A method for predicting the cutting points using random sample consensus partitioning technique and AI machine vision.

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Abstracts: Food processing and manufacturing companies that handle large amounts of fish want their fish to be packaged and delivered in uniform quantities. In particular, manual labor is performed by skilled workers for fish that are difficult to trim. Moreover, some fish processing sites employ partially automated processing machines. However, the structure of these machines is too simple to process fish with diverse patterns. Furthermore, these machines exhibit a large amount of error for the target weight. To improve the working environment of food processing and manufacturing companies by solving the aforementioned problems, this study proposes a technique for predicting the cutting points of a fish for each weight by adopting image processing and machine learning. The proposed technique employs a variety of image processing techniques and random sample consensus partitioning to extract the 3D model of the fish and its length, maximum major and minor axes, and volume information from the image of the fish. The model trained with the extracted 3D features and the measured weight information can predict the cutting points for the desired weight from the input fish image. The performance evaluation results of the proposed method indicated that there is an average error of less than 3% between the target and predicted weights. This error level is considered significantly better than 8%, which is the permissible error level in fish processing sites. It is expected that the proposed technique will significantly contribute to the development of an automated cutting system that considers the weight by integrating the technique with the cutting machine and conveyor belt.

Keywords: Image Processing, Random Sample Consensus Partitioning, Machine Learning, Neural Network Model, Cutting Point.

1. INTRODUCTION

AI technology and machine vision were mainly adopted in the aquaculture field. Representative studies have measured the length and weight of live fish to improve the efficiency of managing fish farming [1]. Moreover, AI technology and machine vision were also widely used in several studies to classify caught fish. Balaban pointed out that the classification of Alaskan salmon, which are caught in considerable quantities, is manually conducted, and machine vision is adopted to improve this process [2]. Hauser trained a model to classify three fish species using neural network technology [3].

Despite advancements in fish processing technology, the conventional method of trimming fish manually remains prevalent. Even when various facilities and software for automation are in place, certain steps still require manual intervention. Hence, it is impossible to attain complete efficiency [4]. Because fish processing workers primarily use chainsaws or knives, fish trimming is extremely dangerous. This task also requires numerous skilled workers. Moreover, with the growth of the fishing industry, the amount of catches is also increasing rapidly. Consequently, manual trimming will gradually require more costs [5]. Catering companies that handle large quantities of food also handle numerous fish, which have a high supply and demand. Because these companies distribute food evenly, they endeavor to ensure that the fish are neatly trimmed and cut in uniform quantities before delivery. However, fish have curved shapes and the width from their head to tail is not uniform; hence, it is difficult to cut fish into even pieces [6]. As illustrated in Figure 1, automated facilities exist for cutting fish automatically. However, these facilities cut fish using a fixed frame that does not consider various fish sizes and patterns.

In Hossein's research, the cutting points of the head and abdomen were predicted based on the length and fin information of the fish using an image processing algorithm [7]. However, because Hossein’s research considers the cutting of each fish part, it is difficult to apply it in cutting the fish evenly based on the target weight. In addition, numerous studies have been conducted to predict the weight of fish; however, most of these studies predicted the weight, to classify the fish species or investigate the growth of the fish. Unfortunately, very few studies have been conducted on automation to cut fish according to the desired weight.

Therefore, in this study, to efficiently improve the working environment of fish processing sites in the fishing industry, we propose a technique for predicting the cutting points of fish based on the target weight. The proposed technique adopts image processing and the partitioning random sample consensus to perform 3D modeling and extract 3D feature information. Subsequently, machine learning is performed on the correlation between the extracted three-dimensional feature information and weight, to create a model that predicts the cutting points for the target weight. Finally, the performance of the trained predictive model is evaluated to verify the superiority of the proposed technique.

Following the introduction in Section 1, the remainder of this paper presents related studies in Section 2 and comprehensively explains the proposed technique in Section 3. Next, Section 4 describes the experimental procedure and evaluation results for performance evaluation. finally, Section 5 draws conclusions.

2. RELATED STUDIES

Studies on fish mostly describe methods for managing fish efficiently or classifying fish species in fish farms. Most of these studies achieve their objectives by extracting the external features of the fish from captured images. In a study by Hauser-Davis et al., statistical and neural network techniques were adopted to classify geophagus brasiliensis (acaras), tilapia rendall (tilapias), and mugil liza (mullets), which are predominantly caught in Brazil [3]. In this study, a total of 250 samples were investigated to determine the fish's total length, standard length, head length, head height, and gender information. These data were then trained in a neural network, and an outstanding classification performance was verified.

Balaban conducted research to predict the weight of salmon for four types of Alaskan salmons [2]. First, the best fitting rectangle for the salmon in the captured image is calculated. Next, the area of the salmon was calculated using the sizes of the salmon and best fitting rectangle, respectively. Then, various regression equations were generated to learn the correlation between the area information and the weight. This study asserted that it is sufficient to use only the area information of salmon and a simple quadratic function to estimate the weight of fish.

Man proposed that a digital camera can be used to easily obtain the length information, which is beneficial to classifying fish species [8]. The refraction information using the digital camera lens and the distance between the lens and the fish were adopted to estimate the actual length of the fish. Comparing the measured length and estimated length indicated that a performance with an error of less than 6% was achieved.

Al-Jubouri emphasized the need for machine vision technology in the fish farming field and proposed a method for measuring the length of a freely swimming fish via low-cost machine vision [1]. First, the distance between the camera and the fish was estimated from the images captured by two cameras at different locations. Then, the estimated distance, along with the length of the fish in the image, was used to estimate the length of the actual fish. The length of the fish estimated using the stereo image exhibited an error of less than 1%, thus verifying its excellent performance.

Miranda also mentioned the need for automatic length measurement technology to classify fish species in fish farming. To satisfy this need, Miranda developed a prototype for measuring the length of rainbow trout [9]. Rainbow trout exhibit an instinctive behavior to swim against the water current. Using this characteristic, Miranda designed a prototype for rainbow trout to swim through a narrow waterway. When a trout passes through the narrow waterway, the camera inside the waterway captures the image of the trout, and the length of the trout is estimated using various image processing techniques. A mean absolute error (*MAE*) of 1.413 was achieved for the estimated length, which was inferred to be a fairly encouraging result.

Dmitry pointed out that although various studies accurately infer the morphological characteristics of fish, such as their length and width, fish weight inferences are usually inaccurate [10]. Therefore, the image of the fish was captured, and then the final image was obtained by removing the fish's fins in the image and binarizing it.

Subsequently, the actual weight of each fish was measured, and a dataset was generated for the convolutional neural network-based weight estimation model. The trained weight estimation model achieved a mean absolute percentage error of 4–11% in various experiments.

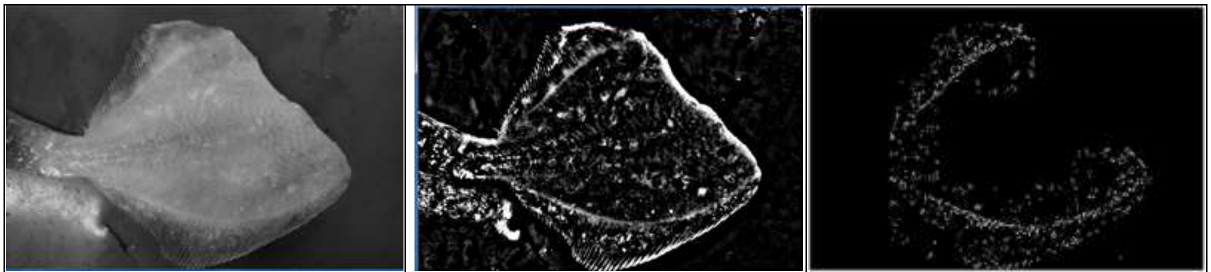
Most of these aforementioned studies describe the method for predicting the weight of fish when they are intact. However, this study attempts to predict the weight of the fish cut to the desired weight according to the request of a catering company. In Hyeon's study, which shares the same goal with this study, weight prediction was attempted using 3D information [11]. In Hyeon's study, a laser scanner was employed to obtain the three-dimensional appearance of the fish, and a method was proposed to calculate the weight of the fish per the length of the fish, based on the obtained 3D appearance information of the fish. Accordingly, it was possible to predict the points where the fish could be cut evenly according to the target weight. Furthermore, the actual weight of the cut pieces was measured, and the study inferred that the error was within 6–8% for each fish species; hence, the prediction method is at a level that can be applied in practice. However, it is excessively time-consuming to utilize the laser scanner to detect the 3D appearance at fish processing sites. Furthermore, fish weights are calculated using uniform density information, although the density of each part is uneven because of fish bones, flesh, and intestines. Owing to these limitations, several improvements are required before this method can be adopted in practice.

3. TECHNIQUE FOR PREDICTING THE CUTTING POINTS OF FISH

This section describes the technique for predicting the cutting point of fish according to the weight, to cut fish into uniform quantities. The proposed technique comprises four phases: preprocessing, 2D fish modeling, 3D fish modeling, and cutting point predictions by weight based on machine learning.

First, an image of the fish is captured in the preprocessor when the fish is put into the preprocessing phase. Then, the image of the fish is preprocessed by an image processing-based filter to perform more efficient 2D modeling. In the 2D modeling phase, the outline of the fish is approximated by a quadratic model. In addition, the 3D appearance of the fish is modeled from the 2D outline model of the fish in the 3D modeling phase. Subsequently, the volume, length, and thickness information are extracted from the 3D modeling. In the cutting point prediction phase, each cutting point for the target weight is predicted by inputting the 3D information extracted in the previous step into the machine learning-based model that predicts the cutting points based on the target weight. The cutting point prediction model is trained beforehand with the weight to obtain the volume, length, and thickness.

Images captured from at least two viewpoints must be provided to extract a 3D appearance. Hence, two cameras in the preprocessor simultaneously photograph a floor plan and front view, which are the views of the fish from above and the front, respectively. Then, the photographed floor plan and front view undergo image processing-based filtering. The image processing techniques adopted include grayscale for reducing the amount of computation for filtering, high pass filter for displaying the rough outline, masking for removing noise, Gaussian blurring, and binarization. These filtering operations can assist in detecting the outline of the fish more efficiently. Figure 1 illustrates the preprocessing process for efficient 2D modeling.

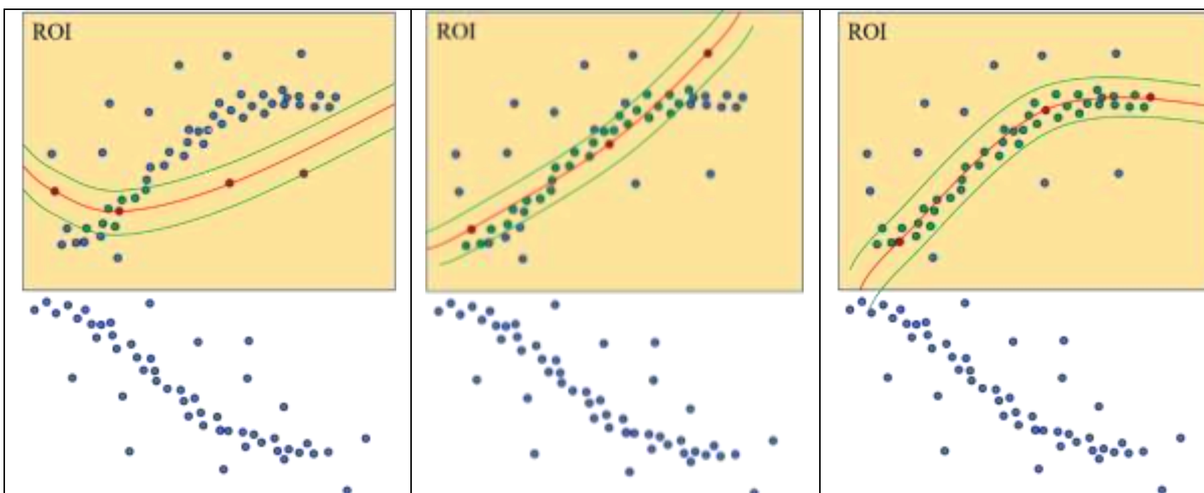


(a) gray scale	(b) high pass filter	(c) masking, gaussian blurring

Figure 1. The preprocessing process for efficient 2D modeling

3.1. 2D Modeling Phase

The 3D appearance extractor comprises an outline modeling phase and a 3D modeling phase. First, the outline of the fish is modeled from the preprocessed floor plan and front view, respectively. For the outline modeling, random sample consensus partitioning was adopted, which is robust in processing speed and noise [12]. To model the 2D outline of the fish, three arbitrary points are drawn from the preprocessed fish image. Then, a quadratic model passing through the three points is obtained. To verify whether the obtained quadratic model can be a suitable outline model, the number of points whose distance to the model is less than or equal to the threshold distance *t* is calculated. This number indicates the number of points close to the drawn model, and the greater this number is, the more suitable the outline model. Finally, three arbitrary points are drawn repeatedly, and the quadratic model with the highest number is selected as the outline model. Each figure in Figure 2 presents the number for the arbitrarily selected quadratic model. Among the three figures, the model in Figure 2(c) has the largest number of points within the threshold distance *t* with 39 points (the red and green dots represent the three arbitrary points drawn to create the model and the points supporting the model, respectively). It is highly probable that the model illustrated in Figure 2(c) is the most suitable model among several models obtained via iteration.



(a) number = 7	(b) number = 27	(c) number = 39

Figure 2. The number for the arbitrarily selected quadratic model

The probability that *m* points drawn in random sample consensus partitioning are inliers of the suitable model is expressed in Equation 1.

$$p = 1 - (1 - a^m)^N \quad (1)$$

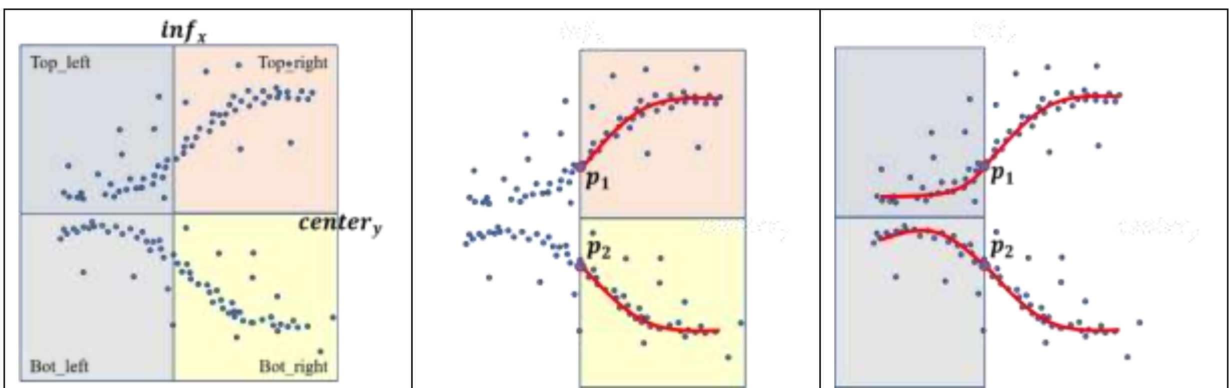
In Equation *1*, *m*, *a*, and *p* denote the number of points drawn, ratio of inliers among all points, and the probability that m points are all inliers when m points are drawn *N* times, respectively. Hence, the minimum number of iterations *N* for drawing a suitable outline model can be derived, as expressed in Equation 2.

$$N = \frac{\log\,(1-p)}{\log\,(1-a^m)} \quad (2)$$

Although random sample consensus partitioning was utilized to model the suitable outline of a fish, an inflection point exists on the fish's tail, where the parabola curves in the opposite direction. Hence, the problem cannot be solved completely. If the upper part of the outline is extended toward the head, the model fitting is unsuitable. The same problem will likely exist if the lower part of the outline is extended toward the tail. Therefore, random sample consensus partitioning is proposed to address this problem. Figure 3 presents the process of random sample consensus partitioning.

Assuming that fish are always placed in approximately similar positions, the inflection point will also be located in approximately similar positions. First, the image is divided into left and right areas relative to the x-coordinate *inf_x* of the average inflection point. In addition, the image is divided into top and bottom areas relative to the center of the fish. Then, the image is divided into four regions (upper left, lower left, upper right, lower right), as illustrated in Figure 3(a).

Next, the outline of the fish is modeled by applying random sample consensus partitioning to the upper right and lower right regions, respectively, as illustrated in Figure 3(b). Here, the point with the smallest *x* value in the outline model of the upper right region is called *p1*, while the point with the smallest *x* value in the outline model of the lower right region is called *p2*. Subsequently, the outline is modeled using random sample consensus partitioning in the upper left and lower left regions. However, when drawing three points for outline modeling, *p1* must be included in the upper left region and *p2* in the lower left region. Accordingly, the outline in the upper left region is connected to the outline in the upper right region, as illustrated in Figure 3(c). Similarly, the outline in the lower left region is connected to the outline in the lower right region.



(a) partitioning (b) right partition (c) left partition

Figure 3. The process of random sample consensus partitioning

3.2. 3D Modeling Phase

This section presents a technique for extracting the 3D appearance of a fish using the outline of the fish detected by random sample consensus partitioning from the floor plan and front view of the fish. Figure 4 illustrates the process of modeling the 3D appearance of a fish.

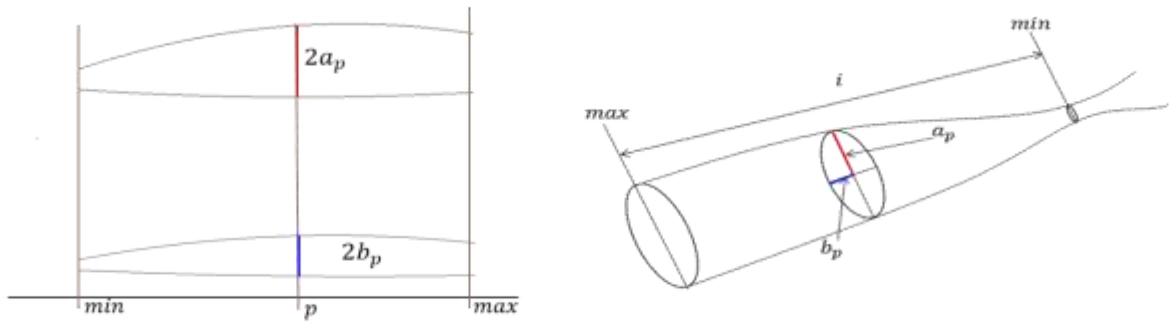


Figure 4. the process of modeling the 3D appearance of a fish

An ellipse is created using the thickness information of the fish at an arbitrary x-coordinate *p* in the two outlines. To create the ellipse, the thickness of the fish at point *p* in the floor plan is defined as *2ap*, and the thickness of the fish at point *p* in the front view is defined as *2bp*. Then, *2ap* becomes the major axis, while *2bp* becomes the minor axis representing an ellipse. Furthermore, a 3D appearance of the fish can be obtained by connecting the ellipses of all sections of the fish.

Here, the area of the ellipse at point p can be calculated using Equation 3. Moreover, Equation 4 can be used to calculate the volume of the fish from its tail to length *i*.

$$Area_p = a_p b_p \pi \qquad (3)$$

$$Vol(l) = \int_0^{l-1} Area_x \, dx \qquad (4)$$

Consequently, 3D information, such as the fish's volume, length, maximum major, and minor axes, can be obtained from the initial image of the fish via three-dimensional modeling. The information on the thickness will hereafter be replaced with the major and minor axis of the ellipse. Machine learning can be performed on the relationship between this 3D information and the observed weight. Moreover, a machine learning-based model for predicting the cutting points for each weight can be implemented.

3.3. Prediction Modeling

The weight of the fish can be obtained by multiplying the calculated volume by density. However, the same density cannot be applied to all parts of the fish because the density differs for each part, such as the part full of flesh and the part with the intestines. Hence, the weight of the fish can be predicted by performing machine learning on the correlation between the 3D information extracted from the image, such as the volume, length, maximum major and minor axes, and the observed weight. A total of 100 samples of the Pacific sauries cut into various lengths were generated for machine learning, as illustrated in Figure 5.

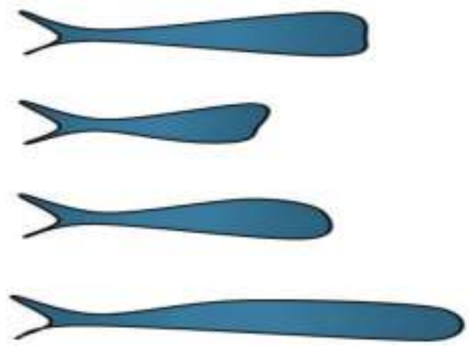


Figure 4. The sample dataset

The 3D feature information was extracted from each sample via preprocessing, 2D modeling, and 3D modeling. Subsequently, the observed weights were all recorded to create a dataset. Length, maximum major and minor axes, and volume were adopted as explanatory variables, and the observed weight was considered a response variable.

An artificial neural network was selected as the technique for performing machine learning on the relationship between the 3D feature information and the weight. Once the pre-trained model for predicting the cutting points receives the 3D feature information from the input fish, the model increases the length *(l)* from the tail direction to the head direction until the predicted weight *pw* becomes the same as the target weight *tw*. When *pw* reaches *tw*, length *l1* becomes the first cutting point for *tw*. When *pw* becomes *2* × *tw*, length *l2* becomes the second cutting point. In other words, the length at which *pw* becomes *n* × *tw* is the *n-th* cutting point.

4. Experiments

A total of 150 Pacific sauries were investigated to verify the performance of the proposed technique. Among them, 30 were cut into various lengths, and they were used to generate datasets for training. The remaining 120 Pacific sauries were adopted for evaluation. Among the 120 Pacific sauries used for performance verification, 60 were employed in the experiment for the target weight of 40g. The remaining 60 Pacific sauries were used in the experiment for the target weight of 60g.

The experimental procedure is presented in Figure 5. First, the Pacific saury is input into the capture box along with the target weight. Here, the Pacific saury is always placed in a fixed position in the capture box. There are two cameras and lighting in the capture box, to capture the floor plan and the front view. When a Pacific saury is photographed in the capture box, the 3D feature information is extracted via preprocessing and modeling. Then, the trained model adopts the extracted information to predict and visualize the cutting points based on the target weight. Finally, the Pacific saury is cut at the predicted cutting points, and the weight of the cut pieces is measured.

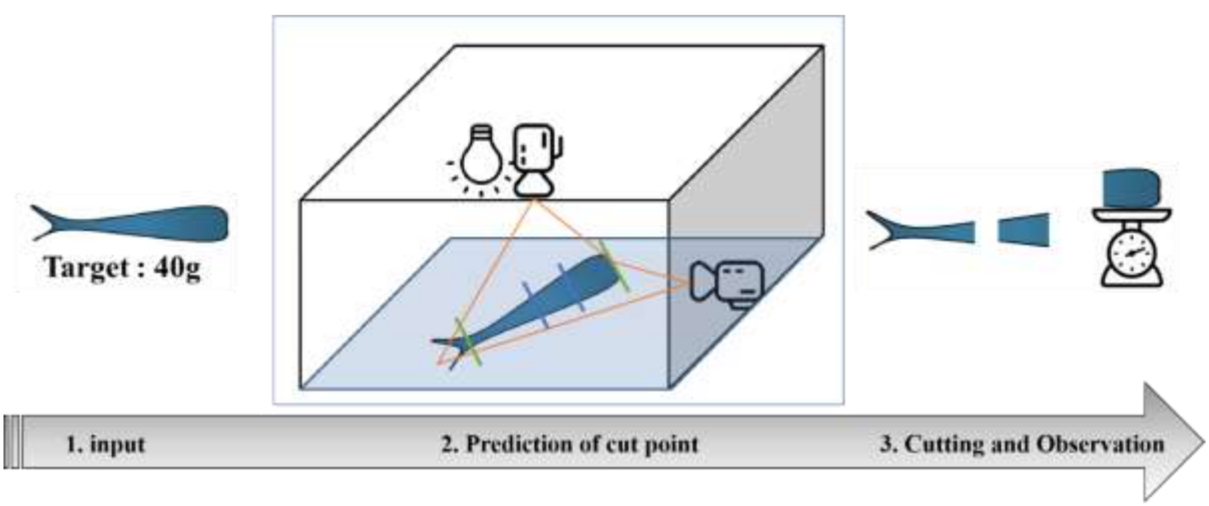


Figure 5. Procedure for evaluating the proposed technique.

The performance was evaluated using the *MAE* and mean relative error (*MRE*) for the measured results, and the formulas for *MAE* and *MRE* are defined in Equations (5) and (6), respectively. Here, $\hat{y}$, y_k, and *n* denote the target weight, *k-th* sample of the observed weight, and total number of samples, respectively.

$$MAE = \frac{1}{n}\sum_{k=1}^{n}|\hat{y} - y_k| \tag{5}$$

$$MRE = \frac{MAE}{\hat{y}} \times 100 \tag{6}$$

In the experiment for the 40g target weight, *MAE, MRE*, and Max Error values of 1.19g, 2.99%, and 2g, respectively, were achieved for the first piece. These results indicate that the first pieces have an error of 1.19g on average. Converting this value to a percentage indicates an error rate of approximately 3%. Furthermore, the value of the largest error was 2g. In addition, for the second piece, the *MAE, MRE*, and Max Error values were 1.42g, 3.55%, and 2g, respectively. For the third piece, the *MAE, MRE*, and Max Error values were 1.41g, 3.54%, and 2g, respectively. The average error rate of all pieces was within the range of approximately 3%.

The permissible error rate of the weight at fish processing sites is within 8%. Therefore, the error rate of approximately 3% achieved by the proposed technique is considered excellent. Moreover, image processing techniques were adopted for 3D modeling, and the processing time was all within 0.01s. Because there is almost no delay, it is expected that the proposed technique can be applied in an environment where a conveyor belt is operated.

Although the performance of the proposed technique was excellent and exhibited a general error rate of within 3% compared to the target weight, it is difficult to completely trust the performance evaluation results. The first reason is that only 150 Pacific saury samples were adopted in the experiment, and this number may be significantly insufficient in evaluating the performance of the proposed technique objectively. For the objective evaluation of the performance, a few thousand or tens of thousands of samples may be required. In addition, the performance evaluation for various fish species should also be considered. However, it is difficult to obtain support for the supply of a large amount of fish. Hence, only a small amount of fish was prepared. The second reason was the difficulty in setting up the experimental environment. To cut fish properly, they need to be maintained in a frozen state. However, the time for maintaining the frozen state of fish at room temperature was very short. Ultimately, it was extremely difficult to preserve the samples without a special experimental environment (fish freezer). Hence, we went through a series of trials and errors while cutting the fish. Finally, there is an optimization problem with setting the parameters for various filters adopted in image processing. Most of the parameters used in the experiment were default values or manually set to be favorable to the experimental results. The method of selecting parameters to achieve objective performance in any environment (lighting, fish species) will definitely be required.

CONCLUSION

To efficiently improve the working environment of fish processing sites in the fishing industry, we propose a technique for predicting the cutting points of fish based on the target weight. The proposed technique adopts image processing and the partitioning random sample consensus to perform 3D modeling and extract 3D feature information. Subsequently, machine learning is performed on the correlation between the extracted three-dimensional feature information and weight, to create a model that predicts the cutting points for the target weight. Finally, the performance of the trained predictive model is evaluated to verify the superiority of the proposed technique. The performance evaluation results of the proposed method indicated that there is an average error of less than 3% between the target and predicted weights. This error level is considered significantly better than 8%, which is the permissible error level in fish processing sites. It is expected that the proposed technique will significantly contribute to the development of an automated cutting system that considers the weight by integrating the technique with the cutting machine and conveyor belt.

However, there were difficulties in configuring the experimental environment for this study; hence, the experiments did not consider a large number of various fish species. In addition, this study did not consider the method of determining the optimal values for the parameters used in image processing. Consequently, this study is insufficient in terms of the commercialization aspect. To apply the proposed technique in actual fish processing sites, the aforementioned problems must be resolved. Therefore, these problems are left as the direction for future studies.

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