

Summarization: Learning a Generalizable Trajectory Sampling Distribution for Model Predictive Control

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Summarization[†]Generated based on Paper from Power and Berenson (2024)

Topic: MPC, Generalizable Trajectory Sampling, Collision-Free Navigation, Prior & Posterior Flow

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Abstract

This document summarizes the core contributions and methodology of the paper "Learning a Generalizable Trajectory Sampling Distribution for Model Predictive Control, Power and Berenson [2024]", focusing on its' main ideas and the core blocks.

1 Core Questions and Answers

(1) What is the problem?

- **Collision-Free Navigation** in Cluttered Environments
- Learning **Generalizable** Trajectories in **Out-of-Distribution (OOD)** Environments

(2) **Why need to solve this problem?** Robotics applications like autonomous driving or manipulation require rapid and reliable trajectory generation. In complex environments, random sampling of control sequences is unlikely to generate low-cost paths, causing robots to get stuck in local optimal. Bridging the gap between sim-to-real models and diverse real-world (eg. OOD environments) scenarios is critical for robust autonomous operation.

(3) How is it different from previous methods?

- Unlike previous work that utilizes simple Gaussian priors or uninformed sampling distributions, this approach employs a **Conditional Normalizing Flow (CNF)** to learn a goal-directed and environment-aware control sequence **Posterior**.
- It is also a sampling-based MPC framework to learn this **Posterior** from a dataset.
- Furthermore, it introduces a novel **Environment Projection** method to adapt to OOD scenarios by converting them to in-distribution representations during online navigation.

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[†]**Disclaimer:** This summarization is for research and study purposes. It represents a personal interpretation and may contain inaccuracies. Feedback or corrections via email are highly appreciated.

(4) Why is it better than previous methods? (Advantages)

- **General Architecture:** The learned distribution can be integrated into different MPC frameworks (FlowMPPI, FlowiCEM).
- **Adaptability:** The projection mechanism allow effective generalizable trajectory sampling to OOD real-world environments.
- **Expressiveness:** It captures multimodal (conditional) trajectories which standard Gaussian-based samplers cannot.

(5) What is the approach itself?

- FlowMPC (FlowMPPI & FlowiCEM)
 - Normalizing Flow:
 - * Prior Flow
 - * Posterior Flow for Sampling
 - MPC (MPPI & iCEM)
 - Projection: Generalizing to Out-of-Distribution (OOD) Environments

(6) What are the applications of it? The approach can be demonstrated on several robotic platforms for collision-free navigation and manipulation tasks:

- 2-D double-integrator
- 12-DoF quadrotor
- 7-DoF kinematic manipulator
- Typically, most robotic manipulators and navigators (eg. for vehicles)

2 The Structure

Summarized Block-Diagram

- Mainly Inference
- Use FlowMPPI as Example

The summarized block-diagram see fig. 1¹.

Original in Paper The original block-diagram see fig. 2.

References

T. Power and D. Berenson. Learning a generalizable trajectory sampling distribution for model predictive control. *IEEE Transactions on Robotics*, 40:2111–2127, 2024.

¹This block-diagram is created through code-based drafting (Graphviz) for efficiency. While visual aesthetics may be limited, the overall structure remains clear.

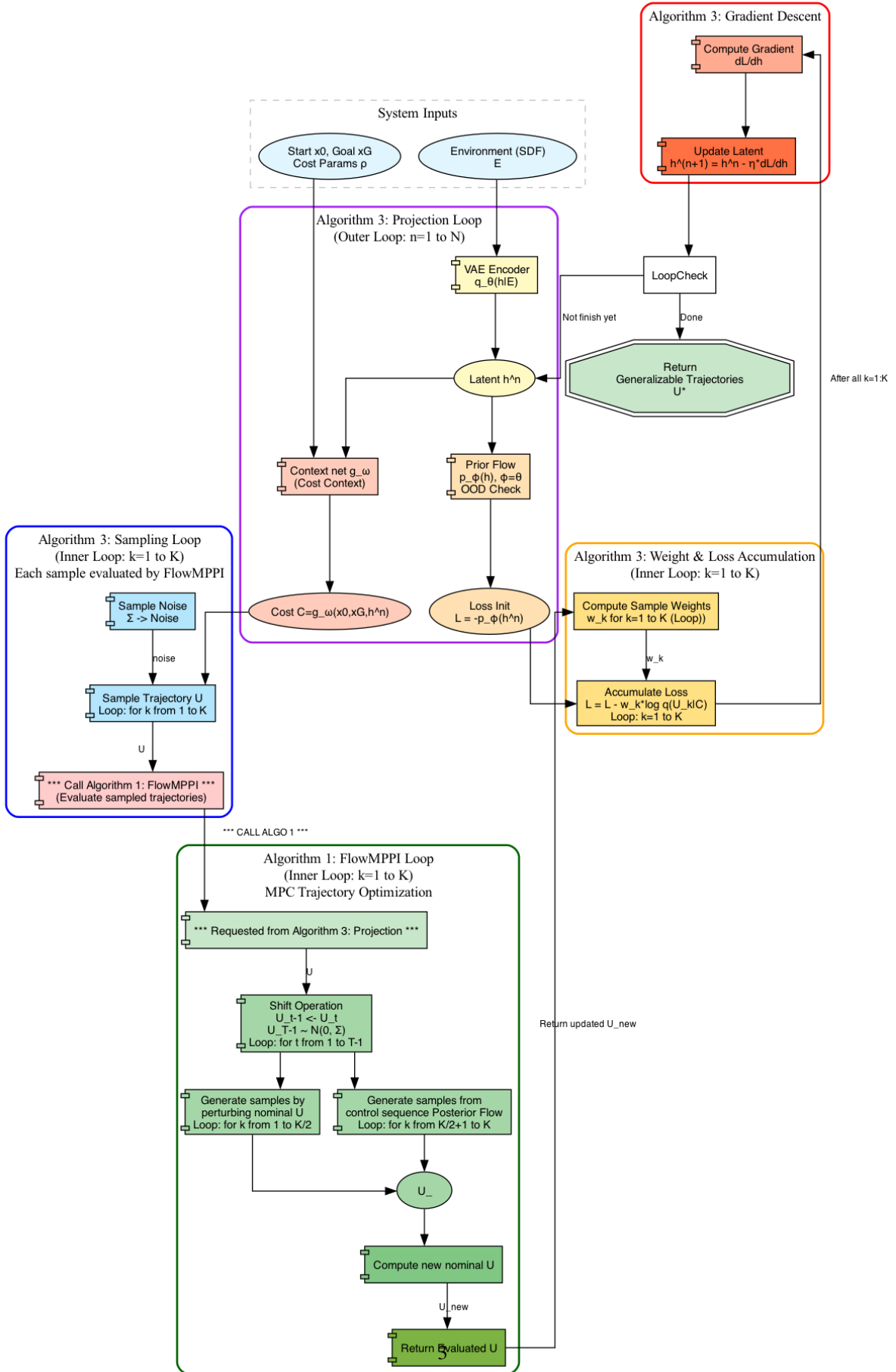


Figure 1: FlowMPC Block-Diagram (Mainly Inference): Use FlowMPPI as Example

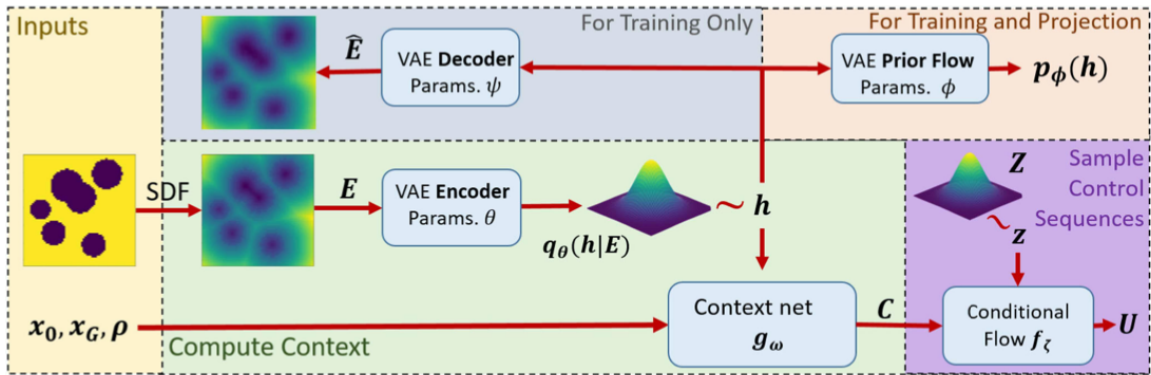


Figure 2: Original Block-Diagram in Paper