Chapter

Cross-Correlation-Based Fisheries Stock Assessment Technique: Utilization of Standard Deviation of Cross-Correlation Function as Estimation Parameter with Four Acoustic Sensors

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Abstract

In the past, cross-correlation-based fisheries stock assessment technique utilized the mean and the ratio of standard deviation to the mean of cross-correlation function (CCF) as estimation parameter. However, in this paper, we have utilized only standard deviation of CCF as estimation parameter to estimate the population size. We utilized four acoustic sensors and considered chirp sound which is commonly generated by damselfish (*Dascyllus aruanus*), humpback whales (*Megaptera novaeangliae*), dugongs (*Dugong dugon*), etc., species to accomplish the simulations. We found that a robust estimation can be obtained using standard deviation of CCF as estimation parameter even when the distances between acoustic sensors are small.

Keywords: acoustic sensor, bins, chirp, fisheries stock assessment, standard deviation

1. Introduction

Passive acoustic monitoring of fish abundance is an emerging field of research among the conservation researchers and marine ecologists. It has upgraded understanding of the temporal distribution and repertoire of soniferous fish and mammals [1–2]. Generally, passive acoustic monitoring is used to have an insight about the population size of soniferous fish and mammals, which are problematic to locate using visual sampling techniques [3–6] in a certain marine area. These types of fishery surveys utilize the advantage of sound production nature of many species of fish and mammals which possess natural acoustic tags. It has the merit of being a non-destructive and non-invasive monitoring technique, unlike the conventional fisheries stock assessment methods, that is, mark recapture techniques, environmental DNA, visual census, echo, minnow traps, etc. [7–8]. Generally, mechanical instrument-based conventional fishery surveys suffer from poor accuracy, time consuming nature, overly human interaction, costly instruments, etc., which can be overcome by passive acoustic monitoring techniques. Passive monitoring can

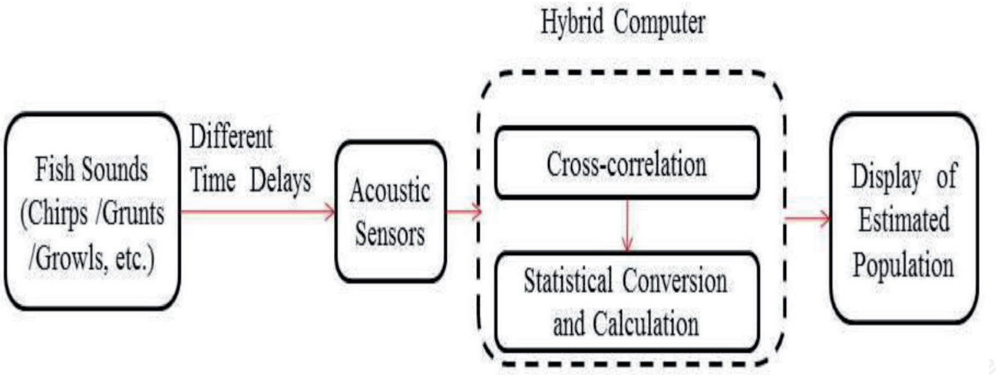

Figure 1.
Simplified block diagram of cross-correlation fisheries-based stock assessment system.

provide unbiased data on the location and movement of sound producing source in underwater situations [9]. Low-frequency (<10 kHz) acoustic sensors, that is, hydrophones, are used to detect natural sound production by fish and mammals [10]. Usually, fish sound is associated with courtship, feeding or aggressive encounters [10]. Researchers categorized the sound types of fish and mammals by different names, that is, chirps, pops, grunts, whistles, growls, hoots, etc., which are associated with their frequency and temporal characteristics [11].

However, cross-correlation-based fisheries stock assessment technique, a passive acoustic survey technique, was proposed in [12–16]. In this technique, the sound signals of vocalizing fish and mammals are processed to estimate their population size [17]. This statistics-based technique has the potential to resolve some main drawbacks of conventional techniques like complexity, reliance on human interaction, time consuming nature of estimation, sensitivity, high cost, etc. A simplified block diagram representation of this technique is illustrated in **Figure 1**.

In the past, the researchers associated with this technique utilized the mean of CCF [12] ratio of standard deviation to the mean of CCF [13–20] to estimate population size. In this paper, we have introduced standard deviation of CCF as estimation parameter to perform our desired estimation. We considered four acoustic sensors case [21], that is, hydrophones, in this research. For four acoustic sensors case, different types of topologies, that is, acoustic sensors in line, acoustic sensors in a rectangular shape, acoustic sensors in a triangular shape, are possible. Similarly, Acoustic sensors in a triangular shape can be a square shape, a rhombus shape or a trapezoidal shape. In this paper, we considered acoustic sensors in line case (ASL case). The main reason of considering four acoustic sensors is increasing number of cross-correlation function ensures better accuracy in this technique [14]. Likewise, from diverse sound types of fish and mammals, we considered chirp sound which is commonly generated by damselfish (*Dascyllus aruanus*), humpback whales (*Megaptera novaeangliae*), dugongs (*Dugong dugon*), etc., species [11]. We organize this paper as firstly, to state the theoretical procedure of our proposed methodology and finally, the theory will be evaluated by simulation. We used MATLAB simulation environment to accomplish our simulation in this study.

2. Utilization of the CCF

The formulation of cross-correlation of sound signals of fish and mammals is analogous to the formulation of cross-correlation of Gaussian signal [22], which are the starting materials to estimate the population size. Chirp sound of fish and mammals are received by the acoustic sensor and recorded in the associated computer in which cross-correlation is executed. Transmission and reception of sound signals are performed for a time frame, called "signal length." Sound (chirp) generating fish and mammals are considered as the sources of sound signals and N fish and mammals are distributed over the volume of a large sphere, the center of which lies halfway between the acoustic sensors. A typical scenario of fish and mammals distribution is shown in **Figure 2**.

In the water medium, a constant propagation speed S_p of sound is considered [23]. **Figure 3** shows an example of 3D estimation area under water space with a single fish N_1 and four acoustic sensors H_1, H_2, H_3, and H_4. We considered the coordinates of H_1, H_2, H_3, and H_4 are (x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3), and (x_4, y_4, z_4) respectively, whereas the coordinate of the fish is (a, b, c). The distance between the acoustic sensors can be calculated as follows:

$$d_{DBS12} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \tag{1}$$

$$d_{DBS23} = \sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2 + (z_2 - z_3)^2} \tag{2}$$

$$d_{DBS34} = \sqrt{(x_3 - x_4)^2 + (y_4 - y_4)^2 + (z_3 - z_4)^2} \tag{3}$$

Here, d_{DBS12} = distance between H_1 and H_2, d_{DBS23} = distance between H_2 and H_3, and d_{DBS34} = distance between H_3 and H_4.

Let us consider, a sound signal coming from N_1 is $S_1(t)$, which is finite in length. The signal received by acoustic sensors H_1, H_2, H_3, and H_4 are Sr_{11}, Sr_{12}, Sr_{13}, and Sr_{14}, respectively:

$$S_{r11}(t) = \alpha_{11} S_{11}(t - \tau_{11}), \tag{4}$$

$$S_{r12}(t) = \alpha_{12} S_{12}(t - \tau_{12}), \tag{5}$$

$$S_{r13}(t) = \alpha_{13} S_{13}(t - \tau_{13}), \tag{6}$$

$$S_{r14}(t) = \alpha_{14} S_{14}(t - \tau_{14}), \tag{7}$$

where α_{11}, α_{12}, α_{13}, and α_{14} are the attenuation due to absorption and dispersion in the medium, and τ_{11}, τ_{12}, τ_{13}, and τ_{14} are the respective time delays for the acoustic signals to reach the acoustic sensors. For four acoustic sensors ASL case, the cross-correlation among the acoustic sensors is taken place for three times, i.e., between sensors H_1 and H_2, H_2 and H_3, and H_3 and H_4. So, the total number of CCF is three.

Therefore, the CCFs are:

$$C_1(\tau) = \int_{-\infty}^{+\infty} S_{11}(t) S_{12}(t - \tau_{11}) d\tau \tag{8}$$

$$C_2(\tau) = \int_{-\infty}^{+\infty} S_{12}(t) S_{13}(t - \tau_{12}) d\tau \tag{9}$$

$$C_3(\tau) = \int_{-\infty}^{+\infty} S_{13}(t) S_{14}(t - \tau_{13}) d\tau \tag{10}$$

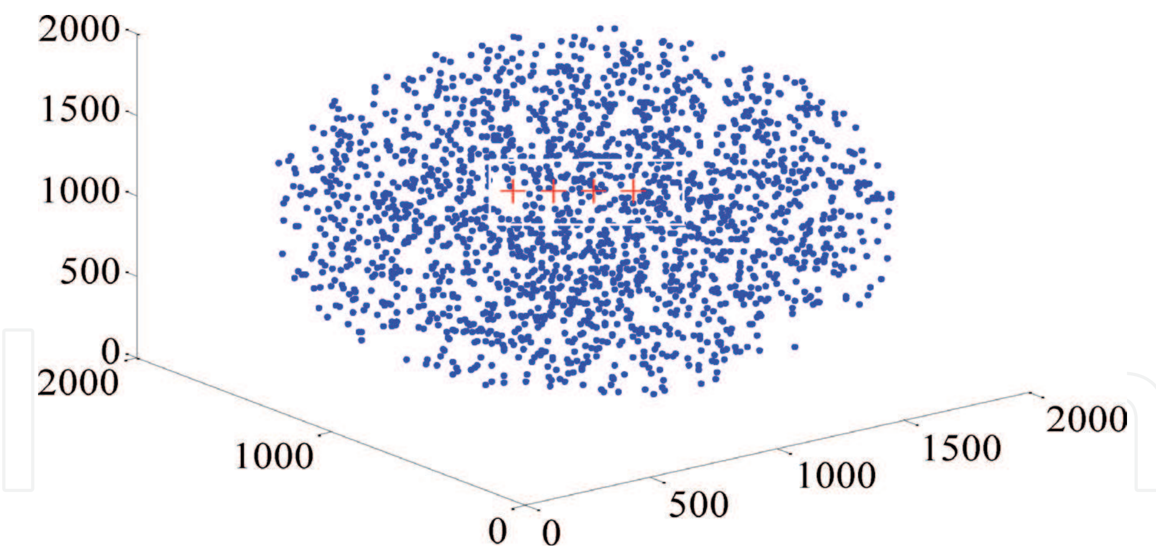

Figure 2.
Distribution of fish and mammals with four acoustic sensors, that is, four pluses (++++).

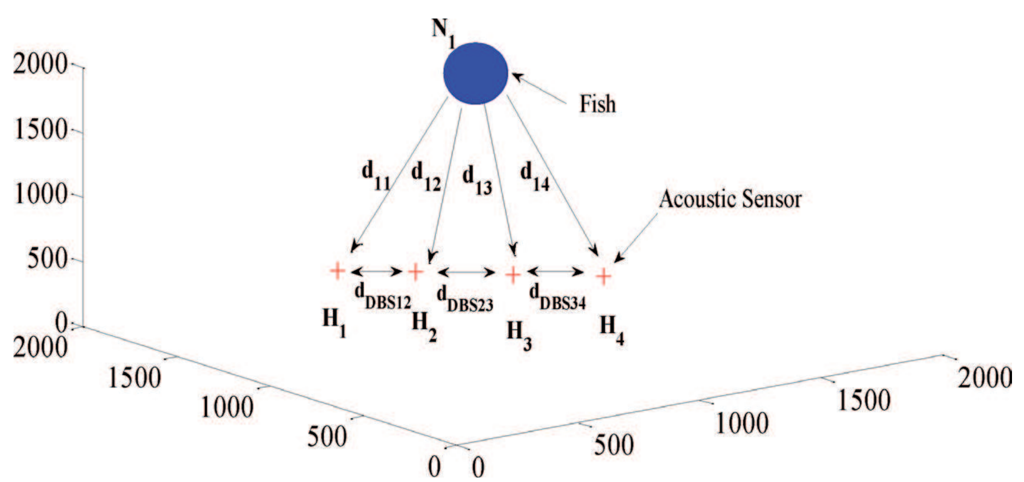

Figure 3.
Diagram of a single fish with four acoustic sensors, H_1, H_2, H_3, *and* H_4.

To find out the CCFs for N number of fish and mammals, we have to take the total sound signals received by the four acoustic sensors.

Thus, the composite signals received by H_1, H_2, H_3, and H_4 are:

$$S_{rt1} = \sum_{j=1}^{N} \alpha_{j1} S_j \left(t - \tau_{j1}\right) \tag{11}$$

$$S_{rt2} = \sum_{j=1}^{N} \alpha_{j2} S_j \left(t - \tau_{j2}\right) \tag{12}$$

$$S_{rt3} = \sum_{j=1}^{N} \alpha_{j3} S_j \left(t - \tau_{j3}\right) \tag{13}$$

$$S_{rt4} = \sum_{j=1}^{N} \alpha_{j4} S_j \left(t - \tau_{j4}\right) \tag{14}$$

Therefore, the total CCFs are:

$$C_{12}(\tau) = \int_{-\infty}^{+\infty} S_{rt1}(t) S_{rt2}(t - \tau) d\tau \tag{15}$$

$$C_{23}(\tau) = \int_{-\infty}^{+\infty} S_{rt2}(t) S_{rt3}(t-\tau) d\tau \tag{16}$$

$$C_{34}(\tau) = \int_{-\infty}^{+\infty} S_{rt3}(t) S_{rt4}(t-\tau) d\tau \tag{17}$$

This is the form of series of delta functions because in cross-correlation procedure one sound signal is the delayed copy of another [22].

3. Theoretical estimation from standard deviation of CCF

As we considered chirp generating fish and mammals to estimate their population size, an introduction to chirp signal is an important task in this perspective. Chirps belong to a swept-frequency sound signal, which possess a time varying frequency. From a sound analysis of *Plectroglyphidodon lacrymatus* and *Dascyllus aruanus* species of damselfish, It was seen that the produced chirps by them was consisted of trains of 12–42 short pulses of 3–6 cycles [12, 24]. The durations varied from 0.6 to 1.27 ms where the peak frequency varied from 3400 to 4100 Hz [25]. Such a sound signal can be represented as [8, 12, 13]:

$$X(t) = A\cos\left[2\pi\left\{\frac{(f_2 - f_1)t^2}{2d} + f_1 t\right\} + P\right] \tag{18}$$

where f_1 = starting frequency in Hz, f_2 = ending frequency in Hz, d = duration in second, P = starting phase, and A = amplitude.

However, the mean of CCF can be expressed by ensemble average of the chirp-signal cross-correlation as [22].

$$\langle C(t)\rangle = Q_T T_r v \int_{-\infty}^{+\infty} d\vec{r}_S \times \delta\left(t + \frac{|\vec{r}_a - \vec{r}_s|}{S_p} - \frac{|\vec{r}_b - \vec{r}_s|}{S_p}\right), \tag{19}$$

where Q_T represents the acoustic power of the received signals from the sources taken to be constant over time and space, v is the creation rate of the sources whose unit is unit time per unit volume, T_r is the total recording time, $\vec{r}_s$ is the path length of sources from the origin, $\vec{r}_a$ is the path length of first acoustic sensor from the origin, and $\vec{r}_b$ is the path length of second sensor from the origin.

Now, the variance of the CCF can be defined as [22]:

$$Var(C(t)) = \langle C^2(t)\rangle - \langle C(t)\rangle^2, \tag{20}$$

where $\langle C(t)\rangle^2$ and $\langle C^2(t)\rangle$ are defined in Eqs. (21) and (22), respectively, as [22]:

$$\begin{aligned}\langle C(t)\rangle^2 = Q_T{}^2 v^2 &\left(\int_{-T_r/2}^{+T_r/2} dt \int_{-\infty}^{+\infty} d\vec{r}_1 \int_{-\infty}^{+t} d\tau_1 G(\vec{r}_1, \vec{r}_a; t-\tau_1) \times G(\vec{r}_1, \vec{r}_b; \tau + t - \tau_1)\right) \times \\ &\left(\int_{-T_r/2}^{+T_r/2} d\tilde{t} \int_{-\infty}^{+\infty} d\vec{r}_3 \int_{-\infty}^{+t} d\tau_3 G(\vec{r}_3, \vec{r}_a; t-\tau_3) \times G(\vec{r}_3, \vec{r}_b; \tau + \tilde{t} - \tau_3)\right)\end{aligned} \tag{21}$$

and

$$\langle C^2(t)\rangle = Q_T v^2 \left(\int_{-T_r/2}^{+T_r/2} dt \int_{-\infty}^{+\infty} d\vec{r}_1 \int_{-\infty}^{+t} d\tau_1 G(\vec{r}_1, \vec{r}_a; t-\tau_1) \times G(\vec{r}_1, \vec{r}_b; \tau + t - \tau_1) \right) \times$$
$$\left(\int_{-T_r/2}^{+T_r/2} d\tilde{t} \int_{-\infty}^{+\infty} d\vec{r}_3 \int_{-\infty}^{+t} d\tau_3 G(\vec{r}_3, \vec{r}_a; t-\tau_3) \times G(\vec{r}_3, \vec{r}_b; \tau + \tilde{t} - \tau_3) \right) +$$
$$Q_T v^2 \left(\int_{-T_r/2}^{+T_r/2} dt \int_{-\infty}^{+\infty} d\tilde{t} \left(\int_{-\infty}^{+\infty} d\vec{r}_1 \int_{-\infty}^{+t} d\tau_1 G(\vec{r}_1, \vec{r}_a; t-\tau_1) \times G(\vec{r}_1, \vec{r}_a, \tilde{t} - \tau_1) \right) \right) \times \tag{22}$$
$$\left(\int_{-\infty}^{+\infty} d\vec{r}_1 \int_{-\infty}^{+t} d\tau_1 G(\vec{r}_1, \vec{r}_b; t-\tau_1) \times G(\vec{r}_1, \vec{r}_a; \tilde{t} - \tau_1) \right) +$$
$$Q_T v^2 \left(\int_{-T_r/2}^{+T_r/2} dt \int_{-\infty}^{+\infty} d\tilde{t} \left(\int_{-\infty}^{+\infty} d\vec{r}_1 \int_{-\infty}^{+t} d\tau_1 G(\vec{r}_1, \vec{r}_a; t-\tau_1) \times G(\vec{r}_1, \vec{r}_b; \tilde{t} - \tau_1) \right) \right) \times$$
$$\left(\int_{-\infty}^{+\infty} d\vec{r}_2 \int_{-\infty}^{+t} d\tau_2 G(\vec{r}_2, \vec{r}_b; t-\tau_2) \times G(\vec{r}_2, \vec{r}_b; \tilde{t} - \tau_2) \right),$$

where $G(.)$ = Green's function. The other parameters signify their usual meanings [22].

Therefore, we can get the standard deviation, σ of the CCF as we know that standard deviation is the square root of the variance.

$$\sigma = \sqrt{Var(C(t))} = \sqrt{\langle C^2(t)\rangle - \langle C(t)\rangle^2} \tag{23}$$

However, to analyze the random signal cross-correlation problem to find the standard deviation in the above way is very hard. Therefore, the problem can be reframed as a binomial probability problem which can make the analysis simpler. Since, cross-correlation function follows the binomial probability distribution in which the parameters are the number of balls, that is, fish and mammals, N, and one on the number of bins, b; therefore, the standard deviation, σ of the CCF is defined as bellow [22]:

$$\sigma = \sqrt{N \times \frac{1}{b} \times \left(1 - \frac{1}{b}\right)}, \tag{24}$$

where N is the number of fish and mammals and b is the number of bins. Here, b can be achieved from the following Eq. [22]:

$$b = \frac{2 \times d_{DBS} \times S_R}{S_P} - 1, \tag{25}$$

where S_R is the sampling rate, d_{DBS} is the distance between equidistant sensors, and S_p is the speed of sound propagation.

From Eq. (25), we can write the following formula:

$$N = \frac{b^2 \times \sigma^2}{b - 1} \tag{26}$$

Therefore, if σ is available from simulation, the estimated population size of fish and mammals, N will be found from Eq. (26).

Now, for four acoustic sensors ASL case, the final standard deviation will be found from the average of σ_1, σ_2, and σ_3.

$$\sigma_{Average}^{3CCF} = \frac{\sigma_1 + \sigma_2 + \sigma_3}{3} \tag{27}$$

Thus, from Eq. (26), we can obtain that

$$N = \frac{b^2 \times \left(\sigma_{Average}^{3CCF}\right)^2}{b-1} \tag{28}$$

Therefore, if σ is available from simulation, N will be found from Eq. (28).

4. Simulation and discussion

Simulations were executed considering that four acoustic sensors lay on the center of a sphere. We also considered a uniform random distribution of fish and mammals. Thousand iterations were averaged to accomplish the simulated results. To ease the simulation, the power difference among the acoustic pulses transmitted by each fish and mammal was considered negligible. Here, we considered $d_{DBS12} = d_{DBS23} = d_{DBS34} = d_{DBS}$. The parameters used in MATLAB simulation are introduced in **Table 1**.

Figure 4 shows the theoretical and corresponding simulated results for the population estimation of fish and mammals in terms of the estimation parameter σ of CCF. The solid lines designate the theoretical results, and the stars, circles, squares, and triangles correspond the simulated results. The variations of b are as results of varying d_{DBS} in the four different **Figures 4(a)–(d)**. The other parameters are same for all the figures.

Figure 5 shows the difference between theoretical and simulated population size of fish and mammals for b = 79. In this figure, the solid line indicates the theoretical results, and the triangles are corresponding to the simulated results. From **Figure 5**, it can be seen that the theoretical and simulated results are closely stayed to each other, which signifies the strength of this population estimation method. Similarly, we can see that the number of bins, b has an impact on the estimation parameter, which is obvious from Eq. (28). We can see that the value of the standard deviation

Parameters	Value
Dimension of the sphere	2000 m
d_{DBS}	0.25, 0.5, 0.75, 1 m
S_P	1500 m/s
S_R	60 kSa/s
Absorption coefficient, a	1 dBm^{-1}
dispersion factor, k	0
b	19, 39, 59, 79

Table 1.
Parameters used in Matlab simulation.

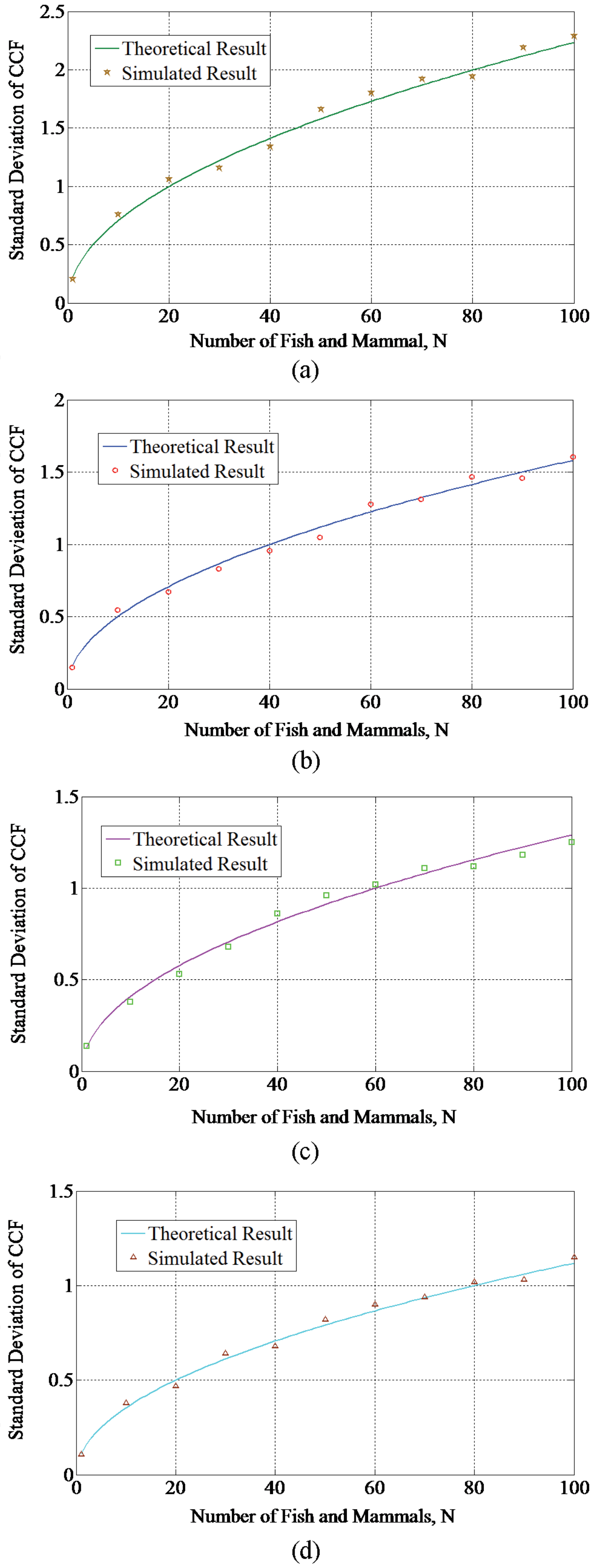

Figure 4.
Number of fish and mammals vs. σ of CCF (a) b = 19 (d_{DBS} = *0.25 m and* S_R = *60 kSa/s) (b)* b = 39 (d_{DBS} = *0.5 m and* S_R = *60 kSa/s), (c)* b = 59 (d_{DBS} = *0.75 m and* S_R = *60 kSa/s), and (d)* b = 79 (d_{DBS} = *1 m and* S_R = *60 kSa/s).*

is lower in case of higher *b* and vice-versa and the simulated results are closer with the theoretical lines also. The figures also illustrate that a very short distance, even to place a single fish between them, between the acoustic sensors can also give a good estimation using this technique.

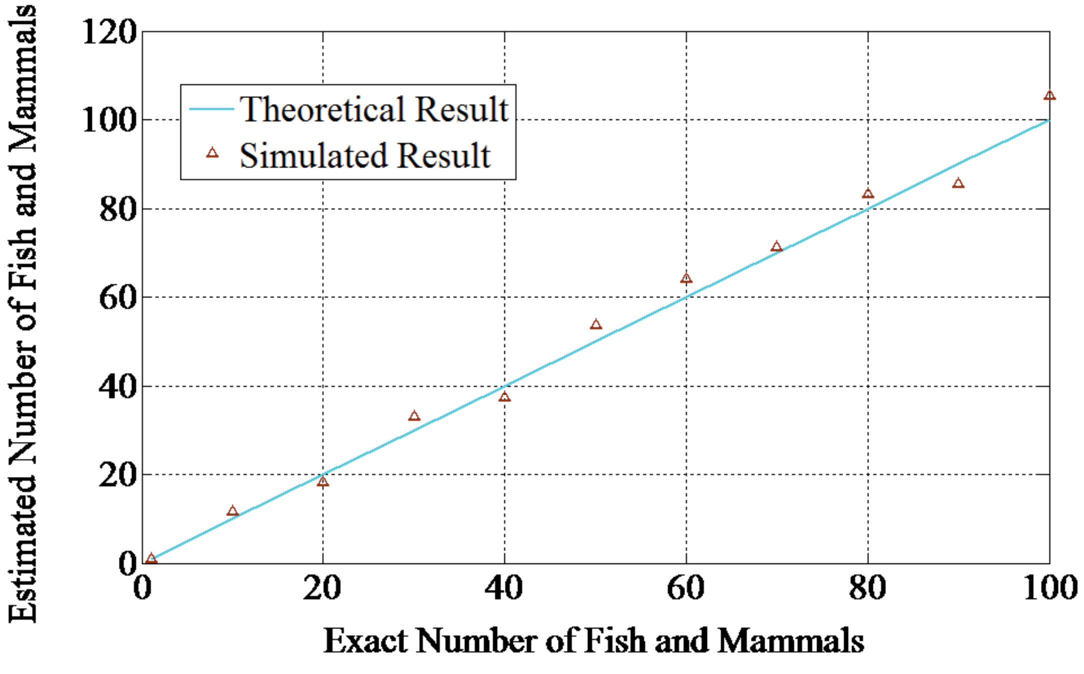

Figure 5.
Exact number of fish and mammals vs. estimated number of fish and mammals for b = *79* (d_{DBS} = *1 m and* S_R = *60 kSa/s).*

However, our work has some limitations, for example, assuming the delays to be integer, negligence of multipath interference, consideration of negligible amount of power difference among the fish sound pulses during transmitting time.

5. Conclusion

Passive acoustic monitoring is a potential tool to survey the population size of fish and mammals in a certain marine area. It can overcome the major drawbacks of conventional techniques. Cross-correlation-based stock assessment technique is also a passive acoustic survey technique dedicated to fish and mammals. An investigation on this technique with different estimation parameters was the cardinal goal of this research. To do that, we performed our desired estimation with standard deviation of CCF as estimation parameter. The small difference between theoretical and simulated results proved that it is highly possible to pursue this passive monitoring technique utilizing standard deviation of CCF as estimation parameter. Here, we considered four acoustic sensors because from the previous research, we found that an increasing number of CCF ensures better accuracy using this technique. In this paper, we considered four different numbers of bins to show its impact on estimation also. It is shown that a robust estimation is possible using standard deviation of CCF as estimation parameter even when the distances between acoustic sensors are small. Therefore, during practical implementation of this technique, these findings will contribute significantly.

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