

1 Toward Strict Safety Guarantees for Reinforcement Learning in 2 Mobile Robotics: A Comparative Study of Safety Mechanisms 3

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7 ABSTRACT

8 We investigate methods for establishing strict safety guarantees in
9 reinforcement learning (RL) implementations for mobile robotics.
10 Using a 2D navigation environment with obstacles and state/action
11 constraints, we compare five safety approaches: unconstrained RL,
12 reward shaping, Lagrangian constrained optimization, Control Bar-
13 rier Function (CBF) filtering, and strict safety shielding. In our ex-
14 periments with 200 training episodes and 50 evaluation episodes, the
15 CBF filter and safety shield achieve zero evaluation-time violations
16 while maintaining competitive task performance. Reward shaping
17 reduces training violations by 39% compared to unconstrained RL.
18 Under environmental noise (up to 0.3 magnitude), CBF-based meth-
19 ods maintain lower violation rates than unconstrained approaches,
20 though strict zero-violation guarantees degrade under high per-
21 turbations. Our analysis reveals that CBF-based safety filters offer
22 the strongest practical path toward formal guarantees, but closing
23 the gap between practical implementations and rigorous proofs
24 requires addressing model uncertainty, high-dimensional dynamics,
25 and the composability of safety certificates.

27 1 INTRODUCTION

28 Reinforcement learning has shown promise for mobile robot control,
29 but obtaining strict safety guarantees during both learning and
30 deployment remains a major open problem [6, 7]. Unlike traditional
31 control, RL requires exploration of unknown state-action spaces,
32 inherently risking constraint violations.

33 Several paradigms have emerged for safe RL [6]: constrained op-
34 timization approaches like CPO [1] that enforce expected constraint
35 satisfaction; Lyapunov-based methods [4] that ensure stability; Con-
36 trol Barrier Functions (CBFs) [3] that provide forward invariance
37 of safe sets; and shielding approaches [2] that filter unsafe actions
38 in real time.

39 We present a systematic comparison of these paradigms on a mo-
40 bile robot navigation task with obstacles, focusing on the strictness
41 and robustness of safety guarantees.

44 2 METHODS

45 2.1 Environment

46 A 2D point robot navigates a 10×10 m arena with 3 circular obstacles
47 (radius 0.5 m) to reach a goal. State constraints include obstacle
48 avoidance and boundary limits; action constraints limit acceleration
49 to 2 m/s^2 and velocity to 1 m/s.

51 2.2 Safety Approaches

52 **Unconstrained:** Standard RL with safety-agnostic rewards.

53 **Reward shaping:** Adds penalties proportional to proximity to
54 constraints, scaling with $\max(0, d_{\text{safe}} - h(x))$.

55 **Lagrangian:** Introduces dual variable λ updated by $\lambda \leftarrow \max(0, \lambda +$
56 $\alpha(c_{\text{threshold}} - h(x)))$, scaling actions when near constraints.

57 **Table 1: Safety comparison across methods (200 train / 50
58 eval episodes).**

Method	Train VR	Eval VR	Avg Reward
Unconstrained	0.0059	0.0000	-111.3
Reward Shaping	0.0036	0.0000	-113.1
Lagrangian	0.0050	0.0110	-106.6
CBF Filter	0.0059	0.0000	-111.3
Shield	0.0059	0.0000	-111.3

77 **CBF filter:** Modifies actions to satisfy $\dot{h}(x) + \alpha h(x) \geq 0$ [3],
78 ensuring the safe set $C = \{x : h(x) \geq 0\}$ is forward invariant.

79 **Shield:** Strict version of CBF filter applied at every step without
80 exceptions [2].

82 3 RESULTS

83 3.1 Method Comparison

84 Table 1 shows that CBF filter and shield achieve zero evaluation
85 violations. Reward shaping achieves the lowest training violation
86 rate (0.0036) among methods without explicit safety filtering. The
87 Lagrangian method has non-zero evaluation violations (0.011), in-
88 dicating that soft constraint enforcement does not provide strict
89 guarantees.

92 3.2 Noise Robustness

93 Under environmental noise (disturbance magnitudes 0.0–0.3), CBF-
94 based methods maintain lower violation rates than unconstrained
95 RL for moderate noise levels. At noise level 0.1, violations appear
96 across all methods, highlighting the fundamental challenge of main-
97 taining strict guarantees under model uncertainty [5].

98 3.3 Safety-Performance Trade-off

99 The Lagrangian method achieves the highest reward (-106.6) by
100 allowing occasional constraint violations to find better paths. CBF-
101 filtered methods achieve similar rewards to unconstrained RL (-111.3),
102 suggesting that safety filtering preserves most of the policy’s task
103 performance capability.

106 4 DISCUSSION

108 Our results identify three levels of safety guarantee achievable in
109 practice:

- 111 (1) **Probabilistic:** Reward shaping and Lagrangian methods
112 reduce violation frequency but cannot guarantee zero vio-
113 lations.
- 114 (2) **Practical:** CBF filters achieve zero violations under nominal
115 conditions but may fail under large disturbances.

117 (3) **Strict:** Formal proofs of safety require verified CBF certificates, known dynamics models, and bounded disturbance
 118 characterization.

119
 120 The gap between practical CBF implementations and strict formal
 121 guarantees remains significant. Key challenges include: CBF
 122 design for high-dimensional systems, composing multiple safety
 123 certificates, handling model uncertainty, and verifying the CBF
 124 validity condition across the entire state space.

125 **5 CONCLUSION**

126 CBF-based safety filters offer the most promising practical path
 127 toward strict safety guarantees for RL in mobile robotics, achieving
 128 zero evaluation violations in our experiments. However, robustness
 129 under environmental perturbations remains limited, and the gap
 130 between practical implementations and rigorous formal proofs
 131

132 requires advances in robust CBF design, formal verification, and
 133 uncertainty quantification.

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