COMPUTER VISION FOR SPLENDID SQUID SIZE AND SPECIES CLASSIFICATION

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ABSTRACT: Thai seafood industry relies heavily on labor intensive work, especially in a classification process. Classifying size and species of splendid squids can be exhausted and prone to errors. This study investigated approaches to automate size sorting of splendid squid and differentiating its species such as L.duvauceli and L.chinensis. Parameters extracted from squids' images for example, area, width, length and constructive geometries were tested for their significance. As functions of these parameters, classifiers for grading size were developed based on regression analysis and neural network models; a discrimination analysis was employed in species sorting. Neural network at the accuracy of 92.67% was found to marginally outperform the regression model (88% accuracy) in size prediction; however, non-linear regression was recommended in practice due to its simplicity to apply. For species differentiation, the discrimination equation was as accurate as the crisp divider (width over length ratio) at approximately 90%. These computerized approaches in size and species classification were proven to be superior to manual practice; they can overcome limitations of work performance due to individual capability and ergonomic factors.

KEYWORDS: *Splendid Squid; Sorting; Image Processing Technique; Neural Network; Regression*

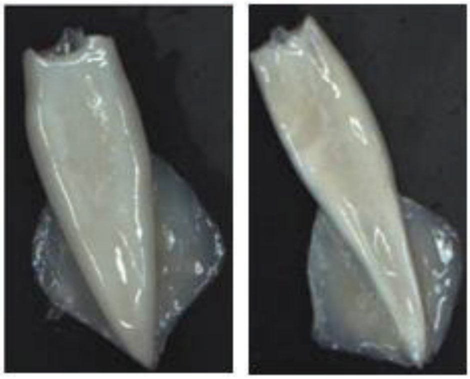
1.0 INTRODUCTION

L.duvauceli and L.chinensis are the most prominent species of splendid squids caught in the fishing ground around the Malay Peninsula, the former of which contributing more than half [1]. They are marketed squids in various forms for example, whole round (squid in its original form), whole cleaned (skinned squid), tube (whole cleaned with head and fin removed), head, and ring (sliced squid's mantle). In processing the squids, classification of size and species plays a great role to ensure that the target yield, as well as customer satisfaction, will be achieved. The National Bureau of Agricultural Commodity and Food Standards (ACFS) [2] categorizes squids into four sizes depending on their weight range (Table 1). Current Thai industrial practice has the squids moved along a conveyor line with workers on both sides. Each squid is picked up, its weight quickly judged by experience and is allotted to its corresponding size basket. At the end of the line, the squids are inspected again for any outstanding errors. Squids that are thought to be wrongly sized are brought back to the line for resizing. Sizing thus relies heavily on human sensory perception. A scale, though sometimes allowed, slows down the sorting process. Effort to predict squid weight based on its external characteristics was reported in [3]. Results indicated that the weight of either species of either sex has a strong exponential relationship with its mantle length. However, significant differences among the relationships between weight and mantle length across sexes and species were investigated. These findings, nevertheless, cannot be adopted for implementation in industrial practice, as distinction between sexes and species cannot be made without sophisticated laboratory equipment. A new method for weight prediction should thus be developed, such that the work could be rapidly performed within an acceptable accuracy and without much difficulty.

Table 1: Weight range of splendid squid and corresponding size code

Size Code	Weight (g/each squid)
Very small	25-50
Small	>50-100
Medium	>100-200
Large	more than 200

Although L.duvauceli and L.chinensis (Figure 1) are visually very similar, slight distinction between them could be observed. The former (Figure 1(a)) on the average has a wider and shorter mantle [3]. This species is more preferable as it has thicker flesh suitable to produce one particular product for example, squid ring. As sorting size and species in practice are carried out simultaneously, workers must be highly skilled and experienced.



(a) (b)

Figure 1: Two prominent splendid squid species caught around the Malay Peninsula: (a) L.duvauceli and (b) L.chinensis

Seafood industries in Thailand are concentrated in the southern provincial area and the workforce usually comes from elsewhere. Uncertainty in labor availability costs this labor-intensive industry a great expense of recruiting and retraining. Unskilled labor, if given the task in the process, would cause yield loss and rework. Labor scarcity and inexperience has become problematic to the industries for quite some time, as well as deterioration of worker performance over time. Evaluation of worker performance in sorting size and species in a seafood company, conducted by the researchers, is presented in Table 2. The evaluation was carried out in accordance with the guideline for measurement and inspection capability studies, detailed in [4]. From the Table, repeatability and accuracy in the sorting process were found surprisingly low - less than 45% and approximate to 70%, respectively with respect to the company aspired work standard of not less than 80%.

Table 2: Workers performance in splendid squid sorting: a study in one Thai company

Attribute	Repeatability (%)	Accuracy (%)
Size	43.75	43.75
Species	72.92	66.67

Implementations of automated system in agricultural products processing are documented extensively. Since products are of high variability in their characteristics, traditional measuring equipment is not always sufficient. Image processing system has gained reputation in agricultural and food research [5], particularly over the past decade. Providing rapid, consistent, accurate and non-destructive inspection, the system has become attractive to industrialists, especially in the midst of labor shortage. Its applications include quality and size evaluation of various agricultural products. The evaluation was performed on different geometric descriptive for example, area, perimeter, length, width and other constructive geometries retrieved from image data. In categorizing shape of strawberries, Bato et al. [6] used a sharing line method to measure *shape* of the fruit from its binary image. A set of lines, used as a parameter to characterize each strawberry, was allocated by k-mean clustering into pre-defined groups. Jarimopas and Jaisin [7] employed Peleg's algorithm to sort sweet tamarinds into three sizes based on their *lengths* measured from images. Defectives were identifiable from breakage observed in the image of the tamarind pod. The same separation algorithm was used in sorting shiitake mushrooms by Chen and Ting [8], classifying them into five groups according to its shape, size, and color. An automated on-line sorting system for green peppers was developed by Cho et al. [9]. Geometric data of the peppers; length and flexure were used as parameters to sort the peppers into four grades. Kashiha et al. [10] estimated weights of pigs in a pen based on their body *area* captured by an image vision unit. An application of computer vision system on classification of squid was introduced by Thammachot et al. [11]. Parameters drawn from squid images: area, perimeter and length were used for size sorting with acceptable results. A ratio of 3.4 between length and width was used to differentiate L.duvauceli from L.chinensis; a smaller value usually reflects the former species.

Studies on applications of vision system on classification of more agricultural products are reported in [12]. In these studies, various classifiers for example, AI techniques such as neural network [12-16], fuzzy logic [17], statistics-based techniques [7, 8, 13, 18] and a rule based system [6] were employed. AI gained popularity over the other techniques when the relationship between the inputs and the outputs was vague or could not be formed explicitly. Neural network used in conjunction with a computer vision system has been widely adopted and proven to be one of the most effective AI techniques in quality inspection of various agricultural products. The number of hidden layers and the number of neurons in each layer are critical factors controlling the learning and classifying ability of the multi-layer neural network (MLNN). Nevertheless, there is no theoretical method, though some heuristics were found in use, to calculate the optimums of such factors [19]. Statistical techniques work equally well if the data show some apparent distributions or trends but there is necessity for some assumptions to be made regarding the particular technique chosen. In our previous preliminary study on splendid squid [11], MLNN was employed as a classifier in size sorting. Although the model achieved acceptable accuracy (more than 80%), in the present study its performance is investigated by employing different transfer functions and adding more parameters to ensure the model optimality. Besides, the fixed threshold used in [11] to differentiate between two squid species did not facilitate the model transition to a fully automated system. It should be automatically adjustable to reflect seasonal changes in squid physiology. A more effective approach is therefore needed to be explored.

2.0 METHODOLOGY

In this section, parameters extracted from squid images are used in developing size sorting approaches: regression and neural network. The other part in this section is the squid species sorting by Discrimination Analysis (DA).

2.1 Analysis of Splendid Squid Images

Although various forms of squids are commercially available, the most demanded products are whole cleaned and tube [2]. Whole cleaned is a skinned squid and if head and fins are removed, it is called tube. In this study, samples of each size and species were randomly picked from a tube processing line. A pilot computer vision system was set up to capture images of the samples. Details are as follow:

i. Data Acquisition

A charged coupled device (CCD) camera was installed in a light control box (0.45 m x 0.56 m x 1 m) to regulate imaging conditions and to minimize noises from surrounding environment. Inside the box, 10-watt fluorescent lamps were fixed to all four edges of the box at 0.4 m above sample. The squid sample was placed on a black background approximately 1 m below the camera. Images of 659 x 490 pixels in resolution were captured using using National Instruments Vision Development software Module AI 2011.

ii. Pre-Processing

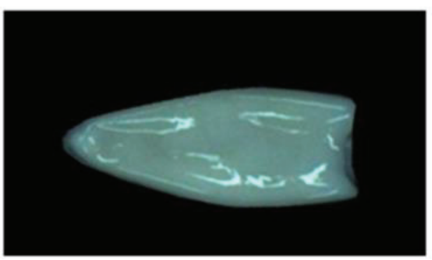
In Figure 2, a grayscale image was converted from an RGB formatted image initially taken. It was then analyzed for its intensity distribution to obtain the best threshold value. From the analysis, the best threshold under this setting to segment the object out of the background was derived (Figure 2(c)). Small objects (noises) and holes were removed from the image by morphology operators before the edge or contour of the region of interest was detected (Figure 2(d)).

iii. Parameter Extraction

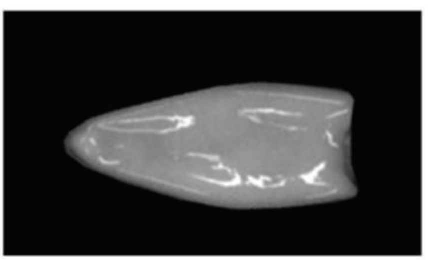
Besides, area, perimeter and width are the common parameters to be considered when size or weight is to be evaluated such as length (Figure 2(e)) and also has a significant relationship with weight [3]. Constructive lines, D1, D2 and D3 were additionally created to observe if they had any influences on size and species identification. The three points: 1, 2 and 3 in Figure 2 (f), were on the contour line where sharp curvatures were prominent. Squids were sampled and divided into two sets; 285 samples for developing and training the models, and 150 samples for testing the model performance. Details according to the size code are tabulated in Table 3.

Table 3: The number of samples for training and testing weight prediction models

Size code	The number of squid samples	
	Training	Testing
Very small	68	35
Small	88	34
Medium	93	42
Large	36	39
Total	285	150

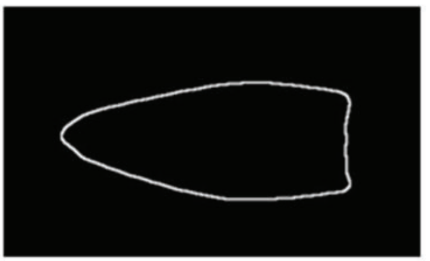


(a)

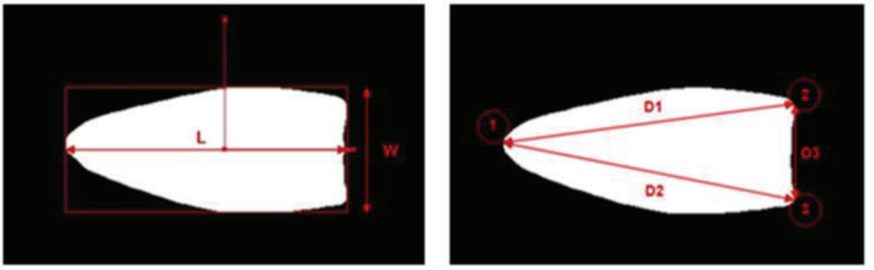


(b)

(c)



(d)



(e) (f)

Figure 2: Analyzing sequence of splendid squid images: (a) RGB image, (b) grayscale image, (c) image segmentation, (d) edge detection, (e) length and width determination and (f) constructive distances: D1, D2 and D3

2.2 Size Sorting

Two approaches for squid size sorting are developed in comparison: (a) a neural network model and (b) regression analysis.

i. Multi-Layer Neural Network (MLNN)

The neural network is remodeled and experimented with different transfer functions from our previous study [11] to ensure the network has reached its optimal performance. Two multi-layer neural network (MLNN) models driven by a back propagation algorithm with three layers: input, output and hidden layers are constructed using MATLAB neural network toolbox. The first model has a quantitative output: *weight*, which is subsequently sorted into pre-defined sizes. Omitting weight prediction to accelerate the sorting process, the output of the second model is finalized in a textual form: size Large, Medium, Small, and Very small. Both models have seven input neurons: area, perimeter, length, width, D1, D2 and D3.

ii. Regression Analysis

In comparison to the neural network, statistics-based models: linear and non-linear regressions are employed to predict squid weight, hence size. By considering the correlation between independent variables and dependent variable, it is evident that weight is highly correlated with all input parameters. However, inter-correlation among the input parameters is also significant. The parameter with the highest correlation; area is chosen to formulate a relationship with weight.

After its weight is estimated by the proposed approaches, each squid is then allotted into a corresponding size in accordance with the schematic diagram in Figure 4. Between the adjacent sizes, there is an allowable weight range that the company and customers can tolerate the errors possibly occurred in the sorting process. For example, although the minimum weight of small-sized squids is 50 g according to Table 1, in practice a squid weight of as low as 48 g can also be accepted into this size. Squids fall into these allowable ranges can be accepted into either size neighboring the ranges.

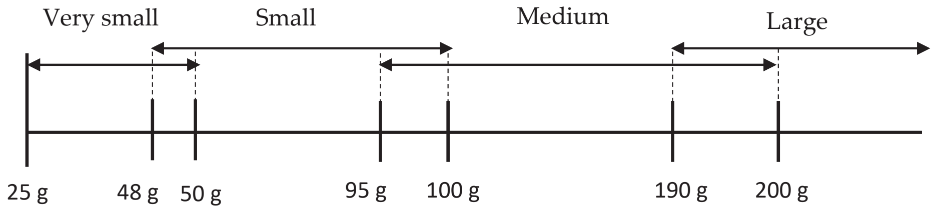


Figure 4: Allowable weight range of splendid squid size

2.3 Species Sorting

Discriminating L.duvauceli from L.chinensis can be simply achieved by visual inspection of an expert. Comparing with L.duvauceli, L.chinensis is more elongated. Based on these observations, geometric descriptive parameters related to shape characterization of the squid mantle for example, length (L) and width (D) are measured. A ratio (R) between the two parameters is calculated using Equation (1).

$$R = L / D \tag{1}$$

When the ratios of 130 randomly selected squid samples of both species are plotted in a frequency diagram, it can be seen that the two distributions are overlapping with the ratio mean of L.duvauceli at 2.861 and that of L.chinensis at 3.809. Separating point must be carefully chosen so that misclassification is minimized. Thammachot et al. [11] used an aspect ratio R = 3.4 to distinguish one species from the other. Squids with ratio less than 3.4 were found likely to be L.duvauceli. Hoewever, derivation of such threshold is subjective to visual capability of the inspector; it lacks a theoretical background to confirm validity and optimality of the number chosen. In this study, a statistical-based Discriminant Analysis (DA) is used in species sorting.

3.0 RESULT AND DISCUSSION

3.1 Results of Size Sorting

i. Squid Size Sorting by MLNN

Two models of MLNN are evaluated for their performance using the test set described in Table 3. In the quantitative model, by applying different transfer functions to the hidden layer and the output layer respectively, the best accuracy it can achieve is marginally higher than 90%. The textual model has less variation in accuracy reported, but the best accuracy it can obtain is approximately 90%. In summary, the accuracy on average sways within the range of 84% to 93% for both MLNN models. The highest accuracy is found within the quantitative model using a 'logsig-pureline' transfer function with 10 neurons in the hidden layer detailed in Table 4.

Table 4: Results of splendid squid size sorting by the MLNN model when the number in the hidden layer is 10

Actual size (150 samples)	Number of squids					Accuracy (%)
	< 25 g	Very small	Small	Medium	Large	
< 25 g (0)	0	0	0	0	0	0
Very small (35)	0	33	2	0	0	94.28
Small (34)	0	2	32	0	0	94.11
Medium (42)	0	0	1	37	4	88.09
Large (39)	0	0	0	2	37	94.87
Average						92.67

ii. Squid Size Sorting by Regression Analysis

A strong relationship between area and weight is detected. At smaller area the relationship appears slightly non-linear; it becomes more linearized as the area gets larger. Both linear and non-linear models are applied to find an equation that best fits into the observed data. Using simple linear regression, the relationship between area (a) and weight (w) is expressed in Equation (2). The square of the correlation coefficient (r^2) value is 96.2%, meaning that about 96.2 percent of weight variation can be explained by this model.

$$w = -54.108 + 0.028a \tag{2}$$

With the second order polynomial regression, the r^2 value is 96.9%.

$$w = -27.672 + 0.02a + 5.38 \times 10^{-7} a^2 \tag{3}$$

Table 5 shows the percentages of correctly sorted test sets (150 samples in total) by the simple linear regression model expressed in Equation (2), with an average of 81.33%. All but the smallest size have sorting accuracy of more than 80%. Interestingly, this model underestimates the weight in the smallest size. The relationship between the squid area and weight is slightly curvy; and the linear model fails to give an explanation in this weight range. In Table 6, the sorting accuracy of the smallest size by the second order polynomial regression model (Equation (3)) is greatly improved for its average size sorting accuracy is 88.00%.

Table 5: Results of splendid squid size sorting by simple linear regression

Actual size (150 samples)	Number of squids					Accuracy (%)
	< 25 g	Very small	Small	Medium	Large	
< 25 g (0)	0	0	0	0	0	0
Very small (35)	15	18	2	0	0	51.43
Small (34)	0	2	29	3	0	85.29
Medium (42)	0	0	1	38	3	90.48
Large (39)	0	0	0	2	37	94.87
Average						81.33

Table 6: Results of splendid squid size sorting by second order polynomial regression

Actual size (150 samples)	Number of squids					Accuracy (%)
	< 25 g	Very small	Small	Medium	Large	
< 25 g (0)	0	0	0	0	0	0
Very small (35)	3	28	4	0	0	80.00
Small (34)	0	2	29	3	0	85.29
Medium (42)	0	0	1	38	3	90.48
Large (39)	0	0	0	2	37	94.87
Average						88.00

iii. Performance Appraisal of Regression and MLNN Models

From the results of both regression and MLNN models, it is found that several wrong-sizing cases have minimal weight prediction errors. But if such errors happen to be around a partitioning line between the sizes, the squid has a greater chance to be sorted to the wrong size. For example, one squid has an actual weight of 98.25 g and it should be categorized as "Medium". But when its predicted weight is 96.03 g, the squid is graded down to "Small". Although the weight prediction error is only 2.22 g (2.25%), the squid is accounted as misclassified.

As a result, besides sorting accuracy, model performance can be evaluated by mean squared error (MSE) using Equation (4). This indicator measures how accurate the model can predict squid weight from input parameters.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2 \tag{4}$$

where $\hat{Y}_i$ is a vector of the predicted values;

Y_i is a vector of the true values;

n is number of samples.

From Table 4, the MLNN model clearly outperforms the regression results, in Table 5 and Table 6, in classifying squids of smaller sizes (small and very small sizes). At other sizes, both approaches provide no significantly different results. Although the average accuracy of the MLNN model in sorting sizes is higher than that of the regressions, it does not have a better capability in predicting the squid weight. For simplicity and speed of sorting, the relationship between the input parameters and squid weight can be sufficiently represented by the quadratic equation. The results confirm a strong contribution of area in weight prediction, whereas other parameters are minimally influential. Comparing to [3], an r^2 from the second order polynomial regression in this study is higher and the equation can be applied in the sorting of any splendid squids in general.

3.2 Results of Species Sorting by Discrimination Analysis

In species sorting, the aspect ratio of length and width is categorized into two groups; with "1" representing L.duvauceli and "2" indicating otherwise. The analysis is carried out by SPSS version 15.0 and the discrimination equation is obtained (Equation (5)). The mean score of each group called as centroid that describes the group position. Significant difference between the centroids signifies high separability between the groups. In this study, Group 1 has a mean score of -0.735 while Group 2 yields 1.679. New cases will be sorted into a group whose centroid their positions are located closest to

$$D_S = -8.019 + 2.546R \tag{5}$$

where D_S is a discrimination score;
R is a ratio of length to width.

Two hundred and thirty squids with 160 of which being L.duvauceli are classified by the discrimination equation. Sorting results are tabulated in Table 9. The average species sorting accuracy is 88.70%. Group 1 or L.duvauceli is classified with slightly better accuracy (89.4%) than Group 2 or L.chinensis (87.10%).

Table 8: Splendid squid species sorting by discrimination equation

Sample No.	Ratio	Discrimination Score	Distance to centroid 1	Distance to centroid 2	Sample classified as
1	3.94	2.01224	2.74724	0.33324	2
2	3.46	0.79016	1.52516	0.88884	2
3	3.03	-0.30462	0.43038	1.98362	1
4	3.53	0.96838	1.70338	0.71062	2
:	:	:	:	:	:
230	3.22	0.17912	0.91412	1.49988	1

Table 9: Results of splendid squid species sorting (1 = L.chinensis, 2 = L.duvauceli)

Species		Prediction by discrimination equation		Total
		1	2	
Justified by the expert	1	143 (89.40%)	17 (10.60%)	160
	2	9 (12.90%)	61 (87.10%)	70

On the average, the sorting accuracy from using a fixed sorting threshold ratio at 3.4 was 90% [11]; from this study results, the discrimination equation from DA performed equally well at 88.70%. However, by employing DA, the sorting system is more adaptable to the change in squid physiology and more suitable to integrate into an automated system. It should be noted here that the accuracy of species sorting is evaluated with respect to justification of experts; there are no measuring equipment available to provide test references.

The capability of the system studied, in comparison with human performance, was superior for both accuracy and repeatability. Computational time of the system can be accelerated by equipment upgrades. One limitation is that flesh quality of the squid cannot be inspected and included as a parameter to predict the squid weight. The approach proposed in this study assumes that squids have homogeneous flesh density and thickness. In reality, if a squid is not well preserved, its quality will quickly deteriorate, resulting in weight loss and color change. Besides, squids at young age have more water content than mature ones; this inconsistent density across squid sizes clearly weakens the linear regression model. Accuracy of weight prediction, hence size sorting, may be enhanced by detection of flesh quality, possibly through additional views of the squid image, or parameters such as color and reflection. If difficulties related to system maintenance and investment can be overcome, automated size and species sorting based on image data would be an economical alternative in the long run.

4.0 CONCLUSION

L.duvauceli and L.chinensis are two prominent species of splendid squids caught around the area of the Gulf of Thailand. They must be undergone classification of size and species before being processed into an intended product. Repeatability and accuracy had been experimented and found that they were well below the standard of the case study factory. A computer vision-based automated system is proposed to improve efficiency of product classification. Squid images were captured and siginificant parameters presumably related to weight and species were extracted. Relationships between the parameters and the desired outputs such as size and species were formulated using Neural network models and regression analysis. It was evident that accuracy of size sorting by polynomial regression (second order) and the neural network models were not significantly different (88.00% and 84.00-93.00%, respectively). The polynomial regression (second order) is recommended, as it is considered simpler. For species sorting, the accuracy derived from the discrimination equation (88.70%) was very close to that obtained from a 3.4 length/width ratio (90.00%). These computerized approaches in size and species classification were proven to be superior to manual practice; they can overcome limitations of work performance due to individual capability and ergonomic factors. Although the first instalment of an automated system can be very high, under uncertainty of workforce availability and fierce industrial competitive environment it is an economical alternative in the long run.

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