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Prediction of shelled shrimp weight by machine vision

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Abstract: The weight of shelled shrimp is an important parameter for grading process. The weight prediction of shelled shrimp by contour area is not accurate enough because of the ignorance of the shrimp thickness. In this paper, a multivariate prediction model containing area, perimeter, length, and width was established. A new calibration algorithm for extracting length of shelled shrimp was proposed, which contains binary image thinning, branch recognition and elimination, and length reconstruction, while its width was calculated during the process of length extracting. The model was further validated with another set of images from 30 shelled shrimps. For a comparison purpose, artificial neural network (ANN) was used for the shrimp weight predication. The ANN model resulted in a better prediction accuracy (with the average relative error at 2.67%), but took a tenfold increase in calculation time compared with the weight-area-perimeter (WAP) model (with the average relative error at 3.02%). We thus conclude that the WAP model is a better method for the prediction of the weight of shelled red shrimp.

Key words: Shelled shrimp, Image, Feature, Length extracting, Weight prediction, Weight-area-perimeter (WAP) model
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INTRODUCTION

Shrimp is very popular seafood in the world. Shelled shrimp is a main form of shrimp products for trading. Grading process is very important for increasing the value of shelled shrimp. Traditionally, grading process is conducted manually, which may cause problems such as low efficiency and even bacterial and chemical contamination.

Machine vision has been widely applied for size and weight evaluation because it is nondestructive and high efficient. In agriculture and food industries, this technology has been used to determine the sizes of seeds (Granitto *et al*., 2002; 2005), pears (Ying, 2000) and beans (Kılıç *et al*., 2007), and to grade apples (Throop *et al*., 2005; Menesatti *et al*., 2009), eggs (Chen *et al*., 2004), oranges and peaches (Blasco *et al*., 2003). Scallops were automatically graded by the area and length by computer vision (Lin *et al*., 2006). Fish features were recognized based on image analysis, including fish length (Dunbrack, 2006; Harvey, 2003; Costa *et al*., 2006), species (White *et al*., 2006), and behavior (Xu *et al*., 2005). Morphological and spectral methods were compared to find the optimum location for shrimp beheading (Ling and Searcy, 1991). Correlation between prawn's size and weight was analyzed and a vision-robotic system was developed for prawn grading and packing (Kassler *et al*., 1993). The weights of different forms of white shrimp and visual quality were determined by machine vision (Luzuriaga *et al*., 1997). Image analysis was also utilized to evaluate carapace length of shrimp (Harbitz, 2007). However, up to now, few machine systems have been developed for shrimp industrial application. Luzuriaga *et al*.(1997) and Kassler *et al*.(1993) demonstrated that there was a strong correlation between shrimp area and weight, but the samples they used were intact. Nevertheless, shrimps in real grading and packing situation usually contain both unbroken and broken ones. If samples are taken randomly from a real production site, the accuracy of the results will be limited. Moreover, shrimp weight prediction by vision may be feasible, but area univariate model is unreasonable when a wider and shorter

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shrimp is probably heavier than a thinner and longer one while their dimensions are the same.

To overcome the limitation of the existing methods for shrimp weight prediction, an improved method was proposed in this paper. The objectives of this study were: (1) to determine morphological features including area, perimeter, length and width, (2) to establish weight predication models with different combination of features and tests, and (3) to compare the time cost of each model.

MATERIALS AND METHODS

Computer vision system

A diagram of a computer shrimp image capture system is shown in Fig.1. The system consisted of a lighting box and a computer. The size of lighting box was 660 mm×680 mm×1300 mm. A sample platform (15 mm×20 mm) was placed at the bottom of the box and covered with dark blue background (fabric). A charge coupled device (CCD) camera (TMC-7DSP, PULNIX) was installed at the center of the box, about 40 cm above the sample platform. Six lamps (F40BX/840, GE) were placed behind the white dousers in both sides of the box. Images were acquired by a Matrox Meteor II/Standard image grabber (Matrox Inc., Canada). The resolution of these images acquired was 3.876 pixels/mm. All images were processed and analyzed using Matlab 6.5 (Mathworks 2002, Natick, MA).

Weight measurement

Shelled red shrimps, originally produced in Zhoushan, Zhejiang Province, China, were purchased from a local market. The weights of shelled shrimps were measured by an electronic balance (Jinnuo Instruments Ltd., China) with accuracy of 0.01 g. Before weighting, water on the shrimp surface was cleaned by absorbent paper.

A total of 150 shrimps were used in this study, including 120 intact and 30 broken ones. The weights of these shrimps ranged from 0.99 to 9.18 g, with 52 shrimps in the range of 0.99~2.00 g, 47 in 2.01~4.00 g, 38 in 4.01~6.00 g, and 13 in 6.01~9.18 g. These shrimps were randomly divided into two groups. One group containing 100 intact and 20 broken shrimps was used for model validation, and the other one was for predication.

Background segmentation

Although by analyzing values of R (red), G (green) and B (blue) channels, background components can be identified in RGB color image (Kim *et al*., 2008), it is unnecessary to keep color information in order to reduce data processing time. Therefore, gray-scale maps were used for image analysis, instead of color ones. To get a clear object, all images were processed as follows: (1) changing RGB images (Fig.2a) to gray-scale maps (Fig.2b) by MATLAB function *rgb2gray*; (2) obtaining an optimal threshold value from histogram by taking the middle value between the two main peaks in the histogram (150 shrimps were determined after analysis); (3) threshold segmentation by MATLAB function *im2bw* (Fig.2c).

Morphological operation

Images after segmentation may contain some flaws such as holes in the background and black area in the object, which could cause errors in area

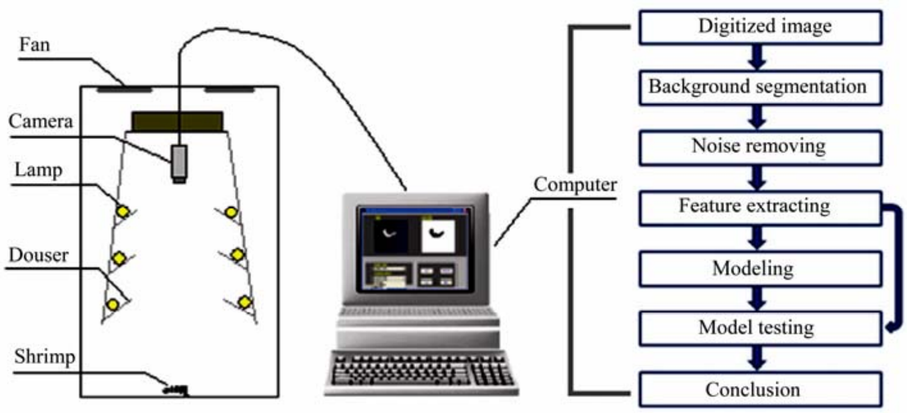

Fig.1 Computer vision system and main steps of weight prediction

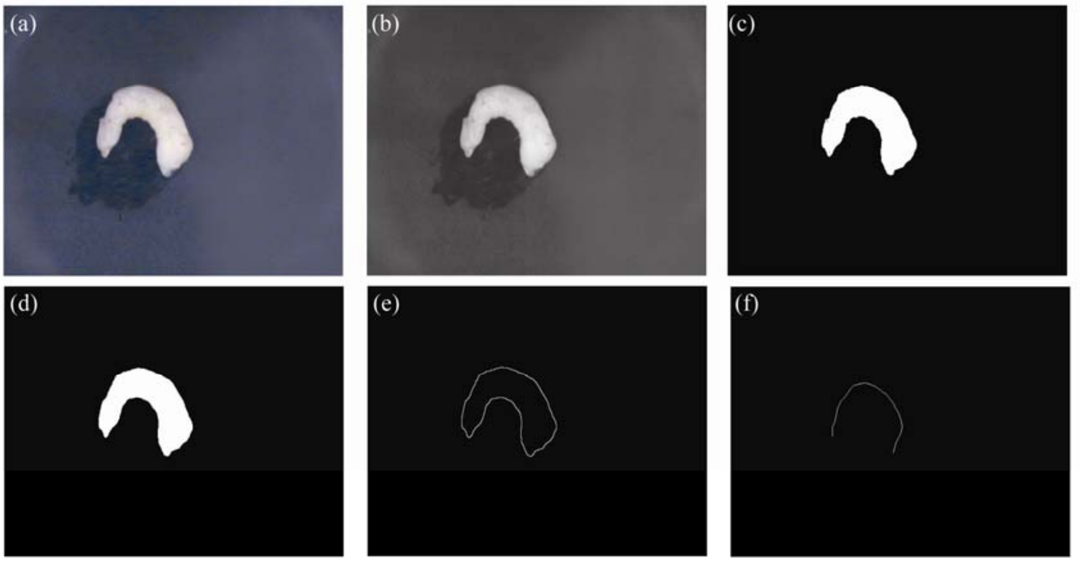

Fig.2 Shrimp image processing and feature extracting

(a) Original image; (b) Gray scale map; (c) Threshold segmentation; (d) Morphological operation; (e) Edge extracting; (f) Image thinning

measurement and other calculations. Furthermore, if the edge of object is very rough, the length of perimeter will be amplified. To solve these problems, morphological open (*imopen*) operation was applied to filter the segmented image (Fig.2d). The structure element (*se*) of filtering was a disk with a radius of 4 pixels. The reasons for one-time morphological opening operation were: (1) holes were all filled after erosion operation; (2) perimeter length decreased significantly (2.65% on average), showing that the edge became smooth; (3) no obvious change of edge length occurred while a second morphological open was done; (4) the operation was beneficial to the next step of thinning process.

Feature extracting

Features of a shelled shrimp image were area, perimeter, length and width.

Area and perimeter

After image pretreated, the area of shrimp could be obtained by MATLAB function *bwarea*. The edge of shrimp was acquired by MATLAB function *bwperim* (Fig.2e).

Shrimp length

The length of shelled shrimp was determined with following procedures:

1. Image thinning. A refined curve with width of 1 pixel was obtained from binary image of shrimp by MATLAB function *bwmorph* with parameter *thin* (Fig.2f).

2. Branch cutting. Although to a great extent morphological operation reduced the number of branches in thinned images and shortened the length of branches, the appearance of branches was still inevitable. Therefore, an end-point-erase (EPE) method was used to cut branches. By bifurcation-point analysis, branches can be found when the number of pixels that a pixel connected in all eight directions was more than two (Fig.3a). Because the length of principal axis was much longer than branches, branches could be removed by removing end points for several times (Fig.3b).

3. Length reconstruction. After EPE operation, the curve left did not represent the real length of shrimp. Thus a slope algorithm was utilized to improve the results as follows: (1) Perimeter and EPE curve were presented in one coordinate figure system (Fig.3c); (2) End points of EPE curve were marked as a at (x_1, y_1) and d at (x_2, y_2). Another point b was took at (x_3, y_3), which was 10 pixels away in the EPE curve from point a. Thus, the slope (s) between a and b was calculated as: $s=(y_1-y_3)/(x_1-x_3)$; (3) Extending the line ab, the end point c was found at the cross of extension of ab and the edge of shrimp (Fig.3c).

Similarly, another end point e could be found; (4) The length of shrimp was evaluated as the sum of EPE curve, lines ac and de.

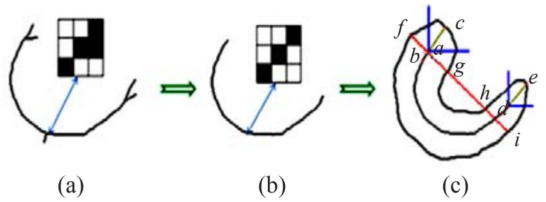

Fig.3 (a) Bifurcation-point analysis, (b) EPE method and (c) length reconstruction

Shrimp width

For a shrimp, the width decreased gradually from the connection of head and body (point a in Fig.3c) to tail (point d in Fig.3c). Added a line fg that was perpendicular to line ab, and points f and g were the crosses between line fg and the edge of the shrimp. The width at point a was determined as the distance of fg. Similarly, the width of shrimp at point d could be evaluated. The width of shrimp was then calculated as the average of the width results at points a and d.

Correlation of weight and image parameters

Although weight-area (WA) model was not comprehensive, the high correlation between weight and area was proved. Based on this result, four patterns of multivariable prediction models were designed as: weight-area-perimeter (WAP), weight-area-length (WAL), weight-area-width (WAW) and weight-area-perimeter-length-width (WAPLW). By fitting with all equations contained in TableCurve 3D software (Systat Software Inc., 2002a), a relationship of $w=c_0+c_1x+c_2x^2+c_3x^3+c_4x^4+c_5y$, where w is weight, x is area, y is the perimeter for WAP, length for WAL, or width for WAW, c_0, c_1, c_2, c_3, c_4 and c_5 are coefficients, was found to have high correlation coefficient for WAP, WAL and WAW models (Table 1). WAPLW method was operated by artificial neural network (ANN) (Costa *et al*., 2006). In order to test the necessity of morphological operation, a control group was utilized as WAP1 (weight-area-perimeter model with data not processed by morphological operation). For a comparison purpose, WA model (Systat Software Inc., 2002b) was also used by fitting data to the equation of $z=c_0+c_1x^{1.5}$.

RESULTS AND DISCUSSION

Considering calculation time as an important factor for the practical application of models, the time cost of each model was measured by recording CPU time under Intel® core (TM) 2 E6550 2.33 GHz, 1 GB memory and 160 GB hard disk. The function in MATLAB was:

```
St=cputime; //Here add the program to be tested.
Et=cuptime–St;
Et; //Et is the time cost in the program calculation which does not contain image acquiring process.
```

Table 1 summarizes the results obtained for all models established in this study in comparison with WA model. As anticipated, the prediction accuracy was significantly improved after combining image area with other data (perimeter, length and width). In previous weight prediction researches, shrimps or shelled shrimp samples were all intact, and their weights could be calculated exactly only by analyzing their areas. However, in commercial processing of shrimp meat, goods cannot be as perfect as the samples in labs, which means that the methods used in the previous researches will lead to a low accuracy of weight prediction. It is a common situation that

Table 1 Parameters, average relative error and timing of different weight prediction models

	c_0	c_1	c_2	c_3	c_4	c_5	R^2	Error (%)	Timing (s)
WA	0.100	3.753×10^{-6}	–	–	–	–	0.980	7.34	0.1700
WAP	1.674	-6.094×10^{-4}	1.677×10^{-7}	-1.032×10^{-11}	2.364×10^{-16}	6.627×10^{-4}	0.989	3.02	0.2340
WAP1	1.286	-3.947×10^{-4}	1.343×10^{-7}	-8.063×10^{-12}	1.824×10^{-16}	8.635×10^{-4}	0.988	4.15	0.1840
WAL	1.415	-5.874×10^{-4}	1.602×10^{-7}	-9.801×10^{-12}	2.240×10^{-16}	-3.323×10^{-4}	0.990	2.79	2.8568
WAW	1.381	-6.109×10^{-4}	1.709×10^{-7}	-1.162×10^{-11}	3.514×10^{-16}	-2.917×10^{-4}	0.989	3.01	2.9270
ANN	–	–	–	–	–	–	–	2.67	3.1131

Error was the average relative error. c_0, c_1, c_2, c_3, c_4 and c_5 were constants in each model shrimps with the same area have different weights or dissimilar areas may have an identical weight, if shrimp samples are composed of both intact and fragmentary ones. To solve this problem, perimeter, length and width were used in combination with shrimp area. As a result, multivariable forecast models such as WAP, WAL and WAW models provided better prediction accuracies than WA model. It is easy to prove that a wider and shorter shrimp has a smaller perimeter value than a thinner and longer one while their areas are the same. Because of their distinct volumes, the wider and shorter shrimp has a heavier weight than the thinner and longer one. This difference could be reflected correctly by all the models except WA, indicating that WA model is not as practically applicable as the others.

On the other hand, when the length data were used for prediction in both WAL and ANN, the average relative error was decreased, but predicted time increased by tenfold. For the first step of length extraction, the MATLAB cost more than 2 s to function, indicating that the two models are not applicable in shelled shrimp producing line.

Table 1 shows that the maximal error of WAP model was 0.34 g (relatively 11.41%), while WAL and ANN models had 0.33 g (relatively 11.18%) and 0.13 g (relatively 8.55%), respectively. Although the results of ANN and WAL models were better than that of WAP, the error of WAP was still considered to be acceptable, and the accuracy could be compared favorably with human eyes. If more precise target image is required in the future, the length of shrimp can be considered for weight prediction, then a rapid length calculation algorithm or better computer hardware will be required.

By comparing the results between WAP and WAP1, image pretreatment was proved to be necessary. It is obvious that shrimp edge was not so smooth especially in the leg part, which might be caused by peeling process. Then the perimeter value is amplified so that it fails to reflect the real dimension of shelled shrimp. After morphological operation, small concave and salient parts of the shrimp edge are erased, so the perimeter value decreases and becomes more useful in demonstrating shrimp size. Therefore, an optimum prediction method can be obtained by the WAP model.

CONCLUSION

A weight prediction method, the WAP model, for shelled shrimp was designed, which includes pretreatment, image feature extraction, and prediction model analysis. This model was tested to have an accuracy rate of greater than 96.9%. In this model, the pretreatment (morphologically open process) significantly improves the prediction accuracy. The feature extracting can remove braches by erasing end points and a slop algorithm can compensate the missing length. The model analysis determines prediction accuracy and running time. Our results demonstrate that it is feasible to use a machine vision system, coupled with image processing methods, to measure the weight of shelled red shrimps. It is more accurate and faster than experienced shrimp grading workers.

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