Quantum Steganography: Hiding Secret Messages in Images using Quantum Circuits and SIFT

Hassan Jameel Azooz*[1], Khawla Ben Salah[2], Monji Kherallah[3], Mohamed Saber Naceur[4]
University of Almuthanna, Iraq[1]
University of Gafsa, Tunisia[2]
University of Sfax, Tunisia[3]
University of Carthage, Tunisia[4]

***Abstract*—In today's era of escalating digital threats and the growing need for safeguarding sensitive information, this research strives to advance the field of information concealment by introducing a pioneering steganography methodology. Our approach goes beyond the conventional boundaries of image security by seamlessly integrating classical image processing techniques with the cutting-edge realm of quantum encoding. The foundation of our technique lies in the meticulous identification of distinctive features within the cover image, a crucial step achieved through the utilization of SIFT (Scale-Invariant Feature Transform). These identified key points are further organized into coherent clusters employing the K-means clustering algorithm, forming a structured basis for our covert communication process. The core innovation of this research resides in the transformation of the concealed message into a NEQR (Novel Enhanced Quantum Representation) code, a quantum encoding framework that leverages the power of quantum circuits. This transformative step ensures not only the secrecy but also the integrity of the hidden information, making it highly resistant to even the most sophisticated decryption attempts. The strategic placement of the quantum circuit representing the concealed message at the centroids of the clusters generated by the K-means algorithm conceals it within the cover image seamlessly. This fusion of classical image processing and quantum encoding results in an unprecedented level of security for the embedded information, rendering it virtually impervious to unauthorized access. Empirical findings from extensive experimentation affirm the robustness and efficacy of our proposed strategy.**

***Keywords*—Clustering; keypoints; k-means; cover image; quantum steganography**

I. Introduction

Digital document transfer via networks is vulnerable to a number of security threats, including attacker interception and modification. Different methods have been developed to safeguard the transfer of digital documents in order to reduce risk. Steganography is one such method, which entails concealing a message within another message or a tangible item. Researchers have recently put forth a number of steganography methods that mix classical and quantum computing methods. For instance, the hybrid quantum k-means algorithms described by Poggiali et al. [9] and DiAdamo et al. [8] combine classical and quantum clustering methods. Jiang and Wang [10] suggested a unique, safe, keyless steganography method based on the Moiré pattern for pictures on quantum computers. Li and Lu [7] introduced a brand-new LSB-based steganography for colored quantum pictures that makes use of reflected Gray coding. Even while these methods have showed potential, steganography still has limitations. For instance, The secret message may be discovered if the steganography algorithm is known or if the cover item is subjected to statistical analysis [21]. This paper introduces a unique method of picture steganography that combines traditional image processing methods with quantum computing in order to overcome these constraints. The proposed method leverages Scale-Invariant Feature Transform (SIFT) for keypoint detection and K-means clustering [6]for image processing before encoding the secret message using quantum circuits. The secret message is then encoded into a Novel-Enhanced Quantum Representation (NEQR) code, providing an additional security layer. The suggested method is used to conceal a hidden message in a handwritten manuscript and document image. The main contribution of this approach lies in its innovative combination of classical image processing techniques with quantum computing to enhance the security and imperceptibility of steganography. Specifically, K-mean clustering introduces It provides an efficient way to group similar keypoints detected by SIFT and group them to find the optimal number of centroids of keypoints in the cover image. This ensures that the secret message is encrypted in a secure and efficient way. Followed by encoding the secret message using quantum circuits and NEQR coding. This not only enhances the security of the hidden message but also maintains the aesthetic quality of the original image. To overcome the limitations of steganography techniques, k-means unsupervised learning algorithm can be used to hide large data sets. It assumes that the detector parameters and K-means are completely synchronized between sender and receiver and that the quantum circuit used for encryption can be transmitted securely. The remainder of this paper is divided into the following sections. For background, in Section II, we review prior initiatives in the field of imagine steganography. We fully describe the methods we want to utilize in Section III. Experimental results demonstrating our approach's effectiveness are described in Section IV. Section V concludes the essay and discusses what happens next.

II. Related Works

An area of study that is expanding quickly and has gotten a lot of attention lately is quantum image processing and information concealing. In order to improve the embedding capability, visual quality, and security of quantum image steganography, researchers have proposed forth several novel techniques for hiding information within quantum images. These techniques include Fourier's Quantum Information Processing [1], Image processing in quantum computers [2], turtle shell algorithm [3], and least significant bit (LSB) replacement [4]. The publication “A novel quantum color image steganography algorithm based on the turtle shell and LSB” [3] describes one noteworthy technique. In order to increase visual quality and security, the authors provide a novel quantum color picture steganography technique that makes use of the human vision system (HVS) model and validates codes. To conceal secret information, the algorithm randomly chooses two channels from each color carrier pixel’s red (R), green (G), and blue (B) channels with varying probability. The grayscale values of the two selected channels line up with a spot in the reference matrix based on a turtle shell. Either the LSB substitution technique or the turtle shell algorithm is used to embed the secret information, depending on whether the point is near the border of the reference matrix or not. The technique of the authors’ unique system is better explained through the use of specialized quantum circuits. According to experimental findings, their algorithm is workable and performs better than competing techniques in terms of security, embedding ability, and imperceptibility. The article “LSB-based Steganography Using Reflected Gray Code for Color Quantum Images” [7] presents another intriguing technique. In order to increase embedding capacity and security for color quantum pictures, this research suggests an LSB-based steganography approach employing reflected Gray code. The authors include four hidden qubits into each pixel of the cover picture using the NEQR encoding for quantum images. In order to lessen distortion in the stego picture and make detection more challenging, they additionally use reflected Gray coding. Mario Mastriani’s works and others are connected. The author in [1], who first up the idea of quantum Fourier transformation and investigated how it affected entanglement, teleportation, and quantum secret sharing. The author in [2] investigates how Quantum Image Processing (QIP) may be used to more effectively represent pictures by storing N bits of classical information in just log2 N quantum bits (qubits) and by using a brand-new LSB-based quantum image steganography algorithm. The many facets of quantum image processing and clustering approaches have also been examined in certain related publications. For instance, [8] provided a useful quantum k-means clustering method and examined its effectiveness and potential uses for classifying energy grids. This research showed how useful quantum clustering methods may be in real-world applications. In contrast to prior studies, our technique first processes the image before encoding the secret message using SIFT (Scale-Invariant Feature Transform) and K-means clustering. K-means is a clustering technique used to divide data into groups, whereas SIFT is an algorithm that finds and characterizes local features in photographs. You use quantum circuits to encrypt a secret message after utilizing SIFT to identify keypoints in a cover picture and K-means clustering to organize them into clusters. The result is a NEQR code. By changing the pixel values of the cover image, you may finally encrypt the secret message in the picture. The main difference between our approach and these related works is that our methodology concentrates on processing the image using SIFT and K-means clustering before encoding the secret message, whereas these works concentrate on improving the embedding capacity, visual quality, and security of LSB-based quantum image steganography or improving the efficiency of k-means clustering through quantum parallelism. Furthermore, unlike previous comparable research, our suggested approach includes machine learning techniques. With regard to your information concealment technique, we specifically use machine learning methods or models like K-means clustering for keypoint grouping or other pertinent activities. In comparison to conventional steganography approaches, our proposed work offers improved performance and flexibility by using machine learning techniques. The efficiency and efficacy of the information-hiding process are increased thanks to machine learning models’ ability to recognize patterns, improve settings, and adjust to changing circumstances. In spite of these developments, there are still several issues and research gaps in this area. For instance, utilizing security metrics like entropy, correlation coefficient, chi-square test, etc. A more thorough security study and comparison with other quantum picture steganography systems already in use are required. Researchers must also take into account how assaults or quantum noise may impair the resilience and dependability of these solutions. Additionally, it is necessary to provide clearer descriptions of how models like HVS are used to choose channels for information concealment as well as their adaptability to various picture kinds and color schemes. To prove practicality and applicability, further experimental findings on real-world pictures or applications are required.

III. Proposed Approach

A. Image Pre-processing

Noise reduction, contrast enhancement, and edge detection techniques will be used on cover images to enhance their steganography. Edge detection will identify the edges of the image, contrast enhancement will change its brightness and blackness, and noise reduction will eliminate any extraneous pixels or imperfections. the things in the picture. The cover picture is then loaded and made grayscale. The keypoints detection technique only functions on grayscale pictures, hence the conversion to grayscale is required.

B. Detection of Key Points

The Scale-Invariant Feature Transform (SIFT) technique will next be used to find relevant regions in the cover picture [24]. Here These strategic places will offer suitable hiding spots for the hidden message. In order to identify, describe, and match local characteristics in pictures, David Lowe created the SIFT algorithm in 1999 [5]. SIFT identifies and characterizes local features in images. It is a reliable option for key point identification since it is invariant to scale, orientation, and affine distortion. SIFT is used by our suggested technique to find key points in the cover picture. Key points are interesting areas of a picture that remain constant despite changes in scale and direction. The scale space of the input image is initially built as part of the SIFT algorithm’s operation. This is accomplished by creating a collection of smoothed pictures by convolving the image with Gaussian filters at various scales. Next, neighboring smoothed pictures in the scale space are subtracted to determine the Difference of Gaussians (DoG). The local extrema (maxima and minima) are looked for across scales and spatial dimensions in the DoG pictures. These extremes might serve as important points. After possible key points have been discovered, they are refined by removing edge responses and low-contrast key points. The prevailing gradient direction in each key point’s immediate vicinity is then used to determine its orientation. The local image patch of each key point is used to construct a description for each of them. Equation [1] shows how the scale space is built using a Gaussian function:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \mathrm{e}^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

where:

- x and y are the pixel coordinates.
- σ is the scale parameter.

C. Clustering of Key Points

In the suggested method, we employed the K-means clustering technique to organize the key points that were identified in the cover picture into clusters [19], [22]. This process is used to locate areas in the image where the hidden message could be hidden. The last places to implant the hidden message will be in the centroids of these clusters (10 centroids were employed can seen in Fig. 1). Unsupervised machine learning technique known as K-means divides a set of data points into K clusters [23]. Stuart Lloyd made the initial suggestion in 1957, and James MacQueen subsequently published it in 1967 [20]. The method updates the cluster centers based on the mean of the data points given to each cluster after repeatedly allocating each data point to the closest cluster center. When the cluster assignments stop changing, the algorithm has reached its convergence. Let $C = \{c_1, c_2, \ldots, c_k\}$ be the set of cluster centers and $\{X = x_1, x_2, \ldots, x_n\}$ be the collection of data points in mathematics. The within-cluster sum of squares (WCSS) [11], which is determined by Eq. (2), is the objective of K-means:

$$\sum_{i=1}^{k} \sum_{x \in C_i} \|x - c_i\|^2, \tag{2}$$

where:

- C_i: the set of data points assigned to cluster i.
- i, and $\|x - c_i\|$: the Euclidean distance between data point x and cluster center c_i.

The key points from the cover picture that were recognized by our suggested method were grouped into clusters using K-means clustering. The K-means method seeks to identify a clustering of the key points such that the key points within each cluster are as near as feasible to one another (in terms of their Euclidean distance) by minimizing the WCSS. As a consequence, a collection of neatly spaced-out key point clusters is produced. These clusters may then be utilized to find possible locations for the hidden message to be embedded. For instance, we may decide to place the hidden message in the pixels that correspond to the cluster centers or those that are a specific distance away from the cluster centers. We can make sure that the embedding spots are selected in a way that will probably retain the aesthetic quality of the cover picture by using K-means clustering to divide the key points into clusters.

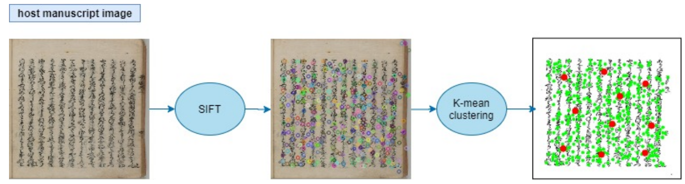

Fig. 1. Identification of the embedding positions.

D. Encoding of Messages

In our suggested method, we harness the power of quantum circuits and keypoint clustering to safely insert a hidden message into a picture. We can find the best places to integrate messages while still maintaining the aesthetic appeal of the cover picture by utilizing keypoint clustering. The K-means technique was used to create these clusters, which may be used to find possible locations for the secret message to be embedded. For instance, we may decide to place the hidden message in the pixels that correspond to the cluster centers or those that are a specific distance away from the cluster centers. We begin by employing SIFT and K-means clustering to find and group the key points, then we use quantum circuits to encrypt the secret message and produce a Novel-Enhanced Quantum Representation (NEQR) coding for the message. This technique is an illustration of the Proposed KeyPoints Clustering and Quantum Circuits technique. First, translate the hidden message into binary form. To do this, transform each character in the secret message to its corresponding ASCII code before converting it to an 8-bit binary string. Let's propose that we have a binary secret message (B message) and a quantum circuit Q with $n = 144$ qubits initialized to the $|0\rangle$ state.

A tensor combination of the several qubit states may be used to describe the starting state of the quantum circuit in Eq. (3):

$$|\psi\rangle = |0\rangle \otimes |0\rangle \otimes \ldots \otimes |0\rangle, \tag{3}$$

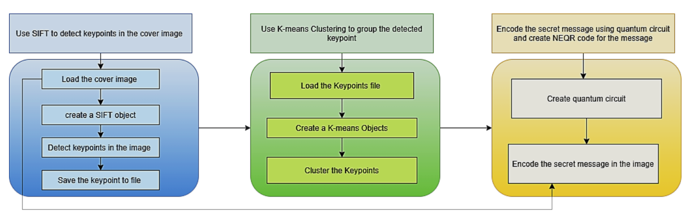

Fig. 2. Overview of the process of encoding messages.

The size of the binary secret message divided by n will determine the number of qubits in the quantum circuit that will be created subsequently. This flips the state of that qubit from $|0\rangle$ to $|1\rangle$. The binary secret message is first encoded into the quantum circuit, and then it is changed into a gate to produce the NEQR code for the secret message. This would produce a gate called neqr_code that would reflect the secret message's NEQR code. Then, using the appropriate files, we load this NEQR code into the cover picture and cluster centers. The cover graphic then contains red markers for the cluster centers. Then, according to each pixel value's binary representation, the binary secret message is concealed in the least significant bit (LSB). This is accomplished by iteratively going through each pixel and changing the value of the blue channel to encode one bit of the binary secret message. A file is then created with the finished stego image. Instead of adding a new signal on top of the cover data, this method provides an extra degree of protection by enclosing the secret message inside the image itself. It is harder for an enemy to discover the hidden message when it is concealed inside the image itself. Furthermore, Fig. 2 illustrates how even if an enemy were to discover its existence, they would still need to understand how it was encoded in order to decode it and obtain the information. Because it is challenging to identify the secret message in the cover image, the system is safe. Each ASCII character's LSB only differs by one bit, making it incredibly challenging to identify. The plan also employs a random scrambling process to further muddle the secret message. The approach is especially effective because it doesn't necessitate sending a lot of extra data. The secret message's ASCII representation is the only extra information that is necessary. NEQR (new enhanced quantum representation), a novel enhanced quantum representation for digital pictures, was put out as an enhancement to the Flexible Representation of Quantum pictures (FRQI) paradigm [12]. Instead of using a qubit's probability amplitude, as in FRQI, the NEQR model stores the basic state of a qubit sequence as the initial gray-scale value for each pixel in an image. The NEQR quantum image can differentiate between several gray scales because the basic states of a qubit sequence are orthogonal [12]. A quadratic speedup in quantum picture preparation, a 1.5X improvement in quantum image compression, and reliable digital image retrieval from quantum images are all demonstrated by NEQR in performance comparisons with FRQI. NEQR also makes it easier to conduct other quantum image operations linked to the picture's grayscale data, such as partial and statistical color operations. As a result, compared to existing models in the literature, the proposed NEQR quantum image model is more adaptable and more suitable for quantum picture representation. The NEQR (new enhanced quantum representation) coding and LSB (least significant bit) replacement are utilized in the proposed method to add another level of security to the encoded communication. While the cover picture's cluster centers are colored red using NEQR coding, the secret message's binary representation is encoded into the pixel values of the stego image using LSB substitution. This provides a way to indicate specific locations where the secret message can be found in the cover image. There are various advantages of using NEQR coding in this project. For instance, it could be harder for an attacker to figure out whether the image contains a secret message. In order to effectively decode the secret message, an attacker has to be familiar with both LSB substitution and NEQR coding. NEQR coding can also give a mechanism to check the message's integrity after it has been encoded. The NEQR code identifies precise spots in the cover picture where the hidden message may be identified (extraction algorithm), and by comparing these marked sites to the original cluster centers, it is possible to identify any alterations made to these locations (for example, as a result of image compression or editing).

Algorithm 1 Clustering of Proposed KeyPoints and Quantum Circuits

Require: Cover Image (CI), Secret Message (SM)

```
CI: Cover Image
SI: Stego Image
SM: Secret Message
BSM: Binary Secret Message
NEQR: Novel-Enhanced Quantum Representation
Output: Stego Image, Decoded Message
Step 1: Detect Keypoints in the CI
Load the CI using OpenCV library.
Create a SIFT object.
Detect keypoints in the CI using SIFT.
Save the keypoints information to a file.
Step 2: Cluster the Detected Keypoints
Load the keypoints file.
Convert the keypoints information.
Create a K-means object with desired clusters.
Perform K-means clustering.
Save cluster centers to a file.
Step 3: Encode the Secret Message using Quantum
  Circuits
Convert the SM into binary.
Create a quantum circuit with qubits equal to BSM length.
for each qubit do
  Check bit value of BSM.
  if bit is '1' then
    Apply an X gate.
  end if
end for
Convert the circuit to a NEQR gate.
Step 4: Encode the Secret Message in the CI
Load the CI again.
Load cluster centers.
Mark centers in the CI with red color.
Create SI copy.
Get SI dimensions.
Initialize binary index to 0.
for each pixel in SI do
  Get pixel value.
  if binary index < BSM length then
    Calculate new pixel value.
    Set blue channel to original value minus LSB plus
      BSM bit.
    Update SI pixel.
    Increment binary index.
  end if
end for
Save SI to a file.
```

E. Secret Message Extraction and Decoding

The original secret message is obtained by extracting the NEQR code from the stego picture. In order to decode the NEQR code, one must first measure the quantum circuit, then take the least significant bit from each pixel value in the stego picture and combine it with other bits to create a binary string. To extract the original secret message, this binary string may then be transformed into a character string. This is how Eq.

TABLE I. STRUCTURAL SIMILARITY INDEX METRICS (SSIM)

Benchmarks	PSNR
Lena	54.2827
Baboon	50.6742
Cameraman	51.410
Toobacoo800	54.6244
MNIST	51.142
IAM dataset	47.016
CASIA Handwriting dataset	47.464
EMNIST	51.1661
Signature dataset	46.0929
Dataset-1	46.555

(4) should be written:

$$b = p \mod 2, \tag{4}$$

IV. EXPERIMENTAL RESULTS

This section presents the outcomes of evaluations conducted on the proposed steganography system. The system was assessed regarding imperceptibility and robustness using widely accepted techniques such as Peak signal-to-noise ratio (PSNR), SSIM, BER techniques, and histogram analysis.

A. Context and Parameters

The proposed algorithm included several vital parameters, such as the number of octaves and the number of scale levels within each octave in the scale. In k-mean, the primary parameter is the number of clusters(K) that have been determined and then applied to the set of squares within the double WCSS set for a range of K values. The quantum circuit parameters are the number of qubits determined by the length and state of the binary secret message.

B. Datasets

In the conducted experiments, a selection of renowned handwriting datasets was employed. These encompass the EMNIST dataset [13], the MNIST database, the IAM handwriting database [14], CASIA Handwriting Database [15], and the Chars74k dataset. These particular datasets furnish an extensive assortment of handwritten characters and digits, thereby serving as a robust testing ground for the algorithm under scrutiny.

C. Imperceptibility

We evaluated the imperceptibility of our steganography system using three metrics: PSNR, SSIM, and histogram analysis. Image quality is quantified by the Peak Signal-to-Noise Ratio (PSNR) [16]. The ratio of the signal's highest achievable power to the noise's power affects the accuracy of the representation [16]. The following Eq. (5). can be used to determine the PSNR, which is typically reported in dB

$$\text{PSNR} = 10 \cdot \log_{10}\left(\frac{\text{MAX}^2}{\text{MSE}}\right), \tag{5}$$

Where MAX is the maximum possible pixel value of the image (e.g. 255 for 8-bit images) and MSE is the mean squared error between the cover image and the stego image. We calculated the PSNR values for several datasets using this equation (Table I).

The Structural Similarity Index Metrics (SSIM), measures the structural similarity between two images. It is designed to capture the perceived change in structural information between two images. The formula for determining the SSIM is as follows [17](6):

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

c represents the cover image, and s represents the stego image.μ_c and μ_s are the average pixel values of images c and s, respectively. These values are used to compare the luminance of the two images. σ_c^2 and σ_s^2 are the variances of images c and s, respectively. These values are used to compare the contrast of the two images. σ_{cs} is the covariance of images c and s. This value is used to compare the structure of the two images. We calculated the SSIM values for several datasets using this equation. And since the resulting number of SSIM ranges from -1 to 1, with one indicating that the cover and stego images are identical. A higher SSIM value that achieved (0.99) indicates that the structural similarity between the cover and stego images is high.

D. Histogram Analysis

It was performed to evaluate the distribution of pixel intensities in the stego images compared to the original cover images. The results displayed in Fig. 3 confirms that the histograms of the cover and the image of Stego were very similar since our steganography system does not introduce significant changes to the histograms of the images. To determine the differences between cover images and stego, we performed a histogram analysis of the pixel difference (PDH) between document images, handwritten manuscripts four benchmarks: man from Standard test images(c1), Tobacoo800(c2), L3iDocCopies(c3) and EMNIST(c4) and the resulting stego images-histogram, respectively (s1, s2,s3,s4) man, Tobacoo800, L3iDocCopies and EMNIST (Table II). The difference values between the cover images and the resulting stego were minimal, which confirms the superiority of our proposed approach in achieving the minimum level of distortion during the data embedding. The images show that our proposed system has a minimal visual impact on the paper, which preserves readability while making it difficult to determine the exact locations of the embedded message. Fig. 4 presents document images and stego manuscripts resulting from the use of the proposed system in including the secret message for three types of dataset used, where it can be seen that the documents remain clear because our system did not affect the image of the document in a way that prevents discovering the location of the secret message being included in it. In addition, the evaluation of our proposed system includes a comparison between SSIM and PISNR in Fig. 5. These results were obtained using ten images from the data set used in evaluating the system, including images of handwritten documents and manuscripts, which show that 54.62 and 0.99 are the average values of PSNR and SSIM of our proposed system, respectively. The maximum values of both PSNR and SSIM are 1, and thus our approach produces high quality images of Stego documents. Fig. 6 presents a comparison of the PSNR of our proposed system with related works, including standard least significant bits (LSB) [3], [Li, Panchi, and Aiping Lu] [7], and [Zhou, Ri-Gui, et al.] [4].

Through this comparison, it can be seen that the method of [3] is superior to other related researches, except for the technique used in Our proposed approach. This confirms the validity of high image quality, which reduces the chances of detecting the Human Visual System (HVS).

TABLE II. COVER-STEGO-DOCUMENT PIXEL DIFFERENCE HISTOGRAM ANALYSIS

Benchmark	Cover image	Stego image	(PDH) analysis
Standard test images (Man)	C1	S1	0.18
Tobacco800	C2	S2	0.21
L3iDocCopies	C3	S3	0.22
EMNIST	C4	S4	0.29

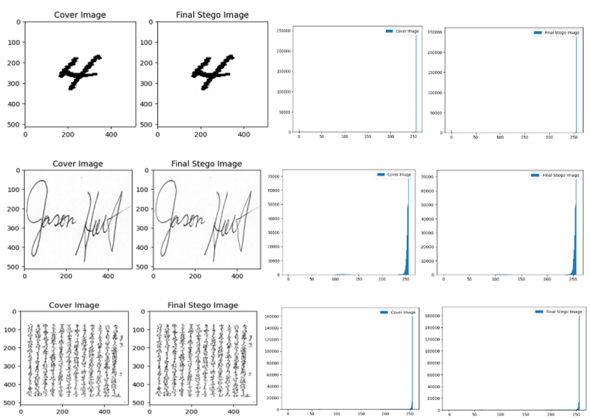

Fig. 3. Histograms of similarity the cover and stego images.

E. Robustness Evaluation

Due to possible rotational distortion brought on by printing and scanning disturbances, the original form of the encoded document must be restored before hidden message detection. That the accuracy ratio of extracted message bits is evaluated using the Bit Error Ratio (BER), which is also used further to evaluate the robustness of the extracted secret message. The Bit Error Rate (BER) measures how accurately a secret message can be extracted from a stego image. It is the ratio between the number of incorrect bits in the extracted message and the total number of bits in the original message [18]. A lower BER value indicates a better resistance to errors or alterations in the stego image as referred in Table III.

TABLE III. BIT ERROR RATE (BER) FOR DIFFERENT BENCHMARKS

Benchmarks	BER
Lena	0.0037
Baboon	0.00601
Cameraman	0.0031
Tobacco800	0.00234
MNIST	0.0027
IAM dataset	0.0073
CASIA Handwriting dataset	0.00741
EMNIST	0.0041
Signature dataset	0.0087
Dataset-1	0.0076

The table demonstrates that our steganography system consistently produced low BER values across multiple datasets, showing that the bit error rate is minimal and the secret

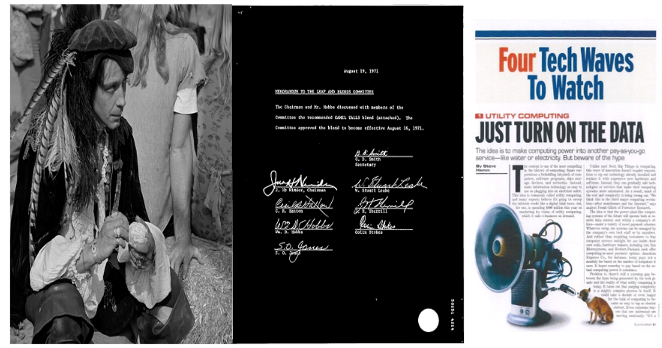

Fig. 4. Stego documents samples

message can be accurately recovered from the stego pictures. In conclusion, the testing findings from our steganography technology demonstrate its high levels of stealth and durability. The method can conceal information in high-quality and structurally comparable images with a low bit error rate.

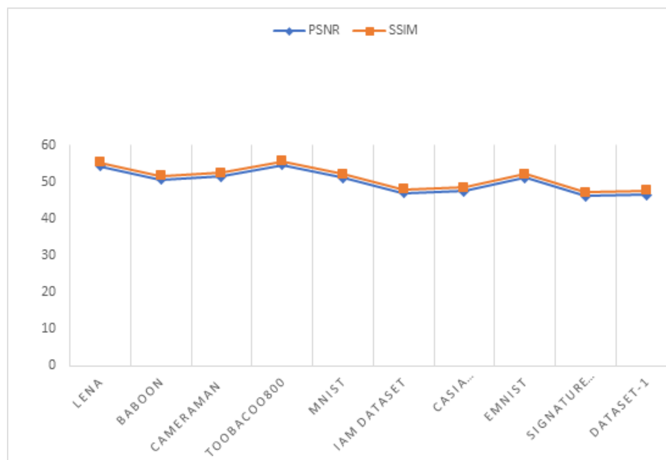

Fig. 5. PSNR and SSIM of ten stego document image quality.

F. Comparison with Related Works

To evaluate the performance of our steganography method compared to the related works, we conducted experiments using specific datasets and measured the PSNR values. The results are summarized in the Table IV:

TABLE IV. COMPARISON AMONG VARIOUS WORKS AND OUR PROPOSED WORK

Dataset	Our Proposed Work	Wang et al. (3)	Li et al. (7)	Zhou et al. (4)
Lena	54.2827	54.59	50.58	50.21
Baboon	50.674221	54.59	-	-
Cameraman	51.410	-	-	50.19

As can be seen from the table, our steganography system achieved competitive PSNR values compared to existing methods on several datasets. These results indicate that our system can hide secret messages in images with high image quality. In summary, our experimental results show that our steganography system achieves high imperceptibility in terms of PSNR. The system can hide secret messages in images with high image quality as measured by this metric.

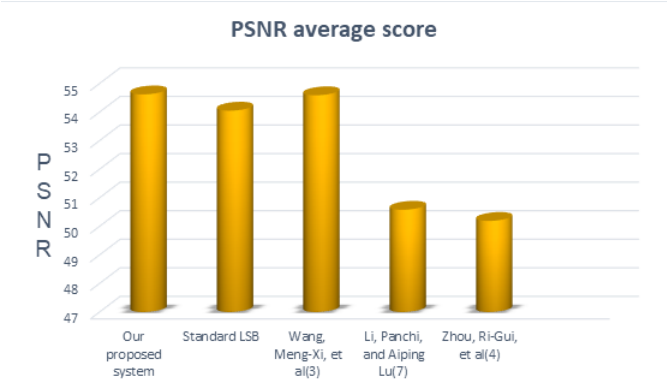

Fig. 6. A comparison of the proposed approach based on peak signal to noise ratio PSNR with state of the art methods.

V. Conclusion

In this paper, we presented a novel steganography system that combines quantum circuits and classical image processing techniques to hide secret messages in images. Our system uses the Scale-Invariant Feature Transform (SIFT) algorithm to detect keypoints in the cover image and K-means clustering to group the detected keypoints into clusters. The secret message is then encoded using quantum circuits, and a NEQR code is created for the message. The NEQR code is embedded in the cover image by modifying the cluster centers' pixel values. This quantum error-correcting code can be used to protect secret messages from noise. The stego image is then created by combining the modified cover image with the NEQR code. The scheme was implemented using the Python programming language and the qiskit library. We evaluated our steganography system regarding imperceptibility and robustness using several metrics. Our experimental results show that our system achieves high imperceptibility as measured by PSNR, SSIM, and histogram analysis. The system also achieves high robustness as measured by BER. Our steganography system provides a novel and practical approach to hiding secret messages in images with high imperceptibility and robustness. The system has potential applications in secure communication and data hiding.

References

[1] Mastriani, M. (2021). Fourier's Quantum Information Processing. *SN COMPUT. SCI.*, 2, 122.

[2] Dendukuri, A., & Luu, K. (2018). Image processing in quantum computers. *arXiv preprint arXiv:1812.11042*.

[3] Wang, M. X., et al. (2022). A novel quantum color image steganography algorithm based on turtle shell and LSB. *Quantum Information Processing*, 21(4), 148.

[4] Zhou, R. G., et al. (2018). A novel quantum image steganography scheme based on LSB. *International Journal of Theoretical Physics*, 57, 1848-1863.

[5] Lim, Jeonghun, and Kunwoo Lee (2019). 3D object recognition using scale-invariant features. In *The Visual Computer* (Vol. 35), 71-84.

[6] Ezugwu, Absalom E., et al. (2022). "A comprehensive survey of clustering algorithms: State-of-the-art machine learning applications, taxonomy, challenges, and future research prospects. In *Engineering Applications of Artificial Intelligence*, 110, 104743.

[7] Li, P., & Lu, A. (2018). LSB-based steganography using reflected gray code for color quantum images. *International Journal of Theoretical Physics*, 57(5), 1516-1548.

[8] DiAdamo, S., et al. (2022). Practical Quantum K-Means Clustering: Performance Analysis and Applications in Energy Grid Classification. *IEEE Transactions on Quantum Engineering*, 3, 1-16.

[9] Poggiali, A., et al. (2022). Quantum Clustering with k-Means: a Hybrid Approach. *arXiv preprint arXiv:2212.06691*.

[10] Luo, J., et al. (2019). A novel quantum steganography scheme based on ASCII. *International Journal of Quantum Information*, 17(04), 1950033.

[11] Witten, D. M., & Tibshirani, R. (2010). A framework for feature selection in clustering. *Journal of the American Statistical Association*, 105(490), 713-726.

[12] Zhang, Y., et al. (2013). NEQR: a novel enhanced quantum representation of digital images. *Quantum Information Processing*, 12, 2833-2860.

[13] Cohen, G., et al. (2017). EMNIST: Extending MNIST to handwritten letters. In *2017 international joint conference on neural networks (IJCNN)*.

[14] Marti, U. V., & Bunke, H. (2002). The IAM-database: an English sentence database for offline handwriting recognition. *International Journal on Document Analysis and Recognition*, 5, 39-46.

[15] Liu, C. L., et al. (2011). CASIA online and offline Chinese handwriting databases. In *2011 international conference on document analysis and recognition*.

[16] Lou, D. C., & Sung, C. H. (2004). A steganographic scheme for secure communications based on the chaos and Euler theorem. *IEEE Transactions on Multimedia*, 6(3), 501-509.

[17] Wang, Z., Simoncelli, E. P., & Bovik, A. C. (2003). Multiscale structural similarity for image quality assessment. In *The Thirty-Seventh Asilomar Conference on Signals, Systems & Computers, 2003* (Vol. 2).

[18] Burie, J. C., Ogier, J. M., & Loc, C. V. (2017). A spatial domain steganography for grayscale documents using pattern recognition techniques. In *2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR)* (Vol. 9).

[19] K. P. Sinaga and M. -S. Yang (2020), Unsupervised K-Means Clustering Algorithm, *in IEEE Access, doi: 10.1109/ACCESS.2020.2988796.*,vol. 8, pp. 80716-80727

[20] Sammut, Claude, and Geoffrey I (2020). Webb, eds, In *Encyclopedia of machine learning. Springer Science & Business Media*

[21] Pardo, Scott, and Scott Pardo (2020). "Multivariate Analysis and Classification." *Statistical Analysis of Empirical Data: Methods for Applied Sciences*, 209-217. `https://doi.org/10.1007/978-3-030-43328-4_16`

[22] Nousi, P., & Tefas, A. (2020). Self-supervised autoencoders for clustering and classification. *Evolving Systems*, 11(3), 453-466.

[23] Na, S., Xumin, L., & Yong, G. (2010). Research on k-means Clustering Algorithm: An Improved k-means Clustering Algorithm. In *2010 Third International Symposium on Intelligent Information Technology and Security Informatics* (pp. 63-67).

[24] Lindeberg, T. (2012). Scale invariant feature transform. *2012: 10491*.