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Recent Advances of Data Compression in Wireless Sensor Network

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Abstract: Wireless Sensor Networks (WSNs) have emerged as one of the most promising wireless communication systems supporting wide variety of applications ranging from military tasks, healthcare, disaster prediction and indoor positioning. The low complexity and cost of the nodes result in constraints such as computational power, communication bandwidth and battery power. Energy consumption is one of the most critical to WSN. In WSN communication, data transmission is considered the largest contributor to total energy exhaustion and apparently, it is influenced by the size of the data. Favorably, data compression can be used to reduce the amount of data that requires to be transmitted and hence prolongs sensor's lifetime. In this study, we survey various approaches, issues and challenges to WSN effiency related to data compression discuss the effect of the data size on the sensor efficiency and how data compression algorithms can be used to address small size data transmission. Finally, recent approaches are reviewed with highlighting of advantages and disadvantages of each solution.

Key words: Wireless sensor networks, various, efficiency, solution, disaster, approach

INTRODUCTION

WSNs is a result of an industrial revolutionary in sensing, computing and communicating technologies altogether combined into a network of single, tiny and low-cost connected devices which are called sensor nodes. This fabrication gives an excellent solution for a wide variety of real-world challenges ranging from environmental monitoring and military surveillance to real-time tracking. As illustrated in Fig. 1, a network consists of different sensor nodes (white) which are commonly manufactured by different vendors that are con-nected together to sense data from the environment before wirelessly forwarding it to the next sensor node, sink or central base station (Karl and Willig, 2007; Wang and Liu, 2011). The collected data from hundreds of distributed sensor nodes is processed and analyzed by high-end devices offlinely (Cerpa *et al*., 2001; Wang and Liu, 2011).

Traditional wireless devices need to directly communicate with the closest base station of a high-power tower. Consequently when many devices fall within a small area, the services may be denied (Praveena *et al*., 2013). In contrast, sensor nodes can communicate with local peers (Ramachandran *et al*., 2011) and adding more nodes within a small area increases the strength of the network. WSNs abilities are increased exponentially when hundreds of sensor nodes are connected within the network. Moreover, nodes within a properly constructed network can be programmed to configure and assemble themselves without any human interference, offering eccentric abilities (Jin *et al*., 2015). The ability to connect many nodes simplifies the extendability of an overall sensor network by adding more devices with minimal configuration cost. In addition, a node failure within this type of system is automatically adapted by the network with minor effect on its operations (Sudha and Valarmathi, 2011).

This robustness has offered great advantanges to the network, however that is only achieveable if the network is alive. Network lifetime is of prime importance and due to resource constrained of each node, plus in some environments physically accessing the deployed nodes is close to impossible, there always need to minimize the usage of node's resources over time such as system storage, processing power and most importantly energy consumption. Without affecting the smoothness of the running network that is by reducing the functionalities, for a given fix battery size, there are two ways of extending the lifetime of the network that are via.

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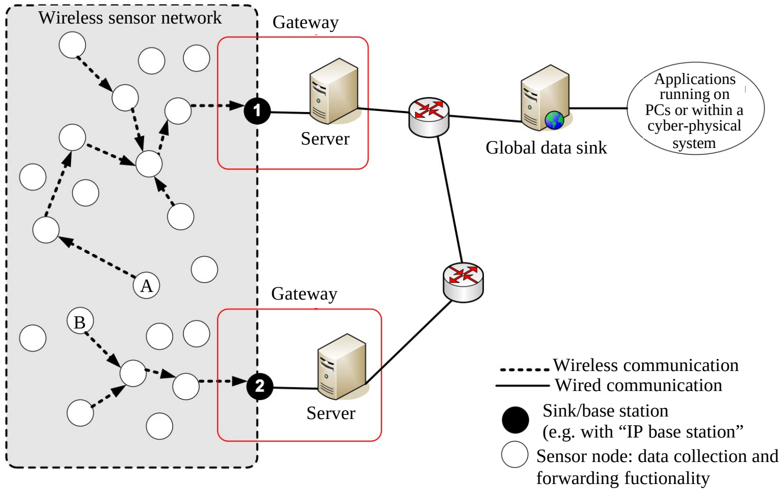

Fig. 1: General overview of a wireless sensor network

harvesting energy from external source such as solar power and wind energy and minimizing the usability of battery by optimizing the running application such that battery is at an optimal usage. By the latter, we can further divides into two that are network based and node based consumptions. Packet routing, channel assignment and clustering are some examples of network related issues. Issues that are contributed by the individual nodes such as system security, data privacy and data compression being the factors to workability and efficiency of the node's operations.

In this study we investigate the current state of the advancement of data compression techniques in WSNs. Initially, it may seems unnecessary but as the WSNs becomes more and more exposed to various applications such as that caters multimedia transmission, data compression appears to play bigger roles in ensuring the longevity of the networks. Traditional techniques were designed with no concern of resources constraint and thus become less applicable for WSNs. Until now, plenty of techniques specific for WSNs were developed. However, to the best of our knowledge there is no article that offers a comprehensive review for the up to date.

MATERIALS AND METHODS

WSN architecture: A WSN is a dynamic network that may consist of various types of sensor nodes that are heterogeneous in terms of software and hardware. All sensor nodes share the same construction layout but may exhibit technical differences in terms of processing speed, memory space, sensor type and other capabilities. Essentially, the sensor node consists of a sensing unit, processing unit, communication unit and power supply

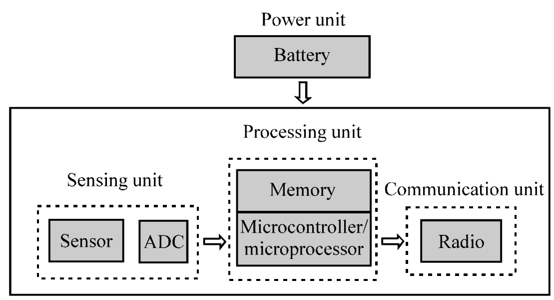

Fig. 2: Structure of sensor node

(Akyildiz *et al*., 2002a, b; Rahman, 2010). Figure 2 illustrates these major components. Concise descriptions of the components of a WSN are as follows:

Sensing unit: A sensing unit is composed of a collection of sensors that are used to measure different phenomena. The sensor converts physical phenomena into electrical signals. These signals are converted to a digital form via. an Analog-to-Digital Converter (ADC) which is a unit embedded in the sensor. The type of sensing unit determines the outcome and usage of the sensor node.

Processing unit: This unit consists of a processor (microcontroller) and system memory (RAM) with a previously-installed operating system and timer. This unit is responsible for processing and storing collected data by using the timer for process sequencing. The overall performance of this unit defines the performance of the sensor node.

Communication unit: This unit which consists of a transmitter and a receiver is used for communication between nodes either by taking information from the processing unit and sending it to the outside world or by re-routing the received packets. Network protocols are responsible for directing communication through the communication channels. The data rate and communication range are confined by this unit.

Power unit: The power unit is one of the most important components of a sensor node (Akyildiz *et al*., 2002b) because it provides the energy for other units. This unit is typically connected to a battery or power generator as a power source. The sensor nodes life is limited by this unit.

While understanding the structure of sensor nodes is essential, it is also, necessary to be familiar with the communication architecture of WSNs. A WSN is constructed with a slight difference from conventional computer networks. WSN communication architecture includes the following integral entities (Ahmed *et al*., 2012).

Sensor node objectives are to communicate over a multi-hop wireless medium and to route back the collected data to the user via. a base station or sink. A sink or base station is located near the sensor environment and functions as a communicator between sensor nodes and the user. The communication with the user is achieved via. convenient communication types such as Wi-Fi, 4G or any other com-munication medium. A hop-to-hop infrastructure is used to route the collected data from sensor nodes. It should be noted that to achieve maximum efficiency, the WSN does not abide to the OSI Model architecture of a standard network.

Efficiency in WSN: In general, the term efficiency refers to the ability to minimize the wastage of system resources such as materials, energy, efforts, money and time with minimum loss in the performance and accuracy of the system output. This term has the same meaning in the WSN. With the limitation of a sensor node any wastage in the available resources may affect the sensor performance and thus the whole network. The processes that are executed within a network and sensor node itself are data sensing, processing and transmitting. In the sensor node, data processing includes but not limited to, data securing, verifying and forwarding. In an overall network, the main process is to route the packets to the base station. All these processes work with limited computational power and memory space to handle data. Also, the processes work with limited bandwidth to transmit data. All processes are supplied by a limited energy source.

Finding the best route for packets delivery can be a valid solution to minimize the energy consumption and thus to prolong the overall network lifetime. However, many sensor nodes fail due to the excessive energy consumption due to the internal processes such as data processing and securing. In fact, collecting only valuable data can be a solution to minimize the processing tasks in sensor node. However, this solution contradicts the true concept of efficiency, since, it does not affect the accuracy of system output. Therefore, we have to look for the common influential factor that minimizes all these resources and achieves the real concept of efficiency. That factor is the data size.

Understanding the effects of the data size on the efficiency of the WSN requires taking a closer look into the transmitted message size. WSN applications require disseminating a large amount of data within the WSN (Aboelela, 2014) and therefore, many studies have been directed towards algorithms with capability to handle and to process that significant amount of data. In reality, this data is not a set of large segments. If we take a closer look at it, we will find it as a set of thousands or even millions of small packets that contain few hundreds of bits that are generated and transmitted by thousands of sensor nodes. Those few hundreds of bits do not only contain the sensed data but also, protocol headers and packet header fields. Those packets are small because of many factors such as the limited bandwidth of the sensor node and the nature of sensed data which is relatively small. In fact many researchers have been trying to make the packets even smaller because of the following facts.

The size of the transmitted packets influences the Energy Consumption Efficiency (ECE) of the sensor node directly (Xia *et al*., 2012). As mentioned previously, the error rate and packet loss in the WSN are very high (Hassanein and Luo, 2006). Therefore, as long as the packet becomes larger, the amount of data loss becomes bigger.

Large packet size with a limited bandwidth requires much more time to be transmitted (Hull *et al*., 2003) and as a result, there is more delay in packet delivery. This delay affects the WSN application requirements and the accuracy of data processing.

However, there is a limit to minimizing the packet size and the sensed data. Using a smaller packet size requires more processing to generate the packets and more network collision due to the huge number of packets that are transmitted within the network. Because of that recent studies have been aiming to find the optimal packet size to balance between efficiency factors (Akbas *et al*., 2014). That means data optimization issue at one layer can be seen as performance optimization issue at higher layer.

and packet size should shift to a higher level of optimization and efficiency. The packet should be able to hold more data without increasing its size to achieve higher efficiency. The packet fields should be compressed to minimize the packet size without increasing the amount of packets and computational process to generate them. This can be achieved by using data compression techniques but the fact is that current compression techniques are not efficient enough when applied to small packet. In fact, some of these techniques are incapable of compressing the small data and a consequence causes data expansion instead.

To obtain an efficient data compression algorithm for the WSN, we have to understand the efficiency requirements of the WSN. There are four main requirements for an efficient WSN and sensor node. All of the following requirements should be achieved or traded off to maintain one from the other.

Minimum memory usage and allocation duration: Both system memory and flash memory are limited and therefore, they should not only be used with the minimum amount but also not be allocated for a task for a long time. This helps to avoid the deadlock of a task or its delay due to memory allocation requirement.

Low computational overhead: The main concept of executing all tasks within deadline in a sensor node is by switching rapidly between them. Each task should be done without any delay that may lead for an inaccurate output and therefore, the computational overhead and complexity of the task have to be minimal.

Energy efficiency: As the energy resource is limited, the efficiency can be achieved if the energy resource is used in a way that allows the usage of the limited battery for a longer time.

Minimum bandwidth usage: The sensor node uses a limited communication channel not only to send its data but also, to forward other sensors packets. Therefore, an efficient bandwidth usage means using the available limited bandwidth to transmit and forward the sensed data to the base station within an acceptable time span and bandwidth capacity.

Proposing a compression algorithm as a solution to improve the efficiency of the WSN needs determining the cost of applying such a technique in terms of system resource usage and energy consumption. The compression technique has been widely used to improve the sensor node and the network efficiency by minimizing data size to increase energy efficiency and the lifetime of the sensor node (Jancy and Kumar, 2015). Also, it helps to cut down the computation and communication cost. However, this does not mean that the compression itself has no cost and effects on the sensor node's efficiency. Applying any compression technique requires a particular system specification such as data type and size and a slice of execution time. This means that applying inappropriate compression technique within WSN may lead to a counterproductive result. The data after compression may need more resources and energy for processing or transmitting rather than that of the original data. Therefore, based on the most recent proposed WSN compression solutions (Antonopoulos and Voros, 2016; Liang and Li, 2014; Yin *et al*., 2015), we can define the conditions that should be achieved in order to guarantee the solution is efficient for the WSN. If the total value of resource usage, time span and energy consumption of any application is symbolized as RT E then:

RTE of compression algorithm+RTE of data processing/transmitting of compressed data≤RTE of processing/transmitting the original data

These requirements narrow down the number of techniques that can be used with a sensor node and raise the demand to design a new compression algorithm specifically for the WSN limitations and applications.

Data compression: Data compression is a technique that reduce the total length of data by minimizing the num-ber of bits that are required to represent each data block (individual character of string). Statistically, a shorter description is allocated for high probable objects and longer description for less probable objects. This allocation is based on a model which is a collection of rules and data used to determine the allocation code (s).

In computers, the information is stored in a form of files. Those files are broadly catego-rized into two types with regard to compression. Multimedia files such as images, digitized audio and video. Secondly, word-based file and binary files such as database and executable files. Depending on the recoverability requirements of the aforementioned types, the data compression techniques have been broadly divided into two major categories which are lossy and lossless data compression.

In particular, the term of data compression refers to two sub-algorithms, compression and decompression (Nelson and Gailly, 1995). The compression algorithms aim to generate the D_c value which is the compressed data, from the input value D by reducing the redundancy of the input stream. This process reduces the data reliability and makes more supine to errors, so, the data integrity

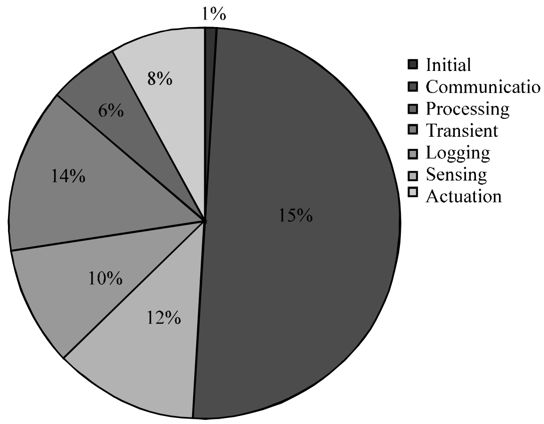

Fig. 3: Power consumption estimation of sensor tasks (Halgamuge, 2009)

technique is required to detect errors and thus, increases the reliability (Pu, 2005). Alternatively, the decompressing process reconstructs the data value X from compressed data D_c. Recoverability requirement determines whether the reconstruction scheme is necessary to guarantee X to be identical to D or otherwise (Nelson and Gailly, 1995).

Designing a compression algorithm must maintain the following parameters for the compression and decompression cycles:

- The quality should be high on both the coded and later on the decoded data
- The cost should be effective for the implementation
- The technique's complexity should be minimal
- The compression and decompression processes must execute within certain time spans

Data compression in WSN: In WSN nodes, there are three main power consumption tasks: processing, sensing and communicating. Figure 3 shows an estimated required power for executing different tasks belong to sensor nodes. Communication being the most energy consuming (Kimura and Latifi, 2005) and it is significantly affected by the size of data that need to be transferred or re-forwarded (Yan-Li *et al*., 2010). Favorably, data compression technique can be used to address this issue and as a consequence could possibly extend the node lifetime and improve the collective ability of the entire network by minimizing the amount of data that needs to be transmitted or received (Sheikh and Dakhore, 2015).

Execution of the instruction consumes much less power than data transmission. Chen *et al*. (2009) and Verdone *et al*. (2010) showed that executing three million instructions consumes energy equal to transmitting 1,000 bits by radio over a 100 m distance. It means that energy should be saved theoretically even when using 1,000 32 bit instructions to compress one bit only data (Barr and Asanovic, 2006). Hence, reducing the data size by using compression methods imposes significant impact on energy conservation of sensor nodes and therefore the whole WSN.

Data compression requirements in WSN: The general-purpose data compression algorithms were designed to work in high-end devices with no energy boundaries, producing a high compression ratio, saving storage space and for a case of lossy compression, minimizing distortion. However, with the WSN, the main purposes are different. The compression algorithms should maintain the following characteristics.

Reduced energy consumption: The primary goal of using data compression techniques with WSN is to minimize the energy consumption by reducing the radio traffic. Hence, the overall energy consumption of the compression algorithm should be very low.

Low computational overhead: The compression computational processes should be as minimal as possible to avoid disrupting the ordinary tasks of the sensor node. Using the micro-controller for a long time may monopolize its usage for compression tasks only.

Small memory footprint: The available memory and flash memory space in a sensor node is very small and therefore, any algorithm should be runnable with less than 10 kB of memory and 64 B of flash memory. Preferably, there should be a large margin available for the operating system or any other software in order to ensure greater stability. The memory requirements of the compression algorithm must be small to work within this limitation.

Small storage: The available storage space is also, limited to a few hundreds kilo-bytes. This amount of memory is used to store the operating system, compiler and other miscellaneous software that provides the sensor with additional properties. Therefore, the code size of the algorithm and the output compressed data should be very small.

Data compression type in WSN: There are two main approaches for data compression in the WSN: local data compression and distributed data compression (Srisooksai *et al*., 2012). Each approach has its own advantages and disadvantages.

Distributed data compression: This is an asymmetric coding that uses the correlation amongst the sensor

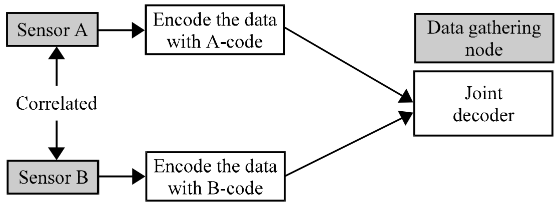

Fig. 4: Distributed coding approach

nodes to compress the data. Each sensor encodes its own data with a particular code before transmitting it to the base station where the data belonging to the group of sensors is combined. This approach works according to the Slepian-Wolf theorem which proves that two or more correlated data streams can be encoded independently and then, at a receiver side, the date can be decoded jointly with a rate equal to their joint entropy (Schonberg *et al.*, 2004). In the WSN, the data can be restored at the other ends according to the code of each sensor (Jiang and Li, 2010). Using this particular approach, many techniques have been developed such as Distributed Transform Coding (DTC) (Sadler and Martonosi, 2006), Compressed Sensing (CS) (Candes *et al.*, 2006), Distributed Source Coding (DSC) (Pradhan *et al.*, 2002) and Distributed Source Modelling (DSM) (Xiao *et al.*, 2006). Figure 4 shows the basic concepts of the distributed compression approach.

Local data compression: In this approach, the compression tasks are performed lo-cally on the individual sensor node by taking advantage of the temporal correlation of sensed data. Three techniques fall under this approach: dictionary-based, proba- bilistic and the hybridity of both. Huffman coding, s-LZW and RLE are examples of this compression technique. Between the two approaches, local data compression produces much better compression ratio and it is known to be more efficient than the other (Kolo *et al.*, 2012). Therefore, many interest were directed towards researches on local data compression for both compression types, lossy and lossless.

The critical measurement with WSN real-time monitoring application raises the need to store and transmit the raw form of data (Yan-Li *et al.*, 2010). Due to the sensitiveness of data, WSN requires a lossless data compression method that is efficient and consumes low energy. Sensor node limitations and the data compression algorithm requirements limit the number of applicable compression algorithms that can be used with the WSN (Long and Xiang, 2012). The existing data compression algorithms were originally designed for saving storage space without any concern for the energy consumption or limited resources. However, there are some lossless compression algorithms that can be implemented with the WSN such as run-length encoding, Huffman coding and LZW (Lempel Ziv Welch) coding (Lei-Ding *et al.*, 2009) because those algorithms require lower computational effort and memory occupation. Even though run-length coding is considered as the simplest algorithm amongst all compression algorithms, S-LZW remains the flagship of compression algorithms because of its performance in memory occupation, latency and compression effects (Mudgule *et al.*, 2014; Yan-Li *et al.*, 2010). Nevertheless, S-LZW still requires an improvement in coding efficiency to work better with the WSN. Many algorithms have been inspired from those three algorithms to present a suitable compression technique for the WSN.

Figure 5 shows the classification of data compression algorithms that are classified in recent papers with the origin of the adapted algorithms (Campobello *et al.*, 2015; Jiang and Li, 2010; Min *et al.*, 2012; Song, 2013; Srisooksai *et al.*, 2012; ZainEldin *et al.*, 2014) and these algorithms are used with the WSN.

Small data compression challenges: The term 'small data' can have various meanings depending on the field of usage. In the traditional data compression field, it refers to data of size equals to 100 bytes (Pereira, 1998). Nonetheless, in the WSN, the sensor nodes deal with much smaller data sizes. The sensor node is not designed to store the sensed information for a long time because it may fail at any time (Ye *et al.*, 2003) and lose all the sensed data. Therefore, it is equipped with a very small memory capacity. In addition, the transferred data is also, affected by other nodes. Because of that the stored data and the packets that are transferred are very small (Dener, 2014) because it is limited by an inadequate storage capacity. Therefore, the amount of data that can be transferred is very small. Unlike large input data which contains sufficient redundancy characters that allows maximum data compression (Gardner-Stephen *et al.*, 2013), small data encounters many challenges that limit the performance of the existing algorithms.

Data statistics: Compression algorithms use the statistics of data to either generate a dictionary or try to minimize the number of bits required to present each symbol. Most compression algorithms require processing of hundreds of characters to build a sufficient compression model before they start compressing the data. The small data

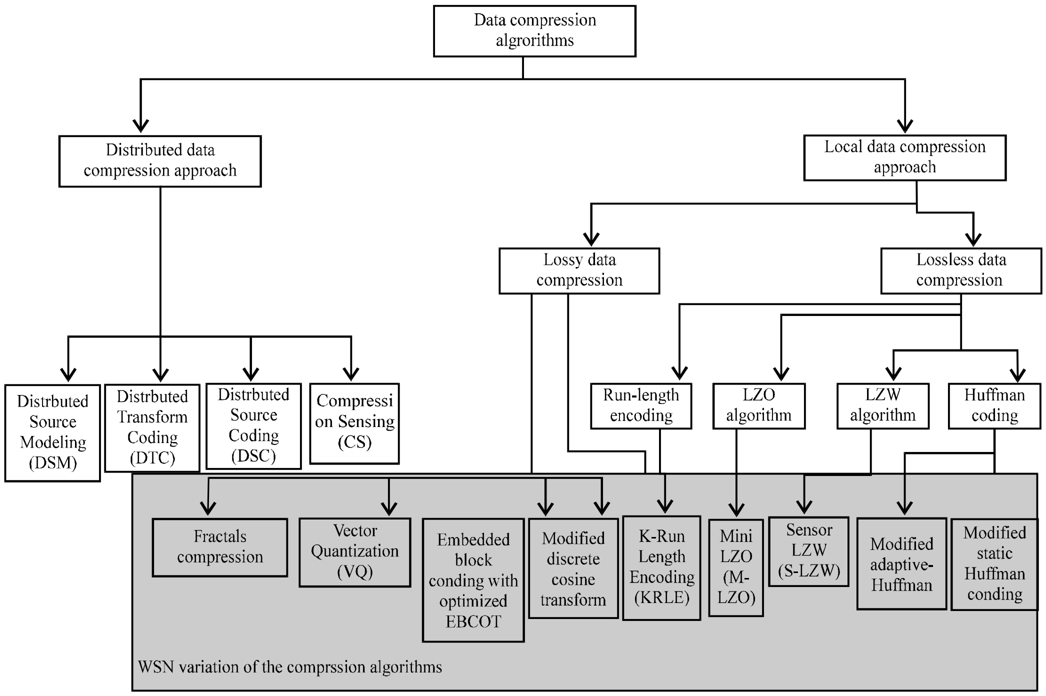

Fig. 5: WSN data compression diagram

contains only a few hundred symbols with a very low rate of reoccurrences. Also, compression in this case may lead to the expansion of the size of data instead of shrinking it.

Compression speed: For some applications, the time needed to transmit or receive the data is very critical. The time required to compress the data should be taken into account and be a part of transmission time. For large input data, compression has been shown to help minimizing the data. Thus, the time needed to compress the data is insignificant compared to the time that it can save from the transmission process. Things can be very different with small data; the time needed to compress and to transmit the data may end up being much higher than the time needed to transmit raw data. Therefore, developing a compression algorithm for small data should not only aim for high compression ratios but also, fast enough compression speeds.

There are many solutions that have been proposed in order to improve the efficiency of the WSN and minimize the transmitted data size using the data compression techniques.

A power aware technique was proposed by Wu and Abouzeid (2004). The proposed solution uses MTE algorithm (Minimize Total Energy) to integrate the local data compression in it. The total energy dissipation has been minimized in MTE by selecting the optimal image compression. The proposed algorithm focused on power efficiency for the sensor nodes without any optimization in terms of video coding and image transmission in the WSN.

A data reduction technique was proposed in Santini and Romer (2006) by using adaptive Least Mean Square (LMS) algorithm with dual prediction scheme. The adaptive LMS pro-duces an excellent performance with low memory and computational overhead. In addition, it did not require any prior data statistical acknowledgment. However, some issues have been addressed with this algorithm. The robustness needs to be provided to handle mes-sage loss. Moreover, the source failure detector is required because the prediction output keeps continuing by the sink even if the source node fails.

By using a low-complexity data model with arithmetic coding and context modeling, Rein *et al.* (2006) introduced a lossless compression technique specifically for short text on embedded systems. Interestingly enough, the technique is made up of a few hundreds lines of source code with 32 kB of RAM. However, it only works with an English text data along with a previous knowledge of data characteristics. Moreover, it is designed for dealing with data series that are larger than 50 B with 32 kB RAM usage which is also, high.

Kumsawat *et al*. (2013) inspired from Skipped High-Pass Sub-band wavelet transform which is called SHPS, a new lossy signal compression algorithm. The proposed algorithm saves computation energy and uses fewer numbers of operations than traditional wavelet transform because it does not need computing high-pass coefficients. The simplicity of the algorithm makes its implementation easy and increases its execution speed. Nevertheless, the algorithm requires an improvement in the quality of the reconstructed signal. Also, it needs an optimization in the technique of compression.

Marcelloni (2008) presented a lossless compression algorithm by modifying the adaptive Huffman coding to obtain better compression ratio with high correlated data. Also, the modified algorithm was efficient and suitable to work with many available com-mercial WSN nodes. Nevertheless, this modification affected the ability of the algorithm to compress low correlated data and led to present a destitute compression ratio.

Strydis and Gaydadjiev (2008) analysed the data compression algorithms to find the most suitable one for biomedical application. The study focused on three constraints: com-pression ratio, compression rate and power consumption. The researchers used a high resource- constrained simulator and the Basic Compression Library (BCL) as an implementation of lossless algorithms such as Huffman and RLE. The data memory size in implanted device ranged between 1-10 kB so, this ranging size is used in the experiment. Huffman algorithm produced better compression ratio than LZW algorithms for small data size (1 kB) but the compression ratio is almost equal to the advantage of execution speed to LZW when 10 kB of data is used. However, in terms of power consumption, the Modified LZW (M-LZW), S-LZW and BCL algorithms are the undisputed winners with highest compression rate as well. The study found out that the M-LZW is the best algorithm for microarchitec-ture system.

Marcelloni and Vecchio (2009) proposed a simple Lossless Entropy Compression (LEC) solution based on static Huffman coding. The proposed solution was developed to limit the computational overhead, memory usage and power consumption of sensor nodes by minimizing the data size that is processed and transmitted by the sensor node. The proposed solution enhanced the compression ratio in comparison with gzip, bzip2, RAR, classical Huffman and arithmetic encodings. In addition, it required a low memory space and can be implemented in a few lines of the code. However, using static Huffman coding in the proposed solution has a significant drawback because it needs prior knowledge of sensed data statistics to assign the probability and compress the data. As a result, it degrades the compression performance and may not be feasible for real-time sensor.

Tharini and Ranjan (2009) modified the adaptive Huffman coding and solve the problem of Marcelloni (2008) with high correlated data by using sets of symbols as a leaf in Huffman tree instead of individual symbols. The modification improves the compression ratio of adaptive Huffman coding by 10-15% and the number of levels in the binary tree is less. Using fewer levels means less memory utilization and computational effort in coding and decoding, so, it is suitable to work with sensor nodes. However, the modified algorithm produced a small compression ratio when using it with high correlated data. Furthermore, it has a high energy consumption.

Yan-Li *et al*. (2010) addressed the lack of LZW algorithm and proposed a solution for this restriction. First, they reduce the dictionary size and decode the single characters correctly by omitting the individual characters from the dictionary. Next, they use two bytes to store the dictionary address space so it is more suitable to work with limited memory nodes. Furthermore, it saves memory space and provides high efficiency by limiting the substring length in the dictionary. Finally, since, LZW has a high-efficiency with the text file, the non-text file was converted to a text file. However, the proposed solution does not offer a solution to another major problems in LZW which are the limitation in compressing the non-document file and the growing of dictionary size when data size is increased.

Maurya *et al*. (2011) proposed a compression algorithm that decorated the sensed data by using the median predictor. Even though the proposed algorithm is simple and needs a few code lines to be implemented, it uses the LEC compression table concept and that means it has the same complexity of LEC. The low compression efficiency compared with LEC is another drawback of the proposed algorithm.

El Assi *et al*. (2013) proposed a compression algorithm for the WSN based on minimalist, streaming and adaptive compression algorithms. The concept of Minimalist is using the minimum possible amount of resource to perform the compression operation. When Streaming means that no buffer is required in compression and adaptive means that the output variable-size is generated based on the number of input bytes. The proposed algorithm is a lossless compression that does not need any data correlation or similarity and compressing only single-precision floating point data. However, the floating-point should not exceed 7.

Otherwise, it will be truncated. Furthermore, it must have scientific notation equal or less than the power of 32.

An efficient lossless compression algorithm has been suggested by Misbahuddin *et al*. (2014) for cluster-based WSN. The proposed solution compressed the payload size and re-duced overall power consumption. The performance of the proposed solution has been evaluated using compression ratio. However, the result shows that the suggested algorithm produces a good compression ratio with high byte repetition and low power consumption. Nevertheless, the results have not been compared with other compression algorithms. More-over, the compression ratio depends on the byte repetition and that means it does not work with low reputation data and small data size.

A lightweight data compression has been suggested by Medeiros *et al*. (2014) for the WSN. The proposed algorithm uses Huffman coding to compress data depending on sensed data characteristics and produce a less complicated algorithmic without affecting the compression ratios. One of the shortcomings in this solution work arises when we have a long data size that is limited to a particular range values when constructing the Huffman tree. In addition, it adapts the dataset to be with a particular data type by casting the data value, so, the algorithm was inefficient when in need of the precise data value.

Liang and Li (2014) presented a novel efficient and highly robust lossless data compression algorithm for the WSN which significantly outperforms popular WSN lossless algorithms such as LEC and S-LZW. It was named a Sequential Lossless Entropy Compression (S-LEC). For the various WSN data sets, S-LEC presents a high robustness and efficiency. S-LEC addresses the weaknesses of the LEC and extends it to handle the lack of robustness. In addition, the proposed algorithm is simple enough to be implemented with WSN nodes limitations. However, the proposed algorithm still consumes much energy compared with the S-LZW and the compression rate is low due to the high number of instructions. The high memory usage is another drawbacks of the S-LEC.

When the traditional compression algorithms work after converting the signal from analog to digital, Leon-Salas (2015) proposed a low complexity lossy compression algorithm that works on analog domain. The proposed solution presents a compression converter of analog-to-digital sensed signal and omits the quantization part of standard data compression solution scheme. Furthermore, the new solution has been tested on the programmable hardware circuit and shows a low hardware complexity requirements with low energy consumption and high performance. However, the new compression solution has not been tested to show the compression ratio. It focused on the complexity without the concern of the compression ratio and data size that can be compressed in the new solution. Therefore, the proposed solution needs to be improved and to be compared with other compression algorithms in term of compression ratio.

Dutta (2015) addressed the issue of the medical field that is the need of transmitting massive high-quality sensed medical data from sensors to the base-station. They proposed a data compression technique that is optimized specifically for the medical data. The proposed solution is robust to transmission errors and uses a fuzzy-logic route selection to maximize the lifetime of the sensor nodes. Furthermore, it is geographical/location independent. The proposed compression technique performs in two steps which are transforming image and encoding of coefficients. An adaptive edge-based fuzzy filter has been used to reduce the noises and artifacts of the decompressed data. The resulted images after decompressing the data have a low degradation in the image quality that cannot be recognized by the Human Vision System (HVS). Yet, the proposed solution is not completely a lossless compression algorithm so it cannot be used with critical data such as text. Furthermore, the complexity of the proposed solution may not be suitable for many sensor nodes abilities.

Alsalaet and Ali (2015) proposed a data compression solution to compress vibration signals based on Modified Discrete Cosine Transform (MDCT) followed by Embedded Harmonic Components Coding (EHCC). The proposed solution applied EHCC to exploit a harmonic redundancy of vibration signals and improve the compression ratio. This solution has been designed to work fast and efficiently on the sensor node by using the modified variant of DCT. However, it obtained a lossy compression for a specific type of data which is the vibration signals. The compression ratio should be very high especially with lossy compression but it presents about 16% in the best case. Moreover, the amount of lost-ness which is measured by PSNR, shows an increment when data size is increased. These disadvantages may limit the implementation of this technique in many applications of the WSN.

RESULTS AND DISCUSSION

Table 1 shows a summary of a list of some recent most solutions that were proposed for compressing data within the sensor networks. As a result of these investigations, we found that the existing compression algorithms, to some extent have some serious limitations that are as follows:

Table 1: Summary of data compression prior works

Title	Researcher's/Year	Proposed technique	Advantages	Drawbacks
Power aware image transmission in energy constrained wireless networks	Wu and Abouzeid (2004)	Using MTE algorithm to compress loosely and integrate data inside it	Minimizing total energy dissipation	Focusing only on the power efficiency without optimizing coding compres-sion
An adaptive strategy for quality-based data reduction in wireless sensor networks	Santini and Romer (2006)	Using adaptive least Mean square algorithm with a dual prediction scheme to minimize the data size in the WSN	Produce high performance with low memory usage and computational overhead Not require a prior knowledge of data statistics	Robustness is very low. Its applications are very limited
Compression of short text on embedded systems	Rein *et al*. (2006)	Using a low-complexity data model with arithmetic coding and context modelling to provide lossless data compression for WSN	Compression short text messages and requires a few hundred lines of code to be developed	Working only with English text characters and requiring a large amount of data and system memory
Wavelet-based data compression technique for wireless sensor net-works	Kumsawat *et al*. (2013)	Lossy compression algorithm for signal compression based on SHPS	Saving computation energy in use fewer number of instructions than standard wavelet	Requires an improvement in the quality of signal reconstruction and optimization in compression rate
Profiling of lossless-compression algorithms for a novel biomedical-implant architecture	Strydis and Gaydadjiev (2008)	Analyzing the data compression algorithms to find the best techniques for biomedical data	Used a variant parameters to analysis the algorithms	Has a lack in energy consumption comparing. Not included the latest techniques in the compression list
An efficient lossless compression Algorithm for Tiny Nodes of Mon-itoring wireless sensor networks	Marcelloni and Vecchio (2009)	A simple Lossless Entropy Compression (LEC)	Improved the compression ratio and memory usage	Require prior knowledge of sensed data statistics and low performance
Design of modified adaptive Huffman data compression algorithm for wireless sensor network	Tharini and Ranjan (2009)	Modifying the adaptive Huffman coding to compress the low correlated data losslessly	Improved the compression ratio up to 15% and minimized the number of binary tree levels Low memory usage	It produces a low compression ratio with high correlated data and consumes high energy
Improved LZW algorithm of loss-less data compression for WSN	Yan-Li *et al*. (2009)	Improving the LZW compression algorithm to produce an efficient lossless compression algorithm	Reducing the dictionary size and provide an accurate signal characters	It does not solve the issue of the growing dictionary that in LZW and its efficiency is high only with text data type
Median predictor based data compression Algorithm for wireless sensor network	Maurya *et al*. (2011)	A lossless compression algorithm to decorated and compression data using median predictor	It is simple and needs few code lines to be implemented	Low compression efficiency compared with LEC algorithm and it has the same complexity of LEC algorithm
Resource-efficient floating-point data compression using MAS in WSN	El Assi *et al*. (2013)	Lossless compression algorithm to minimize transmitted data size using MAS concepts	No need high data correlation and has a high performance	Limited to floating-point data and has an issue with the floating-point that exceed 7 digits
An Efficient and robust data Compression algorithm in wireless Sensor networks	Liang and Li (2014)	A novel efficient and robust lossless compression based on LEC algorithm named Sequential-LEC	High robustness and efficiency. Sim ple enough to be used with the sensor node limitation	Low compression rate and consumes much energy because of the robustness instructions and LEC compression complexity The memory usage is high
Lightweight data compression in wireless Sensor networks using Huffman coding	Medeiros *et al*. (2014)	Compressing the data losslessly based on Huffman coding and sensed data characteristics	Less complicated than Huffman coding without affecting the compression ratio	Has an issue with large data compression because data value is limited in compression
An efficient lossless data reduction algorithm for cluster based wireless sensor network	Misbahuddin *et al*. (2014)	Compress the payload size of the transmitted data using efficient loss-less compression algorithm	Reducing overall energy consumption and producing a high compression ratio	Requiring a high byte repetition to produce a high compression ratio
Low-complexity compression for sensory systems	Leon-Salas (2015)	Compress an analog signal using a low complexity lossy compression algorithm	Low hardware complexity, low energy consumption with a high speed compression	Has not been tested to show the compression ratio and focusing only on the complexity of the algorithm itself
Medical data compression and transmission in wireless Ad hoc networks	Dutta (2015)	Lossless data compression for medical sensed image data using fuzzy logic	Robust to error and able to maximize sensor lifetime by using fuzzy logic route	It is not a completely lossless compression and it is more complex than many other image compression techniques
Data compression in wireless sensor network using MDCT and embedded harmonic coding	Alsalaet and Ali (2015)	Lossy compression for vibration signals using data compression techniques	Improving compression ratio and minimizing energy consumption	Hight lostness in data value when the ata size increased

Existing algorithms are built based on complex algorithms that were designed for high-performance computers withan ability to compress the data on the fly without much concern for the simplicity or system resource usage. Applying these algorithms to work with the sensor node's limitations requires deprecating some

Table 2: Existing algorithms limitations

	Characteristics and limitations				
Algorithm	Dictionary limitation	Prior computations	Bytes repetition required	Built based on	Main objective (s)
LZ77	No limit	No	-	Yes	Compression ratio
LZMA	-	Yes	LZ77/LZ78	Yes	Compression ratio
S-LZW	512 items/unlimited	No	LZW	Yes	Compression ratio/minimal Resource Usage
m-LZO	No limit	No	LZO	Yes	Compression speed/minimal Resource Usage
Gzip	No limit	Yes	LZ77 and Huffman coding	Yes	High compression ratio
Huffman coding	-	Yes	-	Yes	Compression ratio
Adaptive Huff man coding	-	Yes	Huffman coding	No	Compression ratio/real time compression

complex processes in order to improve its performance. However, there are processes that cannot be stripped down and this hasbecome the bottlenecks to the performance improvements.

Existing algorithms rely heavily on the bytes (characters) repetition. Data repetition can exist at string level, byte (character) level and sub-byte (bit) level. String or byte repetition is important for both entropy-based and dictionary-based algorithms in building up an optimal compression module (tree) or compression dictionary, respectively. In fact, it is the biggest contributor to an efficient compression ratio. However, this data characteristicmay not exist especially in the case of small data communication.

The computational overhead of the proposed solutions is high and that may cause disruption on the execution of the ordinary tasks of the sensor node and thus consumes more energy.

Memory consumption is largely affected by the volume of pre-compression processes. In dictionary-based algorithms, the memory is used when reading, updating and searching the dictionary. In the entropy-based algorithm, the memory is used to calculate the probability distribution of symbols and store in a tree-like structure. Based on the intrinsic complexity of these two processes, the amount of memory and thus the processing power used in the dictionary-based algorithm is reported to be less than that of the entropy-based algorithms (Stolikj *et al*., 2012). As such dictionary-based algorithms are to work with sensor node much more efficient than the entropy-based. However, the requirement imposed by this algorithm is still considerably high as compared to sensor node's capability. The key to these performance parameters is the size of the dictionary and the number of items in it. For example, searching for an item in the larger dictionary requires more resources than that of a smaller one. In fact, the size of the item itself also affects the usability of resources. Therefore, limiting the number of dictionary items (such that found in S-LZW) or limiting the size of each item alone is not sufficient to prevent the other limiting parameters from growing unlimited. Instead, the dictionary should have a limited number of items and each item should not be bigger than some pre-defined value. However, the dictionary of the existing algorithms is designed to hold a maximum possible amount of high reoccurrences string, therefore, putting some limits on the number of items may affect the compression ratio.

Table 2 generalizes the main characteristics and possible limitations exhibited by some compression algorithms thatare used in WSN. The investigated parameters form the basis to good performance achievement of each algorithm and that are of compression ratio, resource consumption and execution speed. The algorithms LZ77, LZW, LZMA and Gzip are the most widely used in traditional computer applications for best compression ratio, however, they come with not much concern on optimal resources consumption.

Much better algorithms that are used with the WSN, Huffman coding (best algorithm in terms of code representation) and Adaptive Huffman coding (the adaptive Huffman algorithm for real-time compression), S-LZW (the flagship compression algorithm of the WSN), were designed to produce the best compression ratio with minimum resource consumption. We notice that S-LZW has a limit in the number of items in the dictionary but not in size of the dictionary it self because each item is allowed to contain more than one byte.

Otherwise, in terms of compression speed, the m-LZO was specifically designed for this purpose and therefore can be used as a benchmark for evaluating new algorithm's.

These seven algorithms are shown to cover most part of investigations with regards to the efficient data compression algorithms for WSNs. Many more algorithms are available but they are excluded from the list due tobeing rarely used and sometimes do not have a standard implementation for WSN and is not suitable for many applications. It may seem obvious that the best solution is to design an algorithm starting from the ground up to work specifically with the WSN requirements and limitations.

CONCLUSION

Compression algorithms are developed to minimize the amount of resource that requires handling the data in the sensor node. As specified in a comparative study, the current compression techniques are able to save the sensor node energy but each of them has it own limitation and a specific application that work efficiently with it. The lossy compression algorithms provide a better compression ratio while lossless algorithms are able to preserve the data when it decompressed. To sum up, using a specific compression technique highly depends on the application requirement that a WSN was designed for as well as the speci-fication of the sensor node.

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