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by Zhiheng TANG

Project Proposal of “Advanced Image Processing and Machine-learning Techniques for Film Restoration”

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1 Introduction

Before the introduction of digital media, the archived film has been the primary media of video documenting for a relatively long time. To preserve the originality of the archived film is of great importance since many of the archive films possess high historical or artistic value. In some countries, archive films are regarded as valuable heritage and an enormous amount of effort has been made in film archival and restoration.

Unlike digital media, archived films are prone to degradation due to abrasion and impropriate storage. Repeated use of films mainly results in scratches on the screen and the degree of degradation increases each time. Impropriate storing environment leads to dirt accumulation or chemical change of the film, where random size and shape of sparkle, blotches, and noise occurs.

Traditional restoration approaches aim to analyze the degradation process and try to reverse it by physical and chemical means. Usually, the degradation process is complex and increase analyzing difficulties. Note that those procedures are also irreversible. It is under high risk due to the high uncertainty of the result.

After the transitions to digital media, historic films have been scanned and archived in digital form, which leads the restoration research to the digital field. Compared with traditional approaches, digital restoration is much more convenient for experimenting without the fear of causing any damage and a great amount of research has been conducted.

Many techniques and algorithms have been invented by academic and industry collaborations by now, which can be categorized into non-deep-learning methods and deep-learning methods. non-deep-learning methods. Non-deep-learning methods usually seek the correlation between consecutive films and detect artifacts from discontinuity. Deep-learning methods will attempt to train a deep neural network to only select undegraded pixels while artifacts are ignored.

There is also an interesting fact that different defect types can be detected and restored individually. Kokoram [1] has found that the defects can be identified and categorized in terms of their "intensity, shape, size, appearance, etc.", which can be located and restored individually. In project BRAVA [2], the defects were well classified, typical among which are dirt, line scratches, brightness variation, and frame vibration. According to those identifiable characteristics, we can apply different techniques to detect and remove them individually. Based on this discovery, the research on single defect types become meaningful and practical.

This project will mainly focus on the generic methods of artifact detection and restoration algorithms. One or more non-deep-learning methods and deep-learning methods will be tested. We will compare the restoration quality of different techniques and try to make possible improvements. Meanwhile, this project will explore if there is an algorithm that can also be applied to color artifacts and scratches detection. Hence, the procedure between general artifacts, color artifacts, and scratches needs to be compared.

2 Objective

This project aims to detect and restore the artifacts in a generic way. The expected outcomes of the algorithm include:

- At least one conventional method and one deep-learning-based method of general detection and restoration are tested in the project.

- The algorithm of each method should be realized in the form of computer programs and successfully restore the given archive films.

- The quality of the restoration process of each technique should be evaluated

- Explore an algorithm that can not only deal with general artifacts but also color artifacts and scratches.

3 Methodology

3.1 Conventional General Artifact Detection and Restoration

3.1.1 Automatic restoration framework

Traditional methods of general detection assume that most of the defects only appear in a single frame and they determine whether a frame is degraded or not by comparing it with previous and subsequent frames. Typical ones are spike detection index (SDIp) [4] and the Markov random field (MRF) based detector [5]. After that, Wang and Mirmehdi [6] proposed an automatic restoration framework (ARF) to further improve the detection accuracy and computational efficiency.

ARF assumes the appearance of a defective pixel as a stochastic pixel-change event. The temporal and spatial information is represented by the hidden Markov model (HMM) and the MRF model. An HMM observation sequence will be first generated for the current frame. It will then be used to examine each new observation sequence via a leave-one-out process to generate defect alarms.

According to Wang and Mirmehdi [6], the defect map "encapsulates the defects very well, but suffers from many false alarms." Therefore, it will be followed by a two-stage false alarm elimination process. The first stage is adding MRF enforcing spatial continuity constraints. The second stage is the pyramidal Lucas-Kanade feature tracker [7], which imposes correlation constraints on temporal pixel sequences. The two stages will eliminate false alarms and improve the accuracy of the defect map.

With the defect map from the detecting procedure, the marked positions are replaced by the maximum likelihood of original pixels, which are decided by information from subsequent frames.

3.2 Deep-Learning-Based General Detection and Restoration

3.2.1 Deep Learning Method

Ulyanov et al. [8] have proposed an artifact detection and restoration approach using deep convolutional neural networks (ConvNets). The approach fits the network to a single degraded image and lets the network weights serve as a parametrization of the restored image. By training the network using the single degraded input image *and* the handcrafted structure of the network used for reconstruction, the weights can maximize the likelihood to restore the original image.

This approach can be applied to perform different tasks. It can be used to (1) denoise the images by reversing the noise occurrence process. It can also do (2) super-resolution, which is converting a low-resolution video to high-resolution video and (3) inpainting, which is to fill in large missing areas of the frame.

3.3 Color Artifacts Detection

Several color artifacts detection methods will be explored to find any similar steps related to general detections.

3.3.1 Traditional Methods

Color artifacts are often single-color regions with random size and shape. A way to select the artifact regions is to manually set a certain range of R, G, B values based on the color features of the artifacts where those pixels fall in. Usually, an artifact mask is generated, and the content will be filled by information extracted from previous and subsequent frames.

3.3.2 Spatiotemporal Methods

Yadav et al. [7] proposed a spatiotemporal detection and restoration approach of the color artifacts, which focus on the correlation of the consecutive frames. The detection process consists of two steps: (1) Artifact mask generation, and (2) False alarms removal. In artifact mask generation, the artifact pixels can be considered to be sparse elements. Due to the correlation between frames, seeking the correlation between frames can be equalized to minimizing the rank of matrix M in R, G, B color plane respectively. Then the rank-sparsity incoherence principle proposed by Chandreshaken et al. [9] is exploited to detect the possible location of the artifact pixels. In False alarms removal, the mask of nearby degraded and undegraded frame are compared to locate the false alarms.

3.4 Scratch Detection

The same as color artifacts detection, several scratch detection methods will be explored to find any similar steps related to general detections.

3.4.1 Canny Filter and Hough Transform

Traditional methods of scratch detecting include the Canny edge detector, which examines the sudden intensity change in each frame and Hough transform, which can be used to detect prominent lines in binary images.

3.4.2 Robust Automatic Line Scratch Detection in Films

Newson et al. [10] proposed a robust automatic line scratch detection approach to improve performance and reliability. The first step of the approach is to mark all edges using a pixel-wise detection criterion, which is the same as the Canny filter. In order to eliminate all false detections except the scratches, instead of using Hough transform, the approach uses the (1) Contrario approach, (2) Locally Adaptive Grouping, and (3) Maximality to detect the line scratch. The main idea is to determine the probability of whether it is a line scratches and use a threshold to eliminate all false alarms. It is more flexible than the Hough transform. After that, the result is further filtered to eliminate the false alarms due to thin vertical structures that are part of the captured scene.

4 PROJECT SCHEDULE

Milestones	Calendar Date	Work Progress/R&D Deliverables

1st Project Milestone: (2th month from commencement)	2020/5/27	1. One or more non-deep-learning methods (Hidden Markov) model is developed 2. Preliminary algorithm and code are built
2nd Project Milestone: (4th month from commencement)	2020/7/27	1. A method based on Deep Image prior is developed. 2. Preliminary algorithm and code are built
3rd Project Milestone: (2th month from commencement)	2020/9/27	1. Non-deep-learning and deep-learning method experiments result with guaranteed quality.
4th Project Milestone: (4th month from commencement)	2020/11/27	1. All techniques and performances are compared and evaluated. Improvements in the algorithms have been proposed.

5 REFERENCES

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ORIGINALITY REPORT

%28	%17	%25	%15
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Xiaosong Wang, M. Mirmehdi. "Archive Film Defect Detection and Removal: An Automatic Restoration Framework", IEEE Transactions on Image Processing, 2012 Publication	%8
2	link.springer.com Internet Source	%5
3	Victor Lempitsky, Andrea Vedaldi, Dmitry Ulyanov. "Deep Image Prior", 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018 Publication	%2
4	Yadav, Ravindra, Saumik Bhattacharya, K. S. Venkatsh, and Sumana Gupta. "A spatiotemporal restoration of partial color artifacts in archival films", Signal Image and Video Processing, 2016. Publication	%2
5	www.bmva.ac.uk Internet Source	%2

6	Submitted to Higher Education Commission Pakistan Student Paper	%2
7	Jingjing Wu, Shujuan Song, Wei An, Deqiang Zhou, Hong Zhang. "Defect Detection and Localization of Nonlinear System Based on Particle Filter with an Adaptive Parametric Model", Mathematical Problems in Engineering, 2015 Publication	%1
8	Xuewei Li, Ruiguo Yu, Hongqian Shen, Mei Yu, Xi Wei, Jiang Han, Jialin Zhu, Jie Gao, Zhiqiang Liu, Yulin Zhang. "Blind Image Inpainting Using Pyramid GAN on Thyroid Ultrasound Images", 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2019 Publication	%1
9	Submitted to Taibah University Student Paper	%1
10	Alasdair Newson, Andres Almansa, Yann Gousseau, Patrick Perez. "Robust Automatic Line Scratch Detection in Films", IEEE Transactions on Image Processing, 2014 Publication	%1
11	export.arxiv.org Internet Source	%1

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13	Submitted to The Hong Kong Polytechnic University Student Paper	%1

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