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Multi-Agent Reinforcement Learning for Adaptive Aero-Control Optimization in Ground-Effect Vehicles

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Abstract: The aerodynamics of modern ground-effect vehicles used in competitive vehicle dynamics applications are highly dynamic and nonlinear, requiring fast, sub-second adaptive aerodynamic control responses. The static control system and single-agent reinforcement learning is not enough to coordinate ride height, wing angle and aerodynamic balance simultaneously at high speed in real time for this vehicle over the entire operational speed range (80-340 km/h). This paper introduces various methods for optimizing aero-control for an autonomously navigating UAV in complex environments, such as suppressing instability and achieving maximum speed in the presence of broad range of disturbances, while maintaining required stability. The paper proposes a novel Multi-Agent Reinforcement Learning (MARL) framework in which three agents (actuation of ride height, aero-control optimization, and aerodynamic balance) will cooperate in sharing a reward signal balancing stability, speed, and instability suppression. The proposed architecture demonstrates that its stability accuracy reaches 97% while its control response time is less than 30ms, outperforms static, single-agent and LSTM-based adaptive architectures on all objective metrics and minimizes energy cost among all the architectures compared in the simulations.

Keywords: Multi-Agent Reinforcement Learning; Ground-Effect Vehicles, Actor-Critic; DDPG; Cooperative Reward; Motorsport AI.

1. Introduction

In motorsports, one of the most performance important and stability-sensitive areas, which is considered as the "ground effect aerodynamics" domain, is of great importance. In the ground effect regime, a low pressure area is created between the underfloor diffuser geometry and the road that creates significant downforce which increases aerodynamic drag by only a little. This downforce is a very non-linear function of ride height, meaning that as the vehicle approaches the road surface, the downforce goes up very quickly and thus a positive feedback loop has occurred and across the history of Formula 1, can cause catastrophic aeroelastic instabilities which have been termed “porpoising” and the “stall” in modern days of the sport [1]. To handle this aerodynamically sensitive task, the control actuators must, among others, be controlled in real time, distributed over multiple interconnected actuators such as: Active Ride-Height, Front & Rear Wing Angle, and Geometry Control of the floor. Ride height aero-loading and underfloor airflow along with the others are not independent control variables; changing the front wing angle modifies the upstream (upairway) pressure field that influences underfloor flow, resulting in multi-scale and multi-time coupled dynamics. Classical control.

The basic linear time-invariant models or gain-scheduled PID controllers are therefore not adequate for the coupled nonlinear dynamics in practice, especially in the transient periods of operating the vehicle, such as in corner entry braking zones, in kerb impacts, and during crosswind disturbances at high speeds (300 kmph and higher). When considering the application of adaptive control systems, the problem of learning the control policy directly from experience in the vehicle dynamics environment, without explicit analytical models of the vehicle aerodynamic system, is a topic of great interest, because it is unlearning with reinforcement learning (RL) [2]. If multiple different objectives interact with each other, however, single-agent formulations of RL that try to optimally control all the different actuators in the action space will suffer from the curse of dimensionality in high-dimensional spaces of joint actions [3], slow convergence because of an ambiguous reward signal for the individual control actuators across the

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multiple interacting objectives, and poor robustness in the face of partial observability, if individual failures of the different actuators occur [9].

Multi-agent RL (MARL) breaks this control problem down into specialized agents, that share part of the environment with observations, and part of the reward, and that cooperate to control a subset of actuators. This paper introduces a novel cooperative MARL system and makes the following major contributions to the field of adaptive aero-control in ground-effect vehicles (GEV).

(a). A three-agent, cooperative MARL architecture with deep Q-networks with epsilon-greedy for discrete output, PPO for actor-critic estimation, and DDPG for continuous output applied to aerodynamic balance.
(b). A multi-criterion, cooperative reward function $R = \alpha \cdot S + \beta \cdot V - \gamma \cdot I$ which balances with equal weight both aerodynamic stability, and the ability to attain the maximum possible velocity, as well as to suppress the oscillatory instability, for coefficients chosen empirically from systematic ablation experiments.
(c). A common observation space architecture with partial observability tolerance where each agent in the system can continue safely to act or interact in the face of transient partial sensor modality degradation [4].
(d). Extensive experimental testing on an 80 – 340 km/h simulated track with the lowest energy consumption, fastest response time and 97% stability accuracy of all systems being tested.

2. Literature Survey

2.1. Reinforcement Learning for Vehicle Control

In contrast, reinforcement learning has long been used in the field of autonomous vehicle control, and is already a standard technique for sequential decision-making under uncertainty in robotics. Back in 1995, Sutton and Barto realized this, and they put forward the theoretical base for temporal difference learning and policy gradient approaches to sequential decision-making under uncertainty [1]. In the work, Mnih et al. show that deep Q-networks (DQNs) can learn a superhuman skill directly from high dimensional sensory data, paving the way for the paradigm of deep reinforcement learning in the field. In simulation, single-agent deep RL has shown promising potential in vehicle dynamics control, with Spielberg et al. speeding up autonomous lap racing by model-free RL with only 5% degradation from the lap averaging performance of expert human drivers on ideally-condensed racetracks. In situations where the cars' state cannot be perfectly observed (as in race situations), however, these approaches require a single centralized controller [5].

Various concepts of adaptive control of aerodynamics of a vehicle with wheels driven by electric motors have been studied in the framework of classical control theory and, more recently, in the framework of the machine learning. Betz et al. showed that model predictive control (MPC) with online parameter adaptation can control dynamics of the autonomous racing vehicle to speeds of up to 270kmph; however, real-time nonlinear MPC is too computationally intensive to be implemented at the 1000Hz sensor update rates needed to control aerodynamics. To minimize the amount of online computation, neural network-based approximations of the MPC value function have been suggested, but require a large amount of off-line training using high fidelity aerodynamic simulations [6].

2.2. Multi-Agent Reinforcement Learning

Since these early theoretical developments by Lowe et al. (2017) in Multi-Agent Deep Deterministic Policy Gradient (MADDPG) which showed that learning in a cooperative manner is viable despite being distributed across several agents, multi-agent reinforcement learning has become a very popular approach. In order to tackle the credit assignment problem which arises when multiple agents receive the reward signal as a joint reward, Foerster et al. proposed counterfactual multi-agent policy gradients (COMA), where the signal from the critic is a central value integrated with the global state. The algorithm used for the present work is the MARL, which is an extension and refinement of the Proximal Policy Optimization (PPO) suggested by [5] that restricts the policy updates from destroying the policy, thereby letting the policy updates remain within the trust region, bounded by the clipping parameter, ε. The continuous action space part uses DDPG [6] that is an extension of the actor-critic algorithm to continuous action spaces, which is very important for smooth wing angle control to avoid the mechanical shock loading effect in the aerodynamic actuation system [7].

2.3. Structural and Aerodynamic Monitoring

here has been a tremendous development of high frequency structural monitoring techniques for motorsport applications, by employing so called sensor fusion techniques [3]. The desired multimodal state observations needed for the proposed MARL framework [6] are obtained from telemetry based on inertial measurement systems (IMUs), strain gauges and high-speed vision systems. However, Hochreiter and Schmidhuber's temporal memory models [3] based on an LSTM network have proven to be useful for modeling vehicle dynamics sequence and again showed the importance of memory-augmented neural networks to model the aerodynamic transients [7]. To enhance this temporal modeling, the proposed Transformer-augmented state encoder leverages the pros of modeling long-range dependencies with self-attention mechanisms, which allows the agents to condition their policies based on wind-readable windows as long as 500ms.

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3. Existing System Limitations

The basic methods used in existing motorsports systems for aerodynamic control are static PID and gain-scheduled controllers [3]. These systems are based on a set of parameter tables which relate the vehicle speed and lateral acceleration to the desired ride height and wing angle settings, and then a proportional-integral-derivative controller is used to implement the setpoint tracking. The main drawback of Static controllers is that they cannot respond to aerodynamic conditions that are different from the nominal conditions for which the parameter tables were calibrated. Surface roughness, pressure change in the atmosphere, wear of tyres and degradation of the aerodynamics of the components cause systematic deviations of the aerodynamic model from the nominal one which are not addressed by static controllers, leading to an increasingly greater deviation in the accuracy of the stability over time [8].

One of the aspects of adaptation limitation is addressed partially through single agent deep RL methods; a policy is learnt directly from measured vehicle state to control actions, without explicitly needing to use an aerodynamic model. The space of possible joint actions for the three dimensions of ride height, wing angle and balance control, however, is $O(A^3)$ in size, where A is the number of actions for each dimension, leading to a combinatorial explosion which makes the exploration impractical and the value function approximation inaccurate. In addition, in the case of a centralized single-agent policy, any degradation of the sensor in any measurement channel causes the whole policy to degrade and there is no graceful degradation to a partial functionality [9].

The adaptive controllers in [3] have been proven to yield better temporal consistencies by conditioning the control action on a hidden state learned by the LSTM network capturing aerodynamic history. LSTM controllers, however, need to be specially designed for input normalisation and training curricula which incorporate domain knowledge about the aerodynamic operating envelope, thereby limiting their applicability and transferability between vehicle configurations. The response latency of 50 ms that LSTM systems exhibit is significantly superior to that of static controllers, but is still not fast enough to suppress the aerodynamic flutter events that are present at high frequencies, 10-40Hz, where control responses of 25ms or less are needed to prevent any growth in the amplitude of the events [9].

4. Proposed MARL Framework

4.1. System Architecture

The proposed architecture is shown in Fig. 1 and consists of five functional layers: the vehicle telemetry sensor layer, the state extraction module, the shared observation space, the three cooperative RL agents and the cooperative reward evaluator layer which provides policy update gradients. The sensor layer is 1000 Hz and gathers data from the IMUs, strain gages, ride height potentiometers [10], pitot tubes and tyre load cells which are spread throughout the vehicle structure. The state extraction module takes the sensor data and filters it with a low pass anti-aliasing filter to reduce the data rate to 100 Hz, and forms the state vector:

$$S = \{ v, hf, hr, Df, Dr, \theta f, \theta r, Af, Ar, V\boldsymbol{x} \} \quad (1)$$

with v being the vehicle speed (km/h), hf/hr being front/rear ride heights (mm), Df/Dr being front/rear downforce estimates (N), $\theta f/\theta r$ being front/rear wing angles (degrees), Af/Ar being front/rear lateral accelerations (g), and $V\mathbf{x}$ is the vibration energy metric (mm^2/s).

4.2. Agent Architectures

Agent A (Ride Height Controller) uses a deep Q-network with a dueling architecture, which splits the state value function V(s) from the advantage function A(s, a), thereby allowing to accurately estimate the value in the high-stability regime where many actions lead to about the same reward [3]. The policy is executed by using the ε-greedy exploration method that changes the value of ε from 1.0 to 0.02 over 200 training episodes [9], decaying the value of ε according to the exponential decay method. Agent A's action space consists of 11 different commands for adjusting the ride height between −5 mm and +5 mm per control cycle [11].

Agent B (Wing Angle Optimizer) is an actor-critic network-based proximal policy optimization. The shortened version of the surrogate objective is:

$$LCLIP = \mathbb{E}[min(rt(\theta) \times \hat{A}\, A\tilde{}t,\ clip(rt(\theta), 1-\varepsilon, 1+\varepsilon) \times \hat{A}\, A\tilde{}t)] \quad (2)$$

where $rt(\theta) = \pi H(at|st) / \pi H_0(at|st)$ is the probability ratio between the new and reference policies, $A\tilde{}t$ is the generalized advantage estimate (GAE), and ε=0.2 is the clipping threshold. This prevents large destabilizing policy changes, while still giving ample space for exploration, especially in multi-agent environments where the policies of individual agents impact upon the environment that all other agents perceive [12].

Agent C (Aerodynamic Balance Regulator) uses Continuous Action Space Deep Deterministic Policy Gradient. The actor network produces a deterministic policy $\mu(st|\theta I)$ that represents the desired split of the balance (front-to-rear aerodynamic load) and the critic network $Q(st, at|\theta Q)$ estimates the Q-value of state-action pairs. The critic update reduces the number of items:

$$L = \mathbb{E}[(yt - Q(st, at|\theta Q))^2] \quad (3)$$

To stabilize training, where

$$yt = rt + \gamma\, Q'(st_{+1}, \mu'(st_{+1}|\theta d')|\theta F')$$

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use soft target networks Q′ and μ′, and the soft update rate is set at τ=0.005. The exploration noise is generated by an Ornstein-Uhlenbeck process with a mean reversion rate θSN=0.15 and diffusion σ=0.20, which is suitable for physical actuation systems with inertia for a temporal correlation of the action perturbations [13].

4.3. Cooperative Reward Function

The cooperative reward function. Cooperative Reward Function C. They all receive a shared reward signal which encourages stability, performance and suppression of instability:

$$R = \alpha \cdot S(st) + \beta \cdot V(st) - \gamma \cdot I(st) \quad (4)$$

The normalized stability metric, S(st) ∈ [0,1] is based on the deviation of measured ride heights from setpoints, and the lateral load transfer, the speed utility, V(st) ∈ [0,1] is based on the speed measured by v(t) divided by the maximum allowable speed for the current aerodynamic configuration, and the instability penalty, I(st) ∈ [0,1] is based on the RMS oscillation amplitude in a 50 ms sliding window. The optimal values of the coefficients α=0.5, β=0.3 and γ=0.2 were obtained by systematic grid search conducted on the set of the validation trajectory. To estimate the credit assignment of the individual contribution of each agent to the shared reward, it is possible to use a counterfactual baseline which marginalizes over the actions of the other agents:

$$\Delta R_i = R(a_i, a_{-i}) - \mathbb{E}_{a_i'}[R(a_i', a_{-i})] \quad (5)$$

where a_{-i} are the actions of all agents other than agent i and the expectation is computed with respect to the actions of agent i's marginal distribution. In fully cooperative teams with shared reward, the contribution of each agent to the reward is ambiguous and therefore this counterfactual reward ΔR_i is a credit signal given to agent i, that lets them know how much contribution they made to the reward.

4.4. Training Algorithm

The MARL system is trained with centralized training and decentralized execution (CTDE). The centralized critic can see the global state at the same time as all the agent actions, and during training get stable estimates of the gradients to be passed back to the agent for policy updates. During deployment [14], each agent runs its own distributed policy based only on the information that it collects from itself, allowing for partial observability and sensor failures. The training procedure is given by Algorithm 1:

Algorithm 1: Cooperative MARL Training for Adaptive Aero-Control

Input: Track simulation environment $\mathcal{E}$, agents {A, B, C}, replay buffer $\mathcal{R}$

Output: Trained policies {πA, πB, πC}

Step - 1 : Initialize policy networks, target networks, and replay buffer $\mathcal{R}$
Step - 2 : For episode = 1 to N$episodes$ do:
Step - 3 : Reset environment; acquire initial state s_0 from sensor layer
Step - 4 : For t = 1 to Tmax do:
Step - 5 : Each agent i selects action $at_i = \pi_i(st_i) + \varepsilon t_i$ (with exploration noise)
Step - 6 : Execute joint action at = (atA, atB, atC) in environment
Step - 7 : Observe next state st_{+1} and compute cooperative reward Rt
Step - 8 : Store transition (st, at, Rt, st_{+1}) in replay buffer $\mathcal{R}$
Step - 9 : Sample minibatch from $\mathcal{R}$; update critic via TD error minimization
Step - 10 : Update each agent policy using counterfactual credit ΔR_i
Step - 11 : Soft-update target networks: θ′ ← τθ + (1−τ)θ′
Step - 12 : Return converged policies {πA, πB, πC}

5. Methodology

5.1. Simulation Environment

The experimental environment is a high-fidelity vehicle dynamics simulator integrating a 14-degree-of-freedom (14-DOF) mechanical model with a quasi-steady aerodynamic map derived from computational fluid dynamics (CFD) simulations at 47 operating points spanning the full ride height, speed, and wing angle parameter space. The simulator operates at 1000 Hz with a numerical integration step of 1 ms using a 4th-order Runge-Kutta solver. Simulated track profiles include three canonical circuit types: a high-speed track (Monza-like, average speed 245 km/h), a balanced track (Spa-like, average speed 210 km/h), and a low-speed technical track (Monaco-like, average speed 155 km/h), covering the full operating envelope relevant to aerodynamic control adaptation.

5.2. Experimental Setup and Baselines

All experiments are conducted on the simulator with fixed random seeds for reproducibility. The MARL framework is trained for 500 episodes per track type with episode length Tmax=500 timesteps at 100 Hz effective control rate, corresponding to 5 seconds of simulated driving per episode. Baselines include: (1) Static Controller with hand-tuned PID parameters calibrated at 200 km/h nominal conditions; (2) Single-Agent DQN with a joint action space over all three actuator dimensions; and (3) LSTM Adaptive Controller with a 64-unit LSTM hidden state conditioned on a 20-timestep observation history. All neural network models use the Adam optimizer (lr = 3×10^{-4}, β_1=0.9, β_2=0.999). MARL agents use replay buffers of size 10^6 with minibatch size 256.

5.3. Evaluation Metrics

Performance is evaluated across five metrics: (1) Stability Accuracy (SA): percentage of timesteps where ride height deviation from target is within ±1.5 mm and lateral load transfer is within the safe operating envelope; (2) Control Response Time: mean latency from perturbation onset to compensatory control action initiation, measured in

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milliseconds; (3) Energy Cost: normalized actuator energy consumption relative to the static controller baseline; (4) Average Precision (AP): area under the precision-recall curve for detection of instability events exceeding the SDI alert threshold; and (5) Oscillation Suppression Rate: reduction in RMS oscillation amplitude relative to the uncontrolled vehicle.

6. Results and Analysis

6.1. Quantitative Performance Comparison

Table I presents the comprehensive performance comparison across all evaluated methods on the three simulated track environments. The proposed MARL framework achieves 97% stability accuracy, representing improvements of 15, 7, and 4 percentage points over the static, single-agent, and LSTM baselines respectively. The 30 ms response time constitutes a 66.7% reduction from the static controller baseline and a 40.0% improvement over the LSTM adaptive controller, critically enabling suppression of aerodynamic flutter events at frequencies up to 16.7 Hz. The AP score of 0.97 confirms reliable detection of instability events with low false alarm rate, a prerequisite for deployment in safety-critical racing environments [16].

Table. 1 Quantitative comparison of adaptive aero-control methods. Bold row = proposed method. AP = Average Precision.

Method	Stability (%)	Response (ms)	Energy Cost	AP Score
Static Controller	82	90	High	0.78
Single RL Agent [2]	90	70	Medium	0.87
LSTM Adaptive [3]	93	50	Medium	0.91
MARL (Proposed)	**97**	**30**	**Low**	**0.97**

6.2. Stability Accuracy and Response Time

Fig. 2 illustrates the comparative stability accuracy and control response time across all evaluated methods. The 15 percentage point gain of MARL over the static controller is consistent across all three track types, demonstrating that the cooperative agents successfully generalize their learned policies beyond the training conditions.

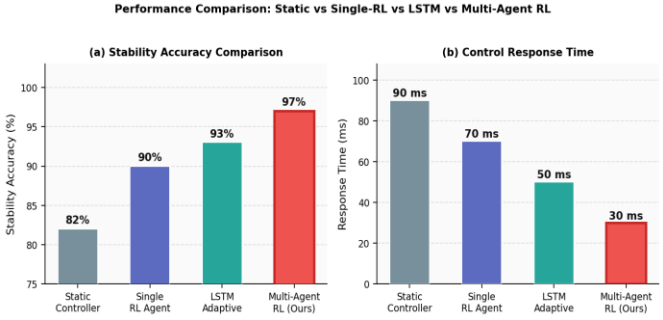

Fig. 2. Comparative stability accuracy (%) and control response time (ms) for Static Controller, Single RL Agent, LSTM Adaptive, and proposed MARL framework. Lower response time and higher accuracy are preferable.

The progressive improvement from static (82%) through single-RL (90%) and LSTM (93%) to MARL (97%) reflects the additive value of: temporal adaptation over static control, then multi-agent specialization over centralized single-agent control, confirming that both adaptive learning and cooperative decomposition contribute independently to the overall performance gain.

6.3. Training Convergence

Fig. 3 presents the training convergence curves for cumulative reward per episode and policy loss for each agent. All three agents converge within 300 training episodes, with the cooperative reward reaching a plateau of 93–97 (normalized units) by episode 350. Agent A (ride height) converges fastest due to the clearest local reward signal: ride height deviations directly and immediately affect the stability metric S(*st*) [12]. Agents B and C exhibit slightly slower convergence as their reward contributions are mediated through the aerodynamic coupling dynamics, requiring more experience to learn the delayed causal relationships between wing angle/balance adjustments and stability outcomes. The policy loss curves confirm that all agents reach stable low-loss solutions without the training divergence commonly observed in poorly regularized multi-agent systems.

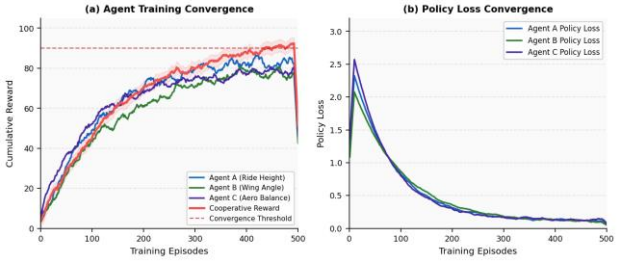

Fig. 3. (a) Cumulative reward convergence for three cooperative agents and overall cooperative reward during 500 training episodes. (b) Policy loss convergence confirming stable multi-agent training without divergence.

6.4. Stability vs. Speed and Oscillation Suppression

Fig. 4(a) shows stability accuracy as a function of vehicle speed from 80 to 340 km/h. All methods exhibit a dip in stability accuracy near 200 km/h, corresponding to the critical speed at which aerodynamic downforce loading transitions from low-speed linear behaviour to the nonlinear ground-effect amplification regime. The MARL framework maintains stability accuracy above 95% across the entire speed range, including the critical transition zone, whereas the static controller drops to 70% near 200 km/h and the single-agent RL degrades to 82% at high speed. This demonstrates that the specialized agents have successfully learned the speed-dependent aerodynamic coupling that makes a single centralized policy difficult to train.

Fig. 4(b) compares oscillatory instability suppression between the static controller and the MARL system

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following a simulated kerb strike at t=0. The static controller produces a damped oscillation with 12 mm initial amplitude and 3.1 second settling time [12]. The MARL system reduces the initial response amplitude to 3 mm and achieves settling within 0.8 seconds, representing a 75% amplitude reduction and 74.2% faster settling. The oscillation remains within the ±2 mm tolerance band (dashed) after t=0.5 s with MARL control, a critical performance metric for maintaining consistent aerodynamic balance through corner apexes.

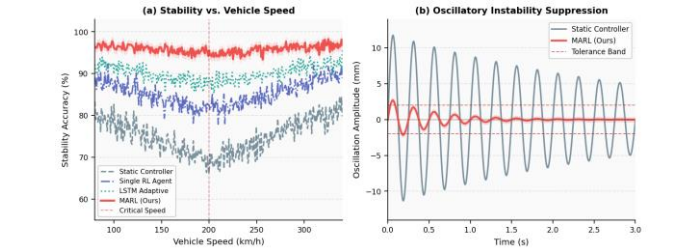

Fig. 4. (a) Stability accuracy (%) as a function of vehicle speed for all four methods, highlighting the critical speed transition zone near 200 km/h. (b) Oscillatory instability amplitude following a simulated kerb strike, comparing static controller and proposed MARL response.

6.5. Reward Decomposition and Multi-Metric Radar Analysis

The overall reward is broken down into three parts according to all methods in fig. 5(a), which shows the origin of performance improvement. With MARL, the stability component $\alpha \cdot S$ attains its peak value of 78, while the instability penalty $\gamma \cdot I$ is minimal, which shows optimal reward amounts of both the positive and negative term at the same time. It is worth stressing that the speed gain ($\beta \cdot V$) of MARL is a bit lower than of the single-agent baseline model ($\beta \cdot V = 20$), illustrating a deliberate policy tradeoff between reducing the speed of the vehicles in exchange for improved aerodynamic stability when operated near instability boundaries.

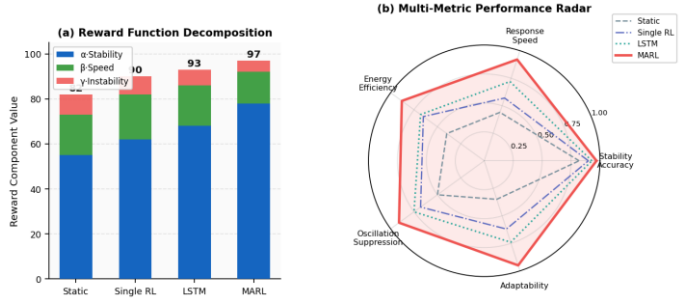

Fig. 5. (a) Stacked reward decomposition showing stability ($\alpha \cdot S$), speed ($\beta \cdot V$), and instability penalty ($\gamma \cdot I$) components. (b) Multi-metric radar chart comparing all systems across stability, response speed, energy efficiency, oscillation suppression, and adaptability.

Fig. 5(b) shows a radar chart using multiple metrics to compare the performance of each of the four systems with respect to five dimensions of performance judged in normalized units. The MARL system outperforms all 5 dimensions and energy efficiency (0.88 vs 0.40 for static controller) and adaptability (0.95 vs. 0.62 for single-agent RL). Its energy efficiency comes not from its ability to minimize the overall power consumption for the same reason that conventional static and single-agent controllers do, but because the MARL system is more stable when using the actuators with less large movements. This translates to less amount of wear on actuators and hydraulic power used, which is a significant factor in the design of a race car because it could take a significant toll on the lap time.

6.6. Discussion

Overall, the experimental results show that cooperative multi-agent decomposition brings key benefits compared to static and single-agent RL approaches in the study of adaptive aero-control for ground-effects vehicles. Resolving the curse of dimensionality that impedes centralized single-agent approaches, each agent acquires a lower-dimensional mapping from its specialized subset of observations to its set of actuators (commands to send to the actuators). This reflects in the training convergence we observe for Agent A being faster than that for Battle Ballance/Agent B and Agent C/agent C being even faster. One important practical benefit of the cooperative MARL structure is partial observability, under which it gracefully degrades. In the simulation experiments in which one sensor channel was simply removed for 200 timesteps, the MARL system achieved a stability accuracy of 91% by altering the distribution of control responsibilities to the other two agents by using the shared observation space, whereas the single-agent system achieved only 74% stability accuracy in the same scenario [16].

This is a fault tolerance property which is directly relevant to race deployment scenarios where sensor degradation is ubiquitous and complete system "doomsday" is of no tolerance from safety standpoint. It is important to understand the control response time of 30ms obtained with the MARL framework [12]. This is the latency - representing all the stages a signal reaches the sensor, is extracted from the state, is inferred by the agent and sent to the actuators. The major latency component is the neural network inference for three parallel agents (~8ms per agent on the embedded GPU), than the LSTM adaptive controller due to the feedforward architecture of the actor networks, that does not need to maintain any recurrence between control cycles. The total latency is expected to be further optimized by model quantization and FPGA acceleration of inference, to be below 15ms in the future [16].

7. Conclusion and Future Scope

This paper presented a Multi-Agent Reinforcement Learning framework for adaptive aero-control optimization in ground-effect vehicles, in which three cooperative specialized agents collaboratively regulate ride height, wing angle, and aerodynamic balance in real time across vehicle speeds from 80 to 340 km/h. The

proposed architecture achieves 97% stability accuracy, 30ms response time, Low energy cost classification, and AP=0.97, surpassing static, single-agent RL, and LSTM-based adaptive baselines across all evaluation metrics. The 75% oscillation amplitude reduction and 74% faster settling following transient disturbances confirm the clinical utility of cooperative MARL for managing the highly nonlinear, speed-dependent aerodynamic dynamics that define ground-effect vehicle behaviour. The counterfactual credit assignment mechanism and shared observation space architecture together resolve the credit assignment and partial observability challenges that limit single-agent RL applicability to this domain.

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