

A Robust Signal Processing Approach of Underwater Network Size Estimation Taking Multipath Propagation Effects into Account

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Abstract: Underwater network size estimation is inefficient by applying conventional protocol based techniques used for terrestrial networks due to non-negligible capture effect, long propagation delay, high absorption and dispersion of the medium. For this reason, a statistical signal processing approach based on cross-correlation has been proposed in our previous works, which is equally applicable to any environment networks. Initially, this estimation approach was formulated without considering multipath propagation effects. But, one of the common difficulties of underwater or terrestrial wireless communication is multipath propagation. Multipath spread is more severe in underwater acoustic channel (UAC) than terrestrial radio channel. This paper aims to address the multipath propagation issue. To mitigate the effects of multipath propagation, a robust estimation approach using cross-correlation of Gaussian signals received at two sensors has been investigated in this paper.

Keywords: Cross-correlation Function (CCF), Dispersion Coefficient (k), Multipath Propagation Effects, Network Size Estimation, Underwater Acoustic Channel (UAC), Underwater Network

1. Introduction

Aqueous environment observation has become increasingly important and underwater networks are deployed for the purpose of scientific exploration, pollution monitoring, oceanographic data collection, discovering natural resources, surveillance etc. To fulfill these tasks, it is very important to know the number of operating nodes available in a network to ensure proper operation and maintenance of the network. This justifies the necessity of underwater network size estimation. A brief literature review on network size estimation methods is given below to further justify the necessity of cross-correlation based cardinality estimation approach.

A cardinality estimation technique based on Good-Turing estimator [1] of the missing mass has been proposed by Budianu et al. [2, 3] for terrestrial sensor networks. In RFID systems, different protocols [4–6] have been used for tag estimation, which is similar to size estimation in wireless communications network. Size of a network can be estimated

using distributed orthogonalization [7]. Another cardinality estimation technique for wireless mobile ad hoc networks has been proposed in [8, 9], using two novel statistical methods, called the tokened random walk and the circled random walk. For size estimation of dynamic anonymous networks, two leader-based counting algorithms based on a technique that mimics an energy-transfer between network nodes have been investigated in [10]. Estimation of network cardinality by distributed anonymous strategies relying on statistical inference methods has been considered by Varagnolo et al. [11]. Previously mentioned techniques do not consider the unique characteristics of UAC [12] such as non-negligible capture effect, strong background noise, large propagation latency and high path loss. So, they are not suitable for underwater network size estimation.

Considering capture effect of underwater environment, a size estimation method has been proposed by Howlader et al. [13, 14], which is similar to probabilistic framed slotted ALOHA. Howlader et al. also proposed a delay insensitive estimation process based on ALOHA protocol [15] to

overcome the limitation of long propagation delay of UAC. An intermission-based underwater network size and structure estimation technique has been investigated by Blouin [16]. Protocol dependency of these techniques [13–16] limits their usefulness in underwater environment. In order to obtain a size estimation technique with reduced protocol complexity, Anower *et al.* introduced a signal processing approach based on cross-correlation of Gaussian signals received at two sensors [17, 18], which is equally suitable for any environment networks. An improved cross-correlation based size estimation scheme using three sensors has been proposed by Chowdhury *et al.* [19, 20], which shows better estimation performance in terms of estimation accuracy, time and energy [21]. Several assumptions have been made in the initial formulation of cross-correlation based estimation process. The assumptions of unity signal strength, infinite bandwidth of Gaussian signals, equal received power (ERP) from each node, infinite signal length have been investigated and removed in [22–26].

One of the remaining assumptions that requires further investigation is the assumption of no multipath propagation. Like terrestrial wireless communications network, multipath propagation is also occurred in underwater wireless communications network (UWCN), which results in inter-symbol interference (ISI). Typical multipath spreads in the commonly used radio channels are on the order of several symbol intervals, whereas in UACs they increase to several tens or a hundred of symbol intervals for moderate to high data rates [27], which implies more severe effects of multipath in UWCN.

The severe effects of multipath propagation is considered in this paper to estimate the size of UWCN and a robust estimation approach based on cross-correlation of Gaussian signals received at two sensors is proposed to compensate the effects of multipath. The rest of the paper is arranged as follows. Section 2 contains the background of this work. A robust estimation process in presence of multipath signal propagation is proposed in Section 3 with the corresponding simulation results. In Section 4, concluding remarks of this paper is presented with future directions.

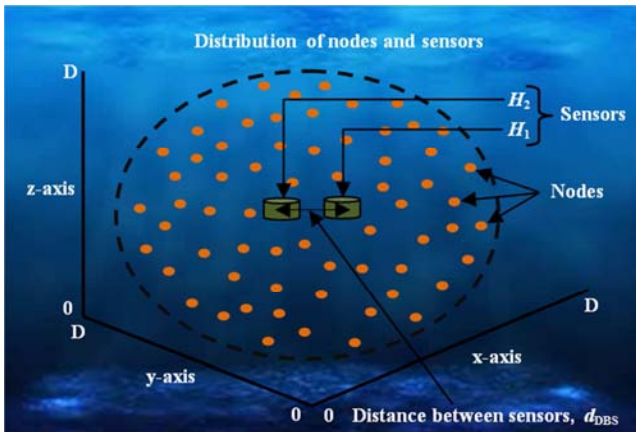


Fig. 1. Distribution of underwater network nodes with N transmitting nodes for two-sensor scheme.

2. Background

Cross-correlation based size estimation procedure using two sensors [17, 18] is described in this section as background for better understanding of multipath compensation technique. In this estimation process, a three-dimensional spherical region has been considered as an UWCN that contains N transmitting nodes which are uniformly distributed over the volume of a large sphere and two spatially separated receiving nodes (H_1 and H_2) which are located at the middle of the sphere for estimation purpose as shown in Fig. 1. In this case, transmitting nodes are called nodes and receiving nodes are called sensors. The first step of this estimation scheme is to formulate cross-correlation function (CCF). For this formulation, the 3D space is taken as a cube such that the dimension of the cube is equal to the diameter of the sphere, and two sensors and nodes are placed similar to the Fig. 1.

The sensors (H_1 and H_2) initiate the estimation process by sending probe request to N nodes. It is assumed that, all nodes can transmit Gaussian signals in response to that probe request using acoustic wave as the underwater communication carrier. Simultaneously transmitted Gaussian signals from N nodes in response to the probe request reached the sensors with the corresponding time delays and attenuations. The signals at each sensor location are superimposed on each other to form the composite Gaussian signals, $S_{rc1}(t)$ and $S_{rc2}(t)$, which are then received by H_1 and H_2 , respectively. CCF ($C(\tau)$) is formulated by cross-correlating the composite signals received by H_1 and H_2 . Due to the simultaneous transmission from all nodes, the total estimation time is less for this scheme even at the presence of large propagation latency of UWCN [21].

Gaussian signal has a certain characteristics that, cross-correlation of two Gaussian signals results a delta function, which is the basic idea of this estimation approach and also the reason of using Gaussian signals as transmitted signals. Thus, CCF due to composite Gaussian signals takes the form of a series of delta functions [17] as shown in Fig. 2. Amplitudes and positions of these delta functions depend on the attenuations and the delay differences of the signals coming to the sensors, respectively. In this process, the positions of the deltas in the CCF are referred to as bins. If N is larger than the number of bins, b , there will be more than one delta in a bin due to the same delay differences. This increases the amplitude of the deltas in the bins (as shown in Fig. 2),

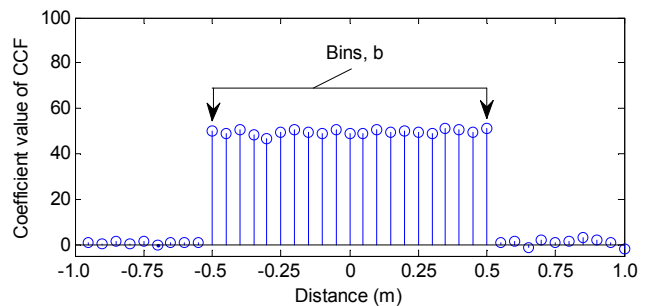


Fig. 2. Bins, b of CCF obtained with $N (=1000)$ nodes.

where b is given by [28]:

$$b = \frac{2 \times d_{\text{DBS}} \times S_R}{S_P} - 1 \quad (1)$$

Here, d_{DBS} is the distance between the sensors, S_R is the sampling rate and S_P is the speed of acoustic wave propagation.

Ratio of standard deviation (σ) to the mean (μ), R of CCF is chosen as the estimation parameter of this process, as it requires no prior knowledge of the signal strength from the nodes [22, 29]. To overcome the difficulty of determining σ and μ of the CCF using complex statistical expressions, the cross-correlation problem is being reframed into probability problem [18] using the well-known occupancy problem [30]. After reframing, R of CCF can be expressed as [17]:

$$R = \frac{\sigma}{\mu} = \frac{\sqrt{N \times \frac{1}{b} \times (1 - \frac{1}{b})}}{N \times \frac{1}{b}} = \sqrt{\frac{(b-1)}{N}} \quad (2)$$

Using this expression, network size, N can be estimated, as we know b from (1) and can calculate R from the CCF.

Since all the transmitted Gaussian signals are combined at the sensors and node specific signals are irrelevant for size estimation, the concept of capture effect does not apply to this method. Moreover, this technique requires a simple protocol for probing to initiate the simultaneous transmission, which eliminates the problem of using medium access control protocol

in UWCN. The total estimation process of two-sensor scheme is represented through a block diagram in Fig. 3.

3. Effect of Multipath

In previous section, estimation is performed considering only one (direct) path. But practically, signals may propagate through different paths to reach the sensors due to the reflector present in the medium and the dispersive nature of the wave. In the underwater environment with an acoustic wave, the seabed and sea surface will be the two major reflectors. To make the estimation process robust, multipath effects are considered in two-sensor scheme using one direct path and two indirect paths (due to both surface and bottom reflections) as shown in Fig. 4 and 5. As the direct path is always shorter than the indirect path, the powers of the direct path signals will be stronger than those of the indirect path signals.

Strengths of the deltas in the CCF depend on the signals' strengths [22], which indicate that, the deltas due to the direct path will be dominant and contribute more to form the CCF. As the CCF due to direct path is sufficiently dominant, standard deviation and mean of this CCF will be greater than that of the CCF due to indirect path. So, ratio of standard deviation to the mean of CCF considering multipath, R can be approximated by the ratio of standard deviation to the mean of CCF due to only the direct path.

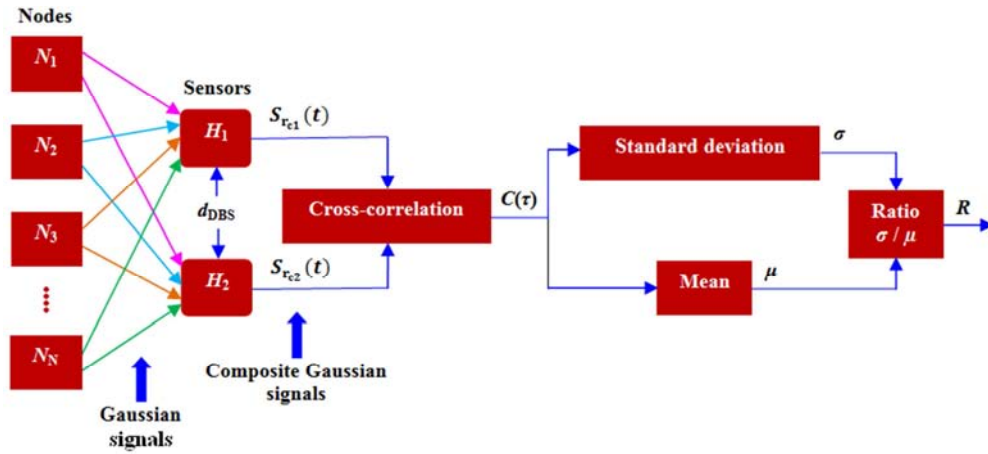


Fig. 3. Block diagram representation of the estimation process for two-sensor scheme.

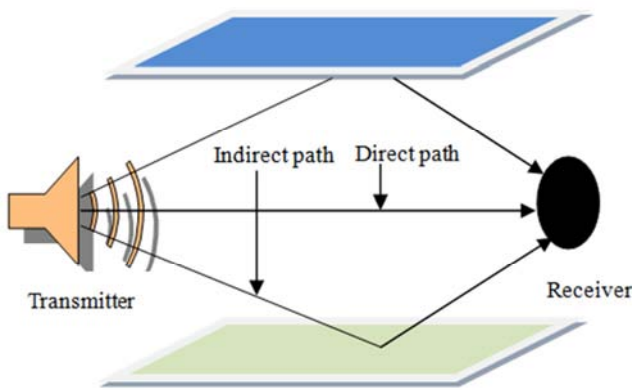


Fig. 4. Concept of multipath: one direct and two indirect paths.

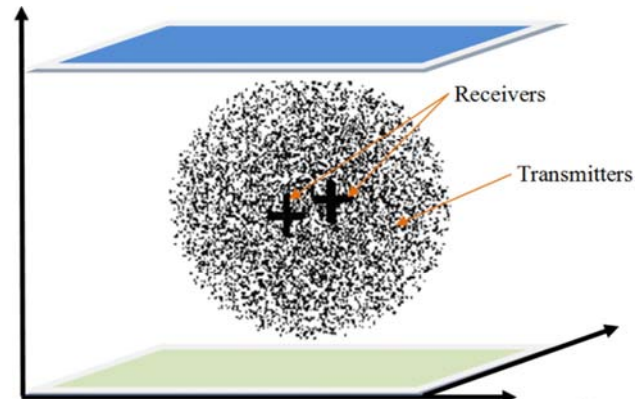


Fig. 5. Distribution of transmitters and receivers (+) with two reflectors.

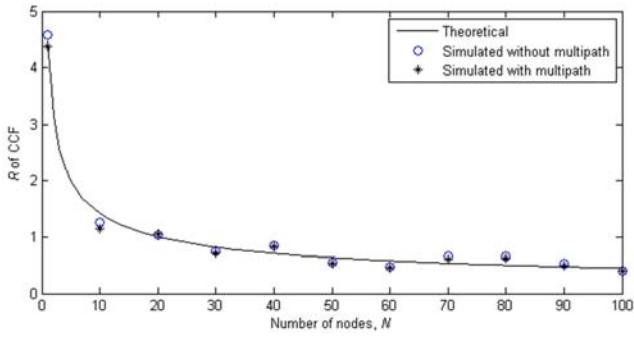


Fig. 6. Rs of CCF; $k = 3$ and $b = 19$ ($d_{DBS} = 0.5m$ and $S_R = 30kSa/s$).

The results in Fig. 6 show the effectiveness of two-sensor scheme in case of multipath reception. The solid line indicates the theoretical results and the stars and circles indicate the simulated results with and without multipath, respectively. It can be seen that the two simulated results are sufficiently close to each other and both follow the theoretical results. So, we can say that, multipath delay has negligible impact on the estimation results. Simulated results of Fig. 6 are obtained in matlab programming environment using dispersion coefficient, $k = 3$ and $b = 19$ ($d_{DBS} = 0.5m$ and $S_R = 30kSa/s$). Other parameters used in the simulation (throughout the work unless otherwise mentioned) are: dimension of the cube, $D = 2000m$; signal length, $N_s = 10^6$ samples (because the required N_s for accurate estimation using two-sensor scheme is greater than or equal to 300000 samples [26]); $S_p = 1500m/s$; SNR = 20db; absorption coefficient, $a = 1$ (implying equal received power of direct path signals from all

nodes); $N = 10$ and number of iterations, $u = 1$.

Multipath effects on the estimation process has been neglected based on the assumption that, indirect path signals' strengths are sufficiently lower than those of direct path signals. This is true for high values of k . But, indirect path signals' strengths cannot be neglected for low values of k . In that case, indirect path signals can contribute significantly to form the CCF. So, estimation parameter derived from the CCF due to multipath can not be approximated by that due to only the direct path in case of low dispersion factor. For this reason, a generalized estimation approach for any dispersion factor by compensating the multipath effects is provided in this section to increase the robustness of cross-correlation based size estimation method.

We know that, path loss depend on a , k and distance between transmitter and receiver, d [31]. But, in this approach only the distance dependent spreading loss is considered as path loss, because $a = 1$ due to ERP case. ERP case can be obtained using probing technique. It is noted that, ERP implies equal received power of direct path signals from all nodes. Now, to properly demonstrate the robust estimation process with multipath effects due to both surface and bottom reflections, let us consider a similar simulation environment as discussed in the previous section. The theoretical & simulated results for the CCF from such an arrangement of 100 nodes with 9 bins ($d_{DBS} = 0.25m$ and $S_R = 30kSa/s$), 100 iterations and different k values, are presented in Fig. 7 to 10.

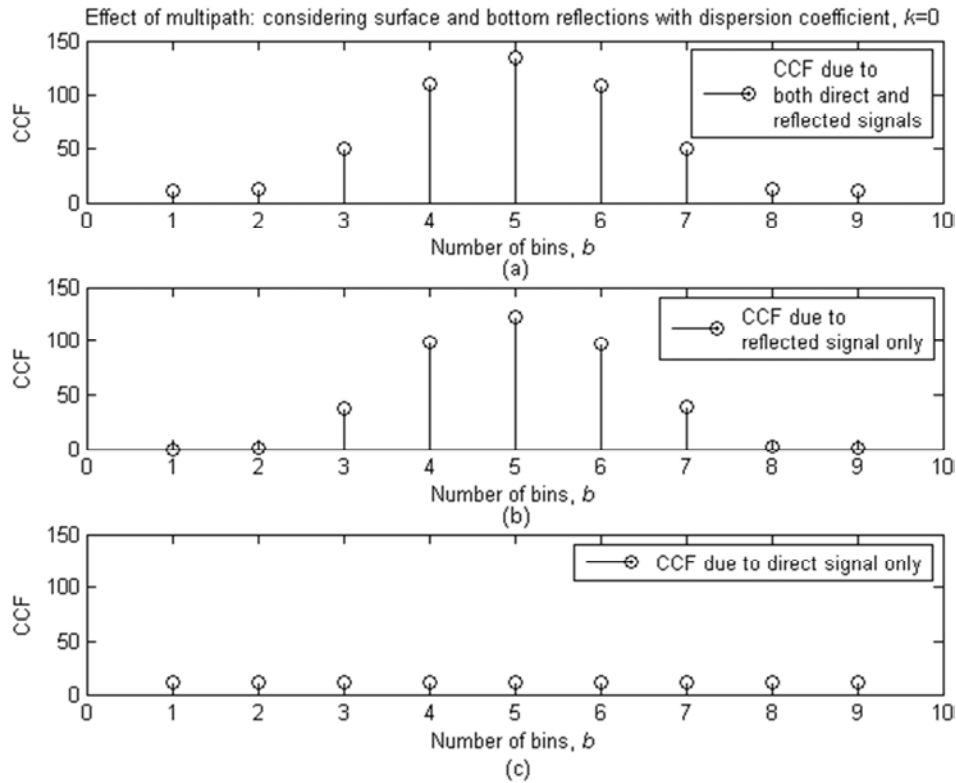


Fig. 7. CCFs with $k = 0$ from: (a) both direct and reflected signals (surface and bottom); (b) only reflected signals; and (c) only direct signal.

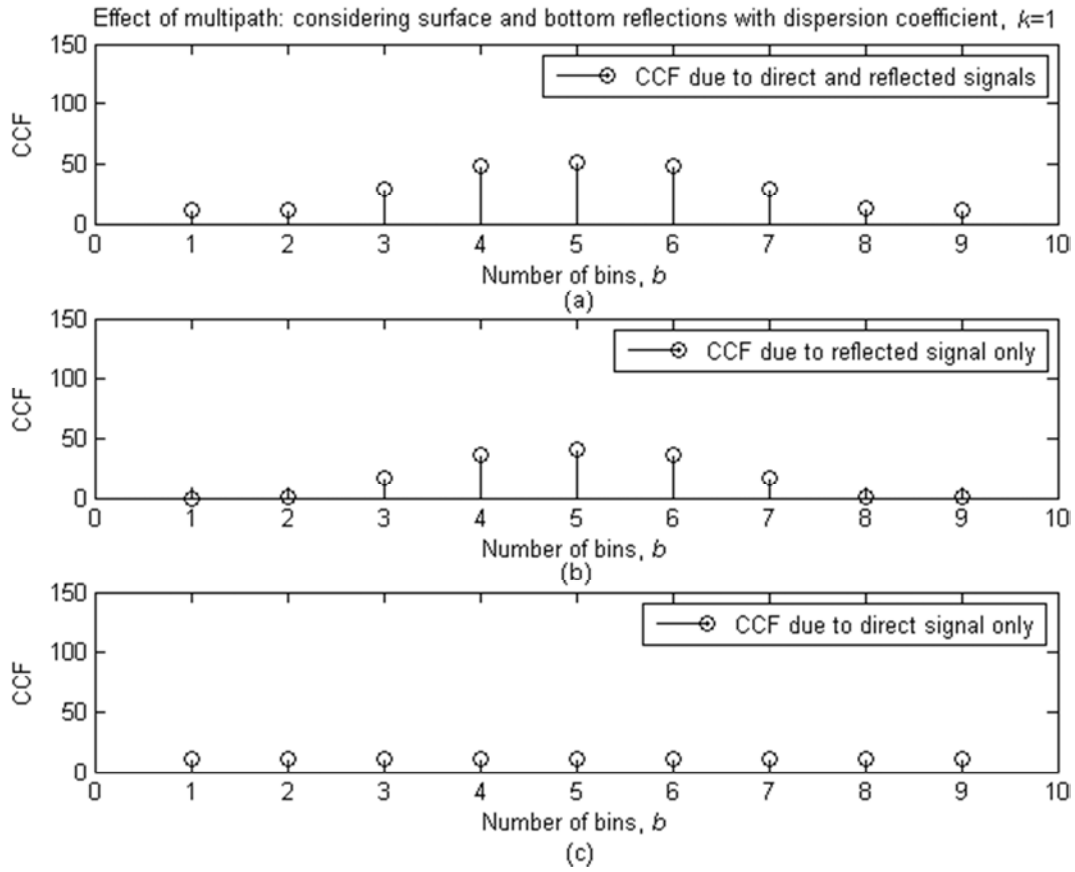


Fig. 8. CCFs with $k = 1$ from: (a) both direct and reflected signals (surface and bottom); (b) only reflected signals; and (c) only direct signal.

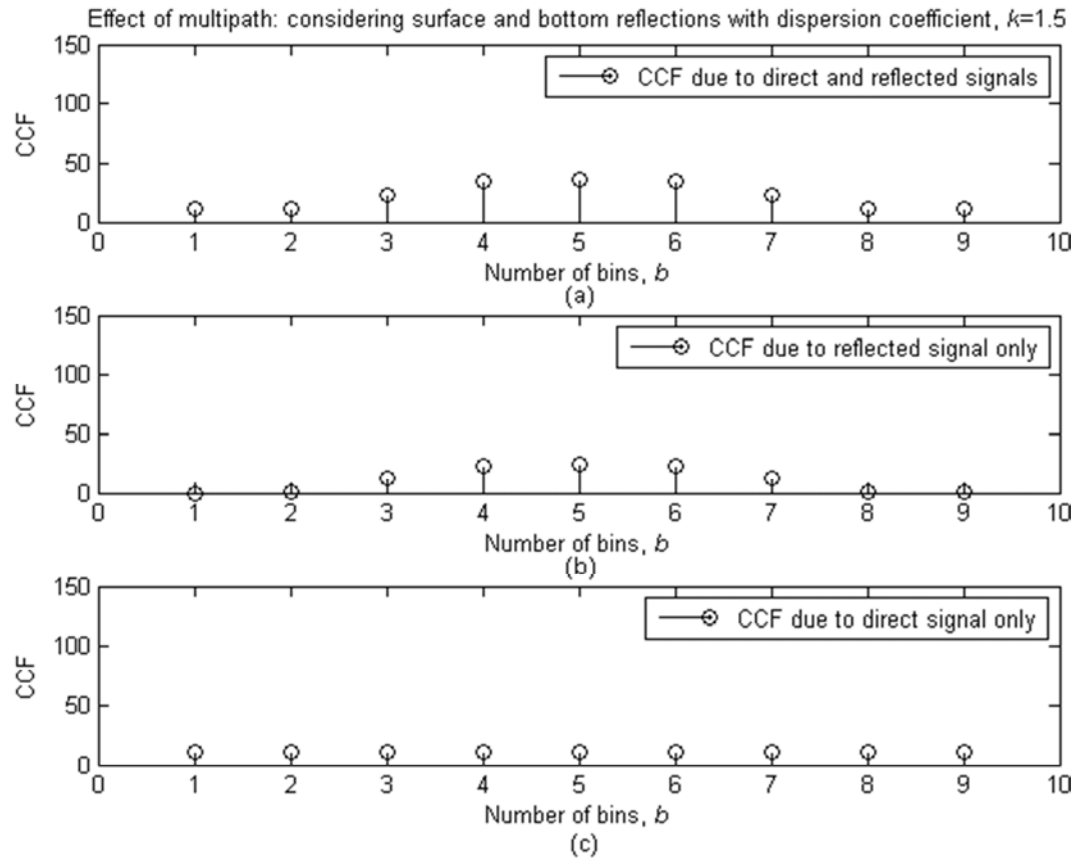


Fig. 9. CCFs with $k = 1.5$ from: (a) both direct and reflected signals (surface and bottom); (b) only reflected signals; and (c) only direct signal.

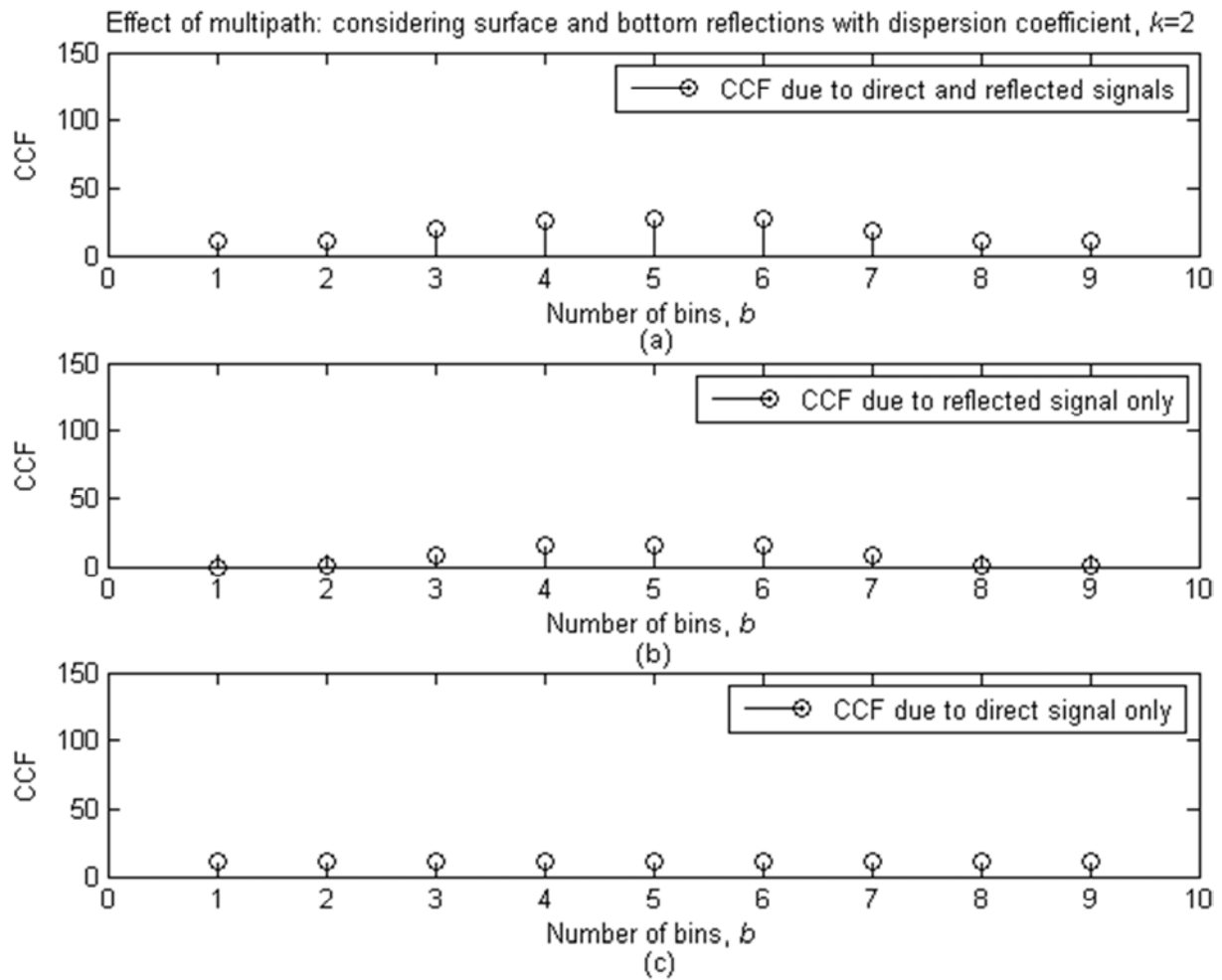


Fig. 10. CCFs with $k = 2$ from: (a) both direct and reflected signals (surface and bottom); (b) only reflected signals; and (c) only direct signal.

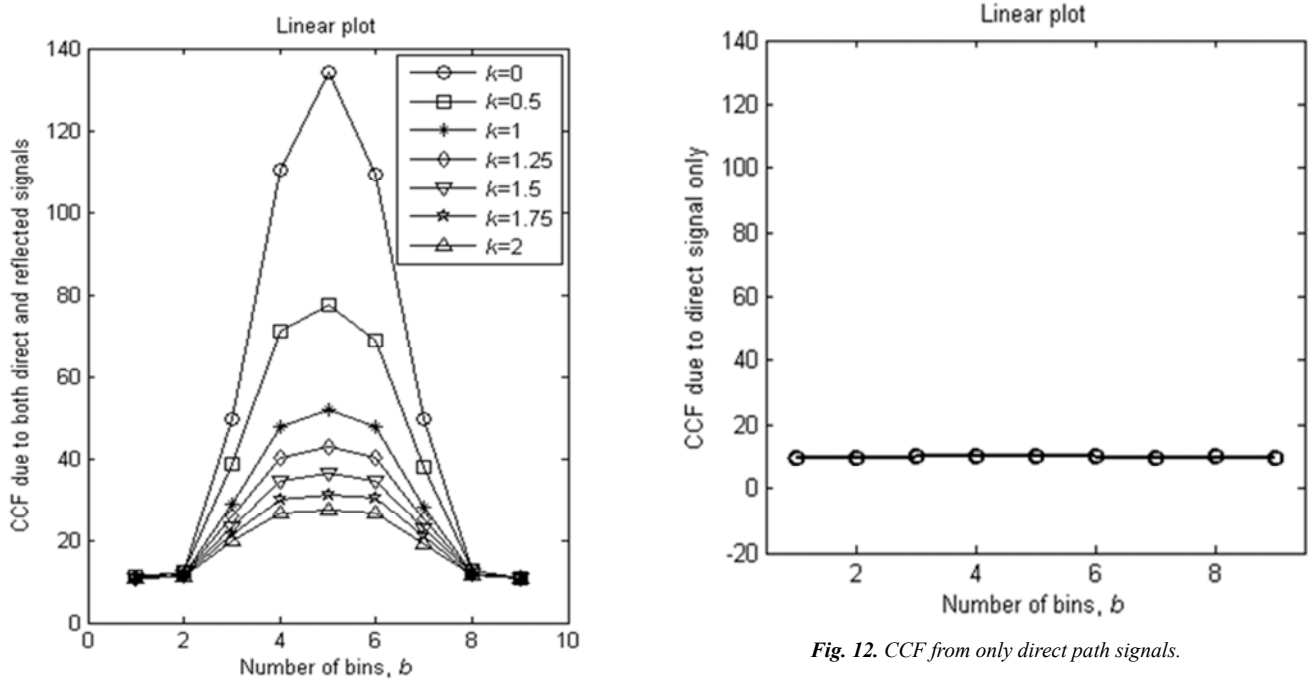


Fig. 12. CCF from only direct path signals.

Fig. 11. CCFs with different k (0, 0.5, 1, 1.25, 1.5, 1.75 and 2) from both direct and reflected signals (surface and bottom).

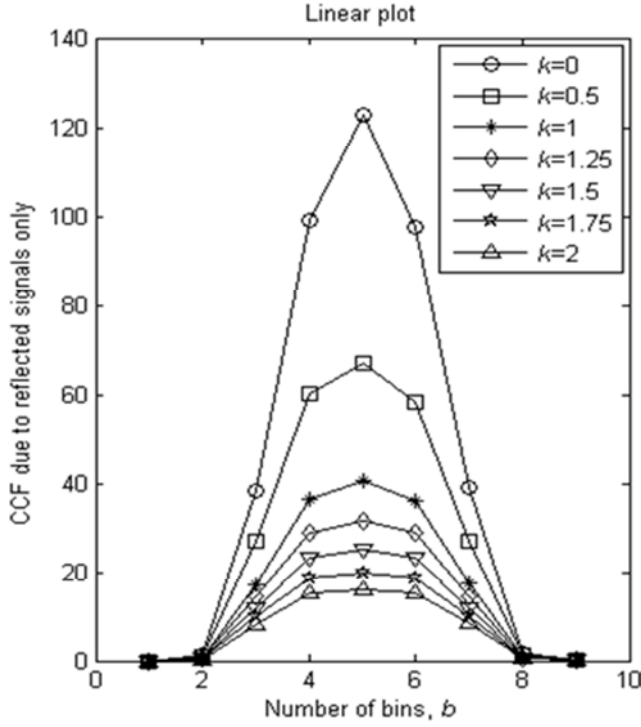


Fig. 13. CCFs with different k (0, 0.5, 1, 1.25, 1.5, 1.75 and 2) from only reflected signals (both surface and bottom).

The values of dispersion coefficients are: $k = 0$ in Fig. 7, $k = 1$ in Fig. 8, $k = 1.5$ in Fig. 9 and $k = 2$ in Fig. 10. Each of these figures has three separate plots: the top for CCFs with multipath, i.e., one direct and two indirect path signals are responsible for forming the CCF, the middle for CCFs due to reflected (both surface and bottom) signals only; and the bottom for CCFs due to only direct signals, i.e., without multipath, as in Section 2. These figures show that, dispersion coefficient has no effect on the CCFs due to only the direct path signals as ERP case is considered for these signals. It has already been known that deltas without multipath, i.e., with only direct path, follow a random distribution to form the CCF; this will also be true for deltas with indirect paths. Thus, the CCF with multipath will be the summation of three random variables. To clarify the above discussion, Fig. 11 to Fig. 13 are plotted.

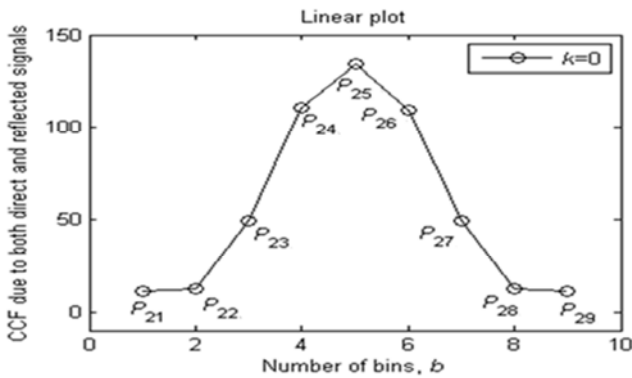


Fig. 14. Peaks of deltas in bins of CCF due to both direct and reflected signals with $k = 0$.

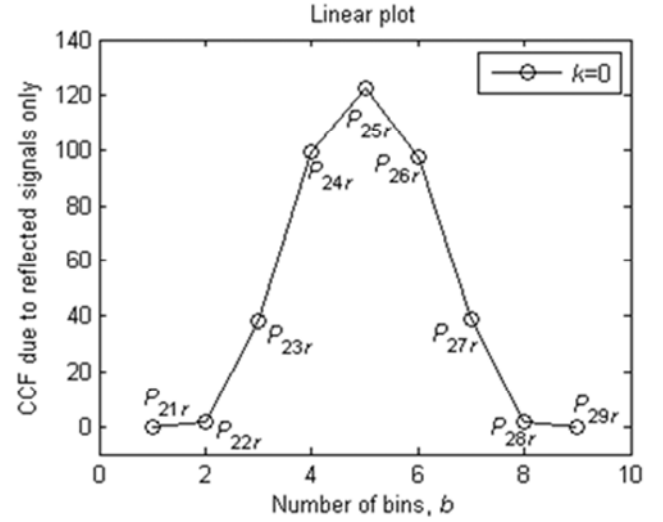


Fig. 15. Peaks of deltas in bins of CCF due to only reflected signal with $k = 0$.

These results demonstrate that, multipath effect decreases with increasing k and can be neglected because of the higher values of k in a practical underwater acoustic environment. The investigation of neglecting multipath effect on estimation due to both surface and bottom reflections has already been provided in this section. Now, we develop a generalized size estimation process using the ratio of the standard deviation to the mean of the CCF by compensating multipath due to both surface and bottom reflections with any possible values of k . Let us consider a CCF for $b = 9$ with multipath (one direct and two indirect paths from both surface and bottom reflections), in which the delta peaks in the bins are $P_{21}, P_{22}, P_{23}, P_{24}, P_{25}, P_{26}, P_{27}, P_{28}$ and P_{29} , as shown in Fig. 14, and the corresponding peaks for the direct and reflected paths are $P_{21d}, P_{22d}, P_{23d}, P_{24d}, P_{25d}, P_{26d}, P_{27d}, P_{28d}$ and P_{29d} , and $P_{21r}, P_{22r}, P_{23r}, P_{24r}, P_{25r}, P_{26r}, P_{27r}, P_{28r}$ and P_{29r} , respectively, as shown in Fig. 15, where $P_{21} = P_{21d} + P_{21r}$, $P_{22} = P_{22d} + P_{22r}$, $P_{23} = P_{23d} + P_{23r}$, $P_{24} = P_{24d} + P_{24r}$, $P_{25} = P_{25d} + P_{25r}$, $P_{26} = P_{26d} + P_{26r}$, $P_{27} = P_{27d} + P_{27r}$, $P_{28} = P_{28d} + P_{28r}$, and $P_{29} = P_{29d} + P_{29r}$.

It is shown in these figures that, not all bins are affected by the reflected signals and there is a mirror effect with respect to the middle bin. The affected bins are 2 to 8 and, due to the mirror effect, the peaks of the 2nd & 8th, 3rd & 7th, 4th & 6th bins are similar. As only the CCF with multipath is available in this process, it will have to suffice for the estimation. However, using a similar process to that for finding the ratio of the standard deviation to the mean of the CCF to estimate the number of nodes without multipath is not appropriate in this case, because of the extended peaks due to the signals of the reflected paths. But, if we can deduct the extended peaks from the CCF with multipath, the process will be exactly the same as that for the CCF without multipath and will be appropriate for estimation. To do this, we represent the peaks due to both direct and reflected signals (Fig. 14) as percentages of the peaks due to only reflected signals (Fig. 15).

The process of obtaining percentages is:

$$\text{Percentage at 1}^{\text{st}} \text{ bin, } p_{m21} = \frac{P_{21r}}{P_{21}} \times 100\%$$

where, P_{21r} represents peak at 1st bin due to reflected signal only and P_{21} represents peak at 1st bin due to both direct and reflected signals.

Similarly for the affected bins, the percentages are obtained using the following expressions:

$$p_{m22} = \frac{P_{22r}}{P_{22}} \times 100\%, \quad p_{m23} = \frac{P_{23r}}{P_{23}} \times 100\%,$$

$$p_{m24} = \frac{P_{24r}}{P_{24}} \times 100\%, \quad p_{m25} = \frac{P_{25r}}{P_{25}} \times 100\%,$$

$$p_{m26} = \frac{P_{26r}}{P_{26}} \times 100\%, \quad p_{m27} = \frac{P_{27r}}{P_{27}} \times 100\%,$$

$$p_{m28} = \frac{P_{28r}}{P_{28}} \times 100\%$$

Detailed results are provided in Fig. 16 to 18. These percentages are independent of the number of nodes but dependent on the dispersion coefficient, k , and the number of bins, b . We investigate the percentages for different values of k with 9 bins, as shown in Fig. 16 and 17. Fig. 16 shows the percentages of deltas due to reflected signals in each affected bin of the CCF. The percentage contributions of the different affected bins for different k are presented in Fig. 17. To obtain the percentages for any k , the percentages of all affected bins are expressed in terms of k using 4th-degree approximations, as shown in Fig. 18. The approximated expressions are:

$$p_{m22} \approx p_{m28} = 1.3k^4 - 6.4k^3 + 11k^2 - 12k + 11 \quad (3)$$

$$p_{m23} \approx p_{m27} = 0.34k^4 - 0.71k^3 - 0.93k^2 - 15k + 77 \quad (4)$$

$$p_{m24} \approx p_{m26} = -1.3k^4 + 7k^3 - 15k^2 - 4.4k + 90 \quad (5)$$

$$p_{m25} = -0.21k^4 + 2k^3 - 7.8k^2 - 7.3k + 92 \quad (6)$$

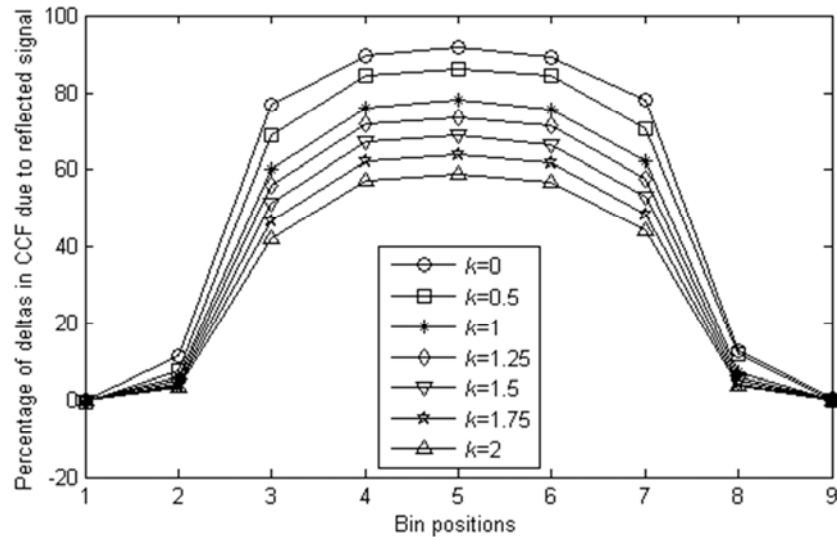


Fig. 16. Percentages of deltas in affected bins of CCF due to reflected signals (both surface and bottom) with different k (0, 0.5, 1, 1.25, 1.5, 1.75 and 2).

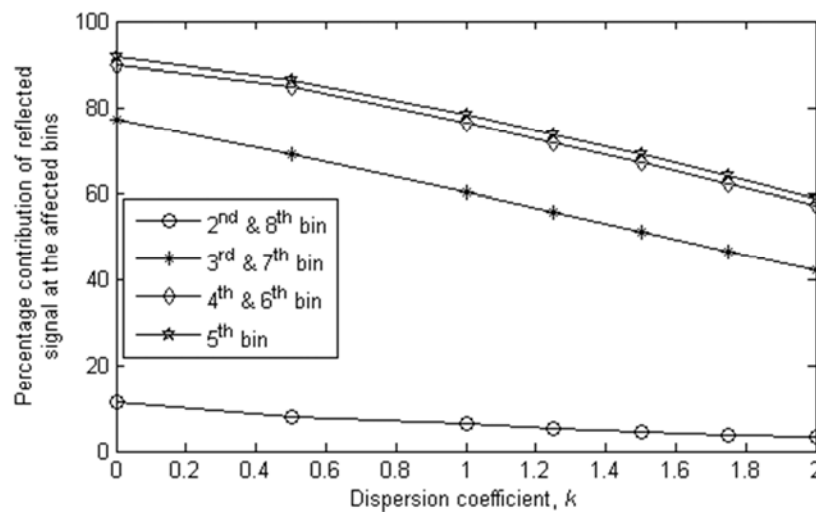


Fig. 17. Percentage contributions of reflected signals (both surface and bottom) in affected bins for different k (0, 0.5, 1, 1.25, 1.5, 1.75 and 2).

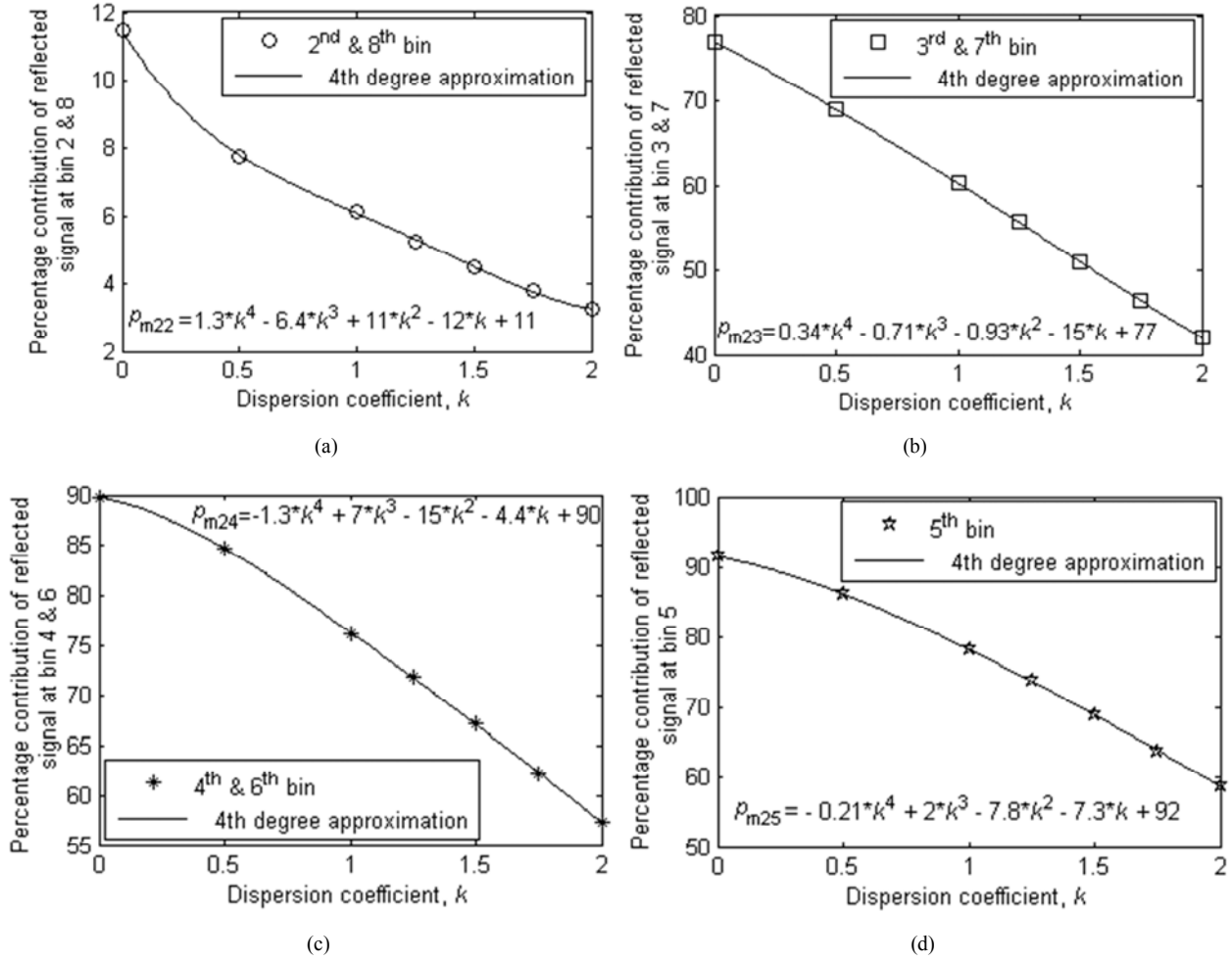


Fig. 18. Percentage contributions of reflected signals (both surface and bottom) for different k (0, 0.5, 1, 1.25, 1.5, 1.75 and 2) in: (a) bin 2 and 8, (b) bin 3 and 7, (c) bin 4 and 6, and (d) bin 5.

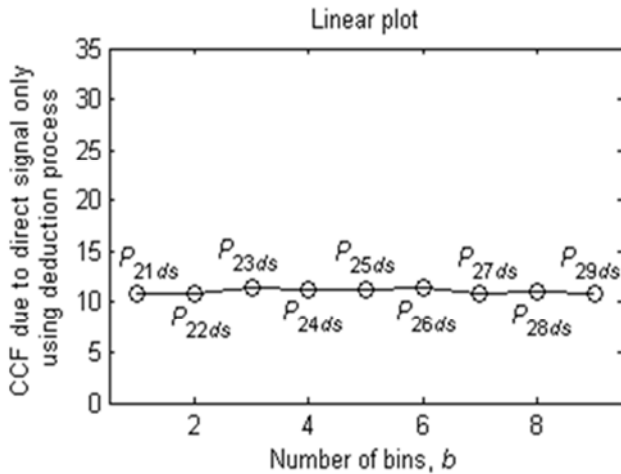


Fig. 19. CCF after deduction.

Now, to obtain the estimation parameter, i.e., the ratio of the standard deviation to the mean of the CCF, deductions of the extended peaks of the corresponding bins are obtained as follows. In bin 1, the deducted peak is:

$$P_{21ds} = P_{21} - p_{m21}\% \text{ of } P_{21}$$

Similarly, for the affected bins, 2 to 8, the deducted peaks are:

$$\begin{aligned} P_{22ds} &= P_{22} - p_{m22}\% \text{ of } P_{22}, \quad P_{23ds} = P_{23} - p_{m23}\% \text{ of } P_{23}, \\ P_{24ds} &= P_{24} - p_{m24}\% \text{ of } P_{24}, \quad P_{25ds} = P_{25} - p_{m25}\% \text{ of } P_{25}, \\ P_{26ds} &= P_{26} - p_{m26}\% \text{ of } P_{26}, \quad P_{27ds} = P_{27} - p_{m27}\% \text{ of } P_{27}, \\ P_{28ds} &= P_{28} - p_{m28}\% \text{ of } P_{28}. \end{aligned}$$

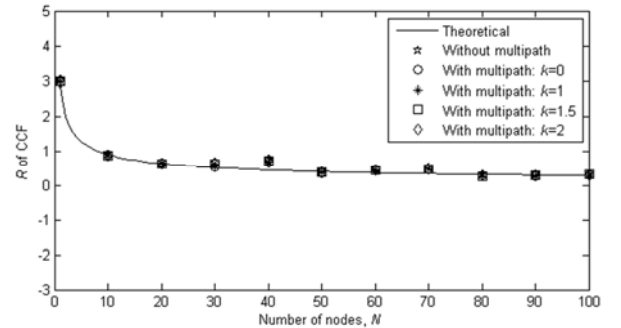


Fig. 20. R_s of CCF: comparison of results from theoretical, simulated without multipath and simulated with multipath (using proposed multipath compensation technique with both surface and bottom reflections) for different k (0, 1, 1.5 and 2) using $b = 9$ ($d_{BS} = 0.25m$ and $S_R = 30kSa/s$).

The peaks of the CCF after deduction for 100 nodes with 100 iterations are shown in Fig. 19. To demonstrate the effectiveness of the process, the R_s of the CCF after deduction for different numbers of nodes with one iteration are plotted in Fig. 20 using $b = 9$ ($d_{\text{DBS}} = 0.25\text{m}$ and $S_R = 30\text{kSa/s}$). It can be seen from the results that the technique is good enough to estimate in multipath environment.

4. Conclusion

This work is done to mitigate the effect of multipath signal propagation on cross-correlation based underwater network size estimation technique. It is shown that, efficient estimation is possible in case of high dispersion factor by neglecting the multipath effects due to negligible strengths of indirect path signals. Considering the possible scenario of low dispersion coefficient, a generalized estimation process for any dispersion factor has been demonstrated in this paper by compensating the multipath effects. The robustness of this estimation approach in multipath environment has been verified by simulation. It is noted that, only the two-sensor case of cross-correlation based estimation method is considered in this paper. In future, our plan is to investigate the effects of multipath on three-sensor schemes. Current research is going on to analyze the estimation performance in various shaped network with random placement of sensors and different distribution of nodes. Finally, conducting experimental estimation using this technique is our ultimate goal.

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