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Efficient and Reliable Image Communication over Binary Erasure Channel based on Compressed Sensing

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Abstract – **Efficient transmission of compressed images over wireless channels is a critical issue for several real-time applications. Almost similar problems arise with compressed sensing image transmissions and it poses significant challenges in terms of data integrity as well as efficient utilization of available bandwidth. In recent years, compressed sensing has evolved as a promising technique for sparse signal recovery, allowing the reconstruction of images from highly compressed measurements and efficient channel utilization. In this study, we investigate the communication of compressed sensing images over a *binary erasure channel* (BEC), a common channel model with random packet losses and it has been observed that the compressed sensing also takes care of the channel perturbations to some extent along with data compression to improve channel utilization. This paper proposes an inherent framework of compressed sensing along with its reconstruction technique to recover original images communicated over a binary erasure channel (BEC) without using any error-correcting codes.**

Keywords – **Sounding rocket, Conformal antenna, Hilbert curve, U-slot.**

I. Introduction

The transmission of images over wireless channels is a common requirement for several real-time applications, including wireless visual sensor networks, video surveillance via fixed or drone cameras, remote imaging, smart agriculture, and video calls via 4G and higher generation cellular networks, etc. [1, 2, 3]. It poses two important challenges in minimizing energy requirements at the device level by generating less compressed data and maximizing bandwidth utilization for achieving reliable and high-quality image communication [4, 5, 6]. *Compressed sensing* (CS) has emerged as a powerful technique for acquiring and reconstructing sparse signals, such as images, from a reduced set of measurements. CS exploits the fact that many natural images exhibit sparsity or compressibility in certain domains, allowing for significant data reduction without compromising image quality [7, 8]. This makes compressed sensing an attractive approach for image communication, as it enables efficient transmission of compressed measurements that can be later reconstructed into high-fidelity images. However, when transmitting compressed measurements over unreliable channels, such as the *binary erasure channel* (BEC), additional challenges arise [9]. The BEC model assumes that packets can be either correctly received or erased, without any bit errors.

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This channel model is commonly used to represent packet losses in wireless networks. The erasures introduced by the BEC can result in the loss of crucial information required for image reconstruction, leading to significant degradation in image quality. To address these challenges, various techniques have been proposed to enable reliable image communication using compressed sensing over the BEC. These techniques often combine error protection methods, such as forward error correction, with compressed sensing algorithms to enhance the reliability of the transmission. By introducing redundancy into the compressed measurements, it becomes possible to recover lost packets and improve the reconstruction quality, even in the presence of erasures. Through extensive simulations and performance evaluations; we demonstrate the effectiveness of our proposed scheme in achieving satisfactory reconstruction results and providing better compression performance with images. The following is a summary of the primary contributions of the manuscript.

- An efficient communication technique based on compressed sensing has been proposed over binary erasure channels.
- Unlike any other CS research papers, this paper correlates the losses occurring in the compressed sensing using binary erasure channels. Proposed compressed sensing model shows improvement in reliability as well as efficient transmission in terms of improved compression ratio.
- This paper also proposes an analytical expression for PSNR over binary erasure channels for compressed sensing images based on empirical results.

In this paper, we present the details of our proposed framework, including the compressed sensing method, binary erasure channel, and the reconstruction process in sections I and II. We then evaluate the performance of the proposed scheme under various channel conditions in section III. Finally, in section IV. we discuss the implications of our findings and highlight potential future directions for research in image communication over unreliable channels.

II. Compressed Sensing and Binary Erasure Channel

A. Compressed sensing

Compressed sensing is a method of signal processing that was introduced in 2006 [5-9]. Compressed sensing defined by

$$y = \phi x \quad (1)$$

where ϕ represents a measurement matrix of dimensions $M \times N$ and x denotes the signal. The measurement matrix ϕ can be created using a chaotic map and a random Gaussian matrix. In this paper, we have used Teoplitz diagonal measurement metrics to measure the signal. In this work, we used the conventional *orthogonal matching pursuit* (OMP) algorithm for efficient and reliable reconstruction of the signal [10, 13]. The proposed *Teoplitz diagonal measurement matrix* (TDM) is based on the Toeplitz matrix that only keeps the entities in a diagonal line set as '1'. The construction of TDM is shown below.

$$\Phi_{i,j} = \begin{cases} 1 \ for \ i=j \\ 0, Otherwise \end{cases} \tag{3}$$

where $\Phi \epsilon R^{M\times N}$, $\underline{i} \, \epsilon \, (1, M), j \, \epsilon \, (1, N)$. This is the proposed TDM measurement matrix. Equation (3) describes a Toeplitz diagonal measurement matrix with specific conditions on its elements, where the elements are defined based on the indices i and j. The Toeplitz matrix is characterized by constant values along its diagonals, [10,11]. So, Compressed sensing takes advantage of sparsity in the signal. By using a Toeplitz diagonal measurement matrix, we ensure that certain sparse structures in the signal are maintained, making reconstruction easier.

$$\phi_{M\times N} = \begin{bmatrix} 1 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \tag{4}$$

B. Binary erasure channel

The binary erasure channel is a type of communication channel used in information theory to model a variety of real-world communication scenarios, including wireless communication and data storage systems. In this channel, bits transmitted over the channel can be either correctly received or lost with a certain probability, denoted by p, or they can be intentionally erased. The binary erasure channel is widely used in the design and analysis of communication systems. Because it provides a simple and intuitive model for studying the behaviour of communication channels. One of the key properties of the binary erasure channel is that it is memory-less, which means that each transmitted bit is independent of the others. This property simplifies the analysis of the channel and allows us to use statistical methods to study the behaviour of the channel [9, 10, 11, 12]. In particular, we can use the concept of entropy to quantify the amount of uncertainty or randomness associated with the bits transmitted over the channel. One of the most important applications of the binary erasure channel is in coding theory. It is used in the study of error-correcting codes that can be used to transmit information over noisy communication channels. Error-correcting codes are designed to protect transmitted data from errors and loss caused by noise or other factors.

The binary erasure channel is particularly well suited for the analysis and design of error-correcting codes because it is a simple and tractable model that captures many of the essential properties of real-world communication channels.

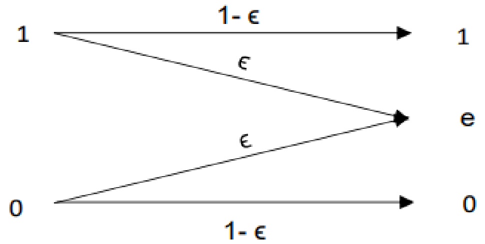

Fig. 1: Binary erasure channel

The binary erasure channel is also used in other areas of communication theory, such as coding for network coding, where coding techniques are used to increase the efficiency of communication networks. Network coding is a method of data transmission in which data packets are combined at intermediate nodes in the network to increase the throughput of the network. Binary erasure channels are often used in the analysis of network coding schemes because they provide a simple and intuitive model for studying the behaviour of the network. In a *Binary Erasure Channel* (BEC) as shown in Fig. 1, the communication system transmits binary input symbols (0 or 1), and the output can be one of three symbols: 0, 1, or an erasure symbol (*e*). The erasure symbol indicates that the receiver could not determine the transmitted bit due to various reasons, such as noise or interference. The capacity $\boldsymbol{C_{BEC}}$ of a BEC with an erasure probability (ε) is given by:

$$C_{BEC} = 1 - \varepsilon \tag{5}$$

This means that the higher rate at which data can be reliably communicated over the channel, considering the erasures, is (1 - ε) bits per channel use. The erasure probability (ε) quantifies the fraction of bits that are erased during transmission. For example, if (ε = 0.2), then 20% of the transmitted bits are expected to be erased. Elias demonstrated that random codes with rates very close to $\boldsymbol{C_{BEC}}$ can be decoded on the BEC with a significantly low probability of error by employing *maximum likelihood* (ML) decoding. The BEC allows for the reliable transmission of information at rates up to 1 - ε. Using random coding techniques combined with maximum likelihood decoding enables the system to achieve these rates while maintaining low error probabilities. This makes the BEC a useful model for understanding communication systems where data may be lost or erased, and it highlights the importance of coding and decoding strategies in ensuring reliable information transfer. Algorithm 1 shows the Compressed Sensing Signal Recovery algorithm takes an input signal x and a measurement matrix ϕ of size M×N. The algorithm then simulates transmission through a Binary Erasure Channel, aiming to output the recovered original signal X'.

C. Capacity of the BEC

The capacity of the BEC denotes the highest rate at which data may be transmitted reliably over the channel. In simpler terms, it represents the highest achievable data transmission rate without any errors or loss of information. Consider a scenario where We have a message of length L that is encoded into a longer data of length n, with both L and n being positive integers. It is logical to have n greater than L to accommodate for the erasures that can occur in the BEC. In our communication model, we aim to transmit encoded information through the BEC without any feedback, meaning the receiver cannot notify us about which bits were erased during transmission. In this scenario, we assume there are no transmission errors, and the receiver gets a sequence of n bits that includes L bits of actual data. The ratio $R:= L/n$ is defined as the code rate, indicating the sequence of information bits per received symbol. Let X represent input data and Y output data. Each code consists of an encoding function f_n: $X_L \longrightarrow X_n$ and a decoding function g_n: $Y_n \longrightarrow X_L$, which guides us on how to decode the channel's output. The input data is binary X: = {0, 1}, while the output data is Y: = {0, 1, e}, where e is an erased bit in BEC. We must also consider the noise in the channel. Let $X(n)$:= (X_1,..., X_n) denote the n bits input into the channel, and $Y(n)$:= (Y_1, ..., Y_n) the n bits output from the channel. The higher probability of error in the code is given by equation (6), which serves as a key metric.

$$p_e(n) := maxP(g_n(Y(n) \neq x|X(n)f_n(x)), x\epsilon X_L \quad (6)$$

for evaluating the performance of our coding strategy. This formulation allows us to evaluate the effectiveness of our decoding function g_n under the constraints imposed by erasures, guiding future improvements in coding techniques to enhance reliability in communication over noisy channels. We are looking at the higher probability that the decoding function, when applied to the channel's output, does not match the originally intended message, with this maximum being considered across all possible input messages.

ALGORITHM 1 MODIFIED COMPRESSIVE SENSING METHOD FOR BINARY ERASURE CHANNEL

Input:*Input Signal x, Measurement matrix* ϕ *of size M×N*

Output: *Recovered Original signal X'*

1. Initialize:

- *Set measurement y as an empty array*

2. Sparse representation

a. *Generate sparse signal using DWT basis transform x:*

b. *Compute y:*

- *Multiply the sensing matrix* ϕ *by the signal x:*

y= ϕ *.x*

3. Transmission through Binary Erasure Channel

a.*Generate the modulated signal y*

1 = 1 - 2y;(BPSK Modulation)

b. Erasure of Probability = ε

Erased Indices = rand (size(y1)) ¡ erasure of Probability c. Demodulated signal = (real(erased In- dices)¡0);(BPSK demodulation)

3. Perform sparse recovery:

a. *Solve the optimization problem to recover the sparse signal X':*

Minimise $||x||_0$ *subject to y1 =* ϕ*.* $x^{'}$

4. Obtain the recovered Original signal X'

end

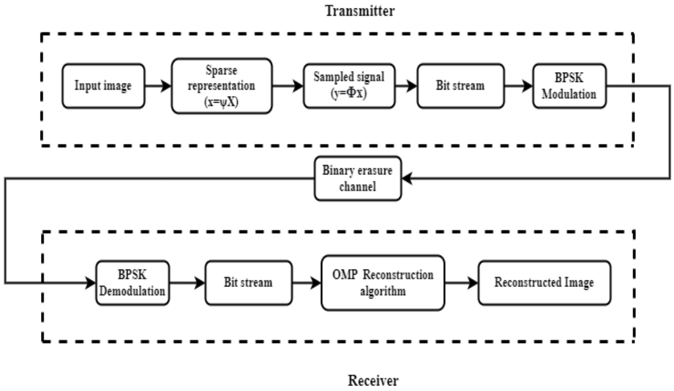

Fig. 2: Block diagram of compressed image communication based on compressed sensing over a binary erasure channel

We define the rate R as attainable for the channel if, for every positive integer n, there are encoding and decoding functions (f_n, g_n) that transform messages of length L into messages of length n. If the probability. $P^{(n)}$ -> 0 approaches 0 as n increases, which means we can transmit without errors in the long run. The maximum rate that can be achieved is called the channel's capacity.

D. Proposed analytical expression for PSNR over binary erasure channel

In this subsection, we obtained the analytical expression for PSNR based on empirical results obtained. The relationship between PSNR and the probability of erasure (ε) is given by:

$$\text{PSNR} = -10 \times \log_{10}(\varepsilon) + \beta \quad (7)$$

where β is a constant ranging from 6 to 10.15 based on obtained empirical data in our simulation. This relationship shows that as the probability of erasure increases, PSNR decreases, indicating lower image quality. In this equation, PSNR serves as a measure of image quality expressed in decibels (dB), with higher PSNR values indicating better image quality. The variable ε represents the probability of erasure, indicating the likelihood of data loss or corruption during transmission; a higher ε corresponds to a greater risk of data loss. The constant β adjusts the relationship between PSNR and ε, typically ranging from 6 to 10.15, thus influencing the baseline PSNR values based on specific channel conditions. The equation highlights that PSNR is inversely proportional to ε. As the probability of erasure increases—indicating more data loss—the PSNR decreases, reflecting lower image quality. This relationship underscores the importance of minimizing data loss during the reconstruction process.

III. RESULT AND DISCUTION

In this section, we illustrate the results of our proposed model to show the ability of the compressed sensing method and consequently its effect on the reconstruction process in wireless communication with a binary erasure channel and the block diagram shown in Fig. 2. The proposed model used a binary erasure channel for transmitting the data but this is a worst-case scenario. In the beginning, we experimented by taking four test images, namely Cameramen, Lena, Boat, and Peppers for end-to-end communication with binary erasure channels with different *probabilities of erasure* (ε). The reconstruction quality is measured by different parameters like *Peak Signal to Noise Ratio* (PSNR), NPCR, MSE, and SSIM [15-21] between the reconstructed image and the original image. The relative various performance analyses are given below. We examine the system performance with subjective received images visualization, different probability of erasure, and peak-signal-noise ratio, respectively. In the simulation, the image in the sparse representation is acquired using TDM measurement matrices, with the OMP algorithm utilized for reconstruction. The reconstruction outcomes for various images, evaluated by Peak Signal to Noise Ratio, are displayed in Fig.3. Fig. 3 shows that Pepper's reconstructed images get better performance than the others. And also shows a high compression ratio that is 0.2 we get a minimum PSNR of 22.2351 dB with the Boat image and a maximum PSNR of 33.1262 dB with the Peppers image.

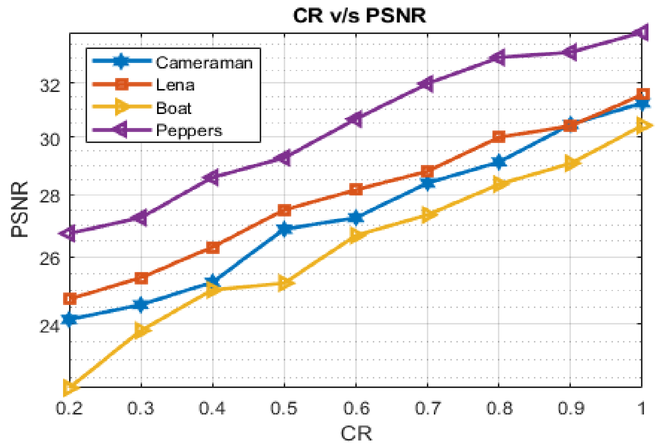

Fig 3. Comparison of Peak Signal-to-Noise Ratio (PSNR (dB)) values for reconstructed images obtained through Compressed Sensing over a binary erasure channel with a fixed erasure probability of 0.01

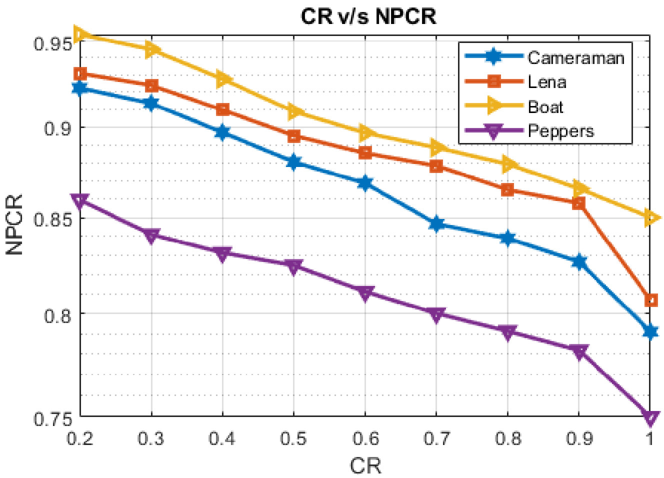

Fig. 4. Comparison of *the Number of pixel change rate* (NPCR) values for reconstructed images using Compressed Sensing over a binary erasure channel with a fixed probability of erasure set at 0.01

A higher PSNR value indicates a better reconstruction quality, as it implies a smaller amount of distortion or noise in the reconstructed signal at the probability of erasure 0.01. The Number of Pixels Change Rates (NPCR) and the Unified Average Changing Intensity (UACI) were used as metrics to evaluate the differences between images.

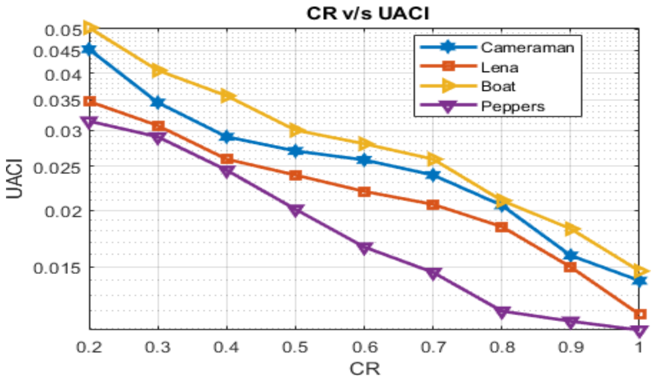

Fig. 5. Comparison of *Unified Average Change Intensity* (UACI) for reconstructed images using Compressed Sensing over a binary erasure channel with a fixed probability of erasure set at 0.01

These two measures are utilized to directly show the variations between the reconstructed images and the test images. NPCR quantifies the rate of pixel changes that occur between two images. It indicates the amount of change or dissimilarity between the original image and the reconstructed image. In the context of these results, decreasing the compression ratio leads to a decrease in NPCR values. This implies that as the compression rate decreases, there is less pixel variation or change between the original and reconstructed images. UACI measures the average intensity difference between corresponding pixels in two images. It quantifies the overall intensity changes or distortions introduced during the reconstruction process. Similar to NPCR, decreasing the compression data rate results in lower UACI values. This means that as the compression rate decreases, the average intensity differences between the original and reconstructed images decrease, indicating reduced distortion. Fig. 4 and Fig. 5 present the NPCR and UACI results, respectively, for the reconstructed images after communication. By analyzing these figures, one can observe that as the compression ratio decreases, the NPCR and UACI values also decrease. This indicates that the reconstructed images are becoming more similar to the original test images, with fewer pixel differences and reduced intensity variations. These findings suggest that decreasing the compression data rate can lead to improved fidelity and similarity between the reconstructed images and the original test images, as reflected by lower NPCR and UACI values. As the probability of erasure increases, more information is lost, leading to decreased fidelity and lower PSNR values in the reconstructed images. Overall, this finding emphasizes the influence of the channel conditions, specifically the probability of erasure, on the quality of reconstructed images when employing Compressed Sensing. The effects of different *Compression Ratios* (CR) on the *Structural Similarity Index Measure* (SSIM) values of test images using the CS method over a binary erasure channel is illustrated in Fig.6. SSIM is a commonly employed objective measure that assesses the similarity between two images. It analyzes the structural details, brightness, and contrast similarities between a reference image and a distorted one. Higher SSIM values indicate a higher level of similarity between the images, with 1 being the ideal value representing perfect similarity. According to the provided explanation, Fig.6 demonstrates how the SSIM values of the test images change with different CRs in the compressed sensing method [22] over a binary erasure channel. The figure reveals that as the CR increases, the SSIM values decrease. This implies that as the compression ratio becomes higher, there is a greater loss of similarity or degradation in the quality of the reconstructed images compared to the original test images. The results indicate that higher SSIM values are consistently associated with higher compression ratios. This suggests that when a higher CR is applied, the reconstructed images have a closer resemblance to the original test images, resulting in a higher level of structural similarity. The figure highlights that the Peppers image has better SSIM performance compared to the other test images. It achieves a higher SSIM value, indicating a greater level of similarity and better preserved structural information in the reconstructed image for this specific image. Overall, Fig.6 provides insights into the impact of different CRs on the SSIM values of test images in the compressed sensing method over a binary erasure channel. It demonstrates the trade-off between compression ratio and image similarity, where higher compression ratios result in decreased SSIM values and reduced similarity to the original images. Additionally, it highlights the relative performance of the Peppers image in terms of SSIM compared to the other test images. It means that our scheme also has very good compression recovery performance. We can see that the Boat image performs the worst among the compared samples, more so at lower compression ratios. The performance of the compressed sensing method over the Binary erasure channel is shown in Fig. 7. When the test images are passed through the compressed sensing method over the binary erasure channel then the performance of the reconstructed image quality is good as compared to without passing through the compressed sensing method. That is when the image is passed through without using the compressed sensing method the reconstructed image quality is worse as shown in Fig 7. The compressed sensing method with compression ratio is one that can maintain a better quality of the received image at a *probability of erasure* (ε) of 0.01. In this manuscript, image communication is implemented using a compressed sensing method over a binary erasure channel. The various standard images are evaluated like the original ones. The PSNR of the suggested method can enhance the quality of the received image with an erasure probability (ε) of 0.01.

We can achieve a satisfactory *peak signal-to-noise ratio* **(**PSNR) value of 31.5617 dB and obtain a well-reconstructed image. The PSNR performances of the reconstructed 'Cameraman,' 'Peppers,' and 'Boats' images, all of which were resized to the same dimensions are illustrated in Fig.8. In this simulation, we employed a compressed sensing scheme for image transmission and compared it to transmit the image without utilizing compressed sensing.

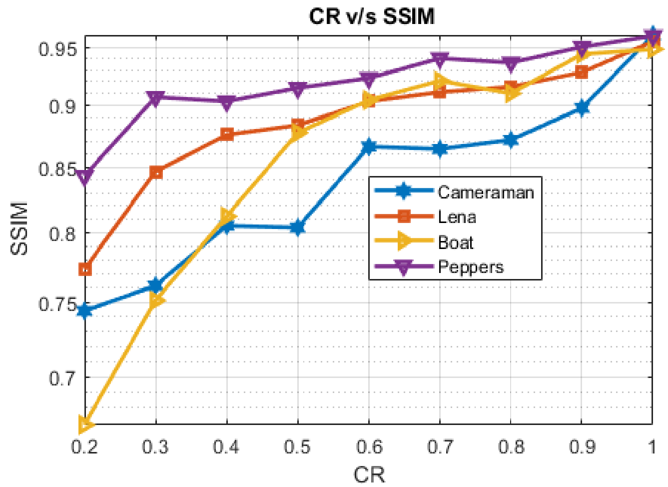

Fig. 6: Impact of compression ratio on SSIM performance over the binary erasure channel with an erasure probability of 0.01.

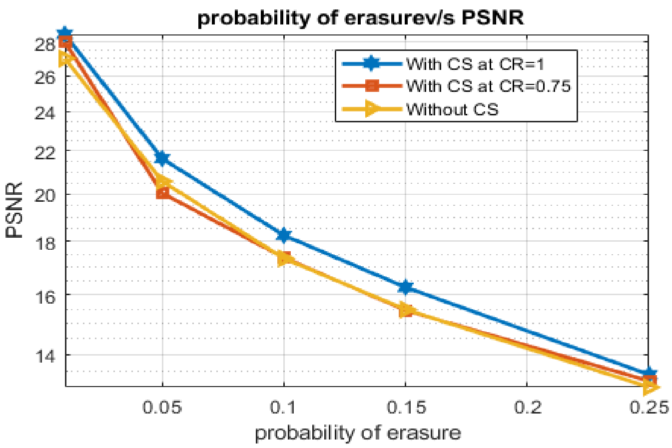

Fig. 7. Comparison of the reconstruction quality of the Cameraman image for the different probability of erasure values

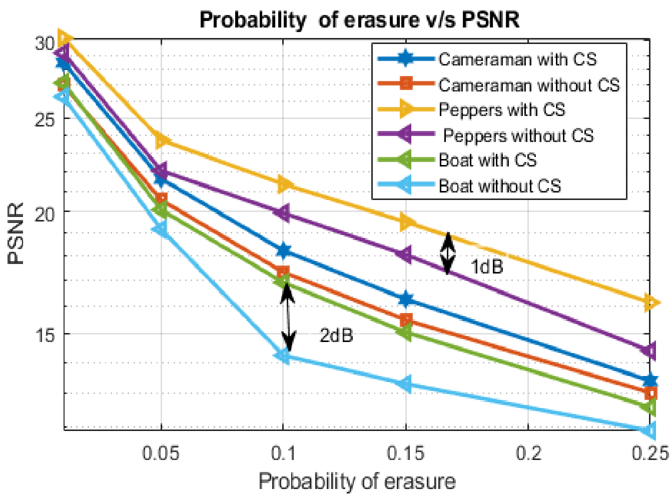

Fig. 8. PSNR (dB) performance comparison of different images over the binary erasure channel

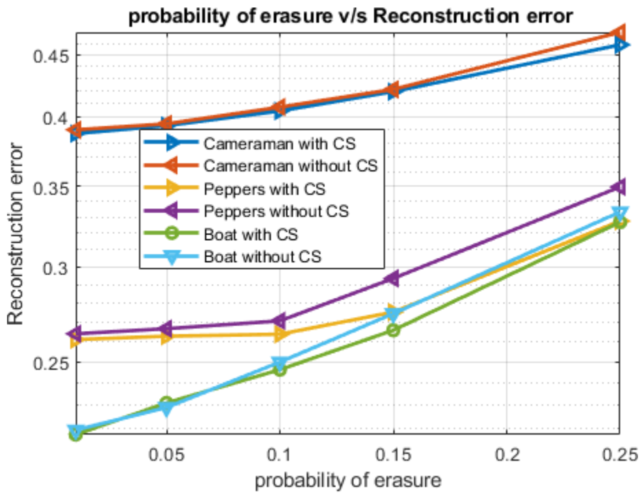

Fig.9. The results of evaluating the error in image reconstruction, comparing the use of compressed sensing versus not using compressed sensing, when transmitted over a binary erasure channel

The results indicate that the worst outcome was observed when the compressed sensing scheme was not used, while better results were achieved when compressed sensing was employed. Furthermore, the boat image exhibited the poorest performance, whereas the Peppers image exhibited the most favourable performance within this figure. Fig.9: The results of evaluating the error in image reconstruction, comparing the use of compressed sensing versus not using compressed sensing, when transmitted over a binary erasure channel. Table 1 demonstrates the calculation and comparison of *Peak Signal-to-Noise Ratio* (PSNR) values for reconstructed images using Compressed Sensing over binary erasure channels with varying probabilities of erasure. The results indicate that as the probability of erasure increases, the quality of image reconstruction proportionally degrades. Notably, the pepper image exhibits superior image quality with a PSNR value of 32.6853(dB), while the cameraman image demonstrates the poorest quality with a PSNR value of 25.8603(dB) when employing the compressed sensing technique over the binary erasure channel. The *Bit Error Rate* (BER) is determined by dividing the number of bit errors that occurred during transmission by the total number of bits transmitted. The evaluation of the proposed compressed sensing method over a binary erasure channel is illustrated in Fig.10. The assessment is based on calculating the *Structural Similarity Index* (SSIM) between the original image and the recovered image using the compressed sensing technique alone, without employing any additional compression methods. This procedure is carried out for every image in the database, and the mean SSIM values are graphed. The graph in Fig.10 demonstrates how the SSIM varies with different probabilities of erasure for different images transmitted through the binary erasure channel.

The results indicate that as the probability of erasure increases, the SSIM values decrease. Overall, the compressed sensing approach demonstrates superior performance, as evidenced by the improved results shown in the figure. Table 2 presents the *Bit Error Rate* (BER) and *Structural Similarity Index* (SSIM) for various message bit lengths under different erasure probabilities [23,24]. The proposed compressed sensing scheme achieves a significantly low BER, indicating effective image reconstruction. The SSIM values, close to 1, show that the reconstructed Peppers images closely resemble the originals, demonstrating excellent performance in high-quality recovery over the binary erasure channel.

TABLE 1

COMPARISON OF PEAK SIGNAL TO- NOISE RATIO (PSNR) VALUES FOR DIFFERENT RECONSTRUCTED IMAGES USING COMPRESSED SENSING OVER A BINARY ERASURE CHANNEL WITH VARYING PROBABILITIES OF ERASURE

Image	Channel	PSNR (dB) (ε=0.01)	PSNR (dB) (ε=0.02)	PSNR (dB) (ε=0.04)	PSNR (dB) (ε=0.08)
Peppers	CS+BEC	32.6853	24.8652	22.2209	19.1404
	BEC	28.0728	24.8360	21.7353	18.7947
Boats	CS+BEC	27.8469	25.1030	22.0436	18.3463
	BEC	26.8603	24.1775	21.1410	17.9173
Camera man	CS+BEC	25.2869	22.1052	20.1721	19.2863
	BEC	24.6440	21.4695	19.7643	18.4493
Lena	CS+BEC	27.2263	25.5896	21.8236	19.8236
	BEC	26.9462	24.1448	20.0570	17.8236

TABLE 2

COMPARISON OF SSIM AND BER VALUES FOR PEPPERS RECONSTRUCTED IMAGES USING COMPRESSED SENSING OVER A BINARY ERASURE CHANNEL WITH VARYING PROBABILITIES OF ERASURE.

Image	Channel	Parameters	ε=0.02	ε=0.04	ε=0.06	ε=0.08
Peppers	CS+BEC	SSIM	0.7091	0.5560	0.4767	0.4169
		BER	0.0098	0.0198	0.0292	0.0390
	BEC	SSIM	0.8751	0.7763	0.7260	0.6742
		BER	0.0031	0.0062	0.0094	0.0126

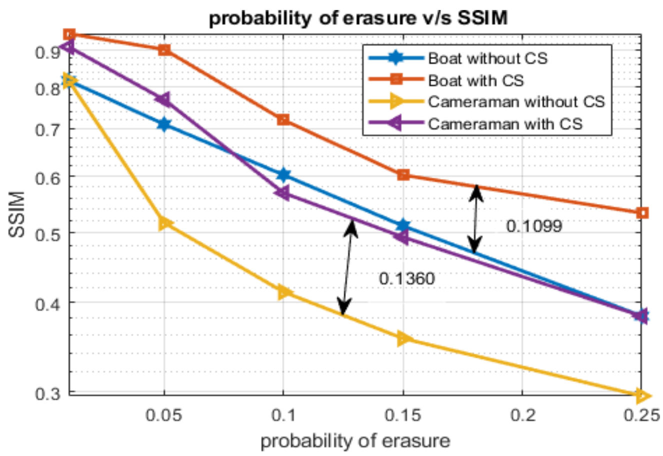

Fig. 10. Comparison of SSIM values between two images using compressed sensing over a binary erasure channel with varying probabilities of erasure (ε)

The table compares two scenarios: a binary erasure channel with compressed sensing and one without, both at varying erasure probabilities. BER measures reconstruction quality, with higher values indicating worse quality, while SSIM quantifies structural similarity, with values closer to 1 signifying higher similarity. Notably, the best image quality was achieved at a probability of erasure of 0.01, with a PSNR value of 32.68 dB. On the other hand, the lowest image quality, with a PSNR value of 18.23dB, was observed when the probability of erasure was 0.08 in Table 1. These values provide an assessment of the reconstruction quality under different erasure probabilities. The results highlight the effect of erasure probabilities and noise on image quality and demonstrate the ability of Compressed Sensing to communicate the sparse signal through the binary erasure channel in figures to the visual analysis under different erasure probabilities, and how the compressed sensing method performs under varying levels of data loss is illustrated in Fig.11. This analysis helps determine the robustness and effectiveness of the compressed sensing technique in reconstructing images accurately despite the presence of erasures. Fig.12 displays the results obtained for four images: Lena, Cameraman, Boats, and Peppers. The figure reveals that there is no noticeable visual degradation between the original and reconstructed images. This is evident from the fact that all reconstructed images achieved acceptable image quality, as indicated by their PSNR values of 24.9059dB with a probability of erasure is 0.02 over binary erasure channel with compressed sensing. The objective results for these four images are presented in the figure as well. Specifically, the reconstructed images closely resemble the original images, achieving PSNR values of 22.3368dB, 24.7223dB, 23.2383dB, and 24.9059dB, respectively. These PSNR values indicate that the proposed compressed sensing scheme is capable of reconstructing images with high quality. Fig.12 confirms that the reconstructed images closely resemble their original counterparts. The similarity is measured through the PSNR values, which indicate how well the compressed sensing scheme was able to recover the images. Overall, the obtained results suggest that the proposed compressed sensing scheme is effective in reconstructing images with good quality, as indicated by the visually similar reconstructed images and the acceptable PSNR values. This highlights the potential of compressed sensing as a viable approach for efficient image compression and reconstruction without significant loss of visual information. The *Mean Opinion Score* (MOS) is a commonly used metric to assess the subjective quality performance of images. It represents the average rating given by a group of human observers or participants to evaluate the quality or subjective experience of a particular stimulus. Figure 14, compares the MOS values for different reconstructed images using *Compressed Sensing* (CS) in two scenarios: one with CS over a binary erasure channel and another without any compression technique over the same channel. The figure depicts the performance comparison of the CS method by evaluating the MOS values for different reconstructed images under varying probabilities of erasure. The figure shows that using Compressed Sensing results in a significant improvement in image quality compared to not using any compression technique. This is evident from the higher MOS values obtained with CS. In the figure, the maximum and minimum MOS values are achieved for both scenarios. For the CS method over the binary erasure channel, the maximum MOS value obtained is 28.2614(dB) at a probability of erasure of 0.01, indicating excellent image quality. On the other hand, the minimum MOS value is 19.1491(dB) at a probability of erasure of 0.08, indicating a slightly lower perceived quality. When the images are passed through the binary erasure channel without any compression method, the maximum MOS value obtained is 26.6308(dB), and the minimum MOS value is 18.2462(dB), both at the same probability of erasure [25-27].

Fig. 11. A visual analysis was conducted to compare the quality of reconstructed images using the compressed sensing method under various erasure probabilities on a binary erasure channel

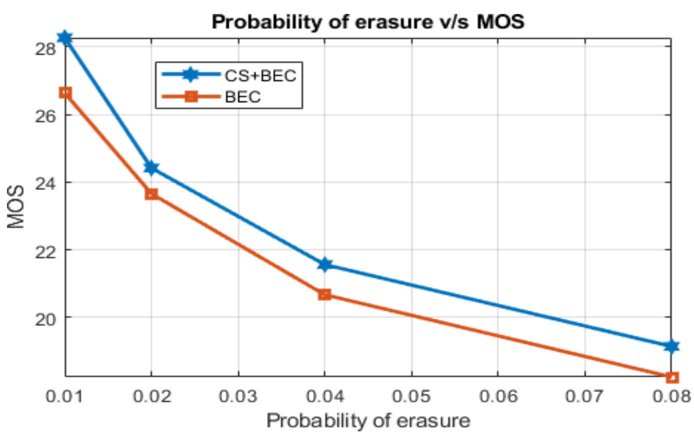

Fig.12. The performance comparison of different reconstructed images based on compressed sensing over the binary erasure channel with varying probabilities of erasure

These values suggest a relatively lower perceived quality compared to the CS method. Based on these results, it can be concluded that the proposed CS method performs better in terms of MOS values, indicating improved image quality compared to the scenario without any compression technique.

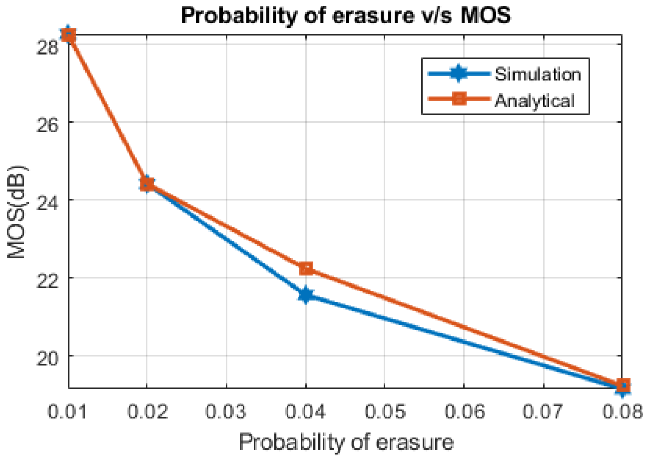

Fig. 13. Theoretical MOS performance and its simulation results of Compressed sensing over a binary erasure channel

The *Mean Opinion Score* (MOS) is a metric commonly used in quality assessment studies to evaluate the subjective opinion of human observers regarding the perceived quality of a signal or image. In this context, it seems that the MOS values were obtained by conducting experiments or surveys with human participants who assessed the quality of the reconstructed images resulting from compressed sensing over the binary erasure channel. Fig.13 displays a graph showing the MOS values obtained from the simulation and theoretical calculations. The simulation refers to the practical implementation of compressed sensing over the binary erasure channel, where real-world experiments or computer simulations were performed to reconstruct images and obtain subjective quality scores. On the other hand, the theoretical values might be obtained through mathematical models or analytical calculations that predict the expected quality performance of the compressed sensing technique. According to the statement, the graph in Fig.13 shows that the simulation and theoretical values exhibit almost similar results. This suggests that the theoretical predictions align closely with the practical outcomes obtained from the simulations or experiments. It implies that the compressed sensing technique performs well in terms of image quality over the binary erasure channel, as indicated by the average PSNR values of the reconstructed images. By taking the average PSNR value of four reconstructed images and comparing it with the average value of the theoretical data, the graph in Fig.13 likely demonstrates the similarity between the two approaches. This agreement between the simulation and theoretical values provides confidence in the accuracy of the theoretical predictions and validates the effectiveness of compressed sensing in this specific scenario. In this section, the goal is to evaluate the performance of compressed sensing in terms of image quality. Two images, ”peppers” and ”boats,” are likely used as test images for the evaluation.

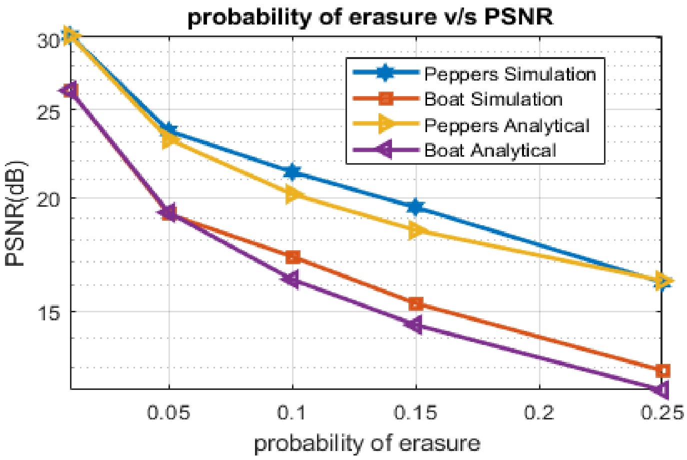

Fig. 14. The Peak Signal-to-Noise Ratio values obtained from simulations and theoretical calculations for compressed sensing applied to reconstruct “peppers” and “boats” images over a binary erasure channel

The PSNR is a commonly used metric in image processing to measure the quality of a reconstructed image compared to the original, and higher PSNR values generally indicate better quality. A key finding from the graph in Fig. 14 is that the PSNR values from simulations and theoretical calculations are nearly identical. This close alignment suggests that the theoretical models accurately predict the performance of compressed sensing in practical scenarios. The results collectively demonstrate the effectiveness of compressed sensing for image reconstruction, as evidenced by the similarity in PSNR values for both the "peppers" and "boats" images. The PSNR values from simulations are derived from practical experiments, while theoretical values are based on mathematical models that account for the characteristics of the binary erasure channel. The similarity between these results indicates that theoretical predictions align closely with practical outcomes, underscoring the effectiveness of compressed sensing for image reconstruction. Fig. 13 and 14 reinforce the effectiveness of compressed sensing techniques in reconstructing images over a binary erasure channel. The close match between simulation and theoretical PSNR values validates the theoretical framework, providing confidence in the application of these methods in practical scenarios.

IV. Conclusion

The performance evaluation of compressed sensing for wireless communication over a *Binary Erasure Channel* reveals several important findings. Firstly, it is observed that the reconstruction quality and information loss are directly influenced by the channel conditions. As the channel conditions deteriorate, both the compressed sensing and the reconstruction algorithm experience a higher loss of information. This highlights the sensitivity of channel impairments even in the presence of compressed sensing. However, compressed sensing improves the PSNR, SSIM, NPCR, UACI, and BER performance appreciably. Furthermore, the results demonstrate that even in challenging channel conditions, such as a probability of erasure around 0.17 - 0.25, a decent level of reconstruction quality can still be achieved. This is evidenced by the obtained average *peak* *signal-to-noise ratio* (PSNR) value of 33.1262 dB and the successful reconstruction of the images. These findings emphasize the potential of compressed sensing in wireless communication systems, even in the presence of channel impairments. However, it also highlights the importance of considering the impact of channel conditions and implementing appropriate channel error control mechanisms and reconstruction algorithms to mitigate information loss.

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