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Robust Data Compression Model for Linear Signal Data in the Wireless Sensor Networks

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ABSTRACT-- The data compression is one of the popular power efficiency methods for the lifetime improvement of the sensor networks. The wavelet based signal decomposition for data compression, entropy encoding or arithmetic encoding like methods are being used for the purpose of compression in the sensor networks to elongate the lifetime of the wireless sensor networks. The proposed method is based upon the combination of the wavelet signal decomposition of the signal compression with the entropy encoding method of Huffman encoding for the purpose of data compression of the sensed data on the sensor nodes. The compressed data (reduced sized data) consumes the less energy for the small packets in comparison with the non-compressed packets, which directly affects its lifetime. The proposed model has been recorded with more than 70% compression ratio, which is way higher than the existing models. The proposed model has been also evaluated for the signal quality after compression and elapsed time. In both of the latter parameters, the proposed model has been found efficient. Hence, the proposed model effectiveness has been proved from the experimental results.

Keywords—WSN efficiency, data compression, multi-objective compression, linear compression.

1. INTRODUCTION

The WSN has a very huge equipped region and it is used in different areas like monitoring of environmental factors, controlling humidity and temperature, controlling traffic, monitoring of individual body organs and so forth. The figure 1.1 depicts a state of WSNs in medical field where the patients are being monitored whether at homes, in hospitals or in open-air where they are doing their daily activities. And this monitored data are then sent to the wellbeing professionals passing through the internet.

A number of applications need security while transporting the information via internet, for instance the scene that is depicted in the figure 1.1, in this the sensor nodes are entrenched in human body and reports to the health professional. As the health experts believe that authentication and access control is must during the transmission. Apart from the health area, other fields like industry, military applications, environmental applications, structural applications also need security during the transmission of information through the internet. So, security is the main concern in wireless sensor network.

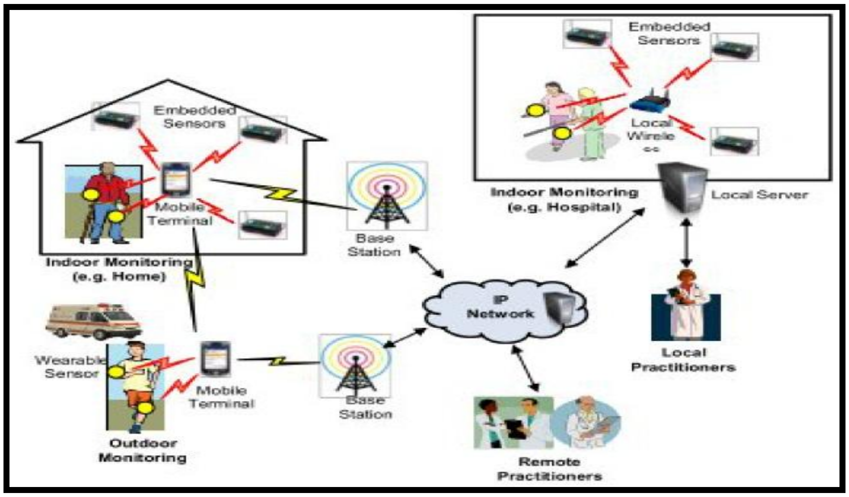

Figure 1.1: Scenario of Wireless sensor network

Compression is the process of reducing the size of a file or of a media such as high-tech graphical images etc, by encoding its data information more efficiently. By doing this, there is a reduction in the number of bits and bytes used to store the information. Therefore, a smaller file or image size is generated in order to achieve a faster transmission of electronic files or digital images and a smaller space required for downloading. Compression basically employs four types of redundancy in the data:

- **Temporal**: This is present in 1D data, 1D signal, Audio etc.
- **Spatial**: It occurs due to correlation between neighboring pixels or data items.
- **Spectral**: This is present due to correlation between colour or luminescence components. This uses the frequency domain to exploit relationships between frequencies of change in data.
- **Psycho-visual**: This redundancy exploits perceptual properties of the human visual system.

Compression is done by using compression algorithms that rearrange and reorganize data information so that it can be stored economically. By encoding information, data can be stored using fewer bits. This is done by using a compression/decompression program that alters the structure of the data temporarily for transporting, reformatting, archiving, saving, etc.

Compression reduces information by using different and more efficient ways of representing the information. Methods may include simply removing space characters, using a single character to identify a string of repeated characters or substituting smaller bit sequences for recurring characters. Some compression algorithms delete information altogether to achieve a smaller file size. Depending on the algorithm used, files can be greatly reduced from its original size.

2. LITERATURE REVIEW

Wafa Elmannai et. al. [2014]: In this paper, the authors have focused on underwater transmission. One of the main limitations of WSNs is the power consumption and short lifetime of the sensors. In this paper, the authors have proposed a new solution for underwater Wireless Sensor Networks to overcome the problem that is caused by the ionized nature of seawater. This work presents a methodology to improve the lifetime of WSNs. The wireless sensors have three main functions: sensing, processing and transmitting. The first two factors consume very less power compared to the third. **Ahmed E.A.A. Abdulla et al. [2012]:** In this paper, they have proposed a hybrid multi-hop routing algorithm, which prolongs the network lifetime of wireless sensor networks by coping with the hotspot problem. Existing routing algorithms developed for wireless sensor networks can be categorized into two classes, flat multi-hop routing algorithms which minimize the total power consumption in the entire network and hierarchical multi-hop routing algorithms which efficiently reduce the amount of traffic flowing through the network by using data aggregation mechanism. **Guangsong Yang et al. [2013]:** In this paper, proposed methodology is the processes of CS aggregation in WSN, including sparse presentation of signal, observation matrix and reconstruction algorithm design. They also discussed the relationship between observations and reconstruct MSE are also discussed. The transmitted data are reduced due to the sparsity of sensing signal, the communication overload of cluster head and slaves also can be reduced which can reduce the energy consumption and prolong the lifetime of the whole WSN. As we know, how to select an optimal transformation basis is directly related to the selection of the follow-up observation matrix, and it will also affect the reconstruction quality. In this paper, they did not do much introduction to the design of the transformation matrix. **Xi Xu et al. [2012]:** In this paper, they have presented a novel power-efficient hierarchical data aggregation architecture using compressive sensing for a large scale dense sensor network. It was aimed at reducing the data aggregation complexity and therefore enabling energy saving. The proposed architecture is designed by setting up multiple types of clusters in different levels. The leaf nodes in the lowest level only transmit the raw data. The collecting clusters in other levels perform DCT to get sparse signal representation of data from their own and children nodes, take random measurements and then transmit them to their parent cluster heads. When parent collecting clusters receive random measurements, they used inverse DCT transformation and DCT model based algorithm to recover the original data. **Henry Ponti Medeiros et al. [2014]:** This study has been focused on lightweight compression mechanism for low resolution sensor nodes based on fixed Huffman dictionaries. Since the proposed scheme presents very modest computational and memory requirements, it can be easily employed in practical wireless sensor nodes. In order to evaluate the method, they have computed the compression ratio obtained in several real datasets containing temperature and relative humidity measurements collected at different locations and during distinct periods of time.

3. EXPERIMENTAL DESIGN

When the data has been processed of the DWT, the total number of transform coefficients is equal to the number of samples in the original data, but the important visual information is concentrated in a few coefficients. To reduce the number of bits needed to represent the transform, all the subbands are quantized. Quantization of DWT subbands is one of the main sources of information loss. In the compression standard, the quantization is performed by uniform scalar quantization with dead-zone about the origin. In dead-zone scalar quantizer with step-size Δ_j, the width of the dead-zone is $2\Delta_j$ as shown in Figure below. The standard supports separate quantization step-sizes for each subband. The quantization step size Δ_j for a subband j is calculated based on the dynamic range of the subband values. The formula of uniform scalar quantization with a dead-zone is

$$q_j(m,n) = \text{sign}(y_j(m,n)) \left\lfloor \frac{|W_j(m,n)|}{\Delta_j} \right\rfloor \qquad (1)$$

Where $W_j(m,n)$ is a DWT coefficient in subband j and Δ_j is the quantization step size for the subband j. All the resulting qunantized DWT coefficients $q_j(m,n)$ are signed integers.

After the quantization, the quantized DWT coefficients are then use entropy coding to remove the coding redundancy.

Algorithm 1: Hybrid compression using discrete wavelet transform

1.) Sensor senses the data
2.) The DWT algorithm acquires the data from the egress channel of sensor node
3.) Decomposes the signal to the level 1 using the daubechies wavelet
4.) Return the upper and lower data band after decomposition known as absolute coefficient and detailed coefficient
5.) The Huffman encoding model acquires the data of absolute coefficient
6.) Return the encoded after the compression application

7.) Forward the data to the base stations (Sink node)
8.) The sink node receives the data on ingress channel
9.) The Huffman encoding model acquires the received data
10.) Return the Decoded data to the runtime memory
11.) The DWT algorithm acquires the data
12.) Regenerate the original form of data from the absolute coefficient data
13.) Obtain the performance parameters.

4. RESULT ANALYSIS

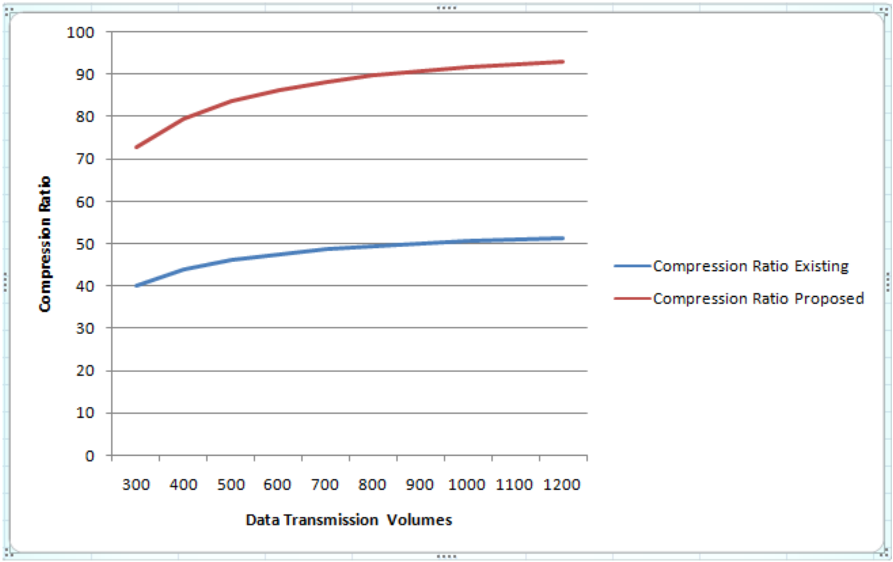

Figure 4.1: Compression Ratio Graph obtained from the simulation model using compression for energy efficiency

The compression ratio (Figure 4.1) is the ratio calculated from the size of the data before and after the application of DWT and DFT compression on the WSN data. The compression ratio represents the effectiveness of the data compression model. The results obtained from the proposed data compression model using DWT are showing that the proposed model has significant difference than the existing models.

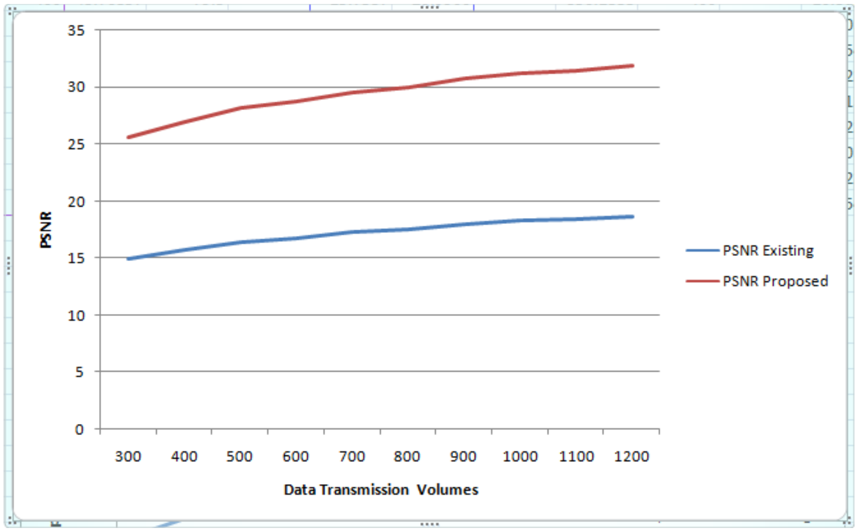

Figure 4.2: Graph of PSNR values collected from the WSN simulation model

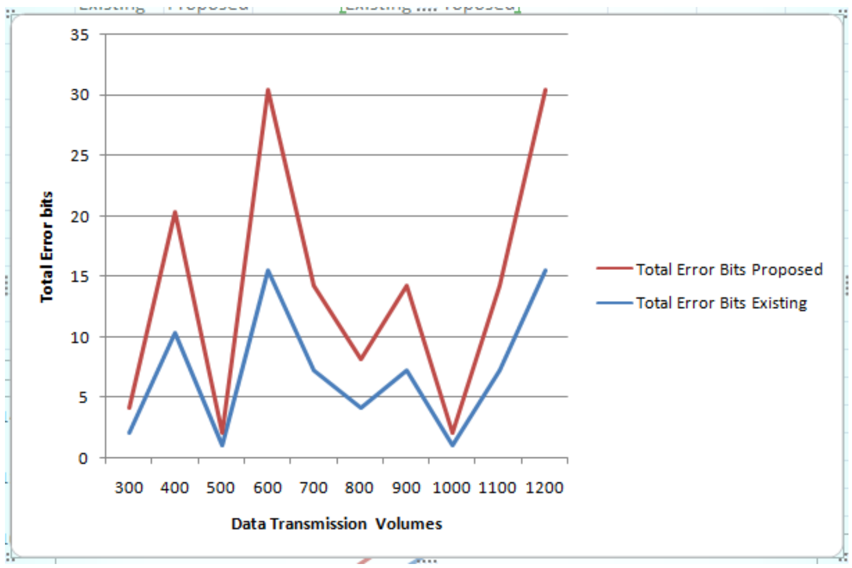

Figure 4.3: Graphical Representation of Total error bits during the communication in the simulation model

In the figure 4.2, the graph of the PSNR values has been shown. The PSNR values have been calculated on the data before compression and after de-compression. The PSNR value represents the quality of the signal after the decompression. The higher is the PSNR value, better is the quality.

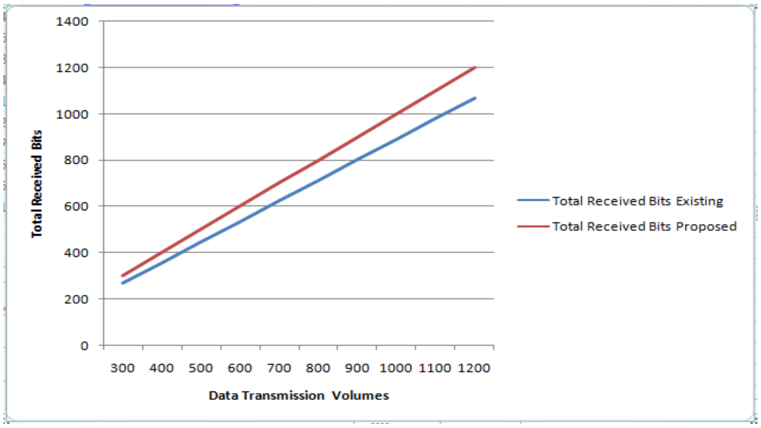

Figure 4.4: Graphical Representation of Total received bits during the communication in the simulation model

In figures 4.3 and 4.4, total number of error bits and total number of received bits has been shown in the graphical form. The total number of the sent bits and total number of received bits can be used to measure the intensity of the lost bits. The higher number of lost bits can adversely affect the performance of the WSN cluster. The WSN cluster may fail to reach its expectations, if there is the increased number of lost bits in the WSN cluster. The number of received bits (Figure 4.4) and number of error bits (Figure 4.4) are representing the difference based on the lost bits. The graphical form of the number of error bits is displaying the number of the bits which are affected by the signal interference during the communication channel. The communication channel may contain signal interference and many other forms of elements which may cause a significant amount of the errors in the bits during the transmissions.

5. CONCLUSION

Dynamically linkable modules can be distributed in wireless sensor networks at a lower energy cost if they are compressed, and thus the lifetime of the sensor network is extended. The best overall energy-efficiency is achieved using improved Discrete Wavelet Transform (DWT). The proposed simulation is prominent to the existing WSN compression techniques, where it has been observed that other techniques are capable of performing data compression for WSN data up to 65 percent overall maximum. The energy savings are nevertheless strongly dependent on the algorithm of choice, the execution speed of the implementation, and the energy cost of radio traffic in relation to the energy cost of micro-controller activity on the sensor nodes. The results of the proposed algorithm are showing the effectiveness of the proposed model. The proposed model has proved its capability of sending the quality signal to the other nodes. The received and sent bits are recorded for the minimal losses, which show a least possible number of lost bits during the transmission.

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