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Privacy Assured and Energy Efficient Image Transmission Using Compressive Sensing

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Abstract—**Now a days imaging systems have wide range of application. Most image processing include treating image as two dimensional signal. So these system need location for image storage and definite bandwidth for transmission depending on application. Foundation of todays digital data acquisition systems is the Shannon/Nyquist sampling theorem, which asserts that to avoid losing information when digitizing a signal or image. According to Nyquist sampling theorem for perfect reconstruction of a signal, one must sample at least two times faster than the signals bandwidth. In many applications uses image compression techniques like JPEG, MPEG sampling is the initial step. Sampling process results in huge amount of samples that will affect the process of storage and transmission in terms of space and bandwidth. Method called compressive sensing/sampling which unifies the process of sampling and compression in to a single task. The idea behind compressive sensing is that a signal having sparse representation can be reconstructed from a set of random projections, that help to represent a signal (image) with less number of samples. This compressive sensing along with certain encryption method like Arnold transform can provide security as well as help to achieve maximum efficiency..**

Keywords—Arnold transform, Compressive Sensing, Bayesian compressive sampling.

I. INTRODUCTION

Digital multimedia signals often need to be transmitted through a channel or a network. Prior to transmission, itis desirable to compress the multimedia signal for efficientusage of storage resources and/or bandwidth of the communication channels. This compression step is performed eitherin a lossy or lossless way depending on the needs of the receiver.In addition, when the content of the media is private,security of the transmission must be considered. Typically,encryption of the compressed multimedia is performed followingthe compression. This step is performed either byconventional cryptographic algorithms or some custom designjoint compression and encryption schemes[1]. The recently proposed compressed sensing (CS) framework[2] is known to unify sampling and compression inorder to reduce the data acquisition and computational loadat sensors, at the cost of increased computation at the intendedreceiver. Compressive sampling relies on the sparseness of the signal and gathers linear measurements $y = Ax$of a sparse signal x, where size of y is a small fraction ofthe samples needed for Nyquist sampling. A is the lineartransform which carries certain regularities. The receiver obtainsthe linear measurements y and reconstructs the imageby solving an optimization problem.Compressed sensing also provides nice encryption properties.The measurements y are a function of sensing matrix$A$. This matrix has pseudo-random entries that can be generatedby using a cryptographic key shared between the senderand receiver. Since the receiver has to know this informationin order to formulate the optimization problem and to reconstructthe signal, the CS measurements can be considered asan encrypted representation of the original signal. This ideahas been briefly mentioned in the literature [3] but has notbeen addressed in detail.In this paper we investigate the security of CS based encryptionmethods. The security of the encryption method relieson the fact that the sensing matrix A is not known to anattacker that does not have the pseudo-random key used togenerate A. We therefore consider attacks aimed at estimatingthis matrix either based on brute force search or utilizingthe symmetry and structure of the CS setup. In addition, wenote that CS based encryption also represents a new type of"robust encryption" that is tolerant to additive noise in theCS based measurements that form the encrypted data andempirically characterize this robustness. Our results indicatethat the CS based encryption is computationally secureagainst the investigated attacks, i.e., in order to be successfulwith high probability the computational requirements renderthe attacks infeasible.

II.Compressive Sensing(CS) concept

Compressed sensing is a recently developed technique that exploits the sparsityof naturally occurring signals and images to reduce the volume of the data using less number of samples, computing the sparsity of the signal. In thetraditional/ conventional approaches the images are acquired and compressed consider figure1, initially image undergo sampling process then compression [1]. Where sampling a continuous

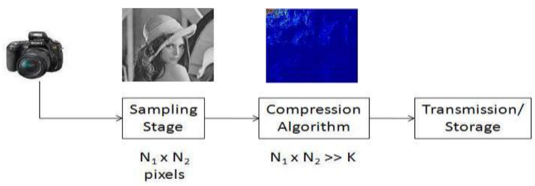


Fig 1: Traditional signal sampling and signal compression..[1]

image f(x,y) is normally approximated by equally spaced samples arranged in the form of an array where each element of the array is a discrete quantity.

Image compression is to reduce irrelevance and redundancy of the image data in order to be able to store or transmit data in an efficient form. Whereas compressed sensing aims to acquire the compressed signals with few numbers of samples and reconstruct the images. This will allow us to acquire the large ground/region with few numbers of input samples. This technique works on the assumption that natural signals/images have inherent sparsity [1].

Compressive sensing holds promising improvements in to limitations. Compressive Sensing (CS) unifies sensing and compression into a single task. Minimum number of samples to reconstruct a signal depends on its sparsity rather than its bandwidth[1]. Signal sparsity critical to CS. CS plays roughly the same role in CS that bandwidth plays in Shannon-Nyquist theory. A signal x ∊ RN is S-sparse on the basis if x can be represented by alinear combination of S vectors of as x =α with S∊N [3]. Recover signal x from measurements y using random matrix Ø.

III.Sparsity

The Shannon/Nyquist sampling theorem specifies that to avoid losing information when capturing a signal, one must sample at least two times faster than the signal bandwidth. Making compression is so crucial in storage and transmission to reduce storage space and bandwidth conservation. Most of the natural images/signals haveinherent sparsity. So the conventional signal compression scheme should acquire the entire signal compression, encode all the samples and finally discard most of the samples this in terms comes encoder overhead of large coefficients. Hence conventional signal processing techniques are less efficient in sparse signal processing. Compressive sensing holds promising improvements in to limitations. Compressive Sensing (CS) unifies sensing and compression into a single task. Minimum number of samples to reconstruct a signal depends on its sparsity rather than its bandwidth[1]. Signal sparsity critical to CS . CS plays roughly the same role in CS that bandwidth plays in Shannon-Nyquist theory. A signal x ∊ RN is S-sparse on the basis if x can be represented by a linear combination of S vectors of as x = α with S∊ N [3]. Recover signal x from measurements y using random matrix Ø. As per the above figure 2,initial step of compressive sensing is signal acquisition, done by measurement matrix Ø of dimension ,mxn which generates randomly [15]. Where signal of interest dimension of mx1 can be represented by representation matrix (Ψ) and sparsity (x). Reconstruction by using reconstruction matrix θ=ØΨ and x so the dimension is mx1.

IV. Challenges of image transmission

Robustness to images are so crucial in transmission. Packet losses decreases the quality of images while transmission [15]. Main challenges of image transmission are,

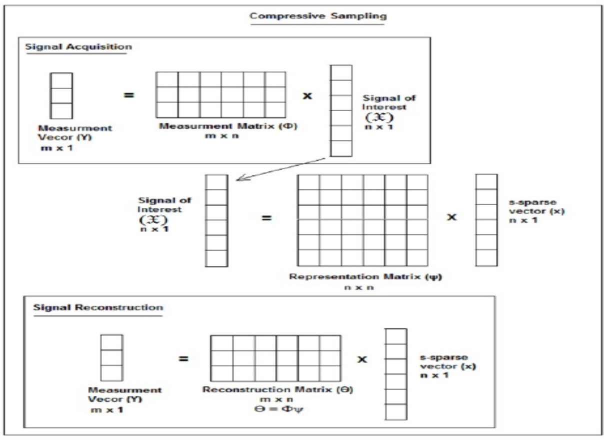


Fig 2: Compressive acquisition and reconstruction….[1]

1. Lack of suitable architecture for transmit large volume of data: When considering image as a data of transmission, many time it need to send large volume of data. But there is lack in suitable architecture for transmit large volume of data.
2. Inefficiency in terms of energy and bandwidth: Energy and bandwidth related to it are the major constraint in transmission but in many times it cannot have to attain maximum efficiency.

V. Arnold transform

Encryption is an efficient way to protect the contents of digital media. Arnold transform is a significant technique of image encryption, but has weaknesses in security and applications to images of any size. To solve these problems, an image encryption scheme using Arnold transform and random strategies. It is achieved by generating random iterative numbers and random encryption order, and scrambling pixels of each block using Arnold transform. It has no size limitation. Image encryption, also called image scrambling, produces an unintelligible or disorder image from the original image. The existing image encryption algorithms can be classified into two kinds. One is spatial-based method; the other is frequency-based method[14].

The spatial-based algorithms are usually achieved by swapping the pixel positions or altering pixel values. Arnold transform [17] is an efficient technique for position swapping, and widely applied to image encryption Arnold transform, is only suitable for encrypting NXN images. It is defined as,

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} (\bmod N)$$

Where (x, y) and (x', y') are the pixel coordinates of the original image and the encrypted image, respectively. Let I(x, y) and I(x', y') represent pixels in the original image and the encrypted image obtained by performing Arnold transform n

TABLE I : TWO-DIMENSION ARNOLD TRANSFORM PERIOD WITH DIFFERENT DEGREE N.

N	2	3	4	5	6	7	8	9	10	11	12	16	24	25
period	3	4	3	10	12	8	6	12	30	5	12	12	12	50
N	32	40	48	50	56	60	64	100	120	125	128	256	480	512
period	24	30	12	150	24	60	48	150	60	250	96	192	120	384

times, respectively. Thus, image encryption using n times Arnold transforms can be written as,

$J(x',y')^\wedge k = AI(x,y)J(x,y)^\wedge k-1$ (ModeN).

$AI(x,y)J(x,y)k = J(x,y)^\wedge k = A^{-1}J(x',y')^\wedge k-1$(ModeN)

Where, ($J(x,y)$ (0)is a pixel of the encrypted image, and J(x, y)(k) is a decrypted pixel performing k iterations.

VI.Minimum l_1 -norm reconstruction

The amplitude distribution of the optimal residual for the l_1-norm approximation problem will tend to have more (zero and very small residuals), compared to the l_1 norm approximation solution.l1 ball has axis aligned shape which helps to introduce a preference for sparse members of solution set. $s^\wedge = \arg\min(\| s^\wedge \|)$ such that $s'\theta = Y$ .The amplitude distribution of the optimal residual for the l_1 norm approximation problem will tend to have more (zero andvery small residuals), compared to the l_2 norm approximation solution.

VII.Greedy algorithm

A greedy algorithm is an algorithm that follows the problem solving heuristic of making the locally optimal choice at each stage with the hope of finding a global optimum.Greedy heuristic may yield locally optimal solutionsthat approximate a global optimal solution in a reasonable time.

A. Baysian algorithm

Bayesian compressive sensing which is probability based and introduces a set of hyper-parameters which properly

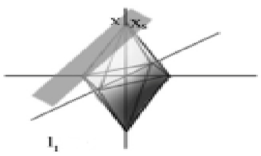
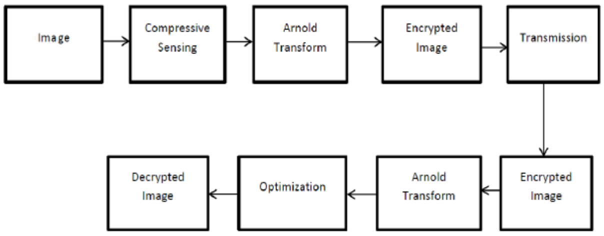


Fig 3. l_1 - Minimization

generates the event signal. The appropriatevalues are iteratively estimated from the received data.

VIII.Block diagram

Privacy assured and energy efficient image transmission using CSsystem can represent by block diagram as below,



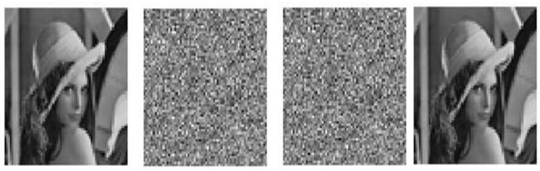
Initially image undergo compressive sensing then apply Arnold transform resultant image will be encrypted image it will transmit to receiver. At the receiver side apply inverse Arnold transform and bayesian algorithm for reconstruction of image.

IX. IMPLIMENTATION

CS theory asserts that one can recover certain signals and images from far fewersamples or measurements than traditional methods use. CS is made this as possible based on two principlessparsity and incoherence. More precisely, CS exploits thefact that many natural signals are sparse or compressible in the sense that they haveconcise representations when expressed in the proper basis. It is based on the ideathat objects having a sparse representation $Y = \phi X$, here X is a matrix which is size ofN X 1 and ϕ is of M X N where X created from original image having size, Z x Z thenY Having size M X 1. So at the receiver side it need a reconstruction by using any ofoptimization methods. here use bayesian algorithm for reconstruction.

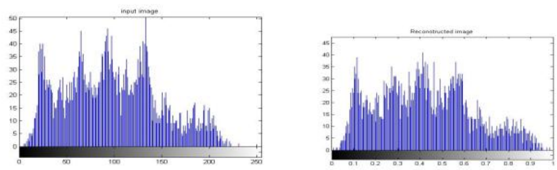
X. SIMULATION RESULT

The results are obtained successfully as figure 4.Figure 4(a) is the input image, figure 4(b) shows the result after applying Arnold transform at transmitter side, figure 4(c)shows the result after applying Arnold transform at receiver side and figure 4(d) shows the reconstructed image using l_1 -



(a) (b) (c) (d)

Fig 4. Results of different levels reconstruction using l_1 - Minimization.

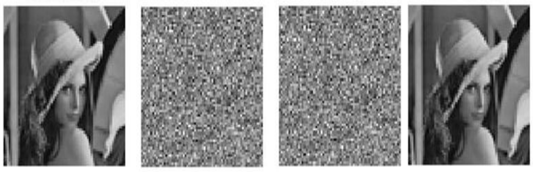


(a) (b)

Fig 5. Histogram of input image and reconstructed image using l_1 - Minimization .

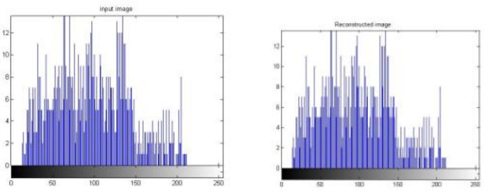
Minimization. Figure 5(a) and 5(b) shows histograms of original and reconstructed images.

Figure 6(a) is the input image, figure 6(b) shows the result after applying Arnold transform at transmitter side, figure 6(c)shows the result after applying Arnold transform at receiver side and figure 6(d) shows the reconstructed image using Bayesian algorithm. Figure 7(a) is the histogram of input image and figure 7(b) is the histogram of reconstructed image using BCS.



(a) (b) (c) (d)

Fig.6. Results of different levels using BCS .



(a) (b)

Fig.7. Histogram of input image and reconstructed image using BCS.

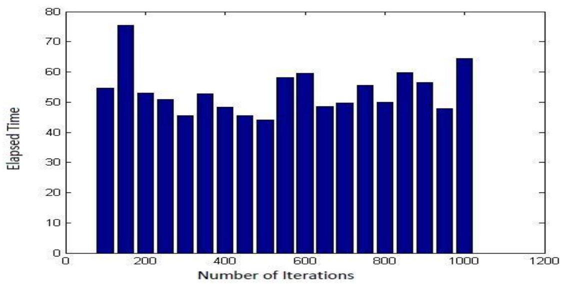


Fig.8.Elapsed time taken corresponding to number of iterations

TABLE II : COMPARISON BETWEEN TWO METHODS

CONCLUSION

Compressive sensing reduces number of data for representingimage. CS is a process which unifies the process of sampling and compression in to a single task. CS selected as the initial stage of this system. During implementation,select input image of lena applied compressive sensing followed by Arnold transformation resultant encrypted image transmitted. At the receiver section inverse Arnold transform applied reconstructed using different algorithms. From Table.II PSNR value using l_1 - Minimization method is lower than BCS . Time taken for doing the whole process in MatlabR2009 using BCS is smaller than time took by l_1 - Minimization .

Reconstruction method	PSNR(decibel)	Elapsed Time(Seconds)
l_1 Minimization.	19.44	443.66
BCS	59.00	52.28

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