Application of Genetic Algorithm for Enhanced and Secured Transmission of Secret Images

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Abstract—This recent and rapid developments in imaging and communication technologies have resulted in a mass generation and transmission of digital images, eventually increasing its number of applications in almost all fields like remote sensing, medicine, agriculture, forensics, defense etc. This demands effective and secure transmission of images over the networks as information is prone to vulnerable threats online. The proposed algorithm guarantees highly secure transmission of secret information in the form of images using Visual Cryptography. Visual cryptography provides a very powerful technique by which a secret image is distributed into two or more shares. These shares are meaningless images and look like random dots. At the point when the shares on transparencies are superimposed precisely together, the original secret can be found without the utilization of computer. One of the main drawbacks of traditional Visual Cryptography is the pixel expansion, where each pixel is represented using m pixels in each resulting shares. The parameter m is known as the pixel expansion. This pixel expansion results in a loss of resolution. The restored secret image has a resolution lower than that of the original secret image. The proposed method enhances the visual quality and resolution of visual cryptography using the genetic algorithm. A Genetic algorithm is an optimization technique based on natural selection, the process that drives biological evolution. GA enhancement is applied to VC shares created in RGB and CMY color space. The proposed method increases the clarity, enhances the degree of detail, improves the contrast, increases the average information content, PSNR value and at the same time maintaining the security of the secret image.


I. INTRODUCTION

The growth of IT and Internet Technologies has opened new opportunities in scientific and commercial applications. Through these technologies, lots of information is transmitted quickly to all parts of the world. However, it also leads to many serious problems such as hacking, duplications and malicious usage of digital information. Security issues become more complex in a network environment. We must ensure that access to the network is controlled and that data is not susceptible to attack through transmission over the network. Many technologies are available to encrypt data and thus help to ensure its privacy and integrity.

The encrypting technologies of cryptography are generally used to protect information. Visual Cryptography (VC) is a powerful cryptography technique for secured image sharing through an unsecured network such as the Internet. VC uses the characteristics of human vision to decrypt encrypted images. It needs neither cryptography knowledge nor complex computation. For security concerns, it also guarantees that hackers cannot recognize any clues about a secret image from individual cover images.

VC encrypts Secret Image (SI) into some n shares of the image. The decryption only requires stacking of n shares on top of each other. It is impossible to retrieve the secret information from n-1 shares of the images. In VC, each pixel in the original secret image is represented using m pixels in each of the ensuing shares. The parameter m is known as the pixel expansion because the recovered image will be m times larger than the secret image [1, 2].

One of the main drawbacks of traditional VC is the pixel expansion. This pixel expansion results in a loss of resolution. The decrypted secret image has a resolution lesser than that of the original secret image [3, 4]. Splitting the secret image into multiple shares in VC has the effect of reducing the contrast in the recovered image. Hence improving the visual quality of VC is a commonly researched area. The proposed method enhances the visual quality and resolution of visual cryptography using Genetic Algorithm (GA).

For grayscale images, the perceived visual feature of the recovered image can be enhanced by using image filtering techniques prior to encrypting the secret image [5]. This proposed study enhances the quality of image using GA and it caters to all kinds of images, color as well as gray. The algorithm performs enhancement in RGB and CMY color space.
A genetic algorithm is an optimization technique based on natural selection, the process that drives biological evolution [6]. The proposed method increases the clarity, enhances the degree of detail, improves the contrast, increases the average information content, PSNR value and at the same time maintaining the security of the secret image.

The main objectives of this proposed method are to formulate a system to send secret image across the network, which has the following characteristics.

1) To create a safe and secure color VC shares from the given original color secret image to be sent across the network, which do not need any computation and decryption algorithm.

2) To generate a robust GA-based enhancement algorithm to improve the quality of VC shares and thereby increasing the clarity of the retrieved secret image.

The paper is organized as follows. Several genetic algorithms used in image enhancement and basic principles of GA are described in Section 2. The proposed genetic algorithm approach for VC share enhancement is discussed in Section 3. In Section 4, the results are analyzed and discussed, followed by concluding remarks in section 5.

II. REVIEW OF LITERATURE

Differentiate improvement strategies are utilized as a part of image and video processing to achieve better visual understanding. In general, histogram equalization based contrast enhancement is attained through the redistribution of intensity values of an input image. Histogram equalization (HE) is one of the most widely used techniques to achieve contrast enhancement, due to its simplicity and effectiveness. The traditional histogram equalization technique [7] is described below:

Consider the input image, \(F(i,j)\) with a total number of ‘n’ pixels in the gray level range \([X_0, X_{N-1}]\). The probability density function \(P(r_k)\) for the level \(r_k\) is given by:

\[
P(r_k) = \frac{n_k}{n}
\]

where \(n_k\) represents the frequency of occurrence of the level \(r_k\) in the input image, \(n\) is the total number of pixels in the image and \(k = 0, 1, \ldots, N - 1\). A plot of \(n_k\) against \(r_k\) is known as the histogram of the image \(F\). Based on Eq. (1), the cumulative density function is calculated as:

\[
C(r_k) = \sum_{r=0}^{r_k} P(r)
\]

(2)

HE maps an image into the entire dynamic range, \([X_0, X_{N-1}]\) using the cumulative density function which is given as:

\[
F(X) = X_0 + (X_{N-1} - X_0)C(X)
\]

(3)

Thus, HE flattens the histogram of an image and results in a significant change in the brightness.

For the image, contrast enhancement Histogram Equalization (HE) is one of the most commonly used methods, but unnatural looking images might be created by them and the images got by these techniques are not desirable in few applications where brightness preservation is essential to avoid annoying artifacts. To rise above such issues contrast enhancement of HDR images using genetic algorithm is proposed. The algorithm implemented here uses the genetic algorithm for the filtering of the image such as noise reduction and enhance the contrast of the image. The algorithm proposed by Ram Ratan Ahirwal [8] performs better as compared to the other HDR contrast enhancement techniques. The idea is to use the genetic algorithm which executes a number of iterations and perceives the regions in the image that need enhancement.

Ming-Suen Shyu and Jin-Jang Leou [9] proposed a genetic algorithm (GA) approach to color image enhancement, in which the enhancement is formulated as an optimization problem. In this approach, a set of generalized transforms for color image enhancement is formed by linearly weighted function, combining four types of nonlinear transforms. The Fitness (objective) function for GAs is formed by four performance measures, namely, the AC power measure, the Brenner’s measure, the compactness measure, and the information-noise change measure. Then GAs is used to determine the “optimal” set of generalized transforms with the largest Fitness function value.

The method by Komal et.al., is using a simple chromosome structure and genetic operators to increase the visible details and contrast of low illumination images, particularly with high dynamic range. The proposed approach maps every gray level of input images to another, so that the resulting image contains more contrast [10].

In chromosome structure based on a look up table technique, proposed by Saitoh [11], a relation between input gray level and output gray level is determined using the genetic algorithm. The minimum gray level is changed to 0 and the maximum gray level is changed to 255 to increase the contrast of an image. In this case, each chromosome \(k\) is represented by a byte string that represents a relation between input gray level and output gray level. The difference \(b(j-1)\) between values of transformed curve \(B(j)\) and \(B(j-1)\), is represented by each byte. Here bit position \(j\) form left edge of a chromosome [11]

\[
B(j) = B(j-1) + b(j-1)(1 \leq j \leq N_{\text{max}} - N_{\text{min}})
\]

(4)

Evaluate the fitness of an individual by the sum of intensities of edges \(E(k)\) in an enhanced image.

The intensity of an edge is calculated by Prewitt operator [12].

In this paper, an attempt is made to enhance the Contrast of VC shares before transmitting the secret using Genetic Algorithms. Image enhancement of VC images are different from other image enhancement procedures as the image is made up of just two intensity values for all color channels. The flowchart of the conventional GA is given in Fig. 1. A genetic algorithm keeps a population of candidate solutions for the problem at hand and makes it evolve by iteratively applying a set of following stochastic operators [13].

- **Selection**: replicates the most successful solutions found in a population at a rate comparative to their relative quality
Recombination: decomposes two distinct solutions and then randomly mixes their parts to form novel solutions
Mutation: randomly disturbs a candidate solution

In this paper, Color VC shares are enhanced using GA and the quality of the shares and the results are compared with various existing contrast enhancement techniques to prove the superiority of the proposed method.

III. PROPOSED METHOD

Most of the objects transmitted across the networks may be vital secret images, and in such cases, the senders have to take information security issues into consideration. Being a type of secret sharing scheme, VC is used in a number of applications. The proposed method converts the color secret image into VC shares and then enhances the quality of the image using GA.

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This is accomplished in two phases.
Phase I: Creation of color VC shares using the SI.
Phase II: Enhancement of VC shares using GA.
The overall architecture of the recommended system is shown in Fig. 2.

A. Creation of color VC shares using the SI

The given Secret Image is split up into 3 color channels (RGB) and two shares are created depending on the intensity of pixel values at the color channel. It expands each pixel into a 2X2 block (Share1 and Share2) to which a color is assigned according to the model presented in Fig. 3. It depicts the 2X2 blocks created for Red channel. Similarly, blocks are created for other channels. All the first shares in the 3 color channels are combined to form VC Share1 and the second shares of RGB are merged to form VC Share2. The two shares created will look like random dots because they have equal number of black pixels and color pixels and will not reveal any information.

**Phase I - VC Creation Algorithmic Description**

| Input | Original Image |
| Output | VC Share1 and VC Share2 |
| BEGIN | | |
| 1. | Read SI that is to be transmitted securely across network |
| 2. | Extract RGB components from each pixel in SI |
| 3. | Check the pixel value of the red (green/blue) component which ranges from 0 – 255 |
| 4. | According to the value of pixels, each pixel is replaced with a 2X2 block and create share1 and share2 as shown in Fig. 3.7. |
| 5. | Repeat step 3 and step 4 for green and blue colors to create share3, share4, and share5, share6 respectively |
| 6. | Shares 1, 3 and 5 are merged to form VC share1 and similarly Share2, Share4, and Share6 are merged to form VC share2 |
| END | | |

At end of Phase I, six shares are created as shown in Fig. 2.

B. VC Share enhancement using GA

The six shares generated in phase I is treated as the initial population. The pixel values of the shares which are either 0 or 255 are added or subtracted with a random number to generate a new minimum and maximum value. Perform crossover and mutation as discussed below. The fitness function is evaluated to find the difference in PSNR between the new population and the original one. If the change is positive then the new shares are combined to form the GA image and it replaces the parent VC share in the next generation and the process is repeated.

**Phase II – VC Share Enhancement using GA - Algorithmic Description**

| Input | Original Image and Six shares created in phase I using 3.3.1.1 |
| Output | Enhanced VC Share1 and VC Share2 |
| BEGIN | | |
| 1. | Generate random population of n chromosomes - Population size is the no. of shares used in GA i.e. 6 |
| 2. | Randomly select a parent share and evaluate the fitness f(x) of the selected population |
| 3. | The new population is created by repeating the steps below until the completion of the new population |
|   a. | Find mean value of the intensity of the pixels below 128 (mean1) and the mean value of the intensity of pixels above 128 (mean2). |
|   b. | Create two random numbers r1 and r2, such that r1 is below mean1 and r2 is above mean2 |
|   c. | The new minimum intensity is r1 and maximum intensity is r2 |
|   d. | Perform the crossover of the parents of corresponding color shares for few random rows from the population to form a new offspring. |
|   e. | Mutate the pixels in a parent and perform the same mutation in the corresponding color share. |
|   f. | Evaluate the fitness function and include the new offspring as the new parent in the population if it satisfies the fitness function |
| 4. | If the end condition is satisfied, return the current population as the best solution and go to step 6. |
| 5. | Go to step 2 with the new set of population |
6. Combine the first set of RGB shares to create VC share1 and the second set to create VC share2 and send it to the receiver on two different channels.

This process is repeated until a termination condition has been reached which is either completed a maximum number of generations (iterations) specified or the fitness function returns negative value continually. Crossover selects genes from parent chromosomes and creates a new offspring. Here it is done by choosing random number of rows from first parent (share1) and then interchanging its content with the second parent (share2) as shown below.

There are different approaches to make crossover, for instance, we can choose more than one crossover points. Specific crossover made for a particular problem can improve performance of the genetic algorithm. After a crossover is carried out, mutation takes place. This is to prevent falling all solutions in population into a local optimum of solved problem. Mutation changes arbitrarily the new offspring. Here mutation is done by randomly interchanging two bits in a row as shown below.

GA VC Share 1, 3, 5 are combined to form secret share1, and share2, 4 and 6 merged to form secret share2 as shown in fig. 2. Secret share1 and Secret share2 which look like random dots are sent securely across the network on different channels.

The same process is repeated for VC shares created in CMY color space

C. Decryption

The process of decryption at the receiving end of the network is very simple. The secret image can be easily recovered from the two the two shares transmitted across the network without any complex computation. Secret Image can be either retrieved by printing the shares on transparencies and overlapping them or by performing OR operation on the GA shares.

IV. RESULTS AND DISCUSSION

The proposed method was tested using Java and Matlab code on standard color and gray images of size 512 X 512, such as Lenna, Baboon, Peppers, Cameraman, and Textimage. The result of Phase I of the proposed method is given in Fig. 4
To compare the performance of the proposed method, the same VC images are enhanced with the contemporary enhancement techniques like Histogram Equalization (HE), Recursive Mean Separate Histogram Equalization (RMSHE), Contrast-limited adaptive histogram equalization (CLAHE), Adjust image intensity (AII) using Matlab. The performance of all these methods is measured qualitatively in terms of human visual perception and quantitatively using standard metrics like Average Information Content (Discrete Entropy), Contrast Improvement Index, Histogram, Peak Signal-to-Noise Ratio (PSNR), Universal Quality Index (Q), Number of Edges, Absolute Mean Brightness Error (AMBE), and Image Enhancement Factor (IEF) to confirm the quality of the decrypted image.

The result of phase I is enhanced using GA and the result of enhancement is given in Fig. 5.

A. **Average Information Contents (AIC)**

\[ E = \text{entropy (I)} \]

returns \( E \), the AIC, a scalar value representing the entropy of grayscale image, where a higher value of Entropy signifies richness of the information in the output image [14]. The entropy of the GA enhanced images is 2-3 times more than the original VC (Table I) demonstrating the richness of the enhanced image (Fig.6).
B. Contrast Improvement Index (CII)

The Contrast Improvement Index (CII) is defined by

\[ CI = \frac{C_p}{C_o} \]  

(5)

where \( C_p \) and \( C_o \) are the contrast values of the proposed and original image respectively [15]. The CII value for the proposed GA enhancement is more compared to different types of HE equalization techniques but is less than Adjust image intensity values (Fig. 7).

![Fig. 7 Comparative Analysis of CII](image_url)

C. PSNR

The peak signal-to-noise ratio (PSNR) in decibels is computed between two images. This ratio is repeatedly used as a quality measurement between the original image and the reconstructed image. The higher the PSNR value better is the quality of the reconstructed image. PSNR is most commonly used to measure the quality of enhanced image. PSNR is most easily defined via the MSE [14]

\[ MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i, j) - K(i, j)]^2 \]  

(6)

The PSNR (in dB) is defined as:

\[ PSNR = 20 \log_{10} \left( \frac{Max[I]}{\sqrt{MSE}} \right) \]  

(7)

The PSNR value rises to more than 200 percent for color and gray images due to GA enhancement. While for Binary images, there is no specific increase in the PSNR value. GA enhancement in CMY color space has an edge over RGB as can be seen from Table I and Fig. 8. For the binary textimage, the PSNR value for VC image is 12.973, for image enhanced using GA (RGB) is 13.03 for GA (CMY) enhanced image it is 5.3089. This is because the Binary image has just two values 0 and 1.

![Fig. 8 Comparative Analysis of PSNR](image_url)

D. Histogram

An image histogram is a graphical illustration of the number of pixels in an image as a function of their intensity. An image histogram is an important tool for inspecting images. Technically, the histogram maps Luminance, which is defined by the way the human eye, perceives the brightness of different colors [14]. The histogram for VC image has only 2 intensity values for each color channel and this is the reason for the low contrast. GA enhancement keeps up only 2 intensity for each share, thus after combining has 4 intensities for each color channel as shown in fig.6(g) and hence the contrast improves.
Table I Results of the proposed Method – Comparison of Standard Metrics

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<th>Enhanced Image</th>
<th>PSNR</th>
<th>Entropy</th>
<th>CHI</th>
<th>Q</th>
<th>No. of Edges</th>
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Table I Results of the proposed Method – Comparison of Standard Metrics

E. Structured Similarity Index (Q)

The Universal Image Quality Index (Q) is a quality assessment measure for images, proposed by Zhou Wang et al., [16] and is defined as

\[
Q = \frac{4\sigma_{xy} \mu_x \mu_y}{(\sigma_x^2 + \sigma_y^2)(\mu_x^2 + \mu_y^2)}
\]  

(8)

where \( \mu_x \) and \( \mu_y \), \( \sigma_x \) and \( \sigma_y \), represent the mean and standard deviation of the pixels in the original image (x) and the reconstructed image (y) respectively. \( \sigma_{xy} \) represents the correlation between the original and the reconstructed images. The dynamic range of Q is (-1, 1). Q value is more for GA enhanced color and gray images compared to original VC and it is less with respect to black and white text image and is given in Table I.
F. Edge Detection

The points at which image brightness varies sharply are normally organized into a set of curved line segments termed edges. Edge of the image is one of the most fundamental and significant features. The principle of edge detection is to find out the information about the shapes and the reflectance or transmittance in an image. Sobel operator is used for edge detection using Matlab [14]. Edges increase from 46194 to 59283 using GA in the case of VC for Baboon image. In general, there is an increase in the number of detected edges except in the case of cameraman image, where the number is less for GA enhanced image in RGB space and is given in Fig. 11.

G. Absolute Mean Brightness Error (AMBE)

The proposed method is trying to preserve brightness mean more and more possible by considering the value of absolute mean brightness error (AMBE). AMBE is calculated from the equation below.

\[ \text{AMBE} = |E[Y] - E[X]| \]  

where E [Y] and E[X] are mean of new and original gray level of the image, respectively. Lesser the AMBE value, higher will be the clarity of the image. AMBE is negligible for GA enhancement and is the maximum in CLAHE (Fig. 12).

H. Image Enhancement Factor (IEF)

It is the measure of the image up gradation. IEF is defined as
Where $I_n$ – Noisy Image, $I_o$ – Original Image and $I_e$ – Enhanced Image. The IEF rises to a highest value of 6.91 from 0.76 for baboon image. The comparative analysis is given in Fig. 13.

**Fig. 13 Comparative analysis of IEF**

V. CONCLUSIONS

A novel secret image sharing scheme with Image enhancement is proposed in this chapter. The contrast loss due to pixel expansion in Visual Cryptography is minimized using Genetic Algorithm optimization. The results show that integrity of SI is superior when compared to normal Visual Cryptography. The merit of the proposed technique is verified with the quantitative metrics namely, Contrast Improvement Index, Discrete Entropy, PSNR, Histogram analysis, and Structured Similarity Index. CII denotes the degree of contrast improvement obtained after enhancement. Entropy measure signifies the preservation of original information content in the GA enhanced Image. The qualitative measure, human visual perception also approves the performance of this technique. The computational complexity is very less in this algorithm. It efficiently enhances both color and gray images. Various fitness functions can be included in future to further augment the proposed system.

REFERENCES


