

New Qubits Steganography Algorithm to Conceal a Secret File In Compressed edge detection operators Based on Optimized Adaptive Neural Networks

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Abstract—A compressed Qubits image steganography based on an optimized adaptive neural networks is proposed in this paper, to solve many problems related to adjustment, size and recognition. that are considered inefficient in image information concealing. We used M-PSO algorithm to determine an optimal target vales of the adaptive neural networks to obtain low noise and high accuracy when the results trained. However, our proposed scheme can separately conceal secret message and the content of cover file.

Index Terms—Qubits image steganography, image compression, edge detection operators,M-pso algorithm, optimized adaptive neural networks.

I. INTRODUCTION

Steganography is an art that disguise information secret image into cover image [1]–[4], steganography is an art or science that means where information of secret image is concealed within an image (cover file) has been widely used through the recent years due to the lowering of the cost of image storage and communication and also due to the weakness of the human visual system (HVS) [4]. Image steganography methods can be classified into two categories: those concealing in the spatial domain and those concealing in the frequency domain [2]–[4]. In the first type, the secret image is concealed directly in the intensity of the cover image file pixels, while in the second type, images are first transformed to frequency domain and then, the secret message is embedded in the transform coefficients, [2], [5].

Quantum digital image processing is one field of the quantum information processing, [1] and it has gravitated many researchers attention. In the recent decades, a quantum computation with information processing have been proposed, such as Shor's integer factoring algorithm and Grover's search algorithm. In quantum representation, quantum image steganography is proposed [2], to conceal the secret information into an other media files termed cover file such as (image, video and etc.) [3]. Starting from Bloch sphere [3], as a geometrical representation of the pure state space of a two levels of quantum system; we can define a quantum image steganography as Xored between a two qubits [4]. The classical representation of the three coordinates axes in which Bloch sphere of the color image is represented are labeled

X, Y and Z. in RGB format (R= Red, G=Green and B=Blue), and any other color will be obtained by mixing different of these three colors. Replacing the tri-dimensional system with (RGB), then we can represent the state of such a qubit as a linear combination on the three coordinates axes [5].

A quantum neural network is proposed [6]–[16], to be used in many applications, one of the most important application will be used in this paper. The quantum steganography can be stated using prior entanglement by combining quantum error-correcting codes with prior entanglement [4], [17]. The preparation of a quantum image can be done by using NEQR model [5], [18], to be used in different operations. In the last years, information concealing using an intelligent algorithm based on quantum computing was proposed [5], [7], [8]. Such methods are used for achieving robust, low cost, optimal and adaptive solutions in data concealing problems [10], [19]. An adaptive neural networks based on quantum computing to conceal a secret information with optimal values of the target using one of the artificial intelligent algorithm is proposed [8], [19]–[29]. This paper proposes a new scheme of quantum image concealing using hybrid adaptive neural networks with a modified particle swarm optimization algorithm based on a new version of adaptive optimal target values. With this scheme, a large amount of qubits can be concealed into a color image with four layers of security [8].

The main idea of our scheme is first to convert the image bits into qubits using Zhang [1] and Cnot [5] models, then compress these qubits with five relevant image edge detection operators. In this paper, we presents a novel scheme for image steganography which is based on a high compress method for color images and another high payload steganography mechanism using a hybrid edge detector.

This paper is organized as follows. A brief introduction about quantum image steganography based on the neural networks with help of particle swarm optimization algorithm to determine the optimal targets in the training process of the adaptive neural networks. Quantum neural networks and quantum gates have been presented in Sec. 2. The new modifying of particle swarm optimization algorithm and quantum training based on EPSO are proposed in Sec. 3. Based on QANN-EPSO and qubits information concealing and extract-

ing procedures is implements in Sec. IV. Experimental data and results are presented in Sec. 5. The paper concludes with Sec. VI.

II. RELATED RESEARCH WORKS

The main objective of image data compression is to decrease irrelevance and redundancy of the image data in order to be able to store or transmit data in an efficient form [10]. Image compression may be lossy or lossless. Lossless compression is preferred for archival purposes and often for medical imaging, technical drawings, clip art, or comics. Lossy compression methods, especially when used at low bit rates, introduce compression artifacts. Lossy methods are especially suitable for natural images such as photographs in applications where minor (sometimes imperceptible) loss of fidelity is acceptable to achieve a substantial reduction in bit rate. The lossy compression that producible differences may be called visually lossless. Many methods was used with image compression in Lossy and Lossless data compression. A lossless data concealing based on block truncation coding was proposed [11], [12]. In [13], [14], a lossless data compression based on Gradient Edge Detection was proposed. The term of edge detection is refers to a set of mathematical methods which aim at identifying points in image at which the brightness changes sharply or, more formally, has discontinuities.

The purpose of detection sharp is to capture important events and changes in properties of the object. There are many methods of edge detection, but most of them can be grouped into two categories: search-based and zero-crossing based [15]. The two categories of edge detection approaches are explained in details in (Section.3.1.1). The edge detection is a statistical approach for gray-level images based on the neighborhood similarity of pixel using a pre-defined intensity range or mean square error and simple statistical approach [16].

An adaptive image steganography based on AMBTC compression was proposed [20]–[23], to provide a hot topic in the design of information concealing algorithm by combination two techniques [24]. This method provides two important advantages, higher capacity and better image quality of the content of information concealing. Lossless steganography using AMBTC for image compression is presented [11], [12], [14], for same and other reasons according to their needed.

A Pixel Value differences was introduced by Wu and Tsai in 2003, that attempts to conceal the secret messages into sharp area. The cover file is partitioned into non-overlapping blocks consecutive pixels [2]. PVD is more imperceptible than human visual system (HVS), the PVP is a requirement designed for steganography technique, which reflects the ability of steganography in maintaining the visual quality of the produced Stego-image [5]. A pixel differences value is released from the values of the two pixels in each block. All possible pixel difference values are classified into a number of ranges. The selection of the range intervals is based on the characteristics of the human visual system to gray value variations from smoothness to contrast. A pixel differences value which is falls in a range with index k is said to have index k . Some bits of the secret message are concealed into a

two pixel block by substituting the Pixel difference value of the block with one with an identical index. The numbers of bits which can be concealed are given by Eq. (1):

$$n = \log_2(u_k - l_k + 1) \quad (1)$$

The new difference $\hat{d}$ is given by Eq. (2):

$$\hat{d} = \begin{cases} l_k + b, & \text{if } d \geq 0, \\ -(l_k + b), & \text{if } d < 0. \end{cases} \quad (2)$$

where b is the value of the sub-streams. The concealing process is finished when all the bits of the secret message are concealed.

III. PROPOSED SCHEME

A. Preliminaries

1) *Edge Detection Operators*: In edge detection operators, there are many methods but most of them can be grouped into two categories: search based and zero cross based. The search-based methods detect edges by first computing a measure of edge strength, usually a first-order derivative expression such as the gradient magnitude, and then searching for local directional maxima of the gradient magnitude using a computed estimate of the local orientation of the edge, usually the gradient direction. The zero-crossing based methods search for zero crossings in a second-order derivative expression computed from the image in order to find edges, usually the zero-crossings of the Laplacian [26], [27], or the zero crossings of a non-linear differential expression. As a pre-processing step to edge detection, a smoothing stage, typically Gaussian smoothing, is almost always applied.

The edge detection methods that have been published mainly differ in the types of smoothing filters that are applied and the way the measures of edge strength are computed. As many edge detection methods rely on the computation of image gradients, they also differ in the types of filters used for computing gradient estimates in the x- and y-directions. A survey of a number of different edge detection methods can be found in [1], [3]–[5], [14], [15], [26], [28]–[38]:

1- Canny edge operator: this detector was first proposed by John Canny to consider the mathematical problem of deriving an optimal smoothing filter given the criteria of detection, localization and minimizing multiple responses to a signal edge [38] He showed that the optimal filter given these assumptions is a sum of four exponential terms. He also showed that this filter can be well approximated by first-order derivatives of Gaussians. Canny also introduced the notion of non-maximum suppression, which means that given the pre-smoothing filters, edge points are defined as points where the gradient magnitude assumes a local maximum in the gradient direction. Looking for the zero crossing of the second derivative along the gradient direction was first proposed by Haralick. [39] It took less than two decades to find a modern geometric variational meaning for that operator that links it to the MarrHildreth (zero crossing of the Laplacian) edge detector [2], [40]. That observation was presented by Ron Kimmel and Alfred Bruckstein.

2- Other first-order method: Different gradient operators can be applied to estimate image gradients from the input image or a smoothed version of it see Eqs. (3) and (IV). The simplest approach is to use central differences [2], [9], [39]–[44]:

$$L_x(x, y) = \frac{-1}{2} \cdot L(x-1, y) + 0 \cdot L(x, y) + \frac{1}{2} \cdot L(x+1, y) \quad (3)$$

$$L_y(x, y) = \frac{-1}{2} \cdot L(x, y-1) + 0 \cdot L(x, y) + \frac{1}{2} \cdot L(x, y+1) \quad (4)$$

Corresponding to the application of the following filter masks to the image data are given in Eq. (5):

$$L_x = \begin{bmatrix} \frac{-1}{2} & 0 & \frac{1}{2} \end{bmatrix} * L \quad \text{and} \quad L_y = \begin{bmatrix} \frac{+1}{2} \\ 0 \\ \frac{-1}{2} \end{bmatrix} * L. \quad (5)$$

The well-known and earlier Sobel is based on the following filters which are given in Eq. (VI):

$$L_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * L \quad \text{and} \quad L_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * L \quad (6)$$

Give such estimates of first order image derivatives, the gradient is then computed in Eq. (7):

$$|\nabla L| = \sqrt{L_x^2 + L_y^2} \quad (7)$$

While the gradient orientation can be estimated by Eq. (8):

$$\theta = \text{atan2}(L_y, L_x) \quad (8)$$

Other first-order difference operators for estimating image gradient have been proposed in the Prewitt operator, Roberts cross, Laplacian and etc. [45], [46]. It is possible to extend filters dimension to avoid the issue of recognizing edge in low PSNR image. The cost of this operation is loss in terms of resolution.

2) AMBTC Method: In 1984, Maximo and Mitchell enhanced the performance optimization variation of BTC called absolute moment block truncation coding. The AMBTC proposed to improve the compression performance of an images to be used in other purposes [24]. AMBTC method was presented [47] which provides an improvement in reconstructed image quality [19], and the aim of AMBTC is to preserve the mean and the first absolute central moment of image blocks [12], [48]. The standard deviation of AMBTC is used along with the Mean Value.

The general procedures of the AMBTC method are given below [11], [12], [19], [49], [50]:

Let $k = n \times n$ be the number of pixels in a block, $x_{i,j}$ is the i^{th} and j^{th} values in the image.

Step1 : the original image O is first segmented into a set of non-overlapping blocks of k pixels.

Step2 : For each block, the values obtained from each pixel block should follow the order of left-to-right and top to-down

and the mean value $\bar{x}$ works as a threshold that separates the pixel into two groups G_0 and G_1 each of them can be stored as value 0 and 1 in the O and it can be calculated and defined in Eq. (9):

$$\bar{x} = \frac{1}{k} \sum_{i=1}^n \sum_{j=1}^n x_{ij}, \quad (9)$$

where x_{ij} indicates the pixel value in the position (i, j) of the block.

Step3 : let m is the number of pixels in G_1 , two outputted levels a and b of every AMBTC-Compressed block is calculated by Eqs. (10) and (11)

$$a = \frac{1}{k-m} \sum_{x_i < \bar{x}} x_i, \quad (10)$$

$$b = \frac{1}{m} \sum_{x_i \geq \bar{x}} x_i, \quad (11)$$

Step4: the compressed trio is then generated, (a, b, O) . The decoding method of AMBTC is very simple, let $bm_1, bm_2, \dots, bm_k$ be the values in O of each compressed trio, and let $r_1, r_2, \dots, r_k$ be the values of reconstructed vector of each image block. The decoding method is presented in Eq. (12):

$$\begin{cases} r_i = a, & \text{if } bm_i = 0, \\ r_i = b, & \text{otherwise.} \end{cases} \quad (12)$$

3) Steganography and Steganalysis Techniques : A reversible steganography can be roughly classified into following two categories:

1. Spatial domain reversible steganography [2], [3], [12]:

This type of reversible steganography directly modifies image pixels in the spatial domain to achieve reversibility [51]. Since this technique is easy to implement, offer a relatively high hiding capacity [6], and the quality of the cover image can be easily controlled, it has become a popular method for reversible steganography.

2. Compressed domain reversible steganography [2], [4]:

Reversibility for this type of steganography is achieved by modifying the coefficients of the compressed code. Since most images transmitted over the internet are in compressed format, insert secret data into the compress domain would arouse little suspicion [9]. However, compressed domain reversible steganography often suffers from high computational cost, low hiding capacity, and low stego-image quality.

B. Scheme description

1) EAMBTC Algorithm: The proposed scheme EAMBTC introduces an edge block truncation coding method in order to obtain good human visual system (HVS) and pixel value differences (PVD), of an images with better compression ratio [8]. The EAMBTC find the gradients from the input image using five edge detection operators, and then divides the input image into non-overlapping blocks consecutive pixels [52]. Quantization is done based on the edge information of each of these blocks. For the non-edges blocks information will be

grouped and compressed to be one region. The algorithm for this method is as follows:

Algorithm 1 Algorithm for Enhancing the AMBTC algorithm (EAMBTC)

Input2: Cover image C_I of size $M \times N$ pixels and block size K by which image is to be transformed into sub-bands using IWT technique, and divided into non-overlapped blocks.

Input2: Secret image S_I of $M \times N$ pixels and block size K by which is to be concealed in a suitable sub-bands of the cover image.

Output: EAMBTC-Compressed cover image CC_I .

- 1: Find the edge map and $emap$ of the C_I . The edge map of the input image is derived by using the different five edge operators which are mentioned in Sec. 3.1.1. The first stage of the method is to reduce the noise which means smothering the image with a different filters. In the second stage, find the intensity gradient and apply an edge thinning technique called non-maximum suppression. Then trace the edges through the image using double thresholds and connectivity analysis.
- 2: Divide the secret image S_I into blocks, of size $k \times k$, where k can be 4, 8, 16 and so on. Then each block W can be represented in Eq. (13),

$$W = \begin{bmatrix} w_1 & w_2 & \cdots & w_k \\ \vdots & \vdots & \ddots & \vdots \\ \cdots & \cdots & \cdots & w_k^2 \end{bmatrix} \quad (13)$$

- 3: Divide the edge map $emap$ into blocks with the same block size k . Each edge block can be represented in Eq. (14),

$$E = \begin{bmatrix} e_1 & e_2 & \cdots & e_k \\ \vdots & \vdots & \ddots & \vdots \\ \cdots & \cdots & \cdots & e_k^2 \end{bmatrix} \quad (14)$$

- 4: Selecting the appropriate blocks to be concealed into an appropriate blocks of the cover image in the Sec. 3.2.3, in such a way that if any of the edge values in E_{k^2} is equal to 1 and not all the edge values are equal to 1 then, the secret image blocks W_{k^2} is defined as an edge block, otherwise a non-edge block. An identifier flag is defined and assigned the value 0 for the edge block and 1 for the non-edge block.
- 5: i.e., if $e_i E(k^2)$, ($e_i == 1$ and not all $e_i == 1$)
- 6: then flag = 0 // edge block
- 7: else flag = 1 // non-edge block

C. New adaptive PSO algorithm with optimal target modified AMPSOANN approach

The particle swarm algorithm is an optimization method based on Darwinian models of natural selection and evaluation [8]. In 1994, The particle swarm optimization algorithm is developed by Kennedy and Elberhart [19]. In particle swarm optimization algorithm, each molecular in a swarm group is

called “particle”, and the position of each particle is predicates solution to a problem. Each particle in the swarm holds its own personal best position it has visited so far, referred to as $pbest$, and the swarm pbest position is referred to as $gbest$. Each particle updates its velocity and position are given in Eqs. 15, 16 and 17 respectively;

$$V_i^k = W * V_i + C_1 * rand_1 * (pbest_i - x_i) + C_2 * rand_2 * (gbest - x_i) \quad (15)$$

$$x_i^k = x_i + V_i^k \quad (16)$$

$$W = W_{Max} - n * \frac{W_{Max} - W_{Min}}{Max_{iteration}} \quad (17)$$

where $rand_1$ and $rand_2$ are two random real numbers in the range $[0, 1]$; c_1 and c_2 are acceleration constants; W is the inertia weight, W_{Max} and W_{Min} are the maximum and minimum inertia weights through the course of the PSO iteration; n denotes the current iteration number; and $Max_{iteration}$ is the given maximum iteration number. The particle swarm velocity on each dimension is limited to $[-V_{max}, V_{max}]$. Usually, the PSO algorithm is terminated with a given maximum iteration number.

The new version of proposed MPSO algorithm with two levels showing below in the Algorithm:

Algorithm 2 : New Modifying of particle swarm optimization algorithm

- 1: Let $[NP]$ be the population size of ANN
- 2: for each $i \in [1, NP]$ do
- 3: for each $j \in [1, Ndim]$ do
- 4: Create randomly an initial population of individual Weights V_i $W_i \forall i = 1, \dots, n$
- 5: end for
- 6: end for
- 7: for all $i \in [1, NP]$ do
- 8: for all $j \in [1, Ndim]$ do
- 9: $gbest_{ij} = argmin(FX_{ij})$
- 10: end for
- 11: end for
- 12: for all $i \in [1, NP]$ do
- 13: for all $j \in [1, Ndim]$ $W^k = W_{Max} - k * \left(\frac{W_{Max} - W_{Min}}{Max_{iteration}} \right)$ do
- 14: $rand_1 = random(0, 1)$;
- 15: $rand_2 = random(0, 1)$;
- 16: $NewV_{kij} = V^k * W^k + C_1 * rand_1 (pbest_{ij} - x_{ij}^k) + C_2 * rand_2 * (gbest_{ij} - x_{ij}^k)$;
- 17: $Newx_{ij}^k = x_{ij}^k + V_{ij}^k$;
- 18: end for
- 19: end for
- 20: $\vec{V}_j = \vec{V}_j \cup \{V_{ij}^k\}$
- 21: $\vec{X}_i = \vec{X}_i \cup \{X_{ij}^k\}$
- 22: End j, k.

Algorithm 3 : Steps of the QANN training algorithm

- 1: **Defin** three layers and its weights:
 - The **Input** layer($|x_i\rangle, \forall i = 1, \dots, n$) it includes n neurons, and it only can receives input single that are composed of $\{HSI \text{ and } VIF\}$ values.
 - The **Hidden** layer ($H_t \forall t = 1, \dots, p$) includes p neurons that receive input signals from the input layer and then share them to each output neuron
 - Let $W(0)$ be a **Weight** matrix.
 - Let $|d_i\rangle$ is consider as **output** layer
- 2: **Given** a set of quantum examples in the form $(|x\rangle, |d\rangle)$
- 3: **Calculate** $W(t) = |x\rangle$, where t is the iteration number
- 4: **Update** the weights following the learning procedures which are given in Eq.10
- 5: **Repeat** steps 3 and 4 until a stop criterion is met.
- 6: **END**.

D. Concealing and Retrieving procedures

In this subsection, we describe a new method to conceal and extract the quantum optimized qubits, using a new method to conceal the optimal qubits;

1) *Concealing procedure*: the Concealing Procedures are given in the following steps:

Input : Qubits optimized of the cover image C_I and secret image S_I .

Step1 : Represent C_I in gray-level and obtain normalized sub-bands of QLL, QHL, QLH and QHH .

The cover file will be partitioned into scales of sub-bands. It is given in the Eq. (18):

$$S(k_1, k_2) = \frac{1}{\sqrt{N_1 N_2}} \sum_{k_1}^{n-1} \sum_{k_2}^{m-1} w_\varphi^{m-1} + WS(Hs) \quad (18)$$

where WS, HS, w_φ^{m-1} and w_ψ , are given by “Eqs. (19), (20), (21) and (22) respectively;

$$WS = \sum_{k_1} \sum_{k_2} w_\psi^i(j_0 k_1 k_2) \psi_{j_0 k_1 k_2}(n_1, n_2) \quad (19)$$

$$HS = \frac{1}{\sqrt{N_1 N_2}} \sum_{i=H,V,D} \sum_{j=0}^{m-1} \quad (20)$$

$$w_\varphi^{n-1}(j_0 k_1 k_2) = \frac{1}{\sqrt{N_1 N_2}} \sum_{n_1=0}^{m-1} \sum_{n_2=0}^{n-1} S(n_1, n_2) \varphi_{j_0 k_1 k_2}(n_1, n_2) \quad (21)$$

$$w_\psi^i(j_0 k_1 k_2) = \frac{1}{\sqrt{N_1 N_2}} \sum_{n_1=0}^{m-1} \sum_{n_2=0}^{n-1} S(n_1, n_2) \psi_{j_0 k_1 k_2}(n_1, n_2) \quad (22)$$

where $i = H, V, D$ and S is a size of image and is equal to $N_1 \times N_2$ **Step3** : Obtain qubits of secret image bands without free qubits to get approximation and detail coefficients. **Step4** : Conceal the approximation coefficients of secret image bands in the second and third LSB planes of QHH and QLH sub bands after encryption.

In this situation, unlimited sub-bands of the secret message are concealed in bytes of the cover file. Suppose S_i and S_j are two secret bits, see “Eqs. (23) and (24);

$$S_i = S_i \otimes b_{i-1} \otimes b_{i-2}, i \leq m-1 \quad (23)$$

$$S_j = S_j \otimes b_{j-1} \otimes b_{j-2}, j \leq n-1 \quad (24)$$

where b_i and b_j are 4^{th} and 5^{th} bits of the cover byte respectively. 3rd and 2nd bits of the cover byte are replaced by these encrypted secret bits. This type of dynamic encryption avoids the need for encryption key. Concealing can be done in the Cr component also in the similar fashion [30]. Here C_1 and C_2 are the modified CLH and CHH . For concealing any two bits of the secret image in one byte of the cover file, two bits from the secret image are *XORed* with two bits of the cover file [31]. In our situation, qubits of the secret file are *XORed* with bytes of the cover file, it is given in Eqs. (25) and (26);

$$S_{m-1_i} = S_i \otimes b_{i-1} \otimes b_{i-2} \quad (25)$$

and

$$S_{n-1_j} = S_j \otimes b_{j-1} \otimes b_{j-2} \quad (26)$$

Step5 : Obtain inverse of IWT to get *stego* - Cb . Then convert to RGB system. **Output** : stego image G .

2) *Retrieving procedures*: The Extracting Procedures are given in the following steps:

Input : Stego image G .

Step1 : Read stego image G and represent in the gray-level format.

Step2 : Obtain qubits of scalable sub bands: GLL, GHL, GLH , and GHH .

Step3 : Extract the encrypted secret sub-bands bits from the second and third bit planes of QLH and QHH.

In this method, unlimited sub-bands of the secret message are obtained from one byte of the stego image coefficient. Then decryption is done as follows: the two encrypted bits are : *XORed* with bits of the stego byte to get secret bits, i.e., as mentioned in “Eqs. (23), (24), (25) and (26).

Step4 : Convert to decimal to get approximation coefficients of secret sub-bands.

Step5 : Obtain an inverse qubits for approximation coefficients obtained in Step 4 and considering zeroes for detailed coefficients. The result is secret image bands. **Step6** : End extracting.

IV. IMPLEMENTATION OF QANN-EPSON METHOD

The concealing processes are shown in Fig. 12, we should explain the whole steps to conceal the secret qubits in the cover file and then implement the machine learning method of QANN-EPSON technique. Fig. 12 shows the concealing steps how to be illustrated to conceal the secret qubits in the cover file which are optimized by EPSON method, the results of this process will reduce the Pixel value difference between the

secret file and the cover file. In the following steps, how to implement the QANN-EPPO method.

Algorithm 4 : Implementation steps of the QANN-EPPO algorithm

- 1: **Input** the secret and cover image files.
 - 2: **Convert** the data inputs using Zhang model as mentioned in Section III-B1 to convert the entered both images from bits form into qubits forms.
 - 3: **Implement** the concealing procedures in the Section III-D1, to conceal the qubits (without the free qubits) which are extracted using EPPO algorithm to obtain an optimal qubits.
 - 4: **Normalize** the input data and the target to be homogeneous to be used in the next step.
 - 5: **Apply** the hybrid adaptive neural network to adjust the mean square error between the Staggered qubits.
 - 6: **Update** the training targets of the networks to obtain last adjustment using EPPO algorithm.
 - 7: **Check** the proposed condition that given in Algorithm1, where this condition is based on the **VIF** value $\forall$ of the qubits.
 - 8: **if** the relevant errors are within the range the proposed conditions **then**
 - 9: Construct new S_I by adding new free qubits to the stego qubits and go to **Step 8**.
 - 10: **else**
 - 11: Adjust the weights values, and then go to **Step 4**.
 - 12: **end if**
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V. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

In this section, we presents the experimental results, there are three main testing rates to evaluate the ability of the proposed scheme [5]. The first rate is the change rate, this kind of rate used for evaluating the concealing procedures, it is also called as concealing efficiency. The other rate is to evaluate the extraction procedures, and also known as steganalysis efficiency. The third testing rate is the security evaluation test which measures the resistance of the steganography against steganalysis scheme. We will present the experimental results of our proposed method, which has been implemented in *MATLABR2011a*.

A. Results discussion and evaluation

1) *Concealing Payload Evaluation*: Concealing payload is a basic measurement to evaluate the steganography scheme performance. Payload refers to the amount of bits that can be concealed into the cover image. High concealing payload is computed using “Eq. (27)

$$E_p = \frac{Max}{C_{I_{WH}}} (\text{bit per pixel}) \quad (27)$$

where Max is the maximum number of the secret message bits that can be concealed into cover image, and $C_{(I_{W,H})}$ are the cover image width and height respectively. Where, all of them are measured by bit per pixel (BPP).

2) *Concealing distortion Evaluation*: Concealing distortion used to evaluate the stego image quality using Peak Signal-to-Noise Ratio PSNR which is calculated using “Eq. (28).

$$PSNR = 10 \log_{10} \left[\frac{255^2}{MSE} \right] (dB) \quad (28)$$

Where MSE is the Mean Square Error, and is refers to the difference value between cover and stego images, which is given in “Eq. (29):

$$MSE = \frac{1}{C_{I_{WH}}} \sum_{i=1}^W \sum_{j=1}^H (C_{ij} - S_{ij})^2 \quad (29)$$

where $C_{(i,j)}$ and $S_{(i,j)}$ are the gray values of pixel (i, j) of the cover and stego images. W and H are the width and height of the cover image (the stego image has the same size).

Figs. 1, 2,3,4 and 5 show the different stego images based on five compressed edge detection operators respectively. The performance evaluation metrics for the stego image is shown in Table. I. Table II shows the Performance metrics for the extracted secret image from different edge detection operators.



Fig. 1: Stego-image based on Canny Operator cover file



Fig. 2: Stego-image based on LapLacian Operator cover file



Fig. 3: Stego-image based on Robert Operator cover file



(a) Input image file

(b) Stego image file

Fig. 4: Stego-image based on Prewitt Operator cover file



(a) Input image file

(b) Stego image file

Fig. 5: Stego-image based on Sobel Operator cover file

There are many modeling tools can be used to train and analysis data in adaptive neural networks. In our method, we used *NNSTART* tool to train and test our network. The *NNSTART* tool it is suitable tool to be used for image recognition and other special processors related to image processing. Table III shows the average values between a different methods have been proposed and our proposed method. The Peak Signal-to- Noise Ratio can be defined by Eq.30,

$$PSNR = 20 \times \log_{10} \left(\frac{2^q - 1}{\sqrt{MSE}} \right) \quad (30)$$

where the MSE extracted from Algorithm 3 between the input and the target.

where the payload capacity 10% means the maximum payload average value of the stego image.

TABLE I: Performance metrics for the stego image

Edge operators	compression ratio	PSNR
Sobel operator	5.4418	41.003574
Canny operator	2.3716	40.999096
LoG operator	2.5196	41.001677
Prewitt operator	5.4491	41.003615
Robert operator	6.7454	41.004315

TABLE II: Performance metrics for the extracted image

Stego image with Edge operators	SNR	SPCC
Sobel operator	38.3	0.9022
Canny operator	36.3	0.8922
LoG operator	32.4	0.8353
Prewitt operator	30.2	0.8351
Robert operator	30	0.8350

TABLE III: The average values of PSNR(db) for the **Lena** stego-image.

Payload capacity	Qubits algorithm	ANN-AGAUAR	Proposed scheme
10%	64.9738	64.11	65.654311

In the Table III, the PSNR value of our proposed scheme it is high compare with the previous method. The obtained high value of PSNR of our proposed method is because the **Mean Square Error** value which is obtained from **QANN-EPPO** method. The following Figs. 11 and 12 describes experimental results of QANN-EPPO algorithm of qubits concealing method and Table III gives the PSNR value between the input qubits and the concealed image.

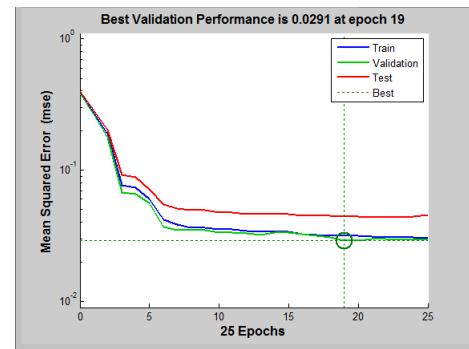


Fig. 6: Mean Square Error with 25 Epochs.

And the Error Histogram with 20 Bins value between Targets and Outputs is shown in Fig. 7, where the 25 Epochs number are shown in Fig.8

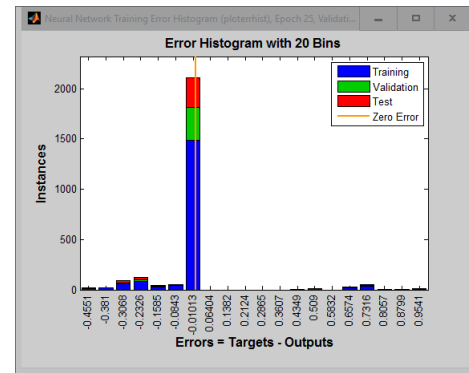


Fig. 7: The Error Histogram between Targets and Outputs.

In this paper, an operating characteristic of the proposed adaptive training networks are given in Fig. 10. Table IV shows the operating characteristics of our proposed training network with the Mean Square Error for each one.

VI. CONCLUSION

In this paper, a qubits image steganography scheme has been proposed, based on an optimized adaptive neural networks. We used two models to optimize the target of the QANNs to obtain low noise and high accuracy. The learning of ability of the

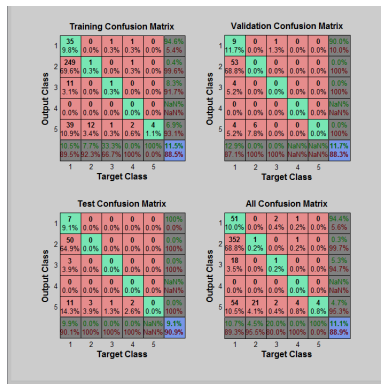


Fig. 8: Training confusion of 25 Epochs.

TABLE IV: The operating characteristics .

Operating characteristics	operating ratio characteristics	Mean Squared Error	Samples ratio
Training ROC	70%	0.037917	358
Validation ROC	15%	0.039069	77
Testing ROC	15 %	0.036863	77

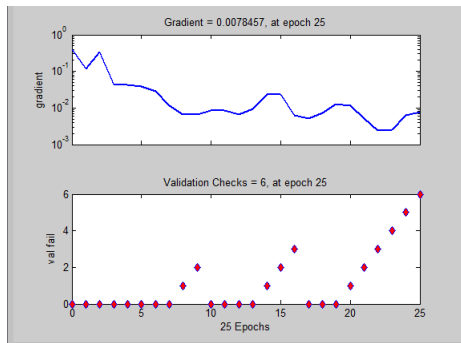


Fig. 9: The training state for 25 Epochs.

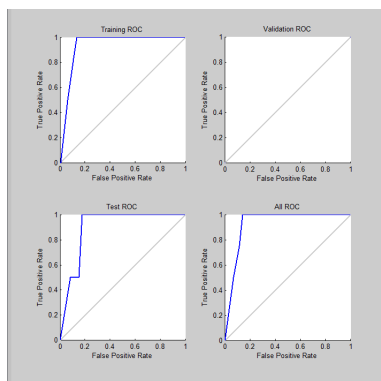


Fig. 10: The operating characteristics of the proposed adaptive training networks

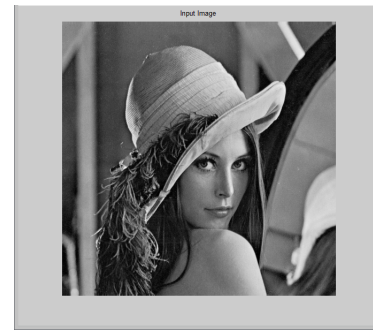


Fig. 11: The original input image.



Fig. 12: The trained steog-image

QANN-EPSo has been investigated through the 4 and 6-bit. Our results suggest that the excellent learning performance of the QANN-EPSo is not simply due to the complex-valued parameters. The scheme that we proposed can significantly avoid the hacking risks. The experimental result shows that we can successfully optimize the targets of the ANNs to be more optimality. The results of the proposed scheme have been analyzed and evaluated using HSI and VIF models. The QANN-EPSo image information concealing can be applied on the basis of different needs.

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