

# **End-to-End Visual Autonomous Navigation with Twin Delayed DDPG in the CARLA and ROS 2 Ecosystem**

**Course:** Aprendizado por Reforço

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# The Autonomous Vehicle Challenge

## Why Autonomous Vehicles?

- Safety: 94% of accidents caused by human error
- Efficiency: Reduced traffic congestion
- Accessibility: Mobility for all

## Traditional Approaches:

- Rule-based systems (potential fields, geometric planners)
- Hand-engineered features
- Limited adaptability in complex scenarios

⇒ Need for learning-based approaches!

# Deep Reinforcement Learning for AV

**DRL Advantages:** (SUTTON; BARTO, 2018;  
PÉREZ-GIL et al., 2022)

- Learn optimal policies through interaction;
- No need for labeled datasets;
- Adaptable to dynamic environments;
- End-to-end learning from sensors to control.

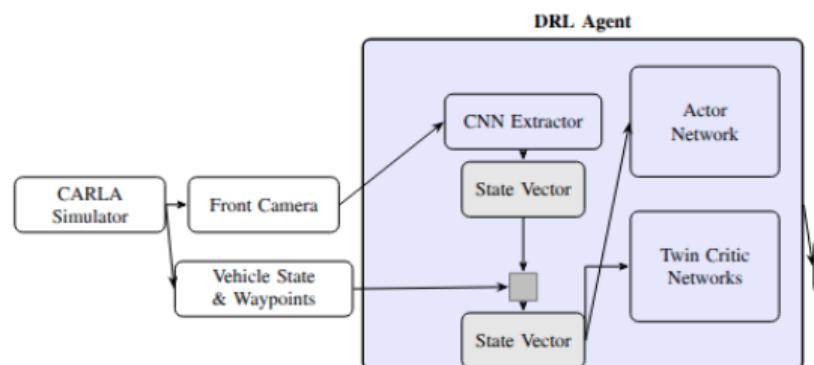


Figure: RL agent-environment interaction loop

# The DDPG Problem: Value Overestimation

## Deep Deterministic Policy Gradient (DDPG):

- Natural fit for continuous control (steering, throttle)
- Actor-critic architecture
- BUT: Suffers from Q-value overestimation bias!

### The Problem

Function approximation errors  $\Rightarrow$  Inflated Q-estimates

$\Rightarrow$  Suboptimal/unstable policies  $\Rightarrow$  Training collapse

**Solution: Twin Delayed DDPG (TD3) (FUJIMOTO; HOOF; MEGER, 2018)**

# Research Objective

## Main Goal

Develop and evaluate an **end-to-end visual autonomous navigation system** using TD3 in a realistic simulation environment

## Key Components:

- ① Camera-only perception (cost-effective approach)
- ② TD3 algorithm to mitigate overestimation bias
- ③ CARLA 0.9.16 simulator + ROS 2 Humble integration
- ④ Modular, reproducible framework
- ⑤ Quantitative comparison with classical baseline

# Twin Delayed DDPG (TD3) - Key Innovations

Three mechanisms to address DDPG's overestimation:

## 1. Clipped Double Q-Learning

Use **minimum** of two Q-networks for target:

$$y = r + \gamma(1 - d) \min_{i=1,2} Q_{\theta'_i}(s', \tilde{a})$$

Prevents optimistic bias from bootstrapping

## 2. Delayed Policy Updates

Update actor & targets less frequently than critics (e.g., every 2 steps)

⇒ More stable value estimates before policy update

## 3. Target Policy Smoothing

Add clipped noise to target action:

# MDP Formulation for Autonomous Driving

**Markov Decision Process:**  $(\mathcal{S}, \mathcal{A}, P, R, \gamma)$

**State Space  $\mathcal{S}$ :**

- **Visual:** 4 stacked front-camera frames ( $84 \times 84$  grayscale)  $\rightarrow$  CNN features
- **Kinematic:** velocity  $v_t$ , lateral deviation  $d_t$ , heading error  $\phi_t$
- **Goal:** next waypoints coordinates (relative to vehicle frame)

**Action Space  $\mathcal{A} \in \mathbb{R}^2$ :**

$$a_t = [\text{steering, throttle/brake}] \in [-1, 1]^2$$

**Discount Factor:**  $\gamma = 0.99$  (long-term planning)

# Reward Function Engineering

**Multi-component reward:**  $R(s_t, a_t) = \sum w_i \cdot r_i(s_t, a_t)$

Component	Purpose	Range
Efficiency	Maintain target speed	-10 to +10
Lane Keeping	Minimize lateral/heading error	-20 to +5
Comfort	Penalize jerk (smooth control)	-5 to 0
Safety	Collision penalty	-500 (terminal)
Progress	Reward waypoint completion	0 to +10

## Design Principles:

- Safety has highest weight (terminal penalty)
- Encourage progress without reckless speeding
- Promote human-like comfort

# Modular ROS 2 + CARLA Architecture

**Key Innovation:** Native ROS 2 Humble + geometry\_msgs/Twist (PÉREZ-GIL et al., 2021; ??)

- Standard message types (no custom CARLA packages!)
- Reduces Docker image by 2.3 GB
- Seamless sim-to-real transition

# CNN Feature Extractor Architecture

## Visual Processing Pipeline:

- ① Input: 4 stacked grayscale frames ( $84 \times 84$ )  $\rightarrow$  temporal dynamics
- ② NatureCNN architecture (from DQN paper):
  - Conv1: 32 filters,  $8 \times 8$  kernel, stride 4
  - Conv2: 64 filters,  $4 \times 4$  kernel, stride 2
  - Conv3: 64 filters,  $3 \times 3$  kernel, stride 1
  - Fully connected: 512 units
- ③ Output: 512-dim feature vector
- ④ Concatenate with kinematic features (53-dim)

## Why this design?

- Proven in Atari DQN (MNIH et al., 2015)
- Captures spatial hierarchies and motion patterns
- Used by (ELALLID; ALAOUI; BENAMAR, 2023) for intersection navigation

# TD3 Network Architecture

**Actor Network  $\pi_\phi$ :**

- Shared CNN (512)
- MLP:  $512 \rightarrow 256 \rightarrow 128$
- Output: 2 actions (tanh)
- LR:  $1e-5$  (CNN),  $1e-3$  (MLP)

**Twin Critics  $Q_{\theta_1}, Q_{\theta_2}$ :**

- Shared CNN (512)
- State-action concatenation
- MLP:  $515 \rightarrow 256 \rightarrow 128 \rightarrow 1$
- LR:  $1e-4$  (CNN),  $1e-4$  (MLP)

**Hyperparameters:**

Parameter	Value
Batch size	256
Buffer size	97,000
$\gamma$ (discount)	0.99
$\tau$ (soft update)	0.005
Policy delay	2
Policy noise	0.2
Noise clip	0.5

All values from original TD3 paper!

# CARLA Environment Configuration

## Simulation Setup:

- CARLA 0.9.16, Town01
- Traffic: 20 NPC vehicles (scenario 0)
- Route: 222m pre-defined waypoint path with turn



Figure: CARLA Town01 testing environment

**Episode Termination:** Collision, off-road, waypoint completion, or 1000 steps

# Baseline Controller Performance

Classical PID + Pure Pursuit (6 episodes, 20 NPCs):

Metric	Mean	Std Dev
<b>Safety</b>		
Success Rate (%)	50.0	-
Collisions/km	2.787	2.850
Min TTC (s)	0.25	-
<b>Efficiency</b>		
Avg Speed (km/h)	24.62	4.92
Completion Time (s)	16.5	4.9
<b>Comfort</b>		
Avg Jerk ( $m/s^3$ )	17.779	1.111
Avg Lateral Accel ( $m/s^2$ )	0.105	0.105

**Key Findings:** High collision rate, abrupt acceleration (high jerk)

# Baseline Trajectory Visualization

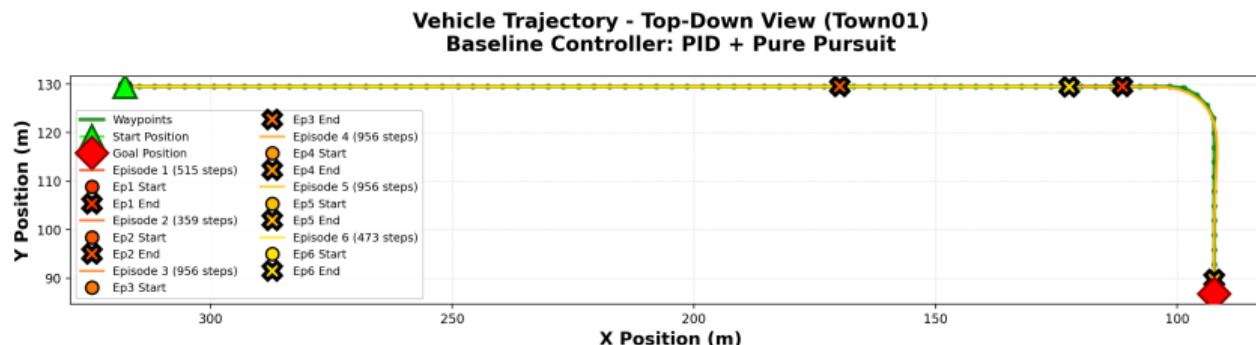


Figure: PID + Pure Pursuit trajectory: reactive behavior, collision in dense traffic

## Observations:

- Follows waypoints accurately in sparse traffic
- Reactive (not predictive) ⇒ collisions in congested areas
- Lacks adaptation to dynamic NPC behavior

# TD3 Training Progress (100K Timesteps)

## Training Phases:

Metric	Exploration	Learning	Late Learn.
Episodes	10	501	100 (final)
Avg Length (steps)	60.4	$180.0 \pm 317.5$	$656.0 \pm 468.8$
Collision Rate (%)	0.0	0.4	1.0
Lane Invasion (%)	0.0	1.0	1.0
Mean Reward	$74.10 \pm 39.62$	$-3.58 \pm 197.05$	$-322 \pm 230$

## Key Insights:

- **Successful system validation** - environment wrapper, reward function, TD3 implementation all working
- Episode lengths increased 10x ( $60 \rightarrow 656$  steps)
- High variance due to stochastic NPC traffic
- **Partial convergence** - requires recommended 1M timesteps

# Computational Constraints & Achievements

## Challenge

Limited access to HPC infrastructure prevented full training (1M timesteps)

Completed only 100K timesteps (10% of recommended duration)

## Despite constraints, we achieved:

- ✓ **Complete system validation** - TD3 + CARLA + ROS 2 integration
- ✓ **Baseline benchmarks established** - quantitative comparison metrics
- ✓ **ROS 2 innovation** - geometry\_msgs/Twist integration (2.3 GB smaller Docker image)
- ✓ **Reproducible framework** - open-source code, config management
- ✓ **Initial policy learning** - episode lengths improved from 60 to 656 steps

**Next Steps:** Complete 1M training on available infrastructure

# ROS 2 CARLA Bridge Innovation

## Traditional Approach:

- Requires building carla\_msgs package
- Custom message types (CarlaEgoVehicleControl)
- Large Docker images, long build times
- Simulation-specific code

## Our Approach:

- ✓ Standard geometry\_msgs/Twist messages
- ✓ CARLA Twist-to-Control node handles conversion
- ✓ No custom package compilation
- ✓ Reduced Docker image: 2.3 GB smaller
- ✓ Build time: 15 minutes faster
- ✓ Platform-agnostic (works with real robots!)

18/28 **Contribution:** Modular architecture enabling seamless sim-to-real transfer

# Main Contributions

## 1. Reproducible TD3 Framework for Autonomous Driving

- Complete end-to-end visual navigation system
- Open-source code with comprehensive documentation
- Configuration management for hyperparameters

## 2. Innovative ROS 2 + CARLA Integration

- Standard geometry\_msgs/Twist (no custom packages)
- 2.3 GB smaller Docker images, 15 min faster builds
- Platform-agnostic design for sim-to-real transfer

## 3. Quantitative Baseline Benchmarks

- PID + Pure Pursuit: 50% success, 2.787 collisions/km
- Establishes comparison metrics for DRL agents
- Highlights limitations of reactive control

# Technical Achievements & Validation

## Validated System Components:

- ✓ TD3 algorithm implementation (clipped double-Q, delayed updates, target smoothing)
- ✓ CNN feature extractor (NatureCNN with 512-dim output)
- ✓ Multi-component reward function (safety/efficiency/comfort)
- ✓ CARLA environment wrapper (Gymnasium v0.26+ API)
- ✓ ROS 2 Humble native integration

## Initial TD3 Training Results (100K timesteps):

- Episode lengths: 60 → 656 steps (10x improvement)
- Collision rate: 0.4% during learning phase
- Demonstrates policy convergence beginning
- High variance due to stochastic traffic dynamics

# Challenges Encountered

## 1. Environment Wrapper Development

- CARLA Python API synchronous mode management
- Sensor callback handling and episode termination logic
- Gymnasium v0.26+ API migration (terminated/truncated separation)

## 2. ROS 2 + CARLA Compatibility

- Ubuntu 20.04 (Python 3.8) vs 22.04 (Python 3.10)
- CARLA 0.9.16 + PyTorch + ROS 2 Humble dependencies
- Solved with geometry\_msgs/Twist approach

## 3. DRL Algorithm Debugging

- Distinguishing bugs from expected stochastic behavior
- Reward function engineering (balancing safety/progress/comfort)
- Validation against reference implementations (Stable-Baselines3)

## 4. Computational Constraints

# Future Work Directions

## Immediate Next Steps:

- Complete 1M timestep training with HPC access
- Evaluate TD3 vs baseline across full metrics
- Analyze learned policy behavior and failure modes

## Multi-Scenario Generalization:

- Test on Town02-07 (transfer learning)
- Weather variations (rain, fog, night)
- Traffic densities (50-100 NPCs)

## Advanced Algorithms:

- Soft Actor-Critic (SAC) with entropy tuning
- Safe RL methods (CPO, RECPO)
- Comparative study: TD3 vs SAC vs PPO

# Future Work (continued)

## Sim-to-Real Transfer:

- Domain randomization in CARLA
- Domain adaptation techniques
- Fine-tuning with real-world data
- Validation on physical vehicle platforms

## Multi-Sensor Fusion:

- Integrate LiDAR point clouds
- Semantic segmentation masks
- Enhanced perception robustness

## Hierarchical Control:

- High-level planning (route selection, lane changes)
- Low-level control (steering, throttle)

# Key Takeaways

## Research Question

Can TD3 address DDPG's overestimation bias for end-to-end visual autonomous navigation?

## Answer:

- ① ✓ System Validated - Complete TD3 + CARLA + ROS 2 framework functional
- ② ✓ Innovation Demonstrated - geometry\_msgs/Twist integration reduces complexity
- ③ ... Training Incomplete - 100K/1M timesteps (10%) due to HPC constraints
- ④ ✓ Foundation Established - Baseline benchmarks + modular architecture for future research

## Impact:

- Reproducible framework for DRL-based AV research
- Standard ROS 2 integration pattern for CARLA

# Thank You!

Questions?

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**Code Repository:** [github.com/ARRETdaniel/av\\_td3\\_system](https://github.com/ARRETdaniel/av_td3_system)

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