SAFEDEC: CONSTRAINED DECODING FOR SAFE AUTOREGRESSIVE GENERALIST ROBOT POLICIES

Anonymous authors
Paper under double-blind review

ABSTRACT

Recent advances in end-to-end, multi-task robot policies based on transformer models have demonstrated impressive generalization to real-world embodied AI tasks. Trained on vast datasets of simulated and real-world trajectories, these models map multimodal observations directly to action sequences for physical execution. Despite promising real-world capabilities, these models are still data-driven and, therefore, lack explicit notions of behavioral correctness. We address this gap by introducing **SafeDec**, a constrained decoding framework for autoregressive, transformer-based robot policies that enforces invariant safety specifications on candidate action trajectories. Task-specific safety rules are expressed as Signal Temporal Logic (STL) formulas and are enforced at inference time with minimal overhead. Our method ensures that generated actions provably satisfy STL specifications under assumed dynamics at runtime without retraining , while remaining agnostic of the underlying policy. We evaluate **SafeDec** on tasks from the CHORES benchmark for state-of-the-art generalist policies (e.g., SPOC, Flare, PoliFormer) across hundreds of procedurally generated environments and show that our decoding-time interventions are useful not only for filtering unsafe actions but also for conditional action generation. Videos are available at **constrained-robot-fms.github.io**.

1 INTRODUCTION

Recent advances in developing large transformer-based models for robotics have enabled general-purpose policies that map multi-modal inputs such as RGB images, natural language instructions, and proprioceptive inputs to action sequences Hu et al. (2023). Shortest Path Oracle Clone (SPOC) Ehsani et al. (2024), PoliFormer Zeng et al. (2025), Flare Hu et al. (2025) and OpenVLA (Kim et al., 2024) exhibit impressive generalization in navigation and manipulation tasks and serve as versatile robot controllers for real-world deployment contexts. However, these models are primarily data-driven and lack any explicit notion of safety. Although these models may implicitly exhibit safety-related behaviors depending on the patterns in their training data, there is no formal guarantee that models will consistently behave safely in all situations. This serves as a limiting factor for deploying these foundation models in the physical world where rule compliance and regulatory safety rule adherence are crucial.

Formal specifications have long been used to specify safety requirements for robotic deployments (Menghi et al., 2019; Farrell et al., 2018). Temporal logics (TL) (Pnueli, 1977) can capture safety constraints on robot behavior, such as "remain within the permitted region zones and avoid dangerous obstacles". Although TL has seen success in classical robotic planning for safety constraint satisfaction, its use for enforcing safety for large transformer-based robot policies remains limited. Additionally, retraining or fine-tuning these large pre-trained models to directly embed temporal logic specification is challenging (Kapoor et al., 2024). First, retraining models is a costly endeavor in terms of computational resources and data requirements. Moreover, due to the stochastic nature of these models, it is difficult to guarantee strict satisfaction of safety constraints through training alone. Hence, there is a pressing need for methods that can enforce safety specifications efficiently at inference time without disrupting the model's pre-trained behavior.

In the field of natural language processing, syntactic constraints have been successfully enforced by applying constrained decoding at inference time (Willard & Louf, 2023; Beurer-Kellner et al.,

2023; AI, 2023). These approaches typically mask out tokens that violate a syntactic constraint defined over token sequences. For example, regular expressions (regex) represent a widely used form of syntactic constraint, requiring that generated token sequences conform to predefined structural patterns (Willard & Louf, 2023; Beurer-Kellner et al., 2023). Inspired by this line of work, we extend the paradigm of constrained decoding to enforce safety constraints over action trajectories in dynamical systems and propose *safety specification aligned decoding (`SafeDec`)* for transformer based policies that ensures generated action sequences provably satisfy Signal Temporal Logic (STL) (Maler & Nickovic, 2004) specifications under assumed dynamics. Our key insight is that decoding-time interventions can be used not just to filter unsafe actions, but to *condition the generation process itself* on specification satisfaction. This conditioning is critical because it steers the model toward generating safety specification satisfying actions rather than relying on post hoc rejection. `SafeDec` reduces risk of infeasible outputs while preserving the original action distribution of the model. To enforce such specifications, we leverage the formal semantics of STL to evaluate candidate actions at runtime and mask those that lead to future violations. Our method is agnostic to the underlying foundation model, requiring only two properties: (1) access to the decoding-layer logits during inference, and (2) access to an approximate dynamics model to predict future states. To efficiently evaluate STL specifications at inference time, we use a high-performance computational graph based library `STLCG++` (Kapoor et al., 2025b). To the best of our knowledge, this is the first work to enforce formal safety on transformer-based robotic policies at inference time using constrained decoding.

Our main contributions are as follows: First, we introduce the novel problem of *constrained decoding for transformer-based policies* under safety STL specifications (Section 3.1). Second, we propose an inference-time technique that reweights or masks candidate actions using STL satisfaction scores in (Section 3.2 and 3.3). Finally, we demonstrate the effectiveness of our method on state-of-the-art object navigation models without modifying model parameters (Section 4).

2 Preliminaries

2.1 Signal Temporal Logic

Signal Temporal Logic (STL) is an expressive framework for defining properties and reasoning over continuous time real-valued signals Maler2004MonitoringTP. Formally, $(\mathbf{s}, t) \models \phi$ denotes that a signal $\mathbf{s}$ satisfies the STL formula ϕ at time t. An atomic predicate of an STL formula is represented by inequalities of the form $\mu(\mathbf{s}(t)) > 0$. The truth value of the predicate μ is equivalent to $\mu(\mathbf{s}(t)) > 0$. Note that with slight abuse of notation, μ represents both the predicate and a function of the trajectory $\mathbf{s}(t)$. Any STL formula consists of Boolean and temporal operations on these predicates, and the syntax of STL formulas is defined recursively as follows:

$$\phi := \mu \mid \neg\mu \mid \phi \wedge \psi \mid \phi \vee \psi \mid \mathbf{G}_{[a,b]}\ \psi \mid \mathbf{F}_{[a,b]}\ \psi \mid \phi\ \mathbf{U}_{[a,b]}\ \psi$$

where ψ and ϕ are STL formulae, $\mathbf{G}$ denotes the globally operator, $\mathbf{F}$ the eventually operator, and $\mathbf{U}$ is the until operator. For example, $\mathbf{s} \models \mathbf{G}_{[a,b]}\psi$ specifies that ψ must be in all times in the given interval, $t \in [a, b]$ of the signal $\mathbf{s}$. Similarly, the operator *until* in $\mathbf{s} \models \phi\mathbf{U}_{[a,b]}\psi$ defines that ϕ must be true until ψ becomes true within a time interval $[a, b]$.

Given a signal s_t representing a signal starting at time t, the Boolean semantics of satisfaction of $s_t \models \phi$ are defined inductively as follows:

$$\begin{aligned}
s_t \models \mu &\iff \mu(s(t)) > 0 \\
s_t \models \neg\varphi &\iff \neg(s_t \models \varphi) \\
s_t \models \varphi_1 \wedge \varphi_2 &\iff (s_t \models \varphi_1) \wedge (s_t \models \varphi_2) \\
s_t \models \mathrm{F}_{[a,b]}(\varphi) &\iff \exists t' \in [t+a, t+b] \text{ s.t. } s_{t'} \models \varphi \\
s_t \models \mathrm{G}_{[a,b]}(\varphi) &\iff \forall t' \in [t+a, t+b] \text{ s.t. } s_{t'} \models \varphi
\end{aligned}$$

Apart from the Boolean semantics, quantitative semantics are defined for a signal to compute a real-valued metric indicating *robustness*, i.e., the strength of satisfaction or violation. For the sake of brevity, the definition of robustness is provided in Appendix A.1.

2.2 Constrained Decoding in Transformers

A large variety of autoregressive transformer-based models generate final outputs by producing a probability distribution over the model vocabulary at each timestep. This distribution is generated by performing a softmax operation over the model's last hidden layer. Then, through the process of *decoding*, tokens are selected to maximize the overall likelihood of an output sequence. In standard decoding, this maximization can be performed by either greedily selecting the most probable token at each step or by using a beam search to maintain multiple high-likelihood candidates. However, this often leads to degenerate output sequences that are repetitive (Holtzman et al., 2019). A common approach is to use sampling strategies like top k (Fan et al., 2018), and nucleus sampling (Holtzman et al., 2019) that introduce stochasticity to encourage more diverse outputs. Constrained decoding (Hokamp & Liu, 2017) modifies this probabilistic selection by pruning invalid tokens to ensure that the generated sequences satisfy predefined constraints. These constraints are often syntactic, such as regular expressions, JSON formatting, or programming language grammars (Welleck et al., 2024). There is also recent work on enforcing *semantic* constraints that ensure coherence of the output or alignment with specific knowledge bases (Peyrard et al., 2024). Formally, constrained decoding can be seen as maximizing the probability of the output sequence subject to a constraint $\mathcal{C}$: $\arg\max_{y \in \mathcal{Y}_\mathcal{C}} P(y \mid x)$ where $\mathcal{Y}_\mathcal{C}$ is the set of sequences satisfying $\mathcal{C}$.

3 Specification-Guided Constrained Decoding

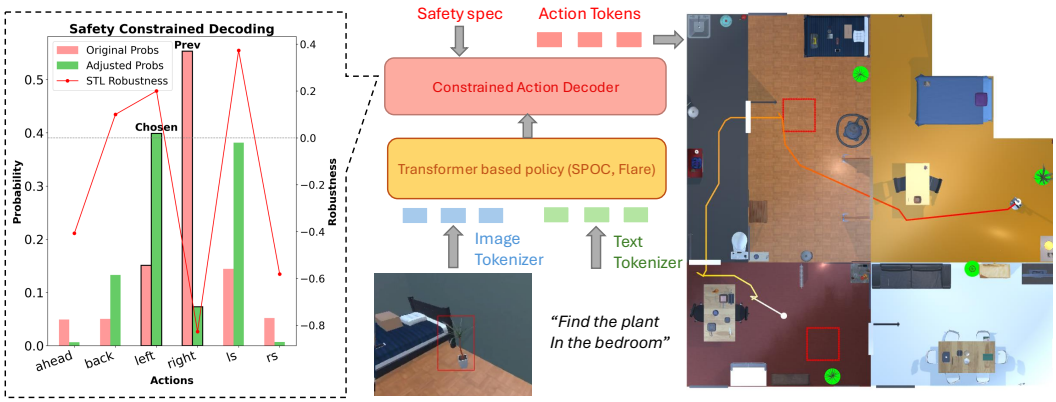


Figure 1: Overview of our specification aligned decoding framework. Given multimodal inputs (e.g., RGB images and natural language instructions), a pretrained transformer-based robot policy (e.g., SPOC) generates candidate actions. These actions are filtered or reweighted by the constrained decoding technique based on STL safety constraints. In the figure, green markers denote target object locations, while red zones represent regions to avoid.

In this section, we introduce a novel problem formulation for `SafeDec` in autoregressive transformer-based robot policies. First, we highlight the challenge in specification checking for these policies in contrast to traditional syntactical constraint checking adopted by LLMs, and our solution to remedy it. Then, we propose two novel inference-time techniques for specification aligned decoding: *Hard Constrained Decoding* (HCD) and *Robustness Constrained Decoding* (RCD).

3.1 Problem Statement

As highlighted in the background section, existing techniques in constrained decoding for language models enforce *syntactic constraints* defined over tokens, such as conforming to a context-free grammar or matching a regular expression. In these setups, constraint checking can be performed in the model's token space.

In contrast, transformer-based policies operate in a physical environment and constraints (captured via temporal logic) are defined over state variables. Since a large class of end-to-end policies solely propose action sequences, specification checking can only be performed as actions are executed

and the environment is simulated forward. In this case, constraint checking cannot be done solely in the token space and requires environmental feedback or a dynamics stepping function. Hence, we leverage an approximate first order dynamics function to compute specification satisfaction of different action sequences proposed by these policies.

Consider a discrete dynamical system with states $x_t \in \mathbb{R}^n$ and actions $a_t \in \mathbb{A}$ at time step t. The system's dynamics are defined by $x_{t+1} = f(x_t, a_t)$ where $f : \mathbb{R}^n \times \mathbb{A} \to \mathbb{R}^n$ maps the current state $(x_t \in \mathbb{R}^n)$ and a discrete action $(a_t \in A)$ to the next state $x_{t+1} \in \mathbb{R}^n$. This system is controlled by a policy that selects an action a_t at each time step based on observations and task context such as user-provided natural-language instructions or goal waypoints.

In this work, we focus on robot policies that generate actions based on multi-modal inputs, including sensor observations (e.g., RGB, depth, LiDAR) and natural language instructions. Let $\mathcal{I}_t$ represent the aggregated input at timestep t. Given the history of encoded inputs up to time t, a transformer-based policy parameterized by θ predicts embeddings for the next $T-t$ actions:

$$\{\hat{e}_{a_{t+k}}\}_{k=1}^{T-t} = \text{Transformer}_\theta\big(\{e_{\mathcal{I}_\tau}\}_{\tau=0}^{t}\big).$$

Each predicted action embedding is decoded into an action $\hat{a}_{t+k} \in \mathbb{A}$, resulting in a predicted action sequence $\{\hat{a}_{t+1}, \ldots, \hat{a}_T\}$, where T denotes the planning horizon.

Now, consider that the system is required to satisfy requirements encoded using an STL formula φ defined over the state variables of the system. Formally, the goal is to ensure that the resulting trajectory satisfies the specification φ:

$$\{(x_0, \hat{a}_0), \ldots, (x_T, \hat{a}_T)\} \models \varphi$$

Most of the existing techniques for specification enforcement perform posthoc manipulation of proposed actions through filtering or rejecting action sequences that violate the specification φ. Although manipulation after sampling can ensure specification satisfaction, it can lead to distorting the model's learned distribution, producing low-likelihood output. This undermines the inductive biases learned during pretraining and leads to degenerate, brittle behaviors. A similar problem was highlighted when ensuring compliance with logical constraints for large language models (LLM) in Park et al. (2024). Additionally, these models decode actions sequentially, where each action a_t is conditioned on previously generated tokens $a_{<t}$. Posthoc manipulation can disrupt this causal chain and lead to a mismatch between the model's internal hidden state and the executed sequence. Hence, we propose the following problem statement:

> *How can we enforce temporal logic constraints during action generation in robot foundation models such that the output sequence (1) satisfies an STL specification φ, and (2) remains faithful to the model's autoregressive distribution $\pi(a_{1:T} \mid \mathcal{I}_{1:T})$?*

Let $\pi(a_{0:T})$ be the *unconstrained* action-sequence distribution produced by the transformer-based policy's decoder (e.g. the softmax over logits generated by the Transformer). We define the ideal constrained distribution over action sequences as:

$$Q_{\pi,\varphi}(a_{0:T}) = \frac{\pi(a_{0:T}) \cdot \mathbf{1}[(x_{1:T}, a_{0:T}) \models \varphi]}{\sum_{a'_{0:T}} \pi(a'_{0:T}) \cdot \mathbf{1}[(x'_{1:T}, a'_{0:T}) \models \varphi]} \tag{1}$$

where $x_{1:T}$ denotes the state trajectory induced by the system dynamics under actions $a_{0:T}$ and $\mathbf{1}[\cdot]$ is the indicator function that returns 1 iff the trajectory-action pair satisfies the specification. Equation 1 is the exact Bayesian conditioning of π on the event that the generated rollout satisfies φ. Hence, sampling from $Q_{\pi,\varphi}$ would give sequences that (i) inherit the original model's preferences encoded in π and (ii) *guarantee* specification satisfaction.

In this work, we propose a technique to overcome the drawbacks of post-hoc safety enforcement methods (such as filtering) by leveraging constrained decoding techniques. Specifically, we propose `SafeDec` : A constrained decoding strategy that integrates STL specifications into the foundation model action selection process itself, ensuring satisfaction without distorting the model's distribution.

3.2 HARD CONSTRAINED DECODING

As highlighted in the background section, in the final layer, predictions are detokenized and a projection layer converts the embeddings into logits over the vocabulary space. These logits are further converted into a probability distribution using a softmax operation. In prior work, for structured output generation in LLMs, some invalid tokens are masked based on syntactical constraints or other criteria (Welleck et al., 2024; Park et al., 2024). This is done by setting their logit value as $-\infty$ before the softmax operation is applied. For HCD, we use a similar approach as constrained decoding literature (Welleck et al., 2024) and mask out predicted action tokens that violate our given STL specification φ during sequential generation. Formally, to enforce the STL specification φ during sequential generation, we adjust the logits at each timestep $t + k$ as follows:

Let $\mathbf{z}_{t+k}$ denote the logits at timestep $t + k$. For each action choice i at timestep $t + k$, we define:

$$z_{t+k}^{(i)} = \begin{cases} -\infty, & \text{if } \hat{x}_{t+k}^{(i)} = f(x_{t+k-1}, \hat{a}_{t+k}^{(i)}) \text{ violates } \varphi \\ z_{t+k}^{(i)}, & \text{otherwise} \end{cases}$$

Here t is the current decision step, k is an index for the look-ahead step $t + k$ within a planning horizon of length T ($k \in [1..T]$), $\hat{a}_{t+k}^{(i)}$ is the action mapping to the token i and $\hat{x}_{t+k}^{(i)}$ is the next state value upon taking this action. This next state is elicited using a simple dynamics model (f) as highlighted in the previous section. Adjusting logits in this fashion ensures that any invalid token with respect to the safety specification will have zero probability of being selected after applying the softmax function.

3.3 ROBUSTNESS CONSTRAINED DECODING

HCD ensures compliance but can lead to compromising task success, which can be undesirable. A similar tradeoff was observed by Liu et al. (2021) when probability space-steering preserved model fluency while reducing toxic continuations compared with hard-filtering strategies that inflated perplexity and eroded diversity. Hence, we propose an alternative approach, called RCD, where we leverage the quantitative semantics of STL specifications (robustness). Unlike HCD, which applies hard masking to completely remove unsafe actions, RCD softly guides the model toward safer actions by incorporating robustness scores that reflect the degree of satisfaction of φ. This is similar to the approach proposed in Liu et al. (2021) where the next-token distributions were re-weighted based on the utility scores provided by another language model. Our utility scores are quantified by the robustness function($\rho(x_t, \varphi)$) that returns a real-valued score indicating how well a predicted state satisfies the specification. Positive robustness values denote specification satisfaction, while negative values capture the degree of violation. A formal definition of robustness in line with the STL quantitative semantics is provided in Appendix A.1.

First, we compute a robustness score for each candidate action: $r_{t+k}^{(i)} = \rho(\hat{x}_{t+k}^{(i)}, \varphi)$ where $\rho(\cdot, \varphi)$ is the STL robustness metric, and $\hat{x}_{t+k}^{(i)}$ is the predicted next state under action $\hat{a}_{t+k}^{(i)}$. This robustness score $r_{t+k}^{(i)}$ quantifies how well each candidate action satisfies the specification φ. These scores are then converted into weights using exponential scaling: $w_{t+k,i} = \exp(\alpha \cdot r_{t+k,i})$ where α is a temperature parameter that adjusts the sharpness of the bias. We use these weights to shift the original logits: $\tilde{z}_{t+k,i} = z_{t+k,i} + \beta \cdot w_{t+k,i}$ where β is a hyperparameter that modulates the tradeoff between specification adherence and the original task objective. Finally, we obtain the action distribution by applying softmax over the adjusted logits: $p_{t+k} = \text{softmax}(\tilde{\mathbf{z}}_{t+k})$

This approach allows for graded preferences that improve flexibility and robustness to dynamics approximation errors. By ensuring that all actions preserve a non-zero probability, the policy remains capable of recovering from errors arising from an imperfect dynamics model. Concretely, if the predicted successor $\hat{x}_{t+1}$ is off by ϵ, an action that appeared marginally unsafe can be safe in the true system, and vice versa. Retaining a weighted down probability for this action gives the sampler a fall-back option whereas HCD would completely rule this action out due to 0 probability. Since we are shifting the probability mass for unsatisfying actions, it is possible that they are still chosen and lead to a violation. However, this is a tradeoff that we allow to achieve a given task objective. We note that this still ensures higher STL sastifaction than unconstrained actions.

4 EVALUATION

4.1 IMPLEMENTATIONAL DETAILS

We comprehensively evaluate our constrained decoding framework on procedurally generated AI2-THOR (Kolve et al., 2022) indoor scenes with diverse objects and layouts using three state-of-the-art (SOTA) generalist robot policies: Shortest Path Oracle Clone (SPOC) (Ehsani et al., 2024), PoliFormer (Zeng et al., 2025) and Flare (Hu et al., 2025). All three are large transformer-based embodied agents trained on extensive language-conditioned robot trajectory datasets. These models achieve strong zero-shot generalization for a vast variety of navigation tasks that span open vocabulary object-goal navigation ("find a mug"), room-to-room traversal ("visit all rooms"), waypoint-based navigation ("move three meters forward and stop near the red rug"), and attribute-conditioned variants ("locate the chair closest to the refrigerator in the kitchen"). These models also demonstrate reliable zero-shot transfer to real-world environments, achieving robust task satisfaction.

In addition, these models capture three different training paradigms for generalist robot policies. SPOC is trained purely with imitation learning from shortest-path rollouts. Poliformer employs a hybrid approach that combines reinforcement learning and imitation learning, enabling it to learn long-horizon structure while retaining expert priors. Flare adopts a large-scale pretraining plus fine-tuning on embodied navigation data in line with recent foundation model training paradigms. This diversity in training paradigms allows us to evaluate the applicability of `SafeDec` across different learning regimes.

In this work, we address safety specifications for robotics and, therefore, select those most relevant to real-world deployment. In particular, we focus on an important class of safety specifications called *invariants*, which are specifications that must be enforced at every reachable state of the system (e.g., "always avoid an unsafe region"). We enforce *geofencing* and *obstacle avoidance* by encoding them as invariant specifications in STL. Specifically, we generate random regions in the configuration space that the robot must either avoid (obstacle zones) or remain within (safe zones), and apply these constraints in real time during execution. The specifications used are: $\varphi_{\text{geofence}} = \mathbf{G}\Big(\bigvee_{i=1}^{N}\Big(x_i^{\mathrm{L}} \leq x \leq x_i^{\mathrm{U}} \ \wedge \ z_i^{\mathrm{L}} \leq z \leq z_i^{\mathrm{U}}\Big)\Big)$, $\varphi_{\text{avoid}} = \mathbf{G}\Big(\bigwedge_{i=1}^{N} \neg\Big(x_i^{\mathrm{L}} \leq x \leq x_i^{\mathrm{U}} \ \wedge \ z_i^{\mathrm{L}} \leq z \leq z_i^{\mathrm{U}}\Big)\Big)$. The size of the regions for φ_{avoid} is 1 m^2. For $\varphi_{geofence}$, we randomly pick a subset of rooms in each house and use each chosen room's full bounds. These safety specifications are common for robot learning applications he2024agile, yun2025safe, kapoor2025demonstrating, zhao2024guard. We encode our test STL specifications using an efficient computational graph-based STL library called STLCG++ that can evaluate multiple state signals in parallel (Kapoor et al., 2025b). This ensures minimal inference overhead at runtime (10^{-5} s per timestep) , which is crucial for policy deployment. For our dynamics model, we assume a unicycle model, an approximate first-order dynamics abstraction widely used in the robotics literature for analysis and control (Cohen et al., 2024). This representation captures the essential kinematics of motion in the plane and is widely used because it is applicable for diverse robotic platforms.

4.2 EXPERIMENTAL SETUP

We compare our proposed techniques with (1) an unconstrained base model and (2) a base model with a filtering mechanism. The filtering mechanism picks a default action (turning left or right in place) upon predicted violation of the safety specification, similar to the Simplex architecture (Sha, 2001). Simplex architecture is a classic scheme in which a high-performance advanced controller is continuously monitored by a provably safe but less capable backup controller. Simplex based techniques have been used extensively for safety-critical robotics and are a widely accepted standard for runtime-safety comparisons. We evaluate performance using two main metrics: STL Satisfaction Rate (**STL St**), defined as the proportion of trajectories that satisfy the specified STL formula, and Task Success Rate (**SR**), which measures standard task success. The three main research questions we investigated in this paper:

1. **RQ1**: Do HCD and RCD provide higher STL satisfaction than the unconstrained baselines?

Decoding	ϕ_{avoid}: STL / SR (% ↑)			$\phi_{geofence}$: STL / SR (% ↑)		
	SPOC	**Flare**	**PoliFormer**	**SPOC**	**Flare**	**PoliFormer**
Unconstrained	72.0 / 82.5	75.5 / 82.0	77.0 / 82.5	78.0 / 81.5	68.0 / 81.0	73.0 / 81.5
Filtering	100.0 / 72.0	100.0 / 78.5	100.0 / 75.5	100.0 / 72.0	100.0 / 66.5	100.0 / 67.5
HCD	100.0 / 72.5	100.0 / 81.0	100.0 / 78.5	100.0 / 76.5	100.0 / 67.5	100.0 / 72.5
RCD	93.0 / 76.0	83.0 / 82.5	87.5 / 83.5	95.5 / 80.0	80.0 / 71.5	85.5 / 77.5

Table 1: Comparison by decoding technique across models (SPOC, FLARE, PoliFormer) for specifications ϕ_{avoid} and $\phi_{geofence}$. Each cell reports STL satisfaction / success rate (%). Higher is better (↑).

2. **RQ2**: Do HCD and RCD preserve task success rates comparable to the unconstrained baselines?
3. **RQ3**: Does RCD achieve better task success than HCD while maintaining high STL satisfaction?

(a) Unconstrained v/s HCD

(b) Unconstrained v/s RCD

Figure 2: Qualitative comparison of decoded trajectories for a sample scene. Each plot shows a top down view of an overlay of trajectories starting from the white dot under the instruction "find an alarm clock". The unconstrained model passes through two forbidden regions (red squares) on the way to the target object located on the table. In contrast, HCD (left) and RCD (right) modify the trajectories to respect STL safety specifications while still reaching the goal. More visualizations are available in the Appendix A.2.

4.3 Results

Our results are highlighted in Table 1. We also visualize sample trajectories in Figure 2 for one scene and task. Unless stated otherwise, all numbers are averaged over 200 evaluation episodes.

RQ1 – STL satisfaction. Both HCD and RCD consistently improve STL satisfaction relative to the unconstrained baselines across all models. For ϕ_{avoid}, unconstrained controllers achieve 72-77% satisfaction, while HCD raises this to 100% and RCD achieves 83–93%. For $\phi_{geofence}$, the gap is even larger: unconstrained models reach only 68–78%, whereas HCD attains perfect compliance (100 %) in all cases and RCD achieves 80–95%. We observe that the Simplex-style filtering baseline achieves similar STL-satisfaction rate as HCD, 97 % for ϕ_{avoid} and 100 % $\phi_{geofence}$. This parity is expected as both methods block any action predicted to violate the specification.

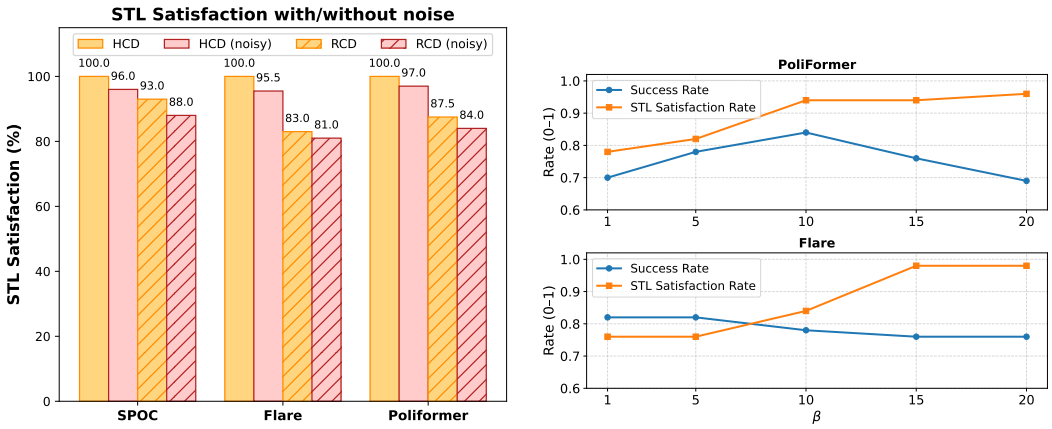
RQ2 – Task completion. Simplex-style filtering attains high satisfaction but sacrifices task success because the agent takes predefined safe actions. HCD shows similar behavior: although safety is maximized, success rates are consistently 5–10% lower than the baseline across models and specifications. However, as HCD factors in base model logits, it is able to achieve higher task satisfaction compared to Simplex-style filtering. In contrast, RCD preserves success rates much closer to the unconstrained level. For ϕ_{avoid}, RCD achieves 82–85% success compared to 82–83% for the unconstrained controllers for Flare and PoliFormer. For $\phi_{geofence}$, it maintains 77–80% compared to 81–82% unconstrained for SPOC and PoliFormer. However, we note that RCD does not fully recover success in every case: on SPOC with ϕ_{avoid} and Flare with $\phi_{geofence}$, task success remains several points below the unconstrained baseline. Nevertheless, RCD enforces safety while avoiding the large performance penalty observed with filtering.

RQ3 – RCD vs. HCD. While both HCD and RCD improve safety over the unconstrained baseline, they differ in how they balance constraint satisfaction with task success. HCD enforces strict STL satisfaction that results in frequent conservatism and lower successful task completion rates. In contrast, RCD's soft penalization leads to higher task success while still maintaining reasonable STL satisfaction. These results show that RCD achieves a better trade-off between safety and goal-directed behavior, especially in settings where occasional low-risk actions can lead to higher long-term rewards.

Overall, Our proposed techniques effectively enforce safety STL specifications during policy execution. HCD ensures full compliance, but occasionally sacrifices task success due to strict truncation. RCD strikes a balance, offering high satisfaction rates and robust performance. This highlights the feasibility of combining learning-based models with formal safety constraints.

4.4 Ablation Studies

Does inaccurate dynamics modeling substantially reduce STL satisfaction? In this work, we assume a simple unicycle dynamics model due it's generalization capability for diverse robotic platforms. Although this represents a high-level abstraction of true dynamics, such modeling simplifications are standard in the formally assured robot safety literature (Cohen et al., 2024). However, both RCD and HCD depend on this assumption and inaccurate modeling can impact STL satisfaction. To evaluate the impact of inaccurate dynamics modeling, we conducted an ablation in which we inject gaussian perturbations into the dynamics (0.01 m per step translational noise i.e. 5% of nominal forward step, 1 ° per step rotational noise i.e. 3.3% of yaw step) for both HCD and RCD. Our results are visualized in Figure 3. Across all three base models, the drop in STL satisfaction rates from baseline to noisy dynamics is relatively small. We observe that `SafeDec` shows graceful degradation under significant per-step disturbances.



(a) Ablation with noisy dynamics

(b) Ablation on varying values of β for RCD

Figure 3: **Ablation studies.** (a) STL satisfaction (%) for HCD and RCD under baseline vs noisy dynamics across base models. (b) Effect of β on success rate and safety satisfaction.

How do varying values of β affect success rate and STL satisfaction in RCD? As highlighted in section 3.3, RCD uses a hyperparameter β that modulates the trade-off between specification adherence and the original task objective. The value of β affects the relative weighting between robustness and base logits. To investigate the impact of β on the success rate and STL satisfaction, we performed an ablation with varying values for β for Flare and PoliFormer. We observe that as β increases for PoliFormer, both STL satisfaction and success rate improve in tandem until β = 10, suggesting that moderate regularization can actually aid policy execution. Beyond this, STL satisfaction continues to improve but at the cost of lower success rates. For Flare, larger β values improve STL satisfaction but reduce success rates. These results highlight that the influence of β is model-dependent but in general demonstrate that `SafeDec` provides a tunable mechanism to balance safety and performance objectives.

5 Related Work

Constraint satisfaction for robotics has been an active area of research that involves techniques such as control barrier functions (CBFs) (Ames et al., 2019), safe reinforcement learning (Gu et al., 2024), and temporal logic-based shielding approaches (Alshiekh et al., 2017). Recently, with the advent of vision language action models and their impressive generalizable capabilities for manipulation, navigation and other tasks, there are growing concerns about ensuring safety and correctness without retraining these large models. Although classical methods offer formal guarantees, they either require pretraining/fine-tuning stage interventions or designing a new classical controller for each safety specification, which can be restrictive. For example, SafeVLA (Zhang et al., 2025) fine-tunes pre-trained foundation models with task-specific safety costs, achieving strong performance in Safety-CHORES tasks. However, the safety specification is expected to be embedded in the training data and loss, meaning the model cannot generalize to new safety constraints at test time. In contrast, ASIMOV (Sermanet et al., 2025) explores rewriting dangerous instructions with better human-aligned alternatives to steer model behavior without modifying model parameters, but lacks trajectory-level formal guarantees. Our technique achieves a middle ground with the ability to adapt to novel specifications at test time without modifying model parameters while requiring minimal assumptions about the underlying model. The closest to our work is SELP (Wu et al., 2025) that proposes LTL-constrained decoding for language model-based plan generation. However, SELP is unsuitable for STL because its Boolean predicate-based LTL cannot encode numeric bounds (e.g. $||x–x_{goal}|| < 0.1m$) and does not possess quantitative semantics, which is crucial for ranking actions. These techniques are also tailored to high-level plans from LLMs, not to the per-step low-level actions generated online by policies.

6 Limitations and Future Work

In this work, we introduce a constrained decoding framework for enforcing safety specifications for large transformer based robot policies. Our approach enables runtime adaptation to novel safety specifications without retraining. Through experiments across multiple simulated environments, we demonstrated that our method significantly improves STL satisfaction while maintaining high task success rates. Our approach makes two critical assumptions that can be a limiting factor. First, we assume access to specifications that are defined over the state space and that these specifications are generated by roboticists. Although this is a common situation for safety critical deployment contexts like aerial robotics (Aloor et al., 2023; Luckcuck et al., 2019), these specifications can be difficult to design and involve access to a localization module that can provide accurate state estimation. We plan to overcome this bottleneck by leveraging open-world safety specifications using recent work on embedding spaces-based logic (Kapoor et al., 2025a) and using large language models for generating high level specifications automatically (Li et al., 2025). Second, our approach also assumes access to an approximate dynamics model to evaluate the impact of actions on future trajectories. While a common assumption for provably safe robotics (Cohen et al., 2024), This can limit applicability of our approach. However, it is possible to mitigate this via learned dynamics models such as MoSim (Hao et al., 2025) or world models proposed in Zhou et al. (2025); Micheli et al. (2023) and we plan to explore this in future work.

REFERENCES

Guidance AI. Guidance: A language model control framework. https://github.com/guidance-ai/guidance, 2023. Accessed: April 27, 2025.

Jasmine Jerry Aloor, Jay Patrikar, Parv Kapoor, Jean Oh, and Sebastian Scherer. Follow the rules: Online signal temporal logic tree search for guided imitation learning in stochastic domains. In *2023 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 1320–1326, 2023. doi: 10.1109/ICRA48891.2023.10160953.

Mohammed Alshiekh, Roderick Bloem, Ruediger Ehlers, Bettina Könighofer, Scott Niekum, and Ufuk Topcu. Safe reinforcement learning via shielding, 2017. URL https://arxiv.org/abs/1708.08611.

Aaron D. Ames, Samuel Coogan, Magnus Egerstedt, Gennaro Notomista, Koushil Sreenath, and Paulo Tabuada. Control barrier functions: Theory and applications, 2019. URL https://arxiv.org/abs/1903.11199.

Luca Beurer-Kellner, Marc Fischer, and Martin Vechev. Prompting is programming: A query language for large language models. *Proc. ACM Program. Lang.*, 7(PLDI), June 2023. doi: 10.1145/3591300. URL https://doi.org/10.1145/3591300.

Max H. Cohen, Tamas G. Molnar, and Aaron D. Ames. Safety-critical control for autonomous systems: Control barrier functions via reduced-order models. *Annual Reviews in Control*, 57:100947, 2024. ISSN 1367-5788. doi: https://doi.org/10.1016/j.arcontrol.2024.100947. URL https://www.sciencedirect.com/science/article/pii/S1367578824000166.

Kiana Ehsani, Tanmay Gupta, Rose Hendrix, Jordi Salvador, Luca Weihs, Kuo-Hao Zeng, Kunal Pratap Singh, Yejin Kim, Winson Han, Alvaro Herrasti, et al. Spoc: Imitating shortest paths in simulation enables effective navigation and manipulation in the real world. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 16238–16250, 2024.

Angela Fan, Mike Lewis, and Yann Dauphin. Hierarchical neural story generation. *arXiv preprint arXiv:1805.04833*, 2018.

Marie Farrell, Matt Luckcuck, and Michael Fisher. *Robotics and Integrated Formal Methods: Necessity Meets Opportunity*, pp. 161–171. Springer International Publishing, 2018. ISBN 9783319989389. doi: 10.1007/978-3-319-98938-9_10. URL http://dx.doi.org/10.1007/978-3-319-98938-9_10.

Shangding Gu, Long Yang, Yali Du, Guang Chen, Florian Walter, Jun Wang, and Alois Knoll. A review of safe reinforcement learning: Methods, theory and applications, 2024. URL https://arxiv.org/abs/2205.10330.

Chenjie Hao, Weyl Lu, Yifan Xu, and Yubei Chen. Neural motion simulator: Pushing the limit of world models in reinforcement learning, 2025. URL https://arxiv.org/abs/2504.07095.

Chris Hokamp and Qun Liu. Lexically constrained decoding for sequence generation using grid beam search. In Regina Barzilay and Min-Yen Kan (eds.), *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1535–1546, Vancouver, Canada, July 2017. Association for Computational Linguistics. doi: 10.18653/v1/P17-1141. URL https://aclanthology.org/P17-1141/.

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. The curious case of neural text degeneration. *arXiv preprint arXiv:1904.09751*, 2019.

Jiaheng Hu, Rose Hendrix, Ali Farhadi, Aniruddha Kembhavi, Roberto Martín-Martín, Peter Stone, Kuo-Hao Zeng, and Kiana Ehsani. Flare: Achieving masterful and adaptive robot policies with large-scale reinforcement learning fine-tuning. In *2025 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 3617–3624. IEEE, 2025.

Yafei Hu, Quanting Xie, Vidhi Jain, Jonathan Francis, Jay Patrikar, Nikhil Varma Keetha, Seungchan Kim, Yaqi Xie, Tianyi Zhang, Shibo Zhao, et al. Toward general-purpose robots via foundation models: A survey and meta-analysis. *CoRR*, 2023.

Parv Kapoor, Sai Vemprala, and Ashish Kapoor. Logically constrained robotics transformers for enhanced perception-action planning. *arXiv preprint arXiv:2408.05336*, 2024.

Parv Kapoor, Abigail Hammer, Ashish Kapoor, Karen Leung, and Eunsuk Kang. Pretrained embeddings as a behavior specification mechanism, 2025a. URL https://arxiv.org/abs/2503.02012.

Parv Kapoor, Kazuki Mizuta, Eunsuk Kang, and Karen Leung. Stlcg++: A masking approach for differentiable signal temporal logic specification, 2025b. URL https://arxiv.org/abs/2501.04194.

Moo Jin Kim, Karl Pertsch, Siddharth Karamcheti, Ted Xiao, Ashwin Balakrishna, Suraj Nair, Rafael Rafailov, Ethan Foster, Grace Lam, Pannag Sanketi, Quan Vuong, Thomas Kollar, Benjamin Burchfiel, Russ Tedrake, Dorsa Sadigh, Sergey Levine, Percy Liang, and Chelsea Finn. Openvla: An open-source vision-language-action model, 2024. URL https://arxiv.org/abs/2406.09246.

Eric Kolve, Roozbeh Mottaghi, Winson Han, Eli VanderBilt, Luca Weihs, Alvaro Herrasti, Matt Deitke, Kiana Ehsani, Daniel Gordon, Yuke Zhu, Aniruddha Kembhavi, Abhinav Gupta, and Ali Farhadi. Ai2-thor: An interactive 3d environment for visual ai, 2022. URL https://arxiv.org/abs/1712.05474.

Manling Li, Shiyu Zhao, Qineng Wang, Kangrui Wang, Yu Zhou, Sanjana Srivastava, Cem Gokmen, Tony Lee, Li Erran Li, Ruohan Zhang, Weiyu Liu, Percy Liang, Li Fei-Fei, Jiayuan Mao, and Jiajun Wu. Embodied agent interface: Benchmarking llms for embodied decision making, 2025. URL https://arxiv.org/abs/2410.07166.

Alisa Liu, Maarten Sap, Ximing Lu, Swabha Swayamdipta, Chandra Bhagavatula, Noah A. Smith, and Yejin Choi. Dexperts: Decoding-time controlled text generation with experts and anti-experts, 2021. URL https://arxiv.org/abs/2105.03023.

Matt Luckcuck, Marie Farrell, Louise A. Dennis, Clare Dixon, and Michael Fisher. Formal specification and verification of autonomous robotic systems: A survey. *ACM Computing Surveys*, 52(5):1–41, September 2019. ISSN 1557-7341. doi: 10.1145/3342355. URL http://dx.doi.org/10.1145/3342355.

O. Maler and D. Nickovic. Monitoring Temporal Properties of Continuous Signals. (3253):152–166, 2004.

Claudio Menghi, Christos Tsigkanos, Patrizio Pelliccione, Carlo Ghezzi, and Thorsten Berger. Specification patterns for robotic missions. *CoRR*, abs/1901.02077, 2019. URL http://arxiv.org/abs/1901.02077.

Vincent Micheli, Eloi Alonso, and François Fleuret. Transformers are sample-efficient world models. In *The Eleventh International Conference on Learning Representations*, 2023. URL https://openreview.net/forum?id=vhFu1Acb0xb.

Kanghee Park, Jiayu Wang, Taylor Berg-Kirkpatrick, Nadia Polikarpova, and Loris D' Antoni. Grammar-aligned decoding. In A. Globerson, L. Mackey, D. Belgrave, A. Fan, U. Paquet, J. Tomczak, and C. Zhang (eds.), *Advances in Neural Information Processing Systems*, volume 37, pp. 24547–24568. Curran Associates, Inc., 2024. URL https://proceedings.neurips.cc/paper_files/paper/2024/file/2bdc2267c3d7d01523e2e17ac0a754f3-Paper-Conference.pdf.

Maxime Peyrard, Martin Josifoski, and Robert West. The era of semantic decoding, 2024. URL https://arxiv.org/abs/2403.14562.

Amir Pnueli. The temporal logic of programs. In *18th Annual Symposium on Foundations of Computer Science (sfcs 1977)*, pp. 46–57, 1977. doi: 10.1109/SFCS.1977.32.

Pierre Sermanet, Anirudha Majumdar, Alex Irpan, Dmitry Kalashnikov, and Vikas Sindhwani. Generating robot constitutions & benchmarks for semantic safety. *arXiv preprint arXiv:2503.08663*, 2025.

Lui Sha. Using simplicity to control complexity. *IEEE Software*, 18(4):20–28, 2001. doi: 10.1109/MS.2001.936213.

Sean Welleck, Amanda Bertsch, Matthew Finlayson, Hailey Schoelkopf, Alex Xie, Graham Neubig, Ilia Kulikov, and Zaid Harchaoui. From decoding to meta-generation: Inference-time algorithms for large language models, 2024. URL https://arxiv.org/abs/2406.16838.

Brandon T Willard and Rémi Louf. Efficient guided generation for large language models. *arXiv preprint arXiv:2307.09702*, 2023.

Yi Wu, Zikang Xiong, Yiran Hu, Shreyash S. Iyengar, Nan Jiang, Aniket Bera, Lin Tan, and Suresh Jagannathan. Selp: Generating safe and efficient task plans for robot agents with large language models, 2025. URL https://arxiv.org/abs/2409.19471.

Kuo-Hao Zeng, Zichen Zhang, Kiana Ehsani, Rose Hendrix, Jordi Salvador, Alvaro Herrasti, Ross Girshick, Aniruddha Kembhavi, and Luca Weihs. Poliformer: Scaling on-policy rl with transformers results in masterful navigators. In *Conference on Robot Learning*, pp. 408–432. PMLR, 2025.

Borong Zhang, Yuhao Zhang, Jiaming Ji, Yingshan Lei, Josef Dai, Yuanpei Chen, and Yaodong Yang. Safevla: Towards safety alignment of vision-language-action model via safe reinforcement learning, 2025. URL https://arxiv.org/abs/2503.03480.

Gaoyue Zhou, Hengkai Pan, Yann LeCun, and Lerrel Pinto. Dino-wm: World models on pre-trained visual features enable zero-shot planning, 2025. URL https://arxiv.org/abs/2411.04983.

A Appendix

A.1 Quantitative Semantics of STL

Given a signal s_t representing a signal starting at time t, the quantitative semantics of satisfaction of $s_t \models \phi$ are defined inductively as follows:

$$\begin{aligned}
\rho(s_t, \mu_c) &= \mu(x_t) - c \\
\rho(s_t, \neg\varphi) &= -\rho(s_t, \varphi) \\
\rho(s_t, \varphi_1 \wedge \varphi_2) &= \min(\rho(s_t, \varphi_1), \rho(s_t, \varphi_2)) \\
\rho(s_t, \mathrm{F}_{[a,b]}(\varphi)) &= \max_{t' \in [t+a, t+b]} \rho(s'_t, \varphi) \\
\rho(s_t, \mathrm{G}_{[a,b]}(\varphi)) &= \min_{t' \in [t+a, t+b]} \rho(s'_t, \varphi)
\end{aligned}$$

A.2 Visualizations

To complement our quantitative results, we provide numerous trajectory plots from evaluations across a diverse set of procedurally generated indoor environments. Figure 4 illustrates representative top-down visualizations of trajectories induced by SafeDec .Each plot shows the agent's starting point and the resulting path under constrained decoding, with red circles marking target objects, green boxes denoting forbidden regions, and orange paths depicting the safe trajectories generated by our method. Together with our quantitative analysis, these qualitative results illustrate the performance of SafeDec across environments and tasks.

Figure 4: Top-down views across indoor environments with `SafeDec` induced trajectories Red circles mark target objects, green boxes are avoid regions, and orange paths show safe trajectories under constrained decoding.