A signal processing approach of underwater network node estimation with three sensors

S. A. H. Chowdhury[1]
Dept. of Electronics & Telecommunication Engineering
Rajshahi University of Engineering & Technology
Rajshahi-6204, Bangladesh.
arif.1968.ruet@gmail.com[1]

M. S. Anower[2] and J. E. Giti[3]
Dept. of Electrical & Electronic Engineering
Rajshahi University of Engineering & Technology
Rajshahi-6204, Bangladesh.
md.shamimanower@yahoo.com[2]
monimala89@yahoo.com[3]

***Abstract*—Estimation of the number of nodes in a communication network is very important, particularly in ad hoc networks. But it is difficult to estimate in underwater wireless sensor networks due to long propagation delay, high absorption, and dispersion. Cross-correlation, a statistical signal processing approach is applied for this purpose, which is suitable for any environment networks. Nodes are considered as transmitters and sensors are considered as receivers. In this work, a node estimation technique for underwater networks is proposed by cross-correlating the signals received at three sensors.**

Keywords—Cross-correlation, node estimation, sensor, underwater acoustic sensor networks (UASN).

I. INTRODUCTION

In recent years, with technological advancements in communications industry and increased knowledge of the reserves of natural resources underwater, research on underwater wireless communication networks (UWCN) has been attracting attention for military and commercial purposes. UWCNs include, but are not limited to; underwater wireless sensor networks (UWSN) using acoustic waves [1], [2] and electromagnetic waves [3], [4]. UASNs are more flexible form of communication in underwater environment, which have several applications, such as oceanographic data collection, pollution monitoring, climatic data collection, underwater exploration, disaster alleviation [5], seismic and acoustic monitoring to surveillance and national security, military and health care, discovering natural resources as well as locating man-made artifacts or extracting information for scientific analysis. Performances of the networks deployed for these applications, depend on the number of active nodes. So, it is an important issue to determine the number of active nodes or transmitters available in the network at any point in time.

A number of node estimation techniques have been investigated so far. For example, in radio frequency identification (RFID) systems, protocols [6]–[10] have been used to estimate the number of tag IDs, which is a similar problem to the estimation of the number of nodes in wireless communication networks. A distributed statistical estimation of the number of nodes has been investigated in [11]. Another node estimation technique has been proposed for wireless mobile ad hoc network using two novel statistical methods, called the circled random walk and the tokened random walk in [12]. A Good-Turing estimator of node estimation for terrestrial sensor networks has been proposed in Budianu et al. [13]–[15]. These systems can be applied in RFID as well as terrestrial systems easily, but the capture effect and long propagation delay does not take into account in these systems, which means that they are not suitable to apply in UASN. A solution to this problem has been investigated in Howlader et al. [16], [17], in which a node estimation technique has been proposed taking the capture effect and long delay into account. The procedure is similar to probabilistic framed slotted ALOHA [18]. A network structure estimation technique for underwater wireless networks has been proposed in [19] based on intermission between the nodes. These techniques are based on protocol(s).

Considering underwater propagation characteristics [20], a cross-correlation based estimation technique with two sensors has been proposed in Anower et al. [21], [22], which does not require any protocol and has tremendous advantage over the conventional protocol based node estimation technique [23]. In this technique, transmitted Gaussian signals from N number of nodes are received by the two sensors. Then, a cross-correlation function (CCF) is formulated by cross-correlating the received composite signals. Number of node is estimated using a node estimation parameter, which is obtained by taking the ratio of standard deviation to the mean of the CCF. A similar node estimation technique is proposed in this paper which utilizes cross-correlation of the signals received by three sensors.

II. CCF FORMULATION

Consider a 3D network containing N nodes, where the nodes are evenly distributed over the dimensions of a large sphere. Three identical sensors are placed in a line inside the network, where the middle sensor lies on the centre of the sphere. The other two probing nodes are placed on both sides of and at equal distances from the middle one along a line as shown in Fig. 1. The transmitted Gaussian signals from N nodes are received by the three sensors and summed at each of these three sensor locations. From these three composite signals, two pair of signals at two pair of equidistant sensors is then cross-correlated to formulate two CCFs.

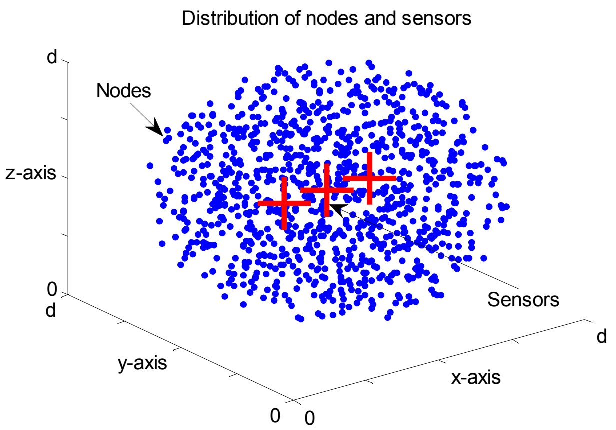


Fig. 1. Distribution of underwater network nodes with N (=1000) transmitting nodes.

To formulate random signal cross-correlation function, in this analysis the 3D space is taken as a cube and three sensors, H_1, H_2 and H_3, and a node N_1, are taken at locations (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 (using rectangular coordinate system), somewhere inside the cube as shown in Fig. 2. The distances between the sensors are then:

$$d_{DBS_{12}} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \quad (1)$$

$$d_{DBS_{23}} = \sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2 + (z_2 - z_3)^2} \quad (2)$$

$$d_{DBS_{31}} = \sqrt{(x_3 - x_1)^2 + (y_3 - y_1)^2 + (z_3 - z_1)^2} \quad (3)$$

Here, $d_{DBS_{12}}$= distance between sensors H_1 and H_2,
$d_{DBS_{23}}$= distance between sensors H_2 and H_3,
$d_{DBS_{31}}$= distance between sensors H_3 and H_1.

The sensors are placed such that, $d_{DBS_{12}} = d_{DBS_{23}} = d_{DBS}$. So, two pair of sensors can be considered to formulate CCF, which in this case are (H_1, H_2) and (H_2, H_3), because each pair of sensors has the same distances between them. Consider that node N_1 emits a signal $S_1(t)$, which is infinitely long. Then the signals received by H_1, H_2 and H_3 are, respectively:

$$S_{r_{11}}(t) = \alpha_{11} S_1(t - \tau_{11}) \quad (4)$$

$$S_{r_{12}}(t) = \alpha_{12} S_1(t - \tau_{12}) \quad (5)$$

and

$$S_{r_{13}}(t) = \alpha_{13} S_1(t - \tau_{13}) \quad (6)$$

where, α_{11}, α_{12} and α_{13} are the respective attenuations due to the absorption and dispersion present in the medium, $\tau_{11} = \frac{d_{11}}{S_P}$, $\tau_{12} = \frac{d_{12}}{S_P}$ and $\tau_{13} = \frac{d_{13}}{S_P}$ the respective time delays for the signal to reach the sensors, and S_P is the speed of wave propagation.

Thus the signals received from N nodes by the three sensors H_1, H_2 and H_3 can be expressed as:

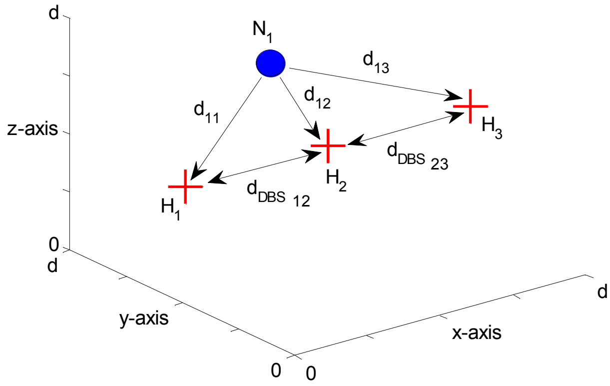


Fig. 2. Underwater network with three sensors (+) and only one node N_1.

$$S_{r_{t1}}(t) = \sum_{j=1}^{N} \alpha_{j1} S_j(t - \tau_{j1}) \quad (7)$$

$$S_{r_{t2}}(t) = \sum_{j=1}^{N} \alpha_{j2} S_j(t - \tau_{j2}) \quad (8)$$

and

$$S_{r_{t3}}(t) = \sum_{j=1}^{N} \alpha_{j3} S_j(t - \tau_{j3}) \quad (9)$$

respectively.

Assuming $\tau = d_{DBS} / S_P$ is the time shift in cross-correlation, and then the CCFs between the signals at the two pair of sensors (H_1, H_2) and (H_2, H_3) are, respectively:

$$C_{12}(\tau) = \int_{-\infty}^{+\infty} S_{r_{t1}}(t)\, S_{r_{t2}}(t - \tau)\, d\tau \quad (10)$$

and

$$C_{23}(\tau) = \int_{-\infty}^{+\infty} S_{r_{t2}}(t)\, S_{r_{t3}}(t - \tau)\, d\tau \quad (11)$$

which take the form of a series of delta functions as they are the cross-correlations of two signals which are the summations of several white Gaussian signals. One such CCF obtained with N (=1000) nodes is shown in Fig. 3.

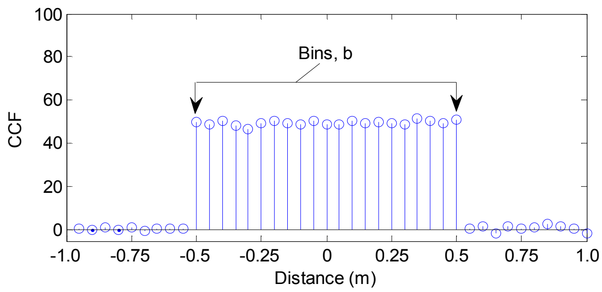


Fig. 3. Bins, b in the cross-correlation function.

Bins, b in the CCF (as shown in Fig. 3) is defined as a place occupied by a delta inside a space of a width twice the distance between sensors and that place is determined by the delay difference of the signal coming to the sensors [23]. The deltas of equal delay differences are placed in that particular bin.

III. Node Estimation

The basic approach for estimation of the number of nodes, N using two CCFs (obtained in section II) is discussed in this section. In this process, the ratio of mean, μ and standard deviation, σ of the CCFs is used as the estimation parameter. First, it is theoretically demonstrated that N is related to the ratio of standard deviation to the mean, $R_{average}^{2CCF}$ of the CCFs and then, the outcome from the theory is verified by simulation.

A. Theory

As it is quite difficult to obtain the standard deviation and mean of the CCFs using statistical expression, the cross-correlation technique is reframed as a probability problem [22], which makes the analysis much simpler. By reframing the cross-correlation problem into a probability problem, the ratio of standard deviation to the mean, R can be expressed as [21]:

$$R = \sigma \div \mu = \sqrt{\frac{(b-1)}{N}} \tag{12}$$

where the number of bins, b is defined as twice the number of samples between the sensors (NSBS), m, minus one.

In case of multiple CCFs, such as in this case, where two CCFs are formulated from two pair of equidistant sensors, two ratio of standard deviation to the mean, R_{12} and R_{23}, can be obtained. Then, the final ratio of standard deviation to the mean, $R_{average}^{2CCF}$ is determined by taking the average of R_{12} and R_{23}. Thus, after some manipulation the final ratio of standard deviation to the mean, $R_{average}^{2CCF}$ can be expressed as:

$$R_{average}^{2CCF} = \frac{R_{12} + R_{23}}{2} = \sqrt{\frac{(b-1)}{N}} \tag{13}$$

This is the theoretical expression of final ratio of standard deviation to the mean of the CCFs, $R_{average}^{2CCF}$, which relate the number of nodes, N, and $R_{average}^{2CCF}$. Using this expression we can estimate N, as we know b and can calculate R_{12} and R_{23} (and, therefore, $R_{average}^{2CCF}$) from the CCFs.

B. Simulation

A similar network to that discussed in section II is employed to perform the simulations. The Gaussian signals (responses to the probe requests from the sensors or autonomous) emitted from the nodes are collected by the sensors. Then two CCFs, $C_{12}(\tau)$ and $C_{23}(\tau)$ are obtained. From these two CCFs, two ratio of standard deviation to the mean, R_{12} and R_{23}, are calculated. By averaging R_{12} and R_{23}, the estimation tool, i.e., the final ratio of standard deviation to the mean of the CCFs, $R_{average}^{2CCF}$ is obtained. Finally, N is estimated using (13) with this $R_{average}^{2CCF}$ and b which is known, as it is a function of distance between sensors, d_{DBS}, sampling rate, S_R and speed of propagation, S_P [23].

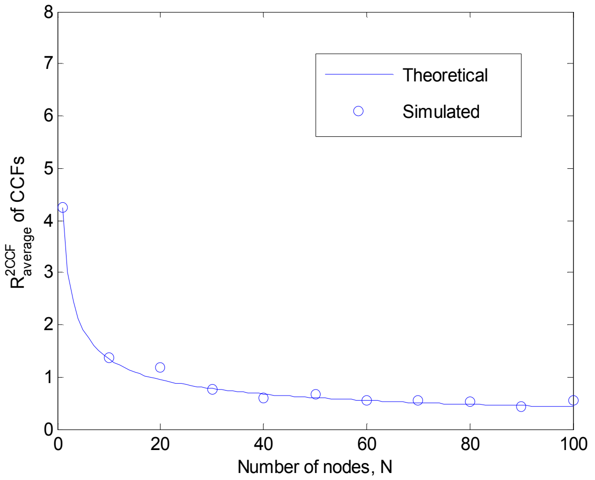
The following parameters are used in the simulations.

- Dimension of the cube, 2000m; for simplicity of calculation. However, it does not matter what the dimension of the cube is within the direct communication range.
- Exact number of transmitting nodes taken are, N = 1, 2, 3, ... , 100; to reduce the simulation time. However, the estimation process is equally suitable for any N.
- Signal length, $N_S = 10^6$ samples; to approximate infinitely long signals.
- Sampling rate, S_R = 30 kHz; as underwater acoustic communications currently operate within the bandwidth (BW) of 1-15 kHz, we arbitrarily choose this value without violating the sampling theorem.
- Speed of propagation, S_P = 1500 m/s; this is the propagation speed of a sound wave as we use the acoustic signal in an UASN.
- Distance between sensors, $d_{DBS_{12}} = d_{DBS_{23}} = d_{DBS} =$ 0.5m; this can be varied.
- Absorption coefficient, a = 1 and dispersion factor, k = 0; which implies no path loss [24].

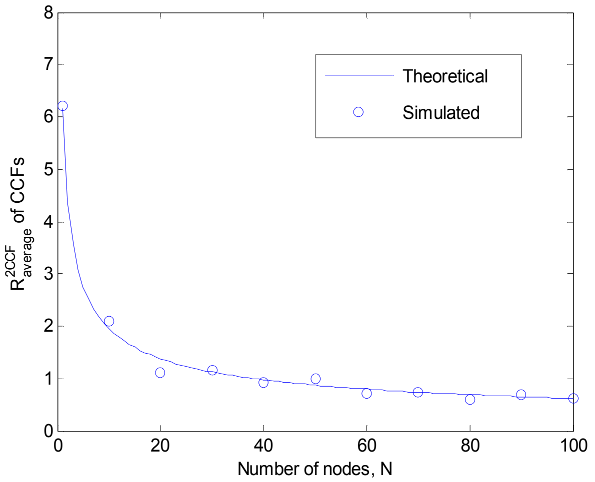
IV. Results and Discussion

Matlab is used as the simulation tool. Some useful simulation results are compared with the theoretical results in Fig. 4 and 5. In the figures, the solid lines indicate the theoretical results (obtained from the mathematical relationships shown in section III.A) and the circles the corresponding simulated results (obtained from simulation discussed in section III.B). Fig. 4 shows the results for N with respect to $R_{average}^{2CCF}$ for different d_{DBS}. The distances between the two pair of sensors are: 0.5m in Fig. 4(a), 1.0m in Fig. 4(b) and 1.5m in Fig. 4(c). In Fig. 5, results of estimated number of nodes (obtained from averaging 500 iterations) with respect to exact number of nodes are shown for different b, obtained by varying distances between the two pair of equidistant sensors, d_{DBS}, and sampling rate, S_R. The values are: 0.5m and 30 kSa/s for b = 19 in Fig. 5(a), 0.25m and 120 kSa/s for b = 39 in Fig. 5(b), 1.0m and 45 kSa/s for b = 59 in Fig. 5(c). The other parameters remain the same as discussed in section III.B. It is apparent from Fig. 4 and 5 that, theoretical and simulation results match, which implies that the estimation process is satisfactory.

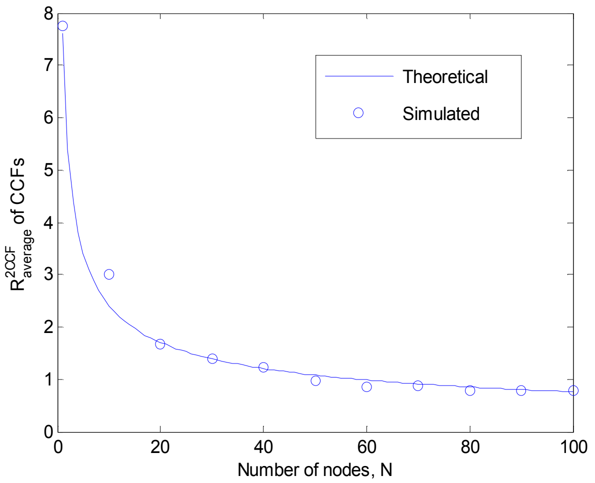
For the sake of comparison with the two sensor technique [21], estimation parameters, R of CCF in two sensor technique and $R_{average}^{2CCF}$ in the proposed technique are shown with error bars in Fig. 6 for b = 19 with d_{DBS} =0.5m and S_R =30 kSa/s. It shows that error bars are small in the proposed technique compared to that of the two sensor technique, which means simulated results of the proposed technique are closer to the theoretical results. This indicates that, number of nodes can be estimated with higher accuracy in the proposed technique compared to that of the two sensor technique for the same



(a)

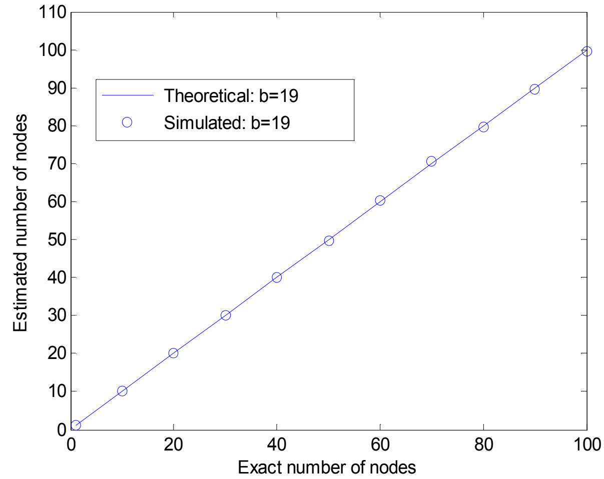


(b)

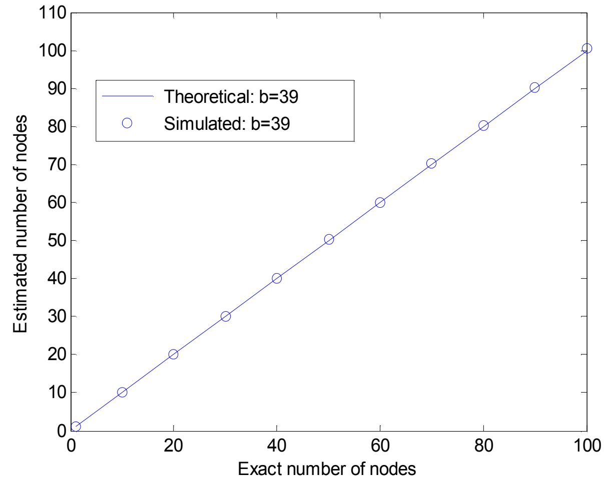


(c)

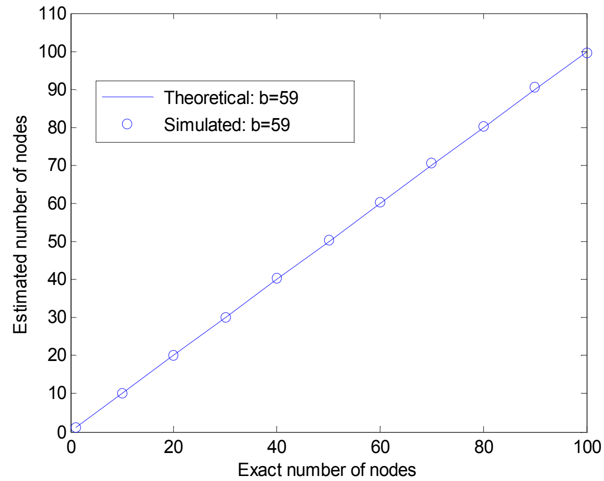
Fig. 4. $R^{2CCF}_{average}$ versus N for b = 19, 39 and 59: (a) d_{DBS} = 0.5m; (b) d_{DBS} = 1.0m; and (c) d_{DBS} = 1.5m. [S_R = 30 kSa/s]



(a)



(b)



(c)

Fig. 5. Comparisons of theoretical and simulated number of estimated nodes for: (a) b = 19; (b) b = 39; and (c) b = 59.

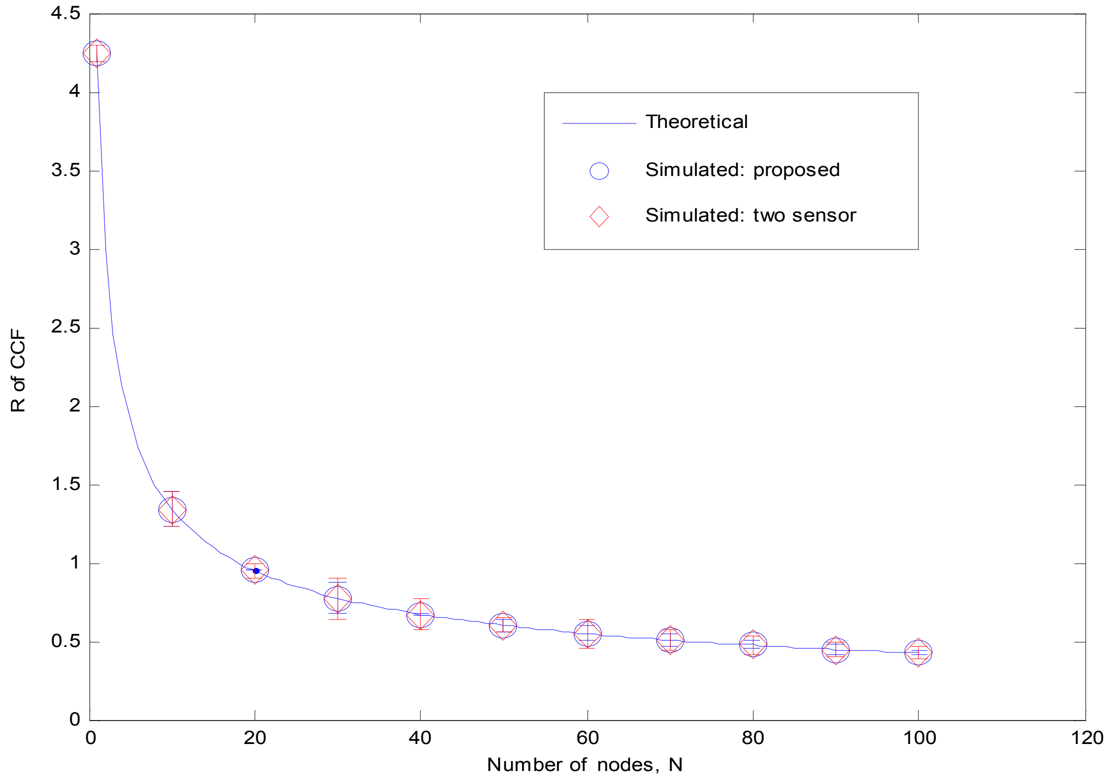


Fig. 6. *R* versus *N* comparison of the proposed and two sensor approach with error bars for $b = 19$ with $d_{DBS} = 0.5$m and $S_R = 30$ kSa/s.

number of iterations. It also indicates that, a particular accuracy can be achieved with less number of iterations in the proposed technique compared to that of the two sensor technique, which implies less required estimation time for the proposed technique with respect to two sensor technique. These results are obtained by assuming that the received power from each node is the same, which can be achieved by sending a probe request from the sensors, and each node setting its transmit power in accordance with the received power from the probes.

V. Conclusion

Accurate estimation of the number of nodes in a communications network plays a vital role for practical applications. Due to the harshness of underwater environment, the existing methods using protocol(s) have some limitations to estimate the number of nodes in underwater networks and require lots of modifications and are inefficient and time consuming. In this paper we have shown that the number of nodes can be estimated using the cross-correlation of random signals with three sensors in underwater network, which will perform better in terms of accuracy and required estimation time than those of the two sensor method. This technique has several limitations as Gaussian signals are used, equal received power is considered, and the delays are considered to be integer. Regardless of these limitations, it might be the useful alternate of the existing techniques. In future, we intend to eliminate these limitations and determine the accuracy of the estimation process.

References

[1] M. Chitre, S. Shahabudeen, L. Freitag, and M. Stojanovic, “Recent advances in underwater acoustic communications & networking,” IEEE Oceans’08, Quebec City, Canada, 15–18 September, 2008, pp. 1–10. doi: 10.1109/OCEANS.2008.5152045

[2] Z. Jiang, “Underwater acoustic networks–issues and solutions,” International Journal of Intelligent Control and Systems, vol. 13, no. 3, pp. 152–161, September 2008.

[3] A. A. Abdou, A. Shaw, A. Mason, A. Al-Shamma’a, J. Cullen, and S. Wylie, “Electromagnetic (EM) wave propagation for the development of an underwater Wireless Sensor Network (WSN),” in Proceedings IEEE Sensors, 2011, Limerick, Ireland, 28–31 October, 2011, pp. 1571–1574. doi: 10.1109/ICSENS.2011.6127319

[4] A. Elrashidi, A. Elleithy, M. Albogame, and K. Elleithy, “Underwater wireless sensor network communication using electromagnetic waves at resonance frequency 2.4 GHz,” in Proceedings of the 15th Communications and Networking Simulation Symposium (CNS’12), San Diego, California, USA, 2012.

[5] N. N. Soreide, C. E. Woody, S. M. Holt, “Overview of ocean based buoys and drifters: Present applications and future needs,” 16th International Conference on Interactive Information and Processing System (IIPS) for Meteorology, Oceanography, Hydrology, Long Beach, California, USA, 2004.

[6] J. Vales-Alonso, V. Bueno-Delgado, E. Egea-Lopez, F. J. Gonzalez-Castano, and J. Alcaraz, "Multiframe Maximum-Likelihood tag estimation for RFID anticollision protocols," IEEE Transactions on Industrial Informatics, vol. 7, no. 3, pp. 487–496, 2011. doi:10.1109/TII.2011.2158831

[7] M. Shahzad, and A. X. Liu, “Every bit counts: fast and scalable RFID estimation,” In Proceedings of the 18th annual international conference on Mobile computing and networking, 2012, pp. 365–376. doi:10.1145/2348543.2348588

[8] M. H. Nazir, S. Mehmood, N. Sheriff, and A. Adeel, “Improved efficient RFID tag estimation scheme,” International Journal of Computer Applications, vol. 47, no. 17 pp. 16–19, 2012.

[9] C. B. Li, H. Li, and P. W. Wang, “Forward predicting and backward verifying tags number estimation in RFID system,” Applied Mechanics and Materials, vol. 321–324, pp. 2902–2905, 2013. DOI: 10.4028/www.scientific.net/AMM.321-324.2902

[10] Y. Zheng, and M. Li, "ZOE: fast cardinality estimation for large-scale RFID systems," In Proceedings IEEE INFOCOM, 2013, 14–19 April, 2013, pp. 908–916. doi: 10.1109/INFCOM.2013.6566879

[11] D. Varagnolo, G. Pillonetto, and L. Schenato, "Distributed statistical estimation of the number of nodes in sensor networks," 49th IEEE Conference on Decision and Control (CDC), 2010, 15-17 Dec. 2010, pp. 1498–1503. doi: 10.1109/CDC.2010.5717355

[12] Shiping Chen, "Estimating the Number of Nodes in a Mobile Wireless Network," IEEE Global Telecommunications Conference (GLOBECOM 2010), 6–10 Dec. 2010, pp. 1–5. doi: 10.1109/GLOCOM.2010.5684126

[13] C. Budianu, S. Ben-David, and L. Tong, “Estimation of the number of operating sensors in large-scale sensor network with mobile access,” IEEE Transactions on Signal Processing, vol. 54, no. 5, May 2006.

[14] C. Budianu and L. Tong, “Estimation of the number of the operating sensors in a sensor network,” presented at 2003 Asilomar Conf. Signals, Systems, Computers, Monterey, California.

[15] C. Budianu and L. Tong, “Good-Turing estimation of the number of operating sensors: a large deviations analysis,” Int. Conf. Acoustics, Speech, Signal Processing (ICASSP), Monteral, QC, Canada, May 2004.

[16] M. S. A. Howlader, M. R. Frater, and M. J. Ryan, “Estimation in underwater sensor networks taking into account capture,” IEEE Oceans’07, Aberdeen, Scotland, 18–21 June, 2007.

[17] M. S. A. Howlader, M. R. Frater, and M. J. Ryan, “Delay-insensitive identification of neighbors using unslotted and slotted protocols,” Wirel. Commun. Mob. Comput., 2012. doi: 10.1002/wcm.2242

[18] M. Kodialam and T. Nandagopal, “Fast and reliable estimation schemes in RFID systems,” in Proc. 12th annual international conference on Mobile computing and networking (MobiCom’06), Los Angeles, California, USA, 23–26 September, 2006.

[19] S. Blouin, "Intermission-based adaptive structure estimation of wireless underwater networks," 10th IEEE International Conference on Networking, Sensing and Control (ICNSC), 2013, 10–12 April. 2013, pp. 146–151. doi: 10.1109/ICNSC.2013.6548727

[20] L. Liu, S. Zhou, and Jun-Hong Cui, “Prospects and problems of wireless communication for underwater sensor networks,” Wireless Communications and Mobile Computing, vol. 8, no. 8, pp. 977–994, 2008.

[21] S. Anower, M. R. Frater, and M. J. Ryan, “Estimation by cross-correlation of the number of nodes in underwater networks,” Australasian Telecommunication Networks and Applications Conference (ATNAC), 2009, 10–12 Nov. 2009, pp. 1–6. doi: 10.1109/ATNAC.2009.5464716

[22] M. S. Anower, M. A. Motin, A. S. M. Sayem, and S. A. H. Chowdhury, “A node estimation technique in underwater wireless sensor network,” International Conference on Informatics, Electronics & Vision (ICIEV), 2013, 17–18 May 2013, pp. 1–6. doi: 10.1109/ICIEV.2013.6572582

[23] M. S. Anower, “Estimation using cross-correlation in a communications network,” Ph.D. dissertation, SEIT, University of New South Wales at Australian Defense Force Academy, Canberra, 2011.

[24] M. S. A. Howlader, “Estimation and identification of neighbours in wireless networks considering the capture effect and long delay,” Ph.D. dissertation, SEIT, University of New South Wales at Australian Defense Force Academy, Canberra, 2009.