SRTTU

Journal of Electrical and Computer Engineering Innovations

JECEI, Vol. 5, No. 2, 2017

Regular Paper

A Signal Processing Approach to Estimate Underwater Network Cardinalities with Lower Complexity

Shaik Asif Hossain[1], Avijit Mallik[2,*], and Md. Arman Arefin[2]

[1]Department of Electronics and Telecommunication Engineering, Rajshahi University of Engineering and Technology, Rajshahi-6204, Bangladesh.

[2]Department of Mechanical Engineering, Rajshahi University of Engineering and Technology, Rajshahi-6204, Bangladesh.

*Corresponding Author's Information: avijitme13@gmail.com

ARTICLE INFO

ARTICLE HISTORY:
Received 09 November 2017
Revised 23 November 2017
Accepted 23 November 2017

KEYWORDS:
Bins
CHIRP signal
Cross-correlation
Underwater network cardinality (Node)
Mean

ABSTRACT

An inspection of signal processing approach in order to estimate underwater network cardinalities is conducted in this research. A matter of key prominence for underwater network is its cardinality estimation as the number of active cardinalities varies several times due to numerous natural and artificial reasons due to harsh underwater circumstances. So, a proper estimation technique is mandatory to continue an underwater network properly. To solve the problem, we used a statistical tool called cross-correlation technique, which is a significant aspect in signal processing approach. We have considered the mean of cross-correlation function (CCF) of the cardinalities as the estimation parameter in order to reduce the complexity compared to the former techniques. We have used a suitable acoustic signal called CHIRP signal for the estimation purpose which can ensure better performance for harsh underwater practical conditions. The process is shown for both two and three sensors cases. Finally, we have verified this proposed theory by a simulation in MATLAB programming environment.

1. Introduction

One of the most important parameters for an underwater network to continue its mechanism is underwater network cardinality estimation. The system performance directly depends on this. It is also essential for a wireless communication network (WCN) as WCNs are categorize by their geographical coverage area such as: terrestrial (TWCN), space (SWCN), underground (UGWCN) and underwater (UWCN).

However, though one of the TWCN covers almost the whole land area of the earth's surface, UWCN has a great practical significance as near about 71% of the earth surface is water area.

A number of investigations regarding cardinality estimation techniques were conducted in the past. Some examples are like these: in radio frequency identification (RFID) systems, protocols [1-8] have been used for the number of tag IDs estimation purposes. For terrestrial sensor networks, a Good-Turing estimator of cardinality estimation has been proposed in Budianu et al. [9-11]. On the other hand, some estimation processes without identification are proposed in [12,13].

However, though these protocols based techniques are operative for RFID networks or terrestrial systems, they do not take into account the capture effect. This makes them unsuitable for harsh underwater environments such as underwater acoustic sensor network (UASN).

A solution has been found in Howlader et al. [14], [15], which proposed a node estimation technique taking the capture effect into account. At this case, the procedure is same as probabilistic framed slotted ALOHA [1]. As a result, it suffers from high path loss, long propagation delay in underwater network.

For long range communication in underwater environment the acoustic wave is used. However, the problems occurs in this case is bandwidth problem, multi-path propagation and low speed of sound. So it can be said that the protocol based techniques are sometimes expensive and ineffective for cardinality estimation in the underwater environment [16].

In this research, a straight forward narrative method called cross-correlation is proposed for underwater network cardinality estimation. We also used an angle modulated sweeping signal called CHIRP signal for the estimation purposes. Several reasons occur behind this uses. Some of those are: this signal passes in a linear or nonlinear way the whole frequency bandwidth from one end to the other end by a sinusoidal waveform of constant amplitude within a certain time. It permits a high resolution on time axis and therefore, it is greatly suitable for ranging. Moreover, it owns a quasi-ideal rectangular spectrum to use the channel's capacity and to offer the lowest spectral power density compared to all other present transmission signals. It proves a very small latency by asynchronously working correlative transmission systems. The transmitted signals from a number of different random signal sources (cardinalities) within range are received by two or three or more than three sensors separated by a certain distance in the region. Then, the received signals are summed at each of the sensors locations, and the signals are then cross-correlated. The mean of the CCF is used to estimate the number of sources.

This research will investigate for both two and three sensors cases for underwater network cardinality (node) estimation process.

2. CCF Formulation

This paper initiates with the formulation of cross-correlation of CHIRP signal [17, 18, 19], which is the earliest materials and method for estimating the number of underwater network cardinalities. All the signals being transmitted are received by the receiving sensor and recorded in the associated computer by which cross-correlation is executed. Transmission and reception of signals are performed for a time frame which is called signal length throughout this paper. At first the CCF formulation process is shown for two sensors and after that similarly performed for three sensors.

2.1. CCF Formulation for Two Sensors

We consider that two receiving sensors are surrounded by N number of cardinalities. A distribution of network cardinalities is shown in a 3D space in Figure 1. Transmitting Cardinalities are the sources of CHIRP Signal and are uniformly distributed over the volume of a large sphere, the center of which lies halfway between the receiving sensors as only a sphere provides equal amounts of signals from every direction. A constant propagation velocity is considered, and here, that is the CHIRP velocity, S_P in the medium.

However, two sensors H_1, H_2 and cardinality (CHIRP transmitting source) N_1 are taken as the in Fig. 2. The sensors H_1, H_2 and the cardinality N_1 is located at the locations (x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3), respectively. If distance between two sensors is d_{DBS}

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

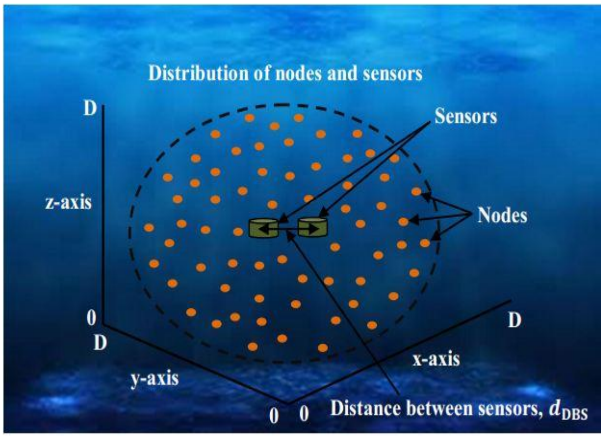


Figure 1: Underwater network cardinalities (nodes) in a 3D space.

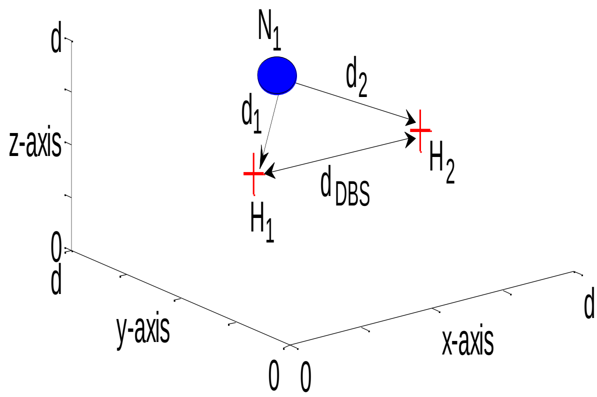


Figure 2: Distribution of the number of cardinalities (nodes) in 3D spaces. (Considering one cardinality).

Consider that, signal coming from the N_1 is $S_1(t)$, which is finitely long .Formerly the signal received by H_1 and H_2 are respectively:

$$S_{r11}(t) = \alpha_{11} S_{11}(t - \tau_{11}) \tag{2}$$

$$S_{r12}(t) = \alpha_{12} S_{12}(t - \tau_{12}) \tag{3}$$

Where α_{11} and α_{12} are the attenuation due to absorption and dispersion in the medium, τ_{11} and τ_{12} the respective time delay for the signals to reach the sensors and S_p is the speed of wave propagation.

Assuming τ_1 the time shift in the cross-correlation and then the CCF is:

$$C_1(\tau)=\int_{-\infty}^{+\infty}S_{11}(t)S_{12}(t-\tau_{12})d\tau \tag{4}$$

which takes the form of a delta function as it is across-correlation of two Signals where one signal is fundamentally the delayed copy of other.

To find the CCF for N cardinalities, we have to take the total signals received by the sensors from the cardinalities which involve transmitting all the signals from the cardinalities and summing them. Now, the received signals by Sensors are: Denoting the total signals at sensor H_1 by S_{rt1} gives:

$$S_{r_{t1}}=\sum_{j=1}^{N}\alpha_{j1}S_j(t-\tau_{j2}) \tag{5}$$

Denoting the total signals at sensor H_2 by S_{rt2} gives:

$$S_{r_{t2}}=\sum_{j=1}^{N}\alpha_{j2}S_j(t-\tau_{j2}) \tag{6}$$

Thus, the final CCF between the signals at the sensors is:

$$C(\tau)=\int_{-\infty}^{+\infty}S_{rt1}(t)S_{rt2}(t-\tau)d\tau \tag{7}$$

Which takes the form of series of Delta function as it is a cross-correlation of two signals which is the summation of several CHIRP Signals.

2.2. CCF Formulation for Three Sensors

During the formulation of cross-correlation function for three sensors, the sensors H_1, H_2, H_3 and a network cardinality, N_1 are located at (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).

Distance between sensors H_1 and H_2

$$d_{DBS_{12}}=\sqrt{(x_1-x_2)^2+(y_1-y_2)^2+(z_1-z_2)^2} \tag{8}$$

Distance between sensors H_2 and H_3

$$d_{DBS23}=\sqrt{(x_2-x_3)^2+(y_2-y_3)^2+(z_2-z_3)^2} \tag{9}$$

Distance between sensors H_3 and H_1

$$d_{DBS_{31}}=\sqrt{(x_3-x_1)^2+(y_3-y_1)^2+(z_3-z_1)^2} \tag{10}$$

At SL case, $d_{DBS_{12}}=d_{DBS_{23}}=d_{DBS}$,

This implies that two CCFs are possible.

At TS case, $d_{DBS_{12}}=d_{DBS_{23}}=d_{DBS31}=d_{DBS}$

This implies three CCFs are possible.

We Consider that the CHIRP signal coming from N_1 is $S_1(t)$, which is finitely long. Formerly the signals received by H_1, H_2 and H_3 are respectively:

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

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

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

Where α_{11}, α_{12} and α_{13} are the attenuation due to absorption and dispersion in the medium, τ_{11}, τ_{12} and τ_{13} the respective time delay for the CHIRP signals to reach the sensors and S_p is the speed of wave propagation .

The CCFs for SL (sensors in line) case are:

$$C_1(\tau)=\int_{-\infty}^{+\infty}S_{11}(t)S_{12}(t-\tau_{11})d\tau \tag{14}$$

$$C_2(\tau)=\int_{-\infty}^{+\infty}S_{12}(t)S_{13}(t-\tau_{12})d\tau \tag{15}$$

Now for TS (triangular sensors) case the additional CCF is:

$$C_3(\tau)=\int_{-\infty}^{+\infty}S_{13}(t)S_{11}(t-\tau_{13})d\tau \tag{16}$$

To find out the CCFs for N cardinalities (nodes), we have to take the total CHIRP signals received by the sensors.

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

$$S_{rt1}=\sum_{j=1}^{N}\alpha_{j1}S_j(t-\tau_{j1}) \tag{17}$$

$$S_{rt2}=\sum_{j=1}^{N}\alpha_{j2}S_j(t-\tau_{j2}) \tag{18}$$

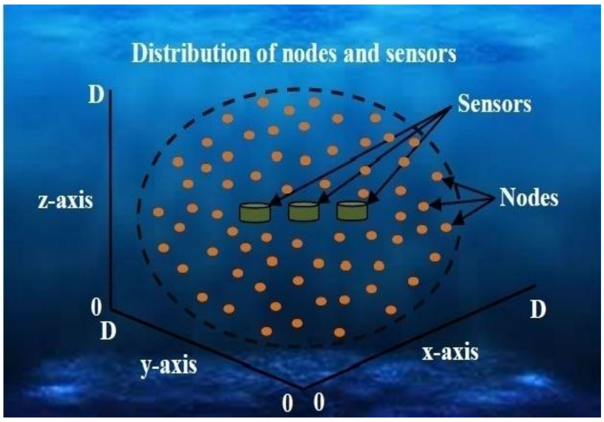


Figure 3: Distribution of underwater network cardinalities (nodes) with N transmitting cardinalities at three sensors SL case.

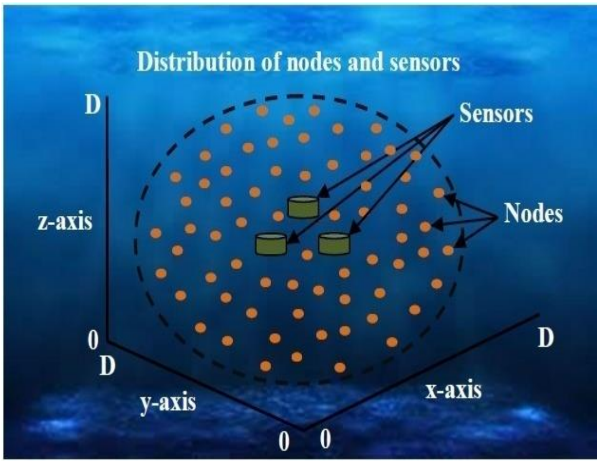


Figure 4: Distribution of underwater network cardinalities (nodes) with N transmitting cardinalities at three sensors TS case.

$$S_{rt3} = \sum_{j=1}^{N} \alpha_{j3} S_j (t - \tau_{j3}) \tag{19}$$

Therefore, the total CCFs are (for SL case):

$$C_{12}(\tau) = \int_{-\infty}^{+\infty} S_{rt1}(t) S_{rt2}(t-\tau) d\tau \tag{20}$$

$$C_{23}(\tau) = \int_{-\infty}^{+\infty} S_{rt2}(t) S_{rt3}(t-\tau) d\tau \tag{21}$$

And for TS case the additional CCF is:

$$C_{31}(\tau) = \int_{-\infty}^{+\infty} S_{rt3}(t) S_{rt1}(t-\tau) d\tau \tag{22}$$

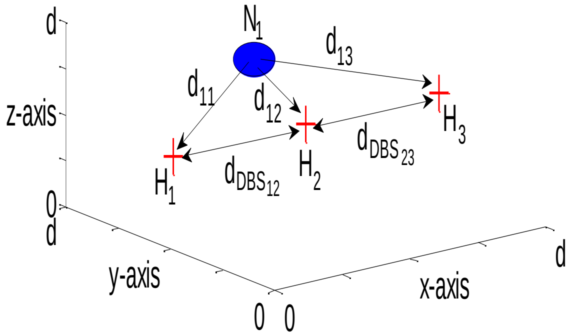


Figure 5: Underwater network with three sensors (+) and one cardinality (node) N_1 at SL case [20].

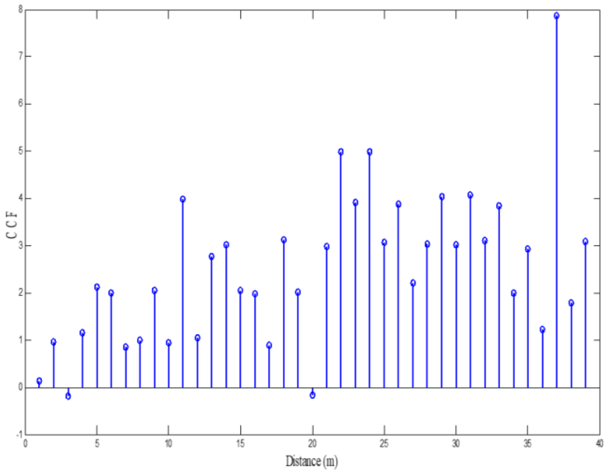


Figure 6: Bins, b in the cross-correlation process.

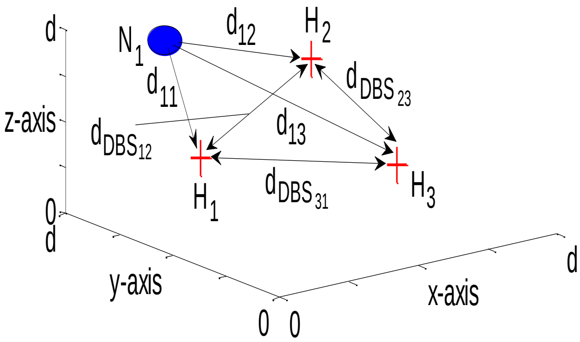


Figure 7: Underwater network with three sensors (+) and one cardinality (node) N_1 at TS case [20].

These take the form of a series of delta functions. Here,

$$\tau = d_{DBS} / S_p \tag{23}$$

3. Estimation Process Using CCF

In the past the cardinality estimation was performed by Gaussian signal [17, 18 and 19]. The ratio of standard deviation to mean was calculated there and used as the estimation parameter. But in this research, we use CHIRP signal and mean of CCF of the received signals as the estimation parameter. These two new attempts will reduce the complexity for both theoretical and simulation purposes.

3.1. CHIRP Signal

A swept-frequency signal named CHIRP Signal is a type of signal which has a time varying frequency. We can express it like: $X(t) = A * \cos(2 * pi * ((f_2 - f_1)t^2 / (2 * d) + f_1 * t + P))$ where f_1 signifies the starting frequency in Hz, f_2 signifies the ending frequency, d indicates time duration in seconds, P indicates the starting phase, and A is the amplitude [21].

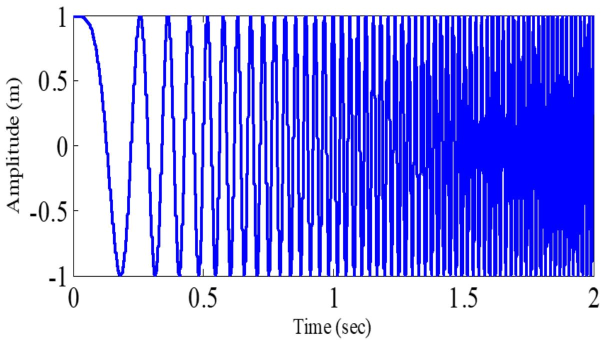


Figure 8: CHIRP Signal.

3.2 Theoretical Estimation of Underwater Network Cardinalities

It is acknowledged that the cross-correlation function follows the binomial probability distribution [18] in which the parameters are the number of cardinalities, N and the number of bins, b [18]. Then the expected value, i.e. the mean, m of the CCF is defined as [18].

$$m = \frac{N}{b} \tag{24}$$

Where b is the number of bins in the cross-correlation process and is achieved from the experimental setup with sampling rate, S_R, distance between sensors, d_{DBS}, and speed of propagation, S_P as [18]:

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

So, we can write:

$$N = b \times m \tag{26}$$

This is the relationship between the number of cardinalities, N and the mean, m of the CCF. Since b is known and m can be measured from the CCF, we can willingly determine the number of cardinalities, N. So, the theory for cardinality estimation from the mean of the CCF for three sensors cases is described below:

For three sensors SL case, the estimation parameter $m_{average}^{2CCF}$ is attained by taking mean, m_{12} and m_{23} from two CCFs. $m_{average}^{2CCF}$ can be expressed as:

$$m_{average}^{2CCF} = \frac{m_{12} + m_{23}}{2} = \frac{\frac{N}{b_{12}} + \frac{N}{b_{23}}}{2} \tag{27}$$

For three sensors TS case, the estimation parameter $m_{average}^{3CCF}$ is found by taking mean m_{12}, m_{23} and m_{31} from two CCFs. $m_{average}^{3CCF}$ can be expressed as:

$$m_{average}^{3CCF} = \frac{m_{12} + m_{23} + m_{31}}{3} = \frac{\frac{N}{b_{12}} + \frac{N}{b_{23}} + \frac{N}{b_{31}}}{3} \tag{28}$$

Now, $b_{12} = b_{23} = b_{31} = b$

As the number of bins, b is a function of d_{DBS}, S_R and S_P, so, it can be obtained for three sensors SL case,

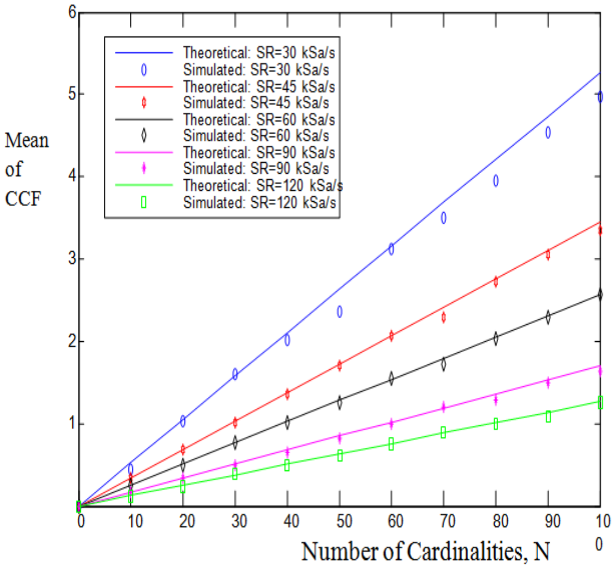
$$m_{avg.}^{2CCF} = \frac{m_{12}+m_{23}}{2} = \frac{N}{b} \tag{29}$$

Similarly, for three sensors TS case we found,

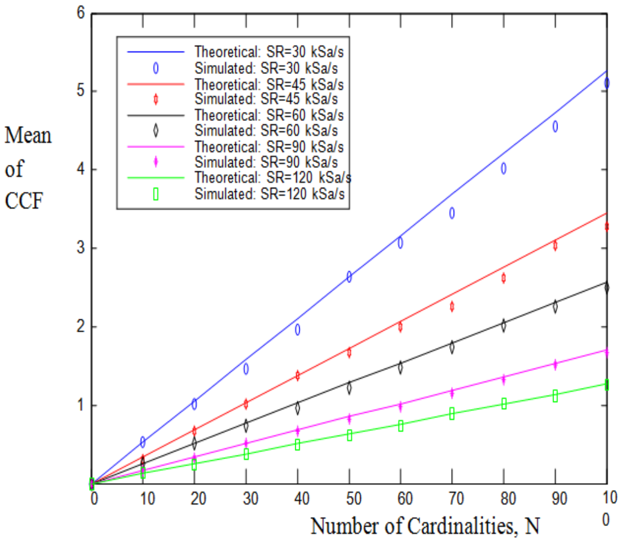
$$m_{avg.}^{3CCF} = \frac{m_{12}+m_{23}+m_{31}}{2} = \frac{N}{b} \tag{30}$$

4. Result and Discussions

The results of the underwater network cardinality (node) estimation come from the noble signal processing approach using cross-correlation are provided bellow:



(a)



(b)

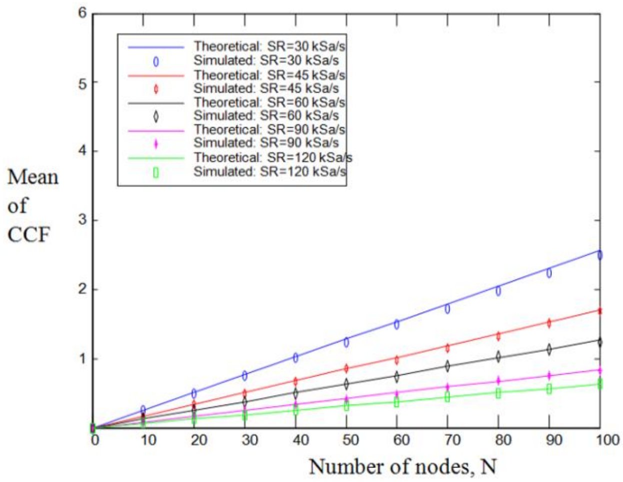


Figure 9: Mean of CCF versus the number of cardinalities (nodes) at different sample per second for (a) two sensors case, (b) three sensors SL case and (c) three sensors TS case.

Figure 9, shows that the theoretical and corresponding simulated results for the estimation of the number of underwater network cardinalities (nodes) in terms of the estimation parameters $m_{average}^{2CCF}$ & $m_{average}^{3CCF}$ of CCF, which displays that the simulations match the theory appropriately.

The parameter values used in this estimation process are: distance between the sensors d_{DBS} =0.5m (for both cases), signal propagation speed, $S_p = 1500\, {}^{m}\!/_{s}$ and the radius of the sphere is 2000 m.

Now, the comparison between the theoretical and simulated number of estimated cardinalities (nodes) (for bin number 39 and sampling rate 60 kSa/s) with respect to exact number of cardinalities (nodes) is shown in fig. 10.

For different sampling rates so as bins, different results of mean estimation process are found.

We have taken a constant 60,000 Sa/s as sample per second. The results of cardinality estimation are founded on it.

On the other hand, we consider five different sampling rates for mean graph (Figure 9) as: 30 kSa/s, 45 kSa/s, 60 kSa/s, 90 kSa/s, 120 kSa/s.

However, at the figures above, the solid line designates the theoretical results and the circles are corresponding to simulated results. From Figure 10, it can be seen that, the theoretical and simulated results are very close to each other, which signify the cogency of this research.

5. Conclusion

The proposed method can solve one of the major problems in underwater network cardinality (node) estimation called complexity problem. At the same time it is greatly suitable for harsh underwater environment.

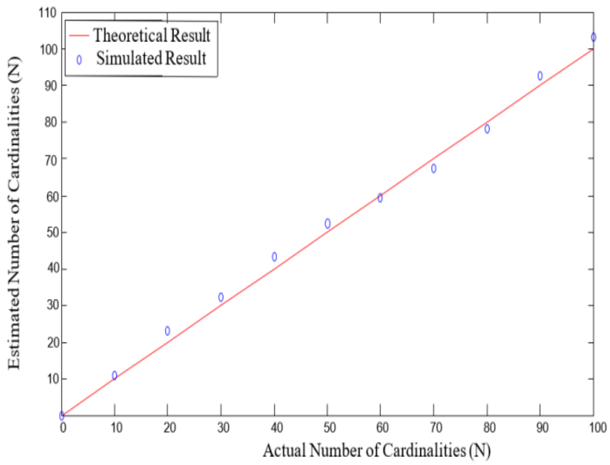
In this instance, CHIRP signal will ensure better propagation characteristics which will develop the practical efficiency more.

However, this method has some limitations like equal received power is considered and the delays are assumed to be integer.

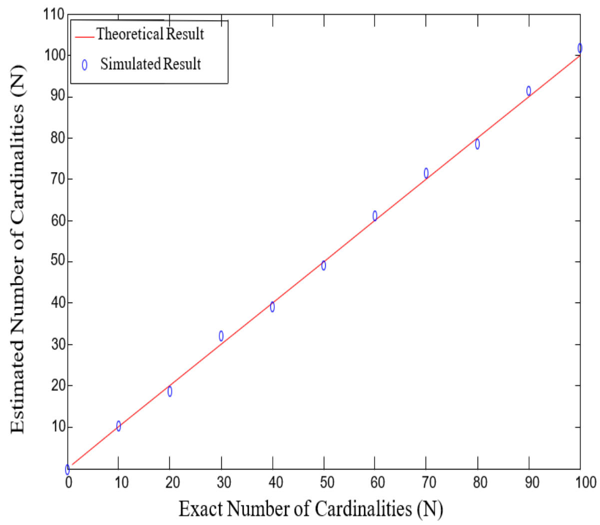
But after all, it is one of the most effective methods as not being human interactive.

6. Acknowledgements

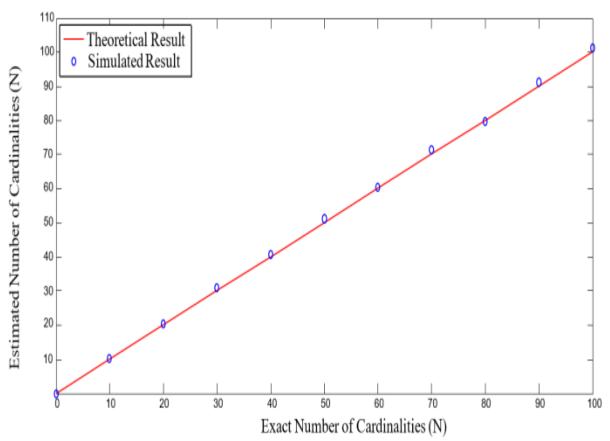
The authors are thankful to the Department of Electronics & Telecommunication Engineering of Rajshahi University of Engineering & Technology for providing computational resources for this work.



(a)



(b)



(c)

Figure 10: Comparison between theoretical and simulated number of cardinalities (nodes)for (a) two sensors case, (b) three sensors SL case & (c) three sensors TS case.(With respect to number of bins =39 & sampling rate= 60kSa/s).

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Biographies

Shaik Asif Hossain was born in Bangladesh on October 15, 1993. He received his B.Sc. in Engineering from the Department of Electronics & Telecommunication Engineering, Rajshahi University of Engineering & Technology, Bangladesh, in December 27, 2015. He is currently working towards M.Sc. In Engineering on Electronics & Communication Engineering at Khulna University of Engineering & Technology, Bangladesh. His research interests include Signal Processing, Wireless Sensor Network, Underwater Communication and Passive Optical Network

Avijit Mallik was born in Dhaka, Bangladesh in 1995. He is currently studying at final year of Mechanical Engineering in RUET, Rajshahi; the second oldest and one of the most reputed engineering university of Bangladesh. He has published several research and technical articles in reputed international journals and also attended 2 international conferences. He is currently working to design an automated gas leakage detection and control system which is a part of his undergraduate thesis.

Md. Arman Arefin was born in Rangpur, Bangladesh in 1994. He is also a final year student of Mechanical Engineering in RUET, Rajshahi. He has published several research and technical articles in reputed international journals and also attended 2 international conferences. He is currently working on solar-air and solar-water heating system which is a part of his undergraduate thesis.

How to cite this paper:

S. A. Hossain, A. Mallik, and Md. Arman Arefin "A signal processing approach to estimate underwater network cardinalities with lower complexity," Journal of Electrical and Computer Engineering Innovations, vol. 5, no. 2, pp. 131-138, 2017.

DOI: 10.22061/JECEI.2017.702

URL: http:// jecei.sru.ac.ir/article_702.html