

An Analysis of Reduced-Scale Mobile Robots in Autonomous Driving Applications

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ABSTRACT: In this paper it is discussed about the Reduced-scale mobile robots (RSMRs) which have gained popularity as a research tool for autonomous driving systems. Along with being more affordable and compact, these smaller robots provide a number of benefits, such as the capacity to test technology in real-world settings with less regulatory obstacles. Up until now, there hasn't been a comprehensive analysis of the application of RSMRs in autonomous driving research, despite their widespread use. We analyze the main techniques applied in the three main domains of autonomous driving: perception (the robot's process of obtaining information from its surroundings), decision-making (the process by which it chooses its next course of action), and actuation (the process by which it carries out its actions). We also look at the primary uses investigated in this research, including parking, navigation and obstacle avoidance, vehicle coordination and hands-free driving.

Keywords: Reduced-scale mobile robots, autonomous driving, Obstacle avoidance, vehicle coordination.

1. Introduction

Both the academic and commercial sectors are paying attention to autonomous driving (AD), which is fast emerging as one of the most fascinating and quickly changing fields of study. It is understandable why so many studies are devoted to creating new models and algorithms to address a range of AD concerns given the potential to improve road safety, reduce traffic congestion, and save energy. To test and refine these breakthroughs, researchers usually use four primary experimental setups: reduced-scale mobile robots (RSMRs), driving simulators, modelling software, and full-sized vehicles [1], [2], [3].

To help minimize accidents, many technologies have been created to warn drivers about potential accidents before they occur. These technologies are essential components of complex driver assistance systems. Vehicles can continuously

scan their environment and detect potential dangers in real time using sensors such as RADAR, LiDAR, and cameras [4], [5].

In this study, we define an RSMR as a small, autonomous driving (AD) configurable robot that resembles a car. As seen in Figure 1, these robots are usually constructed to lower scales, notably at ratios like 1/5, 1/10, 1/16, or 1/20. The three main parts of an RSMR's AD system are typically perception, decision-making, and actuation. A large portion of the study on RSMRs is centred on these topics.

The perception module of the RSMR is equipped with a variety of sensors that help it gather information about its surroundings. These sensors include cameras, LiDAR, radar, and inertial measurement units (IMUs). By collecting visual, depth, and geographical data, the module enables the robot to recognize road signs, track and follow

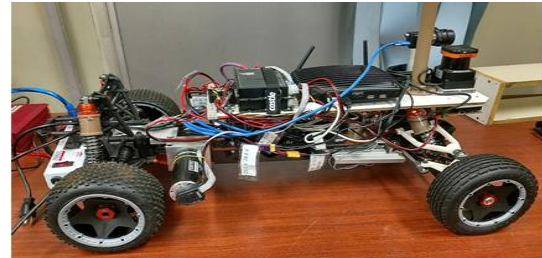
objects, and get a grip on its location and speed. To grasp all this data, we rely on techniques such as sensor fusion, computer vision, and machine learning (ML). These tools help the robot gain a genuine understanding of its surroundings. The information that's processed is crucial for steering the robot's actions and making decisions.

2. Hardware Used

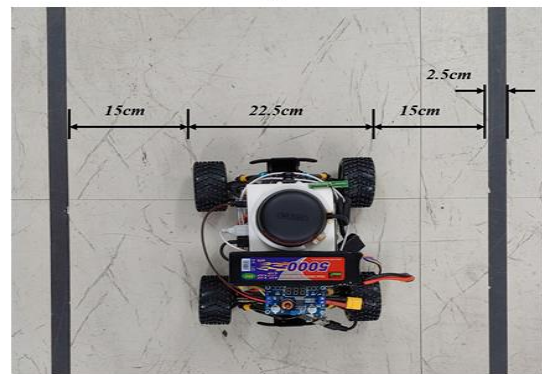
The vehicle platform is built with several essential components to ensure everything operates seamlessly, as shown in Fig 1. At the core of this design is a 1/10 scale race car chassis, which contains two motors and battery packs positioned at the bottom. Each of the four wheels is powered by a brushless DC motor, while steering is handled by a servo motor that employs the Ackermann mechanism [6]. The motors are managed by Vedder's Electronic Speed Controller (VESC) [14].

The platform comes equipped with an IMU, LiDAR, and a camera for gathering data. For wireless communication, it currently relies on an IEEE 802.11ac module, but there are plans to

upgrade to an IEEE 802.11p module in the future for enhanced performance. To meet its processing requirements, the platform is driven by an NVIDIA Jetson AGX Xavier. You can find detailed specifications for each component in Table 1 [14].



(a)

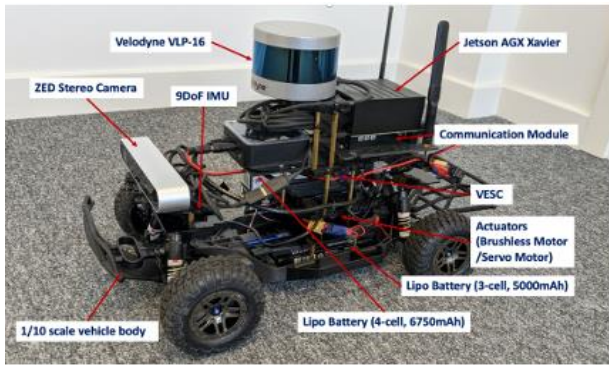


(c)

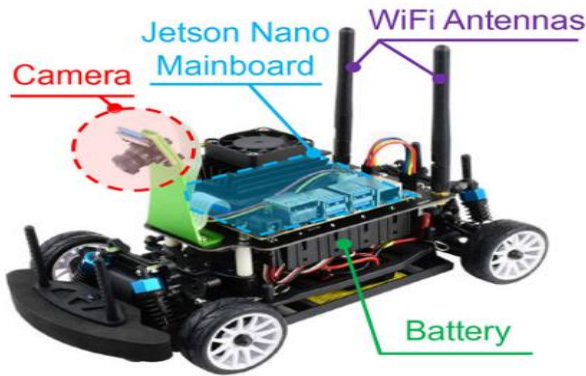
Figure 1: RSMR Schematic Diagrams with Various Scales

Table 1: Hardware specifications of The Vehicle Platform

Type	Model	Detail specifications
Vehicle body	TRAXXAS Slash 4x4 Ultimate	4WD (Four-Wheel Drive), 1/10 Scale Size: 568mm(L) x 296mm(W) Tire Diameter (front/rear): 109.5mm Wheelbase: 324mm
Actuators	Wheels	(TRX3351R) Brushless Motor 3500kV, 4pole
	Steering Angle	(2075R) Servo Motor, Digital high-speed, Metal gear (ball bearing)
Motor Control	VESC	Current, Speed, Duty-cycle, Field-Oriented control available
Battery	TRAXXAS Lipo	3-cell, 11.1V, 25C, 5000mAh
	TATTU Lipo	4-cell, 14.8V, 25C, 6750mAh
Communi-cation	Intel Dual Bank	(AC 8265NGW) 2x2 11ac Wi-Fi delivering up to 867Mbps
Computer	NVIDIA Jetson AGX Xavier	GPU: 512-core Volta CPU: 8-core ARM v8,2 64-bit, 8MB L2 + 4MB L3 Memory:32GB 256-Bit LPDDR4x 137GB/s Vision Accelerator: 7W VLIW Processor Encoder/Decoder: [2x] 4Kp60, HEVC/[2x] 4Kp60, 12-Bit Support



(b)



(d)

(a) 1/5 [15], (c) 1/16 [16] (b) 1/10 [18], (d) 1/20 [17]

3. Methodology

3.1 Perception

Numerous sensors that monitor their internal characteristics as well as their surroundings are installed in RSMRs. These sensors collect data, which is subsequently transformed into quantifiable values and examined to support decision-making. These sensors can be classified as either proprioceptive or exteroceptive [7]. Radar, LiDAR, cameras, and microphones are examples of exteroceptive sensors which collect data about the outside environment. They are essential for tasks including taking pictures of lanes and traffic signs, calculating the separations between barriers, and even interpreting human voice orders.

1) Camera: Autonomous vehicles, or RSMRs, commonly rely on two main types of cameras: standard color (RGB) cameras and those that also capture depth information (RGB-D). Regular RGB cameras are excellent at providing color images and videos, which are crucial for tasks like

recognizing objects, figuring out what they are, tracking how cars and people are moving, and even predicting where they'll go next.

However, RGB-D cameras go a step further. They capture depth maps, which measure the distance between the camera and everything around it. This added depth data lets the vehicle understand the shape of objects, determine their precise location and orientation, and create a 3D model of its surroundings. Back in the day, analyzing images meant sifting through them manually to find the key details, which could be slow and often led to mistakes. But now, deep learning has completely flipped that process on its head. Today's systems can automatically zoom in on what really matters in an image. One of the driving forces behind this leap is Convolutional Neural Networks (CNNs), a technology that makes all of this possible. These come in two flavors: 2D and 3D. 2D CNNs are great for looking at single images—whether they're in color, black and white, or even just simple black-and-white outlines. 3D CNNs, however, are built for video, helping the system understand how things change from one frame to the next, essentially tracking movement over time.

2) LiDAR: LiDAR measures the time it takes for laser pulses to return after colliding with nearby objects. This helps it determine the precise distance of those objects. Despite having a shorter range and usually costing more than radar, LiDAR is far more accurate. The disadvantage is that bad weather, like fog or snow, can obstruct the laser signals, making it hard to use. However, one of its biggest benefits is its ability to create extremely detailed 3D maps, or "point clouds," that give a clear and accurate picture of the surroundings. These maps are very helpful for determining distances, spotting obstacles, and improving navigation accuracy.

3) Global Positioning System: GPS provides the position data—longitude, latitude and elevation—that RSMRs need to navigate and position themselves accurately. That position data—along with precise timestamps from satellite signals—

also helps vehicles sync up and collaborate smoothly. Real-time map updates that improve environmental models and optimize route planning are another benefit of continuous GPS monitoring. But GPS signals can be less reliable in certain environments—like indoors or areas with lots of obstacles. To get around those issues and ensure more accurate, dependable operation, RSMRs often use LiDAR and IMUs as additional sensors to GPS. That way, they can compensate for the GPS signal's limitations.

3.2 Model Based Decision Making

Table 2: Overview of The Decision Making Models of RSMR

Decision-making methods	Principle	Advantage	Disadvantage	Categories of methods	Models and algorithms
Physical motion model	Newton's laws of motion	It offers a straightforward approach with a deterministic analytic solution and serves as the foundation for some complex and hybrid algorithms.	It is excessively simple and can hardly model the decision-making mechanisms of RSMR in complex environment.		differential drive model, four-wheeled omni-directional model, four-wheeled Ackerman model, four-wheeled Mecanum model, bicycle model [74, 75, 76, 69, 70, 71]
Optimization method	Adjusting the values of variables to maximize or minimize the objective function while satisfying a set of constraints	It has clear meanings and strong robustness, and can perform global search within the feasible solution space.	Non-convex objective functions and complex constraints can lead to significant computational burdens and no assurance of the optimal solution.		linear programming [77, 78], quadratic programming [79, 72, 71]
Path planning method	Based on geometry and optimization methods	It has a clear physical interpretation and can ensure safety by avoiding collisions.	It cannot guarantee the optimal path, and sometimes depends on precise environmental modeling.	Offline path planning Online path planning	Pure Pursuit Control [94], Linear Quadratic Regulator [95], Feedback Linearization [96], [97], Fuzzy Inference System [98] Dynamic Window Approach [99, 100], Rapidly-exploring Random Trees (RRT) [101, 102, 103], and Fuzzy Inference System [86].
Imitation learning	Learning the mapping function from environments to expected actions by observing expert driving behavior	It has strong learning ability that enables RSMR to navigate in the desired manner.	Its training requires a large amount of time and computational resources, and its generalization capability is relatively weak.	Traditional Machine Learning Deep Learning	Support Vector Machine [157], Random Forest [111], Bayesian Network [112], Back Propagation Neural Network [68], Fuzzy Inference System [46, 90, 113] Convolutional Neural Network [35, 114, 65, 24], Recurrent Neural Network [108, 107], Generative Adversarial Networks [33], You Only Look Once [34]
Reinforcement Learning	Learning optimal actions through environment interaction, feedback rewards, and trial and error	It does not require a large amount of manually labeled data or expert guidance.	Its training efficiency leaves room for improvement.		Q-learning [116], Deep Q-learning [117, 118, 119, 121, 50], Policy Gradient Algorithm [39, 118, 120, 119], Actor-Critic Algorithm [50]

3.3 Actuation

Actuators which are mostly electric drive motors and steering servos power RSMRs. The vehicle is moved forward or backward by the electric drive motor which converts electrical energy into mechanical energy. The vehicle's acceleration and deceleration can be controlled precisely by controlling the motor speed and torque. The steering servo changes the steering angle so the

Using proven motion models, optimization techniques and path planning methods model-based decision making helps RSMRs in navigation and decision making. Since these methods are based on mathematical models that accurately describe the vehicle and its surroundings, the results are more meaningful and useful. These models allow RSMRs to choose the best and safest routes while considering all the variables. Table II summarizes the main ideas, advantages and challenges of each approach.

vehicle can turn smoothly. Instead of using traditional controls like accelerator, brake pedal or steering wheel, a lot of research on autonomous driving (AD) for RSMRs focuses on controlling the vehicle's linear and angular velocities whereas full scale autonomous vehicles (AVs). By removing the need for more complex mechanics and sensors this simplifies the control system [36]. The technology doesn't need pedal

pressure or steering angle changes by using velocity as the input, it's simpler and more effective. RSMRs can also react to changing conditions better as they can dynamically change their sensors in real time to ensure they maintain the desired speed. However AD algorithms often require control actions to produce stable and smooth motion. Proportional-Integral-Derivative (PID) controllers, Model Predictive Control (MPC), Linear Quadratic Regulators (LQR), Feedback Linearization, Internal Model Control, and Sliding Mode Control are some of the ways to ensure stability. To keep it simple we'll focus on the two most popular ones: MPC and PID controllers [13].

4. Applications

Obstacle avoidance and navigation have a close link to RSMR autonomous driving research. Global route planning sets the overall direction for the car's entire trip. Once the car starts moving local path planning takes control allowing it to make real-time changes to dodge obstacles. We can split these obstacles into two main groups:

static and dynamic, which help the system adapt to changing situations. This approach resembles planning a road trip. Picking the main route from beginning to end is like global path planning [37]. However, the driver needs to make minor adjustments while driving to avoid barriers, traffic, or pedestrians; this is where local path planning comes in handy. Fixed obstacles are things that do not move, like road signs, buildings, and parked cars, whereas moving obstacles are any things that are moving, like other vehicles, pedestrians, and animals. Because a local route plan must mitigate the unexpected and emergent hazards when safely possible, it is often the number one priority [38]. The RSMR will need complete map data to begin its journey. Along with starting and ending points of the journey, route information includes information about the locations and features of any fixed barriers, including size, shape, and location of fixed barriers. The RSMR is also able to alter its routing based on real time perceptions of moving hazards while driving [13].

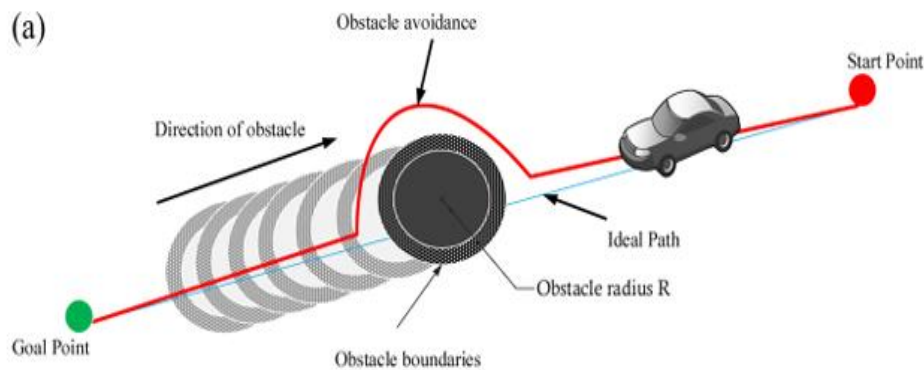


Figure 2: *Navigation And Obstacle Avoidance [34]*

4.1 Vehicle Fleet Coordination

The main purpose of vehicle fleet control is to efficiently manage a set of RSMRs (Robotic Self-Driving Mobile Robots) traveling on similar paths while maintaining a safe distance between them and avoiding collisions. In this scenario, the main goals are to reduce congestion and improve traffic flow. This idea borrows heavily from adaptive cruise control, in the context of the

automobile industry, which has been extensively researched. Fleet control methods have been developed including the behaviour-based approach, virtual structure approach, and leader-follower approach. A more flexible approach is using a time-varying gap which allows the distance from vehicles to vary depending on the speed of vehicles and the distance from each other. For example, Cruz Morales et al. [8] and

Velasco-Villa et al. [9] demonstrated a dynamic gap system that expands as an approaching RSMR closes in on the leading RSMR. This established real-time adjustments allow for fleet coordination greatly improving safety and efficiency, as well as accommodating fluctuations in traffic turning or speeding up or down, however their models do not address the complexity of real world situations, complexity being due to the innumerable potential unmanageable factors (i.e. crossing pedestrians, neighbouring vehicles etc...) and the requirement to yield or slow the vehicle ahead. In these complexity scenarios, vehicles may have to

generate squeeze situations accelerating, decelerating or steering without addressing these variables in standard models.

In addition, most research has occurred for small fleets, usually composed of only two or three RSMRs, so it is not a representative scale of traffic situations in the real world. For example, there might be hundreds of RSMRs in the traffic queue at a busy intersection. Future research should focus on larger fleets and the complications of high-density traffic conditions to increase practicality and scalability of fleet control [13].

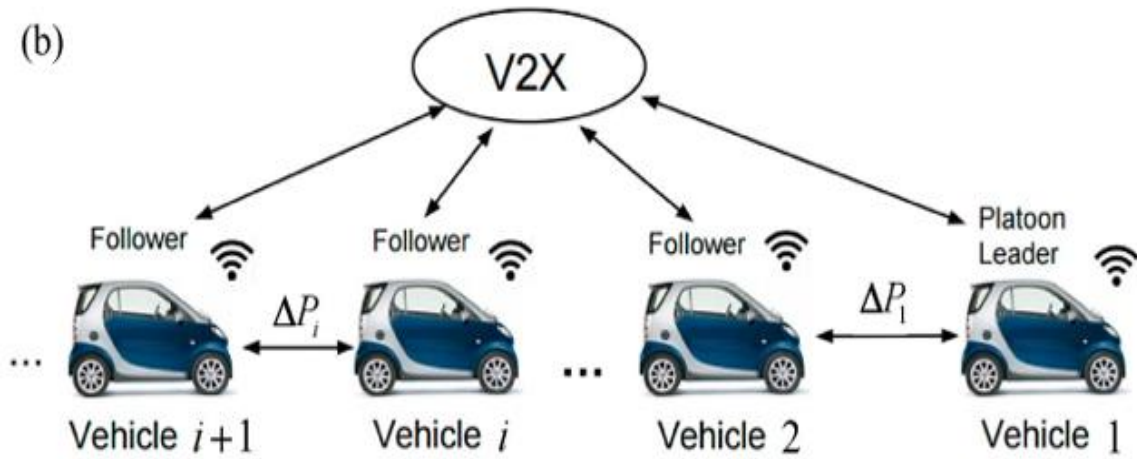


Figure 3: Vehicle Fleet Coordination [35]

4.2 Parking Control

In the case of RSMRs, parking control involves guiding the motion of the car so that it parks exactly in the available parking space. This question has been addressed in a number of studies [10], [11], [12]. One particularly clever approach, by Shen et al. [11], uses a hierarchical controller, and drives a self-driving RSMR (SR) to park, even while another HR is driving in from the opposite direction. The control structure consists of two layers: a high-level strategy predictor and a low-level feedback controller. In the operation of the system, both levels of control are combined. The strategy predictor, powered by a neural network, continuously senses the environment to determine the best possible actions in the situation.

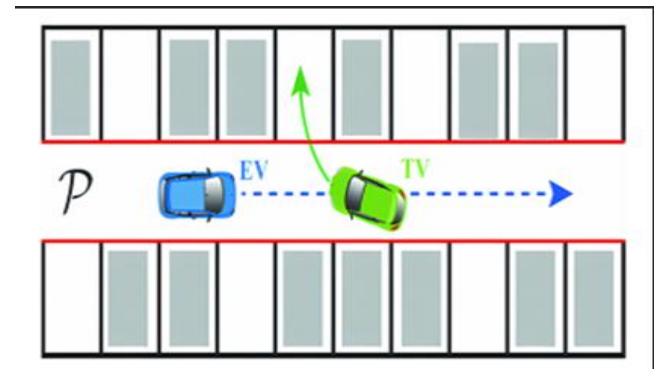


Figure 4: parking control [10]

4.3 Hands-Free Control

When the autonomous driving system requires the driver to take control, the driver should be able to efficiently and quickly regain control of the vehicle. Simple tasks, such as grasping the steering wheel or depressing the pedals, may cause unnecessary delays. In the name of efficiency, Wang et al. [12] designed a hands-free

robotic vehicle control system that allows for a more fluid transfer of control using fuzzy logic. The system utilizes two key indicators of the driver's forearm movement and muscle usage through inertial measurement units (IMUs) and electromyography (EMG). The actions act as visual prompts for the driver and enable the vehicle to interpret the driver's intent without a physical response. The use of fuzzy logic and fair “IF-THEN” rules is used to make sense of

everything, which helps the vehicle select the most appropriate response in real time. This technique also helps ensure the driver is able to engage with the vehicle smoothly and in a reassuring fashion. However, further research needs to be conducted to examine how these beacons mediate driver comfort; specifically, if the technology can be scaled for regular driving situations.

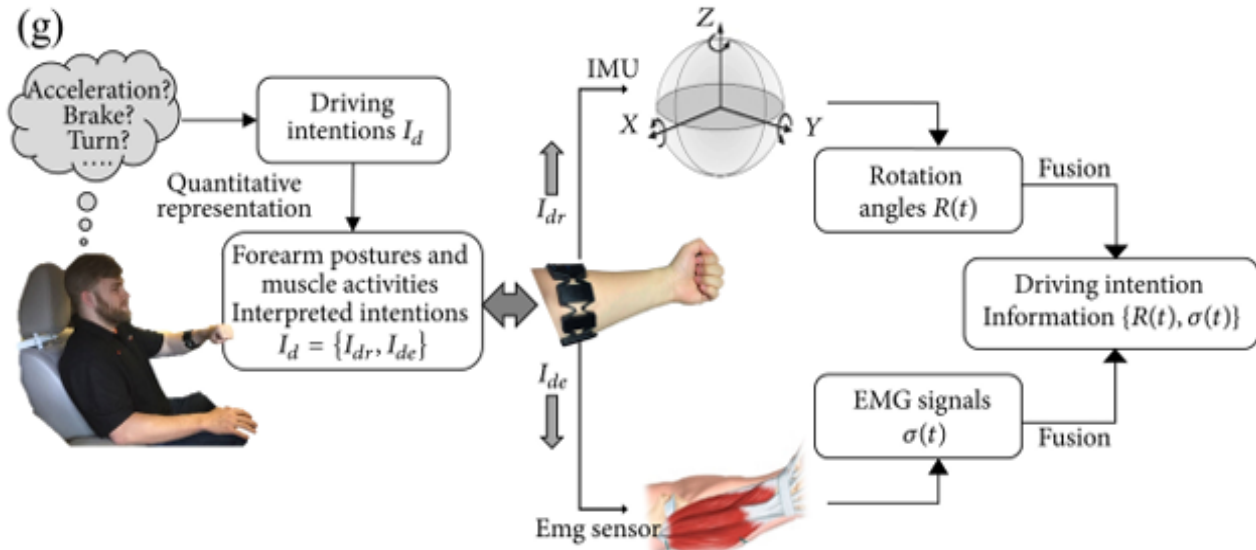


Figure 5: Hands-Free Control [29].

5. Conclusion

This analysis looks at three key dimensions of autonomous driving (AD)—perception, decision-making, and actuation. It touches on important uses currently being researched—navigation, parking, obstacle avoidance, vehicle fleet coordination, and intersection management—but will examine the technologies and techniques commonly utilized in one of these fields. The main aim of research on robotic self-driving mobile robot (RSMR) is the development and evaluation of algorithms that can implement this array of uses efficiently in real life. These brands of research provide essential perspectives that inform the development of applications for autonomous driving in the real world. RSMRs yield more precise information than simulation experiments alone, although RSMRs can simulate many aspects of real traffic and vehicle behaviour. Also, it is critical to remember that

controlled experimental environments cannot imitate the complexity and randomness of real traffic conditions. While much of the current work is aimed at completely autonomous RSMRs, fully autonomous cars are still currently testing and development. Human and autonomous cars are likely to make the predominant part of traffic in the next several years. Models that examine cases in which some RSMRs are completely autonomous and others are hand-operated would help in understanding how both groups co-exist.

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