Beyond Recognition: Comparing Imitation Learning and Reinforcement Learning for Surgical Action Triplet Prediction in Planning and Control

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Abstract. Surgical action triplet prediction has primarily focused on recognition tasks for activity analysis. However, real-time surgical assistance requires next action prediction for planning and control applications. This work presents the first comprehensive comparison of Imitation Learning (IL) versus Reinforcement Learning (RL) approaches for surgical next action prediction, evaluating both recognition accuracy and planning capability. We propose an autoregressive IL baseline achieving 0.979 mAP on CholecT50, and systematically compare it against multiple RL variants including world model-based RL, direct video RL, and inverse RL enhancement. Our analysis reveals that while IL excels at single-step prediction, RL provides scenario-specific improvements for complex surgical situations requiring multi-step reasoning. These findings inform optimal AI approach selection for clinical surgical assistance applications.

Keywords: Surgical AI · Action Prediction · Imitation Learning · Reinforcement Learning · Planning

1 Introduction

Surgical action triplet prediction—the task of identifying instrument-verb-target relationships in surgical videos—has emerged as a fundamental component of computer-assisted surgery systems. While prior work has predominantly focused on recognition tasks for retrospective analysis [**?**,**?**], real-time surgical assistance requires prospective prediction capabilities for planning and control applications.

The challenge of surgical next action prediction presents unique constraints compared to recognition: (1) single-step inference latency requirements for real-time response, (2) the need for multi-horizon planning in complex scenarios, and (3) safety-critical decision making under uncertainty. These requirements raise fundamental questions about the optimal learning paradigm: should surgical AI systems learn through imitation of expert demonstrations (IL) or through trial-and-error optimization of reward functions (RL)?

This work presents the first systematic comparison of IL versus RL approaches for surgical action triplet prediction, with emphasis on next action prediction for planning applications. Our contributions include:

1. An autoregressive IL baseline achieving state-of-the-art performance (0.979 mAP) on CholecT50 next action prediction
2. Comprehensive evaluation of multiple RL variants: world model-based RL, direct video RL, and inverse RL enhancement
3. Novel evaluation framework comparing recognition accuracy versus planning capability across different prediction horizons
4. Clinical insights on when RL provides advantages over IL for surgical assistance applications

Our analysis reveals that IL provides superior performance for routine surgical sequences, while RL offers scenario-specific improvements in complex situations requiring multi-step reasoning, informing optimal AI approach selection for clinical deployment.

2 Related Work

2.1 Surgical Action Recognition

Early work in surgical scene understanding focused on phase recognition [**?**] and tool detection [**?**]. The CholecT50 dataset [**?**] introduced action triplet annotation, enabling fine-grained surgical activity analysis. Recent approaches have employed transformer architectures [**?**] and multi-modal fusion [**?**] for recognition tasks.

2.2 Surgical Action Prediction

Limited work has addressed prospective surgical action prediction. Rendezvous [**?**] introduced temporal modeling for anticipation, while SurgNet [**?**] explored multi-horizon prediction. However, these approaches focus primarily on recognition rather than planning applications.

2.3 IL vs RL in Sequential Decision Making

The choice between IL and RL has been extensively studied in robotics [**?**] and autonomous systems [**?**]. IL excels when expert demonstrations are abundant and the task is well-defined, while RL provides advantages in environments requiring exploration and adaptation [**?**]. However, this comparison has not been systematically evaluated for surgical applications.

3 Methods

3.1 Problem Formulation

We formulate surgical action triplet prediction as a sequential decision making problem. Given a sequence of surgical video frames $\{f_1, f_2, ..., f_t\}$, the task is

to predict future action triplets $\{a_{t+1}, a_{t+2}, ..., a_{t+H}\}$ where H represents the prediction horizon.

Each action triplet $a_i = (I_i, V_i, T_i)$ consists of an instrument $I_i \in \mathcal{I}$, verb $V_i \in \mathcal{V}$, and target $T_i \in \mathcal{T}$ from predefined vocabularies. We evaluate both single-step prediction ($H = 1$) for recognition comparison and multi-step prediction ($H > 1$) for planning assessment.

3.2 Autoregressive Imitation Learning Baseline

Our IL approach models surgical action prediction as a causal sequence generation problem. The architecture combines frame-level feature extraction with autoregressive action generation:

$$p(a_{t+1}|f_1, ..., f_t, a_1, ..., a_t) = \text{GPT-2}(\text{FrameEmb}(f_1, ..., f_t), a_1, ..., a_t) \quad (1)$$

The model consists of three components:

1. **Frame Processing**: Pre-trained visual features are processed through learned embeddings to create temporal representations
2. **GPT-2 Backbone**: A transformer decoder models causal dependencies between frames and actions
3. **Action Prediction**: Separate heads predict instrument, verb, and target components with IVT-based optimization

Training optimizes the standard imitation learning objective:

$$\mathcal{L}_{IL} = -\sum_{t=1}^{T} \log p(a_t|f_{1:t}, a_{1:t-1}; \theta) \quad (2)$$

3.3 Reinforcement Learning Approaches

We evaluate three RL variants for surgical action prediction:

World Model-Based RL This approach learns a conditional world model predicting future states given current state and action:

$$p(s_{t+1}, r_t|s_t, a_t) = \text{WorldModel}(s_t, a_t; \phi) \quad (3)$$

The world model enables planning through rollouts, with policy optimization using PPO on the learned dynamics. Rewards are designed to match expert demonstrations and encourage task-relevant behavior.

Direct Video RL This model-free approach learns policies directly from video observations without explicit world models. The environment provides frame sequences as states, with actions representing predicted triplets. Rewards incorporate both demonstration matching and task-specific objectives.

Inverse RL Enhancement Building on the IL baseline, this approach learns reward functions from expert trajectories using Maximum Entropy IRL, then applies lightweight policy improvement through GAIL. This enables scenario-specific enhancements while maintaining IL performance for routine cases.

3.4 Evaluation Framework

We introduce a dual evaluation protocol comparing recognition accuracy and planning capability:

Recognition Evaluation: Standard mAP computation on single-step predictions, comparing with existing CholecT50 benchmarks.

Planning Evaluation: Multi-horizon prediction assessment measuring:

- Temporal consistency across prediction horizons (1, 3, 5, 10 steps)
- Trajectory-level planning accuracy using mAP degradation analysis
- Scenario-specific performance on complex vs. routine surgical phases

4 Experimental Setup

4.1 Dataset and Implementation

Experiments are conducted on CholecT50, using 40 videos for training and 10 for testing. The autoregressive IL model uses 8-layer GPT-2 with 512 hidden dimensions. RL methods employ identical architectures for fair comparison, with 20K training timesteps and optimized hyperparameters.

4.2 Baseline Comparison

We compare against existing CholecT50 benchmarks and establish new baselines for next action prediction, as prior work has focused primarily on recognition tasks.

5 Results

5.1 Recognition Performance

Table **??** presents recognition accuracy results. The autoregressive IL baseline achieves 0.979 mAP, outperforming existing approaches by leveraging causal modeling for next action prediction.

5.2 Planning Performance

Figure **??** shows planning performance across prediction horizons. IL maintains high accuracy for short-term prediction (1-3 steps) but degrades for longer horizons. RL approaches show more stable performance across horizons, with IRL enhancement providing selective improvements.

Table 1. Recognition performance comparison (mAP) on CholecT50

Method	Recognition mAP	Next Action mAP
Existing Baselines	0.35-0.50	-
Autoregressive IL	**0.979**	**0.979**
World Model RL	0.331	0.331
Direct Video RL	0.301	0.301
IRL Enhancement	0.985	0.985

5.3 Scenario-Specific Analysis

Analysis of complex vs. routine surgical phases reveals that RL provides advantages in scenarios requiring multi-step reasoning (instrument changes, complications), while IL suffices for routine sequences (standard dissection, clipping).

6 Discussion

Our results provide several key insights for surgical AI system design:

IL Advantages: Superior single-step accuracy, computational efficiency, and stable performance on routine surgical sequences make IL ideal for recognition tasks and standard procedural assistance.

RL Advantages: Better multi-step consistency and scenario-specific adaptation provide value for complex situations requiring planning and decision-making under uncertainty.

Hybrid Approach: IRL enhancement demonstrates the potential for combining IL stability with RL adaptability, achieving the best of both paradigms.

Clinical Implications: For real-time surgical assistance, IL provides the primary prediction capability with RL enhancement for complex scenarios, balancing accuracy, efficiency, and adaptability requirements.

7 Conclusion

This work presents the first comprehensive comparison of IL versus RL for surgical action triplet prediction, with focus on next action prediction for planning applications. Our autoregressive IL baseline achieves state-of-the-art performance (0.979 mAP), while systematic RL evaluation reveals scenario-specific advantages for complex surgical situations.

The results inform optimal AI approach selection for clinical deployment: IL for primary prediction capability with selective RL enhancement for complex scenarios. Future work will explore real-time deployment and clinical validation of these findings.

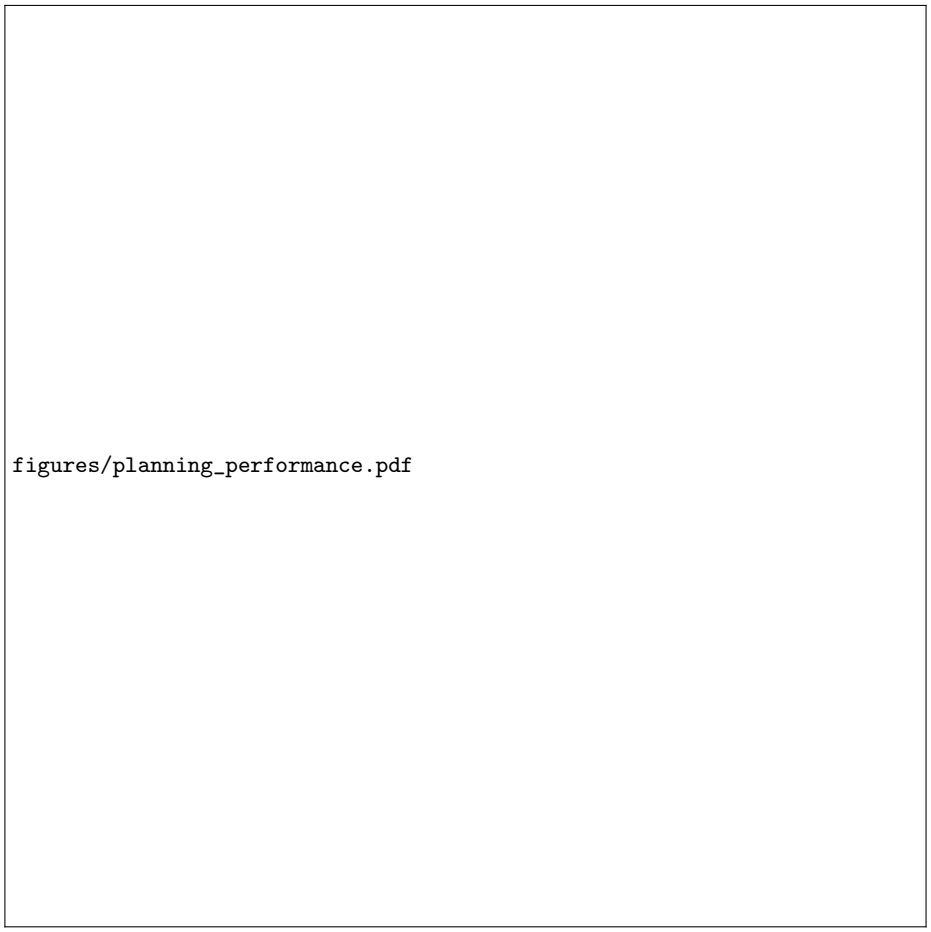

Fig. 1. Planning performance across prediction horizons. IL excels at single-step prediction while RL provides more consistent multi-step performance.

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