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SVD Compression and Energy Harvesting based Energy Efficient 3D-MI-UWSNs

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Abstract—In underwater wireless sensor networks (UWSNs), the limited availability and non-rechargeability of sensor node batteries necessitated the advancement of energy optimization techniques. Optimal clustering is one such technique that reduces the energy consumption of the networks. In this letter, we propose optimal cluster compression technique jointly with energy harvesting. In optimal clustering compression, we perform optimal clustering of networks with singular value decomposition (SVD) as compression technique to reduce the redundant data generated at the cluster heads (CHs). Besides, adopting energy harvesting technique, node batteries are periodically recharged. The performance of the proposed model is evaluated in terms of network lifetime and throughput.

1. INTRODUCTION

Nowadays, underwater wireless sensor networks (UWSNs) have demonstrated strength in various underwater applications like marine hydro-logical data collection, water quality monitoring, marine pollution detection, disaster prevention, etc. Due to the challenging underwater environment condition and immense system costs, the deployment of UWSNs is much arduous in comparison to terrestrial wireless sensor networks (WSNs). Generally, in underwater, acoustic communication is most versatile and widely used because of longer propagation distance. However, it is adversely affected by low communication bandwidth, long propagation delay, high error rate, and channel fading and hinder communication as well. So to address all these shortcomings, magnetic induction (MI) communication is a promising communication paradigm for underwater applications [1, 2]. The energy efficient design of MI underwater sensor network (MI-UWSNs) is required because it consists of many sensor nodes, and these nodes are battery driven. Optimal clustering and data compression technique are the two techniques that can make the system energy efficient [3].

In the literature, many methods have been proposed for energy efficient design of the UWSNs based on radio frequency, magnetic communication, and acoustic wave. In [4], the authors have proposed the concept of a 3-dimensional (3D) multi-layer transceiver coil structure for magnetic induction communication. The performance of the proposed method is analyzed in terms of power received and the maximum achievable communication range. In [5], the authors have investigated the use of a motor-driven rotating permanent magnet as a mechanical transmitter for undersea MI communication. Further, they have also analyzed the frequency dependency on power consumption and power-efficient operating frequency range of the mechanical transmitter. In [6, 7], the authors have designed a transceiver and relay induction coils for energy efficient and fully linked underwater wireless communication networks. In [8], the authors have modeled MI communication channel and performed the theoretical analysis and numerical evaluations based on its propagation characteristics. In [9], the

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authors have developed a technique to reduce the redundancy present in an image signal using K-means clustering. In [10], the authors have focused on reducing the network energy consumption and prolonging the network lifetime using optimal node deployment strategy in Voronoi UWSNs. In [11], the authors presented a novel data gathering scheme in clustered large-scale UWSNs.

From the above literature review, we observe that all the previous works have been performed for the design of energy efficient UWSNs on either clustering technique or data compression. Additionally, it is also inferred from literature review that no one had considered the impact of external noise on the performance of MI-UWSNs. In this presented work, we analyze the optimal clustering compression jointly with energy harvesting for noisy channel.

The primary contributions of the proposed work are as follows;

(i) Analytical formulation of optimal clustering for MI based 3D-UWSNs with consideration of M-QAM (quadrature amplitude modulation) at sensor nodes for a noisy channel.

(ii) Implementation of algorithms for data compression using singular value decomposition (SVD) for MI based 3-D UWSNs.

(iii) Employing energy harvesting technique to achieve additional energy efficiency.

2. NETWORK MODEL

In this work, we consider the scenario of clustered UWSNs, in which hundreds of MI homogeneous sensor nodes with energy-harvesting capabilities are deployed in $M \times M \times M$ cubic volume and are partitioned into small equal segments called clusters. A time invariant additive white Gaussian noise (AWGN) channel is taken in account for communication between the nodes. M-ary quadrature amplitude modulation (M-QAM) technique is employed in this network. Fig. 1 shows the energy dissipation system model of 3D-MI-UWSNs.

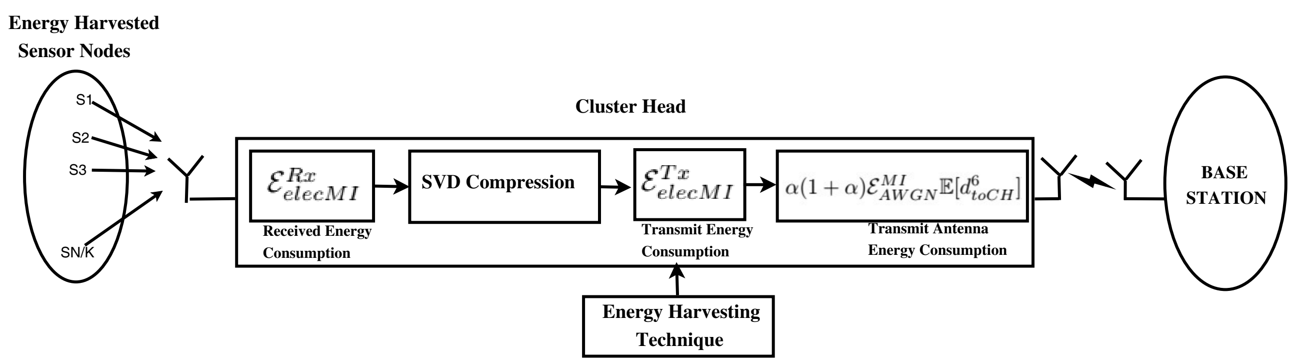


Figure 1. Energy dissipation system model of 3D-MI-UWSNs.

We assume that $\mathcal{N}$ number of sensor nodes are deployed in $M \times M \times M$ cubic volume of side length M to observe an event of interest. Further, assume that $\mathcal{N}$ sensor nodes are distributed into $\mathcal{K}$ balanced clusters so that in every cluster there are $\lfloor \frac{\mathcal{N}}{\mathcal{K}} \rfloor$ nodes where $\lfloor\ \rfloor$ denotes the rounded down to the nearest positive integer. In each cluster, one sensor node will act as CH and remaining $(\frac{\mathcal{N}}{\mathcal{K}} - 1)$ nodes will act as non cluster head nodes (Non-CH). The Non-CH nodes sense data from the underwater media (depends on application) and expend E_{NonCH} amount of energy for forwarding L bits of data to the CH. Further, the CH uses SVD data compression technique to reduce the redundant information present in the data received by Non-CH and finally transmit this to the BS. The purpose of using SVD compression technique is to remove not only the redundant information but also the information that is less relevant.

Let we consider that in each cluster, sensed data from $(\frac{\mathcal{N}}{\mathcal{K}} - 1)$ cluster member nodes and CH node taken over t time instants need to be transmitted via the CH to base station (BS) for a given application. If we arrange this set of input data in the form of a matrix X, where each row of X represents the sensed data taken from given sensor nodes at each time instant. Equation (1) represents the convenient form to represent the data matrix X. Further, to compress the data, matrix X can be decomposed into three matrices by enforcing the SVD that can be U, V, Σ and represented as Equation (1) [12]

$$X^{m\times t} = U^{(m\times m)}\Sigma^{(m\times t)}V^{(t\times t)} \tag{1}$$

where Σ is called as the diagonal matrix, which contains the highest to the lowest singular values (SVs) of X.

In SVD technique, many matrices that exist show that some types of structure contain only a few SVs which leads to accomplishing data compression. Keeping only the SVs found to be significant in matrix Σ increases the chance of getting good approximation of matrix X in such cases. Suppose that if r significant SVs are to be hold in Σ, and assume that matrix XR represents the approximated matrix X. Then, matrix XR can be evaluated by replacing Σ by Σ' given in [12]

$$XR = U\Sigma' V \tag{2}$$

where every matrix can be divided in to submatrices as

$$\begin{aligned}
XR &= \begin{bmatrix} XR_{11}^{(r\times r)} & XR_{12}^{(r\times(t-r))} \\ XR_{21}^{((m-r)\times r)} & XR_{22}^{((m-r)\times(t-r))} \end{bmatrix} \\
U &= \begin{bmatrix} U_{11}^{(r\times r)} & U_{12}^{(r\times(m-r))} \\ U_{21}^{((m-r)\times r)} & U_{22}^{((m-r)\times(m-r))} \end{bmatrix} \\
V &= \begin{bmatrix} V_{11}^{(r\times r)} & V_{12}^{(r\times(t-r))} \\ V_{21}^{((t-r)\times r)} & V_{22}^{((t-r)\times(t-r))} \end{bmatrix}, \quad \Sigma' = \begin{bmatrix} \Sigma_{11}^{(r\times r)} & 0 \\ 0 & 0 \end{bmatrix}
\end{aligned}$$

After doing matrix multiplications in Equation (2) using above matrix, we can express matrix XR as

$$\begin{bmatrix} XR_{11} & XR_{12} \\ XR_{21} & XR_{22} \end{bmatrix} = \begin{bmatrix} U_{11}\Sigma_{11}V_{11} & U_{11}\Sigma_{11}V_{12} \\ U_{21}\Sigma_{11}V_{21} & U_{21}\Sigma_{11}V_{12} \end{bmatrix}$$

From the above it can be observed that only sub-matrices needed to compute the approximated matrix XR are: $\Sigma_{11}^{r\times r}$; $U_{11}^{r\times r}$; $U_{11}^{(m-r)\times r}$; $V_{11}^{r\times r}$; $V_{12}^{(r\times(t-r))}$. Observing the dimensions of each sub-matrix and noting that Σ_{11} is diagonal, it can be concluded that the total number of elements to be stored for those sub-matrices is equal to $(m+t+1)\times r$.

The compression ratio (CR) is expressed as the ratio between the total number of elements in the original matrix X and the total number of elements in the sub-matrices that are needed to compute matrix XR.

$$CR = \frac{(m\times r)}{(m+t+1)\times r} \tag{3}$$

From Equation (3), it can be seen that the number of SVs, r, determines the performance of the data compression in the SVD technique. So, on the basis of SVs data compression is carried out, and it achieves a good trade-off between the CR and loss of information. The proposed algorithm using SVD technique for compressing the data in UWSNs is presented as Algorithms 1.

2.1. Energy Consumption Using SVD Technique

In UWSNs, the energy consumed by Non-CH node to send L bits of data to CH node using MI based communication can be defined as

$$\mathcal{E}_{NonCH} = L\left[\mathcal{E}_{elecMI}^{Tx} + \alpha(1+\alpha)\mathcal{E}_{AWGN}^{MI}\mathbb{E}\left[d_{toCH}^{6}\right]\right] \tag{4}$$

where,

$$(1+\alpha) = \frac{3}{\eta}\frac{2^{(b/2)}-1}{2^{(b/2)}+1} \tag{5}$$

$$\mathcal{E}_{AWGN}^{MI} = \frac{2}{3}\left(\frac{2^b-1}{b}\right)N_0\ln\left(\frac{2}{P_b}\right)\frac{(4\pi)^2 M_l N_f}{G_t G_r} \tag{6}$$

by putting Equations (5) and (6) into (4), $\mathcal{E}_{NonCH}$ becomes

$$\mathcal{E}_{NonCH} = L\left[\mathcal{E}^{Tx}_{elecMI} + \alpha\frac{2}{\eta}\left(\frac{(2^b-1)^2}{b}\right)N_0\ln\left(\frac{2}{P_b}\right)\frac{(4\pi)^2 M_l N_f}{G_t G_r}\mathbb{E}\left[d^6_{toCH}\right]\right] \tag{7}$$

where $\mathbb{E}[d^6_{toCH}]$ represents the expected or average distance between the Non-CH and CH, and it can be evaluated as.

$$\mathbb{E}[d^6_{toCH}] = \frac{\mathcal{K}}{\mathcal{M}^3}\int_0^{\frac{\mathcal{M}}{\sqrt[3]{\mathcal{K}}}}\int_0^{\frac{\mathcal{M}}{\sqrt[3]{\mathcal{K}}}}\int_0^{\frac{\mathcal{M}}{\sqrt[3]{\mathcal{K}}}}\left[\left(x-\frac{\mathcal{M}}{2\sqrt[3]{\mathcal{K}}}\right)^2+\left(y-\frac{\mathcal{M}}{2\sqrt[3]{\mathcal{K}}}\right)^2+\left(z-\frac{\mathcal{M}}{2\sqrt[3]{\mathcal{K}}}\right)^2\right]^3 dxdydz = \frac{583}{20160}\frac{\mathcal{M}^6}{\mathcal{K}^2} \tag{8}$$

Similarly, energy consumed by a CH node to receive L bits data from $(\mathcal{N}/\mathcal{K}-1)$ Non-CH nodes and to forward $L\zeta$ bits of compressed data to the BS can be defined as,

$$\mathcal{E}_{CH} = ((\mathcal{N}/\mathcal{K})-1)L\mathcal{E}^{Rx}_{elecMI} + \zeta L\left[\mathcal{E}^{Tx}_{elecMI} + \frac{2\alpha}{\eta}\left(\frac{(2^b-1)^2}{b}\right)N_0\ln\left(\frac{2}{P_b}\right)\frac{(4\pi)^2 M_l N_f}{G_t G_r}\mathbb{E}[d^6_{toBS}]\right] \tag{9}$$

where $\mathbb{E}[d^6_{toBS}]$ is the expected distance between the CH and BS. The bit error rate (BER) for 16-QAM modulation can be expressed as,

$$P_b^{QAM} = \frac{3}{8}\,\mathrm{erfc}\left(\sqrt{\frac{4E_b}{10N_0}}\right), \quad \frac{4E_b}{10N_0} = SNR\frac{B_N}{R} \tag{10}$$

The signal to noise ratio (SNR) for MI communication system can be written as

$$SNR = P_T - PL - P_N \tag{11}$$

where P_T is the transmitted power, and PL is the path-loss in underwater media. PL in sea water can be defined as

$$PL_{sw} = PL_{MI} + PL_\alpha \tag{12}$$

$$where \quad PL_{MI} = -10\log\frac{R_L\omega^2 M^2}{R_{Tx}(R_L+R_{Rx})^2 + R_{Tx}(X_L+\omega L_{Rx})^2} \tag{13}$$

$$PL_\alpha = 20\log e^{\alpha r} \tag{14}$$

So with the help of Equations (10) to (14) we can easily obtain the actual value of BER (P_b) for MI communication. Hence, the total energy consumption (TEC) for a particular cluster is given as [13],

$$\mathcal{E}_{cluster} \approx \mathcal{E}_{CH} + (\mathcal{N}/\mathcal{K})\mathcal{E}_{NonCH} \tag{15}$$

Thus, TEC per round ($\mathcal{E}^{MI}_{round}$) for $\mathcal{K}$ cluster can be calculated as

$$\mathcal{E}^{MI}_{Total} = \mathcal{K}\mathcal{E}_{cluster} \tag{16}$$

$$\mathcal{E}^{MI}_{Total} = \mathcal{K}\mathcal{E}_{CH} + (\mathcal{N})\mathcal{E}_{NonCH} \tag{17}$$

$$\begin{aligned}\mathcal{E}^{MI}_{Total} = {} & (\mathcal{N}-K)L\mathcal{E}^{Rx}_{elecMI} + K\left[\mathcal{E}^{Tx}_{elecMI} + \frac{2\alpha}{\eta}\left(\frac{(2^b-1)^2}{b}\right)N_0\ln(\frac{2}{P_b})\frac{(4\pi)^2 M_l N_f}{G_t G_r}\zeta L\mathbb{E}\left[d^6_{toBS}\right]\right] \\ & + L\left[N\mathcal{E}^{Tx}_{elecMI} + N\alpha\frac{2}{\eta}\left(\frac{(2^b-1)^2}{b}\right)N_0\ln\left(\frac{2}{P_b}\right)\frac{(4\pi)^2 M_l N_f}{G_t G_r}\frac{583}{20160}\frac{\mathcal{M}^6}{\mathcal{K}^2}\right]\end{aligned} \tag{18}$$

The expected value between the CHs and BS can be found as,

$$\mathbb{E}[d^6_{toBS}] = \frac{1}{\mathcal{M}^3}\int_{-\frac{\mathcal{M}}{2}}^{\frac{\mathcal{M}}{2}}\int_{-\frac{\mathcal{M}}{2}}^{\frac{\mathcal{M}}{2}}\int_{-\frac{\mathcal{M}}{2}}^{\frac{\mathcal{M}}{2}}(x^2+y^2+z^2)^3 dxdydz = \frac{583\mathcal{M}^6}{20160}$$

2.2. Energy Consumption Using SVD and Energy Harvesting Technique

2.2.1. Turbine based Harvester

In underwater media, fluid flow kinetic energy can be converted into the electrical energy by turbine harvesters. The total harvested energy of a stream E_{harv} basically depends on the fluid density (ρ), flow speed υ_f, and wing spanning area A, respectably. So, the total harvested energy E_{harv} can be calculated as [14]

$$E_{Turb\text{-}harv} = \frac{1}{2}\rho A \upsilon_f^3 T \tag{19}$$

In the above equation A value is πr_d^2, where r_d is the wing radius.

2.2.2. Piezoelectric Harvester

Piezoelectric harvester also works on the same concept of the turbine harvester. In this harvester we get the electrical energy from the conversion of ambient energy available in fluid flow. The Piezoelectric harvested energy depends on the pressure difference and cantilever specifications and can be calculated as a [15]

$$E_{Piezo\text{-}harv} = \frac{1}{128}\varsigma^2 \frac{d_{31}^2}{\epsilon_0 \epsilon_r} \frac{BL^5}{T_{pzt}^3} \tag{20}$$

where ϵ_0, d_{31}^2, and ϵ_r represent the absolute permittivity, piezoelectric constant, and relative permittivity, respectively. The clockwise and counterclockwise directions pressure difference (ς) can be defined as $\varsigma_{cw} = \frac{\rho}{2}\upsilon_f^2$ and $\varsigma_{ccw} = -\frac{3}{2}\rho\upsilon_f^2$

$$\mathcal{E}_{Hv} = \mathcal{E}_{Turb\text{-}harv} + \mathcal{E}_{Piezo\text{-}harv} \tag{21}$$

Algorithm 1: Algorithm of Energy Efficiency using SVD for MI based UWSNs

1 *Cluster Head Election Step:*
Among $\mathcal{N}$ randomly distributed MI sensors nodes, $\mathcal{K}$ nodes are elected as CHs and all other nodes to be CM in pursuance of DBS algorithm [11]

2 *Data Transmission Step:*
Non-CH MI sensor nodes send their sensed data once to their CHs at a different t time instant.
Data matrix $\mathbf{X}$ is stored at CHs.
Data compression using SVD are performed at every CH on data matrix $\mathbf{X}$
Based on a value of r chosen to achieve a given CR, form submatrices $\Sigma_{11}^{r\times r}$; $U_{11}^{r\times r}$; $U_{11}^{(m-r)\times r}$; $V_{11}^{r\times r}$; $V_{12}^{(r\times(t-r))}$;
Reconstruct matrix X by calculating XR. Forward the compressed $\mathbf{z}$ data to the BS
Evaluate the compression ratio: $\zeta = \frac{(m\times r)}{(m+t+1)\times r}$
Use ζ value for calculation of TEC per round of network in Equations (18) and (23)
After end of the current round go on the step 1 and start the process again.

2.2.3. Total Energy Consumption Analysis

In underwater, when nodes have energy-harvesting capability, the total energy consumption equation considers harvested energy along with dissipated energy of the each sensor node in network. Hence, the total energy consumption can be calculated as,

$$\mathcal{E}_{Total\text{-}Hv}^{MI} = \mathcal{K}(\mathcal{E}_{CH} - \mathcal{E}_{Hv}) + \mathcal{N}(\mathcal{E}_{NonCH} - \mathcal{E}_{Hv}) \tag{22}$$

$$\begin{aligned}\mathcal{E}_{Total\text{-}Hv}^{MI} = {} & (\mathcal{N} - K)L\mathcal{E}_{elecMI}^{Rx} + K\left[\mathcal{E}_{elecMI}^{Tx} + \frac{2\alpha}{\eta}\left(\frac{(2^b-1)^2}{b}\right)N_0 \ln\left(\frac{2}{P_b}\right)\frac{(4\pi)^2 M_l N_f}{G_t G_r}\zeta L \mathbb{E}\left[d_{toBS}^6\right] - \mathcal{E}_{Hv}\right] \\ & + L\left[N\mathcal{E}_{elecMI}^{Tx} + N\alpha\frac{2}{\eta}\left(\frac{(2^b-1)^2}{b}\right)N_0 \ln\left(\frac{2}{P_b}\right)\frac{(4\pi)^2 M_l N_f}{G_t G_r}\frac{583}{20160}\frac{\mathcal{W}^6}{\mathcal{K}^2}\right] - N\mathcal{E}_{Hv}\end{aligned} \tag{23}$$

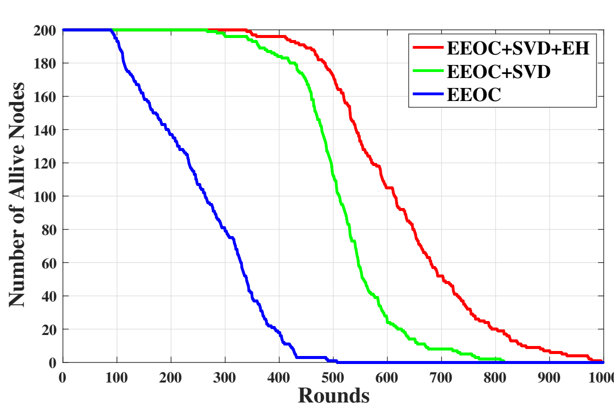
To find the optimal number of cluster that minimizes the total energy consumption, the number of cluster K could be assumed as a continuous variable, and the problem becomes a convex optimization problem.

$$\underset{\mathcal{K}}{\text{minimize}} \quad \mathcal{E}_{Total\text{-}Hv}^{MI} \quad \text{subject to} \quad 1 \leq \mathcal{K} \leq \mathcal{N}$$

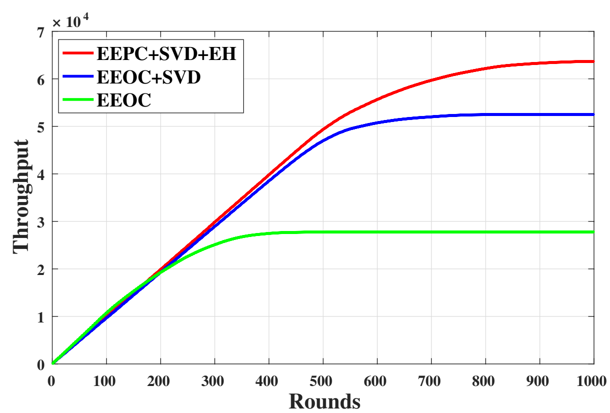
From the total energy consumption of Equations (18) and (23), we can easily obtain the derivative of $\mathcal{E}_{Total}^{MI}$ with respect to $\mathcal{K}$. To find the optimal number of clusters, we have to check the first and second derivatives of $\mathcal{E}_{round\text{-}WR}^{MI}$ with respect to $\mathcal{K}$. Since second derivatives is $\frac{d^2\mathcal{E}_{Total}^{MI}}{d\mathcal{K}^2} > 0$, $\mathcal{E}_{Total}^{MI}$ will be minimum. To find such an optimal value of $\mathcal{K}$, i.e., $\mathcal{K}_{opt}^{MI}$, put the first derivative of $\mathcal{E}_{Total}^{MI}$ with respect to $\mathcal{K}$ equal to zero.

3. RESULTS AND ANALYSIS

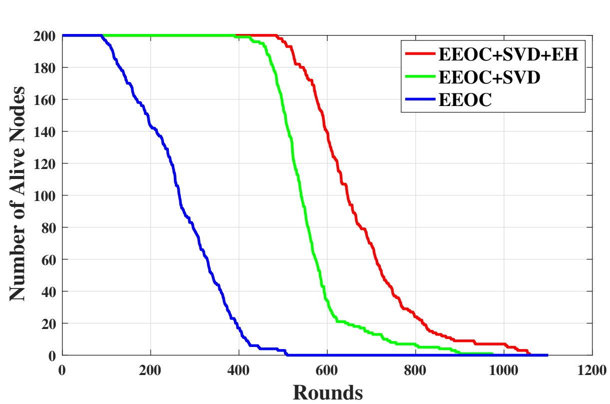
In this section, the network lifetime and throughput performance of the proposed approach are demonstrated on the basis of rounds. Results of lifetime analysis and throughput using the proposed method are depicted in Figs. 2(a), (b), (c), (d). The variation in number of rounds is noted for both number of alive nodes and throughput using energy efficient optimal clustering (EEOC), energy efficient optimal clustering using SVD (EEOC+SVD), and energy efficient optimal clustering using SVD and energy harvesting (EEOC+SVD+EH) method. The network dimension having BS located at the center considered for experiment is $300\,\text{m} \times 300\,\text{m} \times 300\,\text{m}$, and ($\mathcal{N} = 200$) MI-sensor nodes are randomly and uniformly deployed in sensing field. The "Lena" image is used as the original test image for simulation purpose. The values of other parameters used in this simulation are taken from [3, 6, 14, 15].



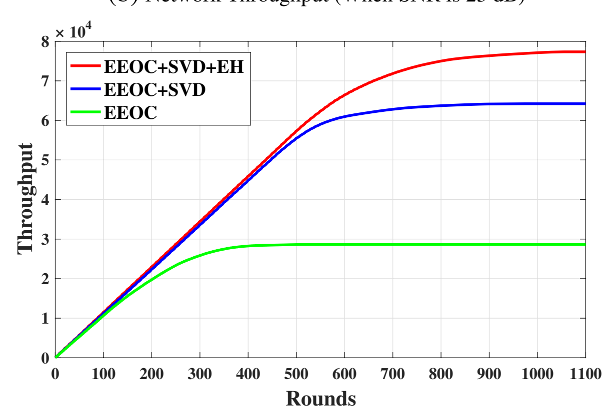
(a) Network Lifetime (When SNR is 23 dB)



(b) Network Throughput (When SNR is 23 dB)



(c) Network Lifetime (When SNR is 20 dB)



(d) Network Throughput (When SNR is 20 dB)

Figure 2. Network lifetime and throughput for different SNR value.

Figure 2(a) gives the number of alive nodes versus rounds plot for an SNR 23 dB and CR = 0.5. From the above plot, we can see that as the number of rounds increases, the number of alive nodes decreases. Here rounds structured with a setup phase and a steady phase and number of clusters in one round remain the same. So, in one round the energy dissipated by the network ($\mathcal{E}_{round}$) consists of the sum of energies dissipated by CHs and Non-CHs. From Fig. 2(a), we can see that for EEOC technique number of rounds goes to 493, for EEOC+SVD technique number of rounds goes to 807, and for EEOC+SVD+EH technique number of rounds goes to 988. EEOC+SVD technique increases the number of rounds because SVD technique reduces the redundancy present in underwater image. So, CHs need to send the lesser number of image data to reconstruct the same image at the BS. Similarly, EEOC+SVD+EH increases the rounds because energy harvesting technique is supplying the some extra energy to the each sensor nodes. From the above results, it can be observe that EEOC+SVD+EH technique increases the round by 495 and 181 respectably with respect to other techniques.

Figure 2(b) shows the throughput (measures the total rate of data sent over the networks) versus number of rounds plot. From the above plot, we can observed that, for EEOC technique throughput is up to 2.8×10^4; for EEOC+SVD it is up to 5.3×10^4; and for EEOC+SVD+EH technique, it reaches up to 6.4×10^4. The throughput of EEOC+SVD+EH technique is more than EEOC and EEOC+SVD techniques.

From the above plot, we can also see that after some rounds throughput is almost constant for EEOC, EEOC+SVD, and EEOC+SVD+EH techniques. This happen because network density is promptly falling in sensor network, and as a result, nodes are unable to find optimal data forwarders.

Figures 2(c) and 2(d) show the number of alive nodes and throughput versus rounds plot for the SNR 20 dB ($CR = 0.7$). From Fig. 2(c), we can observe that, for EEOC technique, the number of rounds is 493, for EEOC+SVD is 870, and for EEOC+SVD+EH is 1076. From the above results, it is inferred that as the CR ratio increases, number of rounds also increases. It occurs because increased CR ratio reduces the amount of data transmission from CHs to BS whose result is the increase of network lifetime. However, increasing the CR ratio results in the decrease in SNR value. From the above Fig. 2(c) we can observe that the EEOC+SVD+EH technique increases the round by 583 and 206 in comparison to EEOC and EEOC+SVD techniques, respectively.

In Fig. 2(d), we can observe that for EEOC technique throughput is up to 2.8×10^4, for EEOC+SVD technique 6.5×10^4, and for EEOC+SVD+EH technique 7.8×10^4. So, from the above result it can be concluded that throughput also increases as a CR ratio is increased, and EEOC+SVD+EH provides more throughput than the other two techniques. The comparison of proposed method based on network lifetime and network throughput is given in Table 1.

Table 1. Comparison of proposed method based on network lifetime and network throughput.

Network Lifetime (in Rounds) when SNR is 23 dB and CR is 0.5		Network Throughput when SNR is 23 dB and CR is 0.5	
EEOC [6]	493	EEOC [6]	2.8×10^4
EEOC+SVD [3]	807	EEOC+SVD [3]	5.3×10^4
EEOC+SVD+EH (proposed)	988	EEOC+SVD+EH (proposed)	6.4×10^4
Network Lifetime (in Rounds) when SNR is 20 dB and CR is 0.7		Network Throughput when SNR is 20 dB and CR is 0.7	
EEOC [6]	493	EEOC [6]	2.8×10^4
EEOC+SVD [3]	870	EEOC+SVD [3]	6.5×10^4
EEOC+SVD+EH (proposed)	1076	EEOC+SVD+EH (proposed)	7.8×10^4

4. CONCLUSION

In this letter, we have proposed an energy efficient optimal clustering jointly with SVD and energy harvesting for 3D-MI-UWSNs. It is observed that optimal clustering with SVD compression enhances the network lifetime and throughput of the considered network. Further, from the results, we also observe that when SVD compression with optimal clustering is used for a network which contains energy harvesting enabled nodes, it saves significant amount of energy as compared to optimal clustering with SVD compression. The energy harvesting technique implemented at nodes supplies some extra energy to it that can withstand more time in network.

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