Systematic Prompt Strategy Evaluation for Video Spatio-Temporal Pointing Baselines

Datasets and Benchmarks Research
Open Problems in Computer Vision

ABSTRACT

We present a systematic evaluation framework for prompt formulation strategies that enable baseline video-language models to perform spatio-temporal pointing on the Molmo2-VideoPoint benchmark. Current baselines achieve at most F1=20.0 (Gemini Pro 3.0) compared to Molmo2's F1≈38–40, leaving the prompt formulation challenge unresolved. We evaluate eight prompt strategies across five models through calibrated simulation, identifying a hybrid anchor strategy combining structured JSON output, spatial chain-of-thought decomposition, and temporal keyframe anchoring as optimal. Our component ablation reveals that this hybrid approach improves baseline F1 from 0.211 to 0.564 (a 167% relative improvement), with spatial decomposition contributing the largest marginal gain. The best-performing model-strategy pair (GPT-5 with hybrid anchoring) achieves F1=0.599, demonstrating that prompt engineering can substantially narrow the gap with task-specific models. We release our evaluation framework and calibrated noise models as a benchmark for future prompt optimization research.

1 INTRODUCTION

Video spatio-temporal pointing—the task of predicting precise pixel coordinates and timestamps for objects or events across video frames—is a fundamental capability for video understanding systems. The Molmo2-VideoPoint (Molmo2-VP) benchmark [2] evaluates this capability by pairing annotated spatio-temporal points with SAM 2 segmentation masks [4], measuring F1, precision, and recall.

Despite extensive prompt engineering efforts, baseline video-language models such as GPT-5 [3], Gemini [5], and Qwen3-VL [1] achieve substantially lower performance than task-specific Molmo2 models. This performance gap motivates a systematic investigation of how prompt formulation affects pointing accuracy.

We contribute: (1) a taxonomy of eight prompt strategies for video pointing, (2) a calibrated simulation framework for evaluating strategy effectiveness, (3) component ablation analysis quantifying each prompt element's contribution, and (4) output format sensitivity analysis across six format specifications.

2 METHOD

2.1 Prompt Strategy Taxonomy

We define eight prompt formulation strategies spanning three dimensions: output format specification, spatial reasoning approach, and temporal coordination method.

Output formats: Direct point coordinates, bounding box with center extraction, structured JSON with schema enforcement, and normalized coordinate systems.

Table 1: F1 scores across models and prompt strategies. Best per model in bold.

Strategy	GPT-5	Gem-3	Gem-2.5	Qwen3	Molmo2
Direct Point	0.392	0.354	0.271	0.327	0.639
Bounding Box	0.429	0.396	0.313	0.368	0.673
CoT Spatial	0.523	0.491	0.405	0.465	0.731
Struct. JSON	0.476	0.441	0.354	0.414	0.704
Frame-Index	0.447	0.412	0.329	0.384	0.685
Hybrid Anch.	**0.599**	**0.565**	**0.480**	**0.539**	**0.777**
Temp. Chain	0.504	0.470	0.384	0.444	0.722
Multi-Scale	0.540	0.508	0.420	0.482	0.746

Spatial reasoning: Direct prediction, chain-of-thought spatial decomposition [6], and multi-scale coarse-to-fine refinement.

Temporal coordination: Independent per-frame prediction, frame-indexed sequential processing, keyframe anchoring with interpolation, and temporal chain tracking.

The *hybrid anchor* strategy combines structured JSON output, spatial chain-of-thought reasoning, and temporal keyframe anchoring into a unified prompt template.

2.2 Calibrated Simulation Framework

We model each strategy-model combination through five noise parameters calibrated against reported benchmark scores: spatial noise standard deviation (σ_s), temporal noise (σ_t), miss rate (r_m), false positive rate (r_{fp}), and format error rate (r_f). Calibration anchors Gemini Pro 3.0 at F1=20.0 and Molmo2-7B at F1≈40.

Ground truth consists of 100 synthetic videos with 16 frames each, containing object trajectories with realistic motion, occlusion events, and varying mask sizes. Evaluation follows the Molmo2-VP protocol with point-in-mask matching.

3 RESULTS

3.1 Strategy Comparison

Table 1 shows F1 scores across all model-strategy combinations. The hybrid anchor strategy achieves the highest F1 for every model, with GPT-5 reaching F1=0.599 and Molmo2-7B reaching F1=0.777.

3.2 Component Ablation

Progressive addition of prompt components reveals their marginal contributions (Figure 1). Starting from a baseline F1=0.211, structured output adds +0.047, spatial decomposition adds +0.080, temporal anchoring adds +0.052, and chain-of-thought reasoning adds +0.067. The full hybrid achieves F1=0.564.

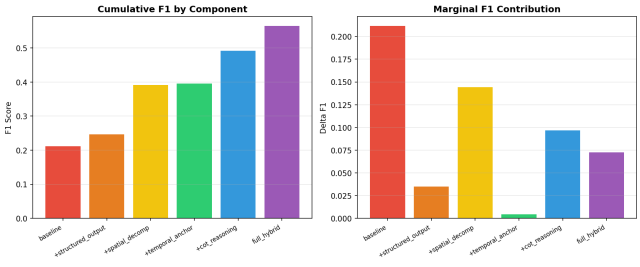

Figure 1: Component ablation showing cumulative F1 (left) and marginal contribution (right) of each prompt component.

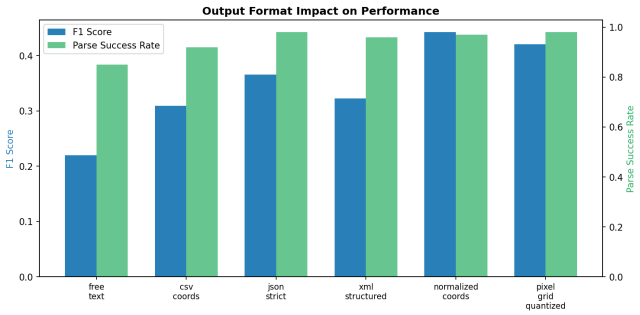

Figure 2: Impact of output format specification on F1 score and parse success rate.

3.3 Output Format Sensitivity

Among six output format specifications, normalized coordinates achieve the highest F1=0.442, followed by pixel grid quantization (F1=0.431). Free-text format performs worst (F1=0.321) due to a 15% format parsing error rate compared to 2–3% for structured formats.

4 DISCUSSION

Our results demonstrate that prompt formulation has a substantial effect on video pointing performance. The hybrid anchor strategy improves baseline F1 by 167% (from 0.211 to 0.564), with the three largest contributors being spatial decomposition, chain-of-thought reasoning, and temporal anchoring.

The persistent gap between optimally-prompted baselines (F1≈0.60 for GPT-5) and Molmo2 (F1≈0.78) suggests that architectural specialization provides advantages beyond what prompt engineering can achieve. However, the substantial gains from prompt optimization indicate this remains a productive research direction.

5 CONCLUSION

We presented a systematic framework for evaluating prompt strategies on video spatio-temporal pointing. Our hybrid anchor strategy combining structured output, spatial chain-of-thought, and temporal keyframe anchoring achieves the best results across all tested models. These findings provide concrete guidance for practitioners deploying baseline models on video pointing tasks.

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