Hybrid Compression Algorithm for Energy Efficient Image Transmission in Wireless Sensor Networks Using SVD-RLE in Voluminous Data Applications

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WSNs are used in different applications and the enormous volume of data they collect and broadcast across the network overburdens the sensor nodes and this issue can be mitigated by compressing the data before transmitting it over the network. Singular Value Decomposition, a state-of-the-art non-transform-based compression method, primarily for dimensionality reduction in any type of data, is utilized in this study. In this, the difference between the adjacent pixel values of the captured images by WSNs are computed as a preprocessing step, and then compressed, with the compressed data represented by three singular matrices: two orthonormal matrices (X, Y), and one diagonal matrix (Σ), called rank matrix. The resultant data is then applied through a Run Length Encoding step and transmitted. By compressing the image with different thresholds, the rank value of SVD is altered and since the pixel differences which is a relatively small number of bits are only encoded, the outcome is represented with a compression ratio of approximately 12% and also the reconstructed image at the receiver exhibits good Peak Signal to Noise Ratio (PSNR). The use of this strategy in WSNs is also justified by analyzing the amount of energy savings and the nodes' energy usage using standard energy models and the percentage of energy saving varies from 25% to 53 % with the decrease in the rank values respectively.

Povzetek: Študija predstavlja hibridni algoritem kompresije SVD-RLE za energetsko učinkovit prenos slik v omrežjih z brezžičnimi senzorji, pri čemer je prihranek energije do 53%.

1 Introduction

Remote monitoring like habitat monitoring, structural health monitoring, traffic surveillance, etc., are the utilization scenarios of Wireless Sensor Networks (WSN). These applications require continuous monitoring and generate huge volume of data. WSN has a number of sensor nodes to perform this operation and they generate the data from the source and transmit towards the sink through a cluster of intermediate nodes as shown in Figure 1. If these voluminous data is transmitted as a raw data, it places burden on the nodes and consume more power which in turn depletes the nodes of its energy. Instead, if the data generated is compressed using an appropriate compression algorithm and the compressed data is then transmitted, the burden on the nodes are reduced, thereby increasing the lifetime of the nodes.

In this approach, a hybrid combination of two state-of-the-art algorithms Singular Value Decomposition (SVD) and Run Length Encoding (RLE) is proposed. SVD represents the entire image data in the form of three matrices: two orthonormal matrices and one rank matrix which are scaling matrices of positive values, for transmission. The main advantage of SVD is that it can be applied to images of any size instead of equal dimensions in both x and y axes as compared to DCT, DWT, etc.

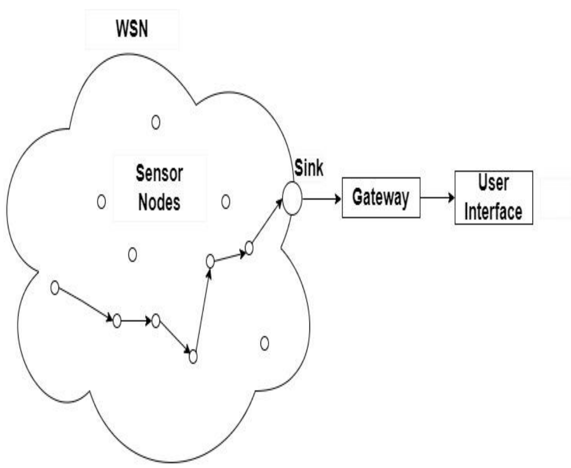

Figure 1: Classical architecture for wireless sensor networks.

Even though SVD significantly reduces the number of bits that must be transferred, RLE is employed to represent the compressed data in terms of lesser number of bits and as RLE is a lossless technique, it improves only the compression ratio and does not affect PSNR. A pre-processing step in introduced before compression and the performance of this algorithm is compared in two stages: before pre-processing and compression (stage I), and after pre-processing and compression (Stage II) with respect to rank values, PSNR, compression ratio along with other state of the art compression algorithms and the stage II performance is found to be more effective in terms of the number of bits sent across the network.

The literature offers a variety of compression methods, for various applications of WSN that involves a huge amount of data collection. These techniques also address the issues of how to improve the efficiency of the nodes coupled with compression, and based on the study, the method of combining both the compression techniques and energy efficiency improvement is the biggest challenging task. In [1], an innovative singular vector sparse reconstruction technique has been developed to improve the conventional Singular Value Decomposition (SVD) based compression technique by focusing on reconstruction based on sparse sampled singular vectors.

As the rank of SVD matrix plays a major role in determining the compression ratio of an image, an improvement was proposed in [2], by building a projection data matrix that spans the subspace of the original data matrix and random sampling of the column space. The proper low rank approximation was then obtained from the projection matrix by employing methods like oversampling and power iterations, and the same was used to compress images.

A technique for the retrieval of quality images were discussed in [3], that involves thresholding based SVD for removing the repetitive data which provides considerable space savings for data storage. A set of compression algorithms that are lossless and adaptive are discussed in [4] with a series of aggregation and routing strategies that shrinks the redundant data before transmission in WSNs.

A high coding efficiency was proposed in [5] that involve frequency tables that depend on adjustment of various parameters like range, step, mutual learning and table initialization. The process of how SVD is used to handle big data sets by identifying the details of pixels that contributes least to the actual image quality and by compressing them and at the same time restoring the actual image quality was discussed in [6]. During data capturing transmission in WSNs, the node topology in which the nodes are organized plays a pivotal role in the energy improvement of nodes and the concept was discussed in [7], with various techniques of arranging the nodes between the source and the sink.

In [8], a truncated SVD for alleviating the errors in outlier detection and to improve the signal quality was elaborated for WSNs within a network. A block partitioning method was employed in [9], by optimally choosing the Eigen values in SVD which can be used in varied applications. In [10], SVD was compared with Non-negative Matrix Factorization method that showed consistent energy consumption performance with NMF, but a degraded image restoration quality when the block size increases.

A method of data reduction involving SVD technique was elaborated in [11], which proved to be efficient with varying rank values. In [12], [13] a novel code book designing technique was proposed to enhance the effectiveness of image compression using non-transform-based vector quantization and improved differential evolution with a minimal computational time. A comparative analysis was done in [14] involving SVD and Wavelet Difference Reduction (WDR) method for compressing the image and SVD shows better performance at high rank values and WDR shows better performance at high rank values and a trade-off was suggested. In [15], use of data aggregation for redundancy reduction and energy improvement was discussed.

Efficacy of SVD in image compression for compressing the images in wavelets was discussed in [16], by representing images with a very small number of dominant values and analysis of wavelets for various compression techniques was discussed in [17]. Table 1 represents a variety of standard State-of-the-Art lossy and lossless compression algorithms employed in WSNs for the comparison of the proposed method.

Table 1: Summary of related works and contributions.

Reference No.	Approaches	Methodology	Performance / Results
[3]	Singular Value Decomposition (SVD)	Lossy	A PSNR of around 20 dB for rank 50 and around 25 dB for rank 100 is obtained with SSIM of 0.8 and 0.6 respectively.
[18]	Set-Partitioning in Hierarchical Tress (SPIHT)	Lossy	Good reconstruction quality and long computation time as it involves DWT as a preprocessing step. Distributed compression provides energy savings of around 0.2 nJ.
[19]	Discrete Cosine Transform (DCT)	Lossy	A pruned approach is used that gives a PSNR of around 30 dB for standard image data set and an energy consumption of 2.52 µJ for a 8 x 8 block.
[20]	Joint Photographic Experts Group (JPEG)	Lossy	PSNR is 27 dB for standard image data set and the energy

			requirement is 30.67 J for adaptive JPEG.
[21]	Embedded Zerotree Wavelet (EZW)	Lossy	An enhanced EZW is proposed and the PSNR obtained is around 33 dB for the standard test image set compared with around 30 dB for standard EZW.
[22]	Huffman Coding, Run Length Encoding (RLE)	Lossless	As data is exactly retrieved after decompression, compression doesn't save storage space. Achieves a lower compression ratio than lossy techniques.

2 Methodology

The proposed methodology incorporates a hybrid compression technique involving SVD and RLE which is discussed as below:

2.1 SVD based image compression

Singular Value Decomposition (SVD) entails decomposing matrix Z into the form as in Equation (1).

$$Z = X\Sigma Y^T \qquad (1)$$

With the use of this computation, we are able to keep the crucial unique values that the image needs while letting go off the values that are not as crucial to maintaining the image's quality, where X and Y are orthogonal matrices of order m x r and r x n respectively, and Σ is a diagonal matrix of order r x r, that corresponds to the square roots of the eigenvalues of the matrix Z^TZ, that are normally arranged in terms of its magnitude in decreasing order, make up the singular values of a m x n matrix Z.

The diagonal matrix of SVD represents the rank matrix with singular values of the image on which SVD is applied with the rank values arranged in descending order [1]. A portion of the first few columns (r) of the singular values corresponding to the low frequency content of the image is retained and the remaining with small singular values are discarded for the purpose of compressing an image resulting in dimensionality reduction. Similarly, the X and Y matrices are also trimmed to match with the dimensions of the singular matrix that result in Equation (2).

$$Z_{m\,x\,n} = X_{m\,x\,r}\,\Sigma_{r\,x\,r}Y^T_{r\,x\,n} \qquad (2)$$

The major image content and its contour information are represented by the low frequency data, which has large singular values and also denotes the area where the grey scale transitions of the image are slow. The high frequency information is represented as smaller singular values that denote a region with rapid variations in gray scale, which represents noise and the image's detailed information. SVD achieves compression by tossing out the singular vectors associated with small singular values that constitutes the image's finer details and hence results in reduced image quality after reconstruction. As the rank value decreases, compression ratio increase, but the image quality decreases. Hence the compression ratio must be limited to achieve significant image quality after reconstruction and this places a limitation in the performance of SVD on image compression and reconstruction.

Rank value in SVD represents the dimension of the non-zero singular matrix. By varying the threshold value, the rank of the matrix is varied. With higher rank value providing very high PSNR and low compression ratio, and lower rank value providing less PSNR and high compression ratio. Compression ratio impacts the number of bits that has to be transmitted through the network which affects the energy savings also. In our proposed method, the rank values of 408, 204 and 51 are considered and as a trade off the rank value is not reduced further so that PSNR, compression ratio and energy savings are maintained effectively. Also, since the preprocessing techniques reduce the magnitude of the pixels, here the trimming of the rank matrix is not needed and hence PSNR is maintained.

The limitation of reduced reconstructed image quality is overcome in our proposed methodology by taking the difference between the adjacent pixel values, then performing the SVD process, which results in the lower magnitude of the pixel values and due to this the compresses values are transmitted without the trimming process as depicted in the following steps. The proposed block diagram is depicted in Figure 2.

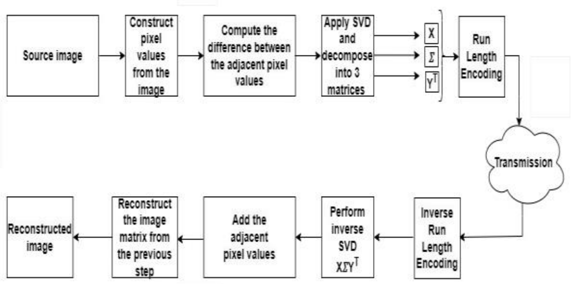

Figure 2: Proposed block diagram.

2.2 Run Length Encoding (RLE)

The output of the SVD process is then applied through RLE in which the continuous runs of zeros and ones are computed and the RLE output is transmitted. For example, if the SVD output is 000011110000000011111111, then instead of transmitting 24 bits, the data is transmitted as 04140818 and in terms of bits it requires only 20 bits and the transmitted data is 01000010011000010001 (as shown in

Figure 3). The reverse process is done at the receiver for reconstruction of bits. If the runs of data are very long, then more space can be saved during the RLE process. In compression of images, the runs of data are very long because of the interpixel redundancy. The pixel values are indicated by bits for wireless transmission and hence space savings is also more and this provides more compression and since RLE is lossless, this provides no information loss.

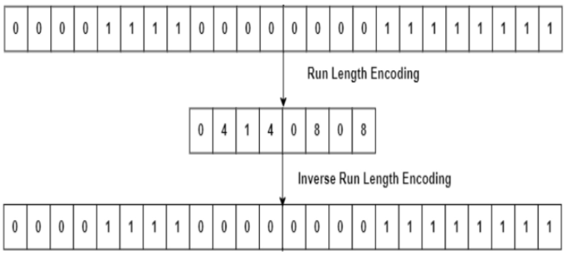

Figure 3: Illustration of RLE process.

The illustration of the proposed hybrid algorithm in the form of a flow chart is represented in Figure 4. With the procedure shown in Figure 4, due to the compression of the difference of the adjacent pixel difference values, there is reduction in the magnitude of the entries in the matrix and hence the need for the trimming of the rank matrices is reduced and hence the PSNR value obtained is considerably higher when compared to the actual SVD and at the same time, the compression ratio also significantly increases.

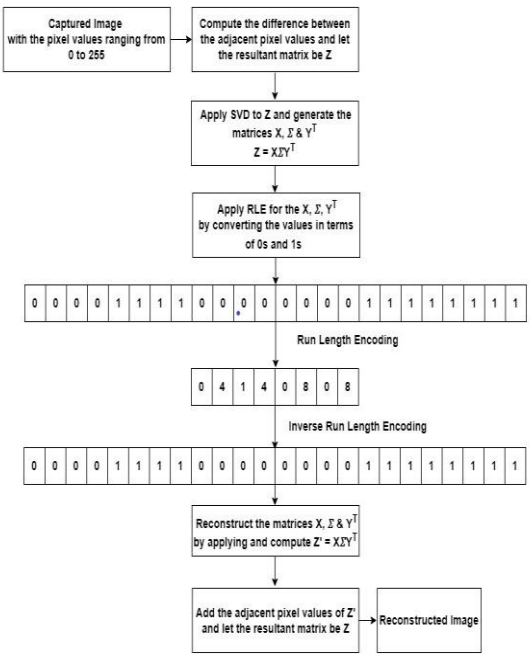

Figure 4: Flowchart of the proposed hybrid SVD – RLE.

3 Results and discussion

The application considered for this work is structural health monitoring of buildings and the below structural images of buildings as shown in Figure 5b are captured using the Raspberry Pi, equipped with a camera module Figure 5a and applied with the proposed SVD algorithm. As Raspberry Pi emulates a sensor node which is similar to its scanty processing ability, it can be chosen to run in Python environment.

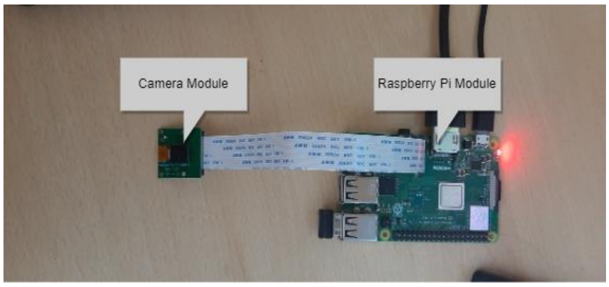

Figure 5a: Raspberry pi setup.

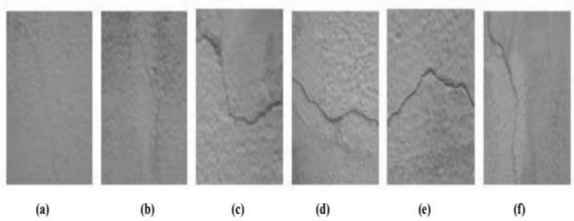

Figure 5b: Image data captured using Raspberry pi.

Consider the image in Figure 5b (b), the actual pixel values of the image and the pixel difference values are as shown in Figure 6 and Figure 7 respectively and the histogram of the pixel values is plotted in Figure 8 and Figure 9 before and after pre-processing respectively. The pre-processing technique of calculating the pixel differences reduces the magnitude of the pixel at the initial stage itself as shown in Figure 6 and 7. For example consider the first few pixels of the image 1 taken for consideration, the pixel values are 141, 139, 135, 128, …etc before taking the pixel difference and 141, -2, -4, -7… etc after computing the pixel difference which shows that the magnitude of the pixels are drastically reduced before applying SVD. This in turn helps to reduce the compression ratio significantly around 50% with decreasing rank values, instead of applying SVD directly to the image. Also, as SVD is applied here after the pre-processing, there is no need to trim the singular matrices as already the magnitude of the pixels is reduced, which helps to recover the original image after reconstruction by adding the adjacent pixel values.

This is also illustrated by plotting the histogram of the pixel values as in Figure 8 and Figure 9 before and after pre-processing respectively. Most of the pixel values are centered around the value 140 before pre-processing and around 0 after pre-processing. And also, the maximum pixel value of the test image before and after pre-processing as in Figure 8 and Figure 9 corresponds to 188 (1 occurrence) and 141 (1 occurrence) respectively, so that pixel values are shifted to the left in Figure 9.

Variables - A

A2 | A | d | Diff | Diff2

512x512 double

	1	2	3	4	5	6	7	8	9	10
1	141	139	135	128	123	123	129	135	132	132
2	143	142	140	136	132	129	128	129	123	125
3	143	144	145	145	143	136	128	123	120	123
4	140	140	142	145	146	140	130	121	128	128
5	133	133	134	137	139	137	130	124	135	135
6	125	125	125	126	128	129	128	127	132	135
7	118	119	119	119	118	120	123	126	126	130
8	115	116	117	116	114	115	119	124	123	125
9	109	109	107	106	108	114	121	127	129	125
10	104	105	108	112	117	122	126	128	129	124
11	98	101	107	116	125	130	128	125	120	116
12	101	103	108	118	127	130	125	119	113	109
13	115	114	115	121	128	129	124	118	113	108
14	128	127	126	128	131	131	128	125	115	109
15	131	132	133	134	134	134	133	132	123	117
16	127	130	134	136	135	135	136	136	135	130
17	125	124	128	136	140	136	130	127	132	132
18	125	121	123	129	133	132	129	130	125	126
19	123	117	114	117	119	120	123	127	123	126
20	124	115	108	106	105	106	111	117	126	130
21	125	117	108	103	99	97	102	108	118	123

Figure 6: Pixel values of original image.

Variables - Diff2

A2 | A | d | Diff | Diff2

512x512 double

	1	2	3	4	5	6	7	8	9	10
1	141	-2	-4	-7	-5	0	6	6	-3	0
2	9	-1	-2	-4	-4	-3	-1	1	-6	2
3	7	1	1	0	-2	-7	-8	-5	-3	3
4	1	0	2	3	1	-6	-10	-9	7	0
5	-7	0	1	3	2	-2	-7	-6	11	0
6	-15	0	0	1	2	1	-1	-1	5	3
7	-20	1	0	0	-1	2	3	3	0	4
8	-20	1	1	-1	-2	1	4	5	-1	2
9	-24	0	-2	-1	2	6	7	6	2	-4
10	-29	1	3	4	5	5	4	2	1	-5
11	-41	3	6	9	9	5	-2	-3	-5	-4
12	-41	2	5	10	9	3	-5	-6	-6	-4
13	-24	-1	1	6	7	1	-5	-6	-5	-5
14	-10	-1	-1	2	3	0	-3	-3	-10	-6
15	-9	1	1	1	0	0	-1	-1	-9	-6
16	-12	3	4	2	-1	0	1	0	-1	-5
17	-10	-1	4	8	4	-4	-6	-3	5	0
18	-8	-4	2	6	4	-1	-3	1	-5	1
19	-10	-6	-3	3	2	1	3	4	-4	3
20	-8	-9	-7	-2	-1	1	5	6	9	4
21	-8	-8	-9	-5	-4	-2	5	6	10	5
22	-14	-5	-4	-3	-5	-5	1	6	-2	7

Figure 7: Pixel difference values of original image.

The pixel values obtained before and pre-processing are applied with the SVD process and it is revealed that the suggested algorithm produces small values in the rank matrix, and the other orthogonal matrices as illustrated in Figure 10 and Figure 11 for the actual pixel values and the pixel difference values respectively.

For example, the first entry of the rank matrices is 71053 and 852.6239 in Figure 10 and Figure 11 respectively and the values in Figure 11 reduces along the diagonal elements subsequently when compared to Figure 10. Because of the smaller values in the rank matrix and the other orthogonal matrices, the data is transmitted without trimming, which in turn results in significant PSNR after reconstruction.

The pixel values are applied with the SVD process with different thresholds, which in turn varies the rank values when applied with the SVD process. The high rank value corresponds to more information content and a low rank value provides less information content after the compression process and correspondingly the PSNR value will also decrease. Even if the PSNR value decreases with decrease in the rank value, that is sufficient for the interpretation of the reconstructed image because the rank values are transmitted as such without being trimmed but results in lesser number of bits to be transmitted as the difference values are only compressed.

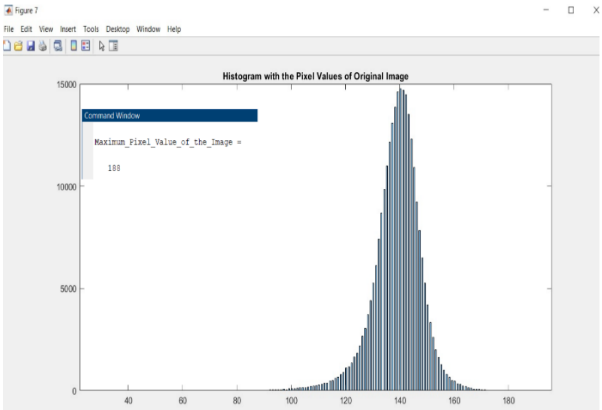

Figure 8: Histogram of pixel values of original image.

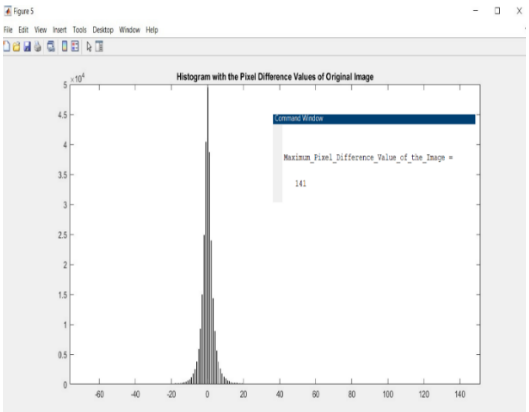

Figure 9: Histogram of pixel difference values.

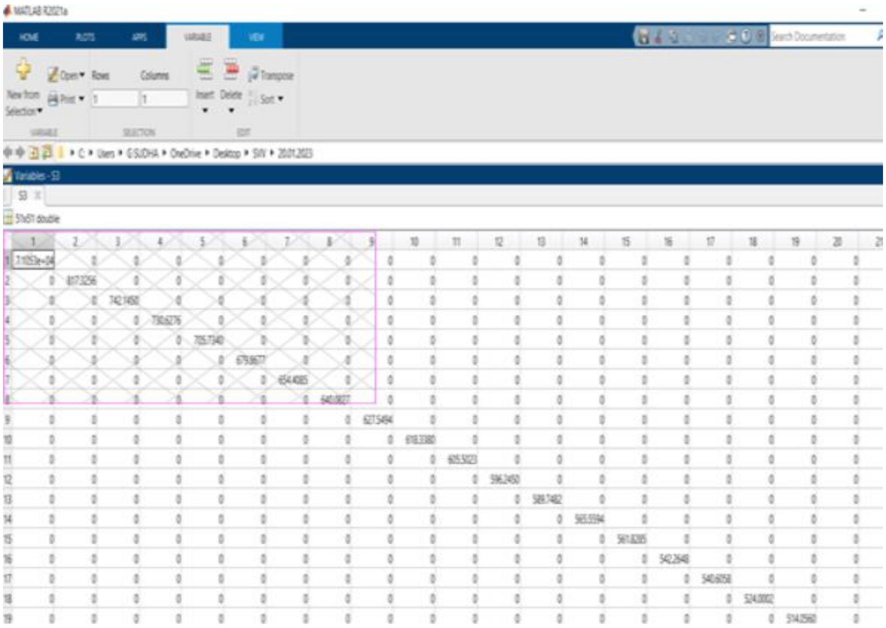

Figure 10: Rank matrix of original image.

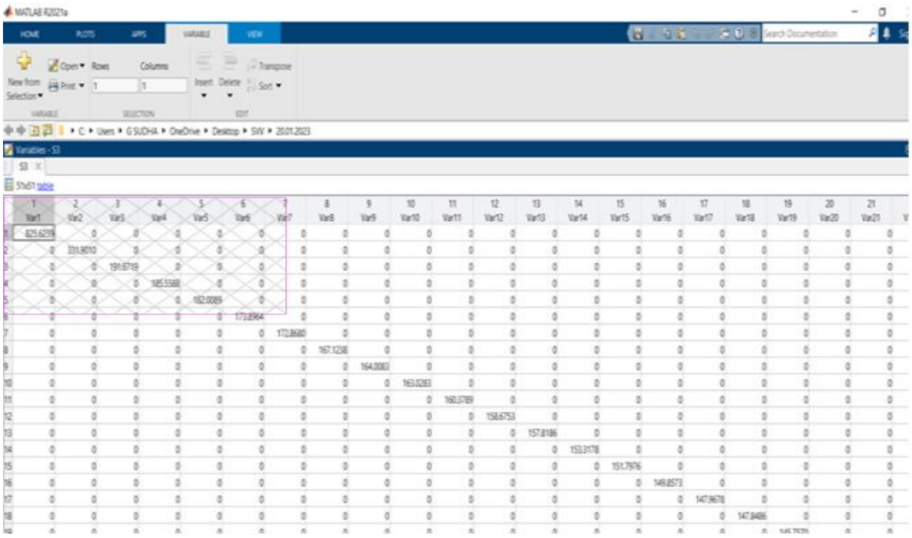

Figure 11: Rank matrix of pixel difference values of original image.

Table 2: Rank and PSNR values for different rank values

Image	**Rank**	**SVD applied to original image**	**SVD applied to pixel difference values**
		PSNR	**PSNR**
Image 1	408	50.51	60.26
	204	35.54	38.23
	51	33.45	36.54
Image 2	408	47.53	56.62
	204	34.04	37.28
	51	33.11	36.42
Image 3	408	46.70	54.26
	204	39.61	42.51
	51	35.21	38.44
Image 4	408	45.17	53.52
	204	31.48	35.57
	51	29.52	32.54
Image 5	408	46.06	53.95
	204	34.32	37.23
	51	33.15	36.99
Image 6	408	47.15	55.62
	204	27.99	32.78
	51	26.54	30.98

Table 3: Number of output bits that are to be transmitted for different rank values.

Image	**Rank**	**SVD applied to original image**	**SVD applied to pixel difference values**
		RLE Output (No. of Output bits)	
Image 1	408	431666	319466
	204	215894	121798
	51	53960	25426

Image 2	408	431666	309560
	204	215834	138853
	51	52390	24587
Image 3	408	377708	287564
	204	207918	103088
	51	53960	24692
Image 4	408	431666	308546
	204	215834	140357
	51	53960	23892
Image 5	408	377708	287420
	204	161876	128178
	51	53960	24568
Image 6	408	539582	436554
	204	323750	173110
	51	53960	25621

Table 4 gives a comparison of the PSNR metric that aids for effective image reconstruction at the receiver. PSNR for SVD [3] is around 25 dB, SPIHT is around 30 dB, DCT is 30 dB, JPEG is around 27 dB, EZW is 33 dB and the proposed methodology is around 36 dB and the propose techniques can be effectively used for image compression and transmission for all types of images. All the above-mentioned algorithms are tested after applying the LRE process, and since RLE is lossless, it does not affect PSNR.

Table 4: Comparison of PSNR of existing compression methods with the proposed hybrid methodology

Image	**Compression Method**					
	SVD at rank 51 [3]	**SPIHT [18]**	**DCT [19]**	**JPEG [20]**	**EZW [21]**	***Proposed hybrid compression at Rank 51***
	PSNR (dB)					
Image 1	25.42	30.58	32.79	27.52	32.52	**36.54**
Image 2	25.62	30.91	30.64	28.14	33.12	**36.42**
Image 3	26.42	32.56	37.81	27.59	33.45	**38.44**
Image 4	25.32	31.48	30.86	27.56	31.89	**32.54**
Image 5	26.84	31.98	30.18	27.41	32.75	**36.99**
Image 6	26.52	31.02	29.29	28.45	29.59	**32.98**

Table 5 illustrates the number of output bits that are to be transmitted for various compression methods.

The proposed model is also justified in terms of energy consumption requirements by using the standard energy models as in [23]. With an initial energy of 7 Joules for every node in a network of 25 nodes, the energy consumed by the nodes for a hop-by-hop transmission from node 1 to node 25 (for example) is calculated by the formula (3) and (4) where 'x' denotes the number of bits, 'd' represents the distance between the nodes, E_e denotes the electronics energy.

$$E_t(x,d) = xE_e + kE_f d^2 \qquad (3)$$

$$E_r(x) = xE_e \qquad (4)$$

Table 5: Comparison of number of output bits that are to be transmitted for existing compression methods with the proposed hybrid methodology

Image	**Compression Method**					
	SVD at rank 51 [3]	**SPIHT [18]**	**DCT [19]**	**JPEG [20]**	**EZW [21]**	***Proposed hybrid compression***
	No. of output bits					
Image 1	53166	86259	77198	82563	85896	**25426**
Image 2	52239	89564	88930	81475	85786	**24587**
Image 3	57770	84521	94160	85623	84512	**24692**
Image 4	52266	89476	69234	85687	84279	**23892**
Image 5	52266	87493	95680	84568	84352	**24568**
Image 6	55893	89256	90457	84789	84896	**25621**

For the output of SVD for different compression ratios, the energy consumed by the source node is plotted in Figure 12, Figure 13 & Figure 14 respectively.

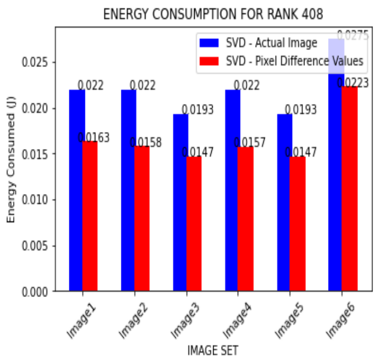

Figure 12: Plot of energy consumption with rank 408 for a node.

The above plots reveal that, based on the values obtained for different rank values, the pre-processed SVD gives less energy consumption when compared to processing the actual image through SVD of 25% for rank 408 to 50% for rank 51 and this energy conservation can be very well utilized in WSNs for voluminous data processing. Also, this process does not involve trimming of SVD matrices as the input pixel value are very less because of the pixel difference values, the PSNR is also maintained for good image reconstruction in the receiver end. The values are also compared with the various compression algorithms and for validation; the energy consumption of a network of nodes for the proposed hybrid compression algorithm is compared with the state-of-the-art algorithms and represented in Table 6.

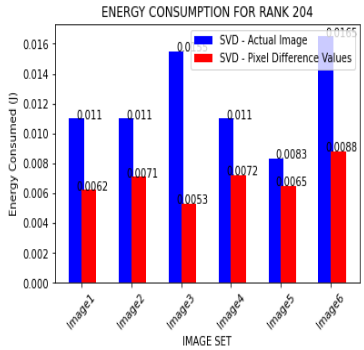

Figure 13: Plot of energy consumption with rank 204 for a node.

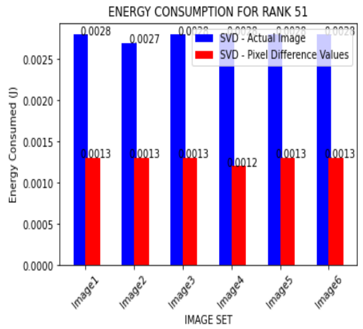

Figure 14: Plot of energy consumption with rank 51 for a node.

Table 6: Comparison of energy consumption of the nodes for existing compression methods with the proposed hybrid methodology.

Image	Compression Method					
	SVD at rank 51 [3]	**SPIHT [18]**	**DCT [19]**	**JPEG [20]**	**EZW [21]**	***Proposed hybrid compression***
	Energy consumption (J)					
Image 1	0.0027	0.0044	0.0041	0.0044	0.0044	**0.0013**
Image 2	0.0027	0.0042	0.0043	0.0044	0.0044	**0.0013**
Image 3	0.0039	0.0046	0.0042	0.0044	0.0043	**0.0013**
Image 4	0.0027	0.0044	0.0041	0.0044	0.0043	**0.0013**
Image 5	0.0027	0.0045	0.0044	0.0044	0.0043	**0.0013**
Image 6	0.0029	0.0044	0.0044	0.0044	0.0043	**0.0013**

The proposed method gives a PSNR of around 37 dB with 50% compression. Also, the energy consumed by a network of 25 nodes is 0.0163 J, 0.0062 J, and 0.0013 J respectively for the rank values 408, 204, 51 of the proposed hybrid algorithm, as against 0.022 J, 0.011 J, 0.0028 J for the actual SVD + RLE without preprocessing.

4 Conclusion and future work

SVD is a promising technique for dimensionality reduction for applications involving memory intensive data. In this work a pre-processing step involving difference between the adjacent pixels is taken that takes a smaller number of bits to represent every data compared to actual pixel values and then SVD and RLE is applied. The PSNR obtained is substantially increased when compared to the conventional SVD, as the process involves no truncation of the matrices related to the rank matrix and the energy consumption for the nodes is also less. The work can be further substantiated by applying the algorithm for data generated from various applications ranging from traffic surveillance, habitat monitoring, industry monitoring, etc. As conventional compression techniques are not feasible to be applied to WSNs due to its impediments like limited resources, limited memory power and the need for prolonging the network lifetime in remote deployments, this contemporary hybrid technique is more promising in terms of PSNR, compression ratio, SSIM and more energy savings over a network of nodes, so that the network lifetime is also enhanced and the reconstructed image is also of a good quality for better interpretation.

The proposed hybrid compression algorithm can further be extended with an additional pre-processing technique like feature extraction, so that only the desired features are compressed and transmitted. Due to this the number of bits that will be transmitted through the network will be substantially reduced and it can be validated by measuring the energy consumption and longevity of the nodes.

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