Initial report: Film damage restoration using diffusion with temporal bias

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1 Introduction

The aim of this final project is to explore the field of image restoration, specifically focusing on old scans of film reels and slides. Image restoration plays a crucial role in preserving and reviving historical media, as many archival films suffer from various forms of degradation over time. These degradations include physical damage such as scratches and dust, and other artifacts introduced during storage.

Traditional film restoration relies heavily on manual labor, with experts cleaning frames individually or using rule-based automated processes. While these methods have been effective in the past, they often require weeks or months to restore just reel of a film. Deep learning and diffusion-based models offer a promising alternative by learning to reconstruct damaged sections while preserving the integrity of the original material. Generative models have demonstrated their ability to recover missing information in images, making them a suitable approach for film restoration.

This project aims to develop a deep learning-based solution tailored to the specific characteristics of 1960s 35mm and 16mm film scans, as well as home video formats from the same period. The goal is to create a model that not only removes dirt and scratches but also ensures that the restored images retain their original texture and grain. To achieve this, the project will leverage state-of-the-art diffusion models and explore ways to condition them on temporal information from adjacent frames, allowing for more coherent and context-aware restorations.

Ultimately, this project seeks to bridge the gap between traditional restoration techniques and modern AI-driven approaches, providing a tool that is both effective and accessible. In addition to developing and evaluating restoration models, the project will also focus on usability, designing an intuitive interface that allows users to visualize and interact with the restoration pipeline easily. Through these efforts, the project aims to contribute to the growing field of AI-assisted film preservation, offering a solution that can be extended to other film formats and historical archives in the future.

2 Objectives

ID	Task	Priority
O1	Propose a solution to **restore damaged scanned film reels.** The solution has to be able to restore damage like dirt or scratches on the film, but keep the characteristic grain of film images and videos. The solution will focus specifically on 1960s 35/16mm movie scans, as well as home videos of the same decade.	**Main objective**
O2	Obtain a usable dataset to train restoration models based on common and real film damage.	**Essential**
O3	Said solution has to be easy to use, as well as visually appealing.	**Essential**
O4	Generalize the model as to be able to restore any type of film scans, not only the ones presented on O1.	**Not essential**

Table 1: Summary of the objectives defining the project

2.1 Tasks

ID	Task	Objective
T1	**Explore dataset options**. Research different resources to be used as dataset (ground truth or testing). By the end of this task there should be a trainable dataset.	*O2*
T2	**Create synthetic ground truth dataset** using real scanned film damage.	*O2*
T3	**Segment** the damaged parts of a frame, without prior knowledge of said film. The proposed model should be able to segment all damaged parts of the film.	*O1*
T4	Propose a model to segment the damaged parts of a frame **having context of other frames** to bias the segmentation model.	*O1*
T5	Research about inpainting models and implement one to start testing the specific use case.	*O1*
T5	Modify an existing inpainting diffusion model in order to, providing context of other frames as a prompt, bias the generation to better adequate said generation to the ground truth.	*O1*
T6	Explore different inpainting architectures to compare performance with the original chosen one.	*O1*
T7	Implement a **graphical user interface** in order to provide an easy and catchy representation of all the parts of the final pipeline and showcase the results of the project in a tidy and usable way.	*O3*

Table 2: Summary of the tasks defining the project

3 Methodology

This project will be developed by what in software development would be called agile development. This type of development is characterized with short work cycles, with predefined objectives (tickets) that have a clear deliverable in mind. For each work cycle, the objectives, as well as the deliverables, will be predefined in this initial report. Subsequently in the following Reports of Progress, a small report shall be written for each work cycle, detailing weather the objectives and deliverables have been met, with a pertinent reasoning in case of failure to do so. These work cycles will be marked by a weekly meeting with the tutor of the project, however this may not coincide with each start of work cycle, as the meeting schedule will be adjusted on a weekly basis.

4 State of the Art

Diffusion-based models have emerged as a powerful tool in image generation. In the defined task for this project, image generation is a key aspect, since in order to restore an image, we need to generate the missing data from the image. Existing solutions include papers like DiffIR [4].

4.1 DiffIR

DiffIR (Diffusion-based Image Restoration) introduces a diffusion-based image restoration pipeline, outperforming traditional CNNs by effectively handling various degradations, such as noise, blur and compression artifacts. To effectively achive this, DiffIR proposes a solution consisting of a compact image restoration prior extraction network (CPEN), which extracts a compact image restoration representation which encapsulates relevant priors for the restoration, a dynamic IR transformer (DIRformer), which restores low quality images using the prior representation given by the CPEN, and a de-noising network.

5 Dataset

Since the focus of the project is restoring film damage while keeping the characteristic grain of developed film, I cannot use the typical image restoration datasets, like LSDIR (reference) since it is focused on a super-resolution restoration, defeating one of the main, self-imposed, restrictions of my project. To achive the objective, I would need a dataset centred around film damage (dirt, hairs, scratches, etc.). Online there is no robust existing dataset for said solution.

The only solution left would be to create my own dataset. There are two methodologies. The first one would be, given original and HQ damaged film scans, to label myself a dataset based on real images. The main problem with this solution is time, since it is very limited for my project. The second solution, which I have chosen, is to create a synthetic dataset using HQ non-damaged film scans. To create the synthetic dataset first I would need HQ isolated film damage to superimpose to the HQ images. FILM-AA [1] provides synthetic damage extracted from 4k scans of damaged film. This solution allows me to create synthetic masks to add to HQ images to create a suitable dataset for the task.

Apart from the already stated benefits of said solution, it gives me the ability to tinker with what films I want to restore, so I can focus on the original objective.

6 Time Schedule

Week	Date	Task Name	Deliverable
1	27/01 - 02/02	Read and research SOTA solutions	-
2	03/02 - 09/02	Explore available online datasets (T1)	Dataset
3	10/02 - 16/02	Implement and create a synthetic dataset (T2)	-
4	17/02 - 23/02	Explore segmentation solutions to detect film damage (T3)	-
5	24/02 - 02/03	T3	Initial segmentation model results
6	03/03 - 09/03	Prepare and redact the initial report delivery	Initial Report
10/03/2025		**DUE INITIAL REPORT**	
7	10/03 - 16/03	Improve the synthetic dataset, T3, T4	Result comparison
8	17/03 - 23/03	Explore inpainting solutions and implement a starting model (T5)	-
9	24/03 - 30/03	T5	Initial inpainting model results
10	31/03 - 06/04	Develop a solution to incorporate temporal bias into the inpainting diffusion model (T6)	-
11	07/04 - 13/04	Prepare a dataset to train *T6* model and train the model	Result comparison
12	14/04 - 20/04	Prepare and redact Progress Report I	Progress Report I
20/04/2025		**DUE PROGRESS REPORT I**	
Week	**Date**	**Task Name**	**Deliverable**
13	21/04 - 27/04	Explore different architectures for inpainting restoration (T7), T6	-
14	28/04 - 04/05	Train and/or test T7 models	Result comparison
15	05/05 - 11/05	Prepare models for GUI (T8)	Model inference service
16	12/05 - 18/05	T7, T8	Final GUI
17	19/05 - 25/05	Prepare and redact Progress Report II	Progress Report II
25/05/2025		**DUE PROGRESS REPORT II**	

18	26/05 - 01/06	Prepare and redact final report proposal	-
19	02/06 - 08/06	Prepare and redact final report proposal	-
20	09/06 - 15/06	Prepare and redact final report proposal	Final report proposal
15/06/2025		**DUE FINAL REPORT PROPOSAL**	
21	16/06 - 22/06	Prepare presentation slides	Presentation
20/06/2025		**DUE PRESENTATION PROPOSAL**	
22	23/06 - 29/06	Prepare final dossier	Dossier
29/06/2025		**DUE FINAL DOSSIER**	

Table 3: Weekly Planning

References

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[4] Bin Xia, Yulun Zhang, Shiyin Wang, Yitong Wang, Xinglong Wu, Yapeng Tian, Wenming Yang, and Luc Van Gool. DiffIR: Efficient Diffusion Model for Image Restoration. pages 13095–13105, 2023.

[5] Enze Xie, Wenhai Wang, Zhiding Yu, Anima Anandkumar, Jose M. Alvarez, and Ping Luo. SegFormer: Simple and Efficient Design for Semantic Segmentation with Transformers, October 2021. arXiv:2105.15203 [cs].

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