Film Line scratch Detection using Neural Network and Morphological Filter

Kyung-tai Kim and Eun Yi Kim
Dept. of advanced technology fusion, Konkuk Univ. Korea
{kkt1341, eykim}@konkuk.ac.kr

***Abstract*— This paper presents a scratch detection method that automatically detects all kinds of scratches from each frame in old films. Generally, the scratch in old films has lower or higher brightness than neighboring pixels in its vicinity and it usually appears as a vertically long thin line. The proposed method is designed from these characteristics of a scratch, thus it consists of two major modules: a neural network-based texture classifier and a morphology-based shape filter with multiple structuring elements. First, the NN-based texture classifier divides the input image into scratch regions and non-scratch regions using the texture property of the scratch. Secondly, the morphology-based shape filter confirms the classified scratch region with structuring elements which is designed based on the shape characteristics of scratches. To assess the validity of the proposed method, the experiments have been performed on several old films and an animation, then the results confirms that the proposed method can detect all kinds of scratches and have the potential to be applied to the commercial systems.**

***Keywords*— film restoration, neural nerwork, morphological filter**

I. INTRODUCTION

Film restoration is to detect the location and extent of defected regions from a given movie film, and if present, to reconstruct the lost information of each regions. In the recent year, Film restoration has gained increasing attention by many researchers, to support multimedia service of high quality [1,2,8].

In general, an old film is degraded by dust, scratch, flick, and so on. Among these, the most frequently degradation is the scratch. 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. The old film includes many kinds of scratches. Then these can be classified according to their length, motion and luminance, as shown in Table 1.

TABLE I. TYPE OF SCRATCH

Kind of scratch	Description
Static scratch	Present at the same position on consecutive frames
Moving scratch	Can change positions during the sequence
Principal scratch	Occurs on more than 95% of the image height
Secondary scratch	The others
Positive scratch	Occurs dark intensity nearby it
Negative scratch	Occurs light intensity nearby it

These types of scratches are easily visible as vertical lines of bright or dark intensity oriented vertically over much of the image. An example of an image affected by scratches is shown in Fig. 1. Fig. 1(a) includes various scratch such as static/principal/positive and static/secondary/positive ones. And Fig. 1(b) show the scratch to be classified as static/principal/negative one.

(a) (b)

Figure 1. Example of scratches: (a) static/principal/positive scratches (“Sit-down sequence”), (b) a static/principal/negative scratch (“Taekwon V sequence”)

Until now, many systems have been developed for automatic scratch restoration. However, most of them have limitation on defecting all kind of scratches, in particular they can be applied for only the static/principal scratches. In [9], a scratch detection method using morphological operator and Kalman’s filter was developed which can detect various degradation such as dust, dirt and scratch. However, it was applicable for only the principal scratches. In addition, it requires a lot of computational time due to using the motion information. In [9], a solution is proposed to detect scratches based on the Weber’s law, where the luminance of scratches is assumed to be constant through the whole film. The main advantage of that work is to be able to detect the secondary/not-alone scratches as well as principal ones, however it has a drawback that users should input the luminance value of scratches beforehand.

This paper presents a scratch detection method that automatically detects all kinds of scratches from frames in old films. The proposed method is designed from the shape and the texture characteristics of a scratch, thus it consists of neural network-based texture classifier and morphology-based shape filter with multiple structuring elements. First, texture classification step divides the input image into scratch regions and non-scratch regions using the texture property of the scratch. The morphology based shape filter confirms the classified scratch regions using structuring elements which is designed based on the shape characteristics of scratches. To assess the validity of the

978-1-4244-1674-5/08 /$25.00 ©2008 IEEE CIS 2008

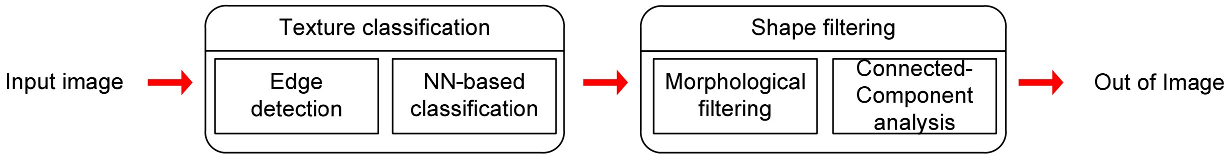


Figure 2. Outline of the proposed scratch detection system

proposed method, the experiments have been performed on several old films and an animation, then the results confirms that the proposed method can detect all kinds of scratches and have the potential to be applied to the commercial systems. The paper is organized as follows. Section 2, describes the overview of proposed method In section 3, texture classification based on neural network will be presented defining the structure of neural network and edge detection, and shape filtering step will be introduced in section 4. The experimental results are shown in section 5. Finally, section 6 drives conclusions and potential future works.

II. OVERVIEW OF THE PROPOSED METHOD

In this paper, we proposed a scratch detection based on neural networks and morphological filters to automatically detect all kind of scratches. The proposed method uses the texture and the shape information of scratch regions.

Generally, a scratch has the following properties:

(1) It has lower or higher brightness than neighboring pixels in its vicinity, which is used as an important cue for scratch detection.
(2) It usually appears as a vertically long thin line.
(3) It has temporal continuity, that is, it appears on the successive movie frames.

The properties (1) and (2) represent the texture and the shape information of a scratch, respectively. And the property (3) shows the motion information of a scratch. These properties help reduce the complexity of the problem, and facilitate the discrimination between the scratches from other regions. However, it is difficult and not resolved to obtain the accurate motion information. Accordingly, we use only the texture and shape properties to reduce the computational time.

Fig. 2 shows the outline of the proposed method. The proposed method is designed from these characteristics of a scratch, thus it consists 2 steps: the first step is texture classification step using the edge detection and the neural network; the second step is shape filtering step using the morphological filter and the connected-component analysis. The texture classification step divides the input image into scratch regions and non-scratch regions using the texture property of the scratch. Here, to reduce computational costs, the NN-based classifier is applied to only the pixels corresponding to the edges. Thereafter, the morphology-based shape filter confirms the classified scratch regions using multiple structuring elements which is designed based on the shape characteristics of scratches. Finally, we use the connected-component analysis result posterior to morphological filtering.

III. FEATURE EXTRACTION

This stage divides the input image into scratch regions and non-scratch regions using the texture property of the scratch. Here, we use a neural network as a texture classifier.

A. *Edge detection*

This paper uses a neural network as a classifier to distinguish an image as the scratches and the non-scratches. As it requires much computational time to scan the whole image using NN-based texture classifier, the NN-based filter is applied for only the pixels mapped to the edges due to the fact that scratch is brighter or darker than the adjacent pixels.

When given an input image, the Prewitt masks are first applied for edge extraction, and then the results are dilated to prevent the loss of the information surrounding edge pixels.

Fig. 3 describes the process to generate the input of neural network. Fig. 3(a) shows the original input image and Fig. 3(b) illustrates the edge detection result. Finally, Fig. 3(c) shows the input of NN, which is the result to apply dilation operation to the Fig. 3(b). Accordingly, the NN-based filter will be applied to Fig. 3(c).

(a) (b) (c)

Figure 3. The example of input of NN: a) an input image (b) edge detection (c) input data of NN

B. *An architecture neural network*

A neural network is used as a texture classifier to identify scratch pixels. In this step, scratch pixels are classed as scratch class and all other pixels are grouped as non-scratch.

A diagram of the neural network-based classifier is shown in Fig. 4. The input layer of the network has L0 nodes, the hidden layer has L1 nodes, and the output layer has 2 nodes. The adjacent layers are fully connected. The hidden layer operates as a feature extraction module. The output layer is used to determine the class of a pixel: scratch or non-scratch. Then, the numbers of input layer and hidden layer are decided by an experiment.

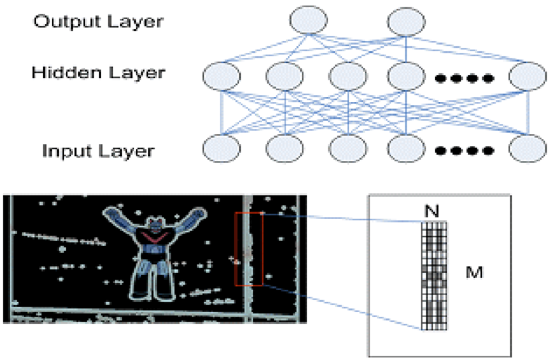


Figure 4. A two-layer feedforward neural networks

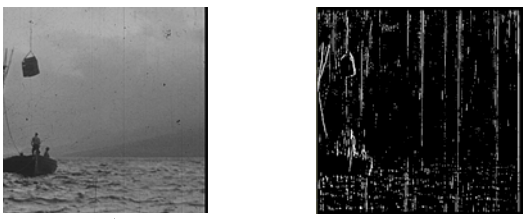
The input layer receives the intensity values of pixels, at predefined positions inside an $N \times M$ window over an input image. The output value of a hidden node is obtained from the dot product of the vector of input values and the vector of the weights connected to the hidden node. It is then presented with the output nodes. The weights are adjusted by training with a back-propagation algorithm in order to minimize the sum of squared error during the training session

C. Classification

Neural networks 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 a edge and its neighboring pixel within a $N \times M$ window.

The value of output node is given as a vector of two floating-point numbers, ranging from 0 to 1, rather than identifier. 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. The classified image is a binary image in which the pixels classified as scratch are white and those classified as non-scratch are black. Fig. 5 shows an example of classification, where the pixels to be classified as scratches are marked white. We can see that all of the scratches are labeled correctly, but there are some misclassified regions as scratch. These regions are filtered out by the shape filter.



(a) (b)

Figure 5. Example of classification: (a) an original frame, (b) classified image

IV. Shape Filtering

Although we use the texture property to make the scratch detection, the detection result from NN includes many false alarms. As such we still encounter difficulties in filtering out high-frequency and high-contrast non-eye scratches. In this paper, we use shape information to remove the miss-classified result of neural networks. Then we first define the strutting elements for expression shape information.

A. Multiple structuring elements for scratch detection

Many morphological filters are commonly designed to remove noisy-gray-level mages by a determined composition of opening and closing with a given structuring element. Morphological filters enable us to control the amount of information to be kept, which is implemented by a shape mask (which is called as a structuring element). Accordingly, we first define some structuring elements to represent the shape information of a scratch.

In our system, the texture classification results include many non-scratches with high frequency and contrast. To remove them, we use the following shape information: the scratch usually appears as vertical long thin line, and then its minimum width is nearby 3~5 pixels. Based on those characteristics, three following structuring elements are defined:

$$B_R = \begin{bmatrix} X & 1 & 1 \\ X & 1 & X \\ 1 & 1 & X \end{bmatrix},\ B_L = \begin{bmatrix} 1 & 1 & X \\ X & 1 & X \\ X & 1 & 1 \end{bmatrix} \text{ and } B_H = \begin{bmatrix} X & X & X \\ 1 & 1 & 1 \\ X & X & X \end{bmatrix}.$$

Here, X is a “don’t-care “variable that doesn’t concern 1and 0. These structuring elements describe the shape of non-scratch. B_H is for horizontal components, B_L and B_R are for diagonal components. These three structuring elements are used to filter the non-scratch regions from texture classification results.

B. Morphological Filtering

Firstly, erosion and dilation with a flat structuring element are used in constructing a morphological filter for images simplification. The erosion $\varepsilon_B(I)$ of an image I by the structuring element B is defined as

$$\varepsilon_B(I) = \min_{(k,l)\in B} I(k,l). \tag{1}$$

In Eq. (1) B is a windows or flat structuring element and $B_{x,y}$ is the translation of B so that its origin is located at (x,y). Similarly, the detection $\delta_B(I)$ of the image I by the structuring element B is given as follows:

$$\delta_B(I) = \max_{(k,l)\in B} I(k,l). \tag{2}$$

Using the erosion and dilation operators, morphological opening $\gamma_B(I)$ and closing operations $\varphi_B(I)$ are given Eqs.(3) and(4),respectively:

$$\gamma_B(I) = \delta_B(\varepsilon_B(I)), \text{ and} \tag{3}$$

$$\varphi_B(I) = \varepsilon_B(\delta_B(I)). \tag{4}$$

The morphological opening operator $\gamma_B(I)$ applies an erosion $\varepsilon_B(\bullet)$ followed by a dilation $\delta_B(\bullet)$. Erosion leads to darker images and dilation to brighter images.

Let N denotes the classified result of neural networks, then the morphological filtering result, S is obtain using the following equation:

$$S = N - \{\gamma_{B_L}(N) + \gamma_{B_R}(N) + \gamma_{B_H}(N)\} \cdot \quad (5)$$

Th The S is calculated though the following steps: (1) Apply closing operation to the texture classification result, N using B_o, B_o and B_o, and then apply OR operation to the results. (2) Subtract the result of (1) from the N. The miss-classified regions are detected though step (1), and then they are removed in step (2). Consequently, only the vertical lines are presented, are considered as scratches.

Finally, we apply a noise filtering using, the connected-component analysis result posterior to morphological filtering. If its height is smaller that 1/10 of the height of the image, a component is considered as a noise, and removed.

Fig. 6 shows result of shape filtering. Fig. 6(a) shows results of texture classification. And Fig. 6(b) shows the results of morphological filtering and then final result of the shape filter is shown in Fig. 6(c).

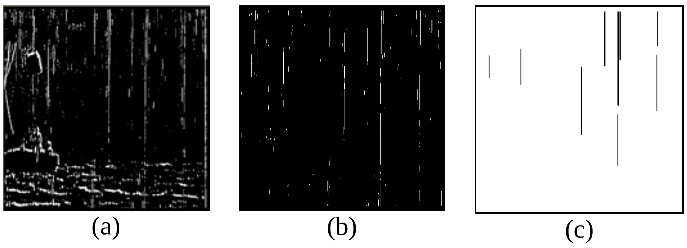


Figure 6. Example of shape filtering: (a) result of texture classification (b) result of morphological filtering (c) result after connected component analysis

V. EXPERIMENTAL RESULTS

The proposed scratch detection method was applied to some old films and animation film. Here, we show the results for the sequence, “Knight,” “Star,” and “Sit-down,” “Taekwon V.” These sequences include the scratches of various types..

For experiments, 100 frames with scratches were manually selected from these sequences. Among these frames, 50 were used in the training process, and the others were used in the testing process.

The neural network used in the experiments had 75 input nodes, 18 hidden nodes, and 2 output nodes. 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 pattern fed to the classifier consisted of pixel values, i.e. a central pixel and neighbors, in a 5×15 window.

The results for several test data were shown in Figs 7 -9.

Fig. 7 shows the detection results of the static/secondary scratches. Figs. 7(a) and (d) show the original frames, each of which is extracted from the ‘Knight’ and ‘Taekwon V’. Fig. 7(b) includes a secondary scratch, while Fig. 7(e) has a principal scratch. Then the classified results by texture classification are shown in Figs. 7(b) and (d). Finally, the scratches regions filtered by shape filtering are shown in Figs. 7(c) and (f). As can be seen in Fig.7, the proposed method regardless of length of a scratch can accurately and automatically static/secondary/negative scratch.

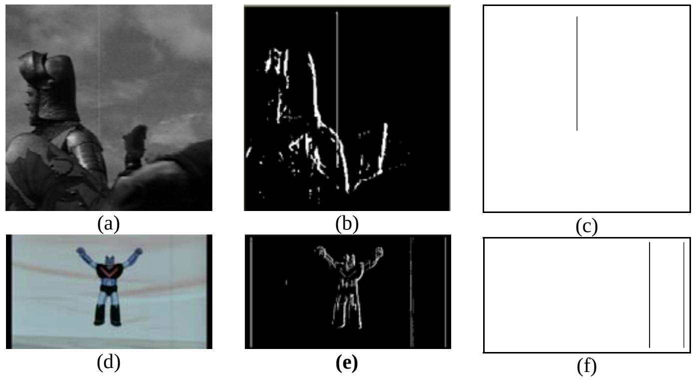


Figure 7. Example of scratch detection (in the sequence “knight” and “TaekwonV”): (a) and(d) input Image, (b) and (d) result of texture classification, (c) and (f) detection scratch

Fig. 8 shows the detection results for the scene including not-alone scratches. Fig. 8(a) is a frame obtained from the old films ‘sit-down’, where includes various types of scratch such as secondary/static/positive, secondary/static/negative and secondary/static/positive scratches. Then the classified image by a neural network is shown in Fig. 8(b). Finally the scratches regions filtered by shape filter are shown in Fig. 8(c). As mentioned before, most of methods in the literature are limited to detect only alone and principal scratches. Unlike them, the proposed method can correctly detect these scratches, as can be seen in Fig. 8.

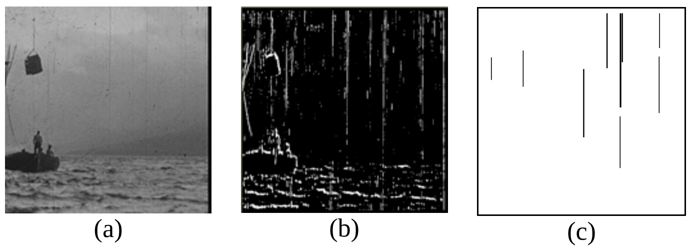


Figure 8. Example of scratch detection (sequence "sit-down."): (a) input Image, (b) result of texture classification, (c) detection scratch

Fig. 9 shows a detection result for an animation ‘Taekwon V’, which is foremost animation data in Korea. Fig. 9(a) shows a frame in the animation, which includes many artificial vertical lines to be regarded as scratches as well as real scratches. The classified image by texture classification is shown in Fig. 9(b). Finally, the scratches regions filtered by shape filtering are shown in Fig. 9(c).

In the experiment, a non-scratch is over-detected. This is due to the fact that the artificial lines in an animation have very similar properties to the scratch. Thus, to solve this problem, future works will include the use of other information such as temporal information. It is expected that the temporal information between the successive frames will help reduce over-detection.

(a) (b) (c)

Figure 9. Example of scratch miss-detection: (a) input Image, (b) result of texture classification, (c) detection scratch

The matrix of experiment result is show in Table 2

TABLE II. THE MATRIX OF EXPERIMENT RESULT

	Scratch	Detection-scratch	Miss-scratch	Over-detection
Sit-down	45	25	20	2
Knight	10	10	0	0
Star	122	65	57	1
Taekwon-V	18	14	4	8

VI. CONCLUSION

An automatic scratch detection method for old film archives using a neural network and morphological filtering was proposed and a system was implemented. The given method was tested on the several old films and animations holding diverse scratches. Experimental results confirm that the proposed method can detect the scratches of various types and have a potential for commercial using.

The main advantage of the proposed method include: 1) it is worked fully automatically, 2) it can detect the scratches of various types, and 3) it can save the computing time because of using the information of spatial domain unlike the common methods which depends on the information of time. However, the proposed method also has several problems. Although it can accurately detect scratches, it has some over-detection. Such an error was caused by low resolution and row contrast between scratch and the neighboring, or by the artificial vertical lines. To solve this problem, future works will include the use of other information such as temporal information. It is expected that the temporal information between the successive frames will help reduce over-detection. In addition, future works include the developing the restoration skills, and incorporating the detection method and restoration method.

result, an automatic recognition system is developed. Our method is component two modules: feature extraction and classification. To describe the color and pattern information from a textile, the color quantization and the wavelet transform are used. And the neural network is used as the classifier.

To assess the validity of the proposed method, it was applied to recognize the human emotions in three textile domains: fashion, interior and artificial data book. And then our method produced the precision of 100% and the recall of 99% on average. This result confirmed that our method has the potential to be applied for various applications such as textile industry and e-Business.

ACKNOWLEDGMENT

This work was supported by Seoul R&BD Program(10581)

REFERENCES

Schallauer, P, Pinz, A. and Hass, W., "Automatic restoration algorithms for 35mm film." VIDERE: J. Comput. Vis. Res., vol. 1, No. 3, 1999

[2] Joyeux, L., Boukir, S. and Besserer, B., "Film line scratch removal using Kalman filtering and Bayesian restoration." WACV2000, Palm Springs, CA, Dec. 2000

[3] Bruni, V. and Vitulano, D., "A generalized model for scratch detection. IEEE Transactions on Image Processing, Vol. 13, No. 1 44-49, 2004

[4] Joyeus, L. et al., "Film line scratch removal using Kalman filtering and Bayesian restoration." IEEE Workshop on the Application of Computer Vision. 2000

[5] Tegolo, D. and Isgro, F., "Scratch detection and removal from static images using simple statistics and genetic algorithms." IEEE ICIP'2001. 265-268, 2001

[6] Maddalena, L., " Efficient methods for scratch removal in image sequences. IEEE ICIP'2001, 547-552, 2001

[7] Kokaram, A. C., "Detection and removal of line scratches in degraded motion picture sequences." Signal Processing, Vol. 1. 5-8, 1996

[8] Kokaram, A.C.,"Motion Picture Restoration: Digital Algorithms for Artifact Suppression in Degraded Motion Picture Film and Video." Springer-Verlag., 1998

[9] Juyeux, L. et al., "reconstruction of degraded image sequences. Application to film restoration.", Image and Vision Computing, Vol. 19, 503-516, 2001