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Video Compressed Sensing using CoSaMP Recovery Algorithm

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Abstract **-The rapid advancement in production of inexpensive cmos, extremely small cameras and microphones and tiny batteries has led to the development of wireless multimedia sensor networks. Wireless multimedia sensor networks have wide applications in multimedia surveillance network, environment monitoring and traffic avoidanceand control system. But sensor devices are curbed in terms of memory, data rate, processing capability .While transmitting a video using compressed sensing through these WMSNsthe memory and PSNR constraints have a significant effect. With the view to minimize the above mentioned constraints, this paper addresses a compressed sensing scheme which adopts the Hadamard matrix for dimensionality reduction and uses CoSaMP (Compressive Sampling Matching Pursuit)recovery algorithm to reconstruct the video .The advantage of Hadamard matrix over other measurement matrix is that it uses significantly less number of elements compared to other measurement matrices. CoSaMP algorithm minimizes time complexity in comparison to other recovery algorithm.**

Keywords- Wireless Multimedia Sensor Networks, Hadamard matrix, Compressed Sensing, DWT, CoSaMP.

I. INTRODUCTION

A Wireless sensor network consists of several sensor nodes whose position need not be pre-defined [2]. The sensor nodes are scattered and these scattered nodes have the ability to collect data and route the data back to the sink. WMSNs are powered by small batteries. Owing to limited lifetime of the batteries video transmission application inWMSNs has the following impedimentssuch as reduced on board memory, and limited computational capability . In addition, WMSNs has other barriers such as power consumption, delay, bandwidth cost. WMSNs are in need of a compression process with acceptablecompression rate and low dynamic memory usage to reducethe number of bits used or representing the video. The adoption of compressed sensing in WMSN for video transmission provides significant improvement to theselimitations. Compressive sensing aims to recover a sparse signal from a small number of measurements at a rate significantly below the Nyquist rate.Compressed sensing involves three basic steps 1.Sparsification 2.Obtaining measurements using measurement matrix 3.Recovery of the signal using reconstruction algorithm.When the original signals can be expressed as a largenumber of zero values, the signal is said to be sparse. Measurement matrix extracts the useful information from the sparse signal. The major advantage of CoSaMPreconstruction algorithm is that the error in the CoSaMP estimate of a sparse vector decays exponentially until achieving a lower bound which is dominated primarily by the noise power present in the measured signal.

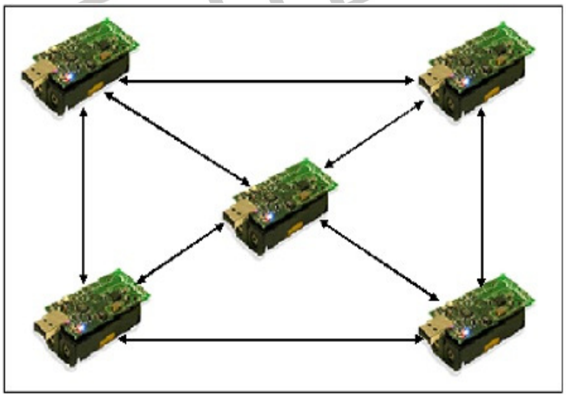

Fig1: Wireless Sensor Nodes randomly deployed

II. RELATED WORKS

In this section, several related works such as sensor networks compressed sensing, measurement matrices are discussed A sensor network is composed of a large number of sensor nodes that are densely deployed [2]. Variousfeatures of sensor nodes ensure a wide range of applications in the areas of military, medicine. In [2] the author discusses the differences between sensor and ad-hoc network. In [10] the author investigates the dynamic measurement rate allocation in block-based DCVS, which can adaptively adjust measurement rates by estimating the sparsity of each block via feedback information. The paper doesn't elaborate on robust algorithm and does not provide accurate side information which could result in sparser representation for the frame. In [5] the author discusses the basics of compressed sensing and how it differs from conventional sensing. The author also lists the advantages of compressed sensing over conventional sampling. The paper clearly expounds the different steps in compresses sensing .The main challenges involved in compressed best sparse representation, measurement matrix and efficient reconstruction algorithm.The paper [1] is encouraged by the simplicity of Hadamard matrices that paves way for the usage of efficient recovery algorithm. This paper investigates the construction of deterministic measurement matrices preserving the entropy of a random vector with a given probability distribution.Some of the advantages are construction time, storage space, image reconstruction effort and easy hardware implementation in comparison with the commonly used measurement matrices. In [6], the author analyses a novel signal reconstruction algorithm Compressive Sampling Matching Pursuit which is robust and offers excellent error guarantees for every target signal. Being an iterative recovery algorithm, it inarguably provides efficient resource usage. The author estimates the operation counts for each step of the algorithm. It is understood from the paper that the CoSaMP identifies many components during each iteration and this makes the algorithm to run at a fast pace.

III. COMPRESSED SENSING

Compressed sensing is a new and emerging approach where sensing and compression is done simultaneously resulting in the significant reduction in the number of measurements required to represent the signal and computation costs at a sensor.CS is based on the key fact that one can represent manysignals using only a few non-zero coefficients. According to Nyquist-Shannon sampling theorem, a band-limited analog signal has to be sampled atleast twice its highest frequency. But in many real time applications the Nyquist rate is quite high that results in too many number of samples. Therefore, we move on to CS which states that one can reconstruct the signal below the Nyquist rate. The compressed sensing theory establishes a necessary sampling condition for the signals which are compressible and sparse. The CS theory states that one can recover a particular signal or an image from fewer measurements M than all the data samples N. CS theory builds on two convention.

[1]Sparsity/compressibility:The effective bandwidth of the signal is greater than the information contained in it. CS makes use of the fact that the data are feasiblyrepresented using fewer measurements.

[2] Incoherence between the Π and sensing modality extends the uncertainty principle between time and frequency. The signals that are sparse in Π must be spread out in the domain in which they are obtained; the sensing vectors must have a dense representation in Π.

Any compressible signal $S \in Q^T$ can be represented as

$$S = C\varepsilon \quad (1)$$

Where C exhibits the $T \times 1$ sparse vector of coefficients such that

$$C_l = \varepsilon^R S \quad (2)$$

S is in time domain and *C*is in ε domain. The compressible signal S can be shown as a linear combination of K vectors with K<<T, and *K*nonzero coefficients and *T−K*zero coefficients in Eq. (1). In many applications, signals have less number of large coefficients. These less number of large coefficient type of signals can be approximated by H. In conventional process, although only*K*largest coefficients are selected and the *(T−K)* smallest coefficientsare discarded, there arises a need to acquire the complete *T*-sample of signal S for computing the complete group of transform coefficients. Thus the traditional compression techniques is inefficient since it computes all *T*coefficients and records all the nonzero, although K<<T. The CS is preferred to traditional sampling for several reasons. Firstly, it reduces the number of measurements. Secondly, CS combines acquisition step and compression step into one step and can directly acquire signals without the intermediate steps. As a result, small number of measurements is only necessary for the purpose of being transmitted or stored rather than the full set of signal samples.
The CS offers *M* measurements with *(K<M<<T)* and enough information to reconstruct S.
The other transform matrix Π is used to obtain the compressed signal W:

$$B = \Pi S \quad (3)$$

Using Eq. (1), the compressed signal can be represented as:

$$B = \Pi S = \Pi \varepsilon C = \tau C \quad (4)$$

Where τ is a $M \times T$ matrix and resulting B is a $M \times 1$ vector. The measurement process for M is non-adaptive and hence, Π is independent on the signal S. Gaussian, Bernoulli, Toeplitz, Circulant are the common measurement matrix available. In order to recover the original signal a reconstruction algorithm is needed. M measurements are needed to recover the original signal. CS transfers $S \in Q^T$ to $B \in Q^M$ .Fig 1 gives the block diagram of Compressed Sensing Framework. The measurements are directly obtained from the input signal by applying a measurement matrix to the sparse vector. These measurements are transmitted or stored for further purpose. Transmitted measurements are reconstructed using recovery algorithms.

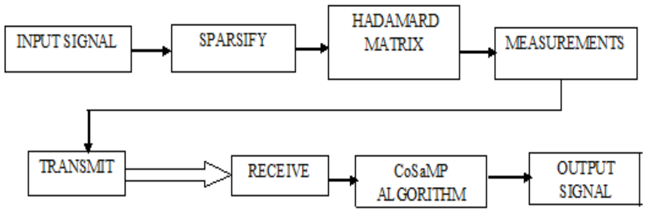

Fig 1: Compressed Sensing Framework

IV. VIDEO CS FRAMEWORK

In this paper, Hadamard matrix of dimensions $m \times n$ is implemented in video compressed sensing framework in order to improve the performance recovery of the video as well to reduce the number of elements stored in the WMSNs. The Hadamard matrix results in PSNR value which is almost equal to that obtained from random Gaussian matrix but reduces memory cost. In the reconstruction process at the receiver side CoSaMP recovery algorithm is implemented, offering precise bounds on storage and computational cost is implemented.

A.Sparse Representation:

Sparsity is an underlying concept in most of the filtering and compression applications today. A signal is said to be sparse or compressible when the transform coefficients vector has a small number of large amplitude coefficients and a large number of small amplitude coefficients. Most of the energy is concentrated in a few transform coefficients (large amplitude). The other coefficients have less contribution in representing a signal vector. In most cases such as speech signals, natural images or video, the signal is correlated enough to represent sparsely in a suitable basis.

B.Measurement Matrix:

The measurement system performs dimensionality reduction. Measurements are able to completely capture the useful information content embedded in a sparse signal. Measurements are information of the signals and thus can be used as features for signal modeling.

1) Hadamard matrix:

A Hadamard matrix of order n (power of 2) is a square $n \times n$ matrix of binary elements with the property that any row differs from any other row in exactly n positions. If we denote the elements by +1 and -1, then the rows or columns of the Hadamard matrix are mutually orthogonal. Hadamardmatrices have been usedin many applications such aserror correcting codes, switchingnetworks and signal processing.

Hadamard matrix for a 'n' dimensional signal is defined as $H_n = \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix}^{\otimes n}, \Re = 2^n, n \in \Upsilon_+$

Where Υ is atomic distribution

$\Re$ is the total number of independent and identically distributed random variables.

$\otimes$ is the kronecker product

1.1) Properties of Hadamard matrix:

1. For a Hadamard matrix H_n of dimension $n \times n$

$H_n H_n^T = nI$, where I is an identity matrix

2. Hadamard determinant bound state $|\det(H_n)| \le n^{\frac{n}{2}}$ equality in this bound is attained for a real matrix M if and only if H_n is a Hadamard matrix

C.Reconstruction Algorithm

CoSaMP algorithm:

CoSaMP algorithm is implemented for recovery of the frames at the receiver's side. It is found to be highly efficient for practical problems as it requires only matrix–vector multiplies with the sampling matrix. For compressible signals, the running time of CoSaMP is found to be O (m.N) while that of OMP is O (K.m.N).

The algorithm is initialized with a minor signal approximation, i.e. the initial residual is made equal to the unknown target signal. For each iteration, CoSaMP performs five following steps:

These steps are repeated until the halting criterion is triggered.

(1) Identification: The algorithm forms a proxy of the residual $er = \Pi res$ and locates the largest components of the proxy.

(2)Merging: The newly identified components $\rho = \sigma \bigcup \sup p(x_{J-1})$ is combined with that of components found in the current approximation.

(3)Estimation: Using least-squares method $es_i \mid_T = \Pi \mid^h{}_\rho \; u$ the approximate the target signal on the merged set of components is estimated.

(4) Pruning: The largest entries in this least-squares signal approximation $x_J = es_{iK}$ are retained

(5)Sample Update: Update the samples $res = u - \Pi x_J$, so that they reflect the residual, the part of the signal that has not been approximated.

V. SIMULATIONS RESULTS

In this section, the video CS was implemented using the Hadamard matrix and CoSaMP algorithm which reduces the time complexity when compared to OMP (orthogonal matched pursuit algorithm) recovery algorithm. The performance of the video compressed sensing using the Hadamard matrix was analyzed using Matlab. A Xylophone video of 32 frames is taken and the size of each frame is 240x320. Each frame is divided into smaller block of size 5x5.To each of these blocks discrete wavelet transform is applied. DWT transform results in four sub-image components such asapproximation details (LL sub band), horizontal detail (HL sub band), vertical (LH sub band) details and diagonal details (HH sub band).

A $m \times n$ matrix is constructedfrom the Hadamard matrix which is a square matrix of size $n \times n$.The dimension of the constructed matrix is varied as 5×9, 6×9, 7×9, 8×9 and PSNR obtained by these measurement matrix is calculated.

Table I Average PSNR value using OMP and CoSaMP recovery algorithm.

Frames	PSNR(Average value) dB using	
	OMP recovery algorithm	CoSaMP recovery algorithm
1	27.8631	27.8703
2	27.8168	27.8287
3	27.7304	27.7546
4	27.9242	27.9387
5	27.9435	27.9547

From Table I it is inferred that as the PSNR value obtained using the CoSaMP recovery algorithm is found to be almost equal to that using OMP recovery algorithm.

Table IIComparison of running times of OMP and CoSaMP algorithm

Number Of Frames	Running Time of recovery algorithm in sec	
	OMP Algorithm	CoSaMP Algorithm
1	60.548	36.869
2	121.096	73.738
3	181.644	110.607

From Table II we infer that the running time of OMP algorithm is almost 1.6 times the running time for CoSaMP algorithm. CoSaMP recovery algorithm is exceptionally faster compared to OMP algorithm.

Table III Number of elements stored to generate the Gaussian matrix and the Hadamard measurement matrix

Measurements	Number of elements to be stored to generate the matrix	
	Gaussian matrix	Hadamard matrix
45	45	2
54	54	2
63	63	2
72	72	2

From Table IIIit is observed that the number of elements required to generate the Hadamard matrix is remarkably lesser than the number of elements needed to generate Gaussian measurement matrix. Thus the Hadamard matrix is memory efficient in comparison with Gaussian measurement matrix.

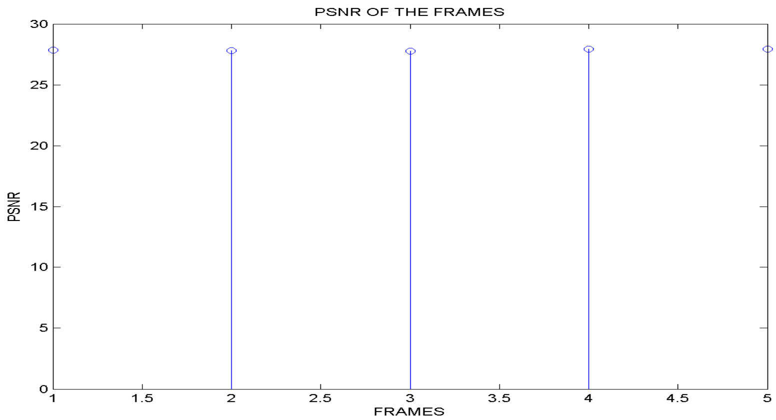

Fig 2: PSNR of first five frames.

The PSNR values from Fig 2 for the first five frames are found to be closer to 27.9dB by using the Hadamard matrix.

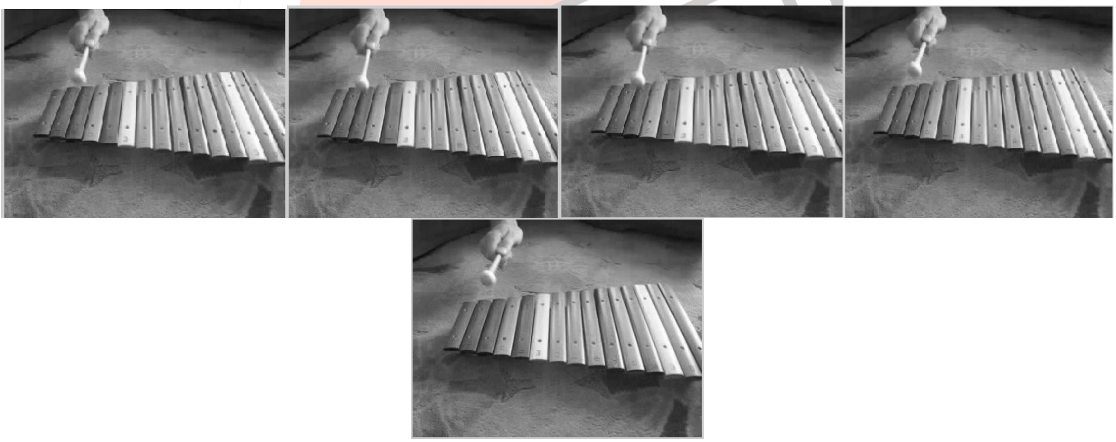

Fig 3: First five frames of the video

Fig 3 shows the original first five frames of the video before applying video compressed sensing.

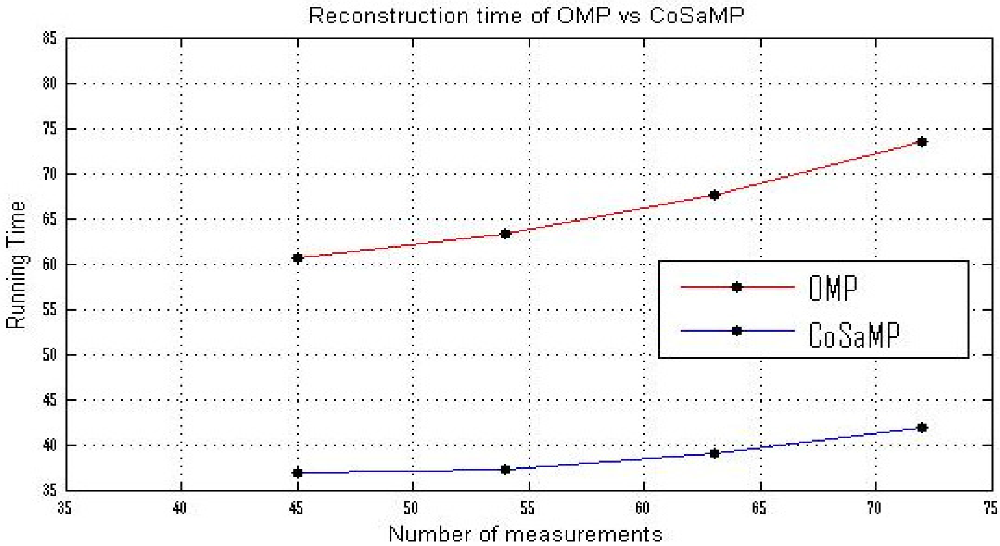

Fig 4: Reconstruction time of OMP vs. CoSaMP

The reconstruction time from Fig 4 of CoSaMP recovery algorithm is very much less than that of OMP.Here the reconstruction time for various measurements are plotted.

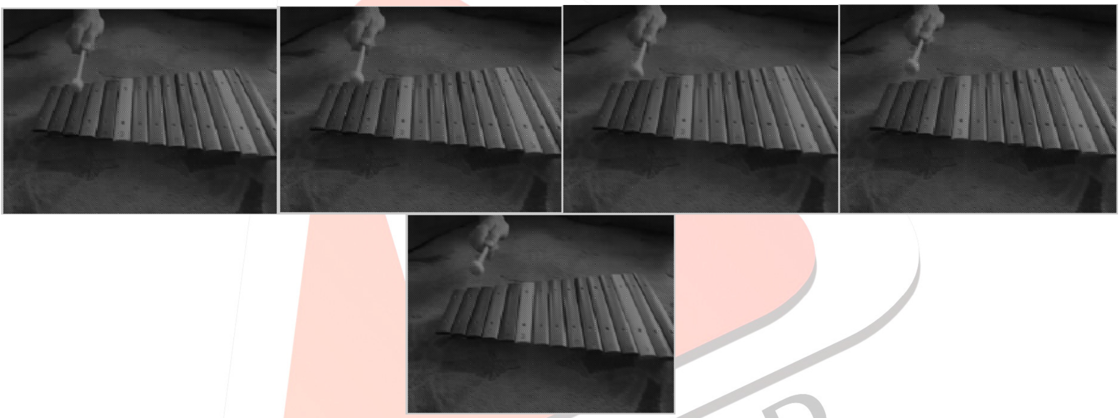

Fig 5: Estimated Frames after applying video compressed sensing

Fig 5 shows the first five estimated frames obtained after applying compressed sensing.By increasing the number of measurements the resolution of the frame can be increased.

By using the Hadamard matrix, the number of elements is exceedingly reduced, hence the on- board memory required is less. In addition, the CoSaMP algorithm efficiently minimizes the execution time even though the PSNR obtained from using CoSaMP is almost same on implementing OMP algorithm. All of these advantages reduces the time complexity, computational and memory cost. Therefore, the video compressed sensing technique used in the paper is well suited for wide range of practical application of WMSNs such as surveillance, tracking, traffic control etc.

VI. CONCLUSION AND FUTURE WORK

In this paper, Hadamard matrix was used as the measurement matrix. The Hadamard matrix shows results of improved recovery performance. The Hadamard matrix reconstructs the original signal with fewer numbers of elements. The CoSaMP algorithm is used for reconstruction of the video at the receiver side which reduces the computational and time complexity.Results show that CoSaMP algorithm recovers the video frames much faster than OMP algorithm. Improvements such as modifying the transform or using a different measurement matrix may produce optimum results. Our future work is to implement the same using TeloSB sensor motes in Contiki OS platform.

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