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Block Based Adaptive Compressed Sensing of Image

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Abstract

Bandwidth has been consistently contemplated as a scarce resource. Nyquist criterion is considered to be the fundamental prerequisite to reconstruct signal with mediocre quality. Compressed Sensing (CS) is an offbeat technology acquire and reconstruct signal extensively far below the Nyquist criterion. In this paper we acquire signals tremendously well than the normal CS method applying the novel technology of adaptive, It increases the efficiency of reconstructed signals by demarcating the image into blocks and constructing a whole new matrix which samples the image blocks adaptively as it demands along with another matrix which samples the image just as done in the traditional CS technique with fixed sampling rates, thus concatenation of the matrices empowers us to proliferate a matrix which would consume immensely low bandwidth and could just be accommodated in nominal memory devises which makes this absolutely pertinent to wireless sensor networks. The channels in wireless sensor network are prominently susceptible to burdensome noise thus we use a new combination of algorithms such as K-SVD and OMP to adequately eradicate the noise and reconstruct the data in the finest possible manner. Our proposed system effectively acquires a greater PSNR and a significantly better reconstruction method than the contemporary methodologies.

***Key Words*:**Adaptive CS, Wireless Sensor Networks, Sampling Rate

1 Introduction

Wireless Sensor Networks consist of a number of base stations and nodes, which act as sensors and are usually used to monitor environmental and physical conditions. The information is communicated through wireless links. The data through nodes can also be connected to other networks.

They have many applications like environmental sensing, health applications, military application and many commercial uses. They are also used widely in traffic management. However, they have limitations like high power consumption, less storage space and less bandwidth requirement.

Bandwidth is a very important resource and its conservation is very important. To reduce bandwidth compression can be done. However Traditional compression techniques like JPEG cannot be used for WSNs due to their channel errors and coding complexity.

CS process can be used. CS achieves sensing and compression at the same time and enables recovery of such signals from samples which are far fewer than that of the Nyquist Shannon theorem for sampling. The image complexity is reduced along with image data. The quality of the reconstructed image is also good. Compressive Sensing (CS) is therefore widely used for signal acquisition and is attracting increasing attention.

CS is a very attractive technique for applications with highdata acquisition cost. For example, it has had notable impacts on medical imaging, sensor networks, and compressive radar. CS however cannot be used in large scale applications since large memory is required for the storage. Thus, block-based CS was proposed to overcome this problem. However, all blocks are sampled at a fixed rate without considering the structural orientation of the blocks.

In block-based CS the image is divided into blocks and are sensed block by block. This reduces the computational complexity. However, all the blocks are sampled at a fixed rate without considering the structural orientation of the blocks. Thus, adaptive CS is done where different sampling rates are assigned based on whether the blocks [3]. The statistical information of the blocks can be used to get the CS measurements. However, the measurement allocation becomes less efficient. Thus, in this paper the sampling rates are assigned adaptively based on whether the blocks are smooth or non-smooth [4]. A smooth block is sampled with a lesser frequency than non-smooth one. For adaptive compression various techniques were used. However, at the encoder the complexity for computation was high. In the algorithm we are using, standard deviations are used to find out the rates for sampling. It overcomes the disadvantages of fixed sampling alone, that is the information of each block is taken into account.. This algorithm can be applied to videos too. Video sequences,that can essentially be considered as sets of images, can be sampled and reconstructed using adaptive CS theory [5]. The image when travelling through the channel, is mixed with noise. Therefore, we apply a denoising algorithm with the help of K-SVD. OMP is used for reconstruction

2 LITERATURE SURVEY

A method to achieve adaptive block-based CS for videos based on the temporal redundancies of the frames is proposed in [4]. CS fails to address the temporal redundancies, which is addressed here. The video is said to achieve a better quality with a lower number of measurements for sampling. It also considers the texture of different regions and adaptively, provides different measurements based on the sparsity of that region. It addresses the fact that different regions in a frame move independently and have different interframe correlation. The frames are divided into non-overlapping blocks. The blocks are then compared to those in the neighboring frames to find out the interframe correlation. Frames are divided to reference and non-reference frames. Different sampling and reconstruction techniques are used based on the block type.

Sampling occurs by exploiting the sparsity of an image. Reconstruction is done by the algorithms, GPSR and min-TV. The average PSNR was obtained for the sample videos.

An adaptive block-based CS sampling scheme was proposed for reweighted images in [5]. The sampling rate and other measurements for each block of the image is obtained by the statistical information present in the blocks. An algorithm is then obtained, to implement the adaptive sampling. For that purpose, it makes use of the statistical information including the variance, entropy and the DCT coefficients of the blocks. An adaptive matrix is applied for sampling the blocks. Measurements obtained are allocated based on a principle. This makes the sampling more efficient, due to allocation of different measurements to different blocks. compared to traditional methods and different statistical parameters, are It prevents oversampling. It leads to a better reconstruction quality than traditional schemes like non-adaptive CS. This scheme is used as the allocation factor and their performances were compared.

A method to adaptively compress videos, by reducing the number of measurements on the coefficients of an image is proposed in [6]. It focuses the measurements on the large valued coefficients. CS deals with signals with sparse coefficients. When the signal representation is nearly sparse, the reconstruction error is directly proportional to the kth term approximation to the signal. In case of non-sparse signals, sparse filtering is used. It is similar to low pass filters used to prevent aliasing of analog signals during reconstruction. A support estimate is used and the signal coefficients that are outside it are weighed down. The adaptive CS scheme is applied for compressive video acquisition. The SNR values are compared for standard CS and adaptive CS. The reconstruction is better in this scheme. The recovery performance is compared to that of standard CS

Section II describes about the traditional and adaptive compressed sensing technique. Section III is about system analysis and Section IV indicates the results we have acquired.

3 COMPRESSED SENSING

A. Traditional Compressed Sensing

CS is a technique used for acquiring and reconstruction of an image using far fewer samples than the Nyquist criterion, Fs>=2Fm.

It exploits the sparsity of the signal and recovers it from a series of sampling measurements. The compressed signal is obtained by solution to undetermined linear equations [2]. According to CS theory, the sampled data y is given by

$$y = \Phi x \tag{1}$$

where, x is sparse representation of the signal and Φ is a random sampling or measurement matrix.

If x is sparse transform domain, this equation can be modified as

$$y = \Phi(\Psi\theta) \tag{2}$$

B. Adaptive Compressed Sensing

In normal CS schemes, fixed measurements are taken for all block irrespective of the block information. Therefore, for efficient compression different measurements are taken for different blocks based on the block structure and statistical information. The adaptive sampling matrix is then applied to the blocks [1]. In this paper, smooth blocks are sampled with lesser frequencies than non-smooth one. Standard deviation is used to find the adaptive rates [1].

- Image is divided into blocks
- The fixed sampling frequency is allotted to all the blocks.
- The total sampling rate M is obtained.
- Upper bound is fixed so that the adaptive sampling frequency doesnt exceed the number of pixels present in the image.
- We fix adaptive sampling frequencies for all the blocks.
- We concatenate the fixed sampling frequencies and the adaptive sampling frequencies.
- Later the values are added with a random noise pattern
- The reconstruction algorithm OMP and K-SVD are used for denoising and optimal reconstruction.

4 SYSTEM ANALYSIS

CS based image compression is a technique which has a capability to achieve a very low sampling rate. In this system a fixed sampling rate is obtained for the image blocks and then each image block would be applied an adaptive sampling rate which is majorly dependent on the particular image blocks standard deviation. Blocks which have more information in it which are technically referred to non-smooth blocks need to be given a higher sampling rate and blocks which have less information in it which is technically referred to smooth block need to be given a lower sampling rate, this is done particularly to reduce the involvement of memory in the reconstruction of redundant pixels. Techniques like JPEG follow the traditional Nyquist criterion for the reconstruction of the image, which perhaps cannot be Implemented on a wireless sensor network because of the increase in the complexity, memory, error susceptibility.

Classical CS when applied is not proven to be efficient because of its complexity but when it is modified on a minor level and the classical CS is implemented on a block of an image the results are Exceptional. The Splitting of a whole image into a number of blocks is the first step of the process.

A. Fixed and Adaptive Rate Allocation

Sampling rates of fixed value are given to the blocks which are present in the image. These measurements forms to become the fixed measurement matrix. Assuming n to be the number of blocks in the image, we calculate the total sampling frequency by multiplying the sampling rate of one block and the block size and the number of blocks

$$M = SR * B * B * n \tag{3}$$

We fix an upper bound so that the total sampling frequency does not go beyond the number of pixels present in the image. The upper bound we assume is

$$0.4 * B * B \tag{4}$$

For the reconstruction of the image in basic quality we assume a fixed sampling rate for each block which is

$$FSR = W * SR \tag{5}$$

where W is a parameter which would vary from 0 to 1. By obtaining FSR we obtain FSF which is fixed sampling frequency. The next step is finding out the standard deviation of each image block. The standard deviation of the image blocks forms to become the adaptive measurement matrix [4], This measurement matrix is slightly uneven the adaptive measurement matrix is a particular type of matrix which is solely dependent on the image content. The changes in between measurements of the adaptive measurement matrix is due to the content present in the image blocks. We calculate the standard deviation of one block divided by all the blocks to land up in the value called P. We calculate the adaptive sampling frequency

$$AM = P_i(M - nFM_i) \tag{6}$$

where M is the total sampling frequency and FM is the fixed sampling frequency, if this value turns out to be higher than the upper-bound then we implement a procedure to allocate S which is

$$S = S + (AM - Upper - Bound) \tag{7}$$

The adaptive matrix and the fixed matrix is obtained.[1]

B. Concatenation

The concatenation of the measurements is the next step where the compressibility of an image block would be examined solely by the adaptive CS matrix. The fixed and adaptive sampling matrix are concatenated to get a new sampling matrix. The values are coded in the transmitter side and they are sent through the channel and the values are decoded in the receiver side. After decoding the values are would result in the measurements which were acquired from the fixed measurement matrix and the adaptive measurement matrix. Then we concatenate both the matrices and then the concatenated output is given to the traditional CS block where the concatenated matrix is considered as Phi and it is multiplied with X which is a sparse matrix and we obtain y.

C. K-SVD

Now Y matrix is sparse encoded with the help of the K-SVD (Singular value decomposition) algorithm. It is based on dictionary training. After K-SVD algorithm application to the data we send the data to the orthogonal matching pursuit algorithm, which is an image reconstruction algorithm which is traditionally used for the reconstruction of the images which are basically compressed with the help of CS [2]. We add a random noise into the data in the channel and then we denoise the added noise in the data.

Denoising algorithm consists of three steps, sparse coding step, dictionary update and reconstruction step which is done by the OMP (Orthogonal Matching Pursuit) algorithm which fundamentally rejects all the noise which is present in the received data and then the signal to noise ratio after the eradication of the noise is better than most of the traditional CS technique application implementations. By this way we obtain a better PSNR value and a better reconstructed image when put under comparison with the original image at a lesser bandwidth and lesser occupancy of memory.The block Diagram is given in fig 1.

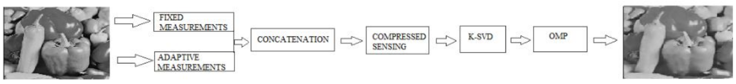

Fig 1.Block diagram

5 RESULT

The image is divided into equal blocks of some block size as in figure 2. Here the image is divided into 16 blocks of the same size.

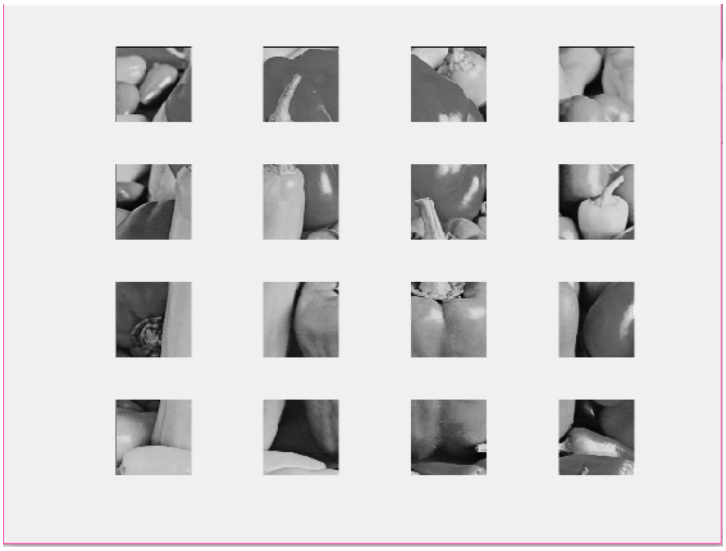

Fig2. Image divided into blocks

A better PSNR is obtained on reconstruction. The noise is removed by denoisal. It is observed that on changing the sampling rate the PSNR changes. More the sampling rate, more the PSNR.

Sampling rates more than 0.3 are taken because lesser sampling rates gives a low reconstruction quality.

Block size is a very important parameter. Small block size increases the computational complexity of calculations. Thus on increasing the block size the PSNR decreases.

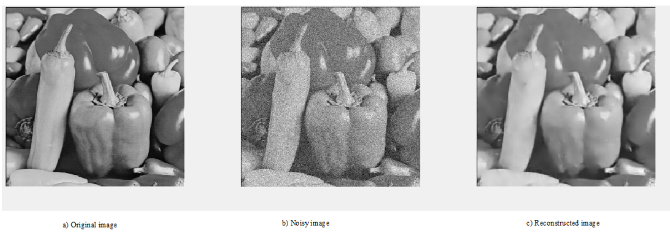

Fig3.Simulation results at sample rate 0.75 a) Original image, PSNR=20.169dB, c) Reconstructed image, PSNR=29.6964dB

Figure.4. represents the fixed sampling rate allocation across blocks. x axis defines image blocks, while y axis defines sampling rates.

Therefore, for fixed sampling rate assignments, all blocks are assigned the same sampling rates.

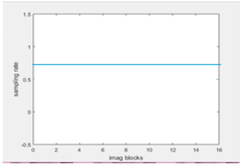

Fig4.Fixed Sampling rates

Figure.5. represents adaptive sampling rate assignments. Each block is an allocated a different sampling rate according to the algorithm. Smooth blocks are allocated algorithm removes the noise and efficiently reconstructs it. A lower frequency and Non-smooth blocks are allocated a higher frequency.

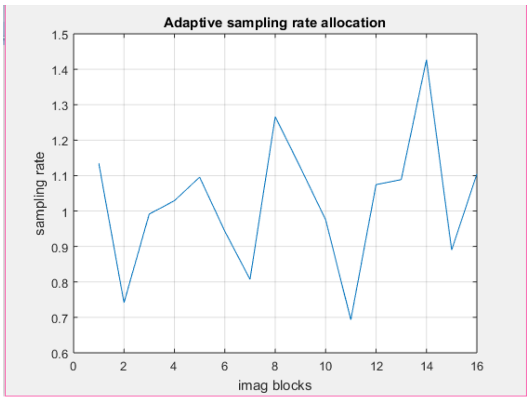

Fig5.Adaptive sampling rates

6 CONCLUSIONS

The image block based adaptive CS algorithm can be used in Wireless Sensor Networks as it is very efficient..Lesser bandwidth and memory can be consumed which is suitable for WSNs. OMP (Orthogonal Matching Pursuit) algorithm is used along with KSVD for denoisal and reconstruction.

The sampling resources are optimized by utilizing the adaptive sampling method based on the proposed algorithm [4]. The transmission of images progressively is obtained by transmitting the fixed measurements and adaptive measurements separately combined with the sampling rate allocation strategy. Improvement in the quality of reconstructed image is obtained in experimental results by using this algorithm. This transmission of image is required in wireless sensor networks which have unstable channels and low bandwidth.

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