Simulation Study of Fish Counting by Multiple Scanning Sonars in a Fish Farm

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Abstract—In fish farming, maintaining the number of fish is important from the viewpoint of stock management, feed volume adjustment, and so on. In this study, we evaluated the use of multiple scanning sonars to estimate the number of fish in a cage. To estimate fish counts based on coordinate information obtained from multiple sonars, we applied a hierarchical clustering method. The fundamental performance of our fish counting system was evaluated using a simulation approach by changing the number of fish, number of sonars, and size of fish. Our system can successfully estimate the number of fish with an error of 1 % or less in certain conditions.

Index Terms—Scanning sonar, fish counting, clustering, group average method, simulation

I. Introduction

Tuna farming has attracted substantial attention owing to the decline in natural tuna populations. At our university, we have been involved in research on tuna farming. In fish farming, maintaining the number of fish is generally important for stock management, feed volume adjustment, and so on. Various studies [1]-[8] and products [9]-[11] are aimed at automatically counting fish. For example, [9] uses a smartphone camera to count fish during movement in a pipe between fish cages.

However, the survival rate of tuna is low, particularly in fish cages. Therefore, the development of stress-fee methods for counting tuna in a cage is important for tuna farming. Sonar-based methods [1], [2] and camera-based methods [3]-[7] are non-contact counting methods. In this study, we evaluated the use of multiple scanning sonars for counting fish in a cage.

In addition, we use a simulation approach to evaluate our counting system. The application of multiple sonars enables more accurate counting compared with previous methods. In addition, by using a simulation approach, the fundamental performance of the newly developed counting system based on multiple sonars can be evaluated using various parameters.

An overview of our fish counting system is illustrated in Fig. 1. In our counting system, we assume that the cage is cylindrical, as is common in tuna farming. Around each fish cage are located multiple sonars that use different ultrasound frequencies to avoid interference. To estimate the number of fish in a cage based on coordinates obtained from multiple sonars, we use a hierarchical clustering method. To demonstrate the fundamental performance of our fish counting system, we evaluate its estimation accuracy by simulation experiments in which the number of fish, number of sonars, and size of fish are varied.

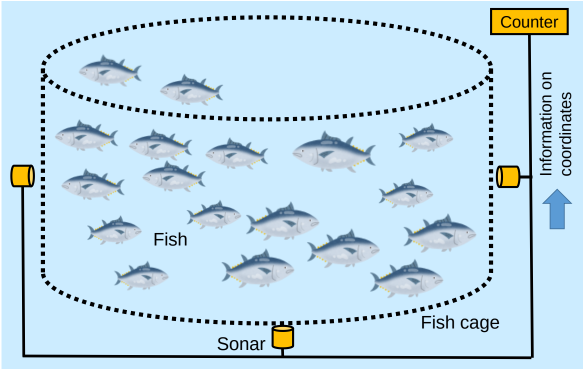

Fig. 1. Fish counting using multiple scanning sonars in a fish cage.

The rest of this paper is organized as follows. In section II, we introduce related work. In section III, we explain the fish farm model, the fish model, and the sonar model adopted in this study. Then, we explain the clustering-based counting method for fish using sonar outputs in section IV. We describe the performance of our method, as determined by a simulation approach, in section V. Finally, we conclude with an outlook toward future work in section VI.

II. Related Work

A. *Research on Fish Counting*

There are some commercially available fish counters for fish farms [9]-[11]. For example, the NEC fish counter [9] is a smartphone application for counting fry flowing through a pipe. However, it cannot be applied to a fish cage. The NEC farmed fish size measurement service [12] uses two stereo cameras not to count fish but to determine the average fish size.

Some researchers have proposed methods for counting fish in fish farms [1], [3], [4], [8] or in natural marine environments [5]-[7]. Most previous work has focused on the use of cameras for counting [3]-[7]. For example, Ref. [4] used an omni-directional camera to count fish in a cage. One drawback of camera-based counting methods

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is that their performance is affected by environmental conditions, such as water turbidity, light intensity, and so on. In addition, the performance of single camera-based counting methods is reduced by occlusions (i.e., when fish hide behind other fish).

An alternative approach for counting fish is sonar-based methods [1], [2]. Sonar is often used to estimate the amount of fish in the sea [13]. Low-cost sonar-based fish detectors are now commercially available (at around 100 USD) for personal use, such as for fishing. Some researchers have applied sonar to fish farms. In [1], dual-frequency identification sonar was used to estimate the number and size of farmed fish. However, in this method, only a single sonar is used.

In this study, we consider the use of sonars for counting fish within a fish cage. The main difference between our analysis and previous studies is our use of multiple sonars for counting fish. In addition, we also use a simulation approach to demonstrate the fundamental performance of multiple sonars.

B. Research on Fish Farm Monitoring

Our research group has previously proposed a fish farm monitoring system [14]-[16]. In this research, the target fish is tuna and a sensor node is attached to fish to monitor the health status of individuals. We previously proposed a method for gathering sensor data from nodes attached to fish at a sink node [14]. We have also shown that fish size influences data collection in a fish cage [15]. In this study, we assume that fish are cuboid in shape for simplicity. We use the same previously described model [15] to investigate the fundamental characteristics of sonar-based counting in fish farms.

III. Model

In this section, we explain the fish cage model, fish model, and sonar model. The fish farm model is based on the fish farm at our university, as in our previous studies [14]-[16]. The major notations used in this paper are summarized in Table I.

TABLE I: NOTATIONS

Fish cage	
R	Fish cage radius
H	Fish cage height
Fish	
N_F	Number of fish
f_i	The *i*-th fish in the fish cage
$\boldsymbol{F}$	The set of all fish
α, β	Cuboid parameters
φ_i	Rotation angle of the *i*-th fish
d_F	Fish size
Sonar	
N_S	Number of sonars
θ	Apex angle of the sensing region of sonar
δ	Angular resolution of sonar
L	Radius of the sonar sensing region
N_C	Number of coordinates
c_i	The *i*-th coordinate obtained from sonars
$\boldsymbol{C_0}$	The set of all coordinates
Counting method	
$\boldsymbol{C_i}$	The *i*-th cluster
$\boldsymbol{C}$	The set of all clusters
D	Threshold of clustering
$\hat{N}$	Estimated number of fish

A. Fish Cage Model

In this paper, the fish cage is a cylinder with a radius of R and a height of H, as shown in Fig. 2. We define the x-, y-, and z-axes as shown in Fig. 2. The number of fish in the cage is denoted by N_F, and the set of fish in the cage is denoted by $\boldsymbol{F} = \{f_i \mid 1 \le i \le N_F\}$.

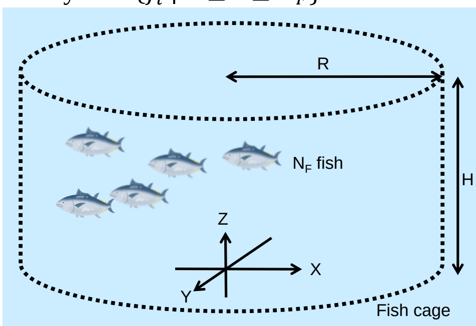


Fig. 2. Fish cage model.

B. Fish Model

For simplicity, we assume that the shape of fish f_i is a cuboid with length d_F, width αd, height βd, and rotation angle with respect to the z-axis representing φ_i, as shown in Fig. 3. Here, α and β are size parameters; we assume α = 0.2 and β = 0.4 [15] in this paper. In addition, we assume that all fish in the fish cage are of equal size and the rotation angle φ_i of fish varies among individuals.

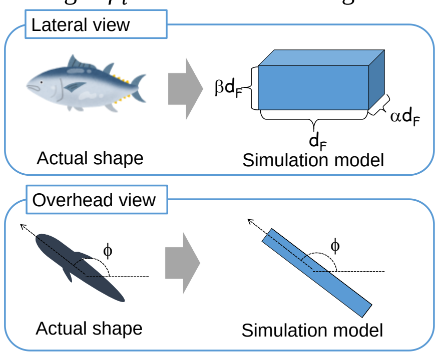


Fig. 3. Fish model.

Here, the size of fish d is dependent mainly on the age of the fish. For example, in tuna farming, when fry are released from an indoor tank to an outdoor fish cage, they are approximately 5 cm in length. After several years, the tuna reach around 100 cm, at which point they are harvested.

C. Sonar Model

In this paper, we assume that there are multiple sonars s_i ($1 \leq i \leq N_S$) near the fish cage. Here, N_S is the number of sonars. Fig. 4 shows an overview of sonar used in this paper. We assume an ideal sonar to evaluate the fundamental performance of our counting system through simulations. Each sonar outputs ultrasonic waves at an interval of δ, as shown in Fig. 4, and the coordinates of obstacles are thus obtained. Here, the j-th coordinate obtained from sonars is denoted by $c_j = (x_j, y_j, z_j)$ and the whole set of coordinates from all sonars is denoted by $\boldsymbol{C_0} = \{c_j \mid 1 \leq j \leq N_C\}$, where N_C is the number of coordinates obtained from sonars.

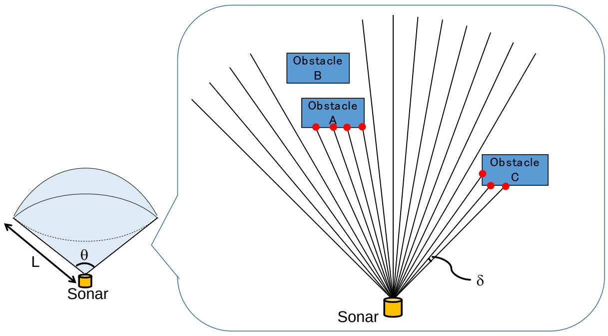


Fig. 4. Sonar model.

The sonar sensing region is a portion of a sphere whose apex angle is θ and radius is L. For example, in Fig. 4, sonar can obtain the information on the coordinates of the red points and can detect obstacles. Here, if an obstacle is located behind the detected obstacle, information about the hidden obstacle cannot be obtained by sonar. This problem is called the occlusion problem in the area of image processing. In Fig. 4, sonar cannot be used to obtain the coordinates of obstacle B but it can be used to obtain the coordinates of obstacles A and C. Here, if there are multiple sonars and one can obtain the coordinates of obstacle B, the whole system can detect all three obstacles.

IV. Method for Counting Fish

In this paper, we use a hierarchical clustering method for coordinates obtained from multiple sonars. Then, the number of fish is estimated based on the number of clusters. Here, we assume that the fish size d_F is known a priori.

The pseudo code for our fish counting method is shown in Fig. 5. The procedure consists of the following three steps.

1. First, N_C clusters ($\boldsymbol{C_1}$, $\boldsymbol{C_2}$, …, $\boldsymbol{C_{NC}}$) are generated, each of which consists of one coordinate. Here, $\boldsymbol{C_i} = \{c_i \in \boldsymbol{C_0}\}$ ($1 \leq i \leq N_C$) is the i-th cluster, and the set of all clusters is denoted by $\boldsymbol{C} = \{\boldsymbol{C_i} \mid 1 \leq i \leq N_C\}$.
2. The two clusters $\boldsymbol{C_p} \in \boldsymbol{C}$ and $\boldsymbol{C_q} \in \boldsymbol{C}$, separated by the minimum distance, are selected from the set of clusters $\boldsymbol{C}$. In this study, we use the group average method as the distance function $d_C(\boldsymbol{C_i}, \boldsymbol{C_j})$ between clusters $\boldsymbol{C_i}$ and $\boldsymbol{C_j}$ as follows:
$$d_C(\boldsymbol{C_i}, \boldsymbol{C_j}) = \frac{1}{|\boldsymbol{C_i}||\boldsymbol{C_j}|} \sum_{c_k \in \boldsymbol{C_i}} \sum_{c_l \in \boldsymbol{C_j}} d(c_k, c_l)$$
Here, $d(c_k, c_l)$ is the Euclidean distance between coordinates c_k and c_l.
3. If the distance $d_C = d_C(\boldsymbol{C_p}, \boldsymbol{C_q})$ is less than or equal to the threshold D, two clusters $\boldsymbol{C_p}$ and $\boldsymbol{C_q}$ are merged into a single cluster and step 2 is initiated. If the distance d_C is greater than the threshold D, the clustering procedure is finished, and the estimated number of fish $\hat{N}$ is calculated as $\hat{N} = |\boldsymbol{C}|$.

Algorithm 1 Method for counting fish

Require: The set of coordinates $\mathbf{C}_0$
Ensure: The estimated number of fish $\hat{N}$

```
procedure ESTIMATINGFISHNUMBER
    Generates clusters C = {C_1, ..., C_{N_C}} from C_0
    D ← d_F
    d_C ← 0
    while d_C ≤ D do
        Find C_p and C_q with the minimal distances
        d_C ← d_C(C_p, C_q)
        if d_C ≤ D then
            Merge two clusters C_p and C_q
        end if
    end while
    N̂ ← |C|
end procedure
```

Fig. 5. Pseudo code for our fish counting method.

In this method, if the threshold D is too small, coordinates for one fish are divided into several clusters, as shown in Fig. 6(a). As a result, the estimated number of fish exceeds the actual number. On the other hand, if the threshold D is too large, coordinates for multiple fish are grouped into one cluster, as shown in Fig. 6(b), and the estimated number of fish is less than the actual number. Therefore, the threshold D should be set appropriately. Here, the maximum distance between coordinates obtained from one fish model is $d_F\sqrt{1+\alpha^2+\beta^2}$, which is the length of the space diagonal of the cuboid. Therefore, the threshold should satisfy $D < d_F\sqrt{1+\alpha^2+\beta^2}$. In this study, we simply use $D = d_F$ as the threshold value.

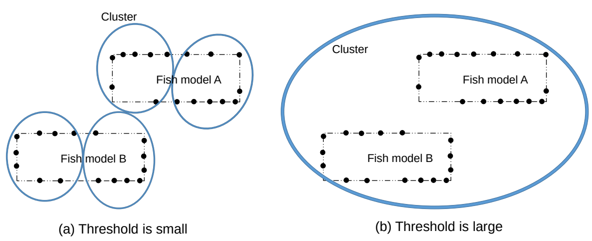


Fig. 6. Examples of settings for the threshold D.

V. Evaluation

In this section, we investigate the performance of our counting method using a simulation approach.

A. Simulation Settings

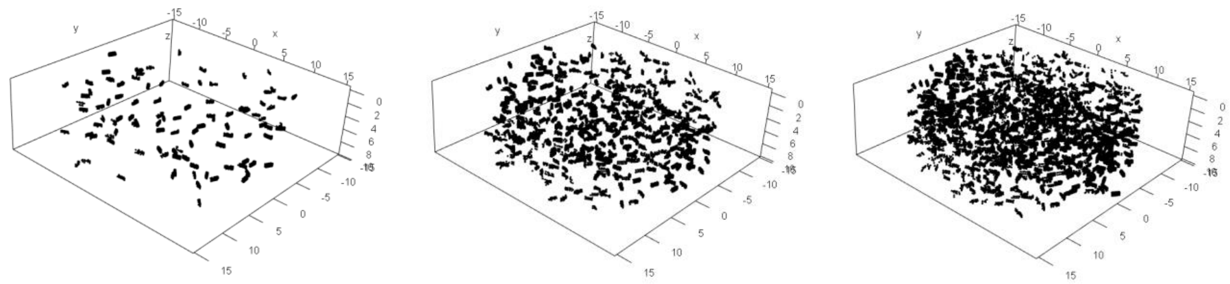
For the fish cage model, we used a cylinder with radius R = 15 m and height H = 10 m, consistent with the size used at our university. The size of fish d_F varies in the range of $0.1 \leq d_F \leq 1.0$.

In the simulation, fish are deployed one by one. The location of each fish is randomly selected in the fish cage, and the rotation angle φ_i of fish f_i is randomly chosen, where $0 \leq \varphi_i \leq 360^{\circ}$. At the time of the deployment of a new fish, if another fish exists in the same area, the location and the rotation angle of the new fish are randomly chosen again.

In this study, we consider a maximum of three sonars, as shown in Fig. 1. The apex angle is set to $\theta = 160^{\circ}$, and the angular resolution is set to $\delta = 1^{\circ}$. The first sonar is located in the center of the fish cage's bottom. The second sonar is located at height H/2 on the side of the fish cage. The third sonar is located across from the second sonar. All sonars are located 3 m away from the fish cage and are positioned facing the center of the cage.

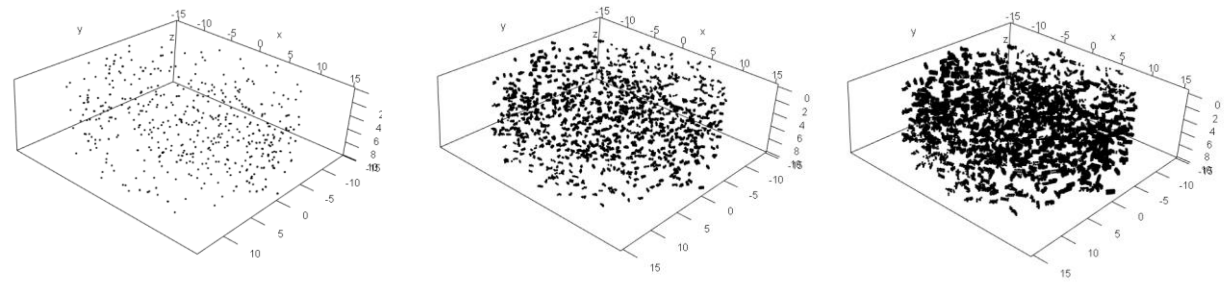
B. Examples of Obtained Coordinates

Figures 7, 8 and 9 show examples of coordinates obtained from sonars. In Fig. 7, the fish size is set to d_F = 1 m, the number of sonars is set to N_S = 3, and the number of fish N_F is set to 100, 500, and 1000. As shown in Fig. 7, the number of coordinates obtained from sonars increases according to the increase in the number of fish.



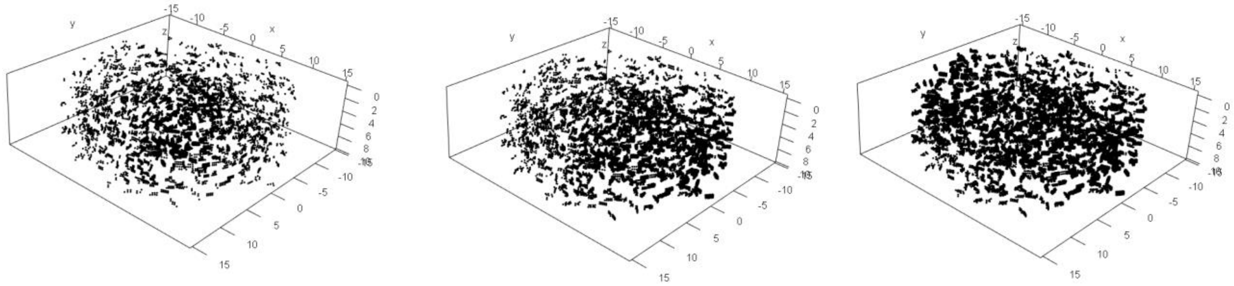
(a) N_F = 100 (b) N_F = 500 (c) N_F = 1000

Fig. 7. Examples of acquired coordinates according to number of fish N_F (d_F = 1 m, N_S = 3).



(a) d_F = 0.1 m (b) d_F = 0.5 m (c) d_F = 1 m

Fig. 8. Examples of acquired coordinates according to fish size d_F (N_F = 1000, N_S = 3).



(a) N_S = 1 (b) N_S = 2 (c) N_S = 3

Fig. 9. Examples of acquired coordinates according to number of sonars N_S (N_F = 1000, d_F = 1 m).

In Fig. 8, the size of fish d_F is varied while the number of fish is N_F = 1000 and the number of sonars is N_S = 3. As shown in Fig. 8, the number of coordinates increases according to the increase in fish size.

In Fig. 9, the number of sonars N_S is varied. In Fig. 9(a), when the number of sonars is one, the first sonar is used. When the number of sonars is two in Fig. 9(b), both the first and the second sonars are used. When the number of sonars is three in Fig. 9(c), all sonars are used.

As shown in these figures, the number of coordinates increases according to the increase in the number of sonars.

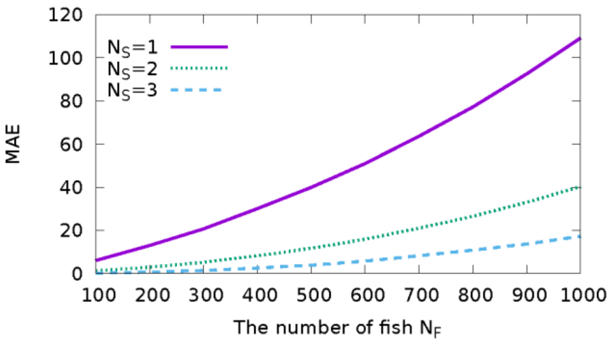
C. Evaluation of Fundamental Performance

We first evaluate the fundamental performance of our counting method. As an evaluation index, we used the mean absolute error (MAE) e_{MAE} and the mean error (ME) e_{ME}, respectively calculated as follows:

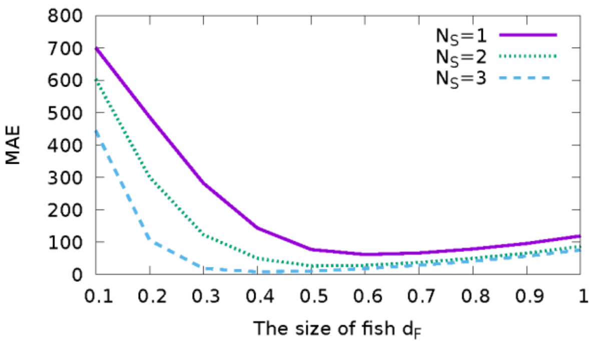
$$e_{MAE} = \frac{1}{M}\sum_{i=1}^{M}|\widehat{N}_i - N_F|$$

$$e_{ME} = \frac{1}{M}\sum_{i=1}^{M}(\widehat{N}_i - N_F)$$

Here, $\widehat{N}_i$ is the estimation result for the i-th simulation, and M is the number of simulations. In this paper, we conducted M = 100 simulations.



(a) MAE according to the number of fish N_F (d_F = 0.5 m)



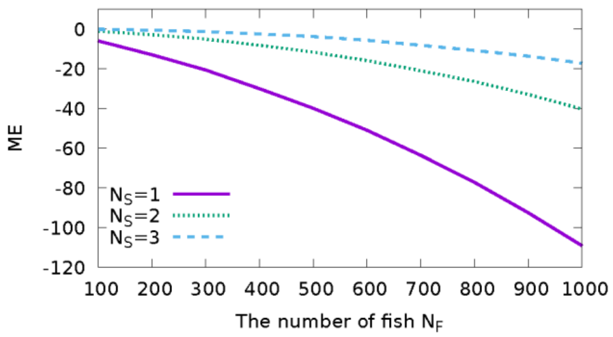
(b) MAE according to the size of fish d_F (N_F = 800)

Fig. 10. Mean absolute error (MAE) according to the number and size of fish.

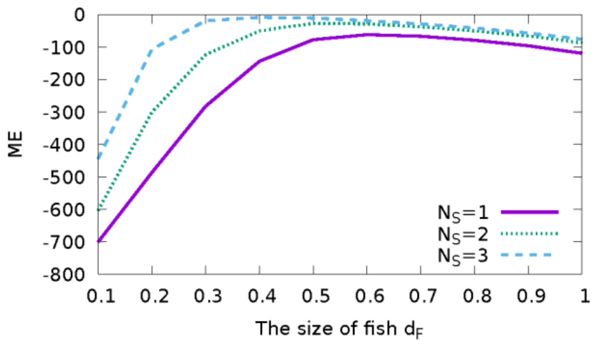
Fig. 10(a) shows the MAE according to the number of fish N_F and the number of sonars N_S when fish size is fixed to d_F = 0.5 m. Fig. 10(b) shows the MAE according to the size of fish d_F and the number of sonars N_S when the number of fish is fixed to N_F = 800. As shown in Figs. 10(a) and 10(b), by increasing the number of sonars, MAE decreases. For example, when the number of fish is N_F = 1000, the MAE is around 100 in the case of a single sonar. By increasing the number of sonars to three, the MAE decreases to around 20. This is because the rate of occlusion decreases as the number of sonars increases, as explained in section III-C.

MAE increases according to the increase in the number of fish N_F, as shown in Fig. 10(a). This is because the rate at which occlusion occurs increases according to the increase in the number of fish in each cage. In addition, because distances between fish also decrease as the number of fish increases, the possibility of obtaining coordinates from multiple fish in close proximity increases and the possibility of failed clustering increases.

We then investigate the relationship between MAE and fish size d_F. As shown in Fig. 10(b), MAE increases as fish size d_F decreases. This can be explained by the small fish size compared to the angular resolution of sonar $\delta = 1^{\circ}$; some fish cannot be detected by sonar. MAE also increases as fish size increases, as shown in Fig. 10(b). This reason is similar to that described in previous section. When fish size increases, the rate at which occlusion occurs increases and the possibility of failed clustering increases. As a result, MAE increases.



(a) ME as a function of the number of fish N_F (d_F = 0.5 m)



(b) ME as a function of the size of fish d_F (N_F = 800)

Fig. 11. Mean error (ME) as a function of the number and size of fish.

Figures 11(a) and 11(b) show ME as a function of the number of fish N_F and the size of fish d_F, respectively. When we compare Fig. 10(a) and Fig. 11(a), the graphs are approximately vertically symmetrical. Figures 10(b) and 11(b) are also approximately vertically symmetrical. This symmetry indicates that the number of fish estimated by our counting method tends to underestimate the actual number. Therefore, the combined effect of multiple fish clustering together and of occlusion are greater than the effect of a single fish clustering into multiple groups.

D. Improved Counting Method and Its Evaluation

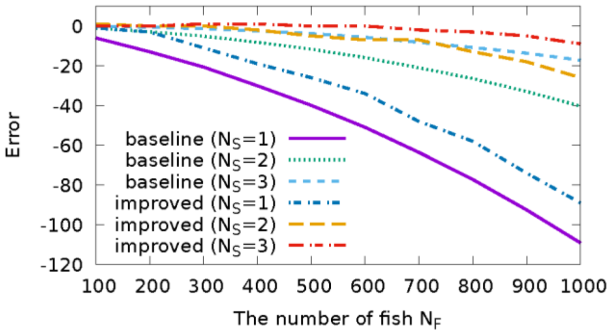
As described in the previous section, our counting method tends to underestimate the number of fish. Here, the low counting accuracy is mainly dependent on the location of fish during the sonar scan. In realistic conditions, the number of fish in a cage does not change frequently. Therefore, for example, it may be possible to scan a fish cage several times a day, and record the best result.

In this section, we consider the following number as the estimate:

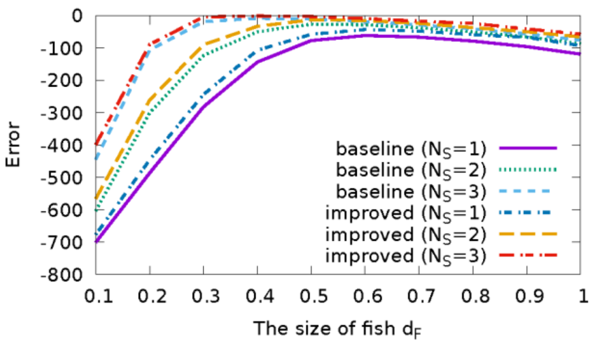
$$\widehat{N}_{\max} = \max_{1 \le i \le M} \widehat{N}_i$$

Here, we assume that scanning is performed M times over a certain time period, and $\widehat{N}_i$ is the estimation for the i-th scan. We refer to this as the improved method. In this case, the estimation error can be calculated as follows.

$$e = N_F - \widehat{N}_{\max}$$



(a) Error as a function of the number of fish N_F (d_F = 0.5 m)



(b) Error as a function of the size of fish d_F (N_F = 800)

Fig. 12. Error as a function of the number and size of fish.

Figures 12(a) and 12(b) summarize the simulation results. For comparison, we also show the results described in the previous section (Figs. 11(a) and 11(b)) as a baseline. As shown in Figs. 12(a) and 12(b), the error of the improved method is smaller than that of the baseline method for all parameter settings. For example, as shown in Fig. 12(b), when the number of sonars is N_S = 3 and the size of fish is $0.3 \le d_F \le 0.6$, it is possible to estimate the number of fish accurately, with an error of 1% or less. When the number of sonars is N_S = 3 and the fish size is d_F = 1.0, the relative error of the improved method is around 7% whereas that of the baseline method is around 9%. To further reduce the error, one approach is to improve the clustering method to account for fish shape. A detailed discussion and evaluation are aims of our future work.

VI. Conclusion

In this study, we considered the use of multiple scanning sonars to estimate the number of fish in a cage. To obtain fish counts based on coordinate information obtained from multiple sonars, we applied a hierarchical clustering method. The fundamental performance of our fish counting system was evaluated by simulations with different numbers of fish, numbers of sonars, and fish sizes.

In future work, we aim to propose a method for estimating the size of each fish in a situation where fish vary in size, and we will also consider error in the sonar results. In addition, we plan to investigate and propose a counting method that uses multiple low-cost and low-performance sonars.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Y. Taniguchi proposed the method and wrote this paper. Y. Taniguchi and K. Oki implemented the simulation code. K. Oki obtained the results and analyzed the simulation data. All authors had approved the final version.

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