How Many Fish in a Tank?
Constructing an Automated Fish Counting System by Using PTV Analysis

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ABSTRACT

Because escape from a net cage and mortality are constant problems in fish farming, health control and management of facilities are important in aquaculture. In particular, the development of an accurate fish counting system has been strongly desired for the Pacific Bluefin tuna farming industry owing to the high market value of these fish. The current fish counting method, which involves human counting, results in poor accuracy; moreover, the method is cumbersome because the aquaculture net cage is so large that fish can only be counted when they move to another net cage. Therefore, we have developed an automated fish counting system by applying particle tracking velocimetry (PTV) analysis to a shoal of swimming fish inside a net cage. In essence, we treated the swimming fish as tracer particles and estimated the number of fish by analyzing the corresponding motion vectors. The proposed fish counting system comprises two main components: image processing and motion analysis, where the image-processing component abstracts the foreground and the motion analysis component traces the individual's motion. In this study, we developed a Region Extraction and Centroid Computation (RECC) method and a Kalman filter and Chi-square (KC) test for the two main components. To evaluate the efficiency of our method, we constructed a closed system, placed an underwater video camera with a spherical curved lens at the bottom of the tank, and recorded a 360° view of a swimming school of Japanese rice fish (*Oryzias latipes*). Our study showed that almost all fish could be abstracted by the RECC method and the motion vectors could be calculated by the KC test. The recognition rate was approximately 90% when more than 180 individuals were observed within the frame of the video camera. These results suggest that the presented method has potential application as a fish counting system for industrial aquaculture.

Keywords: PTV, aquaculture, fish counter

1. INTRODUCTION

In this paper, we propose the basics of a new administration system for aquaculture to be implemented using the algorithm of the PTV analysis method. Today, there are three ways to count a fish in the aquaculture industry. The first is an acoustic method using an acoustic camera(1). In this technique, the image resolution deteriorates, and thus it is not suitable for the task of counting many individual fish in aquaculture farming. The second is checking for the electric potential difference by placing an electrode under water, called a fish counter. It has been used to estimate the regression rate of Atlantic salmon (*Salmo salar*) in Western countries. In Japan, some researchers have also tried to verify this method(2). For implementing this technique, it is necessary to position the sensor in a specific fishway to detect the fish. This makes it difficult to count the number of individuals in general farm cages. The third is video analysis. There are also some techniques that use image processing to extract the foreground(3), and then applying a machine learning algorithm like a neural network to identify each individual fish(4)(5). These techniques use an optical camera to count the number of individuals from the images, just as in our method. However, in the former, the individuals are counted based on the body shape of fish in the images. It is difficult to distinguish individuals in the case of images with overlapping fish. Therefore, the recording conditions under which counting is accurate are restricted, and the number of individuals that can be counted are limited. On the other hand, the proposed method uses the PTV technique, and individuals are identified from a moving image by using a Kalman filter. This allows several thousand or more individuals to be counted, and can be applied to actual fish farming. This study verified the accuracy of the fish detection system by setting up a water tank experiment to build on the basics of a new automated fish counting system.

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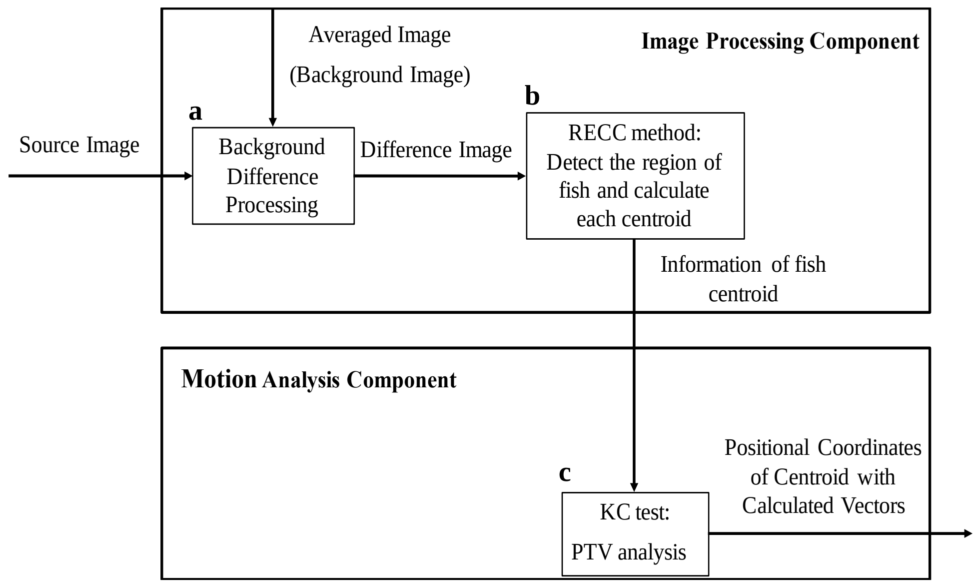

Fig. 1. Procedure overview (a) Applying background subtraction on the sequence of pictures by using the background image. (b) Extracting the centroid of each fish region from the subtracted image by using RECC. (c) Calculating each vector by executing the KC test.

2. MATERIALS AND METHODS

2.1 Experimental equipment

To evaluate an automated fish counting system, we conducted a water tank experiment. The experimental fish used was a Japanese rice fish (*Oryzias latipes*) whose average total length is 2.99 cm. The video camera used was a PIXPRO SP360, which has a 360° spherical curved lens and is able to record a 360° high definition (HD) image without the need for multiple cameras. The outer size of experimental fish tank had a direct of 640 mm, a height of 460 mm. A volume of tank was 100 L. The tank was covered with glass wool to exclude surrounding noise. The experimental method is very simple—the video camera is installed at the bottom of the tank, 250 Japanese rice fish are released into the tank, and a video sequence is captured.

2.2 Analysis Methods

The technique proposed in our study consists of two parts: image processing and PTV analysis. The former is used in abstracting the information of the foreground image to improve the ability to detect the vectors. The latter is used in calculating each vector of the fish by treating one fish as one particle. Image processing can be divided into two categories: background subtraction and the RECC method. Background subtraction is a procedure that removes the background noise. The RECC method is used for detecting foreground regions and calculating the positional coordinates of each of the centroids. For the analysis part, all of the procedure was developed using Visual C++ and MATLAB.

2.2.1 The RECC Method

In this method, each of the fish areas can be considered as regions, which can be defined as connected components in a binary image. The first step is binarization for the analysis images by using an arbitrarily set threshold of brightness. The second step converts the image data to a logical value. The third step detects the connected components whose size is bigger than the threshold of the region size. The final step is to calculate the centroid of each region and to output the positional coordinates of the centroid.

2.2.2 The KC Test

This test used an automatic particle-tracking algorithm for PTV analysis developed by one of the authors(6)(7). In our study, this test is applied to compute each of the motion vectors of the fish by considering the calculated centroids as particles. First, the Kalman filter predicts the information of the particle in time t+1 by using the observed information of the particle in time t. Subsequently, this procedure identifies the observed particle and the predicted particle position by a chi-square test, which evaluates the probability of identification. Subsequently, this test realizes the trace of each particle by repeating a similar process. The particle information to deal with in this study is not only the positional coordinates of the particle but also information such as the components of velocity and acceleration, brightness, and the particle diameter.

2.2.3 Analysis Procedure

An overview of the analysis procedure is shown in Fig. 1. In the first step of the procedure, we converted the video to a sequence of black-and-white photos. The frame rate of the pictures was 10 frames per second (FPS), and the number of pictures was 1000. In the second step, background subtraction was applied for the sequence of pictures by using the average and the standard deviation of the image data. Because the background subtraction with the averaged image was insufficient to retrieve the foreground, the standard deviation was also calculated. In the third step, the subtracted images were subjected to the RECC method for obtaining the centroids data. In this stage, the threshold of brightness was 5.0, and the threshold of the region size was 50.0 pixels. In the final step, the KC test was performed with the centroids data treated as particles.

3. RESULTS AND DISCUSSION

Fig. 2 shows the original image of fishes in the tank. After subtracting the background image from the original one, the centroid of each fish in the original image by using RECC method could be obtained as shown in Fig. 2. Fig. 3 shows vectors of individuals' centroids in an image by using KC test. Fig. 4 shows a sequence of the detected vector numbers and average numbers in all frames. As the lens of the camera was placed above the bottom of the tank, a blind area, in which fish could not be seen, was created. The Japanese rice fish tend to swim at various depths in the tank; therefore, individual images taken by the camera in the visible area were used to evaluate the recognition ability of the system. There were 250 rice fish in the tank, of which 170-190 were confirmed by naked eye observation in the visible area during the recording period. The average number of vectors detected by using the proposed method was 165.

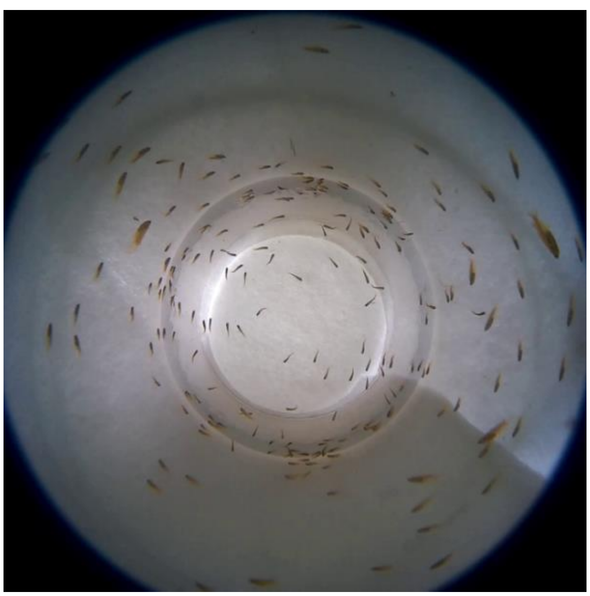

Fig. 2. Original image of fish in the tank.

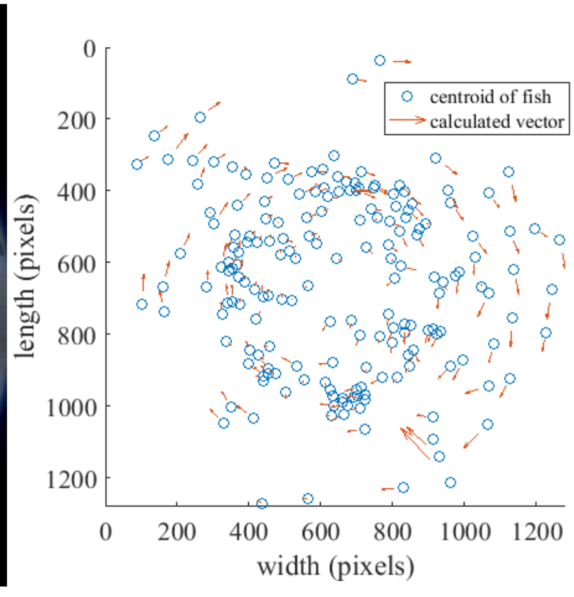

Fig. 3. Centroids of individual fish calculated using RECC and vectors of such centroids calculated using the KC test.

As Fig. 4 shows, sometimes the detected vector number increases irregularly. This can be attributed to the fact that when someone's shadow was photographed within a screen, the brightness changed. Table 1 shows the comparisons of the case with noise and without noise. The data points 1–200 were with no noise and data points 625–646 were with noise due to the shadow. In this table, the term *error* is used to refer to the error compared with the average number observed. Therefore, the recognition rate was defined as 1-error, indicating the ratio of the number of the vectors to individuals in the visible area that exceeding 90% for 100 s observation time. In this time sequence, the average one was 180. In this table, the case without shadow noise is higher than the case with shadow noise in average error rate, but it is including false detections in the case with shadow noise. Fig. 5 shows the centroids and vectors drawn over the original image in the case with and without shadow noise. In the case without shadow noise, position of centroids could be overlapped fish. On the other hand, in the case with shadow noise, there are many centroids plot that has no connection with the position of fish. It is clear that RECC method is affected by the change of brightness like a shadow noise

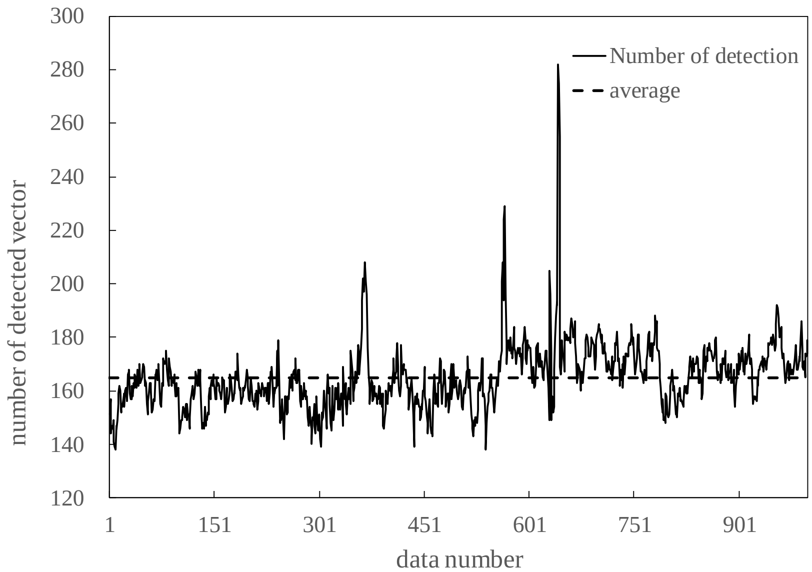

Fig. 4. Variation of the *number of detected vectors* in the image data set. In this figure, the average value of the *number of detected vectors* is 165.

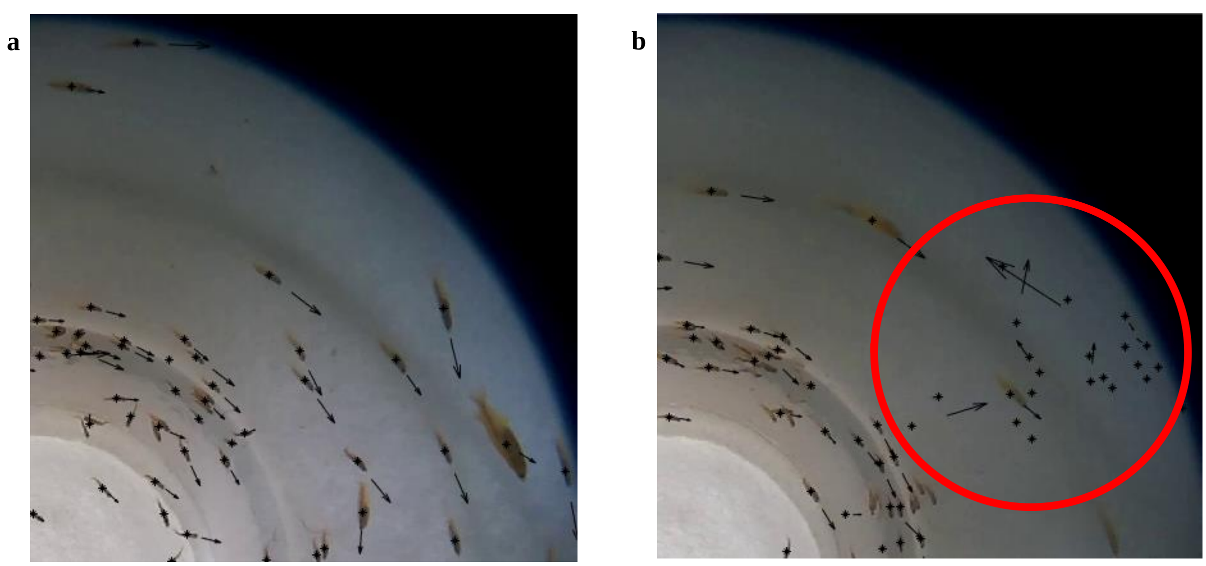

Fig. 5. Comparisons showing the effect of shadow noise (a) Centroids and vectors drawn over the original image without having shadow noise. (b) Centroids and vectors drawn over the original image having shadow noise.

Table 1. Comparisons tabulating the effect of shadow noise. In this table, the column "without shadow noise" indicates the average number of detected vectors obtained from the data points 1-200, and the column "with shadow noise" indicates the average number of detected vectors obtained from the data points 625-646.

		data set	
	total	without shadow noise	with shadow noise
Average of detected vector	165	159	186
Average Error (%)	8	12	3

Although the present algorithm uses only two consecutive images to generate a vector, the recognition rate can be improved by increasing the number of images and generating a more accurate vector of interest. In the fish farming industry, a detection rate of at least 90% is required. Therefore, we need to improve the detection results further before applying this technique to an actual net cage. There are several other problems to be solved before the proposed method can be implemented in the aquaculture industry. As the actual net cages are larger than the present experimental tank, a single camera will not be adequate to capture the entire area. This can be addressed by deploying a multiple camera system that integrates video images captured by cameras at different positions to provide a comprehensive perspective of the net cage by using software that combines video images. Furthermore, the waves generated on the free surface of the water could disturb the stable illumination intensity provided by natural light. The changes in the background brightness induced due to the waves have to be mitigated by applying appropriate tuning images.

4. CONCLUSION

In this study, we propose a new automated fish counting system by using the principle of PTV analysis technique and image processing. The proposed method can be potentially used as a fish counting system for industrial aquaculture. However, in another view, it is also clear that our proposal was affected by background noise sensitivity. We cannot say for certain whether that disadvantage affects the precision in a real net cage at an aquaculture facility. Therefore, we need to verify and study more sample data, especially in a real aquaculture facility.

REFERENCES

[1] Han, J., Honda, N., Asada, A. and Shibata, K., "Automated acoustic method for counting and sizing farmed fish during transfer using DIDSON," *Fisheries Sciense*, 75(6), 1359-1367 (2009)

[2] Gonda, Y., Kondo, Y., Takahashi, N. and Miya, K., "Trials of resistivity fish counters for automatic counting of chum Oncorhynchus keta and masu O. masou salmon migrating in small rivers," *Journal of Fisheries Technology*, 7(1), 1-16 (2014).

[3] Khanfar, H., Charalampidis, D., Yoerger, E. J., Ioup, G., Ioup, J. and Thompson, C., "Automatic Fish Counting in Underwater Video," *Gulf and Caribbean Fisheries Institute (GCFI) proceedings*, 66th, 267-275 (2014).

[4] Newbury, P. F., Culverhouse, P. F. and Pilgrim, D. A., "Automatic fish population counting by artificial neural network," *Aquaculture*, 133(1), 45-55 (1995).

[5] Costa, C., Scardi, M., Vitalini, V. and Cataudella, S., "A dual camera system for counting and sizing Northern Bluefin Tuna (Thunnus thynnus; Linnaeus, 1758) stock during transfer to aquaculture cages, with a semi automatic Artificial Neural Network tool," *Aquaculture*, 291(3-4), 161-167 (2009)

[6] Etoh, T. and Takehara, K., "A New Algorithm for Automatic Tracing Particles," *The Journal of Japan Society of Civil Engineers*, 34, 689-694 (1990).

[7] Takehara, K., Etoh, T., Murata, S. and Mishioku, K., "DEVELOPMENT OF A NEW ALGORITHM FOR PTV," *Journal of JSCE*, 533, II-34, 107-126 (1996).