IOP Conference Series: Materials Science and Engineering

PAPER • **OPEN ACCESS**

Compression-based Block Truncation Coding technique to Enhance the Lifetime of the Underwater Wireless Sensor Networks

To cite this article: Ghufran Ali M. Jawad *et al* 2020 *IOP Conf. Ser.: Mater. Sci. Eng.* **928** 032005

Compression-based Block Truncation Coding technique to Enhance the Lifetime of the Underwater Wireless Sensor Networks

Ghufran Ali M. Jawad, Ali Kadhum M. Al-Qurabat*, Ali Kadhum Idrees
Dept. of Computer Science, College of Science for Women, University of Babylon, Babylon, Iraq
*alik.m.alqurabat@uobabylon.edu.iq; 07802627087

Abstract
Minimizing the number of transmitted/received data represents a big challenge in Underwater Wireless Sensor Networks (UWSNs). Since the data sending/receiving represents the most energy consumer in the Underwater Wireless Sensor. Therefore, it is important to decrease it to save energy and improve the UWSN lifetime. This paper proposes a Compression based Block Truncation Coding (CBBTC) technique to minimize the volume of the transmitted measurements, save energy, thus improve UWSN's lifetime while maintaining the accuracy of the measurements received at the base station. The proposed approach operates inside the sensor nodes and designed to reduce data within each sensor node by compressing it, rather than transmitting the data raw to the cluster head (CH) to conserve the sensor energy. Our suggested technique is verified through experiments on actual data of UWSN and our proposed method is compared with other current approaches to show the superiority in terms of energy-saving, increasing UWSN's lifespan while the fidelity of data is kept.
Keywords— Underwater Wireless Sensor Networks (UWSNs), Data Compression, Energy-saving, Network lifetime.

1. INTRODUCTION

The underwater acoustic sensor network (UASN) or Underwater wireless sensor network (UWSN) represents a specific type of WSN consisting of acoustic nodes for underwater. UWSNs are diffused in a marine or underwater environment because of its ability to observe the surrounding environment. These networks are used in a variety of different applications and are considered as a solution for these applications, like seismic detection, a compilation of oceanographic data, location of mooring points and underwater wrecks, real-time warship tracking, disaster prevention or environmental surveillance, etc. [1]. The sensors in these networks are characterized by small size, restriction in available energy and memory [2,3]. Furthermore, acoustic signals are used in place of radio waves in the sensor nodes for their long-distance transportability due to their use of low frequencies. Sensors in UWSNs, therefore, use too much energy, unlike conventional sensor networks, because of the acoustic technologies utilized in underwater communication [1].

These networks are characterized by their capability to work without supervision in harsh environments where the involvement of human in surveillance schemes is dangerous and unavailing or maybe infeasible. Sensors are supposed to be distributed remotely in these networks, e.g. by clustered bombs or helicopters, in a large geographic region to surveillance environment changes, and to send the gathered data to a particular node named the (sink) [4]. However, sensors are energy-constrained and it is not possible or difficult to recharge or replace their batteries in these environments. Therefore, minimizing the energy usage of sensors is very important to prolong the life of the network as much as possible [5,6].

Since the sensors in the UWSN are powered by small batteries it is not always easy to recharge or replace. Saving energy is a big concern at UWSNs. For this reason, the volume of data transfer must be decreased to prevent overloading traffic on the network. There are many methods to reduce energy consumption and extend the lifetime of networks such as routing, estimation, prediction, clustering, and compression [7,8]. Data compression is one of the useful methods to decrease the volume of data transfer from sensor nodes to the corresponding sink. Sensors in the sensor field perform compression on the collected data in order to send few bits and the receiver will infer the correct data by decompression of transmitted data. The energy required for wireless transmission is reduced when reducing the size of data transmitted [4].

This paper presents the following contributions.

I. A Compression based Block Truncation Coding technique to reduce the size of the transmitted measurements, decrease the consumed energy, thus extend the network lifespan while retaining the accuracy of the measurements received at the base station is proposed. The compression technique exploits the high temporal correlation among the captured data of the underwater sensor nodes and remove the redundant data by the compression to decrease the communication cost of underwater nodes without affecting the received data at the base station.

II. The efficiency of the proposed technique is studied using sensed data from real underwater nodes. The simulation results illustrate the effectiveness of using Block Truncation Coding technique to decrease the volume of data and consumed energy of the UWSNs compared with other approaches.

The remainder of the paper is organized as follows: we describe the related works in Section 2. The proposed Compression-based Block Truncation Coding technique to enhance lifetime of UWSN is described in Section 3. The experimental results are presented in Section 4. Finally, Section 5 concludes our paper.

2. Related works

Many researches have been proposed in UWSN for minimizing the amount of data transmitted by reducing number of bits based on compression technique [9,10]. Compressing data before transmission is one of the major strategies for energy conservation and to prolong UWSNs lifetime.

The authors in [1] proposed a new method of clustering to manage the similarities between node readings spatially. They presume that readings are transmitted to their correct cluster-heads (CHs) regularly from sensor nodes. A two-tier methodology for aggregating data is then introduced. At the first stage, each node cleans its readings regularly to remove redundancies before submitting its collection of data to its CH. If the CH collects all data sets, an improved K-means algorithm based on an ANOVA one-way model is implemented to classify nodes producing similar data sets and combine these sets before they are sent to the sink.

The authors in [3] proposed a Two-Level Data Aggregation (TLDA) method to prolong the PSNs lifetime. TLDA functions in a periodic way. There are two stages of data aggregation in each period. At the sensor node, stage one of data aggregation is implemented. The main operations performed in stage one are gathering data, a variety of various segments with different lengths create by sliding window, and data aggregation using the Adaptive Piecewise Constant Approximation technique to minimize the volume of gathered data in every sensor. At the aggregator, stage two is implemented. This involves grouping obtained data sets with SAX quantization system based on the chaining hash table, identifying and minimizing duplicate sets, finding and integrating duplicate quantities, and sending aggregated data to the base station.

The authors in [11] proposed a cluster-based data aggregation method for energy-saving that operates at two levels and periodically sends data from nodes to their proper cluster heads (CHs). At the node itself, level one of data aggregation is utilized to remove redundant data from the raw data gathered while at level two, the CH tries to find nodes that create redundant sets of data depending on the study of variance using three different tests of Anova.

The authors in [12] proposed a cluster-based data reduction method for energy-saving that operates at two levels. In level one, at each period, the cluster-head (CH) receives a set of representative data from each sensor node rather than receiving the raw data. Once the CH collects data points, the Euclidean distance is used to remove data redundancy that neighboring sensor nodes produced, prior to actually transmitting them to the sink.

To increase data collection effectiveness, the author in [13] suggested a data-sharing decision-making approach dependent on the high similarity of the data collected and the energy usage of the high similarity data compression. Such a strategy of decision making enhances the energy usage of the networks efficiently. The decision-making strategy offers an energy-efficient data share strategy for underwater nodes, which minimizes energy usage in different network settings, by analyzing the uploading energy use, the quality of network communication, and the data similarity.

A new model for Mixed Integer Programming (MIP) is developed by [14] to achieve the maximum lifetime of the network by jointly considering energy harvesting (EH), compressive sensing (CS), and transmission power control (TPC) systems. Results of the performance show that when both methods are combined with TPC, the impact of CS on the network lifetime is higher than EH's. Furthermore, as all three methods are used, the lifespan of the network will be expanded up to three times as opposed to the case if not all three methods are used.

The authors in [15] introduced the dictionary-matrix-based discrete cosine transformation (DCT) for sparse representation. Additionally, the measuring matrix is enhanced for more effective sampling through the steepest descent method. Then we apply a method at the receiving terminal based on an estimated l_0 (AL0) norm to look for the incomplete solution using the steepest form of descent and projections. The sparse estimation is used for analysis, when combined with the calculation matrix and dictionary-matrix.

In [16] the author proposed an energy-efficient compressed data aggregation structure for 3D underwater acoustic sensor networks (UASN). The conceptual architecture consists of two layers aimed at reducing the overall energy consumption of node-sensitive data transmission. The lower layer is the compact layer of sampling, where nodes are separated into classes. Nodes are randomly chosen for sampling, and then send the data through random access channels to the heads of the cluster. The upper layer is the layer for data aggregation, where complete sampling is taken.

In this paper, A Compression based Block Truncation Coding technique is proposed to reduce the volume of the measurements, save energy, thus extend the lifetime while conserving the accuracy of the received measurements at the base station. The compression technique exploits the high temporal correlation among the captured data and removes the redundant data by the compression to decrease the communication cost of underwater nodes without affecting the received data at the base station.

3. The proposed Method

Throughout this part, we describe our processing method for sensor data, to be performed by sensors to reduce data points. Next, we introduce the topology of the network which we are considering in our method.

3.1. WSN topology

In this article, we assume the network to be built on cluster-based architecture. In this architecture, the sensor nodes are grouped into clusters and selecting a super-node for each cluster as a cluster-head (CH). During the deployment of the network, the CH is selected and can be continuously altered over the lifespan of the network. The CH can be a special powerful node or a normal one. Transmission of data from sensor nodes to the corresponding CH is dependent on single-hop communication as shown in Fig. 1. In this article, a periodic fashion of data gathering is used, where the gathered data is sent periodically by each node to the corresponding CH, and then the CH transmits them to the sink. After that, we suggest an energy-efficient approach that compresses data at the level of the sensor node.

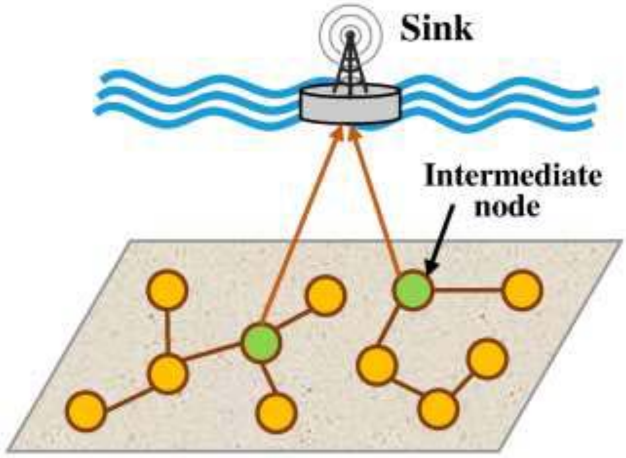

Figure 1. WSN clustering based topology.

3.2. A compression based BTC technique

For every period, a vector of measurements is gathered by every sensor node and then transmit it to the CH in the periodic applications as follows: $R_i = [r_1, r_2, \dots, r_{\tau-1}, r_\tau]$ where τ represents the cumulative number of measurements that were gathered in the period ρ. Mostly, measurements gathered from the sensor in every period, i.e. in R_i, are redundant depending on how the monitored conditions vary. Thus, searching data redundancy in each sensor become crucial to decrease the number of measurements transmitted and to keep the energy of the sensor. Hence, our objective, is to reduce the size of R_i by compressing it using Block Truncation Coding (BTC) method.

E. J. Delp and O. R. Mitchell have developed the Block Truncation Coding (BTC) technique in 1979 [17]. Many enhanced and updated versions of BTC were produced. This technique is commonly utilized in image processing and it is a lossy compression. In our proposed method, the BTC is used to reduce the transmission of data for UWSN. In most cases, a UWSN's sensors are clustered into non-overlapping clusters for connectivity that is reliable and energy conserving. Generally, due to the gradual change in the conditions surrounding the sensor nodes, the intra-sensor measurements collected are often very temporally correlated. This aspect encourages BTC's application to the datasets obtained. The data encoded by BTC is transmitted to the CH in which it is decoded. Such compression of the data in-network decreases the transmitting burden of the sensor nodes and in turn expands their lifespan [2,3]. The volume of the data is decreased due to compression and thus the transmitting load is decreased. Fig. 2 shows the flow chart of the proposed method.

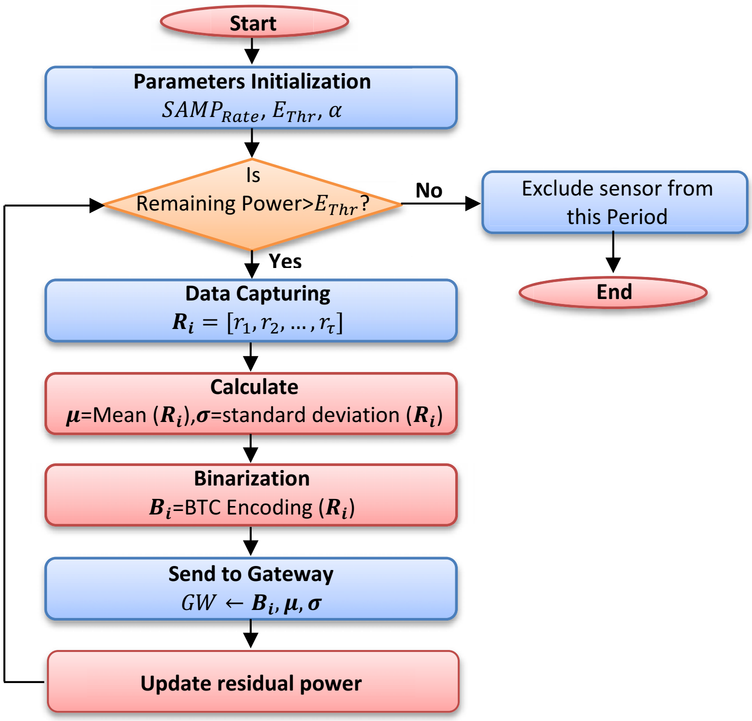

Figure 2. Flow chart of the proposed method.

3.2.1. BTC Encoding (Binarization) of Sensor Data

Take into account the transmission of data from the sensor node to the CH (see Figure 1). The sensor node has collected R_i data measurements. The whole data R_i will be sent to the CH if we don't use BTC encoding. Whereas, when the sensor node uses the BTC on the gathered measurements, only the compressed version of R_i will be sent to the CH. Let μ and σ represent the mean and standard deviation of R_i, that the sensor node computes as in the following Equations:

$$\mu = \frac{1}{\tau} \sum_{j=1}^{\tau} r_j \tag{1}$$

$$\sigma = \sqrt{\frac{1}{\tau} \sum_{j=1}^{\tau} (r_j - \mu)^2} \tag{2}$$

The binarization of vector R_i is obtained as,

$$b_j = \begin{cases} 1 & if \;\; r_j > \mu \\ 0 & otherwise \end{cases} \tag{3}$$

For j = 1, 2, ..., τ. The binary encoded vector is designated as, $B_i = [b_1, b_2, \dots, b_\tau]$. The elements of B_i are 0's and 1's. Algorithm 1 shows the BTC compression technique at the underwater sensor node.

Algorithm 1: BTC Compression

Require: **R**: $sensor\ data\ contains\ \boldsymbol{\tau}\ measurements$
Ensure: $\boldsymbol{B}$: $binary\ encoded\ vector$

$sum \leftarrow 0, sum_1 \leftarrow 0$
$\boldsymbol{for}\ i \leftarrow 1\ to\ \tau\ \boldsymbol{do}$
    $sum = sum + r_i$
$\boldsymbol{endfor}$
$\boldsymbol{\mu} \leftarrow sum/\tau$
$\boldsymbol{for}\ i \leftarrow 1\ to\ \tau\ \boldsymbol{do}$
    $sum_1 = sum_1 + (r_i - \mu)^2$
$\boldsymbol{endfor}$
$\boldsymbol{\sigma} = \sqrt{sum_1/\tau}$
$\boldsymbol{for}\ i \leftarrow 1\ to\ \tau\ \boldsymbol{do}$
    $\boldsymbol{if}\ (r_i > \mu)\ \boldsymbol{then}$
        $b_i \leftarrow 1;$
    $\boldsymbol{else}$
        $b_i \leftarrow 0;$
    $\boldsymbol{endif}$
    $B \leftarrow b_i$
$\boldsymbol{endfor}$
$return\ B, \mu, \sigma$

3.2.2. BTC decoding (Decompression) of the Sensor Data

Two essential factors of BTC operation are the High Mean value H and the Low Mean value L. The H and L values are determined according to the sensor node as in the following Equations:

$$H = \mu + \sigma \times \sqrt{\frac{p}{q}} \tag{4}$$

$$L = \mu - \sigma \times \sqrt{\frac{q}{p}} \tag{5}$$

Where p and q are the number of 0's and 1's in the compressed data respectively. After calculating H and L, the CH decoder decompresses the vector B_i data using H and L as in the following Equation:

$$c_j = \begin{cases} L & if \quad b_j = 0 \\ H & if \quad b_j = 1 \end{cases} \tag{6}$$

For j = 1, 2, ..., τ. Here c_j is the ith element of the reconstructed vector C_i. Vector C_i is the sequence of c_j's as $C_i = [c_1, c_2, \dots, c_\tau]$. The decompressed (decoded) data C_i in BTC only has two values H and L and C_i represents the quantized approximation of the original data. Algorithm 2 shows the BTC decompression technique at the underwater sensor node.

Algorithm 2: BTC Decompression

$Require$: $\boldsymbol{B}$: $binary\ encoded\ vector\ with\ \boldsymbol{\tau}\ elements, \boldsymbol{\mu}$: $mean, \boldsymbol{\sigma}$: $standard\ deviation$

Ensure: **C**: *Reconstructed data readings*

```
for i ← 1 to τ do
    if (b_i = 1) then
        q ← q + 1
    else
        p ← p + 1
    endif
endfor
H = μ + σ × √(p/q)
L = μ − σ × √(q/p)
for i ← 1 to τ do
    if (b_i = 0) then
        c_i ← L
    else
        c_i ← H
    endif
    C ← c_i
endfor
return C
```

3.2.3. Sensor to CH Data Compression Ratio

Let m bits be the size of the data element r_i. Now, if we don't use BTC encoding, the packet's total data size with N data elements in bits is:

$$\text{Packet Size without } BTC = N \times m \tag{7}$$

Whereas, when the sensor node uses the BTC on the gathered measurements, the data sent to the CH contains the binary vector B_i of size N bits, μ and σ of size m bits each. So,

$$\text{Packet Size with } BTC = 2 \times m + N \tag{8}$$

Consequently, the BTC compression ratio is,

$$CR = \frac{Packet\ size\ wihout\ BTC}{Packet\ size\ with\ BTC} = \frac{N \times m}{2 \times m + N} \tag{9}$$

3.2.4. Illustrative Example

Let the data sequence be, $R_i = [23, 24, 24.5, 23, 25, 23, 20.5, 21.5]$. Here, τ is 8 which represents elements number. The calculation of mean is μ = 23.0625 and the standard deviation is σ = 1.4017. Hence B_i, is computed using Equation 3 as follows: B_i = [0 1 1 0 1 0 0 0].

After that, H and L are computed using Equations 4 and 5 as, H = 24.78 and L = 21.97. Replacing H for 1's and L for 0's in B_i will give the decompressed data by, C_i= [L, H, H, L, H, L, L, L].

Approximating H and L to their closest integer, we get, C_i = [22, 25, 25, 22, 25, 22, 22, 22].

Supposing the size of the data of each element in R_i is 8-bit, and the number of elements in R_i is 8, so the size of R_i is 8*8=64 bits. The data compressed includes the binary vector B_i of size 8 bits, μ, and σ of size 8 bits each. So, the size of data compressed is 8+8+8=24 bits. The ratio of compression is (64)/(24) = 2.667. It is the ratio of compression for the transmitted data to the CH using BTC technique.

4. EXPERIMENTAL RESULTS

We introduce the simulation findings of our proposed method at the level of the sensor node, in this section. We demonstrate the efficiency of our proposed method in energy-saving and reducing the tremendous volume of data, thereby increasing the network lifespan of real UWSNs, by simulation on real data. The actual data gathered by the Argo project [18] is used in this article. Argo has distributed over 3000 sensors spread across the world's oceans gathering readings of temperature and salinity from the upper $2000\ m$ of depth. In this article, we are focused on 240 sensors that are spread over a region of $5000 * 5000m^2$ in the Indian Ocean. These nodes are then grouped into three clusters of sensors $N_1 = 40$, $N_2 = 80$, and $N_3 = 120$ respectively. So, every node reads actual measurements periodically while implementing the Compression method to its measurements. Every sensor node at the end of this process transmits its set of compression measures to the CH. We are focused on one sensor measurement area in this paper: the temperature. We assessed our proposed method with the following performance measures being taken into account: Ratio of remaining data after aggregation/compression, compression ratio, data accuracy, Percentage of data Sent to the CH, energy consumption and lifetime. Besides, we compared our results to those of Harb [1] and PFF [19] results.

4.1. Ratio of remaining data after aggregation/compression

Using data aggregation/ compression, every sensor node is capable of reducing the total number of data gathered at each period by removing redundancy from it. Fig. 3 indicates the data percentage residual that will be forwarded to the CH with and without the node-level aggregation/compression process. The results obtained indicate that, in the worst-case situation, the percentage of residual data at each sensor node, e.g. $T = 200$, are $CBBTC = 2\%$ and $Harb = 24\%$ of its collected data after the aggregation/compression process has been implemented, contrasted with $PFF = 100\%$ of the data obtained without using it. The results show good behavior by each sensor node in terms of removing redundancy in the data. Eventually, we can notice that when T rises, the aggregation/compression phase removes so much data redundancy, because more similar measures will be found at each period.

IOP Conf. Series: Materials Science and Engineering **928** (2020) 032005 doi:10.1088/1757-899X/928/3/032005

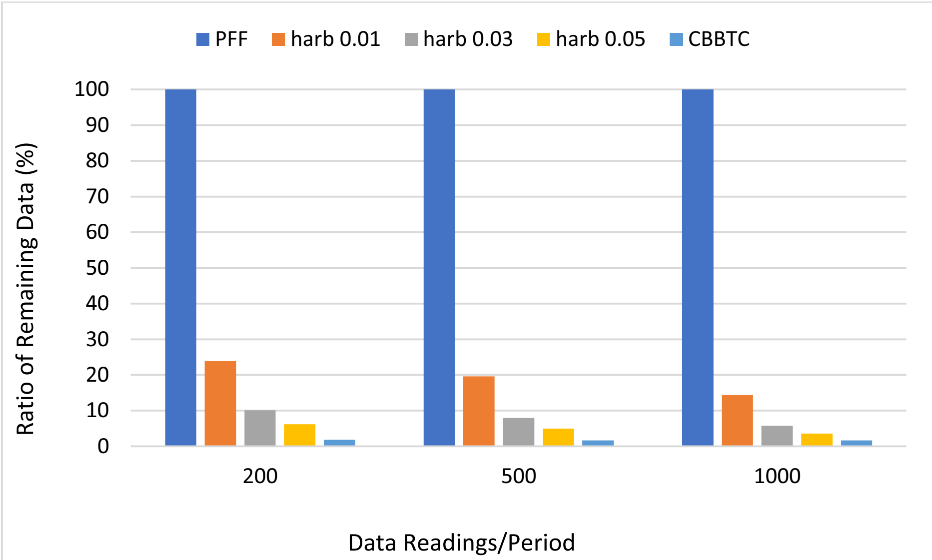

Figure 3. Ratio of remaining data.

4.2. Compression Ratio

Generally, the performance of any compression algorithm is calculated by the use of compression ratio (CR) and is equated as

$$CR = 100 * \left(1 - \frac{no.of\ bits\ in\ compressed\ data}{no.of\ bits\ in\ uncompressed\ data}\right) \tag{10}$$

Figure 4 indicates the results obtained for total compression ratio, while the total number of sensor measurements differs utilizing various methods (PFF, Harb, and CBBTC). In almost all instances, CBBTC provides better performance with respect to mean compression ratios as shown in Figure 4. The findings of the analysis reveal that the compression ratio achieved are 98.3875% and 96.41% when applying CBBTC and Harb respectively. In contrast to PFF with 0% because no compression / aggregation is applied in it. Please remember that, mean μ and standard deviation σ of measurements are always submitted without compression in each data set.

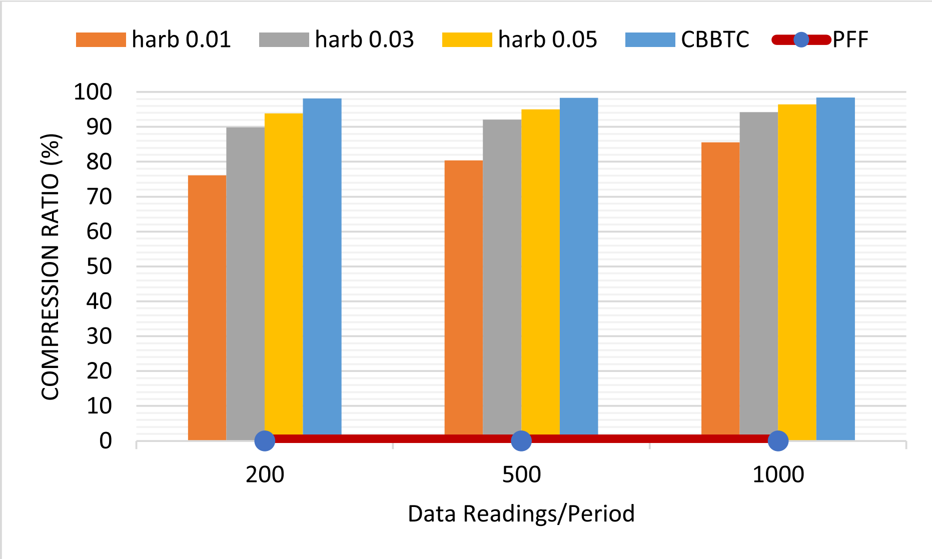

FIGURE 4. Compression Ratio.

4.3. Data Accuracy

The accuracy of data is an essential aspect to consider in WSN, as it directly impacts end-user decision-making. It reflects the proportion of lost measures. It is an assessment of the measures taken by the sensor nodes and has not arrived at the CH nor their similar values. In this article, we used PRD and RMSE to calculate the accuracy of data, as in the following Equations:

$$PRD = \sqrt{\frac{\sum_{\tau}(x(n) - \bar{x}(n))^2}{\sum_{\tau}(x(n))^2}} \tag{11}$$

$$RMSE = \sqrt{\frac{\sum_{\tau}(x(n) - \bar{x}(n))^2}{N}} \tag{12}$$

Where, x is the original data, $\bar{x}$ is the decompressed data, and τ is the number of data measurements.

Table 1 demonstrates the RMSE, PRD and accuracy values between the decompressed data and the original data by utilizing the CBBTC method.

Table 1. Data Accuracy between original and decompressed data.

	Data Readings		
	200	500	1000
RMSE	0.0451255	0.106387	0.138559
PRD	0.0000917	0.000136673	0.000125881
Accuracy	99.0831	95.9736	99.7804

In almost all instances, CBBTC provides better performance with respect to data accuracy. The results show the efficiency of our proposed method in terms of its slight (insignificant) loss of data. Our proposed method gives greater resemblance between the decompressed data and the original data.

Figure 5 shows the process of decompressing the data in the CH for one period using the CBBTC method. From the figure we can find that the decompressed data is very close to the original data.

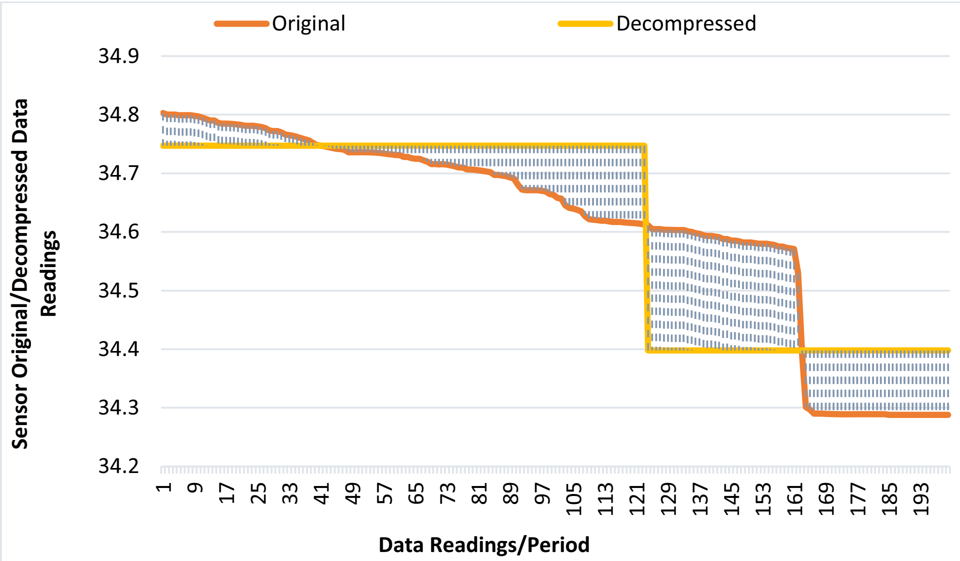

Figure 5. Decompressing data at CH for one period.

4.4. Percentage of data Sent to the CH

In this experiment, the performance of the proposed compression methods is assessed using another criterion, which is the ratio of sent data sets to the CH. Due to the fact that the data readings of UW sensors, which necessary to be sent, are grow explosively; therefore, we need methods to send as little sensor data readings as possible. It is noted that reducing the amount of data (compressing data) have a direct impact on the cost of communication (in terms of energy) for UWSN sensors. Figure 6 demonstrates the ratio of sent data sets to the GW with and without utilizing data compression/aggregation by each UW sensor node based on the following various techniques (CBBTC, PFF and Harb).

Our proposed method does not decrease the number of data transmitted to the CH, but rather represents it (encode it) with another method of lesser volume. The ratio of number of data sent according to the proposed method is 100% with total size is 1.27 KB, compared to 24% with total size is 16,875 KB using Harb method and 100% with total size is 70.31KB using PFF method.

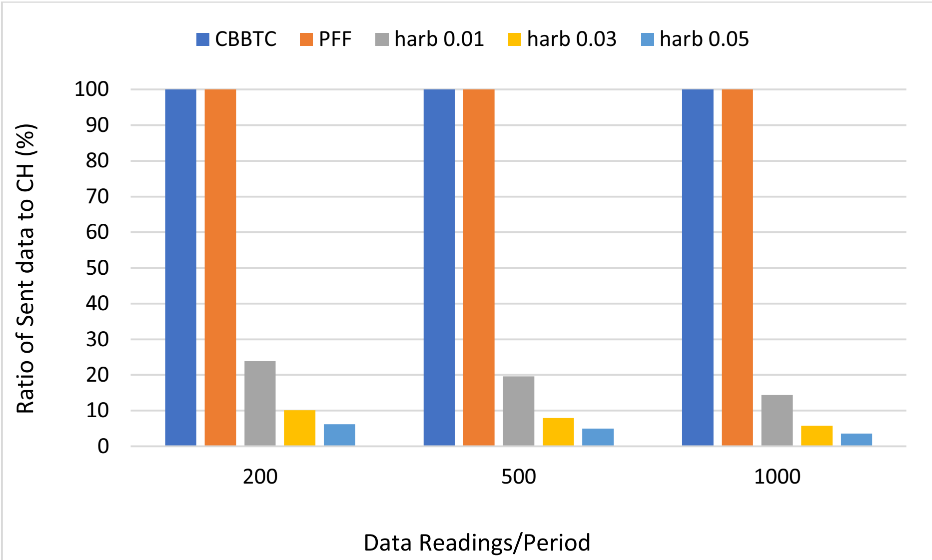

Figure 6. Ratio of sent data to CH.

4.5. Energy Consumption

Lowering the number of data sent can significantly decrease the sensor's energy consumption and prolong its lifetime. Our proposed method lowers overhead by compressing data measures at the level of the sensor node. We have used the same radio model as in [20] to assess energy consumption. For this model, $E_{elec} = 50\, n_j/bit$ is dissipated by a radio to power the receiver or transmitter circuitry and $\beta_{amp} = 100\frac{p_j}{bit}/m^2$ for the amplifier of the transmitter. The cost of transferring a message of size k-bits for a d distance is calculated as shown in the following equation:

$$E_{TX}(k,d) = E_{elec} * k + \beta_{amp} * k * d^2 \tag{13}$$

Figure 7 demonstrates the relation of energy usage with and without the aggregation/compression methods being implemented by each sensor node and when T differs. Given that aggregation/compression methods dramatically minimize redundancy from data obtained by the sensor node (see Figure 3), it enables it to save its energy proportionally when transmitting its data to the CH at each period. It should be noted that our proposed method can retain the energy of a sensor node up to 97% and 88% compared to PFF and Hard respectively.

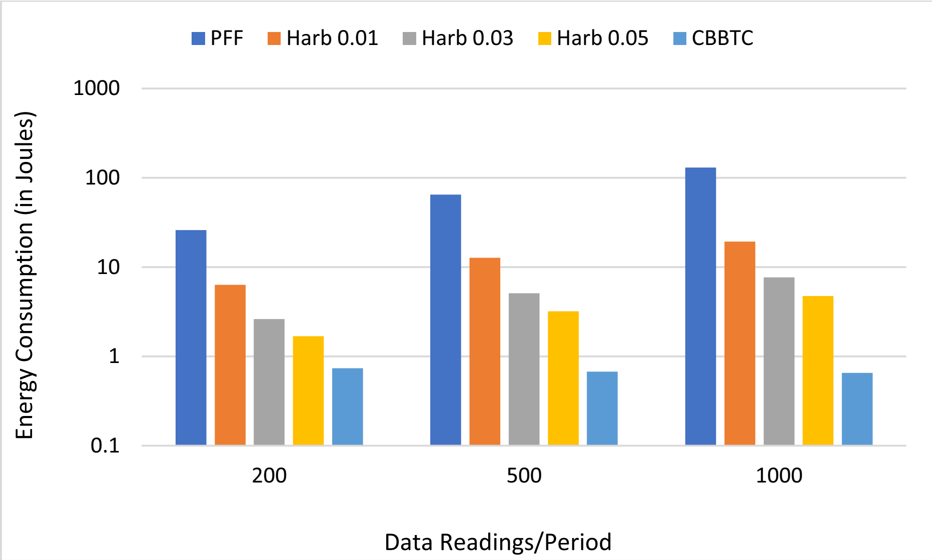

Figure 7. Energy consumption.

4.6. Lifetime

Eventually, we research the effect of data gathering and transmitting on the lifespan of UWSN. As seen in Figure 8, the CBBTC technique provides a longer lifespan of the network as opposed to other methods. In this comparison, each sensor node started its energy to $30mJ$ for all techniques.

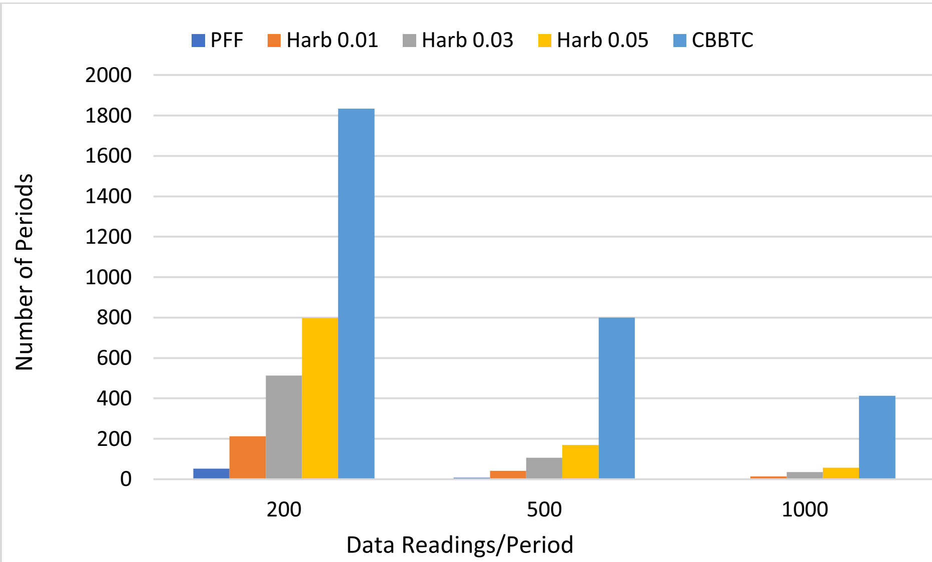

Figure 8. Lifetime of sensor node.

The CBBTC technique increases sensor node lifespan by up to 88% and 97% compared to the Harb and PFF techniques respectively. These findings are got because of the ability of the CBBTC technique in the preservation of the sensor's energy while increasing the lifespan of the UWSN.

5. CONCLUSION

While research into underwater acoustic sensor networks has advanced significantly in recent decades, energy consumption remains the primary constraint to be optimized. In this article, we propose a Compression based Block Truncation Coding (CBBTC) technique to minimize the volume of the transmitted measurements, save energy, thus improve UWSN's lifespan while maintaining the accuracy of the measurements received at the CH. The proposed approach operates inside the sensor nodes and designed to reduce data within each sensor node by compressing it, rather than transmitting the data raw to the CH to conserve the sensor energy. Our suggested technique is verified through experiments on actual data of UWSN and our proposed method is compared with other current approaches to show the superiority in terms of energy-saving, increasing UWSN's lifespan while the fidelity of data is kept.

As future work, we suggest methods to reduce data transmitted at multi-levels: sensor nodes, cluster head, and base station by utilizing optimization methods, machine learning, and artificial intelligence.

6. References

1. Harb H, Makhoul A, Couturier R. An enhanced K-means and ANOVA-based clustering approach for similarity aggregation in underwater wireless sensor networks. IEEE Sensors Journal. 2015 Jun 10;15(10):5483-93.
2. Al-Qurabat AK, Jaoude CA, Idrees AK. Two Tier Data Reduction Technique for Reducing Data Transmission in IoT Sensors. In2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC) 2019 Jun 24 (pp. 168-173). IEEE.
3. Al-Qurabat AK, Idrees AK. Two level data aggregation protocol for prolonging lifetime of periodic sensor networks. WIREL NETW. 2019 Aug 1;25(6):3623-41.
4. Takaishi D, Nishiyama H, Kato N, Miura R. Toward energy efficient big data gathering in densely distributed sensor networks. IEEE transactions on emerging topics in computing. 2014 Apr 17;2(3):388-97.
5. Al-Qurabat AK, Idrees AK. Energy-efficient adaptive distributed data collection method for periodic sensor networks. IJITST. 2018;8(3):297-335.
6. Al-Qurabat A, Idrees A. Distributed data aggregation protocol for improving lifetime of wireless sensor networks. Qalaai Zanist Scientific Journal. 2017;2(2):204-15.
7. Idrees AK, Al-Qurabat AK. Distributed Adaptive Data Collection Protocol for Improving Lifetime in Periodic Sensor Networks. IAENG Int J Comput Sci. 2017 Sep 1;44(3).
8. Al-Qurabat AK, Idrees AK. Distributed data aggregation and selective forwarding protocol for improving lifetime of wireless sensor networks. J. Eng. Appl. Sci. 2018;13(5 S1):4644-53.
9. Al-Qurabat AK, Idrees AK. Adaptive data collection protocol for extending lifetime of periodic sensor networks. Qalaai Zanist Scientific Journal. 2017 Apr 10;2(2):83-92.
10. Idrees AK, Al-Qurabat AK, Jaoude CA, Al-Yaseen WL. Integrated Divide and Conquer with Enhanced k-means technique for Energy-saving Data Aggregation in Wireless Sensor Networks. In2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC) 2019 Jun 24 (pp. 973-978). IEEE.
11. Harb H, Makhoul A, Laiymani D, Bazzi O, Jaber A. An analysis of variance-based methods for data aggregation in periodic sensor networks. InTransactions on large-scale data-and knowledge-centered systems XXII 2015 (pp. 165-183). Springer, Berlin, Heidelberg.

IOP Conf. Series: Materials Science and Engineering **928** (2020) 032005 doi:10.1088/1757-899X/928/3/032005

12. Mortada M, Makhoul A, Jaoude CA, Harb H, Laiymani D. A Distributed Processing Technique for Sensor Data Applied to Underwater Sensor Networks. In2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC) 2019 Jun 24 (pp. 979-984). IEEE.
13. Huang X, Sun S, Yang Q. Data Uploading Strategy for Underwater Wireless Sensor Networks. Sensors. 2019 Jan;19(23):5265.
14. Erdem HE, Yildiz HU, Gungor VC. On the lifetime of compressive sensing-based energy harvesting in underwater sensor networks. IEEE Sensors Journal. 2019 Feb 21;19(12):4680-7.
15. Wu FY, Yang K, Duan R, Tian T. Compressive sampling and reconstruction of acoustic signal in underwater wireless sensor networks. IEEE Sensors Journal. 2018 May 23;18(14):5876-84.
16. Lin H, Wei W, Zhao P, Ma X, Zhang R, Liu W, Deng T, Peng K. Energy-efficient compressed data aggregation in underwater acoustic sensor networks. Wireless networks. 2016 Aug 1;22(6):1985-97.
17. Delp E, Mitchell O. Image compression using block truncation coding. IEEE transactions on Communications. 1979 Sep;27(9):1335-42.
18. Argo project, http://www.argo.ucsd.edu/index.html.
19. Bahi JM, Makhoul A, Medlej M. A two tiers data aggregation scheme for periodic sensor networks. AD HOC SENS WIREL NE. 2014 Jan 1;21(1-2):77-100.
20. Heinzelman WR, Chandrakasan A, Balakrishnan H. Energy-efficient communication protocol for wireless microsensor networks. In Proceedings of the 33rd annual Hawaii international conference on system sciences 2000 Jan 7 (pp. 10-pp). IEEE.