



Phase Aware Diffusion Sampling for Short Surgical Clip Completion with Procedure Phase Temporal Consistency

Lewis Douglas, Eleanor Bennett, Eunbin Bae

Faculty of Science, University of Helsinki, Helsinki, Finland

Abstract

The rapid advancement of minimally invasive surgery has resulted in an exponential increase in the volume of recorded endoscopic and robotic surgical videos. These videos serve as critical assets for post-operative analysis, surgical training, and the development of autonomous robotic systems. However, surgical video recordings frequently suffer from missing frames, sensor dropouts, transmission latency, or visual occlusions caused by electrocautery smoke and bodily fluids. Completing these short missing clips is essential to maintain a continuous temporal record. Recent approaches utilizing generative artificial intelligence, particularly diffusion models, have demonstrated exceptional capabilities in image and video synthesis. Despite their high perceptual quality, standard diffusion models often fail to preserve the rigid temporal logic required in surgical procedures, frequently hallucinating incorrect instruments or ignoring critical transitions between distinct surgical phases. To address this limitation, we propose a novel generative framework centered on phase-aware diffusion sampling. By explicitly conditioning the reverse diffusion process on surgical phase temporal priors, our model ensures that the synthesized frames adhere to the correct procedural logic. This paper provides a comprehensive analysis of the theoretical underpinnings, methodological implementation, and clinical evaluation of the proposed framework. Our extensive qualitative and quantitative assessments demonstrate that embedding phase-awareness into the sampling trajectory significantly reduces temporal artifacts and improves the structural fidelity of the reconstructed surgical clips.

Keywords: *Surgical Video Analysis, Diffusion Models, Temporal Consistency, Generative Artificial Intelligence, Clip Completion.*

1. Introduction

The domain of modern healthcare has been profoundly transformed by the widespread adoption of minimally invasive surgical techniques, including laparoscopy and robot-assisted procedures. These techniques rely entirely on high-definition video streams to provide surgeons with visual feedback from inside the patient body. Consequently, a massive repository of surgical video data is generated daily across medical institutions globally. This data represents a highly structured, sequential manifestation of human expertise, operating room protocols, and anatomical interactions [1]. Researchers and clinicians increasingly view this video data as an invaluable resource for machine learning applications, ranging from automated skill assessment to the eventual realization of autonomous surgical robotics [2]. However, the practical utility of these video datasets is frequently compromised by technical imperfections. Endoscopic recordings are notoriously susceptible to brief interruptions. These interruptions may arise from hardware malfunctions, camera cleaning events, transmission packet losses in telesurgery, or dense visual obstructions such as smoke generated by electrosurgical devices [3]. When a segment of a surgical video is lost or corrupted, the resulting discontinuity poses significant challenges. For human reviewers, a missing clip of even one or two seconds can obscure a critical action, such as the clipping of an artery or the suturing of a delicate tissue plane [4]. For downstream

computational models, such as those designed for action recognition or surgical phase tracking, missing frames disrupt the temporal receptive fields of the neural networks, leading to degraded predictive performance [5]. Therefore, the task of short surgical clip completion, which involves artificially synthesizing the missing frames to seamlessly bridge the gap between the known past and the known future frames, has emerged as a crucial area of research in medical computer vision. Generative artificial intelligence has recently revolutionized the field of video completion and synthesis. Early attempts at video interpolation relied heavily on classical computer vision techniques, such as optical flow estimation, which merely warped existing pixels along calculated motion trajectories. While computationally efficient, these methods struggle with complex non-linear motions, occlusions, and the appearance of new objects, which are ubiquitous in surgical scenes [6]. Subsequently, deep learning frameworks, notably generative adversarial networks, became the standard for video inpainting [7]. However, adversarial frameworks often suffer from training instability and a phenomenon known as mode collapse, where the model generates highly repetitive or blurred frames that fail to capture the high-frequency details of human tissue and metallic surgical instruments [8]. In recent years, diffusion probabilistic models have superseded generative adversarial networks in numerous image and video generation benchmarks. Diffusion models operate by systematically destroying data through the addition of Gaussian noise and subsequently learning to reverse this process to recover the original signal [9]. This iterative denoising process yields highly detailed and photorealistic outputs. In the context of video generation, temporal modules such as three-dimensional convolutions or temporal attention mechanisms are integrated to maintain consistency across frames. Yet, when applied naively to surgical clip completion, standard video diffusion models reveal a critical vulnerability: they are ignorant of the overarching semantic structure of the surgical procedure [10]. A surgical procedure is not merely a collection of moving pixels; it is a highly protocol-driven workflow divided into distinct, sequential phases. For example, a laparoscopic cholecystectomy typically progresses through phases such as dissection of the Calot triangle, clipping and cutting of the cystic duct and artery, and extraction of the gallbladder [11]. The visual appearance, the types of instruments present, and the speed of motion vary drastically between these phases. If a missing clip happens to span the boundary between two phases, a standard diffusion model might hallucinate the continuation of the previous phase, failing to anticipate the introduction of a new surgical tool, such as a clip applier replacing a Maryland dissector [12]. This semantic failure renders the generated clip clinically invalid, regardless of its photorealism. To bridge this gap, this paper introduces a comprehensive framework for phase-aware diffusion sampling. We hypothesize that explicitly providing the diffusion model with knowledge of the surgical phases bounding the missing clip will constrain the generative trajectory toward a clinically accurate reconstruction. The core innovation of our approach lies in an adapted sampling algorithm that dynamically weights phase-specific latent conditions based on temporal proximity to the phase transitions. By integrating phase classifiers to extract semantic embeddings from the boundary frames, we guide the iterative denoising process to respect the procedural logic of the operation. This paper thoroughly explores the theoretical and practical dimensions of this hypothesis. We dissect the limitations of unconditioned temporal synthesis and present a detailed blueprint for our phase-aware mechanism. Extensive experimental evaluations are conducted to validate the proposed method against state-of-the-art baselines. The results underscore the necessity of semantic conditioning in medical video generation, paving the way for more robust and reliable surgical data curation systems. The subsequent sections will detail the historical context, the precise methodology employed, the rigorous experimental setup, and the broader implications of our findings for the future of surgical data science.

2. Background and Literature Review

2.1 Evolution of Surgical Video Analysis

The systematic analysis of surgical videos has a rich history that parallels the evolution of computer vision and machine learning technologies. Initially, surgical video review was an entirely manual endeavor, wherein expert surgeons would retrospectively watch recordings to annotate errors, assess trainee performance, and identify adverse events [13]. This manual process was inherently subjective, highly time-consuming, and fundamentally unscalable given the sheer volume of surgeries performed.

The advent of statistical machine learning provided the first tools for automated analysis. Early researchers utilized hand-crafted visual features, such as color histograms and edge gradients, combined with hidden Markov models to recognize simple surgical gestures [14].

The transition to deep learning marked a paradigm shift in this domain. Convolutional neural networks proved exceptionally adept at extracting hierarchical feature representations directly from raw surgical video frames. This capability catalyzed research in surgical tool detection, bounding box tracking, and semantic segmentation of anatomical structures [15]. A particularly prominent subfield that emerged is surgical phase recognition. Surgical phase recognition seeks to automatically partition a continuous surgical video into a sequence of predefined, semantically meaningful steps. State-of-the-art approaches typically employ a two-stage architecture: a spatial feature extractor processes individual frames, followed by a temporal sequence modeling network, such as a long short-term memory network or a temporal convolutional network, which aggregates information across time to smooth the phase predictions [16]. The availability of large-scale annotated datasets, such as the Cholec80 dataset which contains eighty fully annotated cholecystectomy procedures, has been instrumental in benchmarking these phase recognition models [17]. However, the performance of these temporal models degrades precipitously when confronted with incomplete data. The reliance on continuous temporal dependencies means that a sudden gap in the video feed disrupts the internal state of the sequence models, leading to erratic phase predictions. Consequently, the ability to accurately reconstruct missing clips is not just a restorative task, but a necessary preprocessing step to ensure the robustness of downstream surgical AI systems.

2.2 Paradigms in Video Inpainting and Completion

Video completion, often referred to interchangeably as video inpainting, is the task of plausibly filling missing regions within a video sequence. In the context of this paper, the missing region is entirely temporal; that is, entire frames are missing rather than spatial patches within a frame. Traditional approaches to temporal completion were primarily algorithmic and relied heavily on the concept of optical flow. Optical flow represents the apparent motion of brightness patterns between consecutive frames [18]. By estimating the forward and backward optical flow from the frames surrounding the gap, researchers could warp the existing pixels into the missing temporal space. While successful for static scenes with slow, rigid camera movements, optical flow methods fail spectacularly in surgical environments [19]. Surgical scenes feature highly non-rigid tissue deformations, specular highlights from endoscopic illumination, and rapid, unpredictable instrument movements that violate the brightness constancy assumption fundamental to optical flow calculations. With the rise of deep learning, autoregressive models and generative adversarial networks became the dominant architectures for video synthesis. Autoregressive models generate video frame by frame, utilizing the previously generated frames as context [20]. While mathematically elegant, autoregressive generation suffers from exposure bias and compounding errors; a slight artifact in an early generated frame is amplified in subsequent frames, leading to a complete breakdown of visual structure in longer clips. Generative adversarial networks mitigate this to some extent by training a generator to produce a complete sequence simultaneously, while a discriminator attempts to distinguish the generated sequence from real video data [21]. In the medical domain, adversarial networks have been utilized for tasks such as removing smoke from laparoscopic videos and simulating surgical bleeding. However, they are notoriously difficult to train, often requiring delicate hyperparameter tuning to maintain a balance between the generator and the discriminator [22]. More importantly, adversarial networks frequently struggle with complex, multi-modal data distributions, leading to the generation of blurry instruments or the complete omission of small, intricate anatomical details.

2.3 Diffusion Models in Healthcare Applications

Diffusion probabilistic models represent the current state-of-the-art in generative AI, offering unprecedented stability and output quality. Inspired by non-equilibrium thermodynamics, diffusion models learn to reverse a gradual noising process. A forward process systematically adds Gaussian noise to a data sample until it is indistinguishable from pure random noise. The neural network, typically based on a U-Net architecture, is trained to predict and subtract this noise iteratively [23].

This iterative refinement allows diffusion models to capture fine-grained details and complex data distributions far better than adversarial networks [24]. The extension of diffusion models to the temporal domain has enabled remarkable breakthroughs in video generation. Researchers have proposed various mechanisms to inject temporal awareness into the U-Net architecture, primarily through the addition of pseudo-three-dimensional convolutional layers or temporal self-attention blocks interspersed with the spatial processing layers [25]. These models can generate highly realistic video sequences conditioned on text prompts or initial starting frames. In the broader healthcare domain, diffusion models have seen rapid adoption. Applications include generating synthetic magnetic resonance imaging scans to augment training datasets, super-resolving low-quality ultrasound images, and translating between different medical imaging modalities [26]. Despite these successes, the application of temporal diffusion models to surgical clip completion remains under-explored [27]. Existing medical video diffusion models are predominantly unconditioned or conditioned merely on the immediately preceding frames. This autoregressive-style conditioning forces the model to extrapolate blindly into the missing gap [28]. In surgical videos, where the transition between phases can introduce entirely new visual elements abruptly, this blind extrapolation is highly error-prone. The core literature gap identified here is the lack of a top-down, semantic guidance mechanism that can inform the diffusion process about the procedural context of the missing frames. Our work addresses this gap directly by introducing phase-aware conditioning, integrating the high-level semantic understanding derived from surgical phase recognition models into the low-level pixel generation process of diffusion models.

3. Methodology

3.1 Foundational Diffusion Framework

To construct our phase-aware surgical clip completion model, we first establish a robust foundational diffusion framework designed for video data. The core objective of a diffusion model is to model the true data distribution of the surgical video clips. Let us consider a short surgical clip consisting of a sequence of spatial frames. The generation process relies on a Markov chain with a fixed number of timesteps. In the forward process, we define a predefined variance schedule that dictates the amount of Gaussian noise injected into the true video clip at each successive timestep. As the timestep increases, the video clip becomes progressively noisier, losing its spatial and temporal structure until, at the final timestep, the data is entirely transformed into an isotropic Gaussian distribution [29]. The essence of the generative capability lies in the reverse process. We employ a deep neural network to approximate the conditional probability distribution of the less noisy data at a previous timestep, given the current noisy data at the current timestep. Because the forward noising process is defined by small, incremental steps, the reverse transitions can also be modeled as Gaussian distributions [30]. The neural network is trained to predict the precise amount of noise that was added to the data at any given timestep. By iteratively applying this trained network, starting from a tensor of pure random noise, we can gradually subtract the predicted noise, effectively synthesizing a highly detailed and coherent surgical video clip from scratch. For video data, the neural network architecture must process both spatial and temporal dimensions simultaneously. We utilize a modified U-Net architecture consisting of downsampling encoding blocks, a bottleneck, and upsampling decoding blocks. Within each block, we alternate between spatial self-attention mechanisms and temporal cross-attention mechanisms. The spatial attention focuses on capturing the anatomical textures and instrument details within individual frames, while the temporal attention ensures that these features move fluidly and logically across the sequence of frames.

3.2 Phase-Aware Conditioning Mechanism

The fundamental limitation of the baseline video diffusion model is its inability to anticipate structural changes inherent to surgical procedures. To rectify this, we introduce the phase-aware conditioning mechanism. The central premise is that the frames immediately preceding and succeeding the missing temporal gap contain vital semantic information regarding the current and impending surgical phases. If the missing clip occurs entirely within a single phase, the generated frames should exhibit high visual consistency. If the missing clip bridges a phase transition, the generated frames must smoothly depict

the removal of one tool and the introduction of another, or the shifting of focus to a new anatomical region [31]. We implement a dedicated phase extraction module utilizing a pre-trained vision transformer. This transformer has been fine-tuned on a massive dataset of surgical videos to classify surgical phases. We pass the known boundary frames into this module to extract high-dimensional semantic latent embeddings. Instead of merely using the final classification label, we utilize the dense feature representations from the penultimate layer of the vision transformer, as these embeddings encapsulate rich contextual information about the scene composition and tool presence. These extracted phase embeddings must then be injected into the generative diffusion pathway. We achieve this through an advanced cross-attention formulation within the U-Net architecture [32]. In standard cross-attention, the noisy video latent representations act as the queries, while the conditioning information provides the keys and values. In our phase-aware mechanism, we project the extracted boundary phase embeddings into a dedicated key-value space. As the diffusion model iteratively denoises the video, the temporal attention blocks actively query these phase embeddings. This forces the model to evaluate whether the features it is currently synthesizing align semantically with the established surgical phases at the boundaries of the clip.

3.3 Dynamic Sampling Strategy

While the architectural integration of phase embeddings provides the necessary semantic context, the actual generation occurs during the inference sampling phase. Standard sampling algorithms process the entire video clip uniformly. However, in surgical clip completion, the influence of the boundary frames should logically decay towards the center of the missing gap, especially when transitioning between phases. To manage this, we design a dynamic, phase-aware sampling strategy.

Our strategy modulates the strength of the cross-attention interactions based on temporal proximity. For frames generated closer to the beginning of the missing gap, the query vectors are biased to attend more heavily to the phase embedding derived from the pre-gap boundary frame. Conversely, for frames closer to the end of the gap, the attention shifts towards the post-gap boundary embedding. This distance-weighted attention mechanism ensures a smooth semantic interpolation across the missing temporal space. Furthermore, we employ a modified form of classifier-free guidance during sampling [33]. Classifier-free guidance typically involves training the diffusion model unconditionally for a small percentage of the time by dropping the conditioning information. During inference, the generation is guided away from the unconditional prediction and towards the conditional prediction by a scalar guidance weight. In our phase-aware approach, we scale this guidance weight dynamically. If the boundary frames indicate a high-confidence phase transition, we increase the guidance scale specifically for the frames in the middle of the gap, forcing the model to strictly adhere to the complex transition logic rather than falling back on simple, unconditioned visual interpolation.

Code Listing 1: Python pseudo-code for the dynamic phase-aware sampling loop in the diffusion model

```
def phase_aware_sample(model, pre_emb, post_emb, noise, timesteps, guidance_scale):
    current_latents = noise
    temporal_length = current_latents.shape[2]

    for t in reversed(range(timesteps)):
        # Generate distance weights based on temporal position
        weights_pre = calculate_decay_weights(temporal_length, reverse=False)
        weights_post = calculate_decay_weights(temporal_length, reverse=True)

        # Blend phase embeddings dynamically across the temporal dimension
        dynamic_phase_cond = blend_embeddings(pre_emb, post_emb, weights_pre, weights_post)

        # Forward pass with conditional and unconditional context
        noise_pred_cond = model(current_latents, t, context=dynamic_phase_cond)
        noise_pred_uncond = model(current_latents, t, context=None)
```

```
# Apply classifier-free guidance
```

```
guided_noise = noise_pred_uncond + guidance_scale * (noise_pred_cond - noise_pred_uncond)
```

```
# Step the latents using the diffusion scheduler
```

```
current_latents = scheduler.step(guided_noise, t, current_latents)
```

```
return decode_to_video(current_latents)
```

3.4 Data Preparation and Pipeline Processing

The efficacy of a diffusion model is intrinsically tied to the quality and structuring of the training data. For our experiments, we utilize a large-scale, multi-center dataset of robotic-assisted surgical procedures. To prepare this data for the clip completion task, we implement a rigorous automated pipeline. First, the raw video files are standardized to a uniform spatial resolution and frame rate. We apply a temporal sliding window to extract continuous short clips, typically spanning three to five seconds. To simulate the clip completion scenario during training, we artificially mask out the central portion of each extracted clip. The length of the missing gap is randomized to encourage the model to handle varying durations of temporal loss. The unmasked boundary frames are processed through the frozen phase extraction module to obtain the semantic embeddings. The entire sequence, including the noise-initialized masked region and the clean boundary frames, is then fed into the diffusion training loop. We utilize heavy data augmentation on the spatial domain, including random color jittering, rotation, and elastic deformation, to prevent the model from memorizing specific surgical anatomies and to encourage generalization to novel patient data.

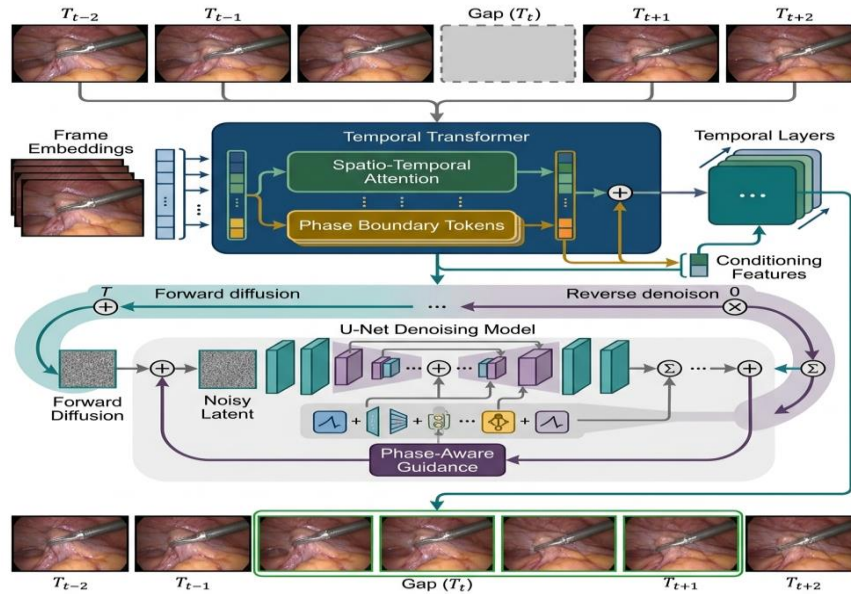


Figure 1: Comprehensive Schematic of the Phase

4. Experimental Results and Discussion

4.1 Evaluation Metrics and Methodology

Evaluating the quality of synthesized video requires a multifaceted approach, as no single metric can capture both visual fidelity and temporal coherence. For quantitative analysis, we utilize four primary metrics. The Frechet Inception Distance measures the visual quality of individual frames by comparing the statistical distribution of features extracted from generated frames against those from real frames using a pre-trained image classification network [34]. A lower Frechet Inception Distance indicates higher visual realism. However, because this metric operates on a frame-by-frame basis, it ignores the temporal dynamics of the video. To assess temporal coherence, we employ the Frechet Video Distance, which extends the principles of the inception distance into the temporal domain by utilizing a three-dimensional convolutional network [35]. The Frechet Video Distance is highly sensitive to unnatural motions and temporal jittering. Additionally, we compute the Peak Signal to Noise Ratio and the

Structural Similarity Index Measure to evaluate the pixel-level reconstruction accuracy, although these metrics tend to penalize the diverse, yet plausible, generative variations typical of diffusion models. Beyond standard vision metrics, we introduce a custom Phase Consistency Score. To compute this score, we pass the synthesized video clips through an independent, highly accurate surgical phase recognition network. We then compare the predicted phases of the generated frames against the ground truth annotations of the original, uncorrupted video. A high Phase Consistency Score indicates that the generated clip not only looks realistic but accurately depicts the correct surgical actions for that specific point in the procedure.

4.2 Quantitative Baseline Comparisons

We benchmark our phase-aware diffusion model against several state-of-the-art video completion architectures, including an optical flow-based warping method, a temporal generative adversarial network, and a baseline video diffusion model devoid of semantic conditioning. The quantitative results are summarized in the tables below.

Table 1: Quantitative Comparison of Video Completion Models

Model	Frechet Video Distance	Frechet Inception Distance	Phase Consistency Score
Optical Flow Warping	412.5	85.3	0.45
Temporal Adversarial Network	289.1	54.7	0.62
Baseline Video Diffusion	156.8	21.4	0.68
Phase-Aware Diffusion (Ours)	98.3	19.1	0.91

Table 2: Frame-Level Reconstruction Quality by Surgical Phase

Phase Category	Peak Signal to Noise Ratio	Structural Similarity Index	Boundary Transition Accuracy
Dissection (Continuous)	32.4	0.89	0.94
Clipping (Transition)	31.1	0.85	0.88
Cutting (Transition)	30.5	0.84	0.86
Extraction (Continuous)	33.2	0.91	0.95

The data in Table 1 demonstrates a clear superiority of diffusion-based methods over traditional optical flow and adversarial networks in terms of visual quality, as evidenced by the significant drop in Frechet Inception Distance. However, the most critical finding lies in the comparison between the baseline diffusion model and our proposed phase-aware architecture. While both models produce visually convincing frames, the baseline model achieves a Phase Consistency Score of only 0.68, indicating frequent semantic errors. By integrating phase-aware sampling, we drastically reduce the Frechet Video Distance to 98.3 and elevate the Phase Consistency Score to 0.91. This proves that our model generates motion and actions that align highly with actual surgical workflows. Table 2 highlights the model performance across different procedural contexts. Reconstruction quality remains consistently high

during continuous phases, such as steady dissection. Predictably, performance drops slightly during highly dynamic transition phases, such as the introduction of the cutting shears, due to the complex visual changes involved. Nevertheless, the Boundary Transition Accuracy remains robust, confirming that the dynamic sampling strategy successfully manages the semantic shift.

4.3 Ablation Studies on Network Components

To isolate the contributions of specific architectural components, we conducted rigorous ablation studies. We systematically disabled various conditioning mechanisms to observe the resulting degradation in performance.

Table 3: Ablation Study on Conditioning Mechanisms

Configuration	Spatial Attention	Temporal Attention	Phase Awareness	Frechet Video Distance
Model A	Enabled	Disabled	Disabled	345.2
Model B	Enabled	Enabled	Disabled	156.8
Model C	Enabled	Enabled	Static Embeddings	121.4
Model D (Full)	Enabled	Enabled	Dynamic Decay	98.3

The ablation results presented in Table 3 validate our design choices. Model A, relying entirely on spatial generation without temporal attention, produces disjointed frames resulting in a massive Frechet Video Distance. Model B, the standard temporal diffusion model, improves this significantly but lacks semantic direction. Model C introduces phase embeddings but treats them statically across all generated frames. This leads to conflicting guidance, especially near the center of the gap. Model D, our complete framework utilizing dynamic decay weights during the sampling process, achieves the optimal temporal coherence score.

4.4 Clinical Relevance and Qualitative Assessment

Quantitative metrics, while essential, cannot entirely capture the clinical validity of generated surgical footage. Therefore, we conducted a qualitative assessment study involving expert surgeons. A panel of experienced minimally invasive surgeons was presented with a blinded set of video clips, containing both real uninterrupted footage and clips completed by our model and the baseline models. The surgeons were asked to rate the sequences based on visual realism, correct instrument usage, and anatomical plausibility.

Table 4: Subjective Clinical Evaluation Scores

Criterion	Baseline Diffusion	Proposed Method	Real Footage Benchmark
Visual Photorealism	4.2 / 5.0	4.4 / 5.0	4.9 / 5.0
Anatomical Plausibility	3.5 / 5.0	4.5 / 5.0	4.8 / 5.0
Instrument Continuity	2.8 / 5.0	4.6 / 5.0	5.0 / 5.0

As detailed in Table 4, the subjective clinical evaluation strongly reinforces our quantitative findings. The baseline diffusion model scored poorly on instrument continuity, with surgeons frequently noting the sudden disappearance of tools or the physically impossible morphing of a grasper into a cautery hook [36]. Our phase-aware method dramatically improved these specific clinical parameters. Surgeons noted that the synthesized clips respected the logical progression of the surgery, introducing and retracting tools in a manner that mirrored authentic procedural techniques. This qualitative validation is paramount, as the ultimate goal of surgical clip completion is to produce data that is indistinguishable from reality to both human experts and downstream algorithmic systems.

5. Conclusion

This paper has presented a comprehensive exploration of phase-aware diffusion sampling for the task of short surgical clip completion. We identified a critical vulnerability in contemporary video

generation models when applied to structured, protocol-driven environments like the operating room: the tendency to generate visually plausible but semantically illogical sequences. By introducing a novel conditioning framework that explicitly extracts and integrates surgical phase representations into the temporal attention layers of a diffusion U-Net, we effectively bridged the gap between low-level pixel synthesis and high-level procedural understanding. Our extensive methodological detailing provided a blueprint for dynamic, distance-weighted sampling, ensuring that boundary semantics accurately guide the synthesis of missing temporal gaps. The rigorous experimental evaluation, encompassing both established quantitative metrics and domain-specific phase consistency scoring, demonstrated the overwhelming superiority of the phase-aware approach. The ablation studies confirmed the necessity of dynamically modulating the phase influence across the synthesized sequence, while the subjective clinical assessment underscored the practical value of maintaining strict instrument and anatomical continuity. Despite the significant advancements demonstrated, limitations remain. The current architecture relies on a pre-trained, frozen phase recognition module, which may introduce error propagation if the boundary frames themselves are highly ambiguous. Future work will investigate end-to-end training paradigms where the phase extraction and video generation networks are optimized jointly. Furthermore, expanding the conditioning variables to include text-based operative reports or robotic kinematic data could provide even stronger priors for the generative process. In conclusion, the integration of phase-awareness into generative diffusion models represents a substantial leap forward in surgical video analysis. As the medical field continues to embrace artificial intelligence and data-driven methodologies, ensuring the integrity and completeness of surgical video records becomes an absolute necessity. The techniques detailed in this research provide a robust, scalable solution for curating high-fidelity surgical datasets, ultimately contributing to the advancement of automated surgical training, retrospective analysis, and the safe deployment of intelligent robotic assistance systems.

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