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Adaptive motion control for autonomous vehicles

Literature review

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Adaptive control plays a crucial role in the evaluation of autonomous vehicles and robotics, providing systems with the flexibility and robustness needed to operate safely and efficiently in dynamic and uncertain environments. This literature review explores the key concepts, current methods, and practical applications of adaptive control. It focuses particularly on feedback and model-based adaptive strategies such as Model Reference Adaptive Control (MRAC), Self-Tuning Control (STC), Robust Adaptive Control, and Dual Adaptive Control. Recent trends, including the integration of deep learning, reinforcement learning, edge computing, and secure system design, are discussed for their potential to further enhance adaptability and safety. Adaptive control has demonstrated significant impact across a range of real-world applications. In autonomous driving, it enables critical capabilities such as real-time lane changes, smooth intersection navigation, and safe manoeuvring through complex urban environments. In robotics, it supports advanced functions like force-sensitive manipulation and coordinated motion planning in dynamic settings. Despite these advancements, several key challenges occur. High computational demands, safety assurance under uncertainty, and long-term reliability. Overcoming these challenges will be essential for establishing adaptive control as a foundational technology in the future of intelligent autonomous systems.

Key words: adaptive control, feedback control, autonomous systems, autonomous vehicles.

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1 Introduction

Autonomous vehicles are becoming an important part of modern transportation. As technology keeps improving further, more cars are gaining the ability to make decisions and move without human input. To do this safely, effectively, and environmentally friendly, these vehicles need smart control systems that can respond quickly to changes around them. These systems are responsible for actions such as steering, braking, and accelerating, and they must do this correctly even in difficult and unexpected situations.

The major advancement in this area is the use of adaptive control. Traditional control systems follow fixed rules that work well only when everything is predictable. However, roads are not always predictable. Weather conditions, road surfaces, and the behaviour of other drivers can all change suddenly. Adaptive control allows vehicles to respond to these changes in real time by adjusting how they operate. As a result, it could improve comfort, and efficiency.

This thesis is a literature review that explores the current knowledge and latest research in adaptive control for autonomous systems. It focuses on how these control methods work, where they are used, and what challenges they still might face. This thesis also looks at recent trends in the field, including the use of artificial intelligence and learning-based methods. By reviewing these developments, this thesis highlights how adaptive control is helping autonomous vehicles become more reliable, flexible, and capable in real-world, changing environments.

The main questions this thesis aims to answer are:

What is the current state of adaptive control?

What are the state-of-the-art adaptive control methods in autonomous vehicles?

What are the state-of-the-art adaptive control methods in robotics?

2 Control concepts

The development of autonomous vehicles depends heavily on reliable and intelligent control systems. These systems are the foundation that allows a vehicle to make real-time decisions to accurately control motion and positioning. A control system analyses information from the vehicle's sensors and uses this data to determine the needed adjustments to steering, acceleration, and braking to maintain the desired performance. In complex and difficult traffic environments, this becomes critical for safety, energy efficiency, comfort, and coordination with other road users.

As autonomous vehicles must operate under constantly changing conditions, basic, rigid control systems are no longer efficient. Instead, modern autonomous systems rely on more advanced strategies that could either react to errors or adapt to new conditions in real time.

The essential control systems used in autonomous vehicles are feedback control systems that responds to performance errors. Another crucial control method is adaptive control that adjust itself to evolving environments and system behaviours.

2.1 Feedback Control

Feedback control is a crucial component in autonomous vehicle systems. With feedback control, systems are safe, accurate, and stable as the control system can adjust any control inputs based on real-time feedback from the sensors. It mainly focuses on minimising the difference between the desired motion of the vehicle and the actual vehicle state. This kind of process is done by measuring the vehicle's position, speed, and direction and finally comparing the results with the planned motion and making the needed adjustments to fix any kind of mistakes that might have occurred. This is a closed-loop system that improves durability against disturbances, model uncertainties, and dynamic environmental conditions. Feedback control ensures safe and comfortable navigation.

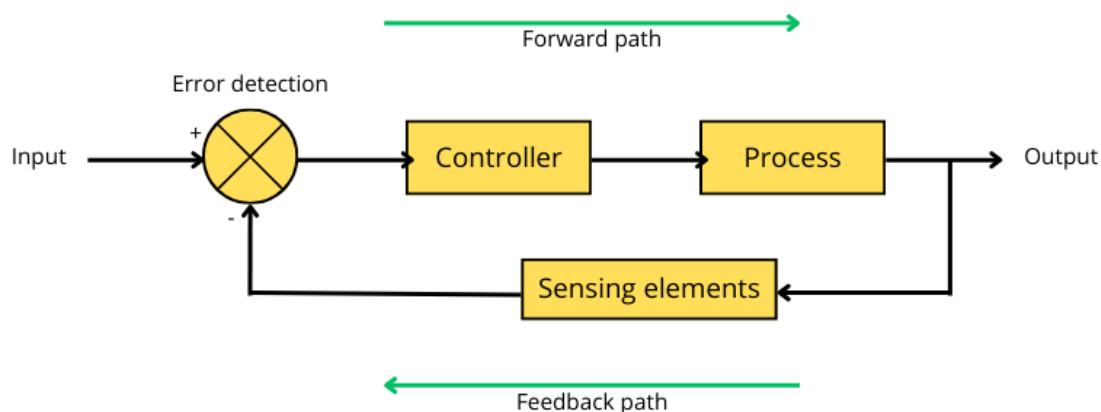


Figure 1 Block diagram of Closed-Loop Control system

One of the most used feedback control systems in autonomous vehicles is called Proportional-Integral-Derivative (PID) controller. PID control system is simple but effective. It operates by adjusting the control inputs between the desired and the actual real system states. Research has shown that PID tuning is essential for improving the performance of the vehicle, especially in changing environmental conditions. For example, research has shown that tuning feedback controller adjustments significantly improves driving performance in autonomous vehicles. It increases stability and adaptability to road conditions such as rain and nighttime driving [1].

Another very widely used feedback control technique is Model Predictive Control (MPC). It optimises control inputs in limited time while ensuring that all constraints are met. MPC feedback strategies have been widely studied for autonomous vehicles. This offers improved path tracking and motion planning [1]. However, MPC requires a lot of computational resources, and this makes real-time implementation a challenge.

In mobile robotics and mechatronic systems, feedback control has also been widely applied through intelligent strategies. For example, radial basis function neural networks have been used in feedback linearization schemes for accurate trajectory tracking in omnidirectional mobile robots facing unmodeled dynamics and external disturbances [2]. Similarly, biologically inspired sliding mode feedback controllers have been developed for underwater micro diving agents, combining robustness and learning using adaptive neural networks [3]. These examples demonstrate the practical utility of feedback control in embedded systems with real-world constraints and uncertainty.

2.2 Adaptive Control

Adaptive control is a main advancement in control systems. It enables autonomous vehicles to dynamically change their control parameters according to surrounding conditions. Unlike the feedback control, which is all about predefined control laws, adaptive control can modify these parameters in real time, depending on external disturbances, environment and vehicle's dynamics. This advancement improves the vehicle's overall performance and robustness in uncertain driving conditions.

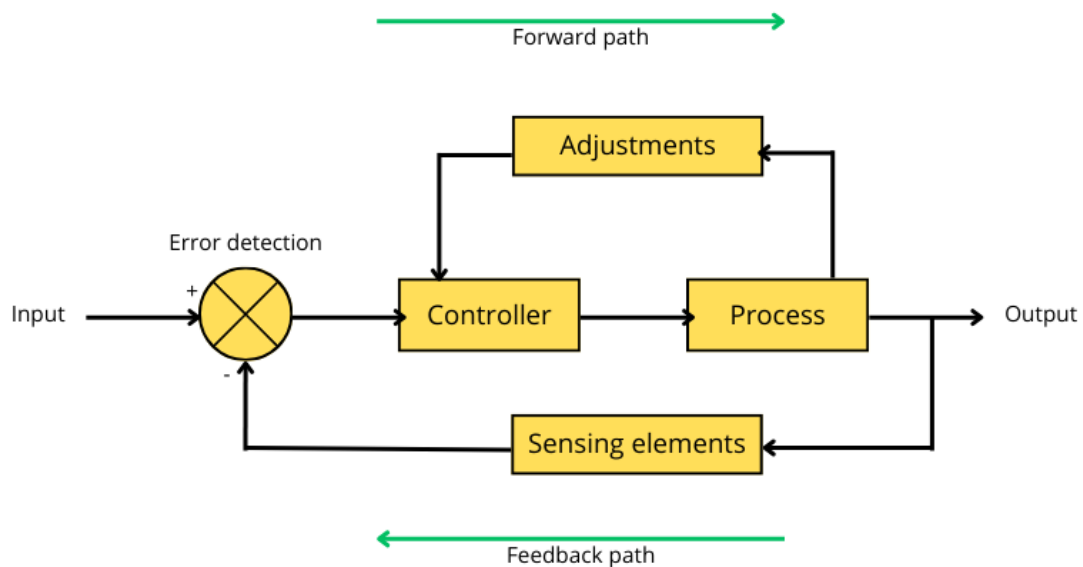


Figure 2 Block diagram of Adaptive Control system

While feedback control systems, like PID and MPC, correct errors and keep the stability, they always rely on fixed settings and may struggle with unexpected changes. This is why control systems have evolved to adaptive control. Adaptive control systems can continuously refine their control strategies by analysing the real-time data coming from the sensors. This allows the autonomous vehicles to handle more disturbances, and varying driving environments.

There are several types of adaptive control systems. They offer different advantages for autonomous vehicles.

Model Reference Adaptive Control (MRAC): This system compares the actual system performance with a reference model and continuously updates the control parameters to minimise any mismatches. MRAC is mostly used in autonomous systems that require accurate path following and fast adjustment to changing road conditions [4].

Recent advancements have made it possible to use MRAC in more advanced self-driving situations, such as high-speed drifting. Zhou et al. introduced a new control method that combines MRAC with a learning technique called Bayesian optimization. Bayesian optimization is an optimization technique that uses a probabilistic model to find the minimum or maximum of computationally expensive function by efficiently selecting the best performed points to next sample. This method allows the system to adjust its control settings in real time, helping the vehicle stay on the right path even if the road friction is misidentified or the vehicle behaves in nonlinear ways [5]. Their control system uses a layered structure that can separate the goals of path following and drifting. This led to better performance and safety in simulated drift tests.

Self-Tuning Control (STC): Self-tuning controller uses online parameter estimation techniques to modify the control gains. This method is mainly useful when the system parameters change remarkably. It ensures that the performance keeps consistent without any manual recalibration [6].

Robust Adaptive Control: This control system integrates robustness principles into adaptive control strategies to handle any uncertainties and disturbances. Robust adaptive controllers are particularly effective in platooning applications, where maintaining safe vehicle distances and coordinated motion are important [7].

One practical application of robust adaptive control was demonstrated by Shu et al. in a novel fully actuated octocopter UAV (Unmanned Aerial Vehicle) capable of independent six-degree-of-freedom (6-DOF) movement. They developed a control strategy that accounts for both parameter uncertainties and external disturbances, such as wind. The system uses sigma-modified adaptive control scheme to maintain stability and performance. The simulation results confirmed that their controller enabled precise trajectory tracking and robust stabilization, even when the thrust coefficients of the rotors varied. This shows the system's resilience in challenging environments [8].

Dual Adaptive Control: This method includes both real-time adaptation and long-term learning. It balances instant control needs with insight for future adjustments. Dual adaptive control is best for handling difficult scenarios where rapid and unexpected environmental changes needs quick corrective action while optimizing control policies over time [9].

One example application of dual adaptive control was introduced by Nguyen et al. for quadrotor UAV (Unmanned Aerial Vehicle) operating under model uncertainties and sensor noise. Their strategy integrates an adaptive filter based on the RMEE (Recursive Minimum Error Entropy) method to reduce sensor noise, and ABSMC (Adaptive Backstepping Sliding Mode Controller) to improve control accuracy. This approach with two different layers not only addresses external disturbances but also discards issues such as channel cross-interference and chattering. Simulation results showed a 93% improvement in control efficiency compared to traditional adaptive methods, especially in hazardous and uncertain conditions [10].

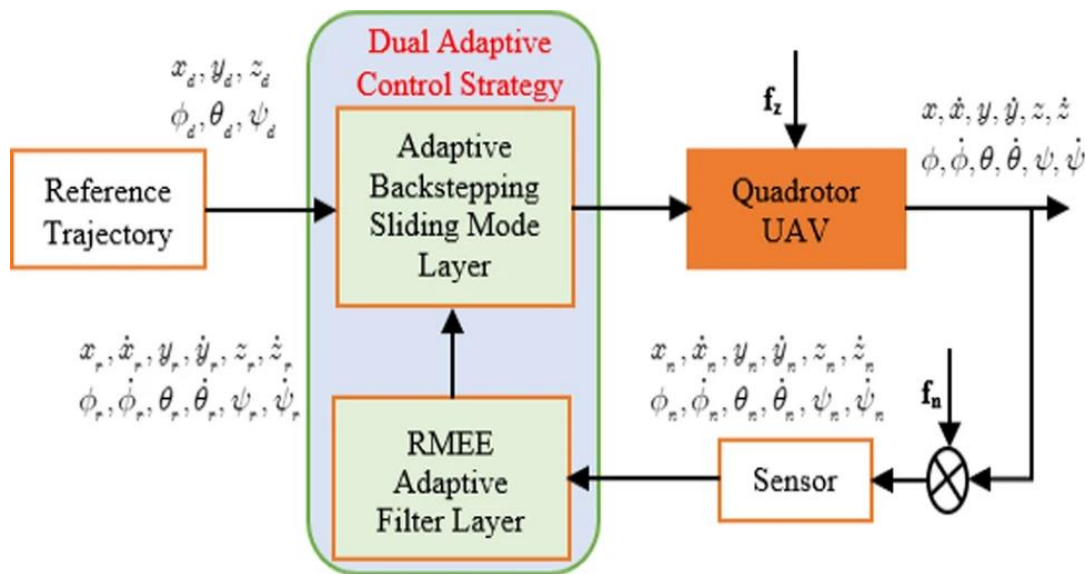


Figure 3 Block diagram of the Dual Adaptive Control strategy [8]

Adaptive control has been successfully applied in different autonomous vehicle applications. In lateral motion control, adaptive strategies improve vehicle stability and handling by continuously adjusting steering and braking inputs [11]. Additionally, the combination of deep learning with adaptive control has improved decision making in self-driving systems. It enables real-time adjustments based on previously learned experiences [12].

Adaptive control represents an important evolution in autonomous vehicle technology. It provides the flexibility and robustness which is needed when navigating through difficult and dynamic environments safely. Adaptive control ensures higher reliability, safety and efficiency in self-driving systems by continuously adjusting the control based on the real-time data.

2.3 Recent Trends in Adaptive Control

The field of adaptive control has developed rapidly in recent years. Driven by increased demands for intelligent, resilient, and scalable autonomous systems. Several innovative developments are now influencing the design of next generation adaptive controllers beyond classical model-based methods.

One of the most impactful trends now is the integration of deep learning and reinforcement learning (RL) with adaptive control. These methods allow control systems to learn complex mappings from high-dimensional sensor data and adapt to unpredictable dynamics without relying on precise mathematical models. For example, deep RL-based controllers have demonstrated strong performance in simulation-to-reality tasks by learning adaptive driving behaviours directly from environmental feedback [12]. However, bridging the gap between simulation training and real-world deployment remains an active research challenge [13].

Another growing trend is the use of adaptive control strategies that incorporate cyber-resilience and secure decision-making. Due to the increasing risk of sensor deception and communication interference, adaptive controllers are now being designed to maintain stability and tracking even under denial-of-service (DoS) attacks. Liu et al. proposed an adaptive secure lateral controller for electric vehicles that is able to switch control modes in real time to mitigate the effects of compromised GPS signals, ensuring continuous lateral control under cyber threats [14].

Furthermore, cooperative adaptive control leveraging V2X communication is becoming increasingly important in connected environments. V2X stands for *Vehicle-to-Everything* communication. It refers to a system where a vehicle can communicate with its surrounding environment. Adaptive platooning strategies are now integrating real-time data from surrounding vehicles and infrastructure to enable more accurate and synchronized control, especially in high-speed traffic conditions. Zou et al. presented an adaptive platoon control

method that ensures inter-vehicle stability and spacing even when faced with modelling uncertainties and network delays [15].

Another major advancement is in edge computing for adaptive control, which reduces the latency of control decision-making by processing data closer to the source (e.g., vehicle edge units). This has enabled real-time adaptive control even in complex, compute-heavy strategies such as adaptive MPC and RL-based controllers [16]. By combining high-speed on-board computation with low-power architectures, adaptive systems can now support rapid decision-making without compromising energy efficiency.

3 Applications

Adaptive control is an important technology that helps various machines and systems adapt to changing surrounding conditions. It makes them more responsive and efficient. In self-driving cars, it can improve traffic handling, navigation in urban environments and highway driving. It makes movements smoother, safer, and more energy-efficient [11], [17]. On the other hand, in robotics, it helps robotic systems with object manipulation, motion planning, and especially collaboration with humans [7], [18]. As technology advances even further, adaptive control is expected to improve decision-making and teamwork with multiple systems. It helps autonomous machines to become even more reliable and practical for real-world use [19], [20].

3.1 Adaptive Control in Autonomous Driving

One of the biggest challenges for autonomous vehicles is navigating through mixed traffic environments, where self-driving cars share the road with human-operated vehicles. Unlike autonomous systems, human drivers may have unpredictable behaviours, such as non-uniform acceleration, unexpected lane changes, and sometimes aggressive actions. To address this, adaptive control algorithms adjust acceleration, braking, and lane positioning in real time, while ensuring that the interactions between autonomous vehicles and human-driven vehicles are flawless [13]. Adaptive control systems use sensors and predictive models to understand how human drivers behave and how they react in real time. This helps traffic move more smoothly and reduces the risk of any accidents [12].

Urban driving environments are more challenging because of the frequent stops, pedestrians, and narrow streets. Traditional planning methods often struggle in crowded areas where obstacles could appear suddenly. Adaptive control improves urban driving by adjusting how the car responds to traffic, traffic lights, and pedestrians. For example, smart braking systems change stopping distances based on road conditions and people nearby. This makes braking smoother and more comfortable for the passengers in the vehicle [18].

Additionally, adaptive control improves roundabout navigation and intersection handling by continuously predicting gaps in the traffic flow. Machine learning-based adaptive controllers enable self-driving cars to determine optimal merging strategies, ensuring effective and collision-free path through intersections without relying only on pre-programmed rules [19].

While urban driving requires refined adjustments, high-speed highway driving presents different challenges, such as merging into fast-moving lanes, handling any possible crosswinds, and adapting to variable speed limits. Adaptive control in highway automation focuses on stability, aerodynamics, and collaborative vehicle coordination. Ren et al. developed an adaptive speed control system that dynamically modifies fluctuations and keeps velocity changes smooth [7].

Another critical aspect of highway automation is adaptive overtaking and lane changing. Unlike simple rule-based lane-change controllers, adaptive control algorithms continuously evaluate overtaking possibility based on real-time vehicle-to-vehicle communication, driver intent prediction, and environmental conditions. This allows for safer and more effective lane changing actions, particularly in crowded highway traffic [17].

3.2 Adaptive Control in Robotics

Robotic systems also operate mainly in highly dynamic and unpredictable environments. As a result, they require accurate and adaptable control mechanisms to work properly and effectively. This can be achieved with adaptive control systems.

One major application is robotic manipulation, where robots handle objects of different shapes, weights, and textures. Unlike traditional fixed-gain controllers, adaptive force control systems can modify the grip pressure and movement based on real-time feedback coming from vision systems and force sensors. Zulu et al. introduced an adaptive impedance control approach that enables robotic arms to pick up fragile objects without breaking them. This improves the usability of the robots, for example, in surgical operations and automated assembly lines [6].

Another main application is adaptive motion planning. It allows robots to navigate safely in various environments. In mobile robotics, adaptive control enables autonomous robots to adjust their speed, avoid obstacles, and optimize movement paths. This is mainly useful in warehouse automation and rescue operations, where robots have to operate in dynamic and unstructured settings [19]. This is all based on the feedback data. A cooperative adaptive control system has been developed for underwater robotic fleets. It allows them to adjust movement based on ocean conditions. The control system improves the efficiency of robotic fleets in deep-sea exploration and environmental monitoring [9].

4 Challenges

While adaptive control has greatly improved the capabilities of autonomous vehicles, its integration still has some challenges. These challenges include computational difficulties, real-time adaptation, changing environmental conditions, hardware limitations, and some legal issues. Solving these challenges is important to make adaptive control systems more useful and effective in real-world applications.

Adaptive control requires a lot of computation to adapt in real-time. Many adaptive controllers, such as MPC and reinforcement learning-based methods, involve hard and complex mathematical models and optimisation algorithms. These require significant processing power to predict behaviour and adjust control parameters in real time. Adaptive MPC needs continuous recalculation of optimal paths. This makes real-time execution difficult in high-speed or dynamic environments. To solve this, researchers are testing faster optimization methods and better hardware to speed up the calculations [11], [12], [20].

Adaptive control systems must work properly in highly dynamic environments with unpredictable conditions. In autonomous vehicles, factors such as road surface changes and weather conditions can dramatically affect the vehicle's behaviour. Similarly, in robotics, uncertain surfaces, sensor failures, and dynamic objects make adaptation more difficult. A major challenge is that not all environmental factors can be accurately modelled or predicted. For example, sudden sensor failures or unexpected pedestrian behaviours can disturb even the most advanced adaptive control systems. To improve robustness, researchers are integrating sensor fusion techniques, randomised models, and machine learning-based adaptation strategies that will allow systems to handle uncertainty more effectively [4], [13], [18].

The performance of adaptive control systems depends mainly on the hardware components used in the systems, including sensors, actuators, and processing units. Many advanced adaptive controllers require high-speed processors and real-time data analysing, which can be challenging to implement on energy-constrained platforms, such as autonomous drones and mobile robots. Future solutions include low-power adaptive algorithms, optimised hardware architectures, and energy-efficient computing techniques [6], [9], [17].

The integration of machine learning and adaptive control has shown promising results, but it has also introduced new challenges. For example, reinforcement learning-based controllers require extensive training data and simulations to learn optimal behaviours. However, the gap

between simulated environments and real-world conditions remains as a major issue. Many learning-based adaptive controllers struggle to adapt when implemented in real-world applications. This leads to potential failures in unseen scenarios. Additionally, learning-based controllers are not always easy to understand or explain, which makes it difficult to analyse their decision-making processes. As a result, they often function like a “black box”. This lack of transparency is concerning in safety-critical applications, such as autonomous driving and industrial robotics, where human operators need explainable and predictable control behaviours [13], [19], [20].

As mentioned, adaptive control brings a lot of advantages to autonomous systems, but it still faces significant technical challenges that must be considered. Researchers continue to explore solutions such as efficient computing methods, sensor fusion, hybrid control strategies, and integration of learning-based approaches to make adaptive systems even more reliable. As these challenges are gradually solved, adaptive control is expected to play an even bigger role in next generation autonomous systems.

4.1 Safety

As one can imagine, safety might be the most critical concern in adaptive control for autonomous vehicles and robotics. Especially when these systems become even more independent in decision-making. The primary challenge is to ensure that adaptive controllers can react correctly in emergency situations, such as unexpected obstacles, sudden braking scenarios, or hardware malfunctions. Since adaptive control systems continuously update their parameters, there is always a risk of unintended behaviour if the adaptation process does not rely on safety constraints [19], [20].

In autonomous driving, safety concerns arise from real-time decision making and collision avoidance. Adaptive controllers must be able to predict and respond to dynamic traffic conditions to ensure that decisions are legal, ethical, and safe for passengers and pedestrians. Many collision avoidance algorithms integrate fuzzy logic, reinforcement learning, or hybrid techniques to improve responsiveness in unpredictable environments. However, these systems must be entirely tested to prevent unpredictable behaviour, or failure under extreme conditions [13], [18], [19].

Another safety issue is duplication and fail-safe mechanisms. Adaptive control systems rely heavily on sensor inputs. This means that a single sensor failure could lead to unsafe results if

proper fallback mechanisms are not in place. Sensor fusion techniques, including Light Detection and Ranging (LiDAR), radar, cameras, and GPS, help to improve robustness by allowing the system to cross-validate information from multiple sources. Additionally, real-time monitoring algorithms can detect deviations in control outputs and trigger emergency overrides if the system behaves unpredictably [6], [12], [13].

In robotics, safety is a major concern when autonomous machines are interacting with humans. Industrial robots equipped with adaptive controllers must ensure that their movements remain precise and collision-free, particularly in collaborative environments. Force and impedance control methods allow robots to adjust their movements in real time when working alongside humans. This will reduce the risk of injuries. Exoskeletons and medical robots also implement adaptive control with safety constraints to ensure that adjustments do not cause any issues to the user [11], [17].

4.2 Reliability

Reliability is another critical challenge in adaptive control, as these kinds of systems must operate continuously and accurately under different conditions. A reliable adaptive control system must be robust to any disturbances, sensor failures, and real-world uncertainties to ensure consistent performance over time.

One key issue when considering reliability is handling sensor noise and measurement inaccuracies. Since adaptive controllers adjust their behaviour based on real-time data, inaccurate sensor inputs may lead to incorrect decisions or unstable system behaviour. Advanced filtering systems, such as Kalman filters and deep learning-based sensor fusion, help improve data accuracy and ensure that control adjustments are based on reliable information [9], [11], [12].

Reliability is also critical in long-term operation, particularly for systems such as autonomous fleets, industrial automation, and space robotics, where continuous adaptation is required. Over time, control systems must account for wear and tear on mechanical components, changing environmental factors, and the aging of software. Self-diagnosing adaptive controllers that monitor system health and adjust parameters accordingly have been developed to address these long-term challenges [4], [7].

Another considerable challenge is fault tolerance. It means ensuring that the system can recover from any unexpected failures without completely shutting down. In adaptive control,

failures can occur due to network latency, hardware malfunctions, or sudden external disturbances. One solution is backup control architectures, where multiple controllers can operate in parallel. This ensures that if one fails, another can take over the control [6], [9].

Also, machine learning-based adaptive controllers must be carefully evaluated for reliability. Unlike traditional controllers, learning-based controllers can learn from experience, but this also means that they may struggle with unfamiliar situations that were not part of their training data. As a result, ensuring reliability in unexpected situations remains a major challenge for learning-based adaptive control [13], [19], [20].

5 Conclusions

This thesis aims to explore the state-of-the-art adaptive control methods in autonomous vehicles and robotics. Through a review of recent research and applications, it is clear that adaptive control has become a key part of how modern autonomous systems operate in changing and uncertain environments.

The review covered different types of adaptive control, including model reference adaptive control, self-tuning control, robust adaptive control, and dual adaptive control. Each of these methods offers different strengths depending on the application. For example, robust adaptive control is helpful for handling disturbances such as wind or sensor noise, while dual adaptive control is useful in situations that require both fast reaction and long-term learning.

The thesis also explored how adaptive control is used in autonomous driving and robotics. In vehicles, adaptive control improves safety, comfort, and efficiency in city traffic, on highways, and at intersections. In robotics, it enables systems to handle complex manipulation tasks, avoid obstacles, and collaborate with other machines or humans. These applications show how adaptive control is essential for making autonomous systems smarter and more flexible.

Recent trends in the field include combining adaptive control with artificial intelligence and deep learning, using secure methods to handle cyber threats, and taking advantage of V2X communication and edge computing. These trends are pushing the technology forward and making it even more powerful.

However, there are still challenges to solve. These include high computational requirements, explainability in learning-based controllers, and the need for stronger safety and reliability guarantees. Solving these issues will be the key to improving adaptive control systems in the future.

In conclusion, today's most advanced adaptive control systems combine real-time adjustment, learning capabilities, and robust performance. As technology continues to advance, adaptive control will become even more important in shaping the future of transportation and robotics.

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