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Zhaoxia WANG
Singapore Management University, zxwang@smu.edu.sg

Haibo PEN

Ting YANG

Quan WANG

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Structure-Priority Image Restoration Through Genetic Algorithm Optimization

ZHAOXIA WANG[1], HAIBO PEN[2], TING YANG[2], AND QUAN WANG[3]

[1]School of Information Systems, Singapore Management University, Singapore 188065
[2]Key Laboratory of Smart Grid of Ministry of Education, Tianjin University, Tianjin 300072, China
[3]Internet FinTech Department, China Banking and Insurance Information Technology Management Company Ltd., Beijing 100144, China

Corresponding authors: Haibo Pen (penhaibo@tju.edu.cn) and Zhaoxia Wang (zxwang@smu.edu.sg)

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ABSTRACT With the significant increase in the use of image information, image restoration has been gaining much attention by researchers. Restoring the structural information as well as the textural information of a damaged image to produce visually plausible restorations is a challenging task. Genetic algorithm (GA) and its variants have been applied in many fields due to their global optimization capabilities. However, the applications of GA to the image restoration domain still remain an emerging discipline. It is still challenging and difficult to restore a damaged image by leveraging GA optimization. To address this problem, this paper proposes a novel GA-based image restoration method that can successfully restore a damaged image. We name it structure-priority image restoration through GA optimization. The main idea is to convert an image restoration task into an optimization problem, and to develop a GA optimization algorithm to solve it. In this study, the structural information of a damaged image, which is represented by curves or lines (COLs), is prioritized to be repaired first. The structural information is classified into relevant and irrelevant information according to the information of their locations. The relevant information is analyzed through the proposed GA optimization algorithm to find the matched COLs. The matched COLs are used to restore the structural information of the damaged area. The textural information will then be restored according to the different partitions separated by the restored structural information. Lastly, through case studies, we evaluate the proposed method by using four typical indices to measure the differences between the original and restored image. The results of case studies demonstrate the applicability and feasibility of the proposed method.

INDEX TERMS Genetic algorithm, image processing, image restoration, relevant information, structure-priority, textural information, curves or lines (COLs).

I. INTRODUCTION

With the advent of social networking platforms, more and more people are sharing their thoughts about products or services by posting text messages, images, audio or video files [1]. Vision is the most advanced human sense [2], as a result, as social media data accumulates, it is not surprising that images play an important role and have become a more and more popular form of data on the Internet. With the significant increase in the use of images over the Internet, image processing and analysis have been gaining much research attention in the transportation, medical, aerospace, energy and other fields [3]–[6].

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As an important carrier of information, on the one hand, missing parts of the images (damaged images) may lead to serious consequences in these fields. On the other hand, there is also great significance to be able to recover the original state of the damaged images in the fields of painting, sculpting, architecture, etc. Digital image inpainting, which can fill in the damaged region caused by human or non-human factors, is a challenging and very important branch of image processing, and different techniques have been applied to various types of damaged image restoration tasks [7]–[9]. In this paper, for the damaged image with structural information, an image inpainting method based on evolutionary algorithm is proposed.

Generally, there are three categories of inpainting methods: diffusion-based techniques, sparse-based techniques and exemplar-based techniques. The most representative model of the diffusion-based approach is the Total Variation (TV) model and it works well for small-size local restoration [10], [11]. But its effectiveness is limited when there is complex structural information in the damaged areas [12], [13]. The image sparse representation has also been introduced to image inpainting problems. Fadili *et al.* and Zhang *et al.* proposed different methods making use of sparse representations over a redundant dictionary to address the problem of image inpainting [14], [15]. However, sparse representation image inpainting methods may fail to recover the structure when filling large missing regions. The other widely used inpainting technique is the exemplar-based method [16]. They either work at the pixel level or at the patch level [17]. These techniques are good for textured and large missing regions, but they may sometimes produce visually inconsistent results. Another previously devised image inpainting method leverages self-organizing maps (SOM) and proposes a multilayer image-restoration approach, in which an image is separated into several layers and the damaged area in each layer is restored respectively [18]. Compared with the most representative TV model, the merits of the SOM-based method have been demonstrated using case studies [18], but the method faces challenges in restoring the structural information of a larger damaged area [18].

In the image processing domain, due to the fact that an image is a combination of discrete points, the applications of intelligent optimization methods still remain an emerging discipline in this field. These optimization methods and their variants are usually used in continuous decision variables optimization problems, such as in Khatir *et al.* [19], Khatir and Abdel Wahab [20]. They introduced the swarm optimization method and the eXtended isoGeometric analysis method to detect and locate cracks within different scenarios. Tiachacht *et al.* [21] also used genetic algorithm for damage identification and quantification in 2D and 3D structures. Rashid *et al.* [22] introduced an enhanced genetic algorithm for ab initio protein structure prediction.

Although the image is a discrete variable, some researchers have also carried out preliminary exploration on the application of optimization algorithm to the image field, and achieving good results. Khan *et al.* [23] used genetic algorithm as part of image classification of apple diseases. In the presented method, genetic algorithm is designed to select the best image feature. In addition, there has been research in other optimization methods, such as the cuckoo search algorithm, BAT algorithm and TLBO algorithm [24], [25], but they have not been applied to image restoration. In the presented method, genetic algorithm is designed to select the best image feature. Wang *et al.* [26] introduced evolutionary algorithm into the process of image inpainting to fit image contour curve. However, the paper only proposed the idea, and did not realize and fully analyze the algorithm. In this paper, we address the problem of damaged image restoration by leveraging the advantages of the global optimization capabilities of genetic algorithm (GA). A method based on GA is proposed to realize damaged image restoration.

The main contributions of this paper are summarized as follows:

(1) Main algorithm: We propose a novel image restoration method that combines genetic algorithm with patch-based inpainting method to solve the problem of missing large area information in images.

(2) Restoration model: In the structure restoration process, we convert an image-restoration task into an optimization problem. The brightness of the relevant area and the matching difference of the i_{th} pair of COLs are leveraged to optimize the structural information to find the relevant COLs in the source area which would then be used to restore the structural information of the damaged area.

(3) Filling order and search space: The waiting-for-inpainting patch filling order is dependent on precedence values which are computed by the priority value described in this paper. Multiple pairs of matched COLs divide the damaged area into several partitions, following this, the textural information is restored according to these different partitions. In this way, we can reduce the search space of the repair process.

This paper is organized as follows. Section I discusses the related works. In Section II, an overview of the proposed algorithm is presented and the main content in our inpainting algorithm is introduced including structural information extraction, matching of relevant COLs, restoration of structural information of damaged area, and repair of damaged region. In Section III, the final experiments of our proposed method and some other state-of-the-art techniques are presented, and the restored results are compared by using subjective visual judgment and four most widely used image quantitative evaluation indices including PSNR, FSIM, SR_SIM, and VSI. Lastly, we conclude our work in Section IV.

II. STRUCTURE-PRIORITY IMAGE-RESTORATION METHOD THROUGH GA

A. THE PRINCIPLE AND HIGH-LEVEL DESIGN OF THE PROPOSED METHOD

The principle of the proposed method is illustrated in Fig. 1. We consider the structural information of the pictures as represented by COLs. Fig. 1(a) shows an original image in which the COLs divide the image into several partitions (A, B, C, D, E and F). Fig. 1(b) shows the damaged image and Fig. 1(c) shows the damaged image with the structural information restored in the damaged area. Fig. 1(d) shows the restored image. As shown in Fig. 1 (a)-(c), some of the COLs are related to the damaged area of the image, while others are not. For example, the COL1 and COL5 in Fig. 1 are both irrelevant to the damaged area. We named these COLs ‘‘irrelevant structural information’’. Some of the COLs are connected to the damaged area, such as COL2, COL3 and COL4 as shown in Fig. 1(b)-(c). These COLs are named

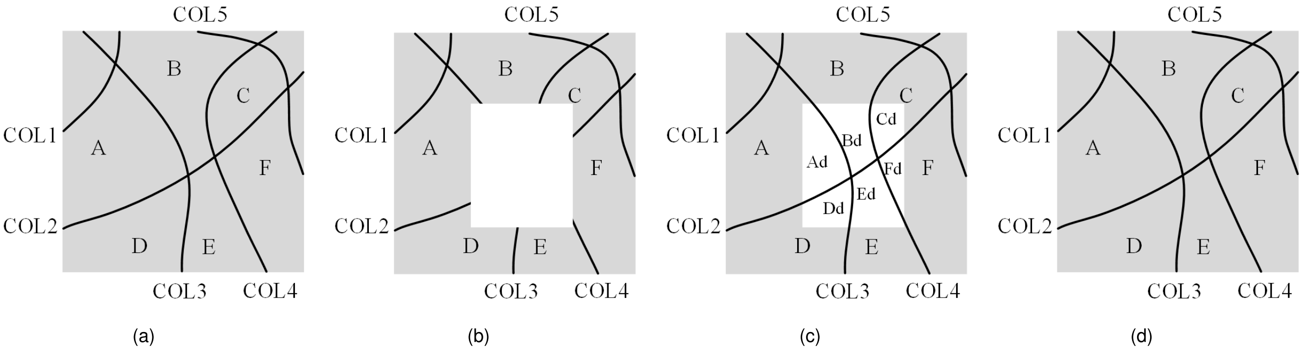


FIGURE 1. **Illustration of the principle of the proposed method. (a) original image, (b) damaged image, (c) the structural information has been restored, (d) the textural information has been restored.**

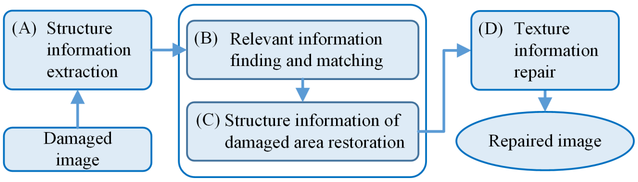


FIGURE 2. **The layout of the proposed scheme. Module (A): structural information extraction; Module (B): relevant structural information finding and matching through GA optimization; Module (C): structural information of damaged area restoration; Module (D): textural information restoration.**

"relevant COLs". The relevant COLs are used to find the matched COLs to restore the damaged structural information. When the structural information is restored, the damaged area will be divided into several partitions (Ad, Bd, Cd, Dd, Ed and Fd) by the restored structure COLs as shown in Fig. 1(c).

The layout of the proposed scheme is shown in Fig. 2. The main scheme includes four modules: Module (A), Structural information extraction; Module (B), Relevant structural information finding and matching; Module (C), Structural information of damaged area restoration; Module (D), Textural information repair.

In Module (A), all the existing structural information of the damaged image is obtained as shown in Fig. 1 (e.g. COL1, COL2, COL3, COL4 and COL5). Module (B) performs relevant information finding and matching through GA optimization. The matched information will be used to restore the structural information in Module (C). After the structural information is restored as shown in Fig. 1(c), the textural information will be repaired in module (D). Since the structural information separates the image into several relatively independent partitions as shown in Fig. 1(c) (Ad, Bd, Cd, Ed and Fd areas), different partitions can be repaired independently and in parallel.

B. STRUCTURAL INFORMATION EXTRACTION

The structural information which is presented by many COLs as shown in Fig. 1 can be extracted using edge detection method [26], [27].

Z_5	Z_2	Z_3
Z_4	Z_1	Z_6
Z_7	Z_8	Z_9

FIGURE 3. **The illustration of connection between the pixels.**

Assuming function $f(x, y)$ represents a grayscale image, we can calculate the gradient of $f(x, y)$ by using the following equation:

$$\nabla f(x, y) = \begin{bmatrix} f_x \\ f_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \tag{1}$$

An image can be described as a lot of pixels that connect to each other directly or indirectly as shown in Fig. 3: Z_1 is connected with 8 other pixels ($Z_2, Z_3, \cdots, Z_9$).

In other words, a digital image can be considered as a discrete binary function, whose coordinates have been rotated 90 degrees clockwise. So the gradient at the location of Z_1 can be calculated simply as follow:

$$\begin{cases} G_x = (Z_7 + 2Z_8 + Z_9) - (Z_5 + 2Z_2 + Z_3) \\ G_y = (Z_3 + 2Z_6 + Z_9) - (Z_5 + 2Z_4 + Z_7) \end{cases} \tag{2}$$

The location of the structural information in the image can be obtained by calculating the value of the modular of the gradient:

$$\|\nabla f(x, y)\| = \sqrt{(f_x)^2 + (f_y)^2} = \sqrt{(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial y})^2} \tag{3}$$

Among the existing edge detection algorithms, the Canny edge detection still has high precision performance. Canny also proposed an edge detection method to reduce noise using a Gaussian filter:

$$G(x, y) = -\exp^{-\frac{x^2+y^2}{2\sigma^2}} \tag{4}$$

where σ is the standard deviation of the Gaussian distribution.

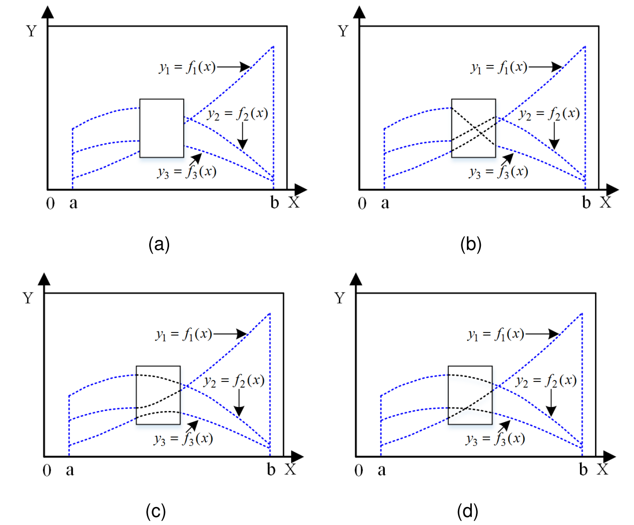


FIGURE 4. **An example illustration of matching COLs: (a) damaged image with the relevant COLs; (b) damaged image with unmatched connection; (c) damaged image with another unmatched connection; (d) damaged area with structural information restored in the damaged area (matched connection).**

The modified image function $g(x, y)$ is obtained by convolving the original image function $f(x, y)$ with the Gaussian function:

$$g(x, y) = G(x, y) * f(x, y) \tag{5}$$

where $*$ is mathematical convolution operator. In this paper, the above Canny method is leveraged to extract the raw structural information.

C. FINDING THE MATCHED INFORMATION AND RESTORING STRUCTURAL INFORMATION BY USING GA OPTIMIZATION

1) PROBLEM DESCRIPTION

We assume that the original image structure is in harmony and conformity with the principle of smoothness. The connections between source areas and damaged areas should be in harmony and have no significant difference as illustrated in Fig. 4.

Figs. 4(a)-(d) show matched and unmatched connections between the relevant COLs. Fig. 4(a) illustrates the damaged area and the relevant structural information (COLs). Fig. 4(b) and (c) illustrate two unmatched connections and Fig. 4(d) shows the matched structural information restoration.

The COLs in the damaged area are missing as shown in Fig. 4(a), and we can restore them by analyzing the relationship between different relevant COLs in the source areas. Figs. 4(b) and (c) show that the connections are not matched well to each other based on certain measures of matching difference to be described later. The connections, which connect the COLs to restore the structural information in damaged areas, should be matched well and the damages should not be detectable by human's eyes after restoration as shown in Fig. 4(d). In order to compute and match the relevant COLs, two matching rules are also proposed:

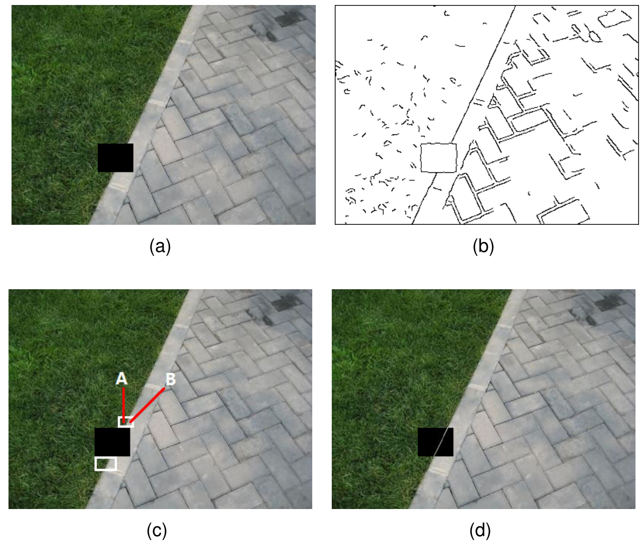


FIGURE 5. **Extracting the relevant COLs and relevant pixels.**

- Rule 1: The number of matched COLs is as large as possible.
- Rule 2: The matching difference between each pair of matched COLs should be as small as possible.

In addition, we adopt two assumptions for considering the applicability of the proposed method:

- There must exist at least one pair of COLs.
- To be considered for a potential matched COL pair, the two COLs must have the possibility of connecting within the damaged area.

It is important to describe the process for converting the problem of the restoration of the damaged image to an optimization problem clearly. A detailed description of the GA optimization solution for restoring structural information is given in this section through a simple example as shown in Fig. 5.

For a damaged image as shown in Fig. 5(a), the damaged area, marked in black, will inevitably form edges that are contours of the damaged area as shown in Fig. 5(b). There are some contours that do not belong to the original image, and we classify them as irrelevant COLs. When the irrelevant COLs are not considered, Fig. 5(c) shows the relevant COLs of the image. We call the pixels that connect the relevant COLs of the source area and that of the damaged area ''relevant pixels'', which are located in the white rectangles as shown in Fig. 5(c). The area of relevant pixels is extracted from the source area of the image and they are connected to the damaged area as shown [26].

One of the relevant COLs can divide the area of relevant pixels into two parts, A and B, as shown in Fig. 5(c). The area of relevant pixels is called the relevant area (such as relevant area A and relevant area B as shown in Fig. 5(c)). We call all the relevant COLs, relevant pixels and relevant area ''relevant information''. This ''relevant information'' is used and analyzed through GA optimization to find the matched COLs and to restore the damaged or missing structural information. Fig. 5(d) shows that structural information has been restored in the damaged area.

The previously mentioned matching difference refers to the difference in the relevant information. Using relevant area A as shown in Fig. 5(c) as a case for analysis, if Z_i represents the brightness value of the i_{th} pixel in the relevant area A of a relevant COL, the average/mean brightness of the relevant area about the relevant COL is:

$$b(A) = \sum_{i=1}^{L} Z_i p(Z_i) \tag{6}$$

where L represents the total number of pixels in the relevant area A; $p(Z_i)$ indicates the proportion of brightness value of the i_{th} pixel in the relevant area A.

An RGB image can be regarded as a collection of 3-dimensional matrices. The value of each pixel according to RGB color component, Red, Green, and Blue are $[x_1, x_2, x_3]$, $x_i \in [0, 255]$, which represents the brightness of the pixel. The pixels with different brightness in area A contribute differently to the average brightness of the selected area A. The brighter pixels contribute more than the less-bright pixels. $p(Z_i)$ can be obtained by the following equation:

$$p(Z_i) = Z_i / \sum_{i=1}^{L} Z_i \tag{7}$$

The relevant information (e.g., COLs and relevant pixels in the relevant area A) is the key element used to find the matched COLs to restore the damaged structural information.

2) DESIGNING THE OBJECTIVE FUNCTION FOR GA ACCORDING TO THE PROBLEM DESCRIPTION

In this paper, a curve fitting method [28] is leveraged to support the design of the objective function of GA. The objective function is designed to find the matched COLs which are used to restore the structural information in the damaged area of the image. The curve fitting method in this section is used to construct the COLs, or mathematical function, which has the best fit to a series of data points, possibly subject to constraints. The curve fitting method can involve either interpolation, where an exact fit to the data is required, or smoothing, in which a ''smooth'' function is constructed that approximately fits the data.

For any COL, $y_i = f_i(x)$ as shown in Fig. 4, its curvature at any point x can be calculated by the following:

$$K_i(x) = \frac{|y_i''|}{(1 + y_i'^2)^{\frac{3}{2}}} \tag{8}$$

The mean rate of absolute change of $K_i(x)$ is:

$$\overline{K} = \frac{1}{b-a} \int_a^b \left| \frac{dK_i(x)}{dx} \right| dx \tag{9}$$

where a and b represent the lower and upper limit of the independent variable x respectively. The optimization objective function g is designed using the following equation accordingly:

$$g = \frac{\beta + \sum_{i=1}^{M} D_i}{M} \tag{10}$$

where β represents a matching threshold, which is designed to prevent the objective function from becoming 0, similar to one of the ways that this issue is handled in the Laplace Smoothing method, where a ''1'' is added to the numerator to prevent the numerator from becoming ''0''. We choose $\beta = 1.2$ in this paper. M is the number of the pairs of connected COLs; D_i represents the matching difference of the i_{th} pair of COLs. D_i can be obtained by the following equation:

$$D_i = \overline{K_i} + \Delta b_i \tag{11}$$

where Δb_i is the difference of the mean brightness of the relevant areas (e.g. relevant area A and relevant area B as shown in Fig. 5(c)) of the i_{th} pair of connected COLs. If the i_{th} pair of connected COLs includes the i_1 and i_2 COLs, Δb_i can be obtained as follows:

$$\Delta b_i = |b_{i1}(A) - b_{i2}(A)| + |b_{i1}(B) - b_{i2}(B)| \tag{12}$$

where $b_{ik}(A)$ and $b_{ik}(B)$ $(k = 1, 2)$ represent the mean brightness of the related areas A and B of the i_{th} relevant COLs, as discussed in the subsection II-C-1) (Fig. 5(d)). According to equations (10) and (11), the new matching difference D_{i+1} should satisfy the following:

$$D_{i+1} < \frac{\beta + \sum_{i=1}^{M} D_i}{M} \tag{13}$$

3) GA ENCODING AND DECODING MECHANISMS

In the process of GA, each solution must be encoded into a string of numbers, which is called a chromosome. Each number in a chromosome is called a gene. Given that there are N relevant COLs, the problem is to find which ones of them should be matched. In this paper, we create a chromosome, which has N genes. The first $(N-1)_{th}$ genes represent an arrangement of the N COLs, and the N_{th} gene represents the number of pairs of COLs to be matched.

The GA is an iterative process which simulates the evolution of biological survival, in which one of the key steps is how to design and evaluate fitness function of each chromosome. Generally, the fitness function is connected to the objective function. The fitness function is obtained using the objective function.

The fitness function proposed in this paper is different from that of the general EA's or GA's. Generally, the fitness function is a non-negative value calculated directly by using the objective function. However, such fitness function may give rise to locally optimal solution rather than globally optimal solution. Therefore, to effectively control the genetic ranges or selections to ensure the globally optimal solution, we proposed new fitness function in this paper. The fitness of the individual in the population is determined by the position of the individual in the ranking sequence, and the position of the individual is determined by its objective function. That is, objective function → position → fitness of the individuals.

All the individuals in the population are numbered or ranked according to their objective function values. The largest is ranked as the first one and the smallest is ranked as the last one, such as: $\{\max(g), \cdots, g(x_i), \cdots, \min(g)\}$. The target is to minimize the objective function: $\min(g)$. When the objective function is the minimum, the fitness is the maximum. The smaller the objective function is, the larger the fitness function will be. It means that the fitness function is inversely proportional to the objective function: $\max(f) \rightarrow 1/\min(g)$. Based on the above analysis, we defined the fitness function to be:

$$f(x) = 2 - max(f) + 2(max(f) - 1)\frac{N_x - 1}{N_{ind} - 1} \tag{14}$$

where N_{ind} is the number of chromosomes. The chromosomes are placed in a descending order according to their objective function value obtained from equation 14, and N_x is the sequence number of the chromosome x. $max(f)$ indicates the maximum value of the fitness function. The higher the value of the fitness of a chromosome, the greater its genetic probability (the probability of the chromosome's gene being selected for retention). Therefore, if the objective function of a certain individual x is the smallest in the population,$min(f)$, its position in the sequence will be the last one. In such a situation, $N_x = N_{ind}$, and then according to equation 14, the maximum value of the fitness function will be obtained as: $f(x) = \max(f) = 1/\min(g)$.

In a generation, several chromosomes will be selected to be inherited to the next generation according to their genetic probability. Before selection, some chromosomes may have mutated, i.e., a gene of a chromosome changes individually with a very small probability, and some pairs of chromosomes may exchange parts of their genes. These two processes make the solution space large enough to prevent the process from falling into local optima.

After enough generations of evolution, the chromosomes which have enough fitness will be found. So, we can obtain the best matching relevant COLs to restore the structural information of the damaged image. In the process of repairing part of the best matching relevant COLs, a uniformly progressive point by point repair strategy is adopted in this paper, and the repair effect is shown in Fig. 5(d). The whole procedure of the matching COLs method based on genetic algorithm is shown in Fig. 6.

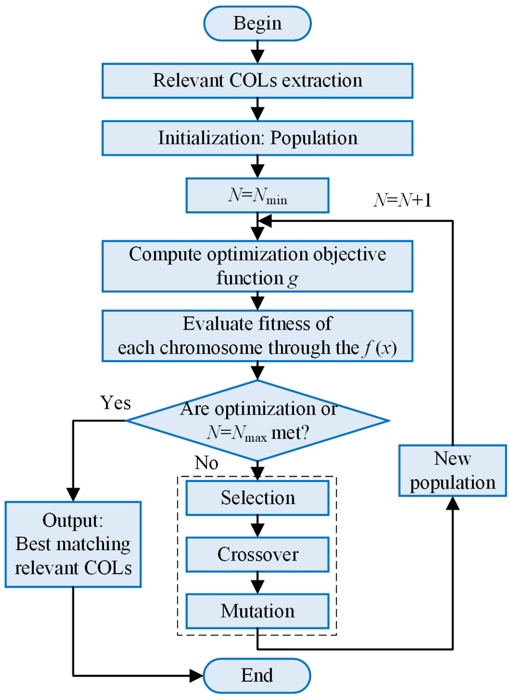


FIGURE 6. Genetic algorithm procedure for matched COLs.

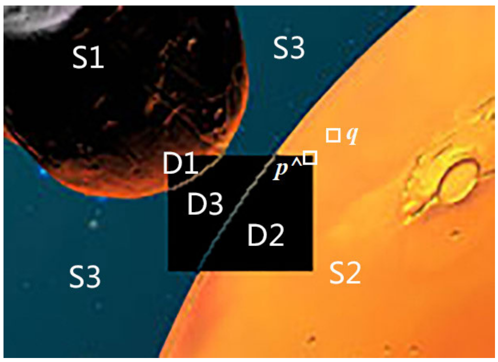


FIGURE 7. Black regions D1, D2, D3 are waiting for being inpainted. p^ represents the initial point determined by highest priority in D2.

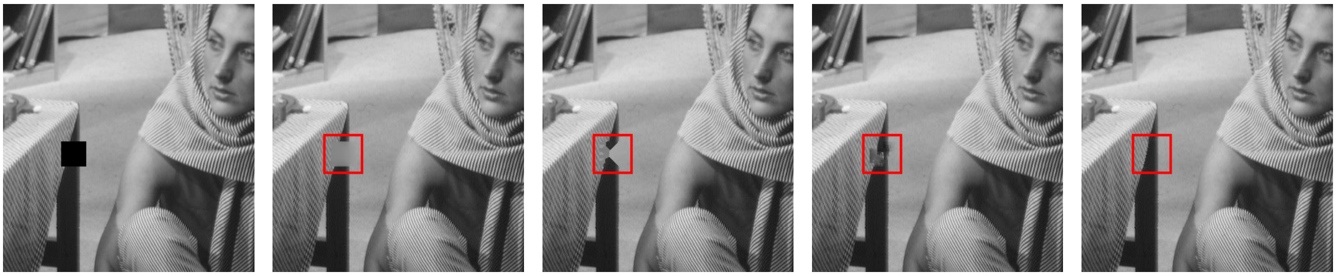
D. RESTORING DAMAGED TEXTURAL INFORMATION

The best matching relevant COLs are obtained as shown in Fig. 7 with another example. The image includes the damaged area (D) and the source area (S). The damaged area (D) is divided into several parts (D1-D3) by the COLs after the structural information is restored. As shown in Fig. 7, the two pairs of connected matching COLs obtained divide the image into three partitions(S1 + D1, S2 + D2, and S3 + D3), and each partition includes two parts: damaged parts (D1 to D3) and source parts (S1 to S3).

In order to improve the efficiency of the proposed method, each partition can be restored independently and in parallel. During the process of restoring images, patches along the fill front are also given a priority value, which determines the filling order. The procedure iterates the following two steps until all pixels have been filled:

1) CALCULATING THE PATCH PRIORITY

In the border-first patch method, the damaged areas connected to the border will be filled first as shown in Fig. 7. We need to consider both the structural information and the textural information. If the patch is too small, it is time consuming to fill a large missing region. If the patch size is too large,



(a) (b) (c) (d) (e)

FIGURE 8. Case 1: a grayscale image of *barbara*. (a) the damaged image, (b) inpainting result of the TV method, (c) inpainting result of previous SOM based method, (d) inpainting result of the pLSA method, (e) inpainting result of the novel proposed method.

(a) (b) (c) (d) (e)

FIGURE 9. Case 2: a grayscale image of *lena*. (a) the damaged image, (b) inpainting result of the TV method, (c) inpainting result of previous SOM based method, (d) inpainting result of the pLSA method, (e) inpainting result of the novel proposed method.

(a) (b) (c) (d) (e)

FIGURE 10. Case 3: a color image of *path*. (a) the damaged image, (b) inpainting result of the TV method, (c) inpainting result of previous SOM based method, (d) inpainting result of the pLSA method, (e) inpainting result of the novel proposed method.

the texture may not be reconstructed correctly. Therefore, taking both the structural and the textural information into consideration simultaneously, we select a patch with a smaller size of 2×2.

For the proposed method, the most important thing is to decide the priority by which the damaged pixels are inpainted first. The priority of a patch is based on the number of the source pixels within the patch $\Psi_{p^\wedge}$. The priority value $P(p)$ of patch $\Psi_{p^\wedge}$ is defined and calculated by the following mathematical equation:

$$P(p) = \max\{(nS(p))\} \tag{15}$$

where, $nS(p)$ is the number of the source pixels within the patch $\Psi_{p^\wedge}$ in source region(S).

2) INPAINTING TEXTURAL INFORMATION

After the patch $\Psi_{p^\wedge}$ in Fig. 7 with the highest priority is calculated, it will be filled with the textural information extracted from the source region, such as S1, S2 and S3. After the patch $\Psi_{p^\wedge}$, which has the highest priority value, is obtained, next, the inpainting procedure will search the source region to find the most similar patch to the patch $\Psi_{p^\wedge}$ by the following equation:

$$\Psi_{q^\wedge} = \min_{\Psi_q \in D}\{d(\Psi_{p^\wedge}, \Psi_q)\} \tag{16}$$

where, $d(p, q)$ represents the distance between two generic patches p and q. It is obtained as the sum of squared differences between the two patches. Then, the corresponding position value of each pixel will be replaced.

This inpainting process copies the textural information from the source region (S) to the target region (D). After the patches $\Psi_{p^\wedge}$ have been replaced by new pixel values, the priorities of the unfilled pixels are updated, and then the new $\Psi_{p^\wedge}$ with the highest priority is calculated and repaired. After the textural information is filled into all the damaged parts, we will finally obtain the restored image.

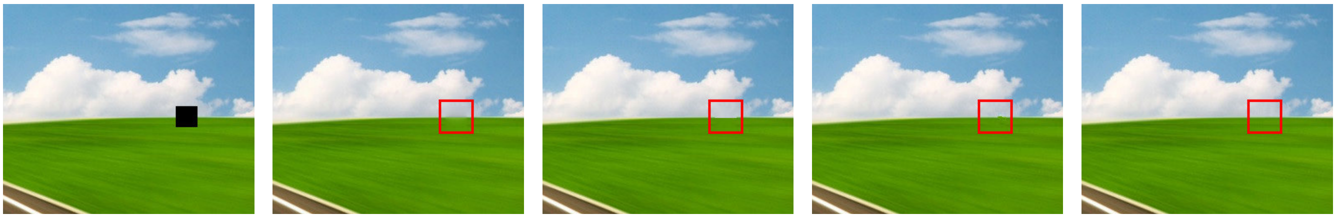

(a) (b) (c) (d) (e)

FIGURE 11. Case 4: a color image of *grassland*. (a) the damaged image, (b) inpainting result of the TV method, (c) inpainting result of previous SOM based method, (d) inpainting result of the pLSA method, (e) inpainting result of the novel proposed method.


(a) (b) (c) (d) (e)

FIGURE 12. Case 5: a color image of *mountain*. (a) the damaged image, (b) inpainting result of the TV method, (c) inpainting result of previous SOM based method, (d) inpainting result of the pLSA method, (e) inpainting result of the novel proposed method.

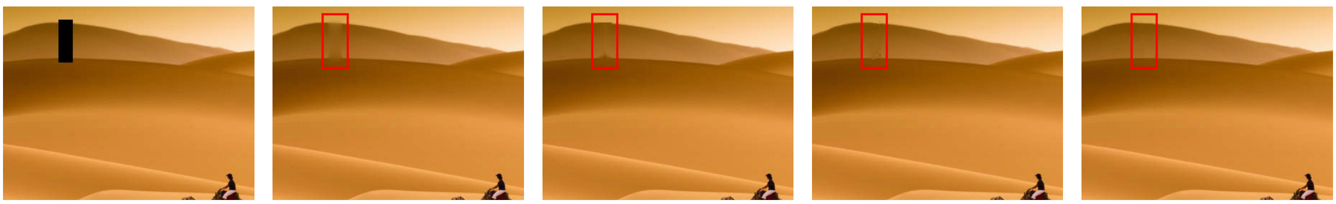

(a) (b) (c) (d) (e)

FIGURE 13. Case 6: a color image of *desert*. (a) the damaged image, (b) inpainting result of the TV method, (c) inpainting result of previous SOM based method, (d) inpainting result of the pLSA method, (e) inpainting result of the novel proposed method.

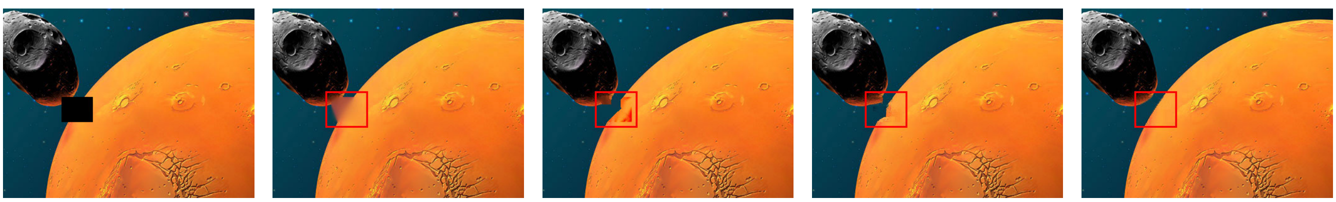

(a) (b) (c) (d) (e)

FIGURE 14. Case 7: a color image of *planet*. (a) the damaged image, (b) inpainting result of the TV method, (c) inpainting result of previous SOM based method, (d) inpainting result of the pLSA method, (e) inpainting result of the novel proposed method.

III. EXPERIMENTAL RESULTS AND DISCUSSION

In all of the experiments, we tested our proposed image restoration algorithm on a variety of natural images. Image dimensions are 512×512, 400×500, and so on. The specific position of each damaged patch was placed at multiple curve contours. All experiments were implemented with MATLAB codes on a PC equipped with 2.2-GHz Pentium and 1 GB RAM. In the meantime, the following genetic parameters were chosen: population size = 20, crossover rate = 0.3, mutation rate = 0.07/number of COLs and iterations = 100.

In this section, the proposed method is used to inpaint different images which include grayscale images as well as full-color photographs. The latter are complex in texture and structure. We have taken eight images, namely ***barbara***, ***lena***, ***path***, ***grassland***, ***mountain***, ***desert***, ***planet*** and ***swan*** of different sizes covered with different black blocks. For all the eight Cases, we compare our proposed method with other state of the art methods such as the TV method and the previous SOM based method. In all the figures of the different Cases studied below, (a) is the damaged picture, (b) is the image resulting from using the TV method in [13], (c) is the

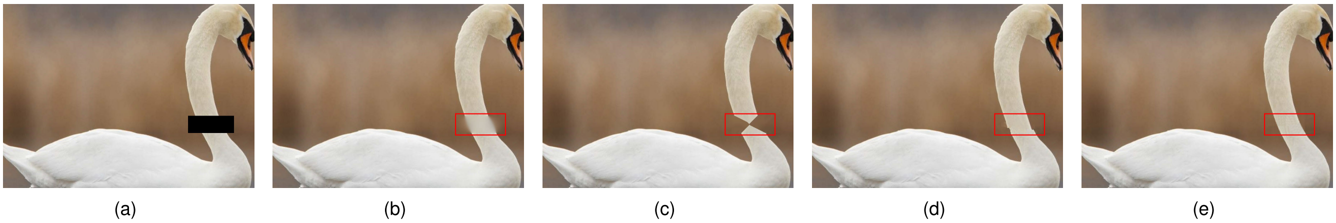


FIGURE 15. **Case 8: a color image of a *swan*. (a) the damaged image, (b) inpainting result of the TV method, (c) inpainting result of previous SOM based method, (d) inpainting result of the pLSA method, (e) inpainting result of the novel proposed method.**

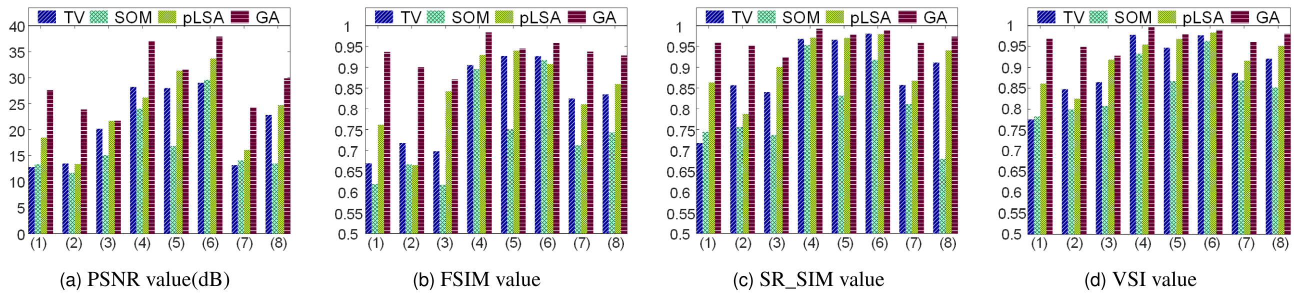


FIGURE 16. **Different quantitative evaluation methods.**

image resulting from using the previous SOM based method in [18], (d) is the image resulting from using the exemplar-based method in [17], and (e) is the image resulting from using the novel method proposed in this paper. It can be seen that (e) is always the best result.

A. SUBJECTIVE VISUAL EVALUATION

The results on two grayscale images are shown in Fig. 8 (Case 1) and Fig. 9 (Case 2). The images used in Fig. 8 and Fig. 9 have dimensions 512×512. The traces of damaged parts can still be seen in the repaired image that was repaired by the other methods highlighted in red rectangle, while no traces of the damaged parts can be seen in the image repaired by our proposed method. In addition, the curved contour part of the restored image is very smooth.

Six full-color photographs which are prominent in texture and structure were also tested as well, and the results are shown in Figs. 10 (Case 3) to 15 (Case 8). For these Cases, the traces of the damaged regions can still be seen easily as shown in Figs. 10- 15 (highlighted in red rectangles) which are images repaired by the other methods, while the human eye cannot discern any trace of the damaged parts in the images repaired by our novel proposed method, as shown in Figs. 10- 15(e). Meanwhile, the curved contour sections of the images repaired by the proposed method look perfectly smooth.

In all of the Cases, it can be observed that certain damaged regions of the image, especially the structural information, could not be restored by the previous SOM method due to the fact that the algorithm is more suitable for scratch removal. The results in all of the Cases demonstrate the ability of our proposed method to inpaint both texture and structure better than the other methods proposed in [13], [18] and [17].

TABLE 1. **Image similarities based on PSNR value with different methods.**

Case example with image format and image names	Methods			
	TV method	previous SOM based method	Exemplar -based method	Novel proposed GA method
Case 1: a grayscale image-**barbara**	12.8263	13.3814	18.4691	27.6043
Case 2: a grayscale image-**lena**	13.4867	11.6976	13.3898	23.8895
Case 3: a colorful photograph-**path**	20.1791	15.1221	21.7176	21.7481
Case 4: a colorful photograph-**grassland**	28.2317	24.0594	26.2036	37.0491
Case 5: a colorful photograph-**mountain**	28.0167	16.8315	31.3752	31.5466
Case 6: a colorful photograph-**desert**	29.0226	29.6020	33.7168	37.9349
Case 7: a colorful photograph-**planet**	13.1800	14.0839	16.0989	24.3226
Case 8: a colorful photograph-**swan**	22.8492	13.4960	24.7022	29.8879
Average performance	**20.9740**	**17.2842**	**23.2091**	**29.2479**

B. QUANTITATIVE EVALUATION

In order to further demonstrate the block recovery effectiveness of the proposed method, we compare the similarity between the original images and the images repaired by the proposed method and other methods. As one of the most widely applied methods to compute image similarity, the Peak Signal to Noise Ratio (PSNR)(dB) [29] is selected as the similarity evaluation method in this paper. The PSNR

TABLE 2. Image similarities value with different methods.

Case example with image format and image names	Evaluation methods											
	FSIM value				SR_SIM value				VSI value			
	TV	SOM	pLSA	GA	TV	SOM	pLSA	GA	TV	SOM	pLSA	GA
Case 1: **barbara**	0.6689	0.6186	0.7617	0.9368	0.7174	0.7449	0.8634	0.9589	0.7754	0.7824	0.8613	0.9686
Case 2: **lena**	0.7170	0.6667	0.6645	0.9000	0.8568	0.7563	0.7878	0.9528	0.8479	0.7993	0.8249	0.9491
Case 3: **path**	0.6980	0.6174	0.8421	0.8709	0.8399	0.7369	0.9005	0.9244	0.8646	0.8076	0.9187	0.9282
Case 4: **grassland**	0.9053	0.8957	0.9296	0.9843	0.9682	0.9539	0.9713	0.9929	0.9782	0.9330	0.9550	0.9961
Case 5: **mountain**	0.9270	0.7508	0.9401	0.9451	0.9662	0.8319	0.9710	0.9782	0.9473	0.8671	0.9682	0.9802
Case 6: **desert**	0.9268	0.9172	0.9075	0.9583	0.9810	0.9181	0.9797	0.9892	0.9770	0.9636	0.9835	0.9899
Case 7: **planet**	0.8250	0.7127	0.8106	0.9376	0.8573	0.8112	0.8678	0.9588	0.8868	0.8684	0.9159	0.9619
Case 8: **swan**	0.8349	0.7432	0.8594	0.9284	0.9115	0.6797	0.9406	0.9741	0.9208	0.8521	0.9515	0.9808
Average performance	**0.8129**	**0.7403**	**0.8394**	**0.9327**	**0.8873**	**0.8041**	**0.9103**	**0.9662**	**0.8997**	**0.8592**	**0.9224**	**0.9693**

between the two images is defined as:

$$PSNR(I_1, I_2) = 10 \times \log_{10}\left(\frac{255^2}{MSE}\right)dB \quad (17)$$

$$MSE(I_1, I_2) = \frac{1}{m \times n}\sum_{j=1}^{m}\sum_{k=1}^{n}[I_1(j,k) - I_2(j,k)]^2 \quad (18)$$

where, I_1 and I_2 are the two images to be compared. In this paper, they are the original image and inpainted image, respectively. MSE is the mean squared error. m and n denote the sizes of the two images to be compared.

The quality scores, PSNR values, for black block recovery of an image for different methods, are shown in Fig. 16 and Table. 1.

From Table 1, we can see that our proposed method gets higher PSNR values than the methods proposed in [13], [17] and [18]. Furthermore, the mean PSNR of 29.2479 by the proposed method is much higher than that of the other three approaches. In addition, we also calculated some other image quantitative evaluation indices including FSIM [30], SR_SIM [31], and VSI [32]. In the above image quantitative evaluation indices, the output values fall in the interval (0, 1] and it equals 1 when comparing between two images that are exactly the same. The corresponding values of these measures for different methods are shown in Table. 2.

As shown in Fig. 16 as well as Table. 2, it can be seen that the performance of the novel proposed method is always better than the TV method, the previous SOM based method and the exemplar-based method for different image cases. The mean FSIM, SR_SIM, VSI of 0.9327, 0.9662, 0.9693 by the proposed method is much higher than that of the other three approaches. These results demonstrate the effectiveness and robustness of the proposed method and it can be applied to any format of images. The results of four kinds of similarity comparison methods are also consistent with the subjective visual evaluation of Section III-A-namely that our proposed method has the best performance.

IV. CONCLUSION AND FUTURE WORKS

We developed a novel image-restoration method through GA optimization. The efficiency of the method was demonstrated by using eight case studies. The case studies showed the usefulness and superiority of the proposed method which can be used to restore large areas of damaged images. The proposed method currently is limited to the restoration of a damaged image in which there is obvious structural information missing.

Despite such an assumption, the proposed method offers new ideas for applying GA to the image-processing domains as well as to other applications in which the problem can be converted to an optimization problem. The research in this paper demonstrates the viability and applicability of the proposed method. In the future, more elaborate analyses and discussions are needed to fully demonstrate the value that the method can generate in the image-processing domains. Based on the proposed method in this paper, further development of the image restoration implementation software for damaged images with irregular edges/shapes in real-life situations will also be part of future work.

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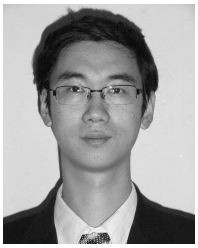
ZHAOXIA WANG was a Scientist, a Senior Scientist, and a Programme Manager with the Institute of High Performance Computing (IHPC), Agency for Science, Technology and Research (A*STAR), Singapore, from 2011 to 2019. She is currently an Associate Professor with the School of Information System, Singapore Management University, Singapore. She has published more than 60 articles published in international journals and conferences. While at IHPC, she spearheaded the development of over five quality IPs as the first inventor and more than ten companies have signed evaluation licenses or commercial licenses on her patents. Her research interests include natural language processing (NLP), natural language understanding (NLU), machine learning, image processing, deep language understanding, intelligent robots, casual reasoning, language understanding, text mining, fine-grained sentiment and emotion analysis, social media content mining and analysis, safety and risk analysis, artificial intelligence (AI), computational intelligence (CI), and their applications. She was awarded the Adjunct Professorship of Tianjin University, in 2015, and the Nanjing University of Information Science and Technology, in 2018.

HAIBO PEN received the Ph.D. degree in electrical engineering from Tianjin University, Tianjin, China, in 2018. He is currently an Assistant Professor with the School of Electrical and Information Engineering, Tianjin University. His research interests include intelligent optimization algorithm, data analysis, and data mining.

TING YANG is currently a Professor of electrical engineering with Tianjin University, China. He is the author/co-author of four books and more than 80 publications in technical journals and conferences. His research interests include intelligent optimization algorithm, communication, intelligent control, and data mining and processing. He is a member of the International Society for Industry and Applied Mathematics (SIAM), a Senior Member of the Chinese Institute of Electronic, and a Committee Member of Electronic Circuit and System. He is the winner of the Education Ministry's New Century Excellent Talents Supporting Plan. He is also the Chairman of two workshops of the IEEE International Conference.



QUAN WANG received the B.S. and M.S. degrees from the Tianjin University of Technology, China, in 2008 and 2010, respectively. He is currently the Division Manager with the Internet FinTech Department, China Banking and Insurance Information Technology Management Company Ltd. His research interests include financial risk management by leveraging artificial intelligence, big data analytics, and image processing.