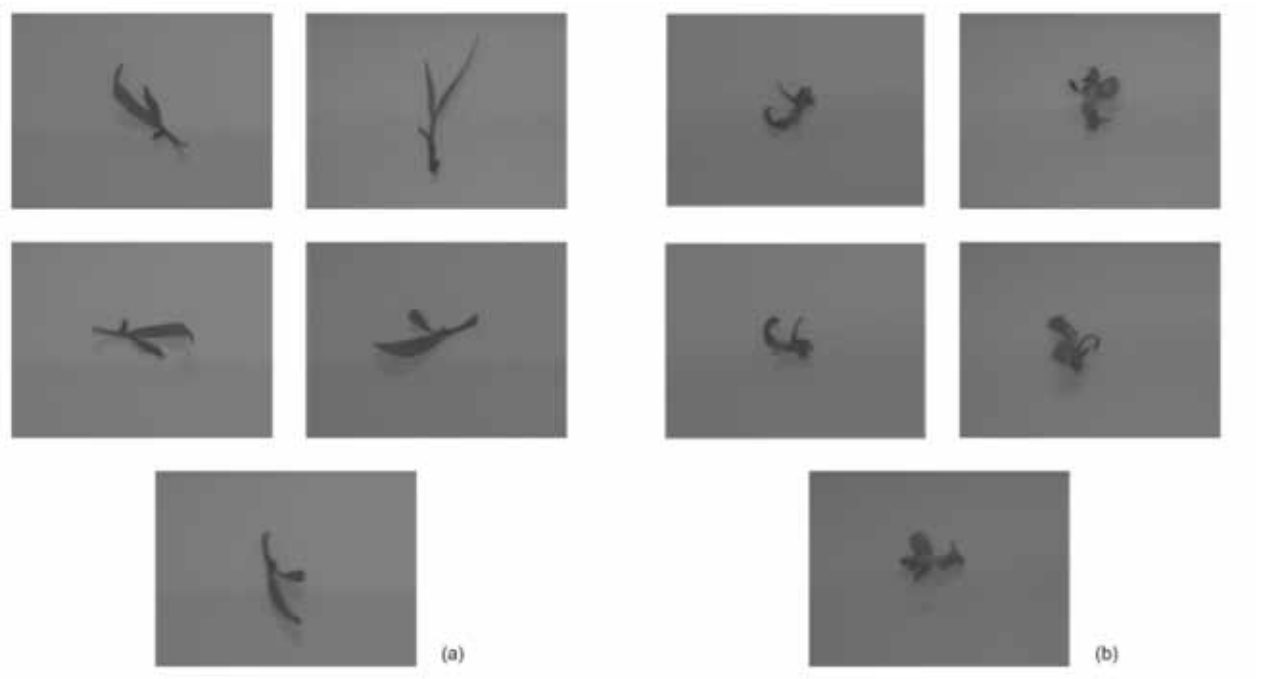

Figure 2. A set of samples of oil palm in vitro *shoots in grey scale: (a) normal* in vitro *shoots, (b) abnormal* in vitro *shoots.*

the cost function as stated in Equation (1), resulting in the binary image $y(x)$.

$$y(x) = \begin{cases} 1, & if\ x < x_{th} \\ 0, & otherwise \end{cases} \quad (1)$$

Figure 3 shows the result of segmentation based on Otsu's optimum threshold value of the thresholding algorithm. It is clear from the result that the algorithm was robust as the shadows in the *in vitro* shoot grey scale images shown before that were caused by false lighting were eliminated completely regardless of their geometrical orientation.

FEATURE EXTRACTION FROM OIL PALM *in vitro* SHOOTS

From the binary or rather segmented images of the oil palm *in vitro* shoots, the features were extracted based on their shape using advance morphological image operation such as thinning and convexity.

Lam and Lee (1992) denoted thinning image as a representation of a pattern by a collection of thin

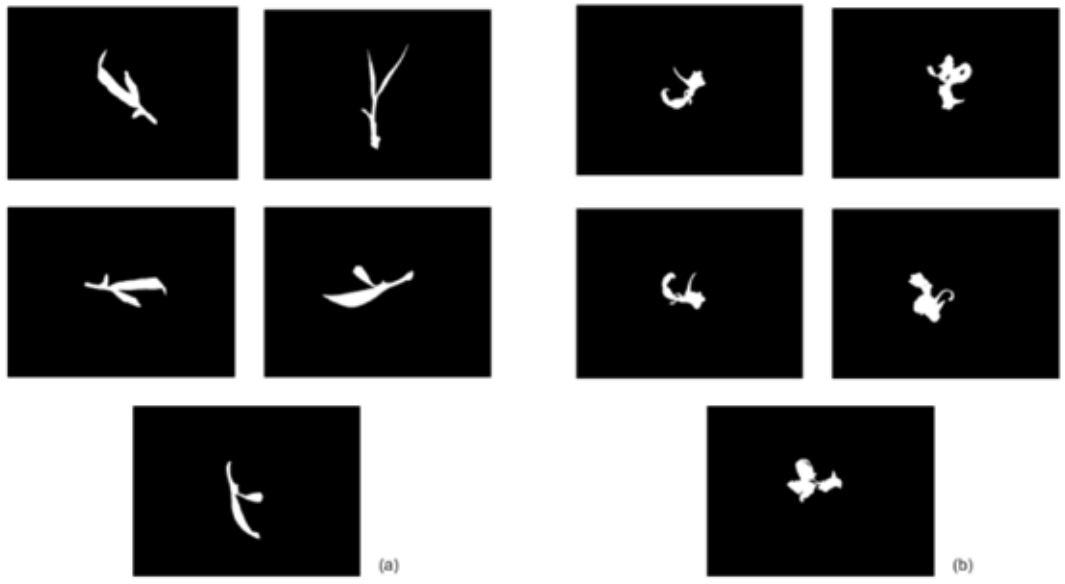

Figure 3. (a) Result of thresholding of normal samples based on Otsu's algorithm, and (b) thresholding result of abnormal in vitro *shoots.*

or nearly thin arcs and curves of the targeted image. Its applications are undoubtedly enormous, from optical document processing to medical applications. Thinning methodology simplifies the image representation of the subject into lines and curves while retaining information about the subject. In this article, the thinning approaches were adopted in order to identify the intersections in thinned images of both normal and abnormal *in vitro* shoots and the blobs that appeared in abnormal shoots.

The earlier hypothesis was made that the normal shoot had a smaller number of intersections compared to curled abnormal plantlets which were predicted to have more intersections. The thinned *in vitro* shoot image not only gave the intersections feature but also other discriminant features. A novel blob find was developed using a morphological union between filled thinning and inverse thinning of the same image. The details of the feature extraction method based on thinned images are discussed below.

Thinning Feature Extraction

Figure 4 shows the transformation from the binary image to the thinned image of selected *in vitro* shoots. The difference in intersections between the normal and abnormal *in vitro* shoot images could be visually observed. A customized algorithm using kernel convolution was used to identify the intersections. *Figure 5* describes the corresponding algorithm. A kernel window of size matrix was used to convolute the thinned image, and the intersection was found if the resulting convolution had four or

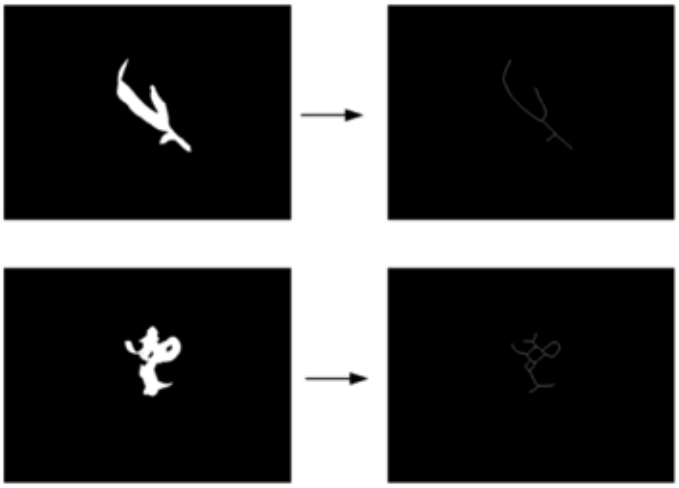

Figure 4. Transformation from segmented image to thinned image.

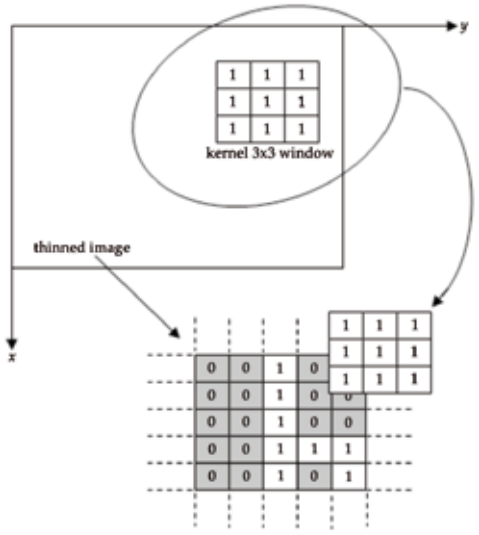

Figure 5. Kernel convolution algorithm to find intersections in the thinned image.

more pixel values of 1. *Figure 6* shows the result of thinning intersections of the images from *Figure 4*. It clearly indicates that the abnormal *in vitro* shoot had more intersections compared to the normal *in vitro* shoot.

In the thinned image of the previous abnormal sample, blobs appeared due to the curled leaves of the *in vitro* shoot. Cultures with curled leaves were discarded because their abnormalities could lead to poor quality plantlets. The hypothesis was made that the normal *in vitro* shoot sample images had no blobs while abnormal - *in vitro* shoot sample images had at least one blob. A novel approach was developed to identify the blobs using the rules of union between the filled thinned image and its inverse. The method is described below:

- apply thinning to the binary image; refer to *Figure 7a*;
- save the thinning image and fill the holes, $r_1(x)$; as in *Figure 7b*;
- inverse the thinned image, $r_2(x)$; as in *Figure 7c*; and
- form the blobs' image, $u(x)$ by the union function, $u(x) = r_1(x) \cup r_2(x)$; as in *Figure 7d*.

From *Figure 7d*, it can be seen that all three blobs were successfully found. This method was rather simple and easy but yet effective in identifying all the blobs in all *in vitro* shoot samples even when the samples were rotated from their original orientation.

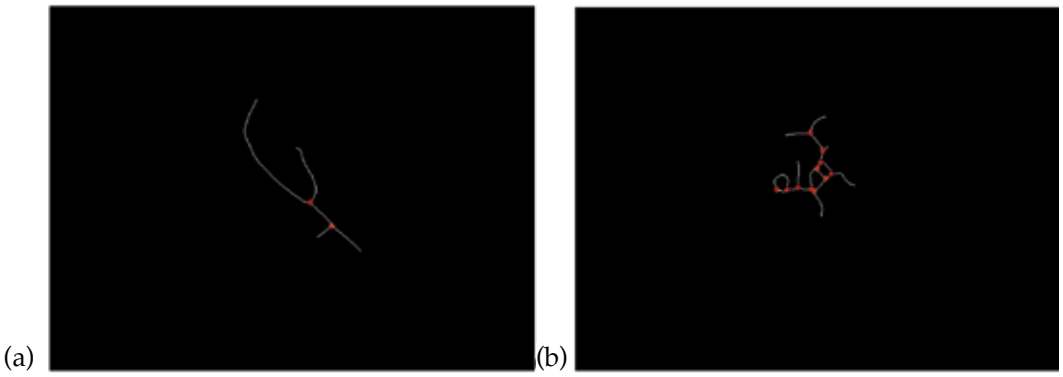

Figure 6. (a) Intersections in thinned image of normal in vitro *shoots, and (b) intersection in thinned image of abnormal* in vitro *shoots.*

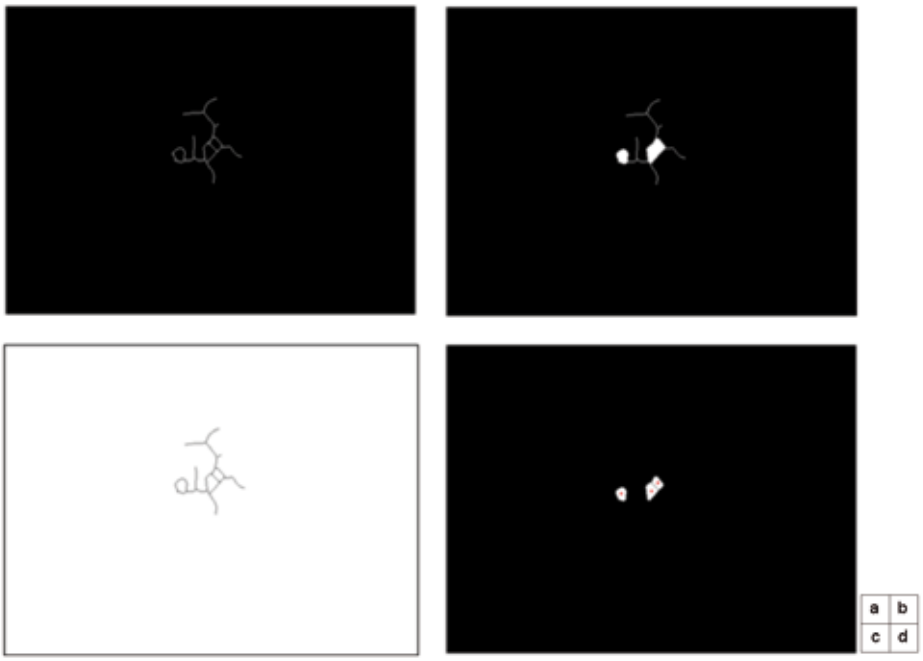

Figure 7. Three blobs found in this abnormal in vitro *shoot image.*

Convexity Feature Extraction

The convex hull of a set of points is the smallest convex set that contains the points, and is generally a fundamental construction for mathematics and computational geometries (Barber *et al.*, 1996). The convex hull is normally used as a shape descriptor of a target in images, and therefore ideal to be applied in extracting discriminant features of *in vitro* shoot images based on their shape.

Figure 8 shows the transformation of the segmented *in vitro* shoot images into the geometrical polygon that best describes the shape of the shoot. It is obvious that the polygon is made up from the convex hull of the *in vitro* shoot images. In order to extract the most discriminant feature between the normal and abnormal shoots based on their convexity, the moment at the edges of the polygon was estimated. The moment can be defined as the corresponding lines that equally split the polygon at about the x-axis and y-axis. It is based on two crucial reference points, which are the centroid of the corresponding convex image and the maximum point in the thinned convex image, as depicted in *Figure 9a*.

The moments were plotted over the convex image as shown in *Figure 9b*, and are represented as lines. A ratio of the moments was used as feature data. The moment ratio, $M_R = L_1 / L_2$, could be defined as the distances between moment L_1 at about y-axis of the points (x_1, y_1) and (x_2, y_2) over L_2 at about x-axis of the points (x_3, y_3) and (x_4, y_4) . The distance metric used is a two-norm Euclidean distance as stated in Equation (2). Let i and j be the two reference points in spatial space, and, therefore, the Euclidean distance, $L_E\ (i,j)$ from point i to point j, can then be found

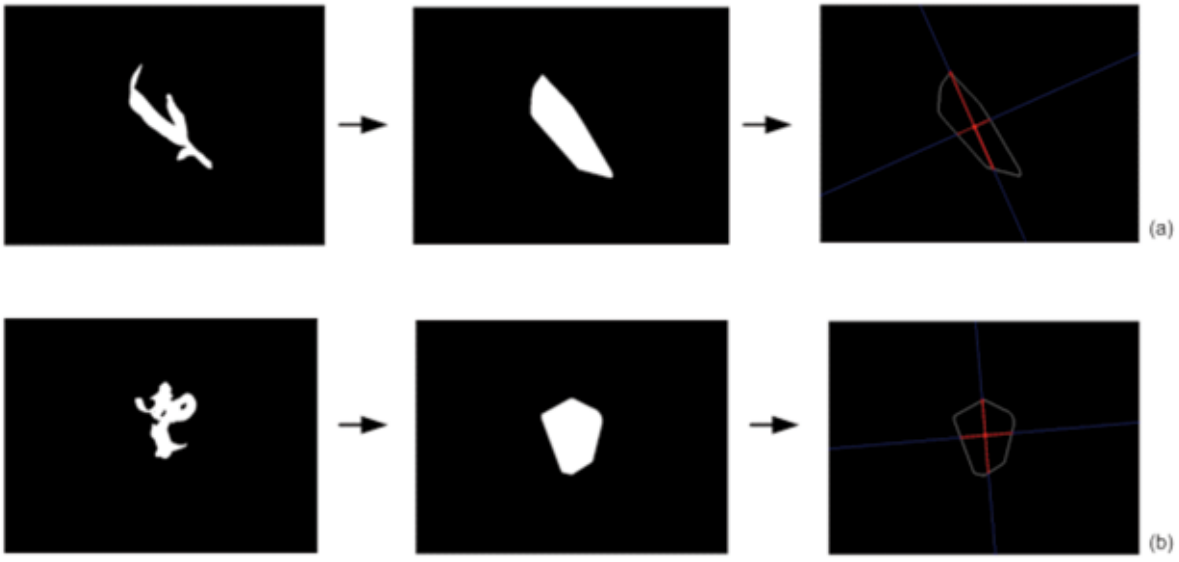

Figure 8. The polygonal convex hull and boundary-descriptor of the segmented image: (a) normal in vitro *shoot sample and (b) abnormal* in vitro *shoot sample.*

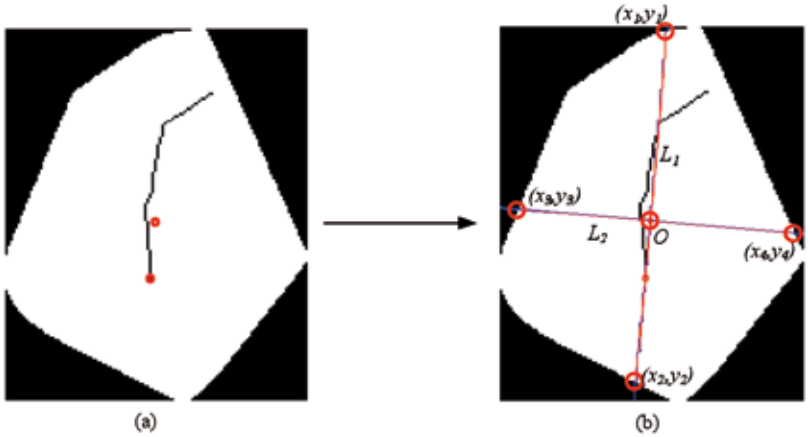

Figure 9. Splitting the convex hull image at about x- and y-axes: (a) two points of reference, the upper point is the centroid of convex polygon while the lower point is the maximum point of the thinned image, (b) the estimated moment of the image based on the two points of the convexity polygon.

(Gonzalez and Woods, 2002) by:

$$L_E(i,j) = \left[(x_i - x_j)^2 + (y_i - y_j) \right]^{1/2} \quad (2)$$

From visual observation of the moments in both normal and abnormal *in vitro* shoot samples shown previously in *Figure 8*, the hypotheses was made that the moment ratio, $M_{R(normal)} >> M_{R(abnormal)}$. This was because the difference between L_1 and L_2 of a good sample is significantly large, while L_1 and L_2 of an abnormal sample was almost the same.

FEASIBLE CLASSIFICATION

The features extracted from the *in vitro* shoot images using morphological operation as discussed in the previous section can be used to recognize the class of the corresponding *in vitro* shoots that is being analysed. The features extracted prior to the sample shape provided robust methods that were not affected by the size and orientation of the *in vitro* shoots.

Twenty preliminary image samples of each category were taken from the tissue culture laboratory and analysed by using the feature extraction methods described earlier. Some of the image samples were actually from the same *in vitro* shoot, except that they were digitized in variations of different angles and orientations. A feature vector containing feature extraction data of each image are tabulated in *Table 1*. Consequently, the classification algorithm could be used for oil palm *in vitro* recognition aforementioned of the feature vector.

A scatterplot of the feature vectors was made. Two-dimensional data were plotted as shown in *Figure 10*. The x-axis represents the intersections in the thinned image while the y-axis represents the moment ratio. The blobs in thinned image feature data were disregarded from the scatterplot because it was easier to view the result in two-dimensional spaces. From the scatterplot, it is apparent that the feature data of the normal group, denoted as '+', differed from the abnormal group, denoted as 'x', in terms of the spatial coordinates. This criterion provides essential discrimination between normal and abnormal sample images. A simple approach in the classification method could yield a feasible solution to this feature vector analysis.

For example, the feature vector was classified using Fisher's discriminant function, and the result was successful. The boundary lines successfully discriminated the normal class data and the

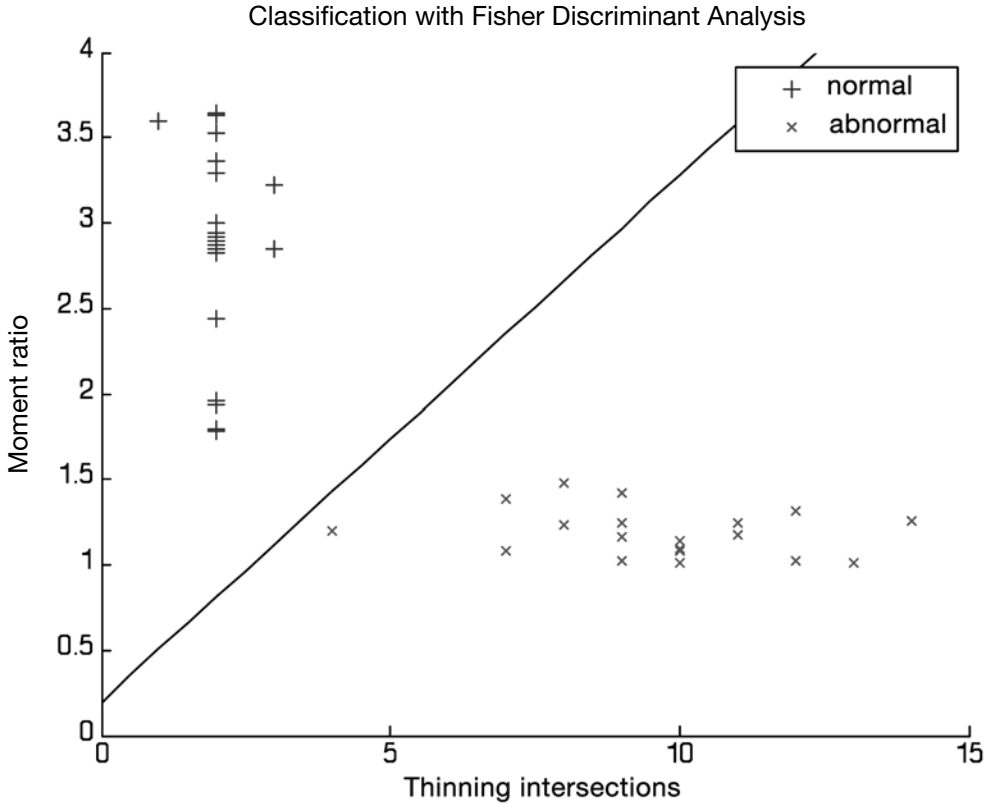

Figure 10. Feature vector scatterplot of 20 samples of each class and simple classification using Fisher's discriminant function.

TABLE 1. SUMMARY OF FEATURES ON 20 IMAGE SAMPLES OF EACH CATEGORY

Sample No.	Normal category			Abnormal category		
	Thinning intersection	Thinning blobs	Moment ratio	Thinning intersection	Thinning blobs	Moment ratio
1	2	0	2.941021	9	3	1.419030
2	3	0	3.222163	9	2	1.023440
3	2	0	3.286566	10	2	1.007398
4	2	0	1.787499	9	1	1.163808
5	2	0	2.821924	11	2	1.171686
6	2	0	2.919994	11	3	1.249083
7	2	0	2.844485	7	2	1.076142
8	2	0	1.796818	10	3	1.091609
9	2	0	2.896154	12	4	1.026415
10	2	0	2.996097	14	4	1.262924
11	1	0	3.596885	7	2	1.388693
12	2	0	3.632933	9	2	1.244582
13	2	0	3.640288	10	3	1.076615
14	2	0	3.357566	8	2	1.232220
15	2	0	3.525470	4	1	1.195865
16	3	0	2.844373	8	2	1.480262
17	2	0	2.875195	12	2	1.318530
18	2	0	2.439964	13	4	1.008047
19	2	0	1.940679	10	3	1.137822
20	2	0	1.953526	13	4	1.008590

abnormal class data at the upper and bottom portions of the boundary line, respectively. This classification method was easy and did not require complex statistical analysis.

CONCLUSION

The use of machine vision for image interpretation of normal and abnormal *in vitro* shoots can be further extended to automate the oil palm tissue culture process. This application can increase the efficiency of mass production of oil palm clones for planting through tissue culture. The vision sensor is perhaps the first step leading to the eventual development of a fully automated system for oil palm clonal propagation.

The feature extraction algorithms were robust and useful in dealing with the various shapes and sizes of oil palm *in vitro* shoots, yielding convincing potential features. As the feature vector was shown to be linearly separable, a simple approach in the classification algorithm could easily solve the recognition problem. Based on this successful experiment, more image samples for algorithm validation will be taken in the near future.

REFERENCES

ABDULLAH, M O; OTHMAN, R; ISHAK, Z; HASHIM, A T and SYED ALWEE, S S R (2005). *Handbook: Photographic Perspective on the Anomalies of Oil Palm*. MPOB, Bangi.

ACHANATIS, V; PELEG, K and ZIV, M (1993). Classification of tissue culture segments by colour machine vision. *J. Agriculture Engineering Research, 55*: 299-311.

BARBER, C B; DOBKIN, D P and HUHDANPAA, H T (1996). The quickhull algorithm for convex hulls. *ACM Trans. Mathematical Software, 22*: 469-483.

GONZALEZ, R C and WOODS, R E (2002). *Digital Image Processing*. 2nd ed. Prentice Hall, USA. p. 85, 286.

GUO, R and PANDIT, S M (1998). Automatic threshold selection based on histogram modes and a discriminant criterion. *Machine Vision and Applications, 10*: 331-338.

LAM, L and LEE, S W (1992). Thinning methodologies - a comprehensive survey. *IEEE Transaction on Pattern Analysis and Machine Intelligent, 14(9)*: 869-885.

OTSU, N (1979). A threshold selection method from gray-level histograms. *IEEE Transaction on Systems, Man and Cybernetics, 9(1)*: 62-69.

PELEG, K; COHEN, O; ZIV, M and KIMMEL, E (1993). Machine identification of buds in images of plant shoots. *Machine Vision and Application, 6*: 224-232.

SAHOO, P K; SOLTANI, S and WONG, A C K (1988). A survey of thresholding techniques. *Computer Vision, Graphics and Image Processing, 41*: 233-260.

SEGZIN, M and SANKUR, B (2004). Survey over image thresholding techniques and quantitative performance evaluation. *J. Electronic Imaging, 13(1)*: 146-165.

SOGEKE, A K (1998). Stages in the vegetative propagation of oil palm, *Elaeis guineensis* Jacq. through tissue culture. *J. Oil Palm Research Vol. 10 No. 2*: 1-9.