Compression of Hyperspectral Image using Compressive Sensing

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ABSTRACT

*A novel approach for the compression of hyperspectral images is described using compressive sensing. It is adopted in latest signal processing technique for acquiring and recovering a sparse signal in the most efficient way. Compressive Sensing is based on sampling theorem which takes less samples for signal processing and gives batter performance than the traditional theoram. Hyperspectral images typically demand enormous computational resources in terms of storage, computation, input/output, throughputs particularly when real-time processing is desired. So, Compressive sensing is best approach for compression of hyperspectral images and transforming to different places with acceptable signal –to –noise ratio (SNR) and compression ratio (CR) than other signal transformation techniques. At reconstruction time of images in compression process if sparse dictionary, OMP algorithm and L*a*b* color space is used with compressive sensing then quality of reconstructed image can be improved and color image is generated.*

Keywords: *Compressive sensing (CS), Hyperspectral Images, Sparse dictionary, OMP Algorithm, L*a*b* color space, Image Compression, Lossless image compression, Lossy image compression*

1. INTRODUCTION

Hyperspectral image has magnetized much attention in wide range of applications service as terrain classification, environmental monitoring, mineral detection and exploration, pharmaceutical counterfeiting, military surveillance.

Hyperspectral imaging consolidate the power of digital imaging and spectroscopy [12]. Hyperspectral camera acquires the light intensity for a large number of contiguous spectral bands for each pixel in an image. It contains a continuous spectrum and can be used to individualize the objects in the scene with great precision and detail. Hyperspectral images provide much more detailed information about the scene than a normal color camera. Hence, hyperspectral imaging leads to a vastly improved ability to classify the objects in the scene based on their spectral properties.
Hyperspectral images provide such high spatio-spectral resolution at the cost of extremely large data size. As these data are very important so after transforming reconstruction of original data is also challenges. They fit perfectly the assumptions underlying CS theory.

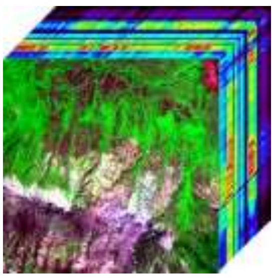

Fig.1 hyperspectral image [13]

In [7], a classic signal processing and imaging system, the samples are obtained through the array of photoelectric sensors and A/D converter which have some inefficiencies in these. It must compress the massive data before transmission and storage. The Nyquist-Shannon rate used in imaging data acquisition for remote sensing is so high that too many samples produced, making compression a necessity prior to storage or transmission. In addition, even though the compressed data is less, the initial samples are larger and all values have to be processed and in order to obtain high-resolution images of different bands. These problems will increase the complexity and cost of the imaging acquisition. So, it is necessary to obtain a new acquisition technology of the low-cost, high efficiency and wide application range for remote sensing imaging to effectively acquire the observation data. A new technology is emerged to capture and represent compressible signals at a significantly low rate is called compressive sensing. The use of CS techniques would allow to design sensors requiring a smaller memory buffer, fewer detectors, and a reduced volume of data to transmit.

2. BACKGROUND THEORY

Image compression mainly classified in to two types:

1. Lossy image compression
2. Lossless image compression

Fig.2 Lossless and Lossy image compression comparison [14]

Lossy image compression is used when less transmission time is in consideration where quality of image is not important.

Types of Lossy Image Compression:

Block Truncation Coding scheme divides the image into non overlapping blocks of pixels and for each block threshold and reconstruction values are determined. Then a bitmap of the block is derived by replacing all pixels whose values are greater than or equal (less than) to the threshold by a 1 (0). Then for each segment (group of 1s and 0s) in the bitmap, the reconstruction value is determined.

In transformation coding technique data is divided in to square blocks and transforms the raw data to a domain that more accurately reflects the information content. Discrete Cosine Transform (DCT) is the most recent known transform in the image compression field because of its excellent properties of energy compaction.

Vector quantization technique following the principle of block coding. It develops a dictionary of fixed-size vectors called code vectors. A vector is usually a block of pixel values. A given image is then partitioned into non-overlapping blocks (vectors) called image vectors. Then for each in the dictionary is determined and its index in the dictionary is used as the encoding of the original image vector.

Fractal coding method decomposes the image into segments by color separation, edge detection, and spectrum and texture analysis methods. Then each segment is looked up in a library of fractals which contains codes called iterated function system (IFS) codes, are compact sets of numbers. Using a systematic procedure, a set of codes for a given input image are determined, such that when the IFS codes are applied to a suitable set of image blocks yield an image that is a very close approximation of the original.

Sub-band coding scheme analysed the image to produce the components containing frequencies in well-defined bands, the sub bands. Afterwards, quantization and coding is applied to each of the bands.

Lossless image compression is used when transmission time of data is not important but quality of image, information, data are important. Most satellite images uses lossless image compression techniques.
Types of Lossless Image Compression:

Run Length Encoding is a very simple compression method used for sequential data and very useful in case of repetitive data. This technique replaces sequences of identical symbols (pixels), called runs by shorter symbols.

Example:
Uncompressed data: BBBWWBBWWWW
Compressed data: 3B2W2B4W

Huffman Encoding is a matter of course technique for coding symbols based on their statistical occurrence frequencies. Huffman code is a prefix code. This means that the (binary) code of any symbol is not the prefix of the code of any other symbol. Most image coding standards use lossy techniques in the earlier stages of compression and use Huffman coding as the final step.

LZW Coding is a dictionary based coding whose full set of strings is determined before coding begins and does not change during the coding process. It is used when the messages to be encoded is fixed and large for instance, an application that stores the contents of a book in the limited storage space. A dictionary is built from old English texts then is used to compress a book. Dictionary based coding can be static or dynamic. LZW is widely used in computer industry and is implemented as compress command on UNIX.

Area Coding is an intensified form of run length coding, reflecting the two dimensional character of images. This is a significant advance over the other lossless methods. The algorithms for area coding try to find rectangular regions with the same characteristics. These regions are coded in a descriptive form as an element with two points and a certain structure. This type of coding can be highly effective but it bears the problem of a nonlinear method, which cannot be implemented in hardware.

In current time, compression of hyperspectral images follows compressive sensing theory which decreases sampling rate than traditional Shannon-Nyquist theorem. In [1] measurement matrix is used with compressive sensing for improving reconstruction quality. Instead of random measurement matrix optimize measurement is proposed to improve reconstruction quality of hyperspectral images by analysing the mutual coherence between measurement matrix and representation matrix using gradient descant method, reduces measurement than iterative method. It improves reconstruction quality, good computational speed but Reconstruction accuracy is low.

In [2] lossy compression algorithm, increasing bitrate obtain the highest achievable SNR but it has been observed previously that a higher SNR may not necessarily correspond to better performance at data-analysis tasks, such as classification, anomaly detection, linear unmixing. Principle component analysis (PCA) is used with JPEG-2000 image compression where removal of lossless storage of anomalous pixels preservation gives batter compression performance than achieved at higher bitrate but algorithm may not work at low bitrate.

Compressive sensing and unmixing[3] (CSU) scheme for hyperspectral data processing does not require forming or storing any full size data cube for hyperspectral data processing. CSU consist mainly three major steps: (1) Data acquisition by CS is spectral signatures of the endmembers are either precisely or approximately known. (2) Data prepossessing by SVD (Singular Value Decomposition) is used for reducing size of observation matrix (number of band to number of endmember). (3) Data unmixing by solving a compressed unmixing model with TV regularization on abundant fractions

This method shows that compressive acquired data of size ranging from 10% to 25% of the full size can produce satisfactory results highly agreeable with the ‘ground truth’. In this method drawback is that endmember spectral signatures are either very rough, highly incomplete or even totally missing.

Compressive sensing and adaptive direct sampling scheme acquired hyperspectral images with less samples than the actual number of pixels, in a low dimensional representation [4]. This scheme provides structured measurement matrix and sparse matrix is used than reconstruction of images performed by simple inverse transform.

Steps of this method: (1) Compressive sensing captures hyperspectral images, captures truly sparse signals in less samples. (2) Adaptive direct sampling (ADS) provides structured, deterministic measurement increases image quality. (3) A novel sampling scheme maintain queue that contain indexes for all coefficient that are to be sampled. In this approach the reconstruction of the image is done by simply an inverse transform and reconstruction is faster, easier and less expansive compared to CS but Loss of information is more.

In [5], presented algorithm for the lossless compression of hyperspectral images based on distributed source coding. It performed on a small block size unit to take advantage of the local correlation of the hyperspectral images which is beneficial for achieving a high compression performance. In this data sources encoded by separate encoder and lossless compression is performed on each source separately. Distributed source coding only transmit the label of the coset to which pixels belongs. Decoder side pixel is reconstructed in the coset and indexed by receiver coset label. Distributed source coding gives low complexity and less error. Using DSC large block size leads to a poor performance.

The nonlinear elastic compression technique uses historical data as a reference [8]. It is based on the general relationship to predict adaptively current image from a previous reference image without loss of any information. Main feature of this method is to find best prediction for each pixel brightness value individually. Satellite images are collected over a regular period of time so rather than transmitting a complete image every time, the difference between the current and previous image data are transmitted. It accommodate batter individual brightness relationship between two date image data sets due to changes of ground cover types during imaging interval. It gives lossless compression.

Compressive sensing method is proposed for acquisition and reconstruction of remote sensing images which have too high resolution [7]. Images are so high that for data acquisition too many samples are there and prior compression is necessary to storage and transmission. Proposed method does few measurement directly instead of traditional sampling method. Here, sampling rate is low and computational complexity transferred from data acquisition to data reconstruction. Compressive sensing method reduce complexity of data acquisition and provides low cost, high efficiency, low complexity, efficient signal acquisition. Compressive sensing method is able to effectively keep original remote sensing image information.

Hyperspectral images have been proved to be effective for wide range of applications but they have large volume and redundant information so it brings lots of inconvenient [6]. By selecting the band from given hyperspectral images and removing redundant component without compromising the original content from the raw image cubes.

Hyperspectral band selection by multitask sparsity pursuit (MTSP) is group wise band selection technique which divided in these three parts: (1) A smart yet intrinsic descriptor for efficient band representation. (2) An evolutionary strategy to handle the high computational burden associated with group wise-selection-based methods. (3) A novel MTSP-based criterion to evaluate the performance of each candidate band combination. The proposed framework can lead to a significant advancement in image compression applications.

Compressive sensing [9]: It is based on the recent understanding that a small collection of non-adaptive linear measurements of a compressible signal contain enough information for reconstruction and processing. It is a signal processing technique for efficiently acquiring and reconstructing a signal.

Compressive sensing (CS) allows to reconstruct sparse signals from a smaller number of measurements than the Nyquist –Shannon criterion. Main properties for CS is Sparsity. Sparse means most of the elements are zero or close to zero. The fraction of zero elements in a matrix is called the sparsity matrix. Sparse data contain many coefficients close to or equal to zero.As well sparsity means elements are should be in some uniform correlation.

Compression of hyperspectral images using compressive sensing gives good performance and during compressive sensing process if optimize measurement matrix is used than reconstruction quality is improved [1]. Compressive sensing works as follow [9]:

Terms used in flow chart:

Reconstructed signals: S
$\{S=y*\Theta^{-1}\}$
X- Image Signal
Y-Observed Vector
S-Sparse Matrix
Θ - Measurement Matrix
Ψ - Dictionary
Φ - Random Matrix

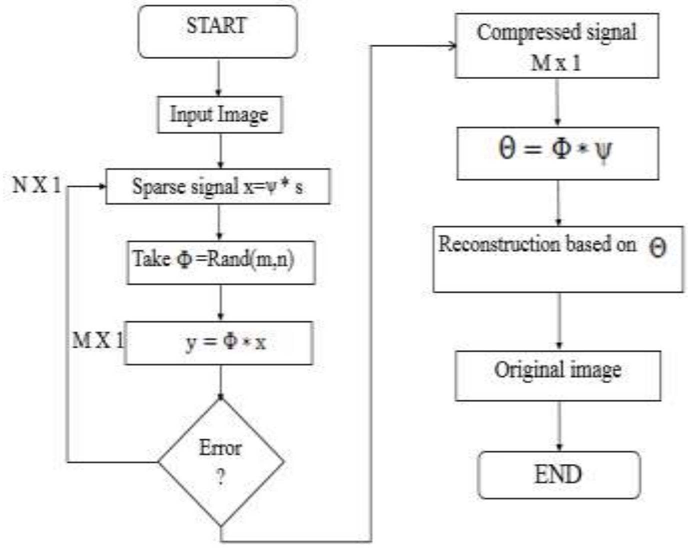

Fig. 4 Flowchart for Compressive sensing

3. PROPOSED SYSTEM

In proposed system compressive sensing is used for compression of hyperspectral image. In prepossessing step RGB image is converted in to L*a*b* color space. In this step only L component is compressed. At reconstruction time color image is produced. In next step transformation is applied for converting image in to signal. Compressive sensing is applied for image compression on signal. Compressive sensing generates sparse Signal. Sparse signals contain minimum number of non-zero elements so computational complexity is reduced.

After sparse signal generation quantization process is applied. It is the process of combining a range of values to a single quantum value. In this similar value pixels are compressed in some quanta according to values of that signal then, inverse process of quantization is done.

After inverse quantization image is reconstructed. In this step for reconstruction of image, L1- minimization process is used for sparse signal recovery. L1- minimization minimize distance of the non-zero entry in sparse vectors. L1- minimization gives very low error and recover signal with great accuracy than other methods [10].

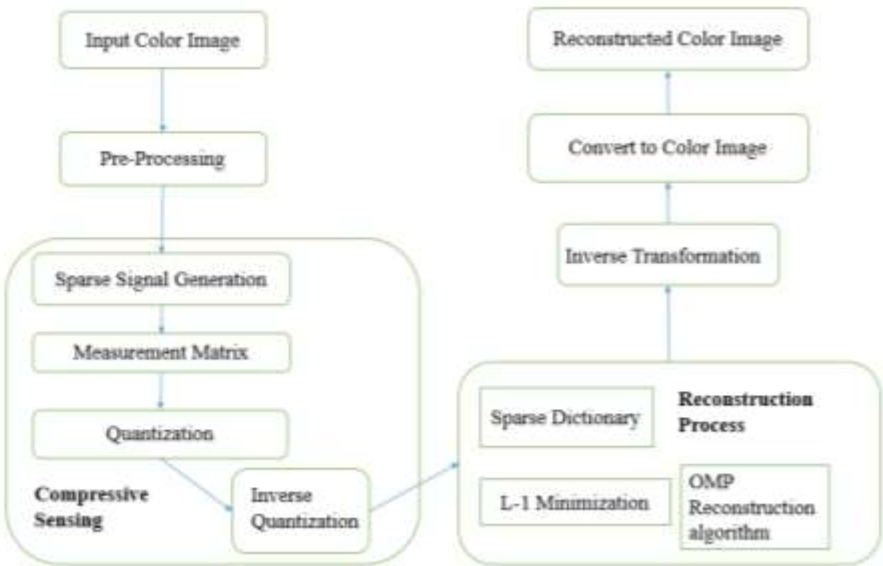

Fig. 5 Proposed System

During L1-minimization process which pixels of sparse signals are missing at the time of recovery is founded using sparse dictionary. Sparse dictionary is base dictionary for sparse signal recovery and it is adaptive and efficient. Sparse dictionary is flexible and compact size dictionary. Sparse dictionary can handle large and higher dimensional signals. Using sparse dictionary pixel to pixel mapping is done so image is enhanced [8]. Here, OMP (orthogonal matching pursuit) algorithm is used to put missing pixels with sparse dictionary. OMP is advantageous because of its speed, ease of implementation and exact recovery of image [12]. At the end of process reconstructed color image is generated.

4. RESULT AND ANALYSIS

For performance analysis and implementing our proposed flow work has been experimented using matrix laboratory software (MATLAB), which is running on laptop with a 2 GHz Core2duo with 2GB RAM and Windows 8 Operating System. In this hyperspectral image 1672*2104*3 is used.

Proposed system gives batter PSNR value at an 8.42 CR for dataset 1. In below figure original and compressed image using proposed method shown. Proposed method gives color image which have NCD 1.012 for dataset 1. Other parameters can be seen in graph which shows that proposed method gives batter performance than CS.

Fig. 6 Original Image of Airport

Fig. 7 Image of Airport after applying proposed method

Small description of parameters used for result analysis of proposed method:

Peak Signal to Noise Ratio (PSNR): It is an expression used as a ratio between the maximum possible values of a signal to the power of distorting noise. PSNR affects the quality of image’s representation. It also described as the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation.

Compression Ratio (CR): It is used to quantify the reduction in data representation size produced by a data compression algorithm. It is mainly used in image compression process. It shows that compression algorithm compares how much percent of original image.

CR = Original Image Size / Compressed Image Size.

Root Mean Square Error (RMSE): RMSE is square root of the mean of the square of all of the error for image. RMSE is very commonly used and it is used to make an excellent general purpose error metric for numerical predictions.

Normalized Color Difference (NCD): It is a color difference between color value of original image and image generated after compression.

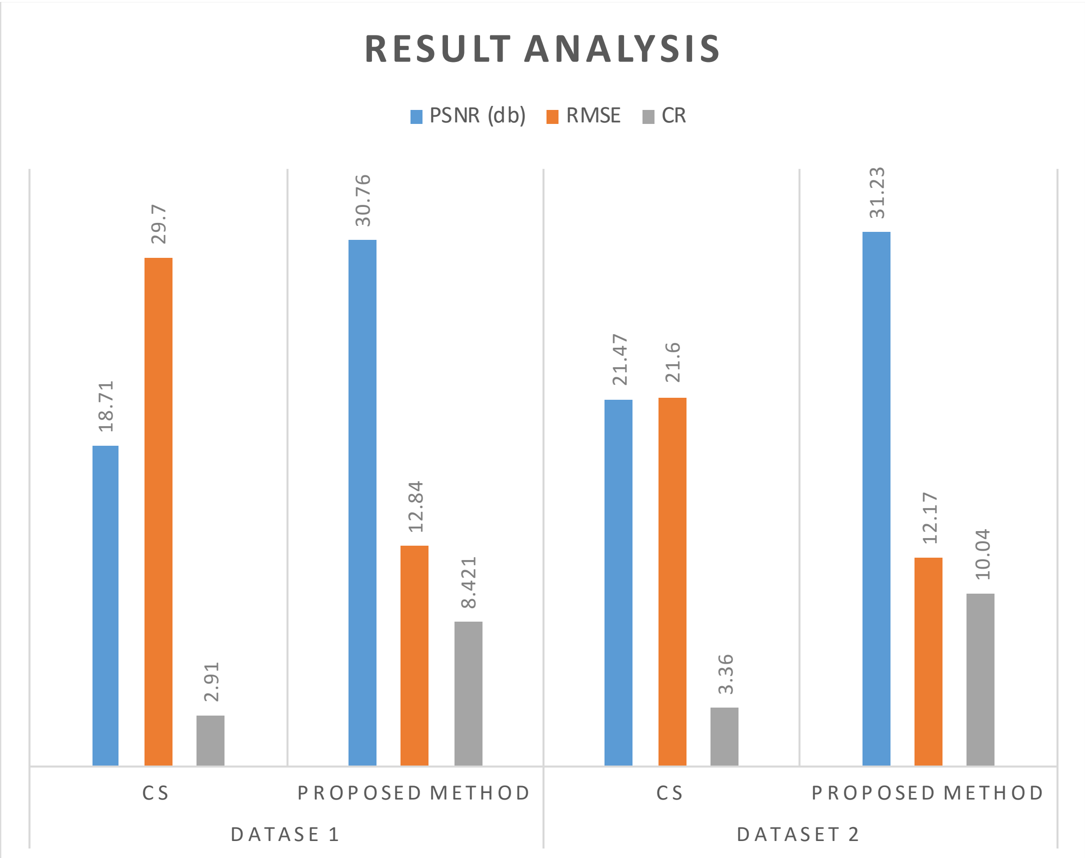

Fig. 8 Result analysis graph

5. CONCUSSION

Compressive sensing (CS) is used for reducing sampling rate for hyperspectral image compression. In proposed system compressive sensing is used with sparse dictionary and OMP method. So, at the time of reconstruction image quality is improved. OMP also used which gives good recovery of image than tradition method. Proposed system increases PSNR ratio at a good compression ratio than old method. It also reduces MSE value and gives higher quality. L*a*b* color space is used in proposed method which gives color image as an output.

6. FUTURE WORK

Proposed method has improved PSNR ratio and color image as an output but it gives poor performance for some images. In future, different methods can be developed which can give good performance for each hyperspectral image.

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