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GA-Based Image Restoration by Isophote Constraint Optimization

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We propose an efficient technique for image restoration based on a genetic algorithm (GA) with an isophote constraint. In our technique, the image restoration problem is modeled as an optimization problem which, in our case, is solved by a cost function with isophote constraint that is minimized using a GA. We consider that an image is decomposed into isophotes based on connected components of constant intensity. The technique creates an optimal connection of all pairs of isophotes disconnected by a caption in the frame. For connecting the disconnected isophotes, we estimate the value of the smoothness, given by the best chromosomes of the GA and project this value in the isophote direction. Experimental results show a great possibility for automatic restoration of a region in an advertisement scene.

Keywords and phrases: image restoration, genetic algorithm, isophote constraint.

1. INTRODUCTION

These days, we often see indirect advertisement captions in TV broadcasting scenes. Examples include logos and trademarks of electric home appliances. However, indirect advertisement is not permitted in public places. Therefore, such advertisements are usually erased by hand after taking a picture or are taped over by sticky bands before taking a picture. Since the early days of broadcasting and photography, these works have been done by professional artists. These procedures require a lot of time and effort for high performance [1, 2, 3]. If there were an automatic method that could restore a region in an image without loss of naturalness, it could be efficiently used where automatic restoration of a region is required. Therefore, one motivation for this paper comes from the need for advertisement caption removal.

Generally, images are produced to record or display useful information. However, because of the imperfections in the imaging and capturing process, a recorded image invariably represents a degraded version of the original image. The undoing of these imperfections can be resolved by various image restoration methods [3, 4]. Approaches to image restoration involve optimization of some cost function with constraints [4, 5]. For example, most commonly used cost functions are constrained least squares (CLS), which directly incorporate prior information about the image through the inclusion of an additional term in the original least-squares cost function. The CLS restoration can be formulated by choosing an $\hat{f}$ to minimize the Lagrangian

$$\min_{\hat{f}} \underbrace{\int_{\Omega} (g - \hat{f})^2 d\Omega}_{\text{term 1}} + \alpha \underbrace{\int_{\Omega} \left(|\nabla \hat{f}|\right)^2 d\Omega}_{\text{term 2}} (x, y) \in \Omega, \qquad (1)$$

where g is the degraded image, f is the original image, and $\hat{f}$ is the estimated image, respectively. In (1), the first term is the same ℓ_2 residual norm appearing in the least-squares approach and ensures fidelity to the data, and the second term is a constraint, which captures prior knowledge about the expected behavior of f through an additional ℓ_2 penalty term involving just the image. The regularization parameter α controls the trade-off between the two terms. Usually, the second term is chosen as a gradient operator, which is the Laplacian operator. However, this method has been well known to smooth an image isotropically without preserving discontinuities in intensity. In addition, it is impossible to restore an original image using the linear technique [6]. Thus, we consider the optimization problem of restoring an image, which has been occluded by the advertisement captions. To prevent the destruction of discontinuities while allowing for isotropically smoothing its uniform areas, we can solve the cost function minimization based on genetic algorithm (GA) with an isophote (curves of constant intensity) [1, 2, 7].

In the proposed technique, image restoration is computed by the propagation of the best chromosome only in the direction orthogonal to the contour that leads to the isophotes. In addition, our technique combines anisotropic diffusion with GA-based image restoration to restore smooth isophotes. That is motivated by a method proposed in [1, 2]. The proposed technique considers that an image restoration problem is viewed as an optimization problem which is solved by a GA. GA can be capable of searching for global optimum in functions. Principal advantages of GA are domain independence, nonlinearity, and robustness [8, 9]. Our technique very well maintains the surround information such as edge or texture. As well as, GA can find the near-global optimal solutions in a large solution space quickly. Since GA provides a robust method of image restoration, it is capable of incorporating arbitrarily complex cost functions [9]. By using various constraints of original image, pixel value of the region to be restored is more real than the other methods. Therefore, images that have been corrupted by captions in advertisement scene can be smoothly restored. Experimental results show a great possibility of automatic restoration of a region in the digital video.

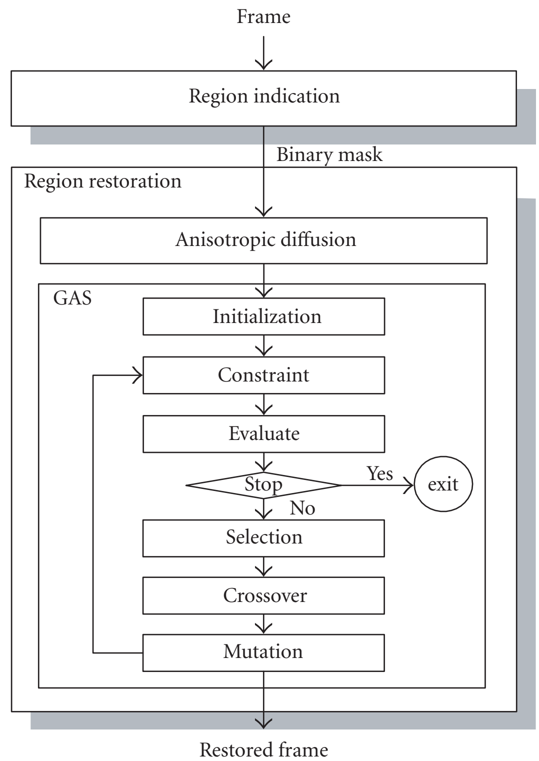


Figure 1: Flowchart of the proposed image restoration technique.

2. OUTLINE OF THE PROPOSED METHOD

2.1. Overview

Figure 1 shows the outline of the proposed technique. The technique first receives a frame that includes captions in the advertisement scene, and then produces a frame that includes the removed and restored captions. We assume that the captions in a frame are noise and they are automatically removed and restored according to the information of the surrounding area. Firstly, the location of caption in a frame is indicated by the user. This step creates a binary mask that covers it completely (the mask can be larger than the actual caption region). In region restoration, an anisotropic diffusion process is first applied to the image in order to smoothly (without losing sharpness) create the isophotes and reduce the noise. Then, the diffused image is restored using a GA with an isophote constraint.

The proposed technique attempts to reconstruct the isophotes by minimizing their curvature at the pixel to be restored, given the constraint of the initial pixels. To find the optimal value at the pixel to be restored, we can phrase the optimization problem using isophote constraints. Find the set of isophotes that (1) preserve the isophotes curvature and ordering, (2) preserve the intensity at the original pixel positions, and (3) each isophote is as smooth as possible [9]. As a result, the proposed technique optimally connects all pairs of geometric information disconnected by a caption.

2.2. Isophote

The proposed technique uses geometric information to reconstruct smoother pixels of the caption region. One of the most significant kinds of geometric information of an image is isophotes. Generally, connecting all surface points with the constant intensity and contrast, the curves are called isophotes or level lines [1, 7]. Isophotes can be computed from all possible connected components that are based on both the pixel value and the spatial relation between pixels. Therefore, isophotes are the lines of equal intensity in a 2D image and the surfaces of equal intensity in a 3D image. In an image, flowlines (gradient curves) are perpendicular to the isophotes at each point, and their tangent direction equals the local image gradient direction.

2.3. Isophote curvature

In our technique, an isophote curvature is used to connect the disconnected isophotes. The isophote curvature κ at any point along a two-dimensional curve is defined as the rate of change in tangent direction θ of the contour, and as a function of arc length s. An isophote curvature of a given surface is computed in two steps [7, 10]: (1) computing the normal vector n of the orthogonal direction to the largest gradient vector g at image f, and (2) tracing the surface points whose normal vector n forms a constant angle.

Let $f(x, y)$ be a gray-value image, and f_x and f_y the derivatives in the x- and y-direction, respectively. At any point (x, y) in the image (Figure 2), we have a gradient vector g, a normal vector n (isophote vector), and an isophote direction θ,

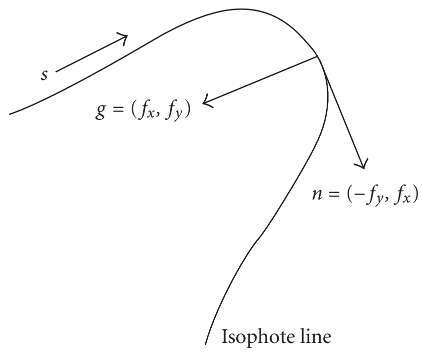


FIGURE 2: Isophote with a gradient vector g and a normal vector n (isophote vector).

$$g = (f_x, f_y), \qquad n = (-f_y, f_x), \qquad \|g\| = \sqrt{f_x^2 + f_y^2},$$
$$\theta = \arccos\left(-\frac{f_y}{\|g\|}\right) = \arcsin\left(\frac{f_x}{\|g\|}\right) = \arctan\left(-\frac{f_x}{f_y}\right). \tag{2}$$

Differentiate along the curve with respect to the isophote line length s is as follows:

$$\frac{d}{ds} = \cos\theta\frac{\partial}{\partial x} + \sin\theta\frac{\partial}{\partial y} = \frac{-f_y}{\|g\|}\frac{\partial}{\partial x} + \frac{f_x}{\|g\|}\frac{\partial}{\partial y}. \tag{3}$$

The isophote curvature κ is the rate of change in isophote direction θ, which is a function of isophote line length s [10]

$$\kappa = \frac{d\theta}{ds} = -\frac{f_{xx}f_y^2 - 2f_xf_yf_{xy} + f_{yy}f_x^2}{\left(f_x^2 + f_y^2\right)^{3/2}}. \tag{4}$$

3. GA-BASED IMAGE RESTORATION

In the proposed technique, GA is used to restore a region in an image. The parameter search procedures of GA are based upon the mechanism of natural genetics, which are probabilistic in nature and exhibit global search capabilities. GA works with a population of chromosomes, each representing a possible solution to a given problem at hand. Each chromosome is assigned a fitness value according to how good its solution to the problem is. The highly fit chromosomes are given greater opportunities to mate with other chromosomes in the population. During each generation, the chromosomes start with random solutions that are then updated and reorganized through GA operators, such as selection, crossover, and mutation [8, 9]. After iteratively performing these operations, the chromosomes eventually converge on an optimal solution. In this paper, a region of an image is efficiently restored by chromosomes that evolve using GA with an isophote constraint. For the image restoration, the propagation of the best chromosomes is computed only in the direction orthogonal to the contour that leads to the isophotes. This method creates an optimal connection of all pairs of disconnected isophotes. The restoration process is shown in Algorithm 1.

(1) Apply an anisotropic diffusion to the region to be restored.
(2) Store the pixels in the restored region into an array.
(3) For each pixel in the array,
  (3.1) determine the initial chromosome;
  (3.2) determine the edges of initial chromosome using the 2D Laplacian;
  (3.3) compute the isophotes direction of initial chromosome;
  (3.4) compute the fitness between the isophote of estimated chromosome value and the isophotes of the neighboring pixels values;
  (3.5) project the value of the chromosome that has the highest fitness into the isophotes direction;
  (3.6) update the values of the pixels inside the regions to be restored.
(4) Iterate steps from (3.2) to (3.6).

ALGORITHM 1: GA-based image restoration process.

A chromosome that represents a solution to the problem is allocated at a pixel. We used a color vector as a chromosome to represent real values of the image. A chromosome consists of RGB feature vectors that are used to assign a fitness value to the chromosome. Fitness is defined as the minimized cost function between the estimated feature vector and the observed feature vector at the location of the chromosome on the image. Using anisotropic diffusion, the initial chromosome is randomly selected according to the value of the smoothed region [4]. If the pixel value smoothed by the diffusion process is X, the initial chromosome at the restored pixel is randomly assigned between $X - 20$ and $X + 20$. Generally, a pixel value in an image is similar to the pixel values of neighboring pixels. The values of the contour pixels in the restored region are obtained clockwise by the best chromosome value of a GA. Then, the obtained pixel values are projected to the continuity of the isophotes at the boundary during generation of a GA.

The cost function for each chromosome is evaluated by comparing the restored image with the original image. In order to find an optimal solution, we use a priori knowledge such as the constraint form of the isophotes curvature evolution to reduce the artifacts of restoration. Here, the optimal solution minimizes the isophotes curvature of the restored image, preserves the color values, and is similar to the isophote curvatures of neighboring pixels. The cost function is defined as follows:

$$E(\overline{V}_N, \overline{k}_N, \Omega) = \underbrace{\int_\Omega (\overline{V}_N - \hat{f})^2 d\Omega}_{\text{term 1}} + \underbrace{\alpha\int_\Omega |\nabla\hat{f}|(1 + |\hat{k}|)d\Omega}_{\text{term 2}} + \underbrace{\beta\int_\Omega (\overline{k}_N - |\hat{k}|)^2 d\Omega}_{\text{term 3}}, \tag{5}$$

Figure 3: Results of the proposed image restoration technique.

where terms 2 and 3 are the constraints, $\overline{V}_N$ and $\overline{\kappa}_N$ are the average pixel value and the average isophotes curvature of neighbor pixels at the restored pixel, respectively, and $\hat{f}$ and $\hat{\kappa}$ are the estimated image and isophote curvature. Term 1 means that the restored pixel value should be similar to the average value of the neighbor pixels at the restored pixel and Term 2 means that it should be as smooth as possible and that the isophote curvature should be minimized. Term 3 means that the isophotes curvature should be similar to the average isophotes curvature of the neighbor pixels at the restored pixel. In the case of a color image, the cost function E_C at each color plane (RGB) is $E_C = E_R + E_G + E_B$.

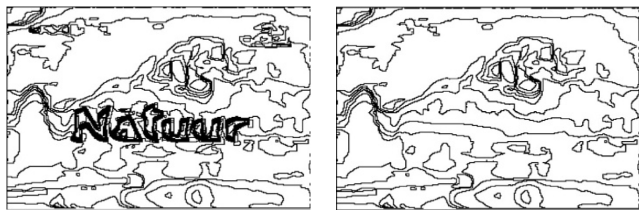


Figure 4: Isophote corrupted by the advertisement caption and the restored isophote.

4. EXPERIMENTAL RESULTS

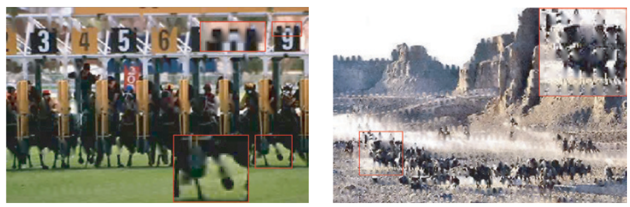
The experiments were performed on a Pentium-1.7 GHz with Windows 98 and implemented using an MS Visual C++. The parameters for the GA were obtained through several test runs. The probabilities of crossover and mutation were fixed at 0.08 and 0.005, and the population and generation size were taken as 1000 and 50, respectively. As mentioned in Section 3, the control parameters of the cost function, α and β, are chosen as 0.15 and 0.3. All examples used frames from advertisement scenes that include captions or product trademarks over TV broadcasting and the size of frame is 320×240. Figure 3 shows the restoration results of a region with an advertisement caption using our technique. The first image in Figure 3 shows various colors and irregular textures. The first six images of Figure 3—clockwise from top left—are an advertisement caption image, an image occluded by a mask, and after 5, 10, 30, and 50 generations of our technique.

The isophotes and 3D plots of Figure 3 restoration results are shown in Figure 4. The isophote plots of Figure 4 are disconnected by the advertisement captions. We can see from these isophotes that a corrupted image is sufficiently restorable from background areas, while its "true" edges are preserved. In the experimental results, we show that the disconnected isophotes of the advertisement captions are optimally connected.

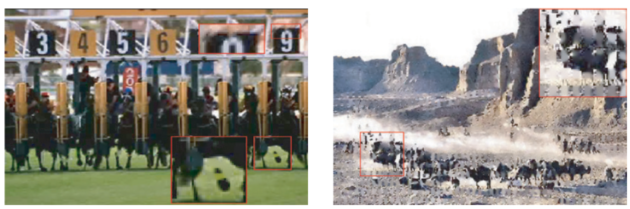
In order to evaluate the proposed method, we compared the results of the proposed technique using an isophote constraint with the image restoration results using Laplacian operators at a constraint of the second terms in (1) as well as image restoration results without a constraint. The results of the image restoration using the above methods are shown in Figure 5. The image restoration result using Laplacian operator does not preserve the discontinuity of edges on the original image and the image restoration results without a constraint blur the edges of the original image. However, our technique preserves the edges of the original image and the image is smoothly restored.

To objectively test the performance of these image restoration algorithms, the improvement in signal-to-noise ratio (ISNR) was used [3]. The degraded image in Figure 5 was made by inserting a caption into the original image. In the case of the color image, the ISNR was employed as the objective performance measure for the three components (R, G, B) of the restored color image. The ISNR of the restored color image, denoted by ISNR_C, is given by $\mathrm{ISNR}_C = (\mathrm{ISNR}_R + \mathrm{ISNR}_G + \mathrm{ISNR}_B)/3$. Table 1 shows the ISNR_C results of each test image. The restoration results by

(a)



(b)



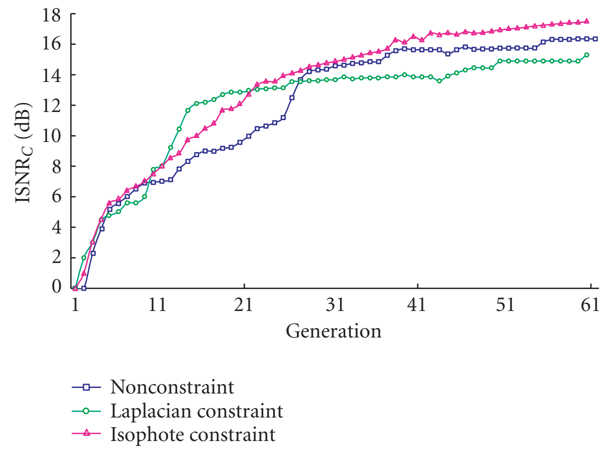
(c)

(d)

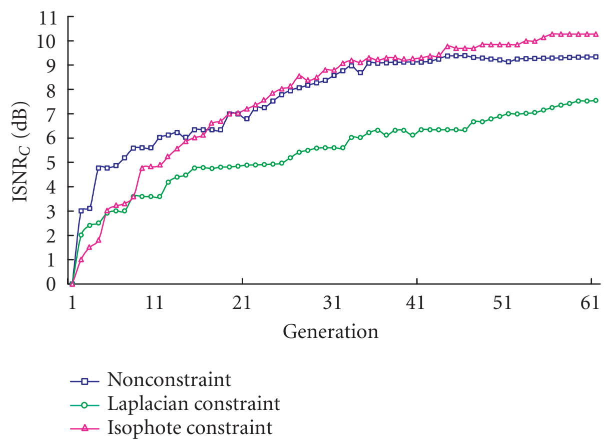
Figure 5: Results of the image restoration using different methods. (a) Synthetic image 1 and 2. (b) Nonconstraint. (c) Laplacian constraint. (d) Our technique.

Table 1: The ISNR_C of restored results using different methods.

(dB)	Nonconstraint	Laplacian constraint	Proposed method
Synthetic 1	16.41	17.01	17.78
Synthetic 2	9.41	9.98	10.96



(a)



(b)

Figure 6: The ISNR_C at different numbers of generations during the image restoration. (a) Synthetic image 1. (b) Synthetic image 2.

our technique using isophote constraint are always better than the Laplacian constraint and nonconstraint methods. The ISNR_C at different numbers of generations during image restoration is illustrated in Figure 6. As the number of generations increases, the overall cost value as well as the corresponding ISNR_C value of the restoration results by the proposed method monotonically improves.

5. CONCLUSIONS

In this paper, we propose an efficient image restoration technique based on a GA with an isophote constraint. The image restoration problem is modeled as an optimization problem that is solved by a cost function with isophote constraint that is minimized using a GA. In the proposed technique, we estimate the value of smoothness, given by the best chromosomes of the GA and project this value in the isophotes direction. This method restores the inside of the region using the geometric features of the image from the surrounding area and can be used to make a natural scene. Experimental results demonstrate that the proposed method has sufficiently good performance. In future studies, we will apply the method to video sequences with a nonstationary background and consider improving the performance for real-time application.

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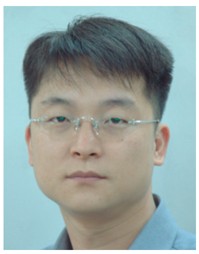

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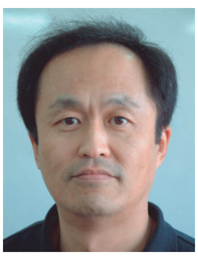

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