Automatic restoration of scratch in old archive

Kyung-tai Kim, Byunggeun Kim, Eun Yi Kim
Dept. of advanced technology fusion Engineering, Konkuk University, Seoul, Korea
kkt1341@konkuk.ac.kr , byunggni@konkuk.ac.kr,eykim@konkuk.ac.kr

Abstract

This paper presents scratch restoration method that can deal with scratches of various lengths and widths in old film. The proposed method consists of detection and reconstruction. The detection is performed using texture and shape properties of the scratches: first, each pixel is classified as scratches and non-scratches using a neural network (NN)-based texture classifier, and then some false alarms are removed by shape filtering. Thereafter, the detected region is reconstructed. Here, the reconstruction is formulated as energy minimization problem, thus genetic algorithm is used as optimization algorithm. The experimental result with well-known old films showed the effectiveness of the proposed method.

Index Terms— *film restoration, scratch, neural networks*

1. Introduction

In the recent years, a film restoration has gained increasing attention by many researchers, to support multimedia service of high quality. The goal of film restoration is to achieve a good quality restoration employing a low computing time with the least operator's interaction.

Among degradations such is dust, scratch, flick and blotch, the most common factors are scratches. Scratches are usually generated by mechanical rubbings during a film copy and appear in the direction of the film strip on successive frames over the film.

Figure 1 shows some examples of degraded regions by scratches in old film, which includes all kind of scratches [1]. As shown in Figure 1, scratches are easily visible as vertical lines of bright or dark intensity, oriented vertically over much of the image. Therefore, the representative characteristics of a scratch can be defined as follows: (1) it has a lower or higher brightness than the neighboring pixels, (2) usually appears as a vertically long thin line, and (3) has a temporal continuity. Among these characteristics (1) and (2) are textural and morphological properties in the spatial domain, while (3) is a continuous characteristic in the temporal domain

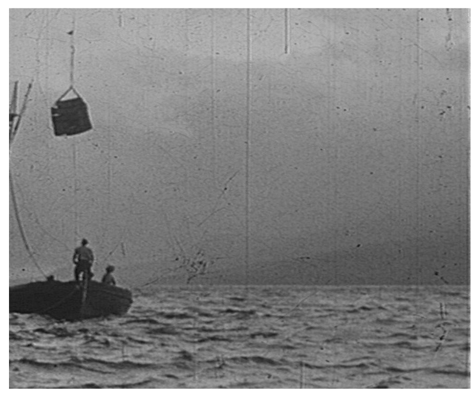

Figure 1. Examples of scratch

Using these characteristics, so far many methods have been developed, however they focused on reconstruction and relatively little has been done in automatic scratch detection. Thus far only two models have been in use. One is Kokaram et al.'s method [2] and the other is Joyeux et al.'s method [2].

Kokaram et al. proposes a spatial model where detection is performed by Hough transform and a Bayesian refinemen, thereafter, the detected scratches are reconstructed using inpainting algorithm. In Joyeux et al's method, a scratch detection is dealt with by means of a temporal representation, i.e., using all frames of the degraded sequence. The detection phase is performed by the Kalman's filter and the Hough transform. And the reconstruction phase is performed by interpolation. The main advantage of Kokaram et al.'s method is that it can deal with various types of scratches, however, it has a tendency to generate too many false alarms. On the other hand, Joyeux et al.'s method used continuous characteristic of scratch to distinguish real scratches from false alarms, thus they employ too many computational costs. In addition, it fails to detect various scratches with different lengths and widths.

1051-4651/10 $26.00 © 2010 IEEE
DOI 10.1109/ICPR.2010.122

Recently, a fusion based approach is introduced to combine the advantages between both approaches [2], which simply combine the results of both models. Although such a method improved the detection accuracy and the quality of restored image, it also inevitably inherited the shortcomings of both models; it missed scratches with short lengths and failed to distinguish real scratches from line components of scene. These problems in detection phase also affected on the reconstruction phase.

Accordingly, this paper presents a new scratch removal method that is to robust to the types of scratches, that is, scratches lengths and widths. For this, we investigated the nature of degradations such as shape and textures, thereafter developed the method based on those properties. The proposed method consists of detection and reconstruction. The detection is performed using texture and shape properties of the scratches: first, each pixel is classified as scratches and non-scratches using a neural network (NN)-based texture classifier, and then some false alarms are removed by shape filtering. Thereafter, the detected region is reconstructed. Here, the reconstruction is formulated as energy minimization problem, a genetic algorithm is used to optimization algorithm.

To assess the validity of the proposed method, it was tested on natural old films, and the results were compared with those of other methods Then, the results showed that the proposed method can improve the performance than existing methods.

2. Scratch detection

To automatically detect all kinds of scratches, a detection method is developed using the shape and the texture characteristics of a scratch. Each frame in old films is first divided into scratch region and others using the texture property, and then over-detected regions are filtered out by the shape property.

Here, neural networks (NN) are used as filters which produce a local window-based classification of image pixels in 'scratch' and 'non-scratch' by analyzing properties of the sub-region of input images. The network receives the gray-scale value of a pixel to be considered as an edge and its neighboring pixel within 5×15 sized window. The width of scratch is fluctuated from 3 to 17 according to the resolution. To solve this problem, the NN requires the normalization process proceeding to receive the input data.

The NN used in the experiments had 75 input nodes, 18 hidden nodes, and 2 output nodes. The value of output node is given as a vector of two floating-point numbers. If the first value be the lager then the second value then it is scratch class pixels, and less than the second values of the non-scratch pixels. As a result of classification, a binary image is obtained in which the pixels classified as scratch are white and those classified as non-scratch are black.

In the texture classified results, non-degraded region with high frequency and contrast are misclassified as scratch regions. To remove them, we use the shape information. Based on those shape properties, three following structuring elements are defined in [3].

Let N denotes the texture classification result, then the morphological filtering result, S is obtained using the following equation:

$$S = N - \{\gamma_{B_L}(N) + \gamma_{B_R}(N) + \gamma_{B_H}(N)\}$$

, where $\gamma_{B(I)}$ is closing operator. Here, the B_H is defined for detecting horizontal component, and the B_L (or B_R) is defined for detecting diagonal component. Through the morphological operation with these structuring elements, the miss-classified degraded regions are removed.

Thereafter, very smaller region is considered as a noise, and removed.

3. Scratch removal

In the proposed method, a scratch reconstruction is formalized in Bayesian approach, so that the reconstruction problem is considered as the minimization problem of the posteriori energy function. Then, energy function is minimized by chromosomes that evolve using distributed genetic algorithms (DGAs).

3.1 Problem specification

Let $S=\{S_s\}$ be the 2-D lattice of $M_1 \times M_2$, such that an element S_s indexes an image pixel at site S. Then, Y is observed image defined on S. And, $X=\{X_s\}$ is color image defined on S, wherein X_s has one color value from RGB color space. Let $\Gamma=(\eta_s)$ be a neighborhood system, where η_s is the set of neighboring site S. Then, X is modeled by Markov random field (MRF) .

Let x be a realization of X, and y^c and y^p be the current frame and previous frame, respectively. Then, a film restoration is formulated estimating x from an observed $y=(y^c, y^p)$. Since a MAP is used as the optimality criterion, the goal is to identify x^* that maximizes the following posterior distribution for a fixed input y.

$$x^* \propto \arg\max_x P(y|x)P(x) = \exp(-U(x) + \exp(-V(x)) \qquad (1)$$

Then the priori is obtained using Gibbs distribution,

$$\exp(-U(x)) = \exp\left[-\alpha \sum_{(c \in C)} \Phi_c(x)\right].$$

A priori energy function, *U(x)* is obtained by the summation of potential $\Phi c(x)$ over all possible cliques. And α is smoothing parameter. The proposed model assumes that the only non-zero potentials are those corresponding to two-pair cliques. As the potential, we used the following function, which was defined in [4].

$$\Phi_c(x) = \left(1 + \left|\frac{x_s - x_t}{\delta}\right|\right)^{-1} \quad (2)$$

, where x_s is a real color value at site *s*, x_t belongs to the cliques of x_s, and δ is scale parameter. $\Phi_c(x)$ has the smaller value if two pixels have more similar color values, thus it try to make a region more smoothing.

The likelihood between real color image and the observed images is defined as follows:

$$V(y|x) = \alpha^c \sum_{s\in S}\left(1 + \left|\frac{x_s - y_s^c}{\delta^c}\right|\right)^{-1} + \alpha^p \sum_{s\in S}\left(1 + \left|\frac{x_s - y_s^p}{\delta^p}\right|\right)^{-1} \quad (3)$$

, where the parameters α^c, α^p, δ^c and δ^p are experimentally determined.

After substituting Eqs. (2) and (3) into Eq. (1), take a logarithm, then the MAP is rewritten as Eq. (4), which is called as a posterior energy function.

$$x^* \propto \arg\min_x \begin{pmatrix} \alpha \sum_{c\in C}\left(1 + \left|\frac{x_s - x_t}{\delta}\right|\right)^{-1} \\ +\alpha^c \sum_{s\in S}\left(1 + \left|\frac{x_s - y_s^c}{\delta^c}\right|\right)^{-1} \\ +\alpha^p \sum_{s\in S}\left(1 + \left|\frac{x_s - y_s^p}{\delta^p}\right|\right)^{-1} \end{pmatrix} \quad (4)$$

,where posterior energy function enforces anticipated regularities by assigning high values to undesirable configurations.

Consequently, a restoration problem is formulated as minimizing the posterior energy function.

3.2 Optimization of Energy function

In the proposed method, a restoration is carried out by chromosomes that evolve using DGAs. A chromosome consists of color feature vector allocated to one pixel. The population of chromosomes is initialized by random values then evolved by iteratively performing GA operators, such as selection, crossover, and mutation, until the stopping criterion is satisfied. These operators eventually lead to a stable value, which is taken as the resulting restoration.

Each chromosome has a fitness value according to how good its solution to the problem is. Here, fitness function is defined as the local energy ($-E_s$).

$$E_s = \alpha \sum_{t\in p_s}\left(1 + \left|\frac{x_s - x_t}{\delta}\right|\right)^{-1} + \alpha^c\left(1 + \left|\frac{x_s - y_s^c}{\delta^c}\right|\right)^{-1} + \alpha^p\left(1 + \left|\frac{x_s - y_s^p}{\delta^p}\right|\right)^{-1}$$

Then, y_s^c and y_s^p are obtained by a block matching.

To maximize its fitness value, each chromosome is evolved by iteratively performing GA operators. In a DGA, these operators function on the neighbors of a chromosome rather than the whole population. Here, the local population is determined by the window $W1\times W2$ centering on a pixel s, which is determined experimentally, according to the type of degradations.

In the proposed method, GA operators used in [5], and stopping criterion are illustrated below

For the stopping criterion, stability is first defined as follow:

$$\text{stability} = \frac{\sum_{s\in R_i}\left(C_s(t) - C_s(t-1)\right)}{\sum_{s\in R_i}\left(D(s)\right)}$$

, where the denominator means the area of degraded region and the nominator is a summation of color differences of chromosomes in between successive generations. That is, the stability means the degree of convergence to a stable solution. Then, the stopping criterion is reached when stability is below a pre-defined threshold value θ and such cases are continuously occurred more than 5 times. Also, the stopping criterion is satisfied when the number of generations exceeds the maximal number.

In GA-based optimization, the population size and mating rates are crucial in performance. Here the crossover and mutation rates were set to 0.5 and 0.01, respectively. And the population size is determined according to the type of degradations, the size of local population is 27, then they are obtained from 3×9 windows centering on the current position at the current frame. These configurations are fixed, regardless of input images.

4. Experiments

To prove the effectiveness of the proposed method, it was tested with scratches collected from well-known old films and animations such as “Star,” “Sit-down,” “Knight,” “Afrique du sud” and “Taekwon V,” and its performance was compared with that of Maddalena et al.’s method [2]. This method consists of detection and removal steps:

- Detection step: Maddalena’s used *union aggregation operator* (Union) fusion and *maximum aggregation operator* (MC) fusion for combining the results by Kokaram et al’s method and Joyeux et al.’s method.
- Removal step: Maddalena’s used the weighted averaging aggregation operator to combine the results by Kokaram et al’s method and Joyeux et al.’s method

Figure 2 shows some restoration results for natural old films Figure 2(a) shows the input images. Figures 2(b) and 2(d) show the detection results of Maddalena et al.’s method and the proposed method, respectively. As can see Figure 2(b), Maddalena et al.’s method included more false alarms than the proposed method, and did not detect many secondary scratches. In contrast, the proposed method correctly detected secondary scratches, as well as principal scratches, and reduced the number of false alarms. Figures 2(c) and 2(e) show the reconstruction results of Maddalena et al.'s method and the proposed method, respectively.

When visually compared with Figures 2(c) and 2(e), the proposed method shows the better performance than Maddalena et al.'s method. In Figure 2(c), the miss-detected scratches are not reconstructed. Moreover, the blurring effects were occurred on those images. Maddalena et al.'s method is fusion of interpolation and inpainting algorithms. Then, the basic idea of interpolation and inpainting algorithms is to recover some lost information using adjacent pixels of both spatial and temporal domain, so it is likely to make some blurred regions in a case of processing the images with noises or the highly textured images. On the other hand, the proposed method is based on optimization of pre-defined functions, so it is relatively robust to such images.

Table 1. An accuracy of detection in natural films

Method	#of test data	Recall	Precision
Maddalena's method	240	61%	56%
Our method	240	75%	81%

The performance comparison between the proposed method and Maddalena et al.'s method is summarized in Table 1. On average, Maddalena et al.'s method produced a recall of 61% and precision of 56%, whereas the proposed method produced a recall of 75% and precision of 81%, indicating an improved performance.

Consequently, experimental result showed that the proposed method can improve the performance than other method

5. Conclusion

This paper presented an automatic detection and removal of scratches for old film restoration, which have been recently explored by many researchers. The experimental results demonstrated the effectiveness of the proposed method in removing scratches.

6. References

[1] Vittoria, B. and Domenico, V., A generalized Model for Scratch Detection, IEEE Transactions on Image Processing 13: 44-50, 2004.

[2] Maddalena, L,. Petrosino, A, and Laccetti, G, A fusion based approach to digital movie restoration. Pattern Recognition. 42:1485-1495. 2009.

[3] K. Kim and E. Y. Kim, Film line scratch detection using texture and shape information, pattern recognition letters, 31(3):250-258, Feb. 2010

[4] Geman, S,. McClure, D, E,. and Geman, D,. A nonlinear filter for the film restoration and other problems in image processing. Journal of Graphical Models and Image Processing. 281-289. 1992.

[5] E.Y. Kim, and S.H. Park, Automatic Video Segmentation using Genetic Algorithms, Pattern Recognition Letters, pp. 1252-1265, Aug. 2006.

[6] Kokaram, A, Ten Years of Digital Visual Restoration Systems. ICIP, 1-4, 2007

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

Figure 2. Reconstruction results for naturally corrupted images: (a) input images, (b) detection results of Maddalena et al.'s method, (c) removal results of Maddalena et al.'s method (d) detection results of the proposed method, (e) removal results of the proposed method