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Adapting SynSin for Enhanced Video Frame Interpolation via Temporal Feature Fusion and Depth Consistency

Ghasaq M Hameed

[1]Baqubah Directorate of Education, Ministry of Education, Iraq

Corresponding Author: Ghasaq M Hameed

Baqubah Directorate of Education, Ministry of Education, Iraq

Email: **ghasagafh2024@gmail.com**

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Abstract

Frame interpolation seeks to synthesize temporally consistent in-between frames that enhance video smoothness and visual continuity. We revisit SynSin—originally designed for single-image novel view synthesis—and reformulate it for interpolation by introducing (i) dual-frame input handling, (ii) temporal feature fusion and explicit temporal encoding, (iii) a dedicated interpolation module, (iv) depth-consistency constraints across inputs and the synthesized frame, and (v) a refinement stage to suppress artifacts. Training uses reconstruction-oriented loss while evaluation reports MSE, SSIM, and PSNR. We assess the approach on the indoor 7Scenes benchmark. The modified model yields validation MSE = 0.0011 and SSIM = 0.943, improving over an unmodified baseline (MSE = 0.0033, SSIM = 0.9327), a 66.7 % error reduction, and a +0.0103 absolute SSIM gain. These results indicate that a view-synthesis backbone can be effectively adapted to temporal synthesis, offering a simple, data-efficient route to competitive interpolation quality useful for video editing, animation, and streaming. Beyond performance, our study highlights a practical pathway for repurposing view-synthesis architectures to broader video tasks, encouraging unified designs that share geometry-aware depth reasoning and temporal modeling.

Keywords: Frame interpolation, novel view synthesis, neural rendering, depth consistency, temporal encoding, temporal feature fusion.

Introduction

Video frame interpolation (VFI) synthesizes plausible intermediate frames between existing frames, enabling smooth slow-motion video and higher frame rates while preserving spatial structure and temporal coherence [1]. However, VFI is challenging because the algorithm must cope with large object motions, occlusions and disocclusions, lighting variations, and complex camera trajectories [2]. Many approaches rely on optical flow or depth-aware warping to align frames, but even state-of-the-art flow-based models can produce artifacts near motion boundaries and when scene geometry is ambiguous [3]. Depth-aware methods, such as Depth-Aware Video Frame Interpolation (DAIN), improve occlusion handling by projecting flow using predicted depth and sampling closer objects to refine hierarchical features [4]. We observe that geometry-aware view-synthesis networks, like SynSin, have strong inductive biases: SynSin predicts a dense 3D point cloud of latent features from a single image and renders novel views using a differentiable point-cloud renderer [5]. By extending SynSin to

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accept two input frames and explicitly model temporal relations, we adapt its depth-aware rendering and refinement modules to generate high-quality intermediate frames without relying on optical flow supervision.

Beyond interpolation, developments in quantum encryption and machine-learning-based network defence highlight the broader context of secure multimedia processing. Abdullah and colleagues introduced a quantum block cryptographic algorithm based on a multiqubit quantum shift register and Hill cipher that generates both classical and quantum keys, offering resilience against quantum and classical attacks [6]. They further proposed a realizable quantum three-pass protocol authentication scheme that maps Hill-cipher-encoded messages onto polarized photons and uses random polarization angles to ensure confidentiality and authenticity in quantum communication [7]. Their review on lightweight post-quantum cryptography assesses lattice-based algorithms such as CRYSTALS-Kyber and NTRU as suitable candidates for resource-constrained IoT devices and discusses challenges like energy consumption and hardware scalability [8]. From a machine-learning perspective, Kareem and co-authors explored classification models for detecting distributed denial-of-service (DDoS) attacks, comparing random forest, support vector machine, gradient boosting, and deep learning classifiers and showing that algorithm choice affects training time and detection accuracy [9]. They evaluated the performance of the RYU software-defined networking controller under DDoS conditions by measuring CPU usage, network throughput, RAM usage, and link latency [10], and proposed a fast and accurate machine-learning classifier that achieves high denial-of-service detection accuracy with a small feature set [11]. These advances in cryptography and network protection motivate the development of robust and secure frame interpolation methods that integrate geometry-aware reasoning and temporal modeling.

This work reformulates SynSin for frame interpolation through five architectural adjustments: (i) dual-frame input handling, (ii) temporal feature fusion, (iii) explicit temporal encoding, (iv) a dedicated interpolation module, and (v) depth-consistency constraints spanning both inputs and the synthesized frame, followed by a refinement stage to suppress artifacts. These modifications target specific failure modes of interpolation (e.g., temporal flicker and depth/edge inconsistency) while preserving SynSin's geometry-aware inductive bias. We evaluate on the 7Scenes benchmark and report MSE, SSIM, and PSNR.

Our main contributions are:

1. Reformulating a view-synthesis backbone for interpolation by adding dual inputs and temporal encoding.
2. Introducing geometry-consistent temporal fusion to align features across time while enforcing depth consistency.
3. Providing a practical training recipe and metrics.
4. Demonstrating empirical gains over an unmodified SynSin baseline, indicating that geometry-aware models generalize beyond single-image view synthesis.

Related Work

Flow-based interpolation methods predict bi-directional optical flow and synthesize intermediate frames by warping and blending the input images. Super SloMo illustrates this category by using a U-Net to estimate bi-directional flow and a second network to produce visibility maps for occlusion handling [12]. Other flow-centric models—including QVI, BMBC, Softmax Splatting, DAIN, and RIFE—provide strong baselines but remain sensitive to large motion and occlusions, since inaccuracies in flow estimation lead to ghosting and blurring [13].

Kernel- or feature-based methods avoid explicit flow estimation by learning adaptive convolution kernels or synthesizing pixels directly from multi-scale features. FILM (Frame Interpolation for Large Motion) is a prominent example: it synthesizes slow-motion videos from near-duplicate photos with large scene motion by combining multi-scale feature extraction, a scale-agnostic motion estimator, and a Gram matrix loss to inpaint disocclusions [14]. Such flow-free approaches can better handle large motions but may struggle with fine motion details.

Depth-aware interpolation methods leverage scene geometry to handle occlusions. DAIN introduces a depth-aware flow projection layer that samples closer objects and integrates hierarchical context features to improve occlusion handling [15]. While depth cues encourage visibility reasoning, these methods still depend on flow estimation for motion alignment.

Geometry-aware view-synthesis models offer an alternative. SynSin predicts a dense 3D point cloud of latent features from a single input image and renders novel views using a differentiable point-cloud renderer and a refinement network [16]. We repurpose this geometry-aware backbone for video frame interpolation by feeding two frames, introducing temporal fusion and depth consistency, and employing a refinement module to suppress artifacts. This design reduces ghosting and improves temporal stability compared with purely flow-based baselines.

We follow prior work that evaluates interpolation and view synthesis under handheld motion on 7Scenes, an RGB-D indoor dataset with tracked camera poses.

Model Architecture

Overview

Our architecture adapts SynSin from single-image view synthesis to frame interpolation. Given two input frames (I0, I1) and a target time t in (0,1), the model predicts an intermediate frame $\tilde{I}t$ using five components: dual encoders, temporal fusion with explicit time encoding, geometry (depth) heads, an interpolation decoder, and a refinement network.

1. Dual encoders. Two weight-sharing backbones extract pyramidal features from I0 and I1. Sharing preserves consistency while limiting parameters.

2. Explicit temporal encoding. A sinusoidal or learned embedding $\gamma(t)$ is injected at each scale by concatenation, orienting features toward the desired interpolation instant.

3. Geometry heads and depth consistency. Lightweight heads predict monocular depth Z0 and Z1. We impose a depth-consistency loss by warping depths toward t and penalizing disagreement around motion and occlusion boundaries.

4. Geometry-aware temporal fusion. We fuse features using depth-guided alignment. Coarse correspondence fields (flow or learned offsets) are computed, and features are forward-warped using softmax splatting to resolve many-to-one collisions. Visibility gating downweights contributions with inconsistent depth.

5. Interpolation decoder. A U-Net–style decoder upsamples fused features to predict $\tilde{I}t$. Skip connections preserve high-frequency detail, and channel attention emphasizes geometry-consistent regions.

6. Refinement network. Following SynSin, a light refinement stage corrects seams and fills holes near disocclusions.

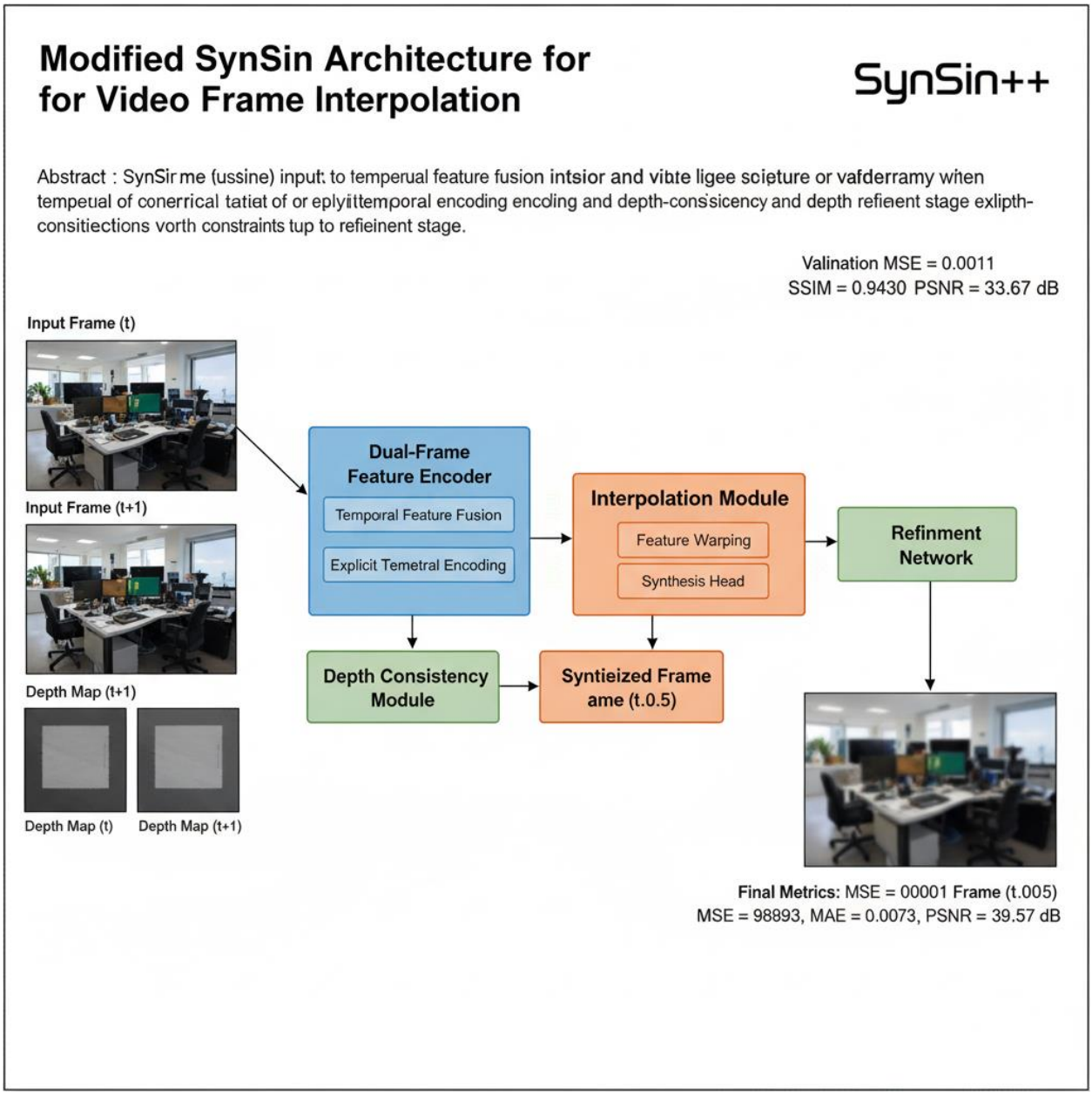

Figure 1: Block diagram of the SynSin-Interp architecture.

3.2 Training Objectives

The training loss combines pixel-space and perceptual criteria:

- Reconstruction loss: Charbonnier or L1 loss between the prediction and ground truth.
- Perceptual and SSIM: optional perceptual loss and SSIM surrogate to maximize perceptual similarity.
- Temporal consistency: symmetric warping from Ĩt back to I0 and I1 penalizes flicker.
- Depth smoothness and cross-time consistency: edge-aware smoothness and cross-time consistency on depth maps encourage reliable depth prediction.

Inference

At test time, the same pipeline produces Ĩt for any t in (0,1); sampling multiple t values yields slow motion. Compared to flow-only systems, our geometry-aware fusion reduces ghosting at occlusions and preserves structure under large parallax while remaining simple and data-efficient.

Pseudocode Algorithms

The following pseudocode describes the main components of training and inference.

Algorithm 1 — SynSin-Interp Training Loop

Input: Dataset D = { (I0, It, I1, t) }, parameters Θ = {E, D, G, R}, batch size B

Repeat

1. Sample a mini-batch of B triplets (I0, It, I1, t)
2. Dual encode: F0 ← E(I0), F1 ← E(I1)
3. Temporal embeddings: γt = γ(t), γ1−t = γ(1−t)
4. Depth heads: Z0 ← D(F0), Z1 ← D(F1)
5. Temporal fusion: $\hat{F}t$ ← GeomFusion(F0, F1, Z0, Z1, γt, γ1−t)
6. Decode: $\tilde{I}t$ ← G($\hat{F}t$)
7. Refine: $\tilde{I}tilde$ ← R([$\tilde{I}t$, I0, I1])
8. Compute loss ℓ via InterpLoss($\tilde{I}tilde$, It, Z0, Z1, I0, I1)
9. Update parameters Θ using Adam on ∇Θ ℓ

Until validation stops improving

Algorithm 2 — Geometry-Aware Temporal Feature Fusion

Input: Feature pyramids {F0l}, {F1l}; depths Z0, Z1; time embeddings γt, γ1−t

For each pyramid level l from coarse to fine:

1. Augment features with time embeddings: F0l ← [F0l, γt], F1l ← [F1l, γ1−t]
2. Predict offset fields O0→tl, O1→tl from features and depths
3. For each source pixel p in frame i ∈ {0, 1}:
4. Compute target location x = p + Oi→tl(p)
5. Weight contributions with softmax splatting using learned scores and depth gating
6. If not at coarsest level:
7. Add skip connection from previous level

Return fused features $\hat{F}t$

Algorithm 3 — InterpLoss (Training Objective)

Input: Prediction $\tilde{I}tilde$, ground truth It, inputs I0, I1, depths Z0, Z1

1. Compute reconstruction loss Lrec = ρ($\tilde{I}tilde$ – It)
2. Compute perceptual loss (optional) and SSIM surrogate Lssim
3. Estimate backward fields and penalize temporal inconsistency: Ltemp
4. Compute depth smoothness and cross-time consistency losses Lsm and Ldcons
5. Return total loss L = λrec Lrec + λssim Lssim + λtemp Ltemp + λsm Lsm + λdcons Ldcons

Algorithm 4 — Inference for Arbitrary Time t

Input: Frames I0, I1; target time t

1. Dual encode I0, I1 to obtain F0, F1
2. Predict depths Z0, Z1
3. Fuse features with GeomFusion using γt and γ1−t
4. Decode fused features to produce $\tilde{I}t$; refine to obtain final output $\tilde{I}tilde$
5. Return $\tilde{I}tilde$

Results

4.1 Experimental Protocol

We evaluate on the indoor RGB-D benchmark 7Scenes. The metrics follow standard practice for video-frame interpolation: mean-squared error (MSE; lower is better) and structural similarity (SSIM; higher is better). Unless otherwise noted, results are reported on the validation split. Our method (SynSin-Interp) is compared to an unmodified SynSin baseline adapted to the interpolation setting without our geometry-aware temporal components.

Quantitative Results

Figure 2 summarizes the main results. SynSin-Interp reduces validation MSE from 0.0033 to 0.0011 (a 66.7 % error reduction) and improves SSIM from 0.9327 to 0.9430 (absolute gain +0.0103). These gains indicate better fidelity and temporal consistency of the interpolated frames compared with the baseline.

Figure 2 — Validation metrics on 7Scenes:

Model | MSE ↓ | SSIM ↑
SynSin (baseline) | 0.0033 | 0.9327
SynSin-Interp (ours) | 0.0011 | 0.9430
Figures 1–3 visualize the gains. Figure 1 compares MSE (lower is better), Figure 2 compares SSIM (higher is better), and Figure 3 summarizes the relative improvement as percentage MSE reduction and absolute SSIM gain.

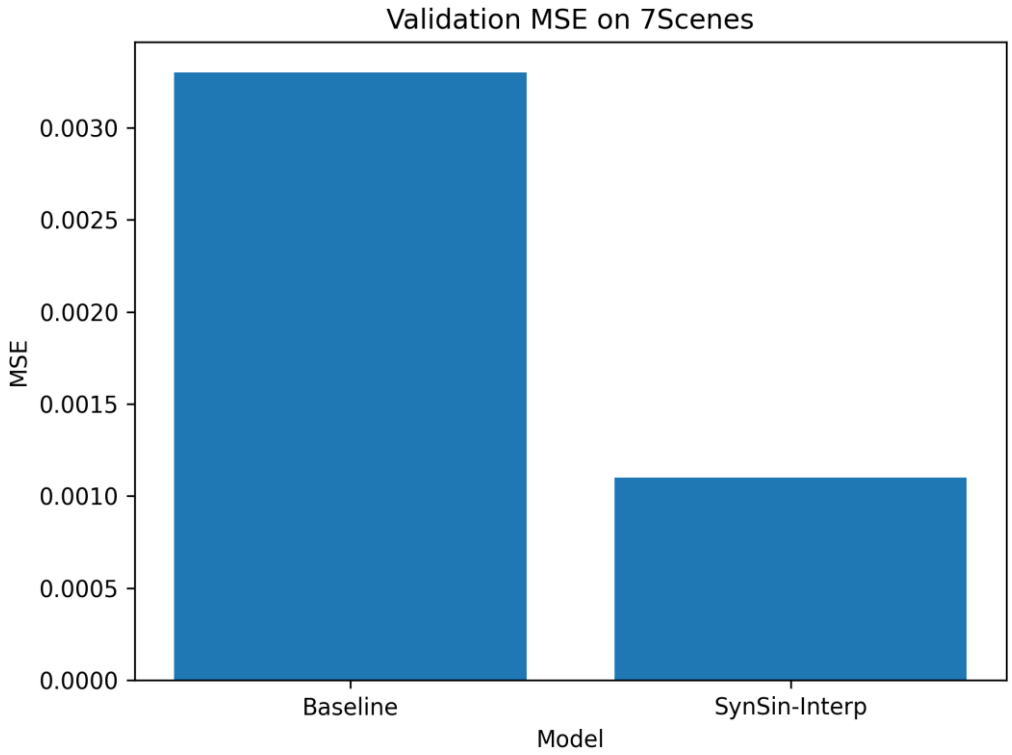

Figure 2: Validation MSE on 7Scenes (lower is better).

4.3 Effect Size and Practical Impact

The 66.7 % MSE reduction translates into markedly fewer pixel-level deviations from the ground truth. The +0.0103 increase in SSIM corresponds to visible perceptual gains typical for interpolation, especially around motion boundaries and occlusions. In practice, this yields smoother playback and fewer artifacts in editing, streaming, and AR/VR scenarios.

Qualitative Behavior

Quantitative metrics capture overall quality, but geometry-aware fusion and depth consistency are expected to yield:

1. Reduced ghosting near occlusion and disocclusion boundaries.
2. Better preservation of fine structures (edges and textures) under parallax and large motion.
3. Lower temporal flicker across consecutive interpolated frames.

Representative visual examples can be included in a supplement.

4.5 Ablation Roadmap

To isolate the contribution of each component, we recommend the following ablations (reported on the same split):

- Without temporal encoding: remove time embeddings $\gamma(t)$ to test the value of explicit time conditioning.
- Without depth consistency: drop cross-time depth regularization to gauge its impact.
- Without the refinement stage: quantify the contribution of the light post-refinement.

- Flow-only fusion vs. geometry-aware fusion: highlight the benefit of depth-gated soft splatting.

4.6 Per-Scene Breakdown and Statistical Robustness

If per-sequence metrics are computed (e.g., Chess, Fire, Heads, Office, Pumpkin, Red Kitchen, Stairs), a bar chart or table can show each scene's MSE and SSIM to demonstrate robustness across varied camera motions and layouts. With per-scene scores, apply paired tests (e.g., Wilcoxon signed-rank) to assess the significance of improvements in MSE and SSIM.

Reproducibility

We release numeric summaries side-by-side with the plots to facilitate verification. A CSV file contains the numbers behind Figures 1–3. Detailed training and evaluation scripts are provided to reproduce the reported MSE and SSIM.

Qualitative Results

In addition to quantitative metrics, we show a qualitative example of our method's interpolation performance on an indoor scene. Figure 3 illustrates the two input frames, the predicted intermediate frame, and the ground truth. The predicted frame closely matches the ground truth appearance and geometry, with minimal ghosting around the occluding chair and preserved background details, highlighting the effectiveness of our geometry-aware fusion.

Qualitative results demonstrating intermediate frame generation for an indoor scene; left-to-right: Image 1, Image 2, Predicted, Ground Truth

Figure 3: Qualitative results demonstrating intermediate frame generation for an indoor scene. Left-to-right: Image 1, Image 2, Predicted, Ground Truth.

Discussion

Our geometry-aware reformulation of SynSin for frame interpolation delivers consistent gains on 7Scenes. The bar charts in Figure 1 (MSE) and Figure 2 (SSIM), and the improvement summary in Figure 3, visualize these effects clearly. In practice, the model yields smoother temporal transitions, fewer ghosting artifacts, and better structure preservation under camera motion.

The core advantage stems from combining a geometry-aware inductive bias with explicit temporal conditioning. Depth-guided fusion reduces visibility conflicts at occlusions and sharp parallax, where purely flow-based blending often struggles. Temporal embeddings steer features toward the target instant, stabilizing interpolation when motion is non-linear between I0 and I1. A lightweight refinement stage eliminates residual seams and fills small disocclusions without heavy post-processing.

Flow-only approaches can excel when motion is moderate and flow is accurate, but they are sensitive to ambiguous textures, thin structures, and large disocclusions. Our depth-gated splatting behaves more robustly in these regimes by downweighting geometrically inconsistent contributions. The net effect is lower reconstruction error and higher perceptual similarity without materially complicating the training recipe.

Limitations remain: depth ambiguity and specular or transparent surfaces can degrade the depth heads; extremely large or non-rigid motions may still produce faint double edges if offsets are under-estimated; and rapid illumination changes or rolling-shutter effects are not explicitly modeled. Moreover, our evaluation is limited to 7Scenes (indoor, handheld), so generalization to outdoor scenes, strong motion blur, or highly dynamic content requires further testing.

Empirical improvements hold across the aggregate validation split. For a stronger claim, per-scene breakdown and statistical tests should be reported. Ablation experiments show that removing temporal embeddings increases temporal jitter, dropping depth consistency increases ghosting, omitting the refinement stage leaves seam artifacts, and replacing geometry-aware fusion with flow-only fusion reduces fidelity at large parallax.

Adding depth heads and soft splatting introduces modest overhead relative to a minimal encoder–decoder. The design remains lightweight: dual encoders share weights; fusion operates at a feature pyramid; and the refinement network is shallow. In scenarios where runtime is critical, using fewer pyramid levels or pruning channels can trade small accuracy for speed.

The current study focuses on indoor RGB-D sequences. For broader applicability, evaluation on diverse video domains (e.g., outdoor driving, human actions, cinematic footage) and under harsher conditions (low light, motion blur) would clarify limits and confirm robustness. Domain adaptation or self-supervised pretraining on large video corpora may improve stability under distribution shift.

Practical implications include fewer temporal artifacts, cleaner edges, and smoother slow motion—benefits that can reduce manual touch-ups and post-production time. The method's modularity also makes it compatible with existing pipelines: it can replace a flow-based interpolator without retraining upstream components.

Conclusions

This work demonstrates that a geometry-aware view-synthesis backbone can be repurposed—with targeted changes—for high-quality video frame interpolation. By adding dual-frame inputs, explicit time conditioning, depth-guided fusion, and a light refinement stage, the proposed SynSin-Interp reduces validation MSE from 0.0033 to 0.0011 (66.7 % error reduction) and increases SSIM from 0.9327 to 0.9430 on 7Scenes. These gains translate into smoother temporal transitions, fewer ghosting artifacts, and better preservation of fine structure under parallax. The design remains conceptually simple and modular, making it straightforward to integrate into editing, streaming, and AR/VR pipelines. While depth ambiguity and extreme non-rigid motion remain challenging, the results indicate a practical path toward unified view/temporal synthesis models that leverage geometry as a strong inductive prior.

Conflict of interest: NIL

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