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Focus on Compressive Sensing in a Single Pixel Camera

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ABSTRACT:

Digital cameras are made from semiconductor. The semiconductor material of choice for large-scale electronics integration (silicon) also happens to readily convert photons at visual wavelengths into electrons. All digital cameras are mega-pixels in range. When we are using this many no of pixels the size will be increased and also complexly is more. When ever size and complexity are increases cost will be increase. Ex:- if we use 5 Mega-Pixel camera 'we will get better quality image than 2 Mega-Pixel camera image' .So, based on this condition if we want better quality image we have to add the few more components(pixels).if we add components automatically size will be increases, complexity is more and cost is high.

In this Project, a new approach to building simpler, smaller and cheaper digital cameras that can operate efficiently across a much broader spectral range than conventional silicon-based cameras is studied. Our approach fuses a new camera architecture based on a digital micro mirror device (DMD) with the new mathematical theory and algorithms of compressive sampling.

CS combines sampling and compression into a single non adaptive linear measurement process. Rather than measuring pixel samples of the scene under view, measure inner products between the scene and a set of test functions. Interestingly, random test functions play a key role, making each measurement a random sum of pixel values taken across the entire image. When the scene under view is compressible by

An algorithm like JPEG or JPEG2000, the CS theory enables us to stably reconstruct an image of the scene from fewer measurements than the number of reconstructed pixels. In this manner sub-Nyquist image acquisition is achieved.

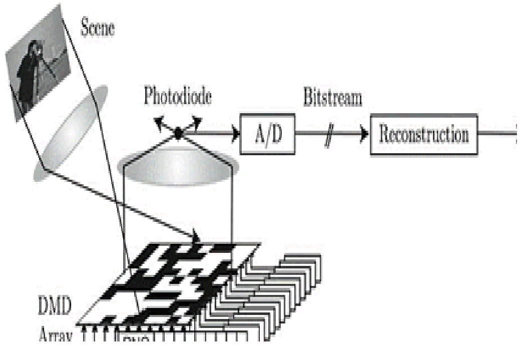
In this Project Compressive Sensing algorithms are studied. Compression and Decompression process also studied using different algorithms such as DCT and Haar wavelet Algorithms.

1 INTRODUCTION

1.1 OVERVIEW

Consumer digital cameras in the mega-pixel range are now ubiquitous thanks to the happy coincidence that the semiconductor material of choice for large-scale electronics integration (silicon).

"single-pixel" CS camera architecture comprises a complexity of the digital camera. In this camera we have DMD instead of mega-pixels,, two lenses, a single photon detector, and an analog-to-digital (A/D) converter The image is then recovered or processed from the measurements by a digital computer. The camera design reduces the required size, complexity, and cost of the photon detector array down to a single unit, which enables the use of exotic detectors that would be impossible in a conventional digital camera. The random CS measurements also enable a tradeoff between space and time during image acquisition. Finally, since the camera compresses as it images, it has the capability to efficiently and scalably handle high-dimensional data sets from applications like video and hyper spectral imaging.



1.2 AIM OF THE PROJECT

Compressive sensing algorithms are used for single pixel camera. Compressive sensing algorithms are used for the image compression and decompression. Aim of the project is studying the algorithms of compressive sensing.

1.3 SCOPE OF THE PROJECT

Code developed in Matlab is converted into c language and the suitable c code of compressive sensing is dumped into Dsp processor and the code will be verified whether the c code is suitable for single pixel camera architecture

2 COMPRESSIVE SENSING

Compressive sensing developed from questions raised about the efficiency of the conventional signal processing pipeline for compression, coding and recovery of natural signals, including audio, still images and video. The usual sequence of steps involved includes the following.

First, the analog signal is sampled by a sensor such as a camera to obtain a sufficiently large number of digital samples. Second, the digitized samples are transformed into a suitable domain to compact the energy (and hence the information) into a relatively small number of numbers, called coefficients. The transformation is chosen to approximate the optimal Karhunen-Loeve transform and results in a representation of the original signal as a linear sum of a set of bases weighed by the coefficients.

Most of the coefficients are small in magnitude and only a few coefficients contain a significant amount of energy. This implies that most of the information in the signal is concentrated in only a few bases of the signal. Third, this sparsity of transform coefficients is exploited to efficiently code the locations of the few large coefficients, and the magnitudes of these large coefficients are quantized and entropy coded. Finally, the coded representation is stored and/or transmitted to a decoder, where the coding and transformation steps are reversed to obtain a good approximation of the original set of digital samples, which can be used for D/A conversion and presentation to a viewer, with a quality close to that of the original sampled scene.

2.1 ALGORITHM FOR HAAR WAVELET USING WAVELET DECOMPOSITION:

Step 1: Read the image cameraman.tif from the user.

Step 2: Using 2D wavelet decomposition with respect to a haar wavelet compute the approximation coefficient matrix CA and detail coefficient matrices CH, CV, CD (horizontal, vertical & diagonal respectively) which is obtained by Wavelet decomposition of the input.

Step 3: From this again using 2D wavelet decomposition with respect to haar Wavelet computes the approximation and detail coefficients which are obtained by Wavelet decomposition of the CA matrix. This is considered as level 2.

Step 4: Again apply the haar wavelet transform from CA matrix which is considered as CA1 for level 3.

Step 5: Do the same process and considered as CA2 for level 4.

Step 6: Take inverse transform for level 1, level 2, level 3 &level 4 that input, CA, CA1, CA2.

Step 7: .Reconstruct the images for level 1, level 2, level 3 &level 4.

Step 8: .Display the results of reconstruction 1, reconstruction 2, reconstruction 3, Reconstruction 4, i.e., level 1, 2, 3, and 4 with respect to the original image.

2.2 SPLIT BREGMAN METHOD TO RECONSTRUCT AN IMAGE

The purpose of Split Bregman method is to recover the image through compressive sensing. It is a technique for solving a variety of L1 regularized optimization problems and is particularly effective for problems involving total variation regularization.

Split Bregman is one of the fastest solvers for total variation denoising, image reconstruction from Fourier coefficients, convex image segmentation and many other problems. This method is a re interpolation of the alternating direction method of multipliers and that is specially adapted to L1 problems.

2.2.1 ALGORITHM

- To reconstruction of image through Split Bregman method, first take the image and that image will be N x N.
- After that take the sparsity of that image and that sparsity must be use only 30% on the k-space data for compressive sensing
- After that build the image with Zero's and One's.
- After building that image does the Sampling, for that take the sampling matrix by using the N x N image randomly. That sampling matrix values should be less than that sparsity value.
- After that, by using compressive sensing data take fft of that image and it will be multiplied with sampling matrix. It can be used for Reconstruction of an image.
- Reconstruction of the image can be done by using MRICS function and that is Recovered image= mrics(R, F, mu, lambda, gamma, nInner, nOuter);
- After Reconstruction of an image just plots the graphs using results.

CONCLUSION

In this Project compressive sensing module is concentrated more. Different algorithms are used for compressive sensing, but in this project compressive sensing using Haar wavelet and split Bergman algorithms are mainly concentrated. The performance of the Haar wavelet and split Bergman is studied and observed.

As per theoretical view, Compressive sensing using Haar wavelet algorithm is best algorithm as per compression and decompression based on the output values. Split Bergman algorithm used for compressive sensing is not better for compression and decompression when compared with Haar wavelet algorithm but it is as best as per the time taken for the reconstruction of the image. Split Bergman is very fast in reconstruction of image when compared with Haar wavelet algorithm.

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