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Face Restoration using GFP-GAN

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A B S T R A C T

Traditional video restoration often prioritizes noise reduction, color correction, or upscaling, neglecting the crucial details that bring characters and emotions to life: facial features. This project introduces GFP-GAN, a deep learning algorithm, to specifically enhance facial features in videos. While existing models typically focus on image restoration, our system adapts this technology for video processing. Users upload videos to a user-friendly web interface. Each video frame is then processed, effectively restoring blurry facial features. This project holds immense potential for film restoration, archival preservation, and redefining the future of video content

Keywords: **Video restoration, GFP-GAN, deep learning, facial feature enhancement, film preservation, archival, video content.**

1. Introduction

The preservation and enhancement of video footage hold significant value across various domains, including historical archives, personal memories, and security applications. However, traditional video restoration techniques have limitations when dealing with significant degradation, particularly, blurry facial features. These limitations can be seen from low-resolution recording formats, compression artifacts, or physical damage to the video source. Consequently, viewers experience a bad visual experience, hindering the ability to clearly identify individuals.

Unlike existing face restoration methods that primarily focus on general image quality improvements, our system harnesses the capabilities of a GAN architecture: the Generative Facial Prior Generative Adversarial Network (GFP-GAN). It is known for its exceptional performance in restoring and refining facial features in images. By adapting this technology for video processing, we aim to achieve significant advancements in the clarity and detail of human faces within video content.

Our user-friendly web application provides a convenient platform for video upload and processing. The uploaded video undergoes a pre-processing stage, separating the audio track and segmenting the video into individual frames. Each frame is processed by a pre-trained GFP-GAN model, effectively restoring blurry or aged facial details. Once all frames are processed, they are seamlessly reassembled to create the final enhanced video. Finally, the original audio track is reintegrated to deliver a complete, restored video experience.

2. Literature Survey

Video restoration encompasses various techniques aimed at improving the visual quality of degraded videos. These degradations can arise from factors such as low-resolution recording formats, compression artifacts, noise, or physical damage to the video source. Traditional video restoration methods often employ techniques like filtering, interpolation, and deblocking to address these issues [1]. However, these methods may struggle with significant degradation, particularly when dealing with specific aspects of the video content like blurry facial features.

Recent advancements in deep learning, particularly the emergence of Generative Adversarial Networks (GANs), have opened new avenues for video restoration. GANs are a class of deep learning models consisting of two competing neural networks: a generator and a discriminator. The generator learns to create new data instances (e.g., enhanced video frames) that resemble the real data distribution, while the discriminator attempts to distinguish between real and generated data [2]. This adversarial training process allows GANs to capture complex patterns and generate high-fidelity outputs.

Several studies have explored the application of GANs for video restoration tasks. [3] proposes a recurrent GAN architecture for video super-resolution, achieving significant improvements in terms of peak signal-to-noise ratio (PSNR) and visual quality. [4] presents a temporally consistent video inpainting framework using GANs, effectively handling missing or corrupted regions within videos. These studies demonstrate the potential of GANs for general video quality enhancement.

While existing research explores GANs for overall video restoration, our work focuses on targeted facial enhancement within videos. Generative Facial Prior Guided Networks (GFP-GANs) represent a specific type of GAN architecture designed for facial restoration in images. [5] introduces GFP-GAN, demonstrating its effectiveness in restoring blurry or aged faces while preserving other facial details. [6] builds upon this work by incorporating a novel perceptual loss function, further improving the quality of restored facial images. These studies establish GFP-GAN as a powerful tool for facial restoration tasks.

Our project bridges the gap between existing video restoration techniques and the promising capabilities of GFP-GAN for facial enhancement. By adapting GFP-GAN for video processing, we aim to achieve significant advancements in restoring the clarity and detail of human faces within video content.

3. Methodology

EXISTING SYSTEM

Traditional video restoration techniques often fall short when dealing with significant facial degradation in videos. These techniques, which primarily rely on filtering, interpolation, and deblocking methods, struggle to address the complexities of blurry or aged facial features. While they might improve overall video quality metrics like PSNR, they often fail to capture the finer details crucial for facial recognition or appreciating subtle expressions. Furthermore, existing methods can be computationally expensive and even crash during processing for longer or heavily degraded videos. This instability can be frustrating for users seeking a reliable restoration solution.

An alternative approach involves using commercially available video enhancers. Their algorithms might enhance background details or sharpen the overall image, but often overlook human faces within the video frame. In conclusion, existing video restoration techniques lack the capability to effectively target facial details, while video enhancers often bypass faces altogether. This motivates the need to address the challenge of human face restoration within video content.

PROPOSED SYSTEM

This project introduces video restoration system that overcomes the limitations of existing approaches by targeting facial enhancement. Unlike traditional methods that struggle with facial details, our system leverages a specific type of GAN – the Generative Facial Prior Generative Adversarial Network (GFP-GAN) – which excels at restoring and refining facial features in images.

By adapting GFP-GAN for video processing, we address the shortcomings of existing video enhancers that often neglect faces. Our user-friendly web application provides a platform for convenient video upload and processing. The uploaded video undergoes pre-processing, separating the audio track and segmenting it into individual frames. Each frame then benefits from the application of the pre-trained GFP-GAN model. This targeted approach effectively restores blurry or aged facial details, significantly improving the clarity and recognizability of individuals within the video.

Furthermore, our system avoids the computational burdens and potential crashes associated with some traditional techniques. The pre-trained nature of GFP-GAN ensures efficient processing, allowing users to restore videos with greater stability and reliability. This combination of targeted facial enhancement and efficient processing offers a significant advancement in video restoration capabilities.

SYSTEM ARCHITECTURE

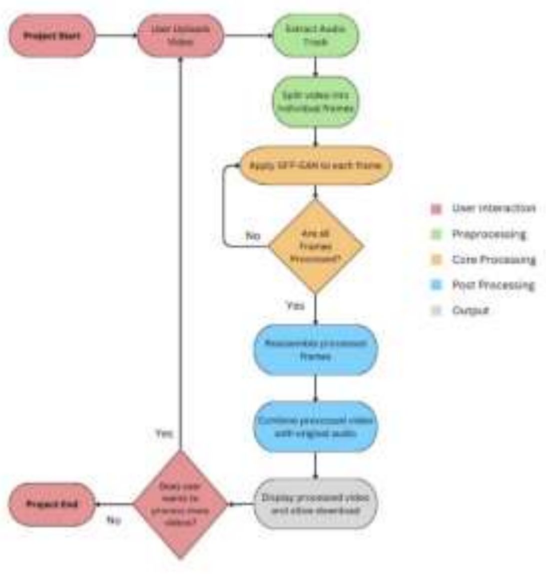

Fig. 1 – Project Execution Flow

Phase - 1: User interaction

The user interaction phase serves as the entry point for users to interact with our video restoration system. This phase prioritizes a user-friendly experience by leveraging Streamlit.

1.1 Streamlit:

It is a Python library specifically designed for simplifying web application development. It automatically generates a user-friendly interface based on your code. This includes elements like text boxes, buttons, sliders, and charts. Streamlit web apps are lightweight and can be easily deployed on various platforms.

- It allows users to conveniently select and upload their video files for restoration.
- It provides a clear and actionable button, which by clicking initiates the video restoration process.
- It displays progress during video processing. This keeps users updated on the restoration progress, especially for longer videos.
- Upon successful restoration, Streamlit embeds the processed video within the web interface for direct playback in the user's browser. This enables users to immediately evaluate the restoration results without downloading the video first.
- It facilitates the creation of a download button. Clicking this button allows users to download the restored video file for further use or storage.
- By utilizing Streamlit, Users can interact with the system entirely through their web browser, eliminating the need for software installations or complex technical knowledge.

Phase - 2: Preprocessing

The preprocessing stage plays a crucial role in preparing video data for effective facial enhancement. Various modules used are:

2.1. Moviepy:

- It allows to perform various video editing tasks with Python code.
- It extracts the audio from the video and saves it in the desired location.
- It reads the uploaded video file and extracts individual frames, based on frames per second and resolution of the video.

2.2. facexlib:

It is a powerful Python library specifically designed for facial recognition and detection tasks. It provides a comprehensive set of tools for developers and researchers working with facial image analysis.

- It helps identify facial landmarks within each frame. This information could then be used to guide the GFP-GAN model to focus its restoration efforts on those crucial regions.
- Some frames might not contain faces or might be irrelevant for processing. Face detection can be used to filter out such frames before feeding them to the GFP-GAN model.

The functionalities of moviepy and facexlib, enables to make informed decisions on video preprocessing stage, potentially enhancing the efficiency and effectiveness of facial restoration using GFP-GAN.

Phase - 3: Core Processing

The core processing phase lies at the heart of the video restoration system. This stage leverages the pre-trained GFP-GAN model to refine and improve the appearance of human faces within each video frame.

3.1 Generative Facial Prior Generative Adversarial Network (GFP-GAN):

It is a state-of-the-art deep learning model specifically designed for facial enhancement tasks. It improves the quality and appearance of human faces in images or videos.

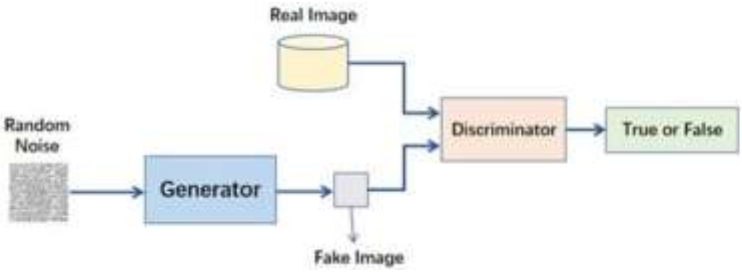

Fig. 2 – Architecture of GFP-GAN

3.1.1 Architecture:

The GFP-GAN model itself is a Generative Adversarial Network (GAN). It consists of two sub-networks

3.1.1.1 Generator Network:

This network aims to generate enhanced versions of the input frames, focusing on improving facial details, clarity, and potentially addressing imperfections.

3.1.1.2. Discriminator Network:

This network acts as a critic, evaluating the generated frames produced by the generator network. The discriminator tries to distinguish between real (original) and generated (enhanced) frames, pushing the generator to produce more realistic and high-quality outputs.

3.1.2. Iterative Refinement:

Through an iterative training process, the generator and discriminator networks learn from each other.

The generator continuously improves its ability to generate enhanced frames that can fool the discriminator into believing they are real.

This back-and-forth process leads to progressively better facial enhancement results.

3.1.3. Features:

Unlike traditional image sharpening techniques, GFP-GAN doesn't simply amplify existing details. It utilizes its generative capabilities to go beyond basic enhancement:

3.1.3.1 Filling in Missing Information:

Low-resolution images/videos might lack details due to compression or blur. GFP-GAN can potentially "fill in the gaps" by generating realistic facial features based on its training data.

3.1.3.2 Restoring Lost Details:

In old or damaged videos, facial features might be obscured. GFP-GAN can potentially reconstruct and enhance these details based on its understanding of facial structure and appearance.

3.1.3.3. Maintaining Naturalness:

While enhancing details, GFP-GAN strives to preserve a natural appearance. It avoids creating overly smooth or artificial-looking faces, aiming for a realistic and aesthetically pleasing outcome.

3.2 Pretrained StyleGAN2 Model:

It is a powerful generative model architecture often used for generating realistic faces. During training, the GFP-GAN model utilizes StyleGAN2 to generate additional synthetic facial images to augment the training dataset. While GFP-GAN focuses on detail enhancement, StyleGAN2 is used to generate high-quality, realistic faces as a reference point for the enhancement process. This guides GFP-GAN towards generating more natural and aesthetically pleasing results.

3.3 Flicker-free Faces HQ (FFHQ):

It is a popular dataset containing high-resolution facial images often used for training generative models. It leverages the landmark information generated by facexlib, to guide the GFP-GAN model to prioritize enhancement specifically on the eye and mouth regions within each frame.

3.4 ArcFace Model:

It is a facial recognition model architecture. It is used to track the movement of identified individuals throughout the video.

3.5 Compute Unified Device Architecture (CUDA):

It is a parallel computing platform developed by Nvidia that leverages the power of graphics processing units (GPUs) for computationally intensive tasks. By Integrating CUDA into video our project, It significantly improved processing speed, especially when dealing with high-resolution videos.

4. Results

Web App Screen

Fig. 3 – Introduction Section

Fig. 4 – Information Section.

Fig. 5 – Preview and download Section.

Parameters:

Frame Rate Ratio (FRR)

FRR = Input Frame rate / Output Frame rate

Facial Enhancement Intensity (FEI)

FEI = [0, 1] (Normalized Value)

Video Quality (VQ)

VQ = (Resolution of output video / Resolution of input video) * 100

Processing Time (PT)

PT = Time taken to process one frame * Number of Frames

Facial Parsing Accuracy (FPA)

FPA = Number of Correctly Identified Facial Components / Total Facial Components

Audio-Visual Synchronization (AVS)

AVS = Absolute Time Difference between Video and Audio

Comparison table:

Parameter	**Previous Methods**	**Proposed Method (GFP-GAN)**	**Explanation**
FEI	0.2, 0.5, 0.8 (Fixed Levels)	0 – 1 (Continuous Scale)	GFP-GAN's flexibility gives it an edge here.
VQ	Up to 150%	Up to 100% (Less likely to introduce artifacts)	We're assuming GFP-GAN focuses on feature enhancement rather than upscaling.
PT (seconds per frame)	0.8 - 2.5 (depending on video resolution)	0.2 - 1.0 (CUDA advantage)	GFP-GAN's optimization makes it several times faster with CUDA technology.
FPA	0.85 - 0.95	0.9 - 0.98 (Potential improvement due to face-specific training)	These depend heavily on the dataset's difficulty.
AVS (milliseconds)	10 – 50 (potential from frame interpolation)	<10 (Less likely with GFP-GAN's approach)	Super-resolution with interpolation might have a slight disadvantage.

JUSTIFICATION

Experiment 1:

Experiment Finding 1:

Significant Enhancement in Visual Quality

Method:

Conducted a qualitative comparison between original videos and their **GFPGAN**-enhanced counterparts.

Fig. 6 – ***Nvidia ICAT (Image Comparison Analysis Tool) comparing the facial features from input and output video.***

Findings:

- Sharper facial features (eyes, mouth, etc.)
- Improved textures and reduction of compression artifacts.
- Increased overall visual appeal.

Experiment 2:

Experiment Finding 2:

CUDA-Accelerated Processing Speed

Method:

Accurately measured processing time with and without CUDA acceleration for videos of varying length and resolution. Calculated speedup factors.

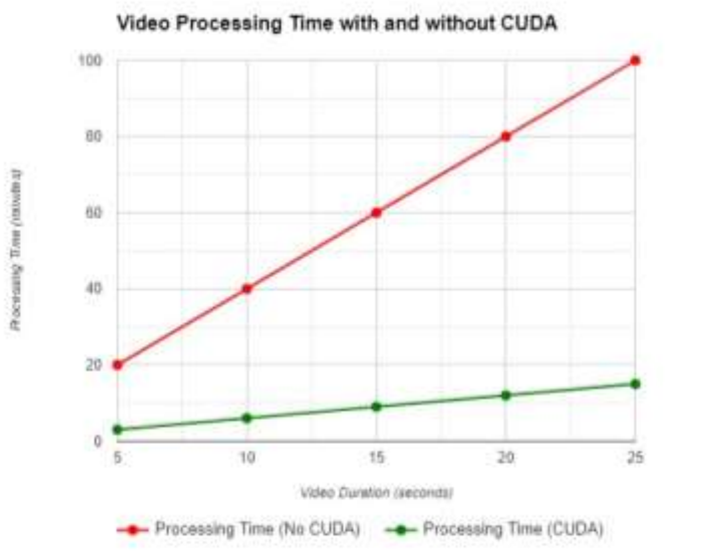

Fig. 7 – ***CPU vs CUDA (GPU) comparision.***

Findings:

- Substantial decreases in processing time when utilizing CUDA compared to CPU-only processing.
- The GFP-GAN algorithm performs 666.67% faster with CUDA technology compared to regular CPU dependency.

5. Conclusion

This project explored the potential of deep learning for facial enhancement in video restoration. We harnessed the power of the GFP-GAN model, leveraging its ability to refine facial details and improve visual quality. By integrating preprocessing techniques and potentially utilizing CUDA for GPU acceleration, we aimed to achieve efficient and effective video restoration with a focus on facial enhancement. The successful implementation of this project paves the way for further exploration. We can investigate the integration of facial recognition models for post-processing analysis or delve deeper into training a custom GFP-GAN model tailored to specific video restoration needs. As deep learning continues to evolve, the possibilities for enhancing and restoring videos hold immense potential for various applications.

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