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MULTIPATH PROPAGATION'S IMPACT ON ESTIMATING THE SIZE OF UNDERWATER NETWORKS

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Abstract

The number of node (cardinality)' is an important operation parameter in networks, and the parameter can be obtained through conventional protocol-based approaches, yet these methods have several drawbacks for underwater presence, including great propagation delay, high error rate, node motion, capture effect that cannot be negligible and significant path loss. In order to design a good cardinality estimator in this unique area of underwater networking, we have considered a statistical signal processing method namely cross-correlation of Gaussian signals observed by sensor arrays. One of the common challenges for underwater wireless communication is multipath propagation of signals, which result in inter-symbol interference (ISI). Multipath may be built up different direct and indirect paths, such as seabed, sea surface and different reflectors etc. In this paper, seabed and sea surface have been considered as the most common underwater acoustic reflectors. It is shown that, due to high dispersion coefficient of the medium, multipath effect is negligible on estimation and a generalized process of multipath compensation for any dispersion factor is obtained to improve the robustness of this scheme.

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Introduction

We are aware that water covers over three-quarters of our world, with the oceans making up around 71% of it. Multipath propagation (Zheng & Li 2013; Luna, Baldoni, Bonomi, & Chatzigiannakis 2014; Chowdhury, Anower, Giti, & Haque, 2014; Yeh, Lo, Tsai, Li, & Winata 2014; Chen, Qiao, Chen, & Li 2013) is the wave propagation form in which a wave arrives at a receiver through multiple paths. Accurate channel estimation is critical for underwater communication systems, especially for the Internet of Underwater Things (IoUT). Unique word OFDM with joint time-frequency channel estimation has been proposed to improve data reliability in multipath underwater channels (Qasem, Tu, Song, Qu, Jabbar, & Esmaiel 2025).

Underwater acoustic channels are susceptible to multipath effects. Acoustic waves within shallow underwater environments follow a direct course and also bounce off the bottom and surface, creating multipath propagation phenomena as a consequence. Even though multipath effects are generally weaker in deeper regions, they do remain present and influence signal transmission. The multipath phenomenon produces delayed replicas of the transmitted signal (Sluciak & Rupp 2013; Cattani, Zuniga, Loukas, & Langendoen 2014; Varagnolo, Pillonetto, & Schenato 2014), leading to Inter Symbol Interference (ISI) within the communication process, and these unique impacts become more pronounced in underwater environments compared to on land; for instance, while multipath extends only a small symbol interval in conventional cellular radio systems, it can be over a few tens, or even hundreds of symbol intervals in an underwater acoustic channel (Climent, Sanchez, Capella, Meratnia, & Serrano 2014; Baronti, Fantechi, Roncella, & Saletti 2012). One commonly used approach for minimizing ISI (Howlader, Frater, & Ryan 2012) is the insertion of a guard interval separating consecutively transmitted symbols, although doing so results in a lower effective data throughput and may increase the likelihood of errors. Designing receivers to respond to extremely lengthy ISI is one method of maintaining a high symbol rate. Only line-of-sight signals are taken into account during the simulation procedure in order to determine the CCF. Underwater multipath propagation and low SNR conditions make delay estimation challenging. Adaptive singular value decomposition (SVD) reconstruction has been proposed to accurately estimate delays in such environments (Li et al., 2025). Multipath signal propagation in underwater wireless channels significantly affects communication reliability. Several modulation techniques have been analyzed to mitigate this issue (Czapiewska, Luksza, Studanski, Wojewodka, & Zak 2025; Anower, Chowdhury, Giti, & Haque, 2014). Therefore, an investigation of multipath impacts on estimation is necessary to ensure the robustness of the estimating process. The two main reflectors in subaqueous conditions where acoustic signals propagate are the seafloor and the ocean's surface layer. Simulations are run first with only the reflection from the seabed, and subsequently with reflections from both the seabed and the water surface included, to demonstrate how this multipath affects estimation.

1. Analysis method

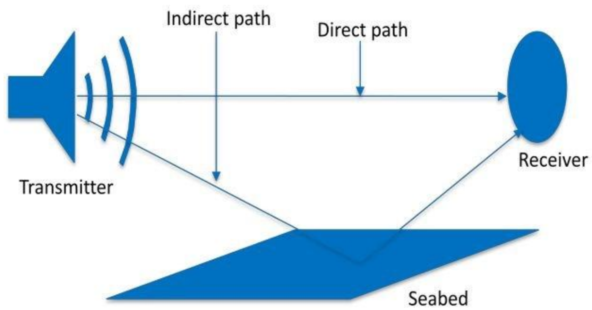

Figure 1: Illustration of a basic multipath phenomenon

Assume that the source generates sends a Gaussian waveform S1(t), treated as having a sufficiently long duration. As illustrated in figure 1, if the signal travels in double directions (direct and indirect), the signal is received at the first receiver (Luna, Baldoni, Bonomi, & Chatzigiannakis 2014; Yeh, Lo, Tsai, Li, & Winata 2014) will be

$$r_{11}(t) = \alpha_{11} S_1(t - \tau_{11}) + \alpha_{1m} S_1(t - \tau_{1m}) \quad (1)$$

In the same way, if another receiver is within range of the communication, Consequently, the waveform observed at the receiver can be expressed as (Chen, Qiao, Chen, & Li 2013)

$$r_{12}(t) = \alpha_{12} S_1(t - \tau_{12}) + \alpha_{2m} S_1(t - \tau_{2m}). \quad (2)$$

In (1) and (2), the α's are attenuations arising from absorption and dissimulated in the medium, and τ's are propagation times. Specifically, α_{11} and α_{12} are attenuations for the direct paths, while α_{1m} and α_{2m} correspond to the indirect paths. The delays are defined as:

$$\tau_{11} = \frac{d_{11}}{c}, \quad \tau_{12} = \frac{d_{12}}{c}, \quad \tau_{1m} = \frac{d_{1m}}{c}, \quad \tau_{2m} = \frac{d_{2m}}{c}$$

where d_{ij} is the propagation distance and c are the sound speed in water.

Assuming $\tau = d/c$ represents the delay identified from the cross-correlation output, the crosscorrelation function (CCF) (Blouin 2013; Anower, Frater, & Ryan 2009; Anower, Motin, Sayem, & Chowdhury 2013; Chowdhury, Anower, & Giti 2014a; Chowdhury, Anower, & Giti 2014b) is given by,

$$
\begin{aligned}
R_{r_1 r_2}(\tau) = &\int_{-\infty}^{\infty} \alpha_{11}\alpha_{12}\, S_1(t-\tau_{11}) S_1(t-\tau_{12}-\tau)\, dt \\
&+ \int_{-\infty}^{\infty} \alpha_{1m}\alpha_{2m}\, S_1(t-\tau_{1m}) S_1(t-\tau_{2m}-\tau)\, dt \\
&+ \int_{-\infty}^{\infty} \alpha_{11}\alpha_{2m}\, S_1(t-\tau_{11}) S_1(t-\tau_{2m}-\tau)\, dt \\
&+ \int_{-\infty}^{\infty} \alpha_{1m}\alpha_{12}\, S_1(t-\tau_{1m}) S_1(t-\tau_{12}-\tau)\, dt.
\end{aligned} \tag{3}
$$

The terms in (3) can be denoted as,

$$C_{dd}(\tau),\ C_{ii}(\tau),\ C_{di}(\tau),\ C_{id}(\tau),$$

representing CCF contributions due to direct–direct, indirect–indirect, direct–indirect, and indirect–direct signal combinations, respectively. The delay differences $\Delta\tau$ determine the peak positions of each term. Since all signal origin at originating from a common source, the signals are correlated but exhibit variations in amplitude and propagation time. Thus, the four terms on the righthand side of (3), being Gaussian correlations, produce four delta-like peaks positioned according to their respective delay differences. Peaks due to similar paths (direct–direct, indirect– indirect) fall within the receiver interval, whereas cross-terms (direct–indirect) produce peaks outside this region. The only peaks within the receiver interval are relevant within the framework of the method presented determining the total count of nodes. Two peaks will therefore appear in the target area associated with a transmitter having two pathways (a single direct path and a single reflected path). Cross-correlation with two transmitters is analogous to this, in which the reflected or scattered path corresponds to perceived functioning as a virtual transmitter, (Bain, Chowdhury, Asif, Anower, Pervej, & Haque 2014; Li, Li, & Wang 2013; Yihong, Quanyuan, Ma, & Liu 2013; Chowdhury 2014; Shah-Mansouri & Wong 2011) as illustrated in figure 2.

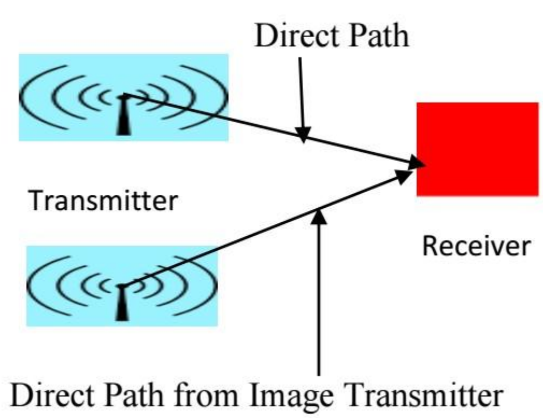

Figure 2: Illustration of a virtual transmitter

In the case of more than one transmitter (Ahmad & Tianfeng 2012; Yihong, Quanyuan, Ma, & Liu 2013; Sluciak & Rupp 2013; Lai, Hsiao, Chen, Lai, & Lin 2013; Chowdhury, Anower, & Giti 2015) exists, as shown in Figure 3, a count of deltas, corresponding to two times the number of transmitters, constitutes the CCF.

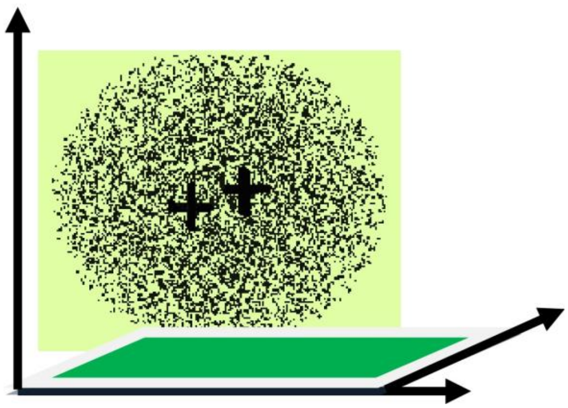

Figure 3: Configuration of transmitters and receivers alongside one reflector

Corresponding multipath effect and the case without multipath is compared in the following figure 4.

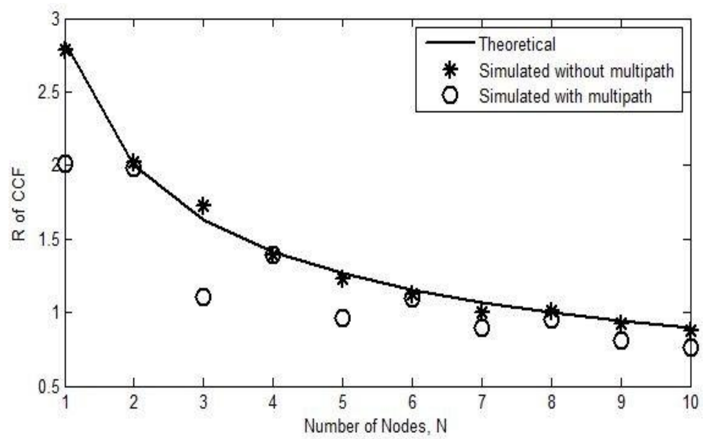

Figure 4: Transmitters and receivers' Rs of CCF with a single reflector: k=0

Realistically, the direct and reflected paths exhibit different power values, influenced by the dispersion coefficient and the estimation methodology. The ERP case is adopted here to investigate multipath phenomena. Multipath propagation and acoustic signal recognition in underwater networks have become increasingly important for accurate node estimation and robust communication (Li, Wu, & Yang 2025). In this scenario, the transmitted power from each node must be adjusted so that the sensors receive equal power levels. Achieving this requires an appropriate probing method for line of-sight communication, specifically along the direct signal paths. Accurate channel estimation in time-varying doubly-selective underwater acoustic channels is crucial for robust signal detection and node estimation (Cui, Zhang, Li, Jiang, Li, & Liu 2025). In reflective scenarios, signals reach the sensors along indirect paths, with their powers affected by the medium's attenuation governed by k. Because the direct path is shorter and signal strength decreases with increasing path length, direct path signals exhibit higher power than indirect-path signals. Consequently, the strengths of these signals influence the corresponding deltas in the CCF. It has been confirmed that deltas in the absence of multipath, that is, involving only direct paths, follow a random distribution to constitute the CCF. This behavior also applies to deltas associated with indirect paths. Consequently, the CCF under multipath conditions can be regarded as the sum of two random variables. To figure out how many nodes there are while taking into consideration multipath effects, you need to use the ratio of the CCF's σ to its average. To do this, you need to show the following: When looking at two random variables, X (the CCF from direct-path signal) and Y (the CCF from indirect-path signal), It is generally known that the variance of the sum of X (the CCF from direct-path signal cross correlation) and Y (the CCF from indirect-path signal cross-correlation) may be written as:

$$\mathrm{Var}\,(X+Y) = \mathrm{Var}(X) + \mathrm{Var}(Y) + 2 \times \mathrm{Cov}(X,Y) \tag{4}$$

Assigning symbols for the variances of X+Y, X, and Y as $\sigma_X{}^2{}_{+Y}$, $\sigma_X{}^2$, as well as $\sigma_Y{}^2$, respectively, with the covariance of X and Y defined as σ_{XY} ,the preceding expression can be written as:

$$\sigma_{X+Y}^2 = \sigma_X^2 + \sigma_Y^2 + \sigma_{XY} \tag{5}$$

By substitution for the covariance the expression can be expressed as: (6) where ρ_{XY} represents the correlation coefficient.

$$\sigma_{X+Y}^2 = \sigma_X^2 + \sigma_Y^2 + 2\rho_{XY}\sigma_X\sigma_Y \tag{6}$$

Thus, the sum of two random variables has as standard deviation:

$$\sigma_{X+Y} = \sqrt{\sigma_X^2 + \sigma_Y^2 + 2\rho_{XY}\sigma_X\sigma_Y} \tag{7}$$

If the parameters are independent or poorly dependent (two CCF), namely, $\rho_{XY} \approx 0$, Eq. (8) becomes simple:

$$\sigma_{x+y}^2 = \sigma_x^2 + \sigma_y^2 \tag{8}$$

Further, the expected value of a sum of two random variables is given by:

$$\mu X+Y = \mu X + \mu Y \tag{9}$$

Thus, the ratio of the standard deviation to the mean of the CCF is:

$$R_{X+Y} = \frac{\sigma_{X+Y}}{\mu_{X+Y}} = \frac{\sqrt{\sigma_X^2 + \sigma_Y^2 + 2\rho_{XY}\sigma_X\sigma_Y}}{\mu_X + \mu_Y} \tag{10}$$

When the variables are scaled differently, if $\sigma_X \gg \sigma_Y$ and $\mu_X \gg \mu_Y$, the expression can be approximated by:

$$R_{X+Y} \approx R_X = \frac{\sigma_X}{\mu_X} \tag{11}$$

The proposed estimation system for calculating the number of nodes, considering multipath effects (specifically double paths: direct and indirect), defines the CCF as the aggregate of two random variables. Given the significant dominance of the direct path's contribution, the previous statement suggests that R_{X+Y}

can be approximated using the ratio R, defined as the σ divided by the average of the CCF component originating from the direct path. The CCF for the direct approach will be nearly binomially Figure 5 Rs of CCF: k=3 distributed, as previously stated.

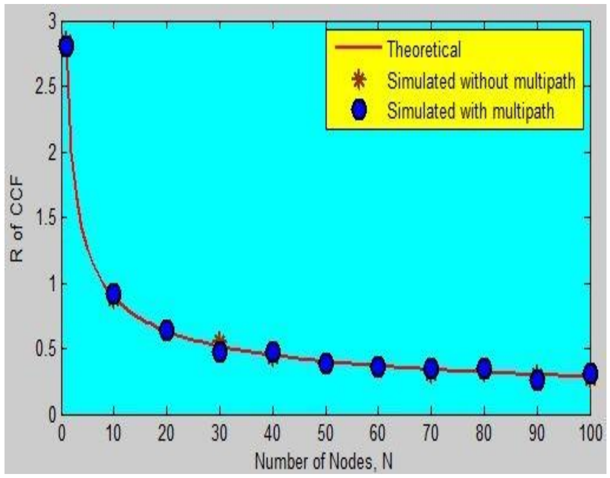

Figure 5: Rs of CCF: k=3

Figure 5 demonstrates the performance of our approach in a multipath receiving of signals by the sensors. It is clear that both sets agree well each other, and also with the theoretical ones. Now going to direct and indirect paths (100 presets) as shown in Figs6 and 7, here the CCF is a sum of three random variables while the dominant influence on the CCF comes from the direct path. Eq. (11) for the ratio of temporal σ to mean in the CCF holds. The estimator R results are organized in figure 8 for surface and bottom reflections. Similar results are shown in Figure 10 and figure 12 for the cases of three and four reflectors placed in equal distances from the network of interest. The distribution of such network with reflectors is shown in figure 9 and in figure 11.

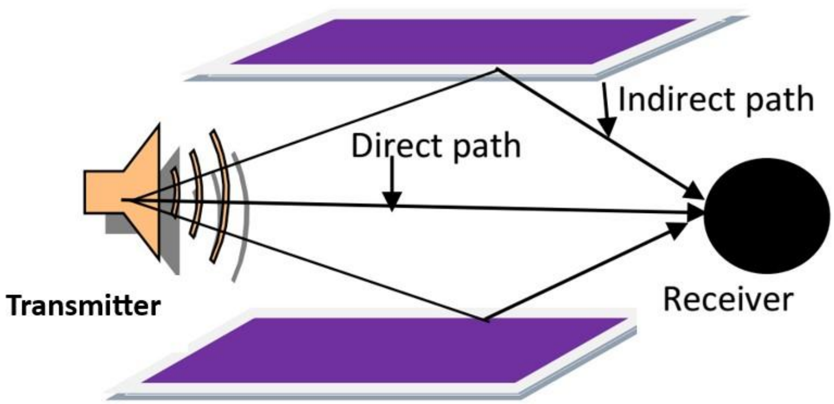

Figure 6: Multipath model consisting of one direct path and another indirect path

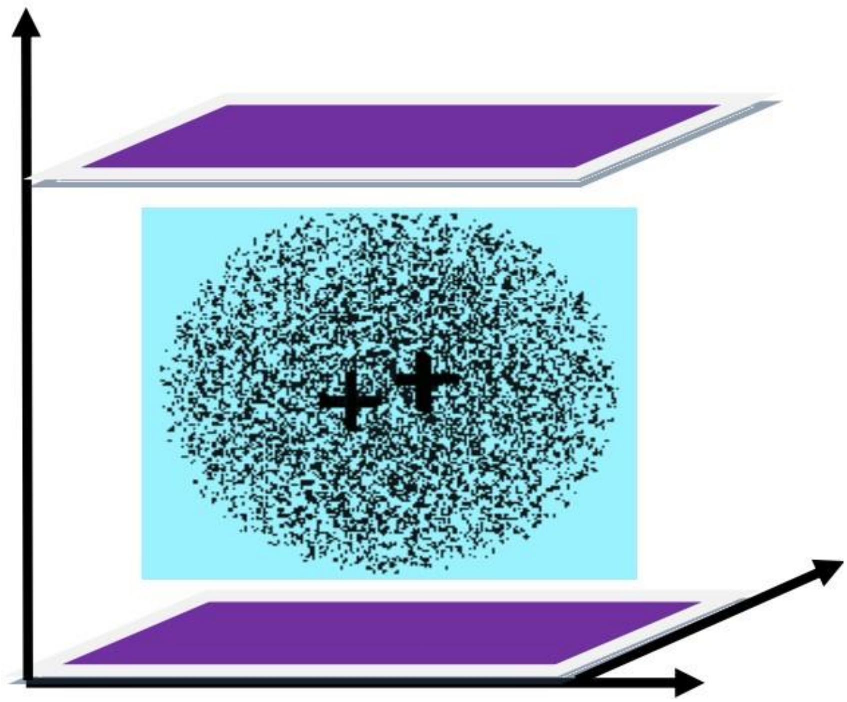

Figure 7: Configuration of transmitters and receivers with double reflectors

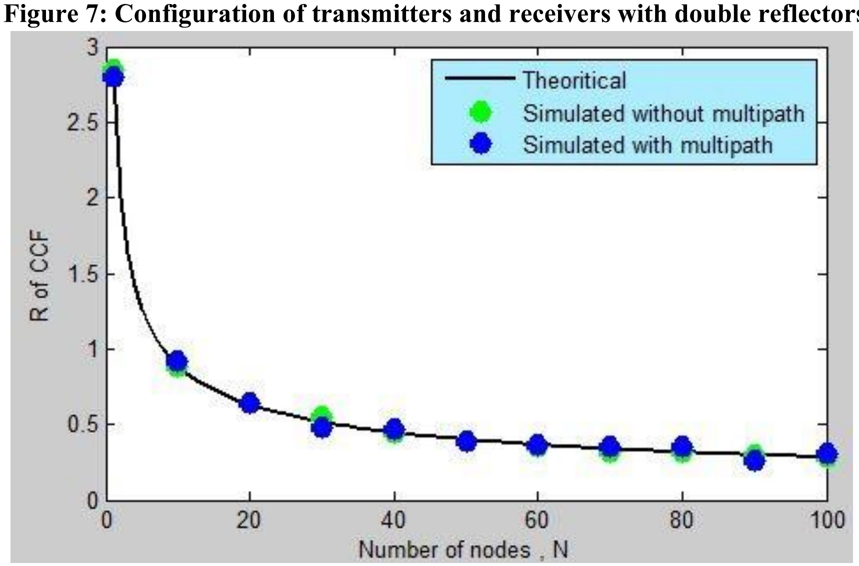

Figure 8: Configuration of transmitters and receivers with double reflectors

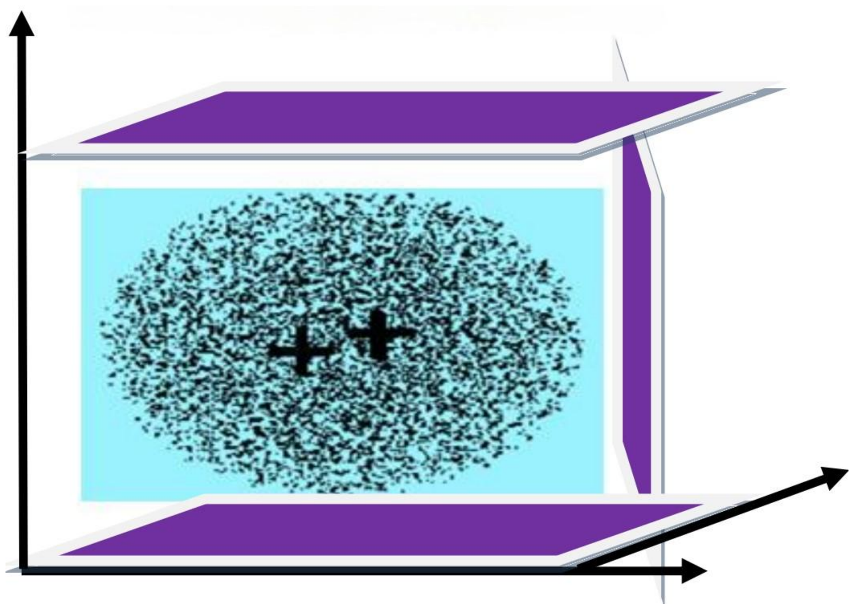

Figure 9: Configuration of transmitters and receivers alongside three reflective elements

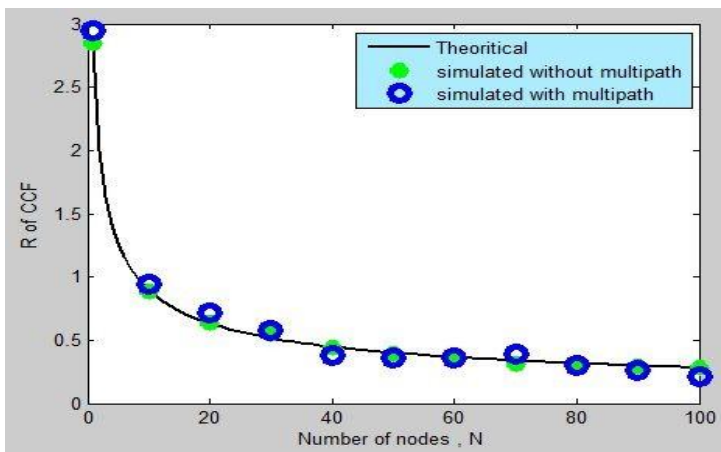

Figure 10: The correlation coefficient R of the CCF is analyzed for a transmitter-receiver system with three reflectors: k=3

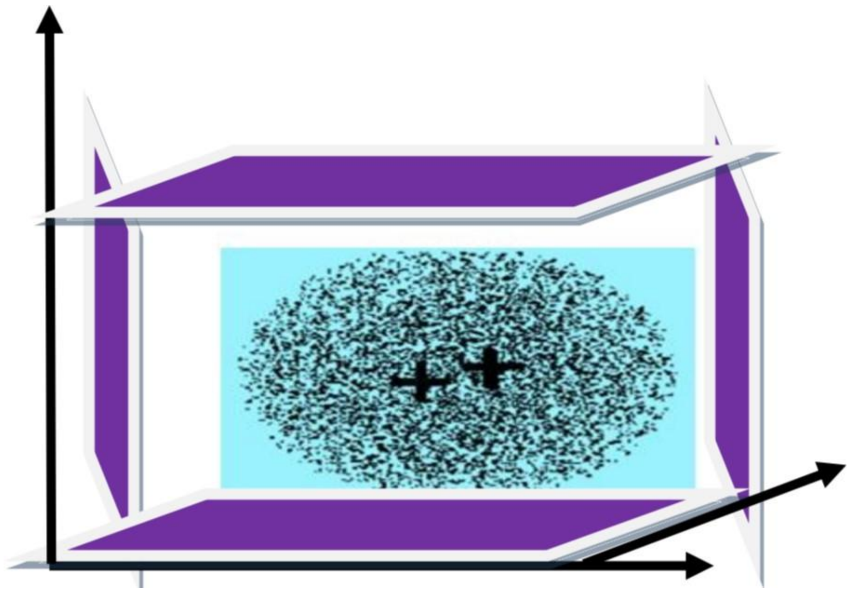

Figure 11: Configuration of transmitters and receivers alongside four reflective elements

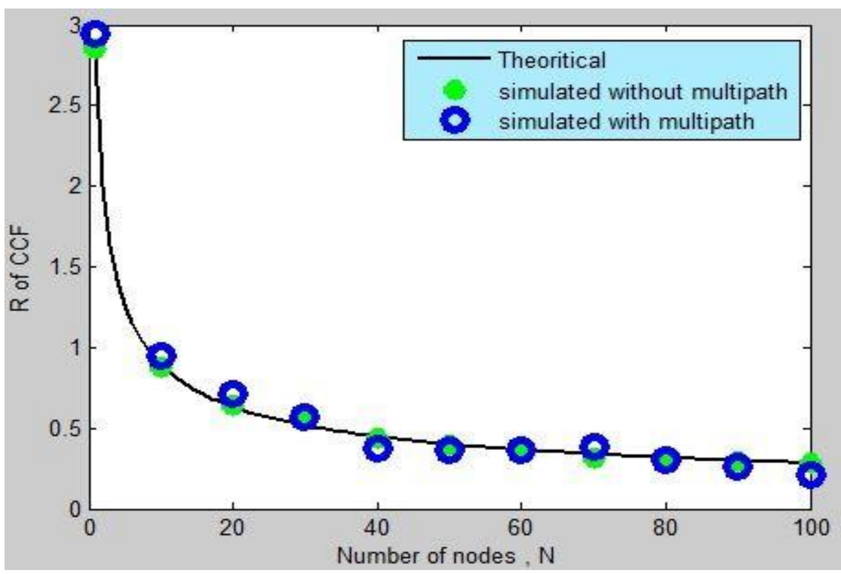

Figure 12: R of CCF corresponding to transmitters and receivers with four reflectors: k=3

2.Estimation results and analysis

2.1. Estimation procedure involving direct and reflected paths

To illustrate how the node-counting approach performs process in the presence of multipath, we consider a three-dimensional spherical region underwater under water transmitters with a pair of sensing units is located at the center, oriented parallel to the seabed. The seabed is treated as the only reflector, generating one reflected path in addition to the direct path. (Anower., Chowdhury, Chowdhury, Giti, Sayem & Haque, 2014). It has previously been shown that in the absence of multipath, the cross-correlation function (CCF) follows a random distribution of delta peaks. This behavior extends to indirect paths as well, and therefore, in the presence of one reflection, the CCF is the summation of two random variables. Simulation results indicate that the impact of multipath decreases with increasing dispersion coefficient k. For practical underwater environments where k is typically high, the effect can be neglected. To validate the robustness of the proposed estimation, Figure 13 presents the metric R, calculated as the dispersion measure (standard deviation) divided by its corresponding average value for 1–100 nodes with 9 bins at k = 1.5. The results confirm that the process remains accurate to provide accurate node-count predictions, even when presence of multipath.

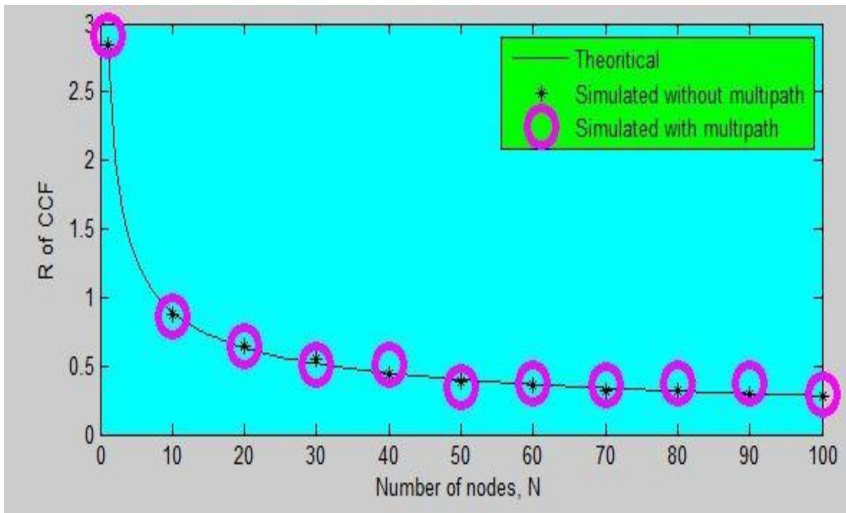

Figure 13: The Rs values of the CCF are compared for the theoretical model, simulation without multipath, and simulation with multipath at k=1.5.

2.2.Estimation procedure involving a direct path along with two reflected paths

In this case, both seabed and surface reflections are considered in addition to the direct path. The experimental arrangement is similar to the previous case, with the only difference being the addition of the upper water boundary is now included as an additional reflecting interface. The generalized calculation of the number of nodes is again performed through the use of R parameter pertaining to the CCF for 1–100 nodes with 9 bins at k = 1.5. As shown in figure 14, the comparison among theoretical results, non-multipath simulation and with multipath demonstrates negligible degradation. The estimation remains valid and accurate, highlighting the robustness of the approach under two-path reflection scenarios.

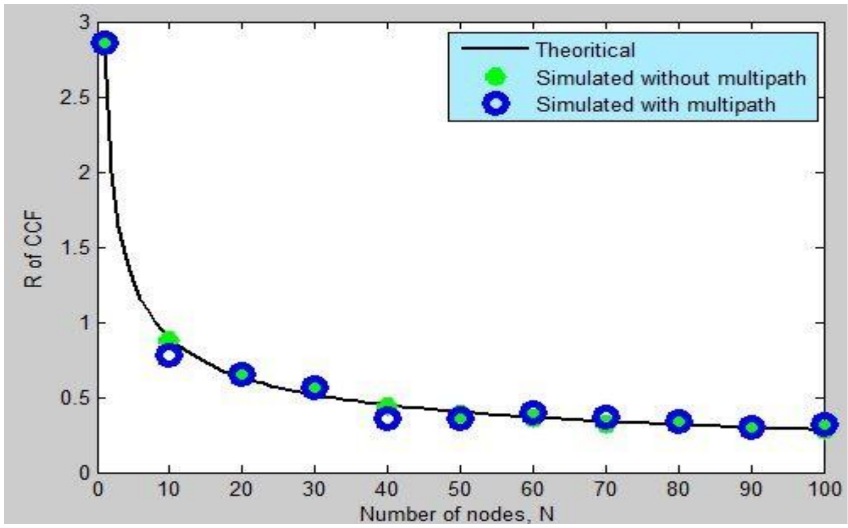

Figure 14: The Rs of CCF are compared for the theoretical analysis, simulation without multipath and simulation with multipath, including both surface and floor reflections, for k=1.5

2.3. Estimation with the direct and three reflected paths

In both cases the direct path signal is the similar as without multipath case. A comparable approach is employed to estimate the scenario involving multipath caused by surface, bottom, and side reflections. Side reflections take place if there is any reflector present inside the region of interest i.e. the communication range where the sensors and transmitters are located. To illustrate the estimation procedure considering multipath effects from surface, bottom, and lateral reflections, a comparable experimental setup to that used for observing multipath effects from surface and bottom reflections can be assumed. The primary distinction between the two lies in the fact that, in the latter, a vertical (with respect to the seabed) reflected plate is treated as a side reflector, specifically, reason due to multipath which is already shown in Fig.9. The results of node number estimation using this configuration for 1–100 nodes, with 9 bins and k=1.5, are depicted in Fig. 15, which illustrates the comparison of the R parameter across the considered node range. Despite the presence of three reflectors, the estimation process continues to provide reliable results.

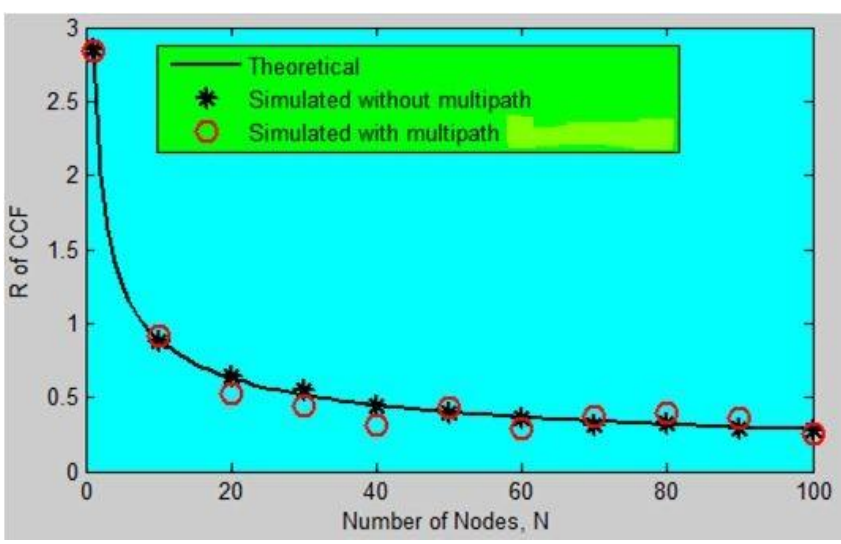

Figure 15: Rs of CCF: comparison of results from theoretical, simulation without multipath and simulation with multipath (with three reflectors) for k =1.5

2.4. Estimation with the direct and four reflected paths

Finally, two vertical side reflectors are added, placed opposite to each other, in addition to seabed and surface reflections. This scenario represents the most complex multipath environment considered in this study. The only difference between the two is that, in the Later, another vertical (with respect to the seabed) The reflected plate is considered a side (opposite to the previous one) reflector, i.e., the reason for the multipath, which is shown in figure 11. The results for the number of node estimation from such a setup for 1- 100 nodes with 9 bins and k=1.5 are presented in Figure 16.

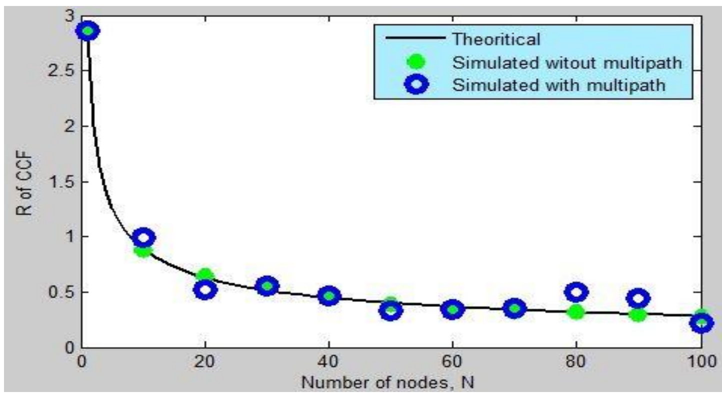

Figure 16: Rs of CCF: comparison of results from theoretical, simulation without multipath and simulation with multipath (with four reflectors) for k =1.5

3. Conclusion and future work

Multipath propagation is an inherent phenomenon in practical wireless and underwater communication networks. This study investigated its impact on network cardinality estimation using a cross-correlation based approach. Different cases were considered: a direct path with one reflected path, and more complex scenarios involving two, three, and four reflectors. Gaussian signals were employed in the analysis because they provide a tractable mathematical representation and help reduce the complexity of the correlation functions. The findings clearly show that when the line-of-sight path represents significantly of higher intensity than the reflected components, the impact of multipath can be neglected. Under such conditions, the estimation results closely match those obtained without multipath, thereby simplifying the estimation process. Conversely, when indirect paths are nonnegligible, the proposed technique remains effective. By interpreting reflected paths as equivalent image transmitters, the cross correlation method ensures that all signal components are accounted for, leading to reliable estimation even in environments with severe multipath. Simulation results for scenarios with up to four reflectors demonstrated that the estimation error remains within acceptable limits, highlighting the robustness of the method. Despite the promising results, several limitations of this work point toward future research opportunities. First, the present analysis focused primarily on a two-sensor configuration. Extending the method to three or more sensors will enable comparative performance studies and provide deeper insights into error reduction. Second, a generalized estimation framework for arbitrary N nodes and M sensors should be developed to improve scalability and adaptability to different network sizes and geometries. Furthermore, the assumptions made in this paper—uniform node distribution, spherical network topology, and centered sensor placement—need to be relaxed in order to approximate realistic underwater environments more closely. Future work should examine heterogeneous and random node distributions, irregular network geometries, and arbitrary sensor placements. Additionally, the effect of environmental factors such as time-varying channels, ambient noise, and doppler shifts should be incorporated into the analysis to improve robustness under realistic operating conditions. Finally, the ultimate validation of the proposed method lies in practical implementation. Future efforts will therefore aim to design experimental testbeds and conduct sea trials to evaluate the performance of the estimator in real-world underwater acoustic networks. Such studies will bridge the gap between theoretical modeling, simulation results, and practical deployment, ultimately contributing to more reliable and efficient underwater communication systems.

Conflicts of Interest

The authors have disclosed no conflicts of interest.

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