Energy Analysis of Compressed Sensing in Wireless Multimedia Sensor Network

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Abstract— **A Wireless Sensor Network (WSN) consists of several sensor nodes deployed in inaccessible areas for monitoring temperature, pressure, vibration, sound, motion etc. A WSN is used for variety of applications such as military, civil, industrial automation, medical, home automation, fleet monitoring, habitat monitoring, preventing theft etc. The availability of inexpensive hardware such as CMOS cameras and microphones has led to the development of Wireless Multimedia Sensor Networks (WMSN) which is used for image and video applications. In case of video applications the captured data will be too large if transmitted as such so it has to be compressed before transmission. Compression in traditional video encoding makes use of motion estimation and motion compensation techniques which requires intensive operations that lead to significant energy consumption and also the storage required is high. This drawback can be addressed by Compressed sensing, an emerging technique that directly obtains the desired samples, thereby reducing the energy consumption, storage capacity and bandwidth used in the network. It is used for reconstructing a signal from the M<<N measurements obtained from sparse or compressible signals, where N is the number of samples required for Nyquist sampling. Compressed sensing can overcome the drawbacks of traditional video encoders by simultaneously sensing and compressing the data at low complexity. The original signal can be recovered from measurements using basis pursuit and greedy algorithms. The objective of this paper is to implement a video compressed sensing framework using Gaussian measurement matrix and reconstruct it using Orthogonal Matching Pursuit algorithm and further transmission energy is analysed for the video compressed sensing framework .**

Index Terms— *Wireless Multimedia Sensor Network; Video Compressed Sensing; Energy analysis*

I. INTRODUCTION

A Wireless Sensor Network (WSN) consists of several wireless nodes that can interact with each other and with their surrounding environment by controlling and sensing physical parameters such as temperature, vibration, sound, pressure etc.WSN can be used in many applications such as battlefield surveillance, environment control, biomedical research, intelligent homes, and health applications. WMSNs technology have emerged due to the availability of CMOS cameras and microphones, which can acquire rich media content from the environment like images and videos. WMSN will enable a wide range of potential application in both civilian and military areas, which require audio and video information. Other applications include multimedia surveillance sensor networks, advanced health care delivery, environmental and structural monitoring.

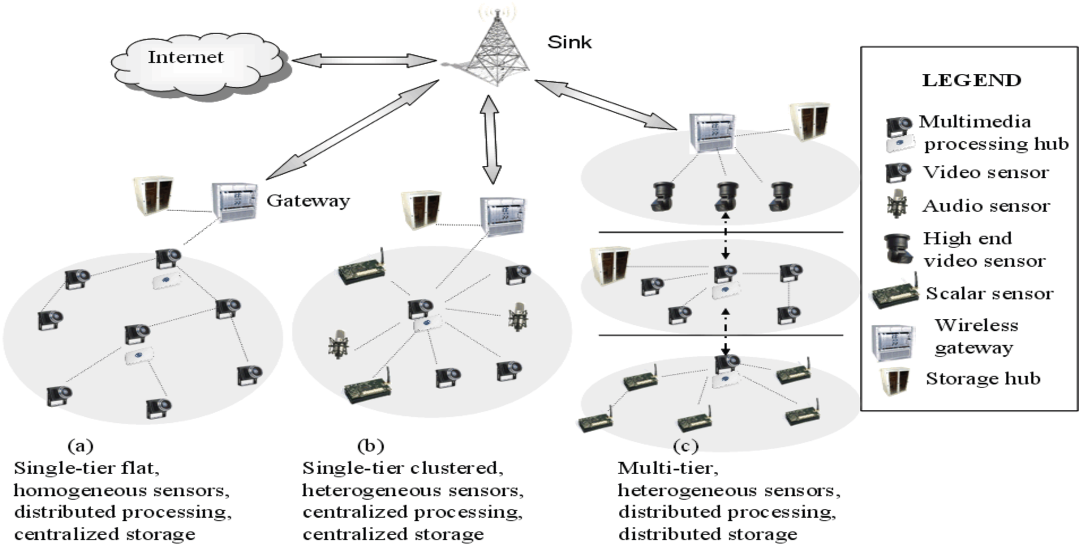

Fig. 1 Wireless Multimedia Sensor Network

The paper is organized as follows; Section II provides a brief survey of related works. Section III provides in detail about Video compressed sensing technique, Section IV explains the Energy analysis for the Video CS framework in detail, Section V discusses the simulation results and analysis finally Section VI gives the conclusions and future work.

II. Related work

In [1], the authors, survey the WMSN applications, their challenges and resource constraints. In addition, they investigate the proposed solutions by the research community to overcome challenges and constraints through architecture design and multimedia encoding paradigms. Moreover, some of the deployed examples of WMSN done by different research groups were also discussed. In addition, the authors provide a detailed discussion of the proposed optimization solutions and research areas of possible improvements.

R. G. Baranniuk [2], presents a new method called as compressed sensing, to capture and represent compressible signals at a rate significantly below the Nyquist rate. This method employs non adaptive linear projections that preserve the structure of the signal; the signal is then reconstructed from these projections using an optimization process.

In [4], the authors evaluated the energy efficiencies of predictive and distributed video coding paradigms for deployment on real-life sensor motes. For predictive video coding, the results show that despite its higher compression efficiency, limitation is that they have not considered the temporal correlation of the data.

Scott Pudlewski et al. [5], presents the design of a networked system for joint compression, rate control and error correction of video over resource-constrained embedded devices based on the theory of Compressed Sensing (CS). The objective of this work is to design a cross-layer system that jointly controls the video encoding rate, the transmission rate, and the channel coding rate to maximize the received video quality.

Scott Pudlewski et al. [9] investigates the rate-distortion performance of video transmission over lossy wireless links for low-complexity multimedia sensing devices with a limited budget of available energy per video frame. An analytical/empirical model was developed to determine the received video quality. The performance was evaluated by comparing the received video quality, computation time, and energy consumption per frame of different wireless streaming systems.

Wen Tao et al. [6], have proposed a new video coding framework based on compressive sensing and curvelet transform. This framework uses compressive sensing to the key frame of test sequence in the curvelet transform domain, and then gains recovery frame via Regularized Orthogonal Matching Pursuit algorithm to achieve data compress.

Mansour, H. and Yilmaz, O [10], proposed an adaptive compressed sensing scheme that utilizes a support estimate to focus the measurements on the large valued coefficients of a compressible signal. A “sparse-filtering” stage is embedded into the measurement matrix by weighting down the contribution of signal coefficients that are outside the support estimate. The performance of the scheme is evaluated with the standard CS using l1 minimization.

In [7], a compressive sensing method was proposed which combines with decomposition of a Matrix into low rank and sparse matrices is proposed to segment the background and extract moving objects in a surveillance video. The decomposition is performed by an augmented Lagrangian alternating direction method. The proposed method is done after a large number of frames are acquired therefore; it is not done in real time.

Zaixing HE et al. [16], defines a simple and efficient measurement matrix for compressed sensing of natural images. Binary Permuted Block Diagonal (BPBD) matrix. The BPBD matrix is binary and highly sparse as it is highly sparse it can simplify the compressed sensing procedure dramatically. He also suggests that BPBD with only 1 submatrix is the simplest measurement matrix for CS.

In [13] the author proposes a fast image recovery using compressive sensing technique. In this technique the image is divided into blocks of n x n pixels and orthogonal matching pursuit (OMP) is applied to each block. Block division approach uses a small matrix that requires less computation time and less memory which makes the technique effective.

In [17] the author used a greedy algorithm called OMP for reconstruction purpose. The author demonstrates theoretically and empirically that OMP can reliably recover a signal with ‘m’ nonzero entries in dimension ‘d’ given O(mlnd) random linear measurements of that signal. The results for OMP are compared with Basis Pursuit (BP) and the results show that OMP algorithm is faster and easier to implement, which makes it an attractive alternative to BP for signal recovery problems.

III. Compressed Sensing

Compressed sensing (CS) [2] a newly proposed approach is used. According to Nyquist sampling t theorem the sampling frequency should be at least twice the highest frequency to recover the signal. However, the compressed sensing technique can sample and represent spatially sparse signals at a rate below the Nyquist rate hence it is also called as sub Nyquist sampling. Various applications of Compressed Sensing are Photography, Holography, Facial recognition, MRI etc. CS is a technique where the sparse signal is multiplied by a measurement matrix to obtain the measurements ($M << N$ where M is number of measurements and N is number of samples) which is less than the samples obtain by Nyquist sampling theorem. Some of the measurement matrices used is Gaussian matrix, Fourier matrix, Bernoulli matrix, Toeplitz matrix etc. These measurements are transmitted and the original signal is reconstructed using algorithms such as basis pursuit and greedy algorithms.

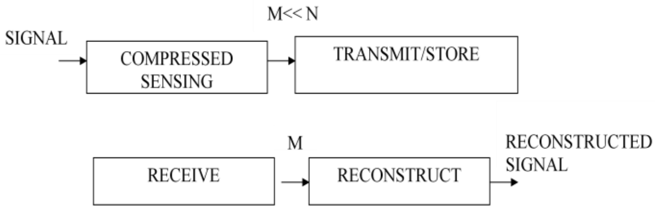

Fig. 2 Compressed Sensing

IV. VIDEO COMPRESSED SENSING FRAMEWORK

In this paper a Video CS framework was implemented using Gaussian matrix as sensing matrix and reconstructed using OMP algorithm. Compressed Sensing is a method that directly acquires measurements without measuring all the samples by applying it to sparse signals or compressible signals. Consider a video sequence which consists of frames represented as $x_j \in R^N$ vector formed from the pixels of the frame j of the video sequence, for j=1,2,……J where J is the total number of frames and n is the total number of pixels in the frame. $X = [x1, x2,....., xJ] \in R^{N \times J}$ be the video volume formed from a video sequence and the total number of pixels is $N1 = NJ$. Each frame is made sparse by using an orthornormal basis of $N \times 1$ vectors $\{\Psi_i\}_{i=1}^{N}$. Using a basis matrix of dimension $N \times N$ with $\{\Psi_i\}$ as columns, the signal can be expressed as

$$x_j = \Psi_i r_j \qquad (1)$$

where r_j is a $N \times 1$ sparse vector with k non zero efficient. The signal x_j is said to be more sparse if it has very few non zero coefficients. This signal is multiplied with the measurement matrix of dimension $\Phi_j \in R^{M \times N}$ to obtain the measurement vector y_j using equation (2)

$$\begin{aligned} y_j &= \Phi_j x_j \\ &= \sum_{j=1}^{J} \Phi_j x_j \end{aligned} \qquad (2)$$

The measurement vector y_j is of length M which is much smaller than the total number of pixels of the frame N. The measurement matrix is generated based on the minimum number of measurements required to reconstruct the signal. The minimum number of measurements is calculated using equation (3)

$$M \geq k \log(N) \qquad (3)$$

where k denotes the sparsity and N is the total number of samples in a frame. Fig.3, 4 shows the block diagram of the video compressive sensing framework. The frames of the input video sequence are derived first and then each frame is divided into blocks of size $n \times n$. Each block is converted into a single vector and sparsified using Discrete Cosine Transform which results in sparse vector. The sparsity level (i.e. number of non zero elements) for each block is found and the minimum number of measurements required is calculated using equation (3). The Gaussian matrix is used as the sensing matrix in this framework and it is generated based on measurements for single block denoted as $M1$. The sparse vector is multiplied with the generated Gaussian measurement matrix to obtain the measurements which is transmitted for reconstruction.

The reconstruction is done using Orthogonal Matching Pursuit (OMP) algorithm which is one of the greedy algorithm proposed for reconstruction. The measurements are given as input to the OMP algorithm and the same measurement matrix is used at the receiver side to reconstruct the original signal. The OMP algorithm finds the estimated vector by going through iterations same as the sparsity level. At each iteration, the estimated vector is found using least square solution and is subtracted from the residual vector. For first iteration the measurement vector itself is considered as the residual vector and is updated at each iteration. The Inverse Discrete Cosine Transform is applied to the estimated vector to obtain the original signal. This Compressed Sensing framework can be used in video surveillance applications in WSN (i.e. energy and memory constraint environment) where detection of anomalies is important. Depending on the purpose of application the quality of the reconstructed output can be varied by reducing or increasing the measurements.

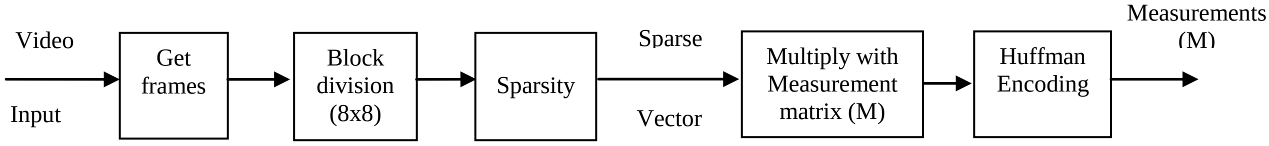

Fig. 3 Transmitter Section

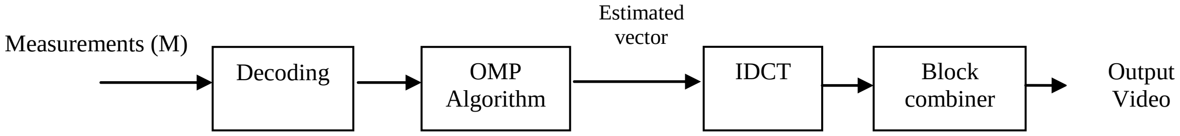

Fig. 4 Receiver Section

V. Transmission Energy Analysis For Video CS Framework

In this section energy analysis for the above framework is done for TelosB mote. TelosB mote operates in 2.4GHz, has 250 Kbps data rate, has a limited memory of 10 KB RAM, 1 MB external flash memory and 3V battery power [14]. In case of video applications data handled by WMSN is to large which can reduced by Compressed Sensing where only the measurements are transmitted thereby reducing the transmission energy

TABLE I Energy For One Bit Transmit For TelosB [4]

S.No	**Mote**	**Energy for 1 cycle count** (nJ)	**Energy for 1 bit transmit** (μJ)
1.	TelosB	1.215	4.000

The transmission energy is obtained by computing the number of bits required to transmit the measurements $M1$ and then multiply with the energy for one bit transmit for TelosB given in Table I. The number of bits required to represent a single measurement in a block is eight bits. Encoding further reduces the number of bits required for transmission. The transmission energy E_{txm} for a single block is computed using equation (9)

$$E_{txm} = [(M1*8)*E1] \tag{4}$$

Transmission energy can be further4 reduced by encoding the measurements. The encoding technique used is Huffman encoding. The bits used for representing the measurements can be reduced after encoding which in turn reduces the transmission energy

VI. Simulation Results And Discussion

The Video CS framework was simulated in MATLAB and the energy analysis was done for the same. The input video sequence considered is the Xylophone video sequence of resolution 240 x 320 from which the frames are derived. Each frame is divided into blocks of size 8 x 8 which results in 1200 blocks per frame and each block is converted into a single column vector of size 64 x 1. Each single vector is converted into a sparse vector by applying DCT and the number of non zero elements in the sparse vector is fixed at $k = 5$ for each frame. The minimum number of measurements required to reconstruct is calculated using equation (3) as $M1 = 21$. The quality of reconstruction depends on the measurements, as the number of measurements increases the quality of the video also increases. The reconstruction is done using OMP algorithm.

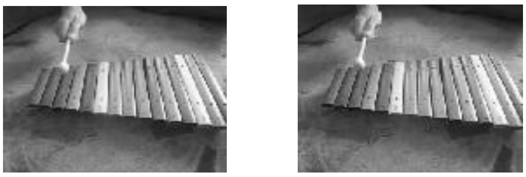

Fig. 5 First two input frames of xylophone video

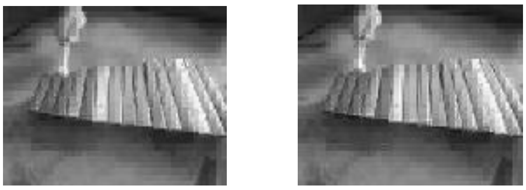

Fig. 6 First two reconstructed frames of xylophone video sequence

Fig. 5 shows the input video frames of the xylophone sequence and Fig. 6 shows the reconstructed video frames using OMP algorithm with $M1 = 35$.

Table 2 Measurements, % reduction of samples, PSNR for Single frame and average PSNR

Measurements per block	**Percentage of reduction of samples**	**PSNR for single frame**	**Average PSNR**
20	69 %	24.2078	24.2795
25	61 %	24.7315	24.3045
30	53 %	24.8679	24.5281
35	45 %	24.9267	24.5446

Table 2 shows the PSNR for single frame for various measurements and also gives the average PSNR value and percentage of reduction of samples. It is inferred that the PSNR increases as the number of measurements increases.

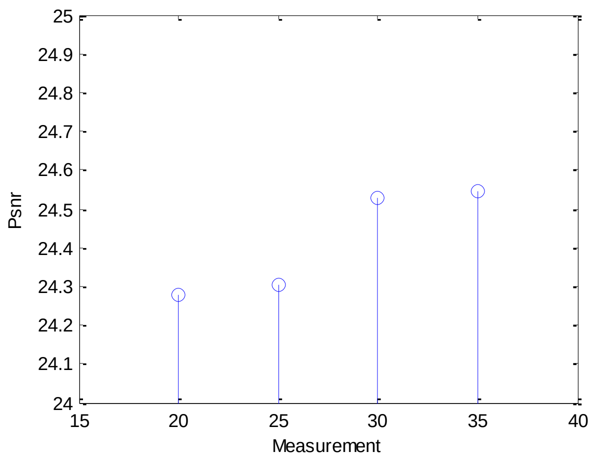

Fig. 7 Measurement vs PSNR

The transmission energy for a single block is computed using equation (4). The number of measurements to be transmitted is 35 and each measurement is represented by eight bits.

$$E_{txm} = [(35*8)*4.000] = 1120\mu J$$

TABLE 3 PSNR, E_{txm} FOR SINGLE FRAME FOR DIFFERENT MEASUREMENTS

Measurements	**PSNR** (dB)	$E_{txm}\,(mJ)$
20	24.8130	768
25	25.0131	960
30	25.3342	1152
35	25.4942	1344

The results show that the energy consumption for transmitting the compressed sensing measurements is less when compared with the raw frame transmission thereby making it best suitable for video surveillance applications in WSN.

VII. Conclusion

Compressed Sensing is an emerging technique which can recover the signal from fewer measurements thereby reducing the energy and memory required for transmitting and storing the measurements. In this paper, a Video Compressed Sensing framework is implemented. The simulation results of the Video CS framework show that the PSNR increases as the number of measurements increases. This Video Compressed Sensing Framework can be used in WSN environment where memory and energy are the major constraints. The Future work is to design hardware for CS framework from which the measurements are obtained directly instead of total samples.

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