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Inpaint Expert: Iterative Flow Completion for Video Inpainting

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ABSTRACT: This project aims to design and implement an internal video inpainting system utilizing the Iterative Flow Completion technique. Video inpainting, a process of filling missing or corrupted regions in video frames, is essential for various applications, such as video restoration and visual content enhancement. The Iterative Flow Completion technique leverages advanced algorithms to propagate information over extended temporal and spatial ranges, ensuring superior accuracy and efficiency in inpainting tasks. In this project, we will explore state-of-the-art inpainting methods and adapt the Iterative Flow Completion approach to address challenges specific to video data. The system will be designed to handle various inpainting scenarios, including occlusions, object removal, and artifact removal, while preserving temporal coherency and maintaining realistic visual results. The proposed system will be extensively evaluated on diverse video datasets to assess its performance, comparing it with existing methods in terms of inpainting quality, computation time, and memory utilization. The proposed system will be extensively evaluated on diverse video datasets to assess its performance, comparing it with existing methods in terms of inpainting quality, computation time, and memory utilization. The expected outcome is a robust and efficient video inpainting solution that can be applied to real-world applications.

KEYWORDS: Video Inpainting, Object Removal, Cross Domain Transformation, Iterative Flow Completion

I. INTRODUCTION

In recent years, the ubiquity of digital video content has led to a growing demand for innovative techniques that enhance and restore the quality of videos. One area of significant interest is video inpainting, a process that involves intelligently filling in missing or corrupted regions within a video sequence. This is particularly important for videos containing gaps, artifacts, or visual inconsistencies, which can arise from various factors such as data loss, compression artifacts, and sensor limitations. Traditional video inpainting methods primarily focus on handling small-scale, local inpainting tasks, where the missing regions are relatively limited in size and context.

However, modern video content often presents challenges that go beyond these traditional methods. This is especially true in scenarios where the missing portions span long temporal ranges, making it crucial to consider temporal consistency and semantic coherence. In response to these challenges, we propose a novel framework titled "Inpaint Expert: Iterative Flow Completion for Video Inpainting". This framework leverages the power of Iterative flow Completion techniques to address the complex task of inpainting large and spatially diverse gaps in video sequences while maintaining both the visual quality and the temporal coherence of the content. The Iterative flow Completion technique leverages advanced algorithms to propagate information over extended temporal and spatial ranges, ensuring



superior accuracy and efficiency in inpainting tasks. In this project, we will explore state-of-the-art inpainting methods and adapt the long-range propagation approach to address challenges specific to video data. The system will be designed to handle various inpainting scenarios, including occlusions, object removal, and artifact removal, while preserving temporal coherency and maintaining realistic visual results. The proposed system will be extensively evaluated on diverse video datasets to assess its performance, comparing it with existing methods in terms of inpainting quality, computation time, and memory utilization.

The paper is organized as follows. Section II describes the related work done previously, that helps to understand and maximize the performance of our model, the literature Survey is helps get to know about previous technology & work. As known the foundation is the Algorithm and Methodology used in the work described in Section III, after it the actual experimental results are displayed in section IV. At the end, section V presents the conclusion.

II. RELATED WORK

Numerous deep learning models employing various modules and propagation strategies have achieved significant success in the field of video inpainting. These approaches can be broadly categorized into a few groups:

3D Convolution: Earlier video inpainting networks used 3D Convolutional Neural Networks (CNNs) or temporal shift techniques to capture spatiotemporal information. However, these methods had limitations such as limited receptive fields and misalignment between frames, making them less effective in handling distant content.

Internal Learning: Some studies have explored internal learning to encode and memorize appearance and motion within videos using deep networks. However, these methods often required individual training for each test video, limiting their practicality.

Flow-Guided Propagation: Video inpainting networks commonly employ optical flow or homography to align neighbouring reference frames, enhancing temporal coherence and information aggregation. However, incomplete optical flow could lead to incomplete propagation. Recent flow-based methods focus on completing the flow first and then using it as a guide for pixel-domain propagation. While this simplifies RGB pixel inpainting, it remains disconnected from the subsequent learnable refinement module, making it challenging to the correct content distortion caused by inaccurate propagation.

[1]. A New Low-Rank Learning Robust Quaternion Tensor Completion Method for Color Video Inpainting Problem and Fast Algorithm In this they discussed the use of quaternion tensor-based modelling for color video processing, specifically addressing the challenging problem of color video inpainting (RQTC). It also mentions a related method, RQMC, for single color image inpainting. [2]. Deep Video Inpainting Detection - VIDNet is introduced as the first learning-based video inpainting detection system with a two-stream encoder-decoder architecture and attention modules, addressing the need for a mitigation solution. [3]. Free-form Video Inpainting with 3D Gated Convolution and Temporal PatchGAN - The paper addresses the challenge of free-form video inpainting for tasks like text removal. It introduces a deep learning model with 3D gated convolutions and a Temporal PatchGAN loss for improved consistency.[4]. Video Inpainting of Complex Scenes - The proposed video inpainting algorithm optimizes a global, patch-based functional, handling complex scenarios like dynamic textures, multiple moving objects, and moving backgrounds. It achieves high-quality results in significantly less execution time compared to the state-of-the-art, requiring only an inpainting mask as manual input.

Sr.no	Paper Name	Author	Algo/Technique/Method
1	New Low-Rank Learning Robust Quaternion Tensor Completion Method for Color Video Inpainting Problem and Fast Algorithm.	Zhi-Gang Jia Jing-Fei Zhu	Low Rank Learning Robust Quaternion Tensor Completion Method
2	Deep Video Inpainting Detection	Abhinav Shrivastava	QDLA Module.

3	Free-form Video Inpainting with 3D Gated Convolution and Temporal PatchGAN	Ya-Liang Chang	3D Gated Convolution and Temporal PatchGAN
4	Video Inpainting of Complex Scenes	Alasdair Newson Yann Gousseau	Automatic Video Inpainting Algorithm

Table 1. Literature Survey table.

III. METHODOLOGY

Iterative flow completion is a term commonly used in the context of computer vision and image processing. It refers to a technique or method used to fill in missing or corrupted information in a sequence of flow fields. In computer vision, flow fields represent the apparent motion of objects in an image or video over time. These fields consist of vectors that describe how pixels or features move from one frame to the next. Iterative flow completion typically involves using iterative neural networks (RNNs) or other sequential modeling techniques to estimate and complete the missing flow vectors. RNNs are well-suited for tasks that involve sequential data because they can capture temporal dependencies and patterns. The goal of iterative flow completion is to improve the accuracy and completeness of flow fields, which can be essential in various computer vision applications, such as object tracking, optical flow estimation, and video analysis. By using iterative models, researchers aim to enhance the quality of motion information, reduce artifacts, and fill in gaps in flow fields caused by occlusions, noise, or other factors.

Noise Reduction: Videos often contain noise that can affect the accuracy of flow fields. An iterative approach can help denoise the flow fields, making them more robust for inpainting tasks.

Adaptive Propagation: Iterative flow completion can adaptively propagate information from neighboring frames to inpaint missing regions. It allows you to refine the propagation strategy based on the estimated flow vectors, improving the quality of inpainting

Integration with Inpainting Models: To use iterative flow completion in your video inpainting project, you can integrate it with existing inpainting models. After estimating refined flow fields, you can use them as guidance or constraints for your inpainting network. This ensures that the inpainting process takes into account the motion information provided by the flow fields, resulting in more realistic and coherent inpainted frames.

Incorporating iterative flow completion into your video inpainting project can lead to better results in terms of inpainting quality, motion consistency, and handling challenging scenarios like occlusions and noise. It enhances the overall performance of your video inpainting system by leveraging the power of iterative neural networks and sequential modeling techniques.

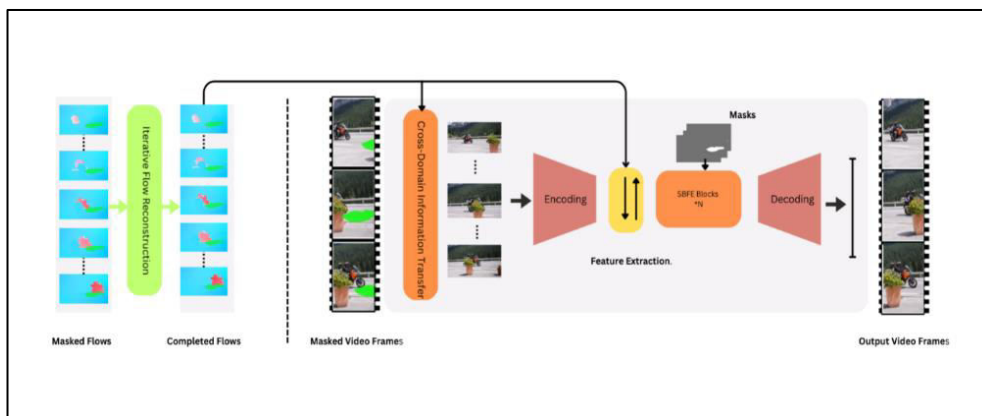


Fig 1: Inpaint Expert comprises three components Iterative Flow Completion, Cross Domain Information Transfer and Subset Based Feature enhancement.

Proposed Method:

[1]. Scope: The proposed system aims to inpaint significant portions of a video that are spatially large and temporally extended. [2]. Challenges Addressed: It addresses the specific challenges of inpainting long-range gaps in video sequences while maintaining quality and coherence. [3]. Techniques Used: The system leverages advanced algorithms, including long-range propagation techniques, deep learning, and attention mechanisms.[4]. Temporal Consideration: It places a strong emphasis on capturing and preserving temporal context, ensuring coherent motion and content over time.[5]. Performance: The proposed system is expected to achieve superior accuracy and efficiency in inpainting tasks, resulting in realistic and coherent visual results.

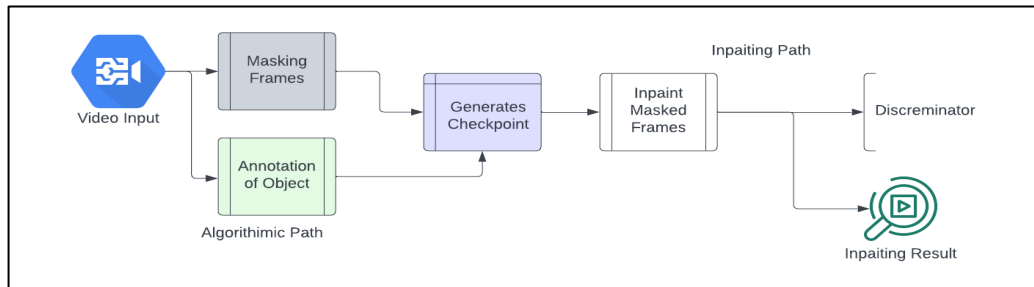


Fig 2: Data Flow Diagram

IV. EXPERIMENTAL RESULTS

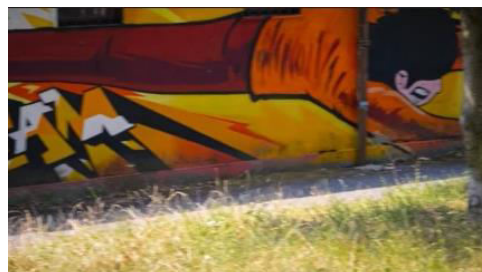
Figures show the results of video inpainting from a video frame and inpainting by using iterative flow completion algorithm. Figs. 3(a) shows the original video frame. (b) is the image obtained by applying mask object from video frame.



(a)



(b)



(c)

Accuracy and Efficiency:

Models	Accuracy								Efficiency	
	YouTube-VOS				DAVIS				FLOPs (10 frames)	Runtime (s/frame)
	PSNR ↑	SSIM ↑	VFID ↓	E_{warp}^* ↓	PSNR ↑	SSIM ↑	VFID ↓	E_{warp}^* ↓		
DFVI	29.16	0.9429	0.066	1.651	28.81	0.9404	0.187	1.596	-	0.837
FGVC	29.67	0.9403	0.064	1.163	30.80	0.9497	0.165	1.571	-	1.795
STTN	32.34	0.9655	0.053	1.061	30.61	0.9560	0.149	1.438	1315G	0.051
FuseFormer	33.32	0.9681	0.053	1.053	32.59	0.9701	0.137	1.349	1025G	0.114
FGT	32.17	0.9599	0.054	1.025	32.86	0.9650	0.129	1.323	-	1.828
E ² FGVI	33.71	0.9700	0.046	1.013	33.01	0.9721	0.116	1.289	986G	0.085
Ours	34.40	0.9700	0.042	1.011	33.80	0.9773	0.098	1.190	983G	0.084

Table 2. Accuracy comparison with other models & techniques.

V. CONCLUSION

In this research, we introduce an innovative and enhanced video inpainting framework named "Inpaint Expert" It combines advanced cross-domain transformation with a Subset-Based Feature Enhancement. These two key modules collectively empower Inpaint Expert with robust and accurate propagation abilities across substantial spatial and temporal gaps, leading to substantial improvements in video inpainting performance. Importantly, these enhancements are achieved without compromising efficiency, as Inpaint Expert maintains high-speed performance and computational efficiency. We believe that the concepts and methodologies embedded in Inpaint Expert have the potential to offer valuable insights and contributions to the video inpainting community.

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