Compressed Sensing Based Image Steganography System for Secure Transmission of Audio Message with Enhanced Security

Muhammad Zaheer† , I.M.Qureshi††,Zeeshan Muzaffar††† and Laeeq Aslam††††
Air University Islamabad

Summary
Research in information security and secrecy is becoming more and more important, as well as, demanding as the information is exponentially exploding. There has been a good bit of focus on cryptography, but with cryptanalysis and crypto attacks, researches have looked into the alternative means, like steganography. Steganography conceals the message into the cover media. In this paper, we have focused on security and payload capacity enhancement of an image steganography system for an audio message by using compressed sensing theory. However, in order to utilize compressed sensing, the audio message is first converted to an equivalent grayscale image which is sparsified using 2D-DCT and thresholding. The sparsified image is further compressed using the proposed compressed sensing algorithm which not only enhances the security but also improves the payload capacity; without losing imperceptibility of the system. The compressed image is embedded in chaotically chosen pixels of the cover image. At receiver the compressed sensing reconstruction algorithm is used to reconstruct the grayscale image which is then converted back to the audio message. Results indicate that the proposed system is highly imperceptible, secure and robust against various image processing attacks. It is able to reconstruct secret audio message with high PSNR value.
Key words:
Image Steganography,Information Security .

1. Introduction

Security and secrecy of the transmitted information is one of the key issues for all the organizations, private or public. Disruption of any of these can result in an economic disaster for any such organization [1][2]. Steganography and cryptography are considered to be effective and well known techniques for providing security to the information to be transmitted [3][4]. Cryptography changes the appearance of the data by encrypting it. On the other hand Steganography hides the message in cover media in a manner to keep it imperceptible and unnoticeable for the third party [5]. Steganography is categorized into image, audio and video steganography according to the type of cover media which has been utilized for hidding the secret data. Image steganography is widely used for hiding text, audio or an image [6]. Due to its high frequency of usage on internet it has gained more popularity than the other two.

A. Literature Review:

The most well-known and commonly used image steganographic method has been LSB Steganography in which the least significant bits (LSBs) of the cover image pixels are replaced with the secret information [7]. Most of the public steganographical softwares, such as S-Tools, EZstego and Steganos are based on this technique. The biggest advantage of this method is its simplicity and ease in implementation [8]. However, all pixels in the cover image cannot tolerate equal amount of modifications making it possible to detect the presence of embedded information. Some Adaptive methods for LSB steganography are introduced in which the amount of data to be embedded in a pixel is variable. These adaptive methods offer better imperceptiblity as compared to simple LSBs substitution schemes [9].

Another objective of a steganography system is to provide high capacity for embedding information. This objective is combined with the imperceptibility of the cover image in modern steganography systems. To enhance capacity of a particular steganography system different techniques involving both the cover image and the payload are explored. Considering the cover image different embedding schemes have been introduced in the literature which use embedding to more bit planes of the cover image using some alternate pixel representation system [10][11]. Considering the payload different compression techniques have been explored to reduce the size of payload, while assuring the correct data recovery on the receiver side.
Nitin Kaul et al [12] presented an algorithm for embedding an audio message in an image. The algorithm is based on audio compression using wavelet transform and LSB embedding for hiding compressed audio message into the cover image. Amol Bhujade et al [13] used RGB image to embed binary audio data. The last two significant bits of Red, Green and Blue component of pixel are used to hide data so that each pixel can hide 6 bits of information.
Devendra Singh Rao et al [14] presented audio embedding in RGB components of the cover image. The selected pixels for embedding information are based on a circle equation where the central pixel of the circle and radius of the circle for embedding information are considered as secret key of the system. RAMESH GOTTIPATI et al [15] presented the scheme for hiding an audio in an image based on the combination of cryptography and LSB

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Steganography. The audio message is encrypted using AES encryption algorithm and the encrypted audio is embedded in an image using LSB embedding.

B. Contribution:

The proposed Image steganography system mainly focuses on enhancing the secrecy and security of the secret audio message. We have proposed an innovative scheme which is based on compressive sensing methodology for images. Compressive sensing is used in various fields for reconstruction of information with very few measurements. The measurements are basically the projection of original information onto the measurement basis, which are of less dimension as compared to the original information. The measurement basis are only known to the intended user. Without the knowledge of measurement basis, reconstruction of information is impossible. This feature of compressive sensing is a captivating factor to employ it for security enhancement of the information. The additional benefit achieved is the payload reduction as we are able to reconstruct the original information from very less measurements.

To employ this framework firstly, we have converted the audio message to an equivalent grayscale image. This image is then sparsified in DCT domain by using thresholding. The sparsified signal is then impressed upon the measurement basis matrix which not only enhances the security but also compresses further the information to be embedded in a cover image. The embedding is done using conventional LSB technique. However the pixels are chosen using the numbers generated by the chaotic equation. At receiver side we have reconstructed the grayscale image successfully using compressive sensing recovery algorithm. The audio message is regenerated using the reconstructed information. In the nutshell compressive sensing has resulted in huge secrecy enhancement, as well as, increase in payload capacity in the cover image.

The results presented show that the proposed system was able to successfully reconstruct audio message at the receiver side with a good PSNR value even after various image processing attacks being applied to the system. The presented results emphasize that the proposed model is highly imperceptible while at the same time offer robustness against various attacks.

The rest of the paper is organized as follows. Section II formulates the problem and provides the detail of each module of the proposed model. Section III presents the results achieved. Section IV concludes the paper.

2. Problem Formulation:

We propose an innovative information security system which utilizes compressed sensing in steganography for secretly transmitting an audio message. The proposed system converts an audio message to a grayscale image that is sparsified using 2D-DCT alongwith thresholding. Compressed sensing further compresses and also adds security to the message. The processed secret message is embedded in the cover image using conventional LSB technique and chaotically selected pixels in the cover image.

This section provides a brief overview of compressed sensing which is the core idea of our proposed model. Use of compressed sensing and embedding of the secret message is discussed in detail. Finally we discuss about decoding and reconstruction of the secret message.

A. Compressed Sensing:

The area of compressed sensing was initiated in 2006 by two groundbreaking papers, namely by Donoho and Cand`es, Romberg, and Tao [16]. Nowadays an abundance of theoretical aspects of compressed sensing are explored in literature. Moreover, this methodology is to date extensively utilized by applied mathematicians, computer scientists, and engineers for a variety of applications in astronomy, biology, medicine, radar, and seismology, to name a few[17][18]. The key idea of compressed sensing is to recover a sparse signal from very few non adaptive, linear measurements by convex optimization. Taking a different viewpoint, it concerns the exact recovery of a high-dimensional sparse vector after a dimension reduction step. The sufficient conditions for compressed sensing are sparsity, incoherent sampling and restricted isometric property.

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i) Sparsity:

To state the problem precisely, let "*f*" be our signal of interest. As prior information, we either assume that f itself is *sparse*, i.e., it has very few non-zero coefficients, or that there exists an n x n orthonormal basis $\psi = [\psi_1 \psi_2 \ldots . \psi_N]$ such that *f* = ψ x with x being sparse [19]. Where *x* is the coefficient of *f* , $x_i = \langle f, \psi_i \rangle$ in terms of the orthonormal basis. The vector x contains many small coefficients which can be discarded without information loss. We can express it mathematically as:

$$f(t) = \sum_{i=1}^{n} x_i \, \psi_i(t),$$

ii) Incoherent Sampling:

Let we have a pair of sensing basis Φ of order m x n and sparse representation basis ψ of order n x n which we need to use in compressed sensing problem. The mutual coherence of the pair *(Φ,ψ)* is defined as:

$$\mu(\Phi, \Psi) = \sqrt{n} \cdot \max_{1 \leq k, j \leq n} |\langle \varphi_k, \psi_j \rangle|.$$

The parameter μquantifies the correlation between the elements of *Φ* and *ψ* which lies in the range[1, √n] . Compressive sensing is based on low coherence requirement. If the coherence is small between a given pair of basis the pair is more suitable to be used in compressive sensing [20]. Random matrices if used as sensing basis are found to be largely incoherent with the fixed sparse representation basis.

iii) Restricted Isometry Property:

This parameter is considered to be directly associated with the robustness of the compressed sensing [21]. A finer measure of the quality of a measurement matrix is provided by the concept of *restricted isometry property*, also known as *uniform uncertainty principle* The s^{th} restricted isometry constant $\delta_s = \delta_s(\mathbf{A})$ of a matrix **A** of order m x n is the smallest $\delta \geq 0$ such that:

$$(1-\delta)\|\mathbf{x}\|_2^2 \leq \|\mathbf{A}\mathbf{x}\|_2^2 \leq (1+\delta)\|\mathbf{x}\|_2^2$$

If this property holds the matrix A is considered to be a transformation that preserves the Euclidian length of S-sparse signal. This ensures that the S-sparse vectors do not lie in the null space of matrix A which if not ensured would make the recovery impossible.

B. Secrecy Enhancement and Embedding of the Secret Message:

The block diagram of the proposed transmitter side that comprises of secrecy enhancement and embedding of the secret message is shown in Figure 1.

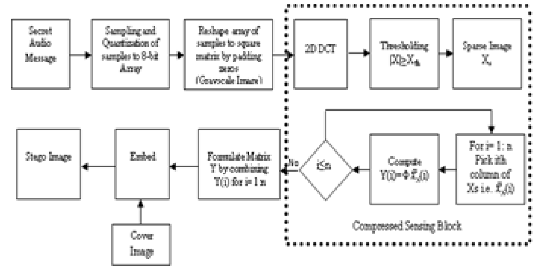


Fig. 1 Secrecy Enhancing and Embedding of the Secret Message Using Compressed Sensing

The steps involve in the process are:

Steps:

1. **Reading Audio Message:**
   The continuous audio message is sampled and quantized to 8-bit format and is saved as an array of samples
2. **Reshaping Array of Samples to Square Matrix:**
   The array of samples is transformed into the closest square matrix orientation where the additional values are filled by using zero padding. The resultant "nxn" square matrix is a grayscale image corresponding to the secret audio message
3. **Applying 2-D Discrete Cosine Transform:**
   The 2D DCT transform is applied to the "nxn" input grayscale image containing secret message using the relation:
   $$X=H*f*H^T$$
4. **Thresholding of the Coefficients:**
   The "nxn" matrix "X" containing DCT coefficients corresponding to the grayscale image is passed through thresh holding module which only retains significant coefficients. All remaining coefficients are set to zero
5. **Applying Measurement basis:**
   The sparsified matrix X_s is than read column by column and each column of size "n x 1" is projected to the measurement matrix "Φ" of dimension "mxn" that contains randomly generated ±1 and is only known to intended user individually using the relation:
   $$Y(i)=\Phi X_S(i)$$
   The resultant column Y(i) is of the dimension "m x 1" which is much lesser than $X_s(i)$ because m<<n.
6. **Reshaping Information for Embedding:**
   After n iterations of step 5 the resultant columns are concatenated to form matrix Y. this Y matrix is of size "mxn" which is ready to be embedded to the cover

7. Embedding the Secret Compressed Information in the Cover Image:

Procedure for embedding is explained in following steps:

I. The pixels of the cover image for embedding are randomly selected using chaotic key

II. Each selected pixel is converted to binary 8-bit format

III. One bit of information is embedded by using LSB replacement of the cover image pixel by the information bit

IV. The pixel is converted back to intensity level

V. After comlete information is embedded the stego Image is ready to be transmitted

VI. Decoding and Reconstruction of Secret Message:

The decoding and recovery of the secret message is illustrated in Figure 2.

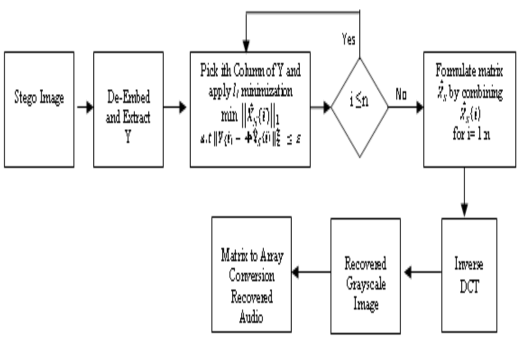


Fig. 2 De-Embedding and Decoding of Image using CS Recovery Algorithm

The steps involved in the reconstruction of the secret message are:

Steps:

The same chaotic key used at transmitter side is used to locate the pixels containg information in the stego image. The information is extracted and given as the form of "m x n" matrix Y.

1. Applying *l_1* Minimization to Reconstruct Information:

Pick one column of recovered Y and apply l_1 minimization subject to constraint as given below:

$$\min \|\hat{X}_S(i)\|_1$$

$$\boldsymbol{s.t}\ \|\boldsymbol{Y(i)} - \boldsymbol{\Phi}\hat{\boldsymbol{X}}_{\boldsymbol{S}}(\boldsymbol{i})\|_2^2 \ \leq \ \boldsymbol{\varepsilon}$$

Here $\hat{X}_S(i)$ is the estimate of i^{th} column of sparsified DCT coefficient matrix of secret image found by solving this optimization problem and $\boldsymbol{\varepsilon}$ is noise variance.

2. Reshaping the Reconstructed Information to Matrix:

After repeating the step 2 "n" times the resultant columns of each iteration are concatenated to find estimate of sparsified DCT coefficient matrix $\hat{X}_S$ of secret image.

3. Applying DCT Inverse:

The 2D inverse DCT transformation is applied to the estimated $\hat{X}_S$ to get the image back using following relationship:

$$\hat{f} = H^T * \hat{X}_S * H$$

4. Conversion to Audio:

The reconstructed image is contains the samples of audio message which are again given the form of an array to play the message

3. Simulation Results:

This section presents the simulation results generated using the proposed algorithm. The selected cover image lena of size 512 x 512 is shown in Figure 3. The grayscale image of size 288 x 288 generated against the secret audio message of 10 seconds duration is shown in Figure 4. We can see in Figure 5 the grayscale image generated against the audio message conveys no information if recovered until someone knows the conversion that was done at transmitter.

Fig. 3 Cover Image

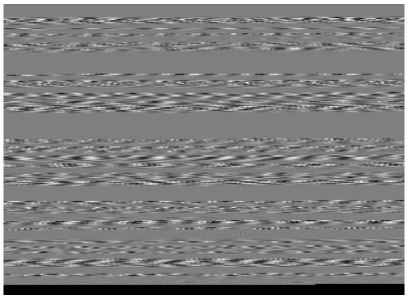


Fig. 4 Grayscale Image generated against audio message

To emphasis on the robustness of the proposed algorithm we have tested our algorithm for four types of image processing attacks that are addition of following types of noise to the system:

1. Gaussian Noise
2. Salt & Pepper Noise
3. Speckle Noise
4. Poisson Noise

The algorithm is tested by varying the noise variance for the above mentioned types of noise. For each value of noise variance the results are generated for the different values of parameter "m" of compressed sensing that is basically the number of rows of the measurement matrix. The value of "m" determines how much the information is being compressed i.e. lesser the value of "m" more is the compression attained. So the payload is minimum when "m" is minimum. Considering the stego image PSNR has been selected as a figure of merit to indicate the imperceptibility achieved after embedding of data, while the PSNR of the regenerated audio signal using the reconstructed grayscale image is used to show the audio message can be clearly understood at receiver side

Table 1 presents the PSNR of the reconstructed audio message when the Gaussian noise is added to the system. Considering the row wise presented results, the first row presents the case when there is no noise added. The PSNR of audio message is presented at different values of "m". We can clearly see the PSNR improves when m is increased because when increasing dimension of measurement matrix more information is retained in the compressed grayscale image which results in better reconstruction of the audio message.

Following the first row the remaining rows present the similar results when the noise is added to the system. Five rows of results following the first row present the PSNR values of reconstructed audio message against noise variance ranging between 0.01 to 0.05. The presented results show the decrease in PSNR of the reconstructed audio message as noise variance is increased but the trend of PSNR improvement with increase in "m" is same for all the presented results.

Table1: PSNR of recovered audio in dB with added Gaussian noise:

var \ m	80	100	120	140	160	180
0	61.09	62.13	63.09	64.22	64.87	65.21
0.01	58.11	59.47	60.39	61.71	61.88	62.90
0.02	57.43	58.62	59.76	60.96	61.03	61.89
0.03	56.8	57.87	58.97	60.03	60.14	61.04
0.04	56.03	57.01	58.09	59.23	59.56	60.44
0.05	55.61	56.34	57.57	58.66	58.89	59.38

Figure 6 shows the graphical representation of the presented results in Table 1. We can see in the graph presented in Figure 5 that the best results are achieved when m = 180.

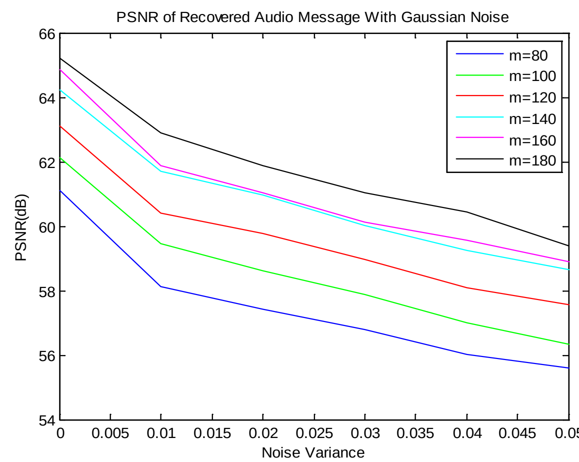


Fig. 5 PSNR of Recovered audio message with Gaussian Noise

Table 2 presents the PSNR of the stego image considering the same format used for audio message in Table 1.

Table 2: PSNR of stego Image in dB with Gaussian Noise

var \ m	80	100	120	140	160	180
0	63.19	62.34	61.93	60.77	60.11	59.88
0.01	60.17	59.39	58.78	57.51	57.25	56.90
0.02	59.56	58.13	57.66	56.66	56.37	56.04
0.03	58.84	57.67	56.97	55.86	55.59	55.49
0.04	58.03	56.88	56.13	55.03	54.96	54.34
0.05	57.51	56.19	55.48	54.39	54.09	53.68

Figure 6 shows the stego image when the embedding is done at m = 180, the effect of noise addition is clear as we can see increasing the value of noise variance further degrades the stego image which in return is responsible for the degradation of PSNR of stego image and the reconstructed audio message.

Fig. 6 Stego Image with Gaussian Noise added at noise variance (a) Zero (b) 0.01 (c) 0.02 (d) 0.03 (e) 0.04 (f) 0.05

Table 3 and Table 4 present the similar results presented in Table 1 and Table 2 for salt & pepper noise.

Table 3: PSNR of audio message in dB with:Salt and Pepper noise

m \ var	80	100	120	140	160	180
0	61.09	62.13	63.09	64.22	64.87	65.21
0.01	59.23	60.03	60.98	62.12	62.77	63.03
0.02	58.45	59.23	60.10	61.57	61.89	62.23
0.03	57.88	58.51	59.23	59.88	61	61.45
0.04	57.02	57.87	58.49	58.93	59.21	59.63
0.05	56.49	57.10	57.78	58.01	58.45	58.76

Figure 7 shows the graphical representation of results presented in Table 3. This graph also follows the same trend as shown in Gaussian case. The PSNR drops with increase in noise variance for fixed "m". The best resuts are attained when "m" is maximum.

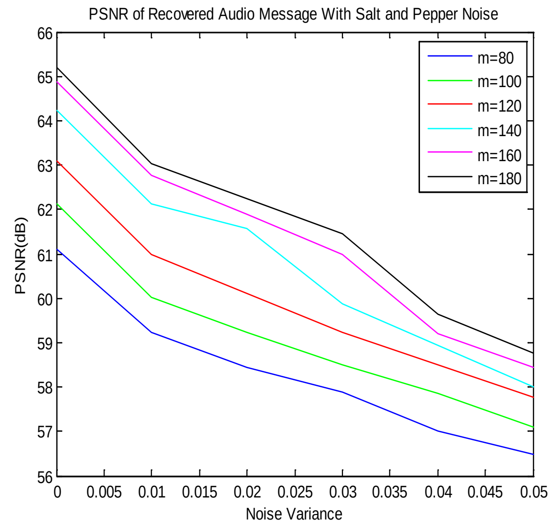
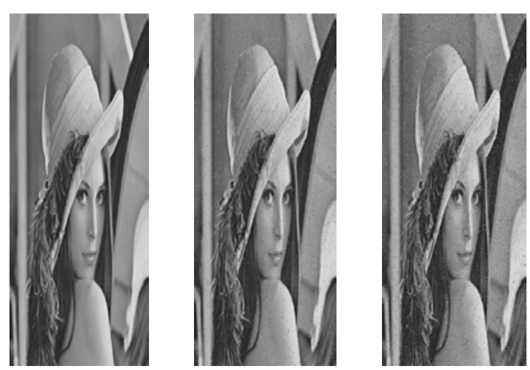


Fig. 7 PSNR of audio message recovered with salt & pepper noise added

Table 4: PSNR of stego image in dB with Salt and Pepper noise

m \ var	80	100	120	140	160	180
0	63.19	62.34	61.93	60.77	60.11	59.88
0.01	61.28	60.47	59.79	58.61	57.97	57.30
0.02	60.47	59.80	58.98	57.88	57.04	56.74
0.03	59.79	58.97	58.07	57.02	56.50	55.89
0.04	58.97	58.18	57.48	56.43	55.93	55.01
0.05	58.11	57.69	56.76	55.68	55.18	54.37

The stego image for m=180 for the different values of noise variance is shown in Figure 8.



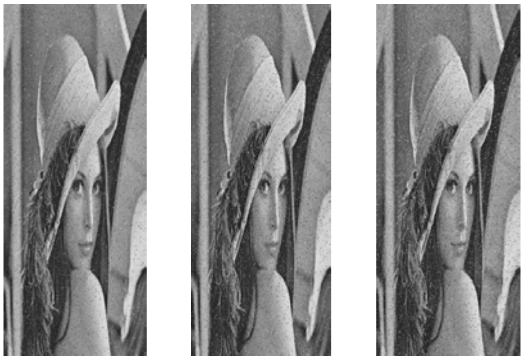


Fig. 8 Stego Image with Salt & Pepper Noise added at noise variance (a) Zero (b) 0.01 (c) 0.02 (d) 0.03 (e) 0.04 (f) 0.05

Table 5 and Table 6 present the results when speckle noise is added to the system. Results are presented in the similar way as in Table 1 and Table 2.

Table 5: PSNR of audio message in dB with Speckle noise

m / Var	80	100	120	140	160	180
0	61.09	62.13	63.09	64.22	64.87	65.21
0.01	59.50	60.19	61.30	62.43	62.91	63.4
0.02	58.89	59.41	60.61	61.68	62.01	62.65
0.03	58.03	58.79	59.88	60.77	61.27	61.85
0.04	57.46	57.97	58	59.83	60.61	61
0.05	56.78	57.28	57.56	58.91	59.71	60.13

Figure 9 shows the results presented in Table 5 in graphical form.

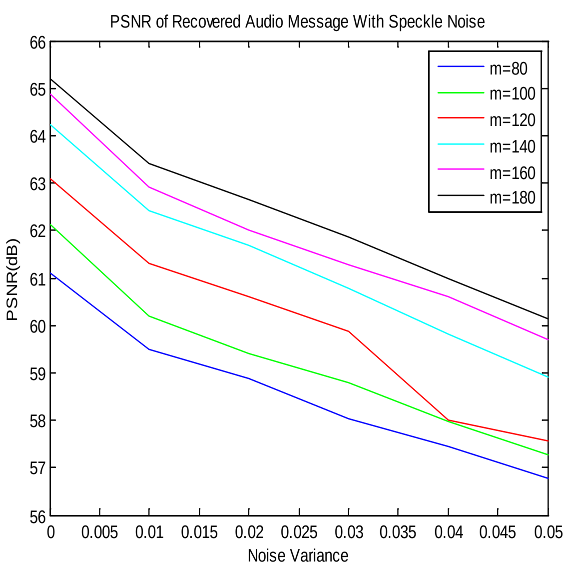


Fig. 9 PSNR of audio message with speckle noise

Table 6: PSNR of Stego Image in dB with speckle noise

m / var	80	100	120	140	160	180
0	63.19	62.34	61.93	60.77	60.11	59.88
0.01	61.46	60.67	59.96	58.83	58.17	57.49
0.02	60.78	59.96	59.18	58.01	57.54	56.92
0.03	59.98	59.04	58.41	57.32	56.82	56
0.04	59.09	58.38	57.63	56.56	56.03	55.41
0.05	58.11	57.76	56.98	55.89	55.29	54.77

Figure 10 shows stego image at m=180 for different values of noise variance.

Fig. 10 Stego Image with Speckle Noise added at noise variance (a) Zero (b) 0.01 (c) 0.02 (d) 0.03 (e) 0.04 (f) 0.05

Table 7 presents the PSNR of reconstructed audio message and table 8 presents PSNR of stego image when poison noise is added to the system. These results are different in a way that poison noise added has a fixed variance. So we have presented results here with no noise added and after noise addition.

Table 7: PSNR of audio message in dB with Poison noise added

m	80	100	120	140	160	180
No noise	61.09	62.13	63.09	64.22	64.87	65.21
Poison Noise Added	60	61.09	62.10	63.18	63.79	64.14

Graphical representation of Table 7 is presented in Figure 11. We can see the increase in PSNR with the increase in the dimension of measurement basis.

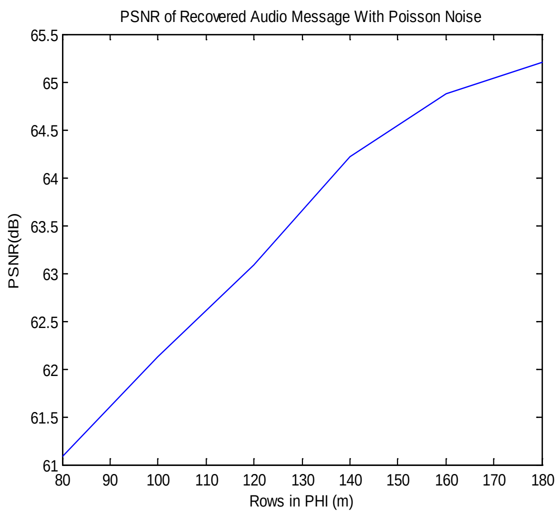


Fig. 11 PSNR of recovered audio with Poison Noise added

Table 8: PSNR of Stego Image in dB with Poison noise added

m	80	100	120	140	160	180
No noise	63.19	62.34	61.93	60.77	60.11	59.88
Poison Noise Added	60.19	59.29	58.80	57.68	57.01	56.76

Figure 12 shows the Stego image with poison noise added.

Fig. 12 (a) Stego Image with no noise (b) With poison noise

All the presented results demonstrate the fact that there is decrease in the PSNR of the recovered audio message and the stego image when the noise is added to the system. The recovered audio has maximum PSNR when parameter "m" is maximum while the PSNR of the stego image is minimum at that time as the embedded information is maximum. The results also present the fact that system performs well even when the noise variance is maximum as the recovered audio has a good value of PSNR at maximum noise addition. These results emphasis on the robustness and security of the proposed system as system performs well in the presence of attacks done by intruder by adding different kinds of noise to the system.

4. Conclusion:

In this paper we have used compressed sensing in steganography to enhance security, secrecy and capacity for audio message in cover image. The audio message is converted to a grayscale image which is sparsified by using 2D-DCT alongwith thresholding. The sparsified image is further compressed using compressed sensing algorithm, resulting into improved security and payload capacity. The compressed information is embedded in chaotically chosen pixels of cover image using LSB embedding. The information is reconstructed at the receiver side using compressed sensing reconstruction algorithm based on l_1 minimization. The results presented highlight the fact that clearly audible audio message with high PSNR has been successfully recovered at the receiver side and the system performs well in the presence of various image processing attacks. For further improvement and enhancement in the proposed model in future, we are interested in exploring different methodologies other than l_1 minimization for reconstruction of the information.

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