IJCTA, 8(2), 2015, pp. 1675-1685

Video Transmission by the Use of Bayesian Compressive Sensing in Wireless Sensor Network

Fereshteh Rahmanian Kooshkaki*, Saeed Mehrjoo and Kia Jahanbin*****

Abstract: Multimedia files transmission and information exchange among network nodes are considered as important topics in wireless sensor networks which significantly depend on restrictions, resources and provided facilities. Algorithm or appropriate method selection for video files transmission considering network working conditions greatly influences of network performance evaluation parameters. By studying the related literature, we concluded that the main effort in transmission and reconstruction of videos and images was based on sampling rate reduction and reduction of algorithm computational complexity. it has been observed that compressive sensing can overcome the current difficulties of video transmission in the wireless multimedia sensor network. First, reduction in the complexity of cryptographic algorithms and low-resistance against error channels can be mentioned. Some researchers challenge implementation of compressive sensing which a non-adaptive theory in video transmission is; it will be discussed later. For this purpose, we intend to present a network system based on compression style, streaming rate control, and video error correction in embedded devices with constrained resources based on the theory of Bayesian compressive sensing which is an adaptive sampling method. Simulation results show that the proposed method has a better performance in terms of fairness rates, delay extent and resistance against noise channels in comparison to other methods.

Keywords: Compressive Sensing, Bayesian Compressive Sensing, Network Optimization, Multimedia Streaming, Sampling Adaptivity

1. INTRODUCTION

Wireless Multimedia sensor networks [1] are self-organising systems which devises has been deployed in their nodes; these devises do the recovery and processing tasks, etc., and provide a combination of heterogeneous video streaming from their resources. Wireless multimedia sensor network also enjoys new capabilities, including camera monitoring, storage and retrieval of its subsequent activities, other potential activities and its related services person locator. In the wireless multimedia sensor network, information essence and the way information is exchanged on the network has special features which their use of special techniques are well-applicable in these networks [1]. One of the challenges in the network is the problems related to video streaming transmission which is still unknown and unresolved, and can be summarized as follows [2]:

- The algorithms computational complexity: Encoders Complexity requires processing of complex algorithms which causes energy consumption to augment. Conventional video coding patterns requires to be reversed for a simple codification which is improper for the embedded video sensors, and causes a lower performance. Besides before encoding, all of encoders' techniques need to access to total video frame (or to several frames).
- Resistance restriction in noise channels: In the protocol stack based on the IEEE 802.11 and 802.15.4 standards, frames are divided into several packets. Even if an error occurs in a bit of a packet in the

* (M.Sc. on Computer Network, Islamic Azad University Kerman Branch), *Email: fereshte.rahmanian@gmail.com*

** PhD (Department of Information Technology Engineering, Faculty of Islamic Azad University Shiraz Branch), *Email: sa.mehrjoo@yahoo.com*

*** (M.Sc. on Computer Network, Islamic Azad University Kerman Branch), *Email: kiajahanbin66@gmail.com*

channel during the transmission, after examining CRC the entire packet is removed. This problem causes video decoder operation in decoding act not to operate independently from i-th coding frame; as a result all the frames will be damaged one after the other. The ideal situation is that when a failure occurs in one bit, it should have intangible impact and the least side effects on video recovery. Downloading video quality should be reduced softly as the quality of channel begins reducing.

- Lack of fairness among video streamings: Video coding with MPEG standards causes the production of unstable signal rates. Frames are divided in to main frames and *differential* frames. *Differential* frames produce less bit rate. Restriction in band width causes a reduction in signal changes rate and an increase in sending delay.

In this paper, we propose an optimization solution based on adaptive compressive sensing which can solve the mentioned problems. In fact, Our goal is to implement a network system that enables data reconstruction by collecting a small number of sensor samples. For signal recovery we are interested in using adaptive compressive sensing [3] which is proved to be a reliable technique for video and image. However, the transmission of images and videos by using adaptive compressive sensing in wireless networks is less introduced; so, a new system, Bayesian compressive Distortion Minimizing Rate Control (BC - DMRC), has been proposed which is designed and set based on one of adaptive compressive sensing methods named 'Bayesian Compressive Sensing'[3]. The system has a cross-layer structure to maximize the quality of the videos and to minimize the computational complexity.

In the second part we will describe the related works. In part three, we review the compressive sensing technique, and Bayesian compressive sensing. In part four, BC- DMRC system architecture is elaborated. Proposed method results in sending videos in wireless sensor networks are shown in part five, and eventually conclusions and the further suggestions are presented in the last part.

2. LITERATURE REVIEW

In classical samplings (that has been used at engineering literature by Shannon for the first time [4]), we are searching for a restricted bandwidth signals by its chronological samples. Nyquist–*Shannon* sampling theory suggests that a signal can be precisely reconstructed by signal sampling if a sampling frequency is two times bigger than the highest signal frequency component. In practice, sampling frequency is mostly assumed more than two times bigger than the necessary bandwidth [4]. In a new method of sampling which is known as the compressive sensing, reducing the number of samples to reconstruct similar signals in a domain known as 'Frequency Domain' is considered as the aim to show sparse representation. In other words, in the favorite frequency domain, the number of non-zero coefficients should be far less than the number of zero coefficients. It is interesting to note that in the case of joining non-zero coefficients, no hypothesis is presented; that's why the bandwidth does not come true less in this case [5].

Now, we will investigate a number of relevant works regarding compressive sensing application on video transmission: In [6], block-based CS natural images and image preparation are suggested according to block-by-block pattern. Recovery image algorithms made use of both linear and non-linear operations such as filtering and convex optimization in conversion fields. Comparison results between block-based CS systems and current CS designs shows that implementation cost is much lower. Candes et al. [7] suggested the image recovery plan by the use of CS so that they can reduce the computational complexity in video/image encoding using compressive sensing process. Encoder divides the image into two parts for the first time, dense and dispersed, where only the dispersed part is encoded using CS. Encoding complexity and the number of random measurements reduces significantly. In [8], it is stated that multimedia sensor networks have been used for critical operations such as camera monitoring, etc. In a WMSN network, storage and transmissions include complex conversions; compressive sensing can reconstruct sparse signals by just few measurements.

This paper suggests a method combined of compressive sensing based on 'Discrete Wavelet Transform'(DWT) and 'Discrete Cosine Transform' (DCT).

The performance of the method in terms of storage complexity level, energy transmission and delay rate is investigated. The results show that the presented matrix is similar to or better than the PSNR in terms of memory usage; matrix of time has been compared to the Gaussian matrix in this paper. According to comparisons, the quality and efficiency of VCS which is a combination of DCT & DWT are much better than the time when the DCT and DWT are being used alone. It is shown that energy transmission gets 50 % less, while delay is reduced 52 % in average. As it is observed, related literature used conventional compressive sensing, but some researchers challenged the implementation of compressive sensing which is a non-adaptive theory for video transmission; they believe using this method is not economic in terms of costs or video quality in comparison with adaptable methods [9]. In the third section, the issue will be explained in more details.

3. REVIEW OF PROPOSED METHOD

3.1. Compressive Sensing

We show signals of a photo by a vector as $X \in R^N$, where N is the vector length. We assume that inverse matrix of $N * N$ exists which is changed to ψ, such that [10]:

$$(1)\ X = \psi Y$$

in which S is a sparse vector, $\|\| S \|_{\bullet} = K$ with $K < N$, and $\|.\|_p$ represents p-norm. This means that a photo is shown as an sparse matrix in some areas of exchange, as well as in the wavelet transform. Signals are measured regarding $m < n$ linear and based on linear measurement operators ψ. Hence [10]:

$$y = \Phi x = \Phi \Psi x = \tilde{\Psi}_x \tag{2}$$

We want to improve the value of X by using Y measurements. Thus, with mentioning So, we offer a solution to Eq. (2) regarding $S^{\bullet}$; each S^* vector is defined as $S^* = S^{\bullet} + n, \in N(\psi)$ defines a solution as Equation (3) . However, in [5] it was proved that Ψ measurement matrix is dispersed enough and k is smaller than threshold (for example x matrix signal is fairly dispersed), and after that s can be improved by Eq. (2). However, the above problem is, in general NP-hard. Columns of matrix Ψ are enough detached. At any time, the solution to the problem is a unique; it is as follows [10]:

$$P\text{\textbackslash}: \textit{minimize } \|s\|_{\text{\textbackslash}} \textit{ subject to} \|y - \Psi s\|_{\gamma}^{\gamma} < \in \tag{3}$$

in which $\in$ is too small. Note that P1 is convex, and the optimization of $\in$ is difficult; its complexity of is as $o(M^{\gamma} N^{\gamma/\gamma})$. The problem is solved through the interior point method era [11]. Although, there are more appropriate effective strategies for reconstruction, the framework presented in this paper is independent of specific methods of reconstruction.

3.2. Bayesian Compressive Sensing

Compressive sensing seeks to offer a simple solution consists of two steps, samples collection and signal reconstruction. Samples are collected randomly, and signals are recovered directly without considering any affiliation with the use of reconstruction sparse entries. Lihan et al. prove that signal structure improved using compressive sensing. In this section, we focus on Bayesian compressive sensing which is developed form of compressive sensing and tree wavelet structures [12].

Recent researches on compressive sensing for examining sparse signals structure, the target is studying Bayesian views. In Bayesian compressive sensing, measurement matrix is produced gradually such that any measurement is done to reach a local optimum. The target signal enjoys statistic characteristics which significantly reduce the number of compressive sensing measurements of Bayesian inference [3]. Based on Bayesian viewpoint, in compressive sensing measurements BCS can estimate error bars in X signal, and can be an optimal adaptive design with CS measurements. In BCS, each of transmission coefficient elements θ are defined as zero-mean [3, 13]:

Each wavelet entry coefficients/spars, models ‘s’ through a random variable Gaussian model [13].

$$si \sim N(.,\sigma_i^{\gamma})i = 1...N, \tag{4}$$

where δ^{γ} is variance which is introduced as a Gaussian precision distribution in many papers. Signal s reconstruction includes two important elements: important and unimportant data. So, matrix s can be shown as $s_m + s_e = s$, in which s_m is substituted by a small zero input, and s_e is set by zero inputs. Both variables, s_m and s_e, can be used as Gaussian random variables with small variance in Eq. (4). However, the second one, the s_m is considered as a Gaussian noise that can always be neglected in a spars signal. The updated system equation is as follows [12, 13]:

$$y = \Phi\Psi^T S_m + \Phi\Psi^T S_e = \Phi\Psi^T S_m + n_e \tag{5}$$

in which n_e is an unimportant item, as a kind of noise. Actually, measured noise has been added up to the stage of sampling. Considering measurement noise, the new equation can be rewritten as below [12, 13]:

$$y = \Phi\Psi^T S_m + n_e + n_w = \Phi\Psi^T S_m + n., \tag{6}$$

in which n_w is the measured noise rate, and $n.$ is the total noise rate in the system. Noises in Gaussian distribution are $N(\cdot,\alpha_.^{-1}) \sim n.$ and on Gaussian precision $\alpha_{\gamma}^{\gamma} = \alpha_.^{-1}$ So, compressive sensing measurements y can be considered as a multivariate distributed Gaussian [3, 12, 13].

$$y \sim N(\Phi\Psi^T S_m, \alpha\alpha_.^{-1}, \tag{7}$$

4. THE BC - DMRC[1] PROPOSED SYSTEM

4.1. Using Adaptive Compressive Sensing for Video Transmission and Compressive Sensing Challenges in This Regard

Various programs challenged compressive sensing application in video transmission. First of all, due to the complexities of various tissues, a communication among different frames is necessary indeed similar scenes must be sent repeatedly one after the other to deliver a video. Second, it should be made certain that that with the constant video scenes velocity, the interval among the adjacent frames should also be fixed. Assuming that hardware sensing collect measurement information with a constant velocity, then it allocates all measurements of a period of time to a common number. However, in a specific scene which is sent, areas with different characteristics are not equally distributed among all the frames. So, given the number of fixed measurements for each frame, they should be properly arranged in a framework to make the best quality. Third, in various scenes, there are various properties and temporal coordination among adjacent frames. Therefore, the number of required measurements in each frame is different. If different frame rate are used for other scenes we can achieve the required level of quality. To address these challenges, regarding a large number of measurements collected in any second, a sample adaptive framework is suggested for various scenes of an image to increase the quality of output satisfactorily [14].

4.2. Architecture of Proposed BC-DMRC System

In this section, we discuss the overall architecture of BC–DMRC. This system delivers a series of photos from frames per second, and transmits the encoded video using the BCS wirelessly. The RTT[2] measures network congestion for sending a video, and also estimates bit error rate[3] for video protection against the channel casualties. The system combines the characteristics of application layer, transmission layer and physical layer to maximize the video quality in a multi-hop wireless network. As shown in Fig. (1), the system consists of four main parts which is presented as follows:

4.2.1. CS Camera

The sub-system saves the CS images. In case study, the image is directly obtained through a linear combination of random set of pixels and their total intensity by a photo-diode. Then produced samples are transmitted to the video encoder.

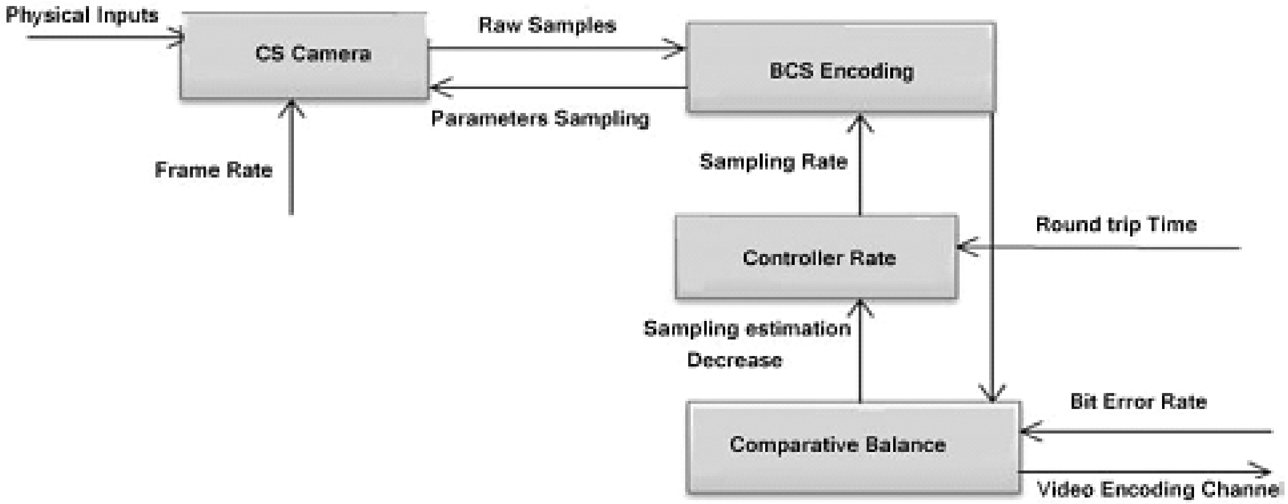

Figure 1: Proposed System Architecture

Compressive sensing (or CS) cameras replace cameras that are conventionally built by a focal plan array with a series of temporal measurements by one or a few diode meters. These cameras notably reduce the cost of infrared cameras, in CS camera temporal measurements have been made by an algorithm that is fed from spatial information of the original image [11].

4.2.2. How Does CS Camera Work [15]?

1. A compressive sensing camera focuses the input data on a Spatial Light Modulator (SLM), or stores on a Digital Micromirror Device(DMD). FPA typically is embedded in an ordinary camera, and DMD replaces FPA device in an ordinary camera .
2. During taking a photo, a series of SLM unique settings are used successively. Each pattern chooses half of the original image. Patterns were determined by a mathematical theory of compressive sensing, and the maximum information on the screen can be used by the system.
3. Any of DMD micro-mirrors can be located 12° left or right. For every measurement, half of the mirrors are placed in a position that they can reflect back on the photo-detector left diode which is focused on their mirrors. As a result, the total light energy or half of it is focused on the diode detector.
4. Photons are changed to digital in an electric signal of half-image or photo by a diode, an amplifier and an analogue transformer. A number of temporal measurements are done on the delivered image. Each measurement depends on the situation of a specific mirror.
5. An image reconstruction algorithm reconstructs the output image using mirrors knowledge pattern and data measurements, and represents it. Reconstruction algorithms are linear; they are proven to be able to reconstruct the original image.

The way CS camera functions is shown in figure 2 [15].

4.3. BCS Video Encoder and Decoder

The receiving encoder receives raw samples from camera; they are changed into compressed video frames. Compression is obtained through the BCS properties, and it is also achieved by temporal correlation among successive video frames. Number of samples and sampling matrixes are defined in the same block. The number of samples or sampling rate are calculated according to the controller input rate while sampling matrix is shared between the sender and receiver before selection.

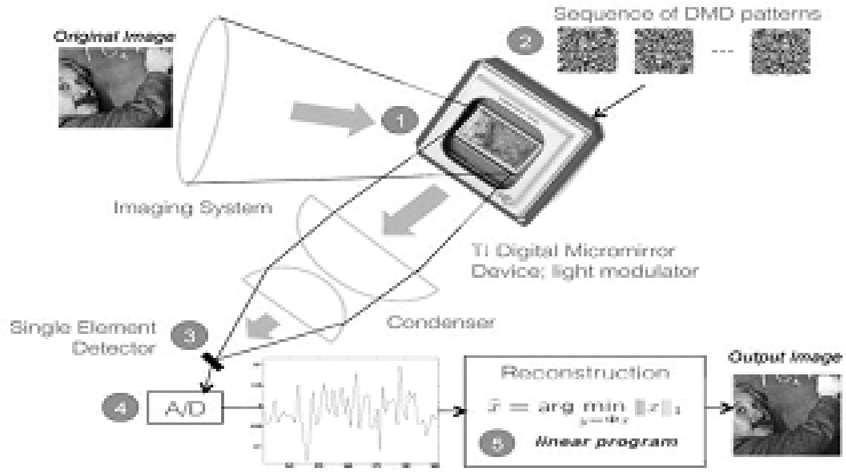

Figure 2: The Way CS Camera Functions[15]

4.3.1. BCSV Encoding Functions

First, image is sampled using BCS equation, Eq. (6); our goal is to improve X signal using Y measurement. By doing this, all the samplings in signal X are sampled making advantage of Bayesian compressive sensing. Then we use Eq. [15]

$$Y = \Psi\Phi\alpha_m. \tag{8}$$

for the representation of the video frames in which Y′ represents an image sampled by BCS. Then, samples are randomly selected from X, and are sent to the receiver.

Video encoding process is different form I frame and P frame [4] which will be elaborated later. I frames are transmitted directly after sampling. But, in construction of P frame, first the image is sampled by BCS sampling; then it is changed to I frame, and finally transmitted. Then, with the use of temporal correlation, following processing is done for frame transmission in the system.

$$DV' = Z_{t-1} - Z_t. \tag{9}$$

here, Z_t includes all the samples in t^{th} frame . DV' is also transmitted using Eq. (6) in a quantized manner. Fig.3 shows the proposed method.

4.3.2. BCSV Decoder Performance

Decoder process is described as follows. First of all, to reconstruct the main frame and V', stated in the previous part we use equation (6). For I frames reconstruction, since they were transmitted directly without any conversion, it is also possible to reconstruct the received samples directly; but in the case of P frame, samples should be reconstructed with DV'. This vector is also reconstructed using Eq. (6). First, t^{th} sampling of P frame is obtained by eq 10.

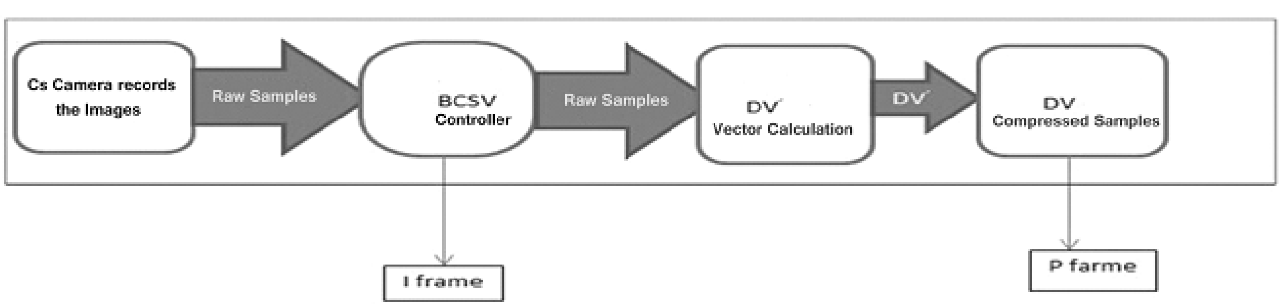

Figure 3. Block Diagram for BCS Video Encoder

$$Z_t = DV' + Z_{t-1}, \tag{10}$$

then Z_t frames are also reconstructed by using Eq. (6) .

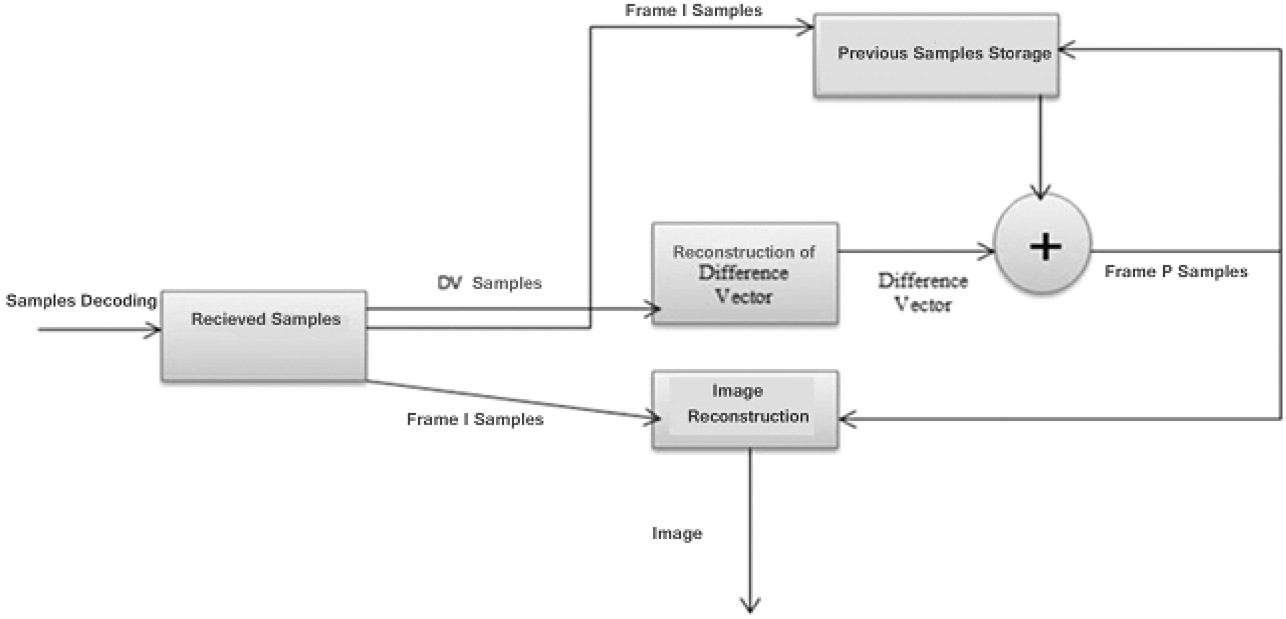

Figure 4: Block Diagram for BCS Video Decoder

4.4. Controller Rate

The sub-system controller rate both provides system fairness, and it attempts to transmit the optimum-quality film via the network. Preventing network intensity, a node considers two main factors for sending data. First of all, the sender must obtain the least bandwidth the film needs to be transmitted in a good and significant quality. Note that this work is different from the current Internet performance which emphasizes on access to fairness in terms of data velocity(film doesn't enjoy such a good quality).

Second, the sender sets up a transmission rate to make sure that the packet loss which occurs due to buffer overflow is reduced. To determine intensity, round time trip (RTT) is measured for video packages. RTT is the amount of time it takes for a packet to reach its destination, and its delivery response to be sent to the source. RTT changes are measured as follows [16]:

$$\Delta RTT_t = \frac{\sum_{I=0}^{N-1} \alpha_i . RTT_{t-1}}{N.\sum_{I=0}^{N-1} \alpha_i} - \frac{\sum_{I=0}^{N} \alpha_i . RTT_{t-i}}{N.\sum_{i=1}^{N} \alpha_i} \tag{11}$$

α_i value is considered as a low-pass filter on round trip time of a packet, and N is the length of DV' vector.

4.5. Adaptive Parity-based Transmission

In compressive sensing, unlike conventional wireless imaging system, sample is of great importance in image reconstruction. Instead, the only major factor in determining image quality is that the number received samples be correct because a sample contained errors can easily be discarded, and its impact on the film quality is low till the time the error rate is trivial. This error detection takes place with a number of pre-defined samples using even parity which is evaluated at the receiver or intermediate nodes. This is useful in most cases especially when BER is low; but its excessive errors are simply neglected. To determine the amount of shared samples in encoding, the amount of the correct samples can be modelled as follows [16]:

$$c = \left(\frac{Q.b}{Q.b+1}\right)(1-BER)^{Q.b}, \tag{12}$$

where C estimates the number of correct samples; b is the number of samples which are coded in common, and Q is quantization rate in samples. In to check for the optimal value of b for BER, it is possible to differentiate from Eq. (10), and it includes a set equal to zero and a solved set for b. Thus [16]:

$$b = \frac{-1+\sqrt{1-\frac{4}{\log(1-BER)}}}{2Q} \tag{13}$$

5. SIMULATION RESULTS

In order to investigate the performance of BC–DMRC system several tests were done. Indeed, the results of the simulation software made by MATLB, product of MathWorks company □□(Natick, MA, USA). In order to study the system presented in this paper, the quality of the video is evaluated by the receiving node. Most measurements, simulation and SSIM[4] are used for checking the quality of the video. SSIM can recognize differences related to photo structure better in comparison to conventional criteria; these differences are easily seen by human eye [16].

5.1. Energy Consumed by Sensors.

The topology of Manhattan network is consisted of 49 nodes (7 * 7). The sender and sink are selected randomly for 10 seeds. All the senders transmit videos for a single destination. Tracking continues according to AODV [17] and IEEE 802.16 MAC 11 b. Model used in wireless radio is set on 914 MHZ and Wave LAN according to DSSS Radio. Physical channel changes the data packets which have a bit error rate, and needs their balance bit to be adjusted.

First of all, BCSV video encoding tracking files are obtained for several Yi values. This tracking file is given to the simulator as an input in which the decision regarding rates control has been made in the simulation schedule. Network simulator determines the sampling rate in YI, and the video size is determined on the basis of this amount. After network simulation, received samples are sent to detector BCSV; as a result, the received video frame is reconstructed again with the use of BCS; then the non-compressed video frames will be sent again; and these two techniques will be compared with each other regarding images. Video films are transmitted simultaneously in the network which are compared by BC-DMRC and C-DMRC (reviewed in [16]) and TFRC. The transmitted Video files vary from 1 to 5 in number, and will be sent 10 seconds after the previous frame (120 frames). Our

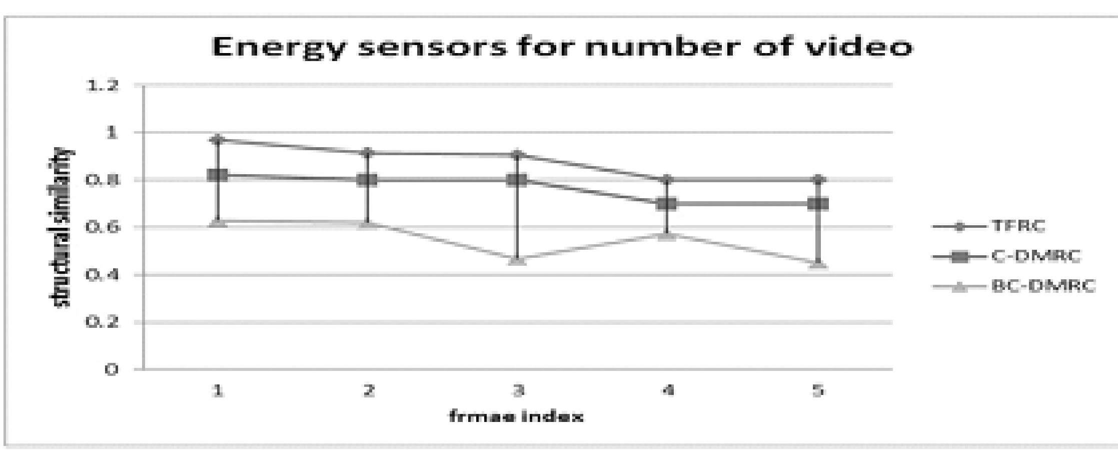

Figure 5: Sensors Energy Consumption by Using several videos

starting rate ensures us that all transmitted films are fairly treated. Figure (5) shows the simulation results. In each simulation, the results of the BC-DMRC are better than the other two. As you can see BC-DMRC approach consumes less energy per sensor than the two other methods, and causes energy saving; thus network lifetime will be increased.

Fairness is shown in Figure (6) in which fairness measurement [18] is used from Jain sayings on fairness; several senders are also used. Once again, it is clear that the BC-DMRC functions better than the other two methods.

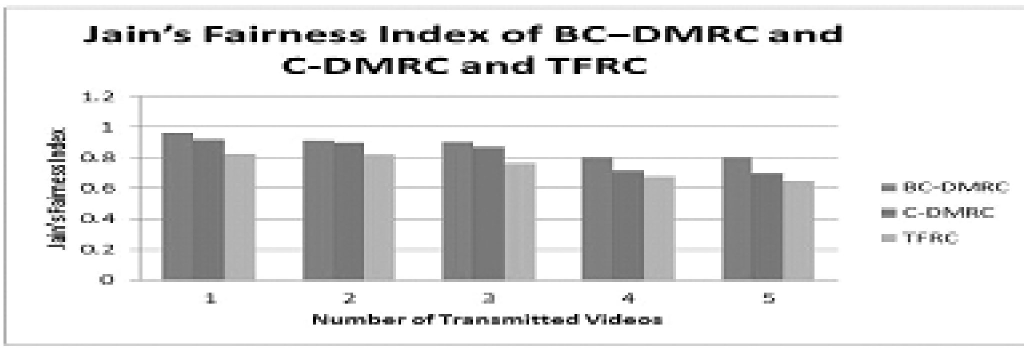

Figure 6: Video Transmission Fairness Indicator Using BC-DMRC and C-DMRC and TFRC

5.2. Reconstruction Error

Consider a signal with a length of N=1000 which includes M=25 spikes that are created by selecting 20 random situations, and then putting +1 and –1 at these points. The image of the φ matrix has been formed with the creation of the first $K * N$ matrix with equality of i.i.d Gaussian distribution $\mathcal{N}(\bullet,)$. Then, the φ lines are normalized to reach a unity in size and in number of lines. To simulate noise measurement, zero-mean Gaussian noise with a standard deviation $...\Delta = \sigma_m$ is added to each of K measurements which define g data. In the experiment k=150. Every image vector is defined as , its related reconstruction error is calculated. For an optimal selection, r_{k+1} has been constructed using Sigma special vector that has the largest eigenvalue. When considering (testifying) an approximate pattern, for loading diameter $\in = 0.1$. due to the non-random tests (that includes main spike signal, 40 image of the initial choice and attributing (filling) empty entries to r_{k+1}, etc.) , we repeated the test one hundred times by average performance of two variances as it is seen in Fig. (7). In (7) it is depicted that error reconstruction of optimal selection was much smaller than random image reconstruction error; this superior performance shows the optimization. In addition, the proposed system would lead to the significant results in comparison with the

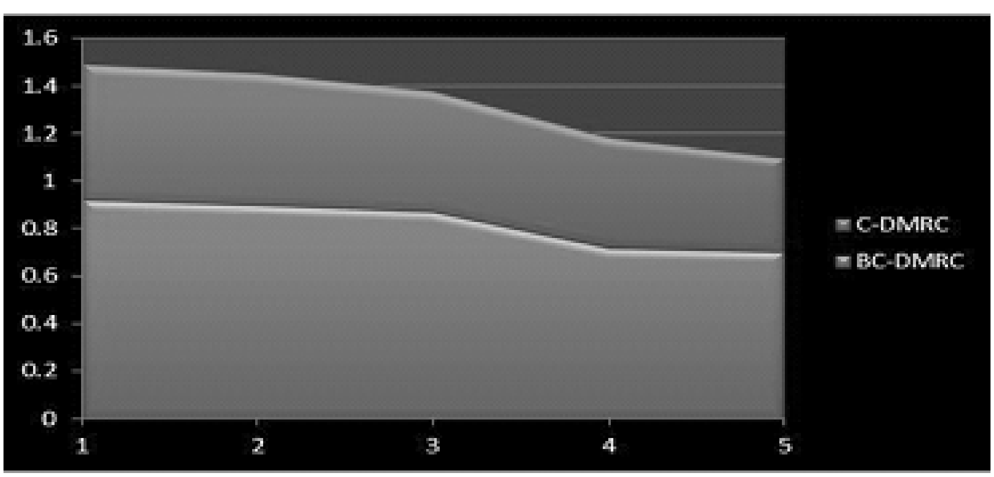

Figure 7: System Error Reconstruction C - DMRC and BC - DMRC

results of a very careful implementation, and it can be argued that BC-DMRC system can be an appropriate method for BCS sampling method.

In figure (8) and (9), an image with a bit error rate rela err=0.21103 is given to BC-DMRC system. There, the original image, the reconstructed signal of the original image, and the reconstructed signal image with error rate can be seen. It is clear that by this error rate the image would be in a good quality.

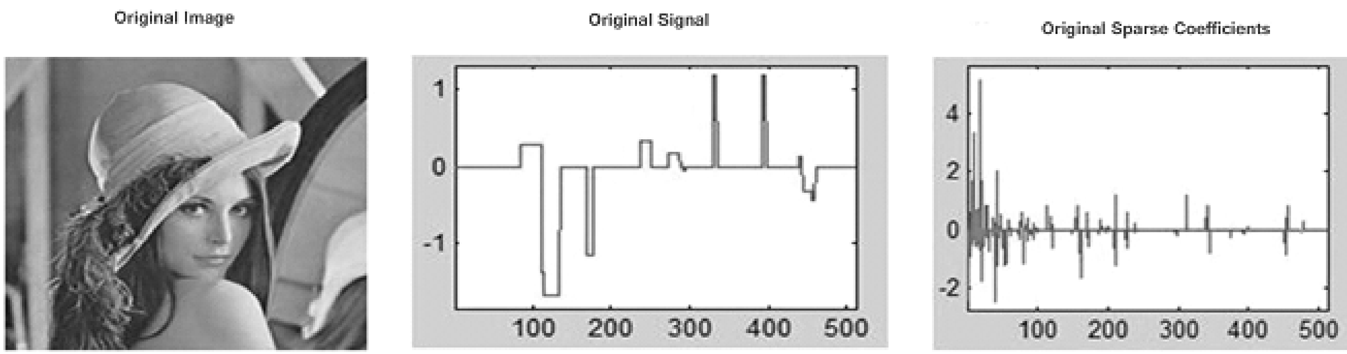

Figure 8: An Image and Its Signals for Testing

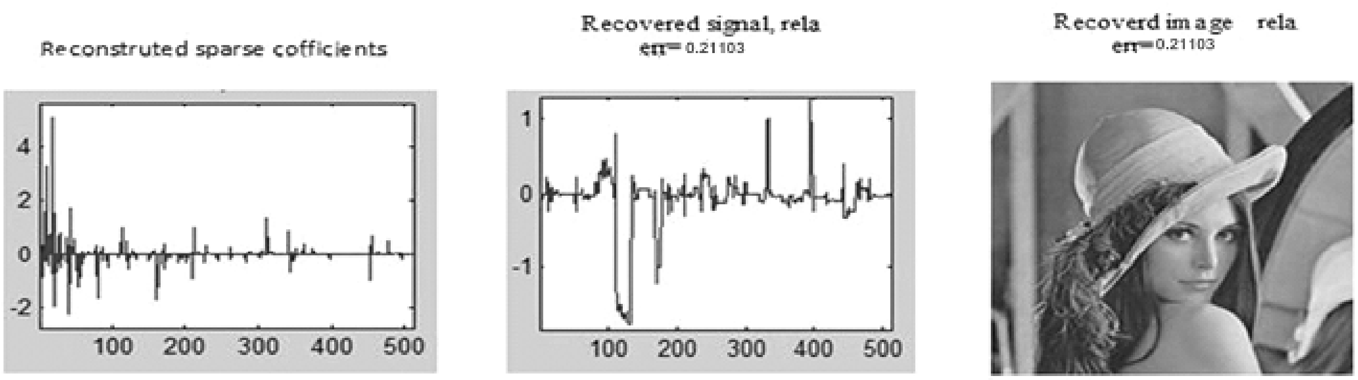

Figure 9: Reconstructed Image with Rela err = 0.21103

6. CONCLUSIONS AND FURTHER STUDIES

In this paper, we introduce a new system of video transmission on wireless sensing networks based on Bayesian compressive sensing. This system has 4 key components that we explained about them in details. The system is able to transmit a high-quality video by reducing the complexity of encoding and decoding algorithms. The simulation results show that we increase the velocity of transmission and fairness and at the same time decrease the delay and error rate in signal reconstruction.

In future works, as there are much faster Bayesian learning algorithms, we can discuss using them in image transmission on wireless sensing networks. Also, analysing the adaptive CS can lead to complete the analysis about formulating prevalent CS in the field of image transmission.

Notes

1. Bayesian compressive Distortion Minimizing Rate Control
2. Round Trip Time
3. BER
4. structural similarity

References

[1] Akyildiz, I.F., T. Melodia, and K.R. Chowdhury, *A survey on wireless multimedia sensor networks.* Computer networks, 2007. **51**(4): p. 921-960.

[2] Pudlewski, S., A. Prasanna, and T. Melodia, *Compressed-sensing-enabled video streaming for wireless multimedia sensor networks.* Mobile Computing, IEEE Transactions on, 2012. **11**(6): p. 1060-1072.

[3] Ji, S., Y. Xue, and L. Carin, *Bayesian compressive sensing.* Signal Processing, IEEE Transactions on, 2008. **56**(6): p. 2346-2356.

[4] Jerri, A.J., *The Shannon sampling theorem—Its various extensions and applications: A tutorial review.* Proceedings of the IEEE, 1977. **65**(11): p. 1565-1596.

[5] Donoho, D.L., *Compressed sensing.* Information Theory, IEEE Transactions on, 2006. **52**(4): p. 1289-1306.

[6] Chen, H.-W., L.-W. Kang, and C.-S. Lu. *Dynamic measurement rate allocation for distributed compressive video sensing*. in *Visual Communications and Image Processing 2010*. 2010. International Society for Optics and Photonics.

[7] Candes, E.J. and T. Tao, *Decoding by linear programming.* Information Theory, IEEE Transactions on, 2005. 51(12): p. 4203-4215.

[8] Razzaque, M.A. and S. Dobson, *Energy-efficient sensing in wireless sensor networks using compressed sensing.* Sensors, 2014. **14**(2): p. 2822-2859.

[9] Nandhini, S.A., R. Sankararajan, and K. Rajendiran, *Video Compressed Sensing framework for Wireless Multimedia Sensor Networks using a combination of multiple matrices.* Computers & Electrical Engineering, 2015.

[10] Huang, H., et al., *Applications of compressed sensing in communications networks.* arXiv preprint arXiv:1305.3002, 2013.

[11] Qaisar, S., et al., *Compressive sensing: From theory to applications, a survey.* Communications and Networks, Journal of, 2013. **15**(5): p. 443-456.

[12] He, L. and L. Carin, *Exploiting structure in wavelet-based Bayesian compressive sensing.* Signal Processing, IEEE Transactions on, 2009. **57**(9): p. 3488-3497.

[13] Babacan, S.D., R. Molina, and A.K. Katsaggelos, *Bayesian compressive sensing using Laplace priors.* Image Processing, IEEE Transactions on, 2010. **19**(1): p. 53-63.

[14] Zhang, X., et al., *Adaptive distributed compressed video sensing.* Journal of Information Hiding and Multimedia Signal Processing, 2014. **5**(1): p. 98-106.

[15] InView, *CS Camera Technology,url:=http://inviewcorp.com/technology/compressive-sensing-cameras/#.ViFuBX4rLIU.* 2015.

[16] Pudlewski, S., T. Melodia, and A. Prasanna. *C-DMRC: compressive distortion-minimizing rate control for wireless multimedia sensor networks*. in *Sensor Mesh and Ad Hoc Communications and Networks (SECON), 2010 7th Annual IEEE Communications Society Conference on*. 2010. IEEE.

[17] Perkins, C., E. Belding-Royer, and S. Das, *Ad hoc on-demand distance vector (AODV) routing*. 2003.

[18] Jain, R., D.-M. Chiu, and W. Hawe, *A quantitative measure of fairness and discrimination for resource allocation in shared computer systems.* 1998.