A Comprehensive Review of Distributed Coding Algorithms for Visual Sensor Network (VSN)

Mansoor Ebrahim, Chai Wai Chong

Faculty of Science & Technology, Sunway University, Selangor, Malaysia
12032389@imail.sunway.edu.my, waichongc@sunway.edu.my

***Abstract*:** Since the invention of low cost camera, it has been widely incorporated into the sensor node in Wireless Sensor Network (WSN) to create the Visual Sensor Network (VSN). Nevertheless, the usage of the camera is bringing with it a lot of new challenges, because all the sensor nodes are powered by batteries. Hence, energy consumption is one of the most critical issues that have to be taken into consideration. In addition to this, the use of batteries has also limited the resources (memory, processor) that can be incorporated into the sensor node. The lifetime of a VSN decreases quickly as the image is transferred to the destination. One of the solutions to the aforementioned problem is to reduce the data to be transferred in the network by using image compression. In this paper, a comprehensive survey and analysis of distributed coding algorithms that can be used to encode images in VSN is provided. The paper also includes an overview of these algorithms, together with their advantages and deficiencies when implemented in VSN. These algorithms are then compared at the end to determine the algorithm that is more suitable for VSN.

***Keywords*:** Visual Sensor Network (VSN), Distributed Coding Schemes, Distributed Source Coding (Slepian Wolf, Wyner Ziv), Compressive Sensing, Image Compression.

1. Introduction

The production of low cost camera has caused Wireless Sensor Network (WSN) [1] to emerge and form the Visual Sensor Network (VSN) [2, 3]. It is a platform that has been widely adopted in various applications, such as armed tracing and surveillance [4, 5], natural catastrophe reprieves [5], health monitoring [5], perilous atmosphere investigation and seismic identifying [6]. Typically, a VSN is constructed by several wirelessly distributed sensor nodes that are capable of harvesting and relaying the information in the network as shown in Figure 1 [7]. These sensor nodes are usually tiny devices with limited processing power [8, 9, 10].

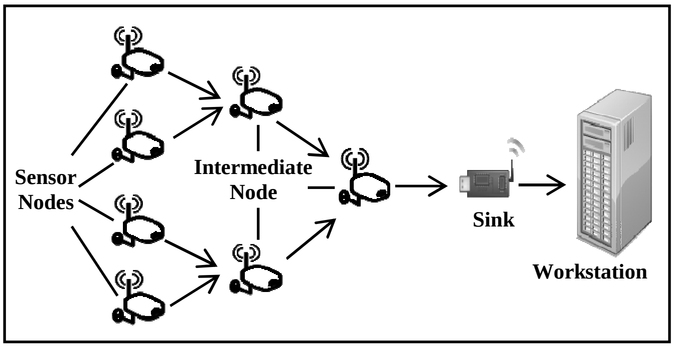

Figure 1. Wireless sensor network architecture

One of the greatest features of VSN is their independent nature. If the sensors are simply dropped in the field, they will group together to automatically construct an extremely flexible, low power network [7], creating an ad-hoc mesh network by initializing connection with every other node in range, and eliminates the necessity for expensive and cumbersome wiring among nodes [11]. However, the use of cameras has increased the amount of data that has to be transmitted in the network significantly, bringing with it greater challenges, such as the limitation of processing power and memory [12]. The VSNs are usually different from the standard WSN in terms of data operation, as in VSN the data is in the form of pixel values (image) whereas, standard WSN operates with scalar data (numeric). Furthermore, in standard WSN a small number of packet losses can vary the gathered data drastically while, in VSN the effect of these losses is altered by making use of the redundant nature of the images. In addition, in VSN all the neighboring node observe the same area of concentration resulting in multiple views of the same sight. Whereas, in the standard WSN distinctive data values are gathered by the neighboring nodes within the same area. However, VSN navigation sensing visualization is restricted.

1.1. Challenging Issues & Possible Solutions:

The transformation of WSN into VSN brings with its diverse resource challenges that primarily include energy consumption, bandwidth, poor computation and processing capabilities [12]. Even though the CPU is considerably powerful and faster than the human mind in terms of processing, however, have limitations in terms substantial processing power, storage volume and communication bandwidth for image processing [13].

In VSN, sensor nodes and intermediate nodes exploit considerable amount of energy to transmit the image data toward the sink, than statistical sensor applications that are built on the WSN, where sensor nodes only accumulate and transmit data such as temperature or pressure value. Besides, the life time of a VSN also reduces quickly due to the additional data transmission. Since the sensor nodes can be deployed in areas that are difficult to reach, the batteries cannot be easily replaced regularly. Hence, the maintenance and replacement can become very costly and time wasting.

In order to overcome the aforementioned problems, many research works [13-33] have been made towards the designing and improvement of effective, reliable and energy efficient image processing algorithms. The problems can be addressed in two ways: i) to take into account redundancy of nodes in a sensor network, ii) to apply compression schemes to decrease the data transmission [15]. In the first case, only a subset of sensor nodes will be selected and used by turns, avoiding the utilization of too much energy by certain sensor nodes and thus increase the network lifespan. However, this approach may not work well when there is no redundant node. It is observed from the research carried out in [16] that the energy consumption for data transmission is higher than that of data processing. Furthermore, research done in [17] clearly verifies that the energy cost of transmitting 1kB information is almost the same for executing 3 million instructions using a 100 million instructions per second (MIPS) /W processor. Hence, when sensor nodes have to frequently monitor and transmit image data for a very long time, compression of data is a very expedient solution.

In VSN, image compression schemes are usually implemented before transmission of the image data. This results in reducing energy consumption, as well as bandwidth usage. Figure 2a and 2b show the effect of transmitted uncompressed and compressed data through a multi-hop network. For example, if each sensor is required to transmit 100kB of uncompressed data, then each intermediate node will have to relay 200kB of data in the network. In contrast, if the use of compression scheme could help to reduce the data transmission by 50kB, the intermediate node will only have to relay 100kB of data, instead of 200kB. Therefore, compress the data before transmission not only help to reduce the load from the sensor node, but also from the intermediate node.

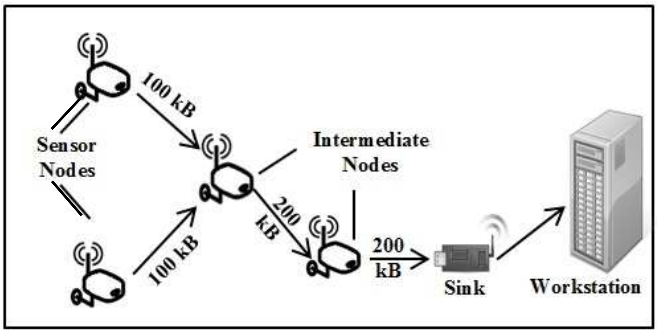

Figure 2a. VSN scheme without image compression

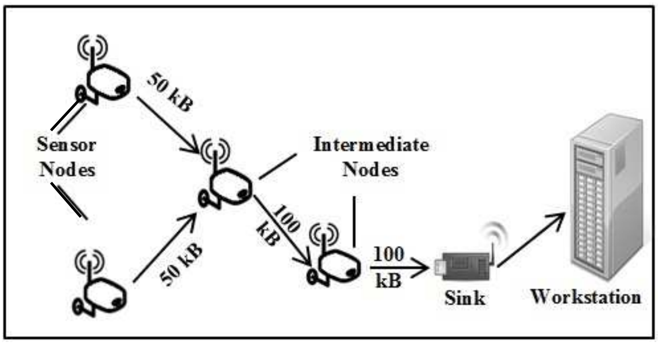

Figure 2b. VSN scheme with image compression

The basic idea of image compression is to reduce the redundant information that is insensitive to the human eye.

1.2. Image Compression Schemes for VSN:

Generally, image compressions for VSN can be categorized into the following subsequent sets as displayed in Figure 3.

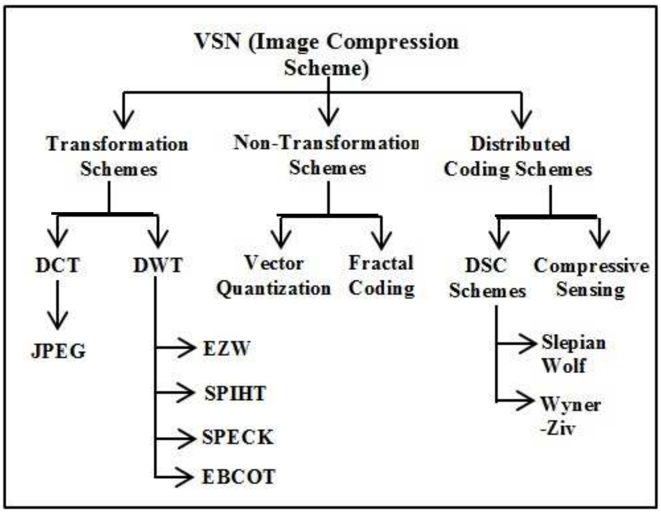

Figure 3. Classification of image compression scheme for VSN

The ordinary compression scheme is only capable of removing the spatial, spectral, and temporal redundancies that appear within the image itself. In cases where the sensor nodes are simply deployed in the field, the field-of-view of the cameras may overlap with each other. Hence, it is possible to further reduce the amount of data to be transmitted, by removing the overlapping regions (interview redundancy), usually achieved by using the distributed coding schemes. Many research works have been done [18-33] on different aspects (audio, video, image) of VSN. However, limited work has been done in the review of distributed coding schemes for VSN. The scope of this research is to discuss and analyze the moderately researched distributed coding schemes. Therefore, transformation/ non-transformation compression schemes for VSN will not be discussed further. However, the detailed description and comparative analysis of the above mentioned transformation/non-transformation schemes can be studied from the research papers [28-51]

In this review paper, the main focus is on the detailed examination of the overall architecture, performance (power management, memory, computational complexity), along with the advantages, disadvantages, implementation, and key issues of distributed coding schemes. The review starts by presenting a comprehensive discussion and analysis on different aspects (overview, architecture, applications) of distributed coding schemes (Distributed Source Coding (DSC), Compressive Sensing (CS)) along with their implementation and most exposed issues for VSN in section 2. In section 3, an in-depth qualitative comparative analysis of state of the art image compression schemes for VSN is provided based on the evaluation criteria and assessment methodology. Whereas, the implementation and simulation of these schemes on standard images and video sequences is carried out in section 4 in order to analyze their performance as well as to support the qualitative analysis results in section 3. The overall conclusion is drawn in section 5.

2. Distributed Coding Schemes:

Distributed coding schemes have appeared to be one of the most projecting and proficient image compression mechanisms for modern image processing and sensor based applications in the recent era. The rapid growth of distributed coding schemes has made them an attractive mechanism for multimedia applications along with VSN standards. Presently, a lot of distributed coding schemes have been developed for digital image and video, as well. The most attractive schemes used in image processing application are Distributed Source Coding (DSC) and Compressive Sensing (CS). An overview of research related to distributed coding schemes, primarily DSC (Slepian-Wolf, Wyner-Ziv) and CS schemes is provided in the following subsections. Numerous researchers have carried out research work on distributed coding schemes mainly focusing on the major issue (energy consumption, image quality, memory) related to image processing in VSN and have proposed different efficient schemes to overcome such problems.

2.1. Distributed Source Coding:

DSC is one of the revolutionizing technologies that have emerged as a mechanism for image compression for sensor networks [52]. The scheme is based on the phenomenon of individual compression of correlated sensor outputs that does not interact with each other i.e. the transmission of a set of independently compressed sensor outputs (no communication with each other) to a common point (base station) for joint decoding [53, 54]. DSC is a fundamental approach that exploits the spatial association of sensor nodes resulting in reduced computational complexity at the sensor node (lower powered devices) whereas, increasing the complexity at the central node (high power devices) without performance degradation. Thus, such features of DSC help to support the energy constraints in VSN [55-58].

Although DSC has been an area of research since the 1970s, but it gains popularity as a key image compression scheme after the current dramatic increase in the adoption of visual sensor applications by the modern world. DSC schemes are used for remote sensing and multi-view images in order to comprehend a low complexity encoder by manipulating interrelated images and the inter-band correlation respectively. With this new DSC model, one of the major difficulties is to achieve the similar proficiency (joint entropy of correlated sources) i.e. compression of correlated sources that are not co-located [59-62]. Different schemes were introduced with DSC such as LDPC [64] code, PRISM [75], Stanford [75], but all these schemes were based on Slepian-Wolf (SW) and Wyner-Ziv (WZ) theorems that increase the range of DSC to many potential applications (sensor network, wireless video) [79].

2.1.1. Slepian-Wolf Image Compression Scheme:

Slepian Wolf (SW) [63] is a mechanism based on lossless image compression. According to [63], the same performance as that of jointly encoded source can be attained when multiple sources having interrelated data are encoded independently. The working principle of SW technique is that each of the interrelated data sets is encoded independently by separate encoder, but the compressed output is decoded together by a single decoder, such a mechanism is known as SW coding, which is a form of DSC. As SW is a Lossless compression scheme, therefore, the output is independent of small errors and losses. One of the attractive features of SW is the manipulation of distinct encoders, resulting in an improved compression ratio as the data sets are interrelated. The general structure of the SW algorithm along with lossless decoder is p shown in Figure 4, that shows that the two different sources are encoded separately using a lossless encoder resulting in compressed outputs that are combined at the decoder end, as the scheme is based on joint decoding process with side information. A complete description of the algorithm with a mathematical model can be found in [63].

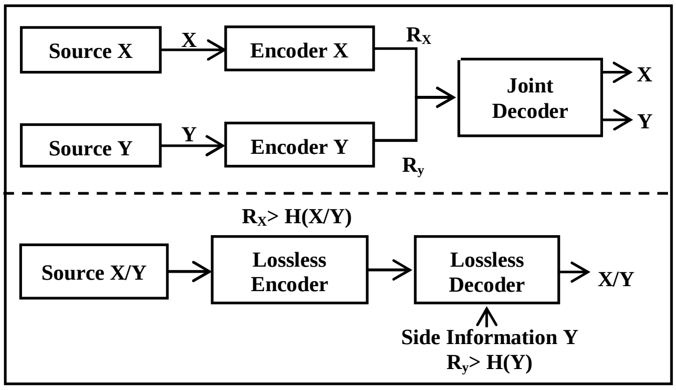

Figure 4. General Structure of SW algorithm along with lossless decoder

The SW coding has practical significances such that for the systems with limited computational resources (battery power and memory) or for a system with physically divided interrelated data sets [70]. The research papers published by different authors in [63-71] have contributed towards the understanding of the concept of SW coding and analyzing its implementation aspects with WSN (especially VSN). In [63], the well-known SW results are provided that describes the rate region for lossless distributed sources. These results have significant effects of information theory problems as varied as sensor networks, authentication, and computational complexity.

In this context, [64] carried out research work on the SW scheme in order to challenge the problem of independent encoding of correlated sources and joint decoding for achieving the SW attainable rate region for random interrelated sources at any instant. In this work, description regarding how distributed linear codes can be used to handle the SW problems as well as embedding of LDPC into the proposed scheme is provided. Moreover, the simulation result and analysis in [64] verifies that the proposed scheme performs well for the entire SW rate region for arbitrarily correlated sources, but for small codes and block sizes.

Further, in research papers [65-67] work on the implementation and analysis of the SW in WSN is provided. The authors have highlighted that SW coding is a promising scheme for WSN (especially VSN) because it can entirely eliminate the data redundancy due to spatially interrelated interpretations. However, these papers mainly focus on the major problem in the implementation of SW in different VSN that includes power constraints and their possible solutions.

The research paper in [65] addresses the rate-allocation problem caused by SW coding when dealing with multiple interrelated sources, resulting in an increase of transmission power consumption of VSN. In addition to this, a novel water-filling algorithm is proposed to identify the optimal rate-point in order to provide lossless recreation of the sources, whereas reducing the overall computational complexity and power consumption of the VSN.

The research paper [66, 67] discusses the energy problems (increased volume of data produced within each cluster resulting in maximum energy consumption) caused by SW coding in clustered based VSN and propose possible solutions such as i) an SW coding based energy-efficient clustering (SWEEC) algorithm that provides better compression rate. The algorithm also improves the overall energy efficiency for transmission in clustered based VSN when compared to the standard SW scheme [63] and the simulation results attained in [66] verifies it, ii) A suitable distributed optimal compression clustering protocol (DOC2) that reduces the volume of data in a clustered network resulting in better intra-cluster communication cost as proved by the simulations in [67] respectively.

Additionally, in [68-71] problems regarding SW scheme are discussed with possible propositions such that [68] proposes a new algorithm named distributed arithmetic coding that make use of arithmetic codes for the distributed case. In particular, this scheme was launched for the SW coding problem, along with a joint decoder, providing satisfactory results over SW, the research paper [69] identifies that the SW problem is related to dual channel coding and establish a liner code book duality in between the SW coding and channel coding. This duality leads the way towards the study of linear SW codes in terms of trade off among error rates at high proportions.

The research paper [70] discusses a novel probability proof of the SW theorem for i.i.d. Sources over finite alphabets by determining that for attaining the standard SW rate region the random codes are linear over the real field. Another constructive approach for the attainability standard SW rate region can be found in the work done in [71]. The work suggests an intuitive approach for symmetric and non-symmetric SW coding that can be used with systematic and non-systematic linear codes and can be extended for more than two sources.

Table 1 presents the performance outcomes for SW coding scheme that are drawn after studying and analyzing the above discussed research literature.

Table 1. Performance analysis of DSC (SW) image compression scheme

Parameters	Performance
Power Efficiency	Moderate power efficiency as it completely removes redundancy produced by spatially interrelated data sets. However, in clustered network the power consumption increases due to increasing in volume of data within each cluster.
Memory Utilization	Minimum memory utilization i.e. it consists of independent encoder phenomenon (correlated data are encoded separately and decoded jointly)
Compression Ratio	Moderate compression ratio.
Complexity	Low complexity level of the encoder side as it consists of individual low complexity encoders i.e. shifting major computational load to the decoder side.
Execution Time	Moderate or low execution time as the processing load is shifted from the independent encoders to a joint decoder.
Lossyness	The overall image quality is moderate or high as SW is of lossless nature.

2.1.2. Wyner-Ziv Image Compression Scheme:

Wyner Ziv (WZ) [72] scheme was proposed in 1976 and is based on the extended idea of SW theorem. The WZ is a lossy compression technique with the Side Information (SI) feature at the decoder. The WZ scheme is based on the same phenomenon as that of SW and obtains similar output results, but with a lossy compression scheme. The WZ scheme assumes that sources are mutually Gaussian i.e. input data sets are encoded within the data set, but are decoded conditionally make use of the SI. The decoder includes earlier decoded data set information in order to attain the SI. In each data set a channel code is applied by the WZ encoder and a set of resulting parity bits are transmitted. The decoder makes use of the parity bits and the SI to complete the decoding [75]. Recently, the WZ coding has been utilized in image/video. Figure 5 presents the overall block diagram of the WZ image compression encoder and decoder, in which the original image is first transformed and then quantized.The quantized image data is passed through the SW lossy encoder without SI. The output is a compressed image. For decoding, the compressed image data is sent to the joint lossy decoder having SI as discussed above. Once done, the remaining steps are performed in reverse order. A complete description of the algorithm with a mathematical model can be found in the research paper [72].

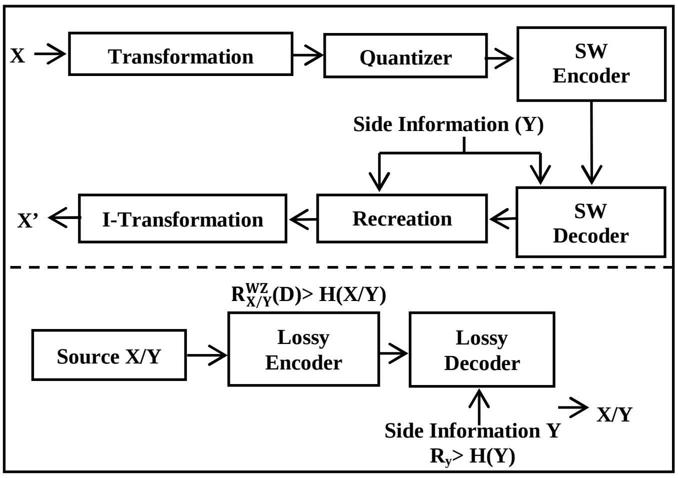

Figure 5. Overall block diagram of WZ encoder along with lossy decoder

The research work by different researchers in [72-79] leads way towards the exploration of the WZ coding scheme.

In [72], the basic WZ algorithm is presented and explained that is derived from the principle of SW scheme. However, WZ makes use of lossy compression scheme assuming that the sources are mutually Gaussian i.e. in WZ Scheme, input data sets are encoded within the data set but are decoded conditionally make use of the SI. This algorithm opens many ways for the development of efficient WZ based approaches for low powered image applications. The research papers [73, 74] provide different approaches by extending the WZ scheme for multimedia networks.

The research work published in [73] is based on the extended version of the WZ network scheme having multi-camera nodes in which the collection point also has a camera attached to it. The previous work and its results for two sources and SI were also presented by the same author in [73]. The paper, extends the work on the previous result by increasing the number of sources to more than two.

Further, it derives an achievable rate distortion region and external bound to the best rate distortion region (only possible where the sources are provisionally autonomous given the SI).

Further, in [74] another modified version of WZ for video coding is proposed that focuses on the motion estimation parameter that is a building block in improving the coding efficiency of WZ video coding. In most of the video coding schemes, motion estimation is performed at the decoder without the availability of the current frame. This results in imprecise motion estimation that causes degradation of coding efficiency. This paper provides an analytical model for the estimation of potential gain by using multi-resolution motion refinement (MMR) and assuming that the decoder has fractional admission to the current frame (frequency domain). The experimental results show that, at high rates, WZ for video coding using MMR is lower than that of the conventional inter-frame coding by a margin of 1.5 dB. However, it outperforms WZ video coding using motion extrapolation by 0.9 to 5 dB. Simulations show a significant gain using real video data. Furthermore, vital gain in simulating real video data has also been observed.

The researches carried out in [75], highlight the problem faced in video coding as well as discuss, analyze and compare the two early solutions, i.e. Stanford, and PRISM based on WZ, designed by the Stanford University and the University of California, Berkeley research teams respectively. This paper mainly focuses on the functional aspects of the two solutions and provides a comparative analysis of both the solution. Further, different issues related to the research of WZ video coding are addressed such as side information creation, iterative decoding, Interrelation noise, rate control, and WZ selective coding.

Further, in [76] another approach for multimedia coding is proposed to focus on designing a low complexity WZ video codec with intra frame encoder and decoder. In this work, the WZ video coding is improved by using run length coding scheme for high frequency coefficients and utilizing them at the decoder side for accurate motion estimation. Such scheme allows the implementation of low delay system with SI generated from the previous reconstructed frame. The experimental results (simulations) verify that proposed WZ codec has impressive gain over traditional DCT-based intra-frame coding. In addition to this, in [77] a new WZ based new multi-view video coding scheme is proposed, in which the complex processes (temporal and interview correlation examination) are shifted from the encoder to the decoder side. This scheme results in the evading of raw data traffic and complex computation. The core part of proposed approach is based on wavelet and SPIHT-based WZ video coding scheme. The results in [77] show that by using the proposed scheme inter-camera interrelation is evaded and computational complexity is shifted to the decoder as well as the coding performance is much better than the conventional intra coding.

In [78,79] the discussion, evaluation and analysis on the application of WZ based schemes on the wireless video sensor network is conducted. The energy efficiency of different video coding schemes for WSN was evaluated and presented in [78]. The analysis performed by [78] shows that predictive video coding provides a higher compression ratio, but utilizes much more energy, whereas distributed video coding shows that the WZ encoder has constantly improved energy efficiency than the PRISM encoder. Further, the author proposes minor alterations in PRISM and WZ encoders in order to get a vital reduction in the energy consumption of these encoders.

In [79], the WZ problem, i.e. coding of the source data with SI existing only at the decoder in the form of a lossy scheme of the source in discussed. The paper explores both the theoretical and numerical designing aspects of WZ scheme based on multi-dimensional nested lattices. Further, a precise calculation on the basis of high resolution assumption is also developed. The results from the above assumption can be used to analyze the performance and can assist as an applied director in selecting worthy lattices for WZ coding. However, the mentioned work has some open problems such as the upper bound expressions used must be improved; the maximization of theta series ' derivative due to the upper bound is another problem. Moreover, the need of more systematic approach to low-complexity code design is to be followed.

Table 2 presents the performance outcomes for a WZ coding scheme that are drawn after scrutinizing the above discussed research papers.

Table 2. Performance analysis of DSC (WZ) image compression scheme

Parameters	Performance
Power Efficiency	High power efficiency as in WZ source data is individually encoded at the encoder and jointly decoded at the decoder. So it involves intra-frame coding and no predictive coding (motion approximation, recompense).
Memory Utilization	WZ is based on the principle of SW so it also provides minimum memory utilization.
Compression Ratio	High compression ratio.
Complexity	Moderate or low complexity level as it consists of low complexity encoders i.e. efficient subdivision of the convolution between the encoder and decoder
Execution Time	Moderate or low execution time as the processing load is shifted from the independent encoders to joint decoder.
Lossyness	The overall image quality is moderate as WZ is of lossy nature.

2.2. Compressive Sensing (CS) Scheme:

Compressive Sensing (CS) [80] is an attractive and effective compression scheme that has achieved popularity as a mechanism in recent years. CS appeals more interest from the researcher of numerous fields such as statistics, information theory, mathematics, signal processing & coding theory and computer science. The conventional methodology towards the transformation of the signal or image is based on the eminent Shannon sampling theorem (the so-called Nyquist rate). The innovative concept of CS opens a new domain for data compression and expects that signals/images can be reconstructed from what earlier supposed to be extremely imperfect information (measurements). CS is mainly beneficial in two situations. Firstly, when direct measurement of high resolution signal is hard to get and results in additional hardware cost. Secondly, when encoding of one or more high resolution signals is difficult, i.e. WSN and multi-view imaging. The detailed description along with algorithm implementation of the CS scheme can refer to [80, 87, 92, 93]. The basic architecture of the whole process of CS algorithm is shown in Figure 6. In encoding process, first the image scene is captured by the image sensor node and then transformed into a small block of size “B×B." Then individual sampling of each block is carried out based on the same measurement matrix “Φ." This transformation of the image into blocks not only provides a simple structure of the sensor node but also tends to a better and fast initial solution of "x" [92]. Afterwards CS is applied to only those blocks that are sparse. The output results in compressed data. In order to attain the original image back the same process is performed in reverse order. The detailed description along with algorithm implementation of the CS scheme can refer to [80, 92, 93].

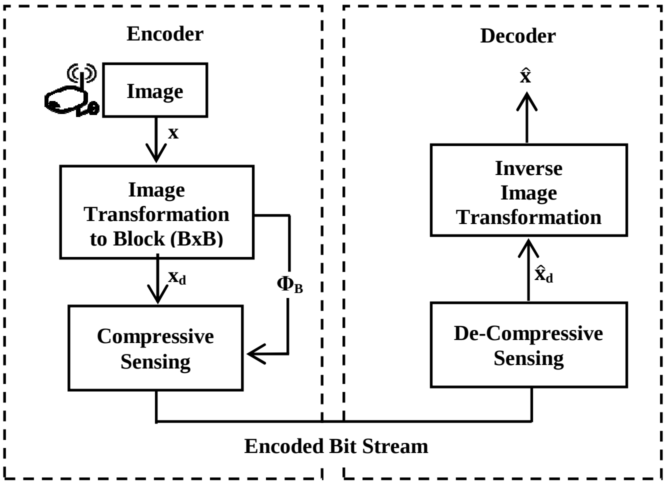

Figure 6. Broad spectrum block diagram of Image compression and decompression by using compressive sensing scheme.

CS is based on the central concept of signal representation by means of a set of linear, non- adaptive measurements i.e. a representation of signal/image by making use of the few non-zero coefficient (sparse expansion) present in the source [86]. In such schemes, the reconstruction of the signal/image from a small set of measurements can be performed by empowering the nonlinear optimization [81, 82, 89]. However, the CS reconstruction must satisfy two properties: sparsity and incoherence i.e. the signal must be sparse in some domain, as well as the encoding matrix and the sparsity basis must satiate [105].

A comprehensive discussion on different aspects of the CS image compression scheme can be found in [80-91]. The research work in [80] provides a detail introduction and analysis of the theoretical and mathematical aspects of CS, and it also discusses its potential applications in signal and image processing. Similarly, in [81] a survey of the theoretical features of compressive sampling is performed, discussing its basic principle based on sparsity and incoherence i.e. signals/ images can be recovered from a small number of samples or measurements other than the conventional methods used. Whereas, in [82] CS is discussed as an alternative to Shannon/Nyquist sampling for sparse attainment or signal compression. The paper mainly focuses on the important performance gains that can be achieved by utilizing more realistic signal models other than simple sparsity and compressibility (inclusion of dependencies) among values and locations of the signal constants that are governing the CS writings.

Further, in [83] the mathematical characteristics of the CS for sparse signals and question related to training and optimal linear projections are discussed. Furthermore, different experimental results are performed to answer the related question. The outcomes show that the trained projection sets can provide much better results than optimal projections.

The applications of CS for WSN data gathering and energy efficiency have been studied in a few papers [84- 88]. The work done in [84] delivers current reviews of CS implementation on WSN. This paper shows that CS embraces encouraging enhancements in order to reduce the characteristic constraints of WSN such as power depletion, lifetime, time delay and cost. In addition, it also analyzes the effectiveness of implementing CS on WSN i.e. CS substitutes the conventional sampling. The CS scheme combines the data collection and compression steps into a single step and does not require intermediate steps to attain the signals. Hence, transmitting the entire image, only a smaller amount of image is required to be transmitted or stored. This paper leads the way towards the improvements revealed by the application of CS in WSN in terms of power management, lifetime, and time delay.

In [85] study and performance (energy, latency) analysis based on the implementation of CS for data gathering in WSN is conducted. In advance, a data gathering problem in WSN is expressed and different solutions are proposed, i.e. tree based and gossip based protocols scalable with energy and latency necessities. The experimental results show that both the protocols perform better for data gathering in WSN in terms of energy and latency. However, a tree based protocol is vulnerable to the link lost.

On the other hand, [86] presents the first complete design for the application of CS in order to gather data for large scale WSN. The benefits that can be delivered by the proposed scheme includes reduction in communication cost without increasing computational complexity, maximum lifetime as well as it can handle unusual sensor outputs efficiently. Moreover, this novel scheme is tested practically and the experimental results verify its competence and toughness. However, the scheme is not appropriate for small scale sensor networks (due to limited signal sparsity).

The research paper [87, 88] also provides details regarding the energy and complexity issues in WSN and proposition of new schemes based on CS. Paper [87] focuses on the temporal-spatial field measurement (data collection) issue in WSN that utilizes maximum energy and propose a scheme based on CS that gathers data from WSN without utilizing maximum energy. The proposed scheme was designed with the idea of performing repeated projections in order to maximize the data volume gain per energy costs. The scheme was tested both theoretically (simulations) and practically (real WSN) and the experimental results in [87] show that the proposed scheme provides a perfect approximation of the indefinite data for assuming energy cost.

Similarly, [88] also proposed a CS based scheme for energy efficient data gather in WSN, emphasis on the sampling rate of the sensor nodes in WSN as most of the energy in WSN is consumed in sampling and transmission. The proposed scheme reduces the sample volume occupied by sensor nodes as well as making use of a new random sampling scheme that take in account sampling connections, hardware restrictions and the transaction among computational complexity and scheme randomization. The scheme was practically implemented and the experimental results in [88] show that the sample volume was limited to a quarter as compared with the samples taken by the sensor nodes, result in the minimum utilization of energy for sampling and transmission. However, these results were tested for real data gathered, i.e. by installing the WSN at Hessle Anchorage of the Humber Bridge location.

The research paper [89-91] discusses the implementation aspects and the possible outcomes of CS scheme. In [89] inspects the gains that can be achieved by the implementation of CS for data (image) collection in WSN, for these two different approaches were proposed (plan-CS and hybrid-CS) in the form of a specific data collection mechanism. The schemes were formulated and were helpful in solving flow-based optimization problems. However, the experimental results show that the first approach does not show any improvement, whereas, in the hybrid CS approach, a substantial improvement can be seen in the throughput. Further, the results were only tested for low-power systems only.

In this context [90] proposes a scheme for altering CS sample volume and update signal recreation in WSN resulting in a reduction in computational complexity, energy and processing time. The proposed scheme was tested theoretically (simulations) in numerous WSN conditions and the simulation results provided in this paper show that the proposed scheme can recreate the output signal by utilizing small sample volumes. Thus, providing better performance in terms of resource utilization, time, and energy efficiency for WSN. In [91], a survey based on the theory of CS as well as implement and analysis of the basic principle of CS (the signal/image can be recreated by making use of the limited volume of samples or measurements) in VSN are provided. Further, the results obtained by CS were compared with the results of JPEG Compression standard that indicates that CS is better in performance (power & memory management, complexity, image quality) than the DCT based JPEG scheme.

Furthermore, there have been only quite a few research approaches proposed [92-98] specifically for CS scheme. The most prominent of them is a block based CS as discussed in [93]. The CS scheme based on block approach provides much better results as compared to the standard CS approach by reducing the computational burden as well as provides very fast image recovery [92]. In [93], a block based compressive sensing approach is proposed in which block-based random image sampling coupled with a projection-based reconstruction is adopted as in [94]. This approach not only promotes sparsity, but also smooths the reconstruction. The proposed algorithm results in the faster speed of the projection-based CS reconstruction with superior image quality, particularly at low sampling rates.

Moreover, [95] reconstructs the multi-view image set jointly, enforcing sparsity not only in each image separately but also in the view-to-view difference images between neighboring views. Whereas, in [96] similar strategy of joint reconstruction as that of [95] is adopted. However, the correlation between neighboring views is taken into account in a more refined way rather than a simple sparsing the image difference. For instance, the neighboring view correlations are represented by a local geometric transformation. In [97, 98], the same joint reconstruction approach is used. However, the view-to-view correlation modeling is based on the reconstructed views to lie along a low-dimensional manifold. The joint reconstruction proposed in [95-98] have few issues related to the computation burdens, particularly so as the number of views increases.

Table 3 presents the performance outcomes for a CS coding scheme that are drawn On the basis of the above discussion and analysis.

Table 3. Performance analysis of CS image compression scheme

Parameters	Performance
Power Efficiency	High power efficiency as it reduces the total amount of data to be processed such that it recreates the signal by using only fewer sampling values than that of Nyquist rate.
Memory Utilization	Low memory utilization as it only makes use of those sample measurements that are necessary for the recreation of signal/ image.
Compression Ratio	The CS scheme provides a High compression ratio.
Complexity	Low complexity level as it consists of simple and low complexity encoder and decoder.
Execution Time	Moderate execution time as it consists of a low complexity encoder and decoder. But, initially it requires the processing of the whole image information from all the sources connected.
Lossyness	The overall image quality is Low i.e. it makes use of a minimum number of sample measurements to encode the image data to reconstruction of images from such small measurements is difficult.

2.3. Prominent Features & Challenging Issues in DCS:

SW is one of the prominent and a proficient distributed coding scheme used for image compression and has gained eminence to be the scheme VSN. SW scheme exploits the data redundancies present within the sensor network by removing them without inter-sensor node interaction. SW scheme consists of low complexity encoders, saving the processing power. However, this scheme is susceptible to some challenges as its practical implementation is difficult and costly because, in SW scheme, each sensor node requires the information about the whole correlation structure of the network in order to encode data resulting in substantial extra cost. Furthermore, the SW scheme is also exposed to the optimal rate distribution problem, i.e. to assign an optimal rate to each node for sending encoded data, when sensor nodes are clustered. In addition, the SW scheme is not robust against transmission errors such as relay and sensor node failure.

WZ coding scheme an improved form of the SW coding scheme, ideally suited for VSN. The WZ scheme has revolutionized the concept of compression in a distributed environment for spatially interrelated data (image/video). The WZ scheme makes use of joint decoders and individually encoded interrelated sources to match the performance of the joint encoder/decoder. The simple WZ encoder's results in greater cost benefits this leads the way towards the development of low power, low cost and memory video encoders, resulting in better rate distortion presentation. However, WZ is exposed to image degradation as it is a lossy scheme. Further, the noiseless interrelation statistics used for decoding, resulting in poor image quality. Furthermore, feedback processing is also considered one of the major issue.

CS shows potential to be an efficient sampling mechanism and helps in improving the power consumption, memory and bandwidth for VSN. The implementation of CS for VSN reduces the total amount of data to be processed such that it recreates the signal by using only fewer sampling values than that of Nyquist rate. This result in an extended lifetime of the sensor node. Furthermore, active node consumes 10 times [92] more power than sleeping nodes, hence by reducing the amount of data to process will also increase the sleep time of the sensor nodes and the power consumption for processing will decrease. Even though with all the current research and major prosperous outcomes, still there are many open issues related to the reconstruction and practical implementation of CS scheme. The present works of CS are more concentrated towards hypothetical characteristics with simulated results, rather than on the realization of practical CS schemes and the exploration of prospective applications based on the principles of the CS paradigm to other signal processing complications.

3. Comparative Analysis of Image Compression Algorithms for VSN:

In order to implement a suitable image compression scheme for a specific application, it is essential to know its strength and limitation. Subsequently, the evaluation of current image compression schemes based on certain parameters is necessary.

3.1. Evaluation Criteria:

The criteria on which the different image compression schemes are being analyzed are;

- **Power Efficiency & Memory Utilization:**

In image processing, power efficiency & memory utilization are the two major factors that are needed to be considered and are defined as the level of performance that describes a system (image compression) in order to achieve best output results, while using least input resources (power, memory).

- **Compression Ratio:**

The compression ratio of an image is defined as the size of the original image divided by the size of the compressed image. The greater the compression ratio the better will be the compression scheme. However, there is a trade-off between compression ratio and image quality.

- **Complexity:**

The complexity of an image compression algorithm is defined as the number of processes performed by the algorithm on a given time frame, i.e. how fast or slow particular algorithm performs for different elements of an image.

- **Execution Time (Encoding/Decoding):**

The execution time for compression scheme is defined as the total time required for the encoding/decoding of a particular image data.

- **Lossyness (loss of information):**

In lossyness certain amount of original image data is lost (pixels are removed/reduced) not important for users, in order to reduce the size of the image data. Although, the reduced file is not identical to the original file.

3.2. Assessment Methodology:

The evaluation procedure was based on a qualitative analysis by studying in detail numerous research works [64-104] conducted on different distributed coding image compression schemes. On the basis of above mentioned criteria, the research papers that provide the best result for the discussed image compression algorithms, i.e. DSC (Slepian Wolf) [65-71], DSC (Wyner Ziv) [73, 75-79], and CS [82, 84, 86, 88,89,91] were scrutinized. Furthermore, the transformation based DWT (SPIHT) [26, 42-49] was also analyzed for comparison with the distributed compression schemes. SPIHT was selected because it is considered most suitable transformation based image compression scheme for VSN scenario. SPIHT not only provides high compression, minimum power utilization but also its hardware implementation is easy as it has a simple encoding and decoding process. Furthermore, the work done in the research paper [25, 33] also validates the analysis. However, not a single scheme completely satisfied the evaluation criteria, with each having greater computational issues than others.

Table 4: Comparative criterion of existing Image compression schemes

Compression Schemes / Parameters	DWT (SPHIT)	DSC (SW)	DSC (WZ)	CS
Power Efficiency	High	Moderate	High	Highest
Memory Utilization	Moderate	Low	Low	Lowest
Compression Ratio	High	Moderate	High-Moderate	High-Moderate
Complexity	Moderate	Low	Moderate -Low	Low
Execution Time	Moderate	Moderate -Low	Moderate	Moderate
Lossyness	High-Moderate	Low	Moderate	Moderate -High

In Table 4, different image compression schemes are analyzed on the earlier discussed criteria. The Table 4 results show that the SPIHT scheme provides moderate or low complexity level. It attains low bit rate with the compressed output bit stream, i.e. do not require extra coding mechanism (entropy or scramble) and use subset partitioning in order to decrease the magnitude comparisons volume in the sorting pass. Furthermore, SPIHT provides moderate or low execution time as it is based on an intensive progressive competence feature in which coding (or decoding) process can be terminated at any point if the recreation of a maximum output image is obtained. However, the greater the information received by the decoder higher will be the image quality. The SPIHT scheme might be exposed to additional memory utilization as it consists of few link lists and some sets requiring more storage capacity.

Besides, SW scheme provides low complexity encoders, low execution time and moderate compression ratios. Although, the power efficiency of SW scheme might be unstable in a few cases such as rate-allocation problem, clustered network problem, and dual channel coding problem. The SW scheme offers moderate power efficiency, i.e. although, it removes complete redundancy of data produced by spatially interrelated data sets that result in low power consumption. However, when SW scheme is applied to clustered network or multiple interrelated sources or with dual channel the power consumption increases (increased volume of data produced within each cluster resulting in maximum energy consumption). Furthermore, as it consists of independent encoder phenomenon (correlated data are encoded separately and decoded jointly) hence, it requires minimum computational resources (memory) and results in low complexity encoders. As SW scheme is a lossless scheme so it provides good quality image outputs with moderate compression ratios. Furthermore, the overall execution time is moderate as the decoding process requires more processing as compared to the encoding process. Moreover, the implementation of such scheme in a real environment is very complex, i.e. it requires previous interrelated structure information (each sensor node must acquire the information of the whole correlation structure), which in large sensor network is difficult to manage. Additionally, this scheme is exposed to transmission errors.

To overcome the problems of SW schemes, the WZ scheme was proposed that is the modified version of the SW scheme (but of lossy nature) and improves the outcomes of the SW scheme by introducing the lossy coding to compress the discrete interrelated signals w.r.t. Fidelity criterion, resulting in less difficult implementation problem, in the real world. The power efficiency of WZ is high such that it consists of individual encoder and joint decoder (low complexity) involving intra-frame coding. This scheme is also robust against channel coding and noise errors, i.e. it does not make use of the predictive looping scheme and delivers independently scalable codec as with the case in SW scheme. However, due to high compression ratio and lossy nature of WZ scheme the output image quality is not that high, i.e. it does not provide efficient handling of the compressed image data throughout the whole time (encoding and decoding). Furthermore, WZ scheme might be exposed to some rate losses (system loss, source coding loss).

The CS scheme that has attained much attention in the recent years and many researchers (discussed earlier) have carried out work in order to analyze its benefits on different low power image compression application. The CS provides the highest power efficiencies such that it focuses on the fact that whole image can be recreated by making use of the only necessary samples of the present image. Furthermore, the sampling rate of CS scheme is much smaller than that of Nyquist rate. In addition to this, the CS scheme has low memory requirements as it deals with the minimum amount of data. Further, the complexity level of CS scheme is low because it consists of simple and low complexity encoder and decoder. The compression ratio in CS scheme is high due to the reason that it makes use of a minimum number of measurements to compress the image. However, in certain cases CS initially requires the accomplishment of the whole image information from all the sources connected so, in such cases the compression ratio is moderate. With this high (some time moderate) compression ratio, the reconstruction of an image is very difficult and might result in degraded image quality. Furthermore, CS is only applicable for sparse data and its practical implementation in the actual world is very complicated, time consuming and expensive. The reason behind is that, the CS scheme does not require prior information regarding the data (image/video) that results in negotiating the amount of constructive power distortion latency reduction. Thus, the prediction regarding the sparse sources in a specific transformation domain is a challenge. In addition, it initially requires a complete source (image / Signal) information (information regarding all the sources that the sensor nodes are sending) which requires extra cost and time.

In order to analyze the above drawn results of image compression schemes in the context of VSN. It can be demonstrated that the implementation of distributed coding schemes for VSN might provide prominent prospective because these schemes do not require additional computational resources (power, memory). In addition to this, these schemes are based on simple individual encoder with a minimum amount of data to process that result in shorter execution time and lower complexity level. Conversely, the DWT (SPIHT) seem to be better in efficiency, compression ratio with moderate or low complexity, execution time and image quality, satisfying the requirement of sensor network to some extent. However, for large network implementation (large amount of sensor nodes and information) DWT (SPIHT) encounters few issues such as image degradation, increase in memory utilization, and increase in computational complexity. In VSN, the distributed coding schemes might be considered as ideal schemes to be implemented as they fulfil all its major requirements.

4. Experimental Results:

In this section, the experimental setup is defined in order to verify the results that have derived from quantitative analysis for different image compression schemes. The experimental setup involves the collection of all the standard test images / videos required for the simulation testing. Then the working model of the selected image compression scheme is simulated and tested on the standard images and video sequences. The image compression schemes are tested for both image and video sequences in order to analyze their performances. The evaluation of the simulated and tested results is carried out by measuring Peak Signal to Noise Ratio (PSNR (dB)) against bit rate as PSNR (dB) is the most appropriate and widely used method for analyzing the output results.

In the evaluation, different image compression schemes are selected, i.e. DCT (JPEG), DWT (SPIHT), DSC (W-ZIV) and BCS-SPL than standard CS as it is observed in [92, 93] that BCS systems provide better performance than standard CS schemes with much lower implementation cost. The reason for selecting these image compression schemes is that according to our detailed quantitative survey all these schemes perform better for VSN scenario. The selected schemes, i.e. BCS-SPL (DCT, DWT, DDWT)[1], DCT (JPEG)[2], DWT (SPIHT)[3] are implemented by modifying the available code[1,2,3] on different 512 × 512 images according to the needs and obtain results. However, for video sequence modified version of BCS for video i.e. MC-BCS-SPL is implemented by modifying and simulating the available code1 and is compared with DSC (W-ZIV) scheme for which the results are directly obtained from [78, 103, 104]. The test image and video database was created from different recourses[4,5,6]. The results obtained are then compared with each other as shown in Table 5 and Figure 7.

4.1. Images:

In Table 5 performances of different selected image compression schemes are analyzed on the basis of PSNR (dB) at different bit rates. Several popular grayscale images of size 512 × 512 are employed. The reconstruction results of the various algorithms under consideration are shown in Table 5.

In most cases, it is evident that the image compression scheme BCS-SPL provides a substantial gain in reconstruction quality over the transformation schemes; on the order of a 1dB to 3dB increase in PSNR (the bold values represent the better PNSR ratio). However, it is noticeable from the results carried out in Table 5 that although, BSC-SPL provides better results, but only at a higher bitrate (>0.5 bpp). Whereas, at lower bit rates (<0.5 bpp) the performance of BCS-SPL is still questionable as the PSNR (dB) is lower as compared to other schemes because the reconstruction process of BCS-SPL might be exposed to blocking artifacts as it is based on block based approach. Furthermore, the

[1] http://www.ece.msstate.edu/~fowler/BCSSPL
[2] http://teresi.us/resources/code/matlab/jpeg.m
[3] http://www.cipr.rpi.edu/research/SPIHT/spiht3.html
[4] http://vision.middlebury.edu/stereo/data/
[5] http://scien.stanford.edu/index.php/test-images-and-videos/
[6] http://see.xidian.edu.cn/vipsl/database_Video.html#image

encoding of the image involves a small amount of sample measurements that might result in prediction errors.

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Table 5: PSNR performance for different images (512x512) in dB for DCT (JPEG), DWT (SPIHT) and BCS-SPL (DCT, DWT, DDWT)

	Algorithm	Bit rate				
LENNA		0.1	0.25	0.5	0.75	1.0
	DCT-JPEG	28.70	31.60	34.90	36.60	37.90
	DWT-SPIHT	**30.68**	**33.99**	**38.51**	40.72	42.19
	BCS- DCT	27.70	30.45	35.77	40.14	44.65
	BCS-DWT	27.81	30.89	36.15	40.55	45.14
	BCS- DDWT	28.31	31.37	36.78	**41.09**	**45.65**
BARBARA	Algorithm	Bit rate				
		0.1	0.25	0.5	0.75	1.0
	DCT-JPEG	23.45	25.20	28.30	31.00	33.10
	DWT-SPIHT	**24.37**	**26.66**	**31.62**	34.48	36.77
	BCS- DCT	22.76	24.38	29.05	**34.93**	**40.76**
	BCS-DWT	22.62	23.94	28.05	33.06	38.29
	BCS- DDWT	22.85	24.29	29.12	33.76	38.89
		Bit rate				
PEPPERS	Algorithm	**0.1**	**0.25**	**0.5**	**0.75**	**1.0**
	DCT-JPEG	28.68	31.36	33.80	34.77	36.33
	DWT-SPIHT	**29.17**	**32.09**	35.18	36.67	37.63
	BCS- DCT	27.88	30.41	34.20	38.73	42.96
	BCS-DWT	28.69	31.04	34.74	39.48	43.65
	BCS- DDWT	28.88	31.44	**35.55**	**40.09**	**44.36**
		Bit rate				
MANDRILL	Algorithm	**0.1**	**0.25**	**0.5**	**0.75**	**1.0**
	DCT-JPEG	22.93	24.36	26.77	28.23	31.38
	DWT-SPIHT	**22.95**	**24.86**	25.04	27.01	28.55
	BCS- DCT	22.31	24.15	29.68	28.28	32.68
	BCS-DWT	22.54	24.33	29.38	28.40	32.78
	BCS- DDWT	22.74	24.57	**26.90**	**28.81**	**33.20**
		Bit rate				
GOLDHILL	Algorithm	**0.1**	**0.25**	**0.5**	**0.75**	**1.0**
	DCT-JPEG	27.62	28.98	32.41	33.58	35.76
	DWT-SPIHT	**27.96**	**29.39**	32.55	34.48	35.82
	BCS- DCT	26.10	28.32	32.57	36.54	41.01
	BCS-DWT	26.71	28.68	32.85	36.99	41.37
	BCS- DDWT	27.80	28.53	**33.11**	**37.08**	**41.53**
		Bit rate				
BOAT	Algorithm	**0.1**	**0.25**	**0.5**	**0.75**	**1.0**
	DCT-JPEG	26.65	29.23	33.23	34.72	37.34
	DWT-SPIHT	**26.91**	**29.36**	33.73	36.34	38.27
	BCS- DCT	25.25	27.98	33.58	38.15	42.89
	BCS-DWT	25.49	28.42	33.88	38.32	43.05
	BCS- DDWT	25.73	28.62	**33.90**	**38.45**	**43.25**
		Bit rate				
WASHSAT	Algorithm	**0.1**	**0.25**	**0.5**	**0.75**	**1.0**
	DCT-JPEG	30.73	31.34	34.42	35.56	37.47
	DWT-SPIHT	**31.87**	**33.18**	35.69	37.04	38.49
	BCS- DCT	31.03	32.07	35.31	38.94	43.19
	BCS-DWT	31.19	32.81	36.59	40.47	44.83
	BCS- DDWT	31.51	32.91	**36.78**	**40.81**	**45.26**
		Bit rate				
ZELDA	Algorithm	**0.1**	**0.25**	**0.5**	**0.75**	**1.0**
	DCT-JPEG	30.94	32.56	36.62	37.78	39.54
	DWT-SPIHT	**33.72**	**36.31**	39.07	40.52	41.44
	BCS- DCT	31.87	34.17	39.07	43.04	47.40
	BCS-DWT	32.01	34.65	39.15	42.96	47.26
	BCS- DDWT	32.14	35.03	**39.46**	**43.26**	**47.56**

4.2. Video Sequence:

In Figure 7, BCS video based scheme, i.e. MC-BCS-SPL is compared with DSC (W-ZIV) scheme for different video sequences. We use the common video sequences "Mother & Daughter" (296 frames), "Foreman" (296 frames), and "Akiyo" (296 frames). These sequences have grayscale CIF frames of size 352×240 or 352×288.

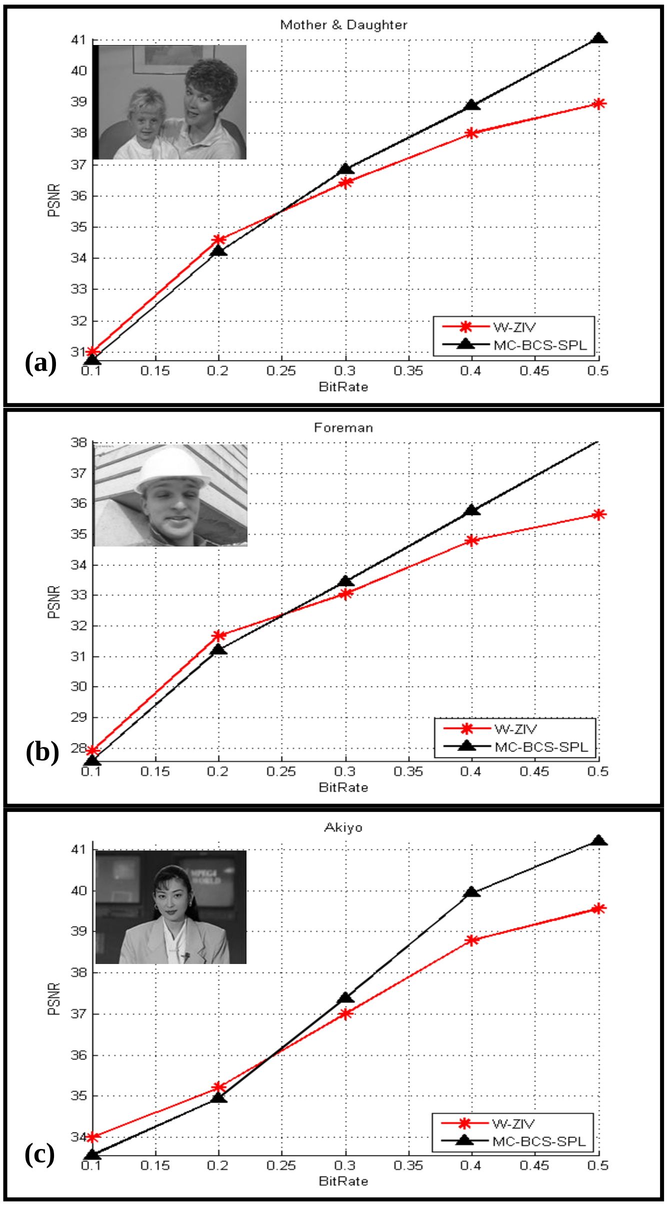

Figure 7. PSNR performance of a) Mother & daughter, b) Foreman, c) Akiyo video sequence (296 Frames) in dB for DSC (W-ZIV) and MC-BCS-SPL

The performance graphs clearly shows that MC-BCS-SPL outperforms and displays significant gain in reconstruction quality DSC (W-ZIV) by order of 1dB to 3dB increase in PSNR. However, at an extremely lower bit rate (<0.25 bpp) the reconstruction gain of DSC (W-Ziv) is marginally higher than the MC-BCS-SPL, this might be due to blocking artifacts, as well as the interpolation scheme used for image predicting, is not efficient enough to predict accurately at extremely lower bit rates (<0.25 bpp).

4.3. Simulation Results Analysis:

The above simulation results (image, video sequence) lead to the conclusion that the BCS-SPL image compression scheme provides better results for both image and video sequences at higher bit rates (>0.5 bpp) whereas, for lower bit rates (<0.5 bpp) its performance still has question marks. The few issues related to the reconstruction process of the BCS scheme at lower bit rates (<0.5 bpp) includes blocking artifact, prediction error and unreliable interpolation process scheme that might result in poor quality reconstructed image at the decoder. Hence, to overcome the aforementioned issues, improvements in the BCS reconstruction algorithm is essential that can be easily implemented and provides better results at lower bit rates (<0.5 bpp) to make it an ideal choice for VSN scenario.

5. Conclusion:

In this paper, a comprehensive survey and analysis of existing distributed image coding algorithms for VSN is provided. Furthermore, the outcomes, short comes and open issues related to distributed coding scheme are also scrutinized. The image compression schemes are distributed into three different paradigms that are transformation based schemes (DCT, DWT), non-transformation based schemes (VQ, FC) and distributed source coding schemes (DSC, CS). However, the main scope of the paper was to analyze distributed coding schemes and the transformation/non-transformation schemes were not discussed.

The thorough study, analysis and simulation results show that the emerging distributed coding schemes (DSC, CS) give new horizon in the area of image compression for in VSN. These schemes provide much better efficiency in terms of computational resources (power, memory), complexity and image quality that it overruled the conventional transformation schemes. In contrast, the distributed source coding schemes (SW, WZ), practical implementation is a big challenge as they require previous information regarding the data dispersal beforehand. Providentially, the emergence of compressive sensing (CS) opens new domain for effective transmission of correlated data, allowing high prospect of signal/image recreation by using the minimum number of unsystematic estimations, i.e. random linear permutations of quantities, provided that the signal/image is sparse. However, the CS reconstruction process is difficult to implement and results in degraded image quality at lower bit rates (<0.5 bpp).

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