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Sparse Sampling in Digital Image Processing

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ABSTRACT

A common goal of the engineering field of signal processing is to reconstruct a signal from a series of sampling measurements. In general, this task is impossible because there is no way to reconstruct a signal during the times that the signal is not measured. Nevertheless, with prior knowledge or assumptions about the signal, it turns out to be possible to perfectly reconstruct a signal from a series of measurements. Over time, engineers have improved their understanding of which assumptions are practical and how they can be generalized. An early breakthrough in signal processing was the Nyquist–Shannon sampling theorem. It states that if the signal's highest frequency is less than half of the sampling rate, then the signal can be reconstructed perfectly. The main idea is that with prior knowledge about constraints on the signal's frequencies, fewer samples are needed to reconstruct the signal. Sparse sampling (also known as, compressive sampling, or compressed sampling) is a signal processing technique for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear systems. This is based on the principle that, through optimization, the sparsity of a signal can be exploited to recover it from far fewer samples than required by the Shannon-Nyquist sampling theorem. There are two conditions under which recovery is possible.[1] The first one is sparsity which requires the signal to be sparse in some domain. The second one is incoherence which is applied through the isometric property which is sufficient for sparse signals Possibility of compressed data acquisition protocols which directly acquire just the important information Sparse sampling (CS) is a fast growing area of research. It neglects the extravagant acquisition process by measuring lesser values to reconstruct the image or signal. Sparse sampling is adopted successfully in various fields of image processing and proved its efficiency. Some of the image processing applications like face recognition, video encoding, Image encryption and reconstruction are presented here.

Keywords – **sparse sampling, image enhancement, Top-Hat and Bottom-Hat transform, Nyquist rate, AFM imaging**

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I. INTRODUCTION

Sparse sampling is a brand new type of sampling theory, It assures the reconstruction of sparse signals and images from the less or incomplete information. The traditional methods that are used for reconstruction of images need its sampling rate to be twice the highest frequency. It also states that the total number of measurements for the discrete signal must be greater than or equal to its original length to make sure the reconstruction of the image. But the Sparse sampling states that with few measurements about the signal it is possible to reconstruct the original signal when assumptions or prior knowledge of the signal is available. It takes benefit of redundancy in the signal. Sparsity of the signal plays a major role in sparse sampling. It minimizes the number of number of non zero elements in the signal. Sparse sampling is a way to achieve a sparse representation of a signal. It is predicated on the idea to take advantage of redundancy (if any) in the signal. Signals like images are sparse, as they comprise, in some representation domain, many coefficients close to or equal to zero. The fundamental of the CS idea is the potential to recover with relatively few measurements [1]. $y = \varphi x$ φ – measurement matrix, x – original image, y – measurement results. The Three stages of sparse sampling are, sparse representation, measurement matrix, and signal reconstruction.

II. APPLICATIONS

The field of sparse sampling is related to several topics in signal processing and computational mathematics, such as underdetermined linear-systems, group testing, heavy hitters, sparse coding, multiplexing, sparse sampling, and finite rate of innovation. Its broad scope and generality has enabled several innovative CS-enhanced approaches in signal processing and compression, solution of inverse problems, design of radiating systems, radar and through-the-wall imaging, and antenna characterization. Imaging techniques having a strong affinity with sparse sampling include coded aperture and computational photography. Implementations of sparse sampling in hardware at different technology readiness levels is available

III. EXISTING SYSTEM

In this method, an unknown noisy image of interest is observed (sensed) through a limited number linear functional in random projection, then original image is reconstructed using the observation vector and the existed recovery algorithms such as L1_minimization. Simulation results inform this method is an efficient method for image denoising. Using classical filter for image denoising, we need to redesign algorithm parameters owing to the change of signal parameters such as frequency, amplitude,

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etc. But in CISD algorithm, we don't need to change the algorithm parameters when the image or noise parameters have been changed. Simulation results show that the performance of sparse sampling denoising is the same as classic filter or in some occasion fairly better than those.

IV. MEDICAL IMAGE ENHANCEMENT USING MORPHOLOGICAL TRANSFORMATION

Medical imaging includes different modalities and processes to visualize the interior of human body for diagnostic and treatment purpose. However, one of the most common degradations in medical images is their poor contrast quality and noise. The existence of several objects and the close proximity of adjacent pixels values make the diagnostic process a daunting task. The idea of image enhancement techniques is to improve the quality of an image. In this study, morphological transform operation is carried out on medical images to enhance the contrast and quality. A disk shaped mask is used in Top-Hat and Bottom-Hat transform and this mask plays a vital role in the operation. Different types and sizes of medical images need different masks so that they can be successfully enhanced. The method shown in this study takes a mask of an arbitrary size and keeps changing its size until an optimum enhanced image is obtained from the transformation operation. The enhancement is achieved via an iterative exfoliation process. The results indicate that this method improves the contrast of medical images and can help with better diagnosis.

4.1 Methods of mathematical morphology act based on the structural properties of objects.

These methods use mathematical principles and relationships between categories to extract the components of an image, which are useful in describing the shape of zones. Morphological operators are nonlinear, and two sets of data are their input. The first set contains the original image and the second one describes the structural element (mask). The original image is binary or in gray level and the mask is a matrix containing zero and one values. It is after applying the final image to the morphological operators that a new value for each pixel is obtained through sliding the mask on the original image. Value 1 in each mask indicates effectiveness and value 0 indicates ineffectiveness in the final image. Different formats can be selected to form a mask. Figure 1 shows a disk-shaped mask with radius of 4 (9 * 9 matrix).

4.2 Methodology

In the research Morphological Transform was implementing in MATLAB. At first we read the original image and calculate its CNR. We will require this CNR value to compare in the next steps. In the next step, we set an arbitrary structural element. We transform the original image and calculate CNR and PSNR values and store them. We compare this CNR value with the original image CNR value and if latter is larger we increase the size of structural element. Then we transform and calculate CNR and PSNR again and compare the current CNR value with the previous one. If the current value is larger we increase the size of structural element again. This goes on like a loop until we reach a point where the last CNR value is smaller than the previous one. We then set a structural element that is smaller than the last one and also set new end value and step of the loop to find out the structural element for whom the image has largest CNR value, meaning the image enhancement is optimum. The value we get at last is the size of our structural element for whom the original image is getting enhanced most. The number of steps and time taken to complete the operation is dependent on a few factors like size of the image, image source, initial condition, amount of noise etc. Figure 3 shows the flowchart of the whole process.

V. SPARSE SAMPLING IN VIDEO ENCODING

Comparatively, It proves that applying sparse sampling in video encoding and reconstruction shows better results than other traditional methods. Another advantage of using sparse sampling in video encoding is, its sampling rate is much lower than the Nyquist rate. First, the inverse discrete cosine transformation is applied to the signal to get the sparsity of the signal then only the sparse sampling can be applied. The total number of nonzero coefficient is much less than the total number of samples.

5.1 Time or space sampling

Analog-to-digital converters, receivers, Space: cameras, medical imaging devices, ... Nyquist/Shannon foundation: must sample at twice the highest frequency

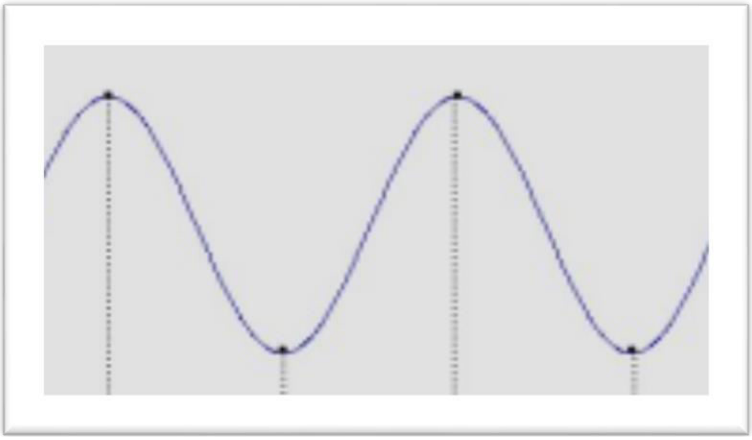

Fig.1. Space sampling

If 'information bandwidth' less than total bandwidth, then should be able to sample below Nyquist without information loss recover missing samples by convex optimization

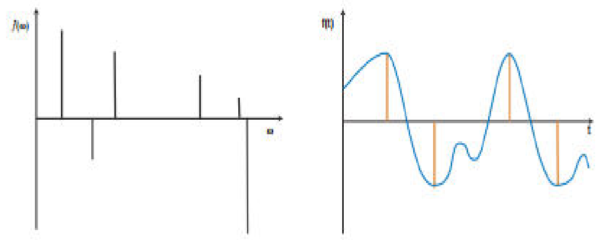

Fig.2. Information loss recovery

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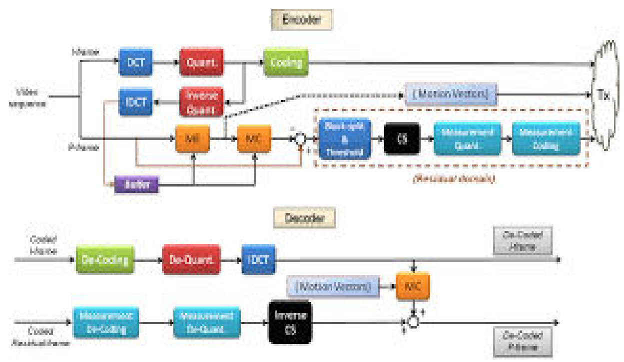

Fig.3. Sparse sampling in video encoding

5.3. SPARSE SAMPLING IN AFM IMAGING

Atomic Force Microscopy is used to sense the surface of an atom or cell with the help of piezoelectric elements. By measuring the hardness of the cell, cancer cells can be identified when comparing with the normal cells. Here, the sample is scanned line by line from the top of the sample and the topography of the sample is obtained. The AFM employs fast scanning over the sample. It takes minutes to successfully obtain an image of the sample. When live cells are observed, the changes can happen within a second. This is where the sparse sampling is introduced which ensures reduced scanning time in Atomic Force Microscopy. Sparse sampling uses the compressed scan rather than the complete surface is being scanned. It uses less measurement compared to the traditional methods. The three steps involved in sparse sampling are sparse representation, projection or measurement and reconstruction. Sparse sampling is effective only when the signal is sparse. When the signal is not sparse in nature there is a need of some transformation to represent the signal as sparse.

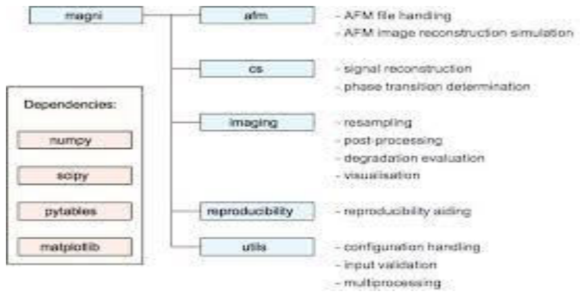

Fig.4. Sparse sampling in AFM imaging

5.4. SPARSE SAMPLING IN IMAGE ENCRYPTION

The term sparse sampling is defined as projection of signal into a sensing matrix to reduce the size of the signal. Sparse sampling provides encryption mechanism because the reconstruction of the signal needs sensing matrix and the dictionary. Fig 3.1: Image Encryption using Sparse sampling. With sparse sampling, simultaneously compression and encryption is done. Ensuring security over data transmission is very important as it contains valuable data. Encryption is the well known mechanism for data security. Encryption is done only after the compression of data when the bandwidth channel is low and it takes considerable energy for transmission in an embedded system. With the sparse sampling, it takes only fewer measurements to reconstruct the original signal when comparing the traditional methods [4].

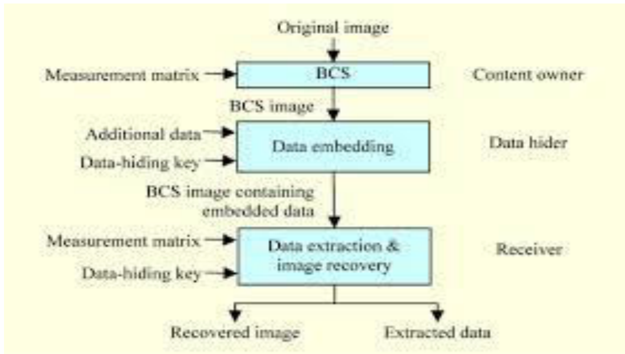

Fig.5. Sparse sampling in image encryption

5.5. SPARSE SAMPLING IN MISSING AREA RECONSTRUCTION

Depending on the end-consumer requirements, clouds in remotely sensed imagery can also or might not represent an undesirable supply of noise. In case they're viewed as a noise supply, numerous methodologies have been developed within the past so as to cope with this trouble. Normally, the commonplace approach first detects the contaminated regions and, in a second instance, tries to dispose of the clouds by means of substituting them with cloud-loose estimations. With the help of Sparse sampling, We can recover an unknown sparse signal from a small set of linear projections. Through exploiting this new and critical end result, we can attain equivalent or better representations by using the use of much less measurements compared with other methods [5]. The three methods to clear up the trouble of the reconstruction of missing statistics due to the presence of clouds are, 1. Basis Pursuit – Uses L1 Normalization for convexification of the problem 2. Orthogonal Matching Pursuit – Improved Solution of Matching Pursit (MP), where elements with the highest correlation are selected and separated and then the iteration follows with the remaining elements. 3. Genetic Algorithm – Best Solution is selected from multiple candidate solution and applied with the help of genetic operators and fitness function.

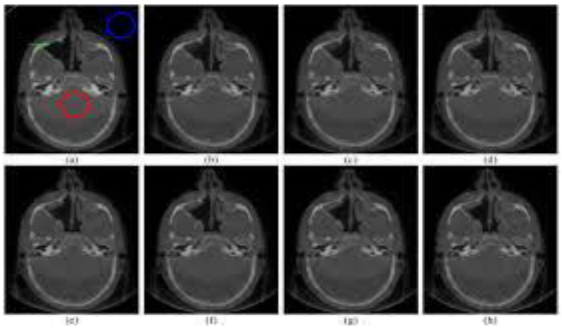

Fig.6. Missing area reconstruction

VI. CONCLUSIONS

This paper presents a Medical Image Enhancement Using Morphological Transformation and a survey of the sparse sampling and its various applications. Areas like Image Compression, encryption, Nano Imaging and Missing area reconstruction were studied, where sparse sampling is adopted to achieve better results. It also discussed the comprehensive sensing in video encoding and missing area reconstruction.

VII. FUTURE WORK

High reconstructed performance compressed video sensing (CVS) with low computational complexity and memory requirement is very challenging. In order to reconstruct the high quality video frames with low computational complexity, this paper proposes a tensor-based joint sparseness regularization CVS reconstruction model FrTVCST (fractional-order total variation combined with sparsifying transform), in which a high-order tensor fractional-order total variation (FrTV) regularization and a tensor discrete wavelet transform (DWT) L0 norm regularization are combined. Furthermore, an approach for choosing the regularization parameter that controls the influence of the two terms in this joint model is proposed. Afterwards, a tensor gradient projection algorithm extended from smoothed L0 (SL0) is deduced to solve this combined tensor FrTV and DWT joint regularization constrained minimization problem, using a smooth approximation of the L0 norm. Compared with several state-of-the-art CVS reconstruction algorithms, such as the Kronecker sparse sampling (KCS), generalized tensor sparse sampling (GTCS), N-way block orthogonal matching pursuit (N-BOMP), low-rank tensor sparse sampling (LRTCS), extensive experiments with commonly used video data sets show the competitive performance of the proposed algorithm with respect to the peak signal-to-noise ratio (PSNR) and subjective visual quality.

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