EDMP: Ensemble-of-costs-guided Diffusion for Motion Planning

Mudumba Karthikeya Prachodhan || Gannoju Akshar Teja || Sambangi Chaitanya

International Institute of Information Technology , Naya Raipur

INTRODUCTION

Motion planning is the process of generating a trajectory from a start to a goal configuration while avoiding obstacles in the robot's environment. In robotic manipulation, ensuring collision-free and kinematically feasible motion is a critical requirement. Traditional planners optimize a scene-specific cost function but often fail to capture the diversity of complex environments, while deep learning approaches require extensive training data and struggle to generalize.

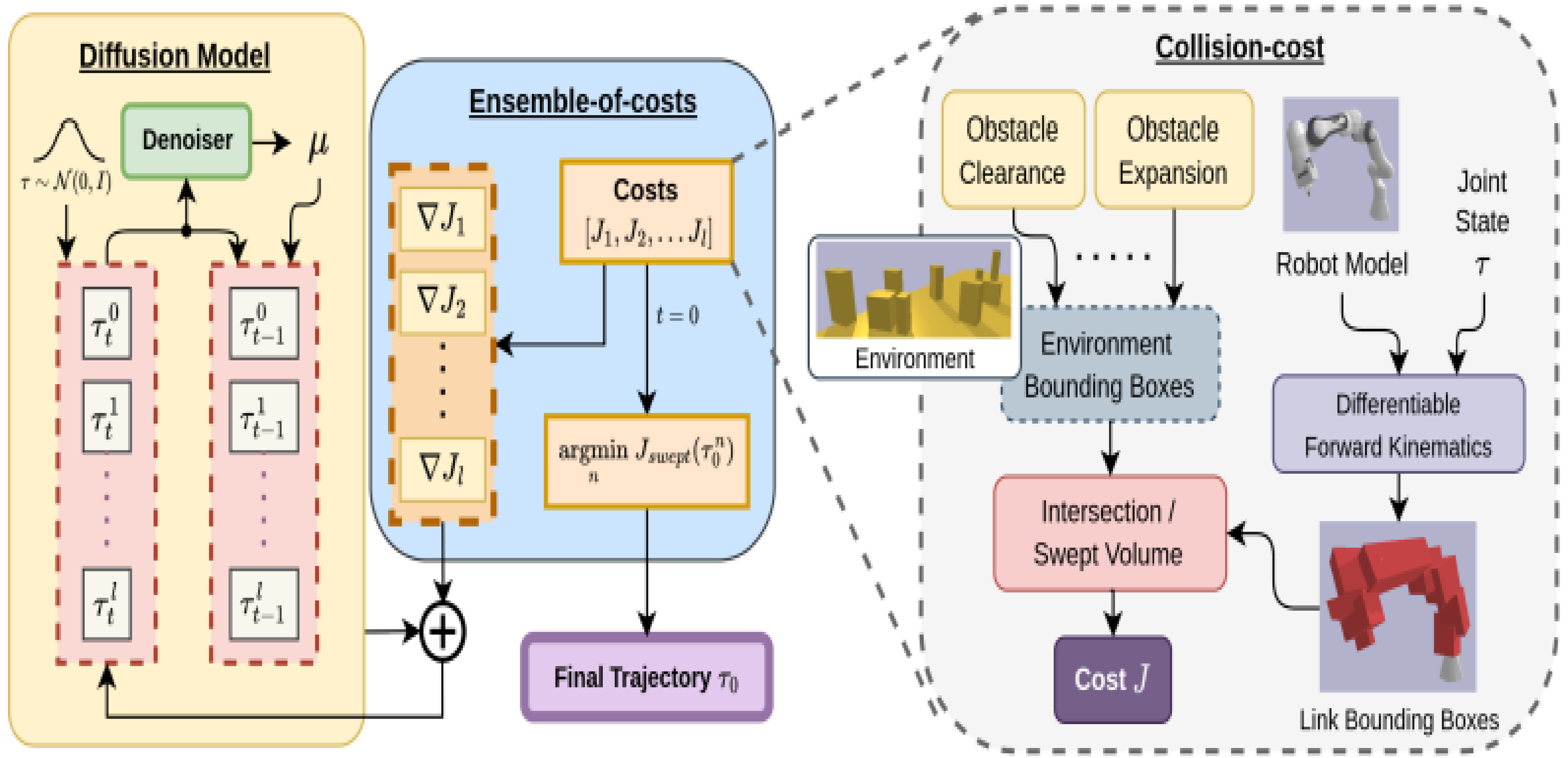
EDMP (Ensemble-of-costs-guided Diffusion for Motion Planning) combines classical and deep-learning-based planning techniques by learning a prior over valid trajectories and guiding them using multiple cost functions at inference time.

- A diffusion model learns smooth, feasible trajectories and is conditioned on the start and goal positions to generate valid paths.
- During inference, multiple cost functions (ensemble-of-costs) are used to guide the trajectory generation, improving generalization to complex and unseen scenes.
- This approach enables **multimodal trajectory generation**, offering multiple valid ways to complete the same task.
- EDMP effectively **bridges the gap between adaptability and efficiency**, achieving high success rates without requiring scene-specific retraining.

OBJECTIVES

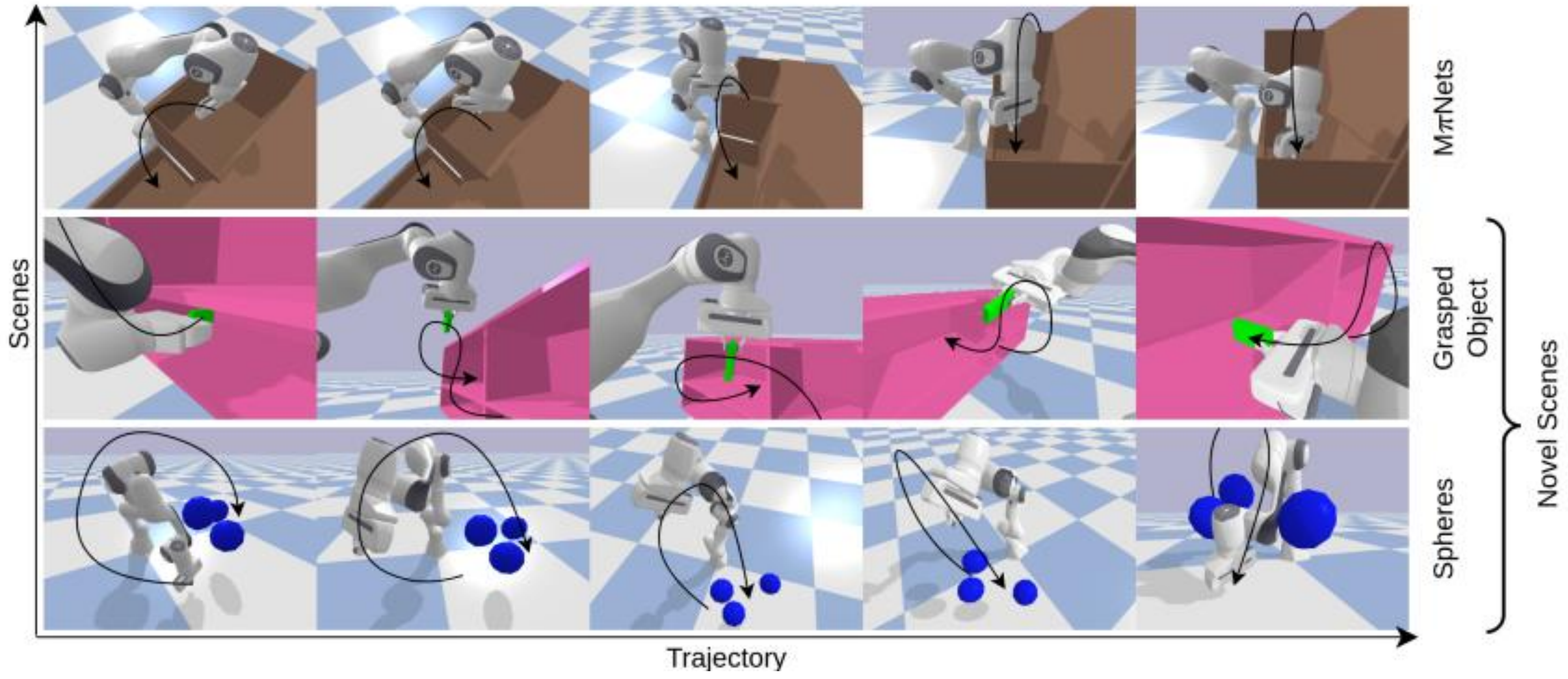
- **To plan robot trajectories using diffusion models**
  Develop a motion planner using diffusion models to learn smooth, kinematically valid trajectories between start and goal states.
- **To incorporate multiple cost functions (ensemble-of-costs) at inference**
  Use an ensemble of cost functions like collision and swept-volume to guide trajectory generation during inference for better adaptability.
- **To generalize motion planning to complex and unseen scenes**
  Enable robust performance in out-of-distribution environments without retraining, improving planner reliability across diverse setups.
- **To generate diverse, multimodal paths from start to goal**
  Produce multiple valid trajectory options, allowing for flexible execution based on downstream constraints like smoothness or safety.

METHODOLOGY



RESULTS

EDMP successfully produces valid and smooth trajectories across diverse, unseen scenes without retraining, even when dealing with obstacles, object grasping, or dynamic scene elements like spheres. This shows its strong generalization capability and robustness in complex motion planning ta



CONCLUSIONS

EDMP combines diffusion models with classical cost functions to generate smooth, collision-free robot trajectories. It works well in complex and unseen environments without needing retraining.

Though it relies on hand-crafted costs and can be slower with many guides, EDMP offers flexible, multimodal planning and strong generalization performance.

Advantages:

- **Combines classical planning generalizability with deep learning efficiency**
  Leverages the strengths of both paradigms to create a planner that is both flexible and effective across various tasks.
- **Works well in novel and cluttered scenes**
  Adapts to unseen environments and obstacle-dense setups without requiring retraining or manual tuning.
- **Generates multimodal trajectories enabling flexible execution**
  Offers multiple valid paths for the same task, allowing selection based on criteria like safety, length, or smoothness.
- **Performs competitively with state-of-the-art planners**
  Achieves high success rates compared to both classical and deep-learning-based methods across benchmark datasets.

Disadvantages:

- **Relies on hand-crafted cost functions**
  Performance depends on the quality and diversity of manually designed cost functions used during guidance.
- **Real-time performance may vary with the number of guides**
  Increased computation with more cost functions may impact planning speed in time-critical applications.

REFERENCES

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