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Autonomous Convoying: A Survey on Current Research and Development

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ABSTRACT Convoying or platooning with a fleet of autonomous vehicles, which is denoted as autonomous convoying in this paper, has attracted increasing attention from the research communities, governments, and private sectors in recent years. Autonomous convoying offers immense opportunities due to its potential in enhancing logistical efficiency as well as reducing road incidents/accidents by eliminating human errors due to stress and fatigue. While humans can make complex decisions, involving humans in decision-making processes often causes delays as compared with those of automated machines. Indeed, human errors cause approximately 90% of road accidents and fatalities. Efficient platooning techniques can also reduce fuel consumption and carbon footprints. This paper presents a concise survey on current research and development initiatives in autonomous convoying while critically discussing the underlying techniques and technologies developed in this domain. Implications of autonomous convoying toward different industries are also analyzed and discussed.

INDEX TERMS Autonomy, convoying, sensor fusion, defense, platooning.

I. INTRODUCTION

A convoy refers to a fleet of moving objects (e.g. vehicles or robots) traveling together under the same command. Moving a fleet of vehicles by following one leader decreases the need for human intervention in operations. There is extensive research in truck convoying in recent years [1]. The functionalities of trucks include delivering goods, moving furniture, people, etc. Although there are several options for delivering goods in small locality, such as using cars, motorcycles, or even drones, people mainly rely on large vehicles to deliver food supply and equipment due to cost effectiveness [1], [2]. A convoy of ships is a common technique of transporting goods and military equipment overseas. People often rely on trains in land transportation [3]. However, rail networks are not available in many places, especially where the population density is low. Since trucks move on roads, truck convoying is becoming popular for transporting goods in many areas [4].

The term autonomous driving is synonymously used as self-driving of vehicles or driverless vehicles. In an autonomous driving scenario, a vehicle moves autonomously towards its destination. In an autonomous convoying scenario, a group of vehicles moves following a single command and considering the presence of other vehicles in the group [5]. Fig. 1 presents an example of an autonomous convoy of military trucks. Autonomous driving and autonomous convoying are two growing research domains. Fig. 2 and Fig. 3 present the number of published papers related to autonomous driving and autonomous convoying from 2005 to 2019, respectively (statistics gathered from Google Scholar on 17^{th} October 2021). As can be observed, research and development (R&D) in autonomous driving far exceeds that in autonomous convoying, noting that autonomous driving research covers that in autonomous convoying. Since R&D on autonomous convoys requires a larger investment, papers pertaining to autonomous driving are roughly 50 times more than those in autonomous convoying.

In this paper, the term autonomous convoying and autonomous platooning are used synonymously. In a convoy, a group of vehicles travels together, providing mutual support and protection [6]. The word ‘platoon’ indicates a group of

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FIGURE 1. An example of autonomous convoying of military trucks consisting of a leader and two followers (Photograph taken during a project demonstration with the Australian Army).

soldiers receives commands from a leader and acts accordingly. However, autonomous platooning is known in the research community as a group of autonomous vehicles moving by following a leader vehicle [7]. There are research studies that focus on efficient autonomous platooning with better fuel efficiency and better usage of road areas [8], [9]. Several researchers have proposed artificial intelligence (AI)-based solutions for the efficient organisation of vehicles [10]. Small vehicles designed to operate at a high speed are efficiently deployed to minimize air drag. Indeed, air drag costs a significant portion of fuel in large vehicles. Therefore, several research studies investigate the use of machine learning methods for prediction of air drag [11], [12]. It is anticipated that more machine learning-based solutions will be available over time.

Many research initiatives received initial funding for military or exploration purposes. As an example, data compression and aircraft research activities were funded mostly for military and exploration applications in the early stages. The resulting benefits have spread across various fields. In this respect, autonomous convoying, which is an emerging technological development, is currently a key area in military research [13], [14]. Military trucks need to ensure continuous supply for troops and civilians. They are prone to attack from enemies and unexpected situations in contested environments subject to extreme weather or geographic conditions. Robust and reliable autonomous convoying technologies can potentially reduce the number of fatalities, fuel consumption, and deaths due to accident.

Autonomous convoying also offers immense commercial potentials. Several companies have started R&D into realisation of efficient and effective autonomous convoys.

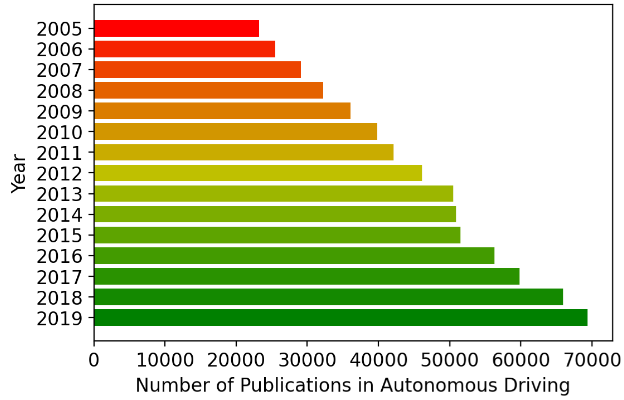

FIGURE 2. The number of publications in autonomous driving in recent years. (Google Scholar, accessed on 17^{th} October 2021).

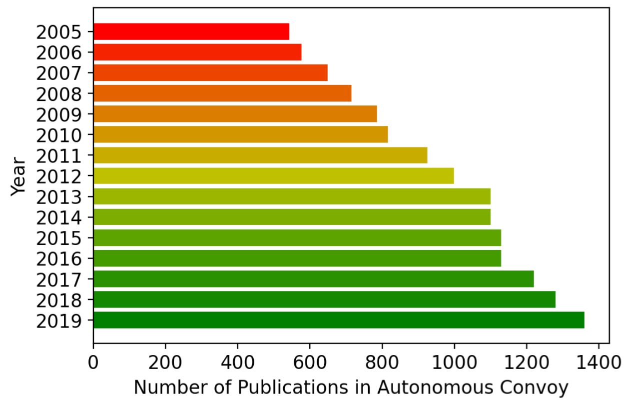

FIGURE 3. The number of publications in autonomous convoys in recent years. (Google Scholar, accessed on 17^{th} October 2021).

A semi-autonomous fleet of trucks reached the Dutch port of Maasvlakte on 7^{th} April 2016 after traveling across Europe as part of the European Truck Platooning Challenge [4], [15]. In this voyage, trucks remained close to each other, in order to move on roads efficiently and to save time and fuel. The distance between trucks is optimized to minimize air friction. The trucks adjusted the distance between them when any vehicle came into the convoy. Trucks communicated using GPS, Radar, and Wi-Fi, and human drivers were presented in each truck to handle emergencies.

The remaining of this paper is organized as follows. Section II presents autonomous convoying methods and techniques through literature review. Section III presents the capabilities with respect to constructing a successful follower in autonomous convoying. Section IV describes R&D in autonomous convoying in different industries. Section V presents advanced techniques for realizing autonomous convoying. Concluding remarks are given in Section VI.

II. AUTONOMOUS CONVOY TECHNIQUES

Autonomous vehicle convoys or platoons, where each vehicle follows the same path traveled by the preceding vehicle by keeping a safe distance, have become very popular.

Autonomous convoying requires the application of several techniques, as described in the later part of this section. It utilizes common path planning methods for keeping a certain formation among all autonomous vehicles. It can potentially solve transportation problems and complete specific tasks more efficiently as compared with the use of single autonomous vehicle. Multi-vehicle convoys are mostly used in military when personnel and resources need to be transported to different locations, and traveling in a convoy provides extra protection for both vehicles and personnel in adverse environments. In addition to military convoys [16], [17], other sectors include commercial vehicle convoys [18], [19] as well as public urban transport convoys [20].

When a convoy of vehicles travel on the road with ideal weather conditions and clear painted lines, a computer vision-based method can be used to detect the painted road lines and keep vehicles in convoy on the road. However, the images of road lines deteriorate due to weather conditions, obstacles, and missing lines, leading to potential failures in utilizing vision-based control methods [21].

Some autonomous convoys apply a leader-follower approach. In this approach, one vehicle becomes a leader, and other vehicles follow the leader. One can design a follower with lower control complexity in a leader-follower configuration with the help of a leader detection algorithm. Such a follower tracks the leader in an off-road situation and in absence of other vehicles. However, moving under congested traffic conditions and sharp road boundaries requires more consideration. It is possible for the leader to deviate slightly from the expected movement, and uncertainty in the follower system can drive the follower out of the road. When the vehicle convoy is in a city or within certain confined environments in industrial settings, such anerror can lead to unwanted events, e.g. hitting a person or an object, destroying a landmark, etc.

A leader-follower convoy configuration consists of a leader vehicle and one or more follower vehicles. Each follower vehicle obtains the direction signals from its preceding vehicle to stay on the travel route. During convoying, these autonomous vehicles use sensing systems to maintain a safe distance from the front vehicle. Every vehicle in an autonomous convoy knows the path and last stop beforehand as well as the current location along the path in real-time. In this respect, the vehicle to vehicle (V2V) communication method [22]–[24] is useful to share information from the leader vehicle to the convoy system and other follower vehicles. As such, an autonomous convoying system requires a shared travelable path, including a map with path points, poses, speed, and other target tracking information through sensors in each vehicle.

As a full autonomy of the vehicle convoy is yet to be achieved, several research groups are working on different approaches to realize autonomous convoying. Some of the existing methods focus on the global positioning system (GPS) and inertial sensing, which can cause computational latencies due to scene generation,

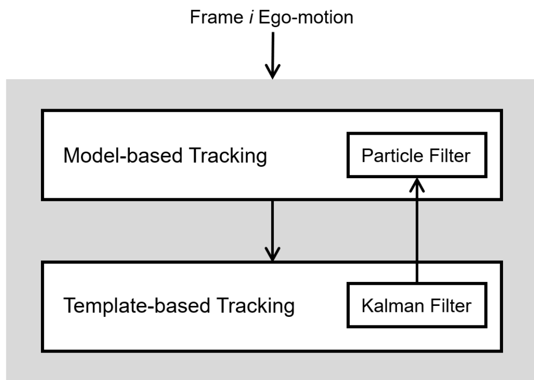

FIGURE 4. The combined model-based and template-based vehicle tracking architecture [25].

simultaneous localization, as well as real-time object detection and classification. Moreover, methods that use the GPS data of the leader do not necessarily deliver enough accuracy to keep an appropriate convoy traveling path. Inaccuracy in GPS data deteriorates the performance of autonomous convoying. There are some other non-GPS-based approaches where each vehicle tracks its predecessor without resorting to waypoints. However, these methods are not applicable for a large convoy due to accumulative errors with respect to following information [21].

Besides computational latencies, fusion methods are also unable to obtain an acceptable accuracy for long convoys. There are some other drawbacks in using autonomous convoying, including the risk of tracking interruptions, which can be catastrophic for travelling in a convoy. According to [26], an embodiment relating to V2V communication is necessary for allowing safe vehicle convoys by using proper communications between the vehicles [27]. Such embodiment method proposed in [26] enables autonomous vehicles in a convoy to move along a path with a leader vehicle being in communication with at least one of the follower vehicles. The leader can be either in an autonomous mode or in a driver-based mode. The wireless data between vehicles can combined with other vehicle sensor data using methods based on real-time GPS and sensor errors aiming to obtain a precise and safe target tracking analysis of locations for the follower vehicles. Using the proposed method, at least one follower should receive communication pertaining to the target offset position and path data. The target offset position provides a target position relative to the leader vehicle and the path information, including a route history and predicted route of the leader vehicle. The route data can include a global position and a GPS solution of the leader vehicle. Tracking data, including a traveled route of the leader vehicle, can be obtained from sensing equipment of at least one of the follower vehicles [26], [28], [29]. The route data and tracking data are compared, to ascertain accuracy between the route data relative to the tracking data. By observing the tracking data and itinerary data, the target offset location is adjusted. A set of route points is computed to offer a trajectory

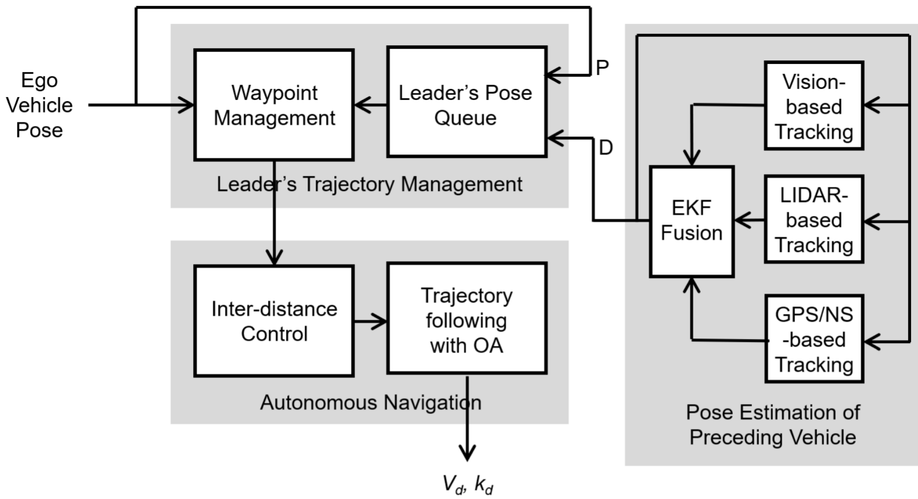

FIGURE 5. General framework of autonomous convoy for each vehicle [22].

travel path from an existing location of at least one follower to the adjusted target offset location. Thus, at least one follower can produce the essential control signals to autonomously transition the follower along with the set of trajectory points to the adjusted target offset location.

Petrov [30], Petrov and Boumbarov [31] developed a kinematic model of a two-vehicle convoy and a vehicle following adaptive tracking controller. The follower vehicle combines lateral and longitudinal control to track the trajectory of the leader vehicle. The follower also maintains a desired inter-vehicle gap. A standard robotic method with homogeneous transformation matrices for modeling the system dynamics is used. The main challenge in developing the controllers for autonomous vehicle tracking is to determine the right trajectory for the follower vehicle. Following the leader vehicle on a curved road segment with a larger or smaller radius and cutting corners is unacceptable.

As the linear and rotational velocities of the leader vehicle and its path curvature radius are unknown constant parameters, the developed adaptive tracking controller using adaptive control law results in asymptotic stabilization of the closed-loop system in error coordinates. The controller receives the relative inter-vehicle positions, orientations as feedback controls as well as approximated velocity of the leader vehicle. With this information, the controller calculates the control velocities of the follower vehicle. With respect to constant velocity maneuvers of the leader vehicle, the two-vehicle convoy can travel concentric arcs of similar radii, keeping a suitable distance between vehicles. This solves the "cutting the corner" issues. For time-varying velocity maneuvers of the leader vehicle, the developed controller in [30], [31] can potentially achieve ultimate boundedness of the closed-loop system in error coordinate. Ollis [21] developed methods for position estimation of an autonomous vehicle convoy. Methods include initializing a convoy state, choosing the next sensor reading, predicting a convoy state, updating the convoy state, and broadcasting the convoy state to vehicles in a multi-vehicle convoy.

Fries *et al.* [25] proposed a robust vehicle tracking system for an autonomous convoy in urban and unstructured environments. A monocular camera is adopted as a nonstationary passive vision system. Passive vision sensors are popular as they are inexpensive and have low power consumption. The advantages of model-based tracking systems [32] and template-based tracking methods using various features to accurately estimate a 3D vehicle pose and the associated velocity combined with a fast (re-) initialization approach are evaluated. Fig. 4 presents a combined model-based and template-based vehicle tracking architecture. The model-based method utilizes a particle filter that requires a hypothesis when the system starts and with the presence of a tracking loss. As such, the template-based tracking method needs to re-initialize the particle filter to detect the tracked leader vehicle rapidly. The results of the proposed method show that vehicles that are not properly visible can be tracked in various weather conditions. A vision-based convoy system with a combined pan-tilt-zoom camera mechanism using the monocular camera was developed [16]. The camera keeps the leader in the follower vehicle's field of view while following the path of the leader vehicle. However, a vision-based convoy is not robust against poor visibility and extreme weather conditions.

Zhao *et al.* [22] developed a general framework comprising a real-time leader path following control system, as depicted in Fig. 5. The system consists of pose estimation of the preceding vehicle, leader path queue management, and autonomous controller for convoying. Algorithms for waypoint management, vision & LIDAR-based vehicle tracking, EKF-based data fusion, adaptive inter-distance control, and model-based trajectory with obstacle avoidance are

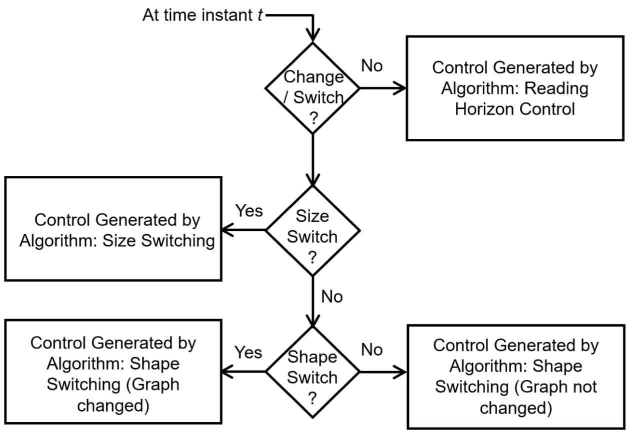

FIGURE 6. A flowchart for handling size/shape switching [33].

developed. Evaluated on unmanned ground vehicles in different terrains, including off-roads, the results show that the proposed method works efficiently and robustly under environmental disturbances. The system robustness is further enhanced with algorithms for multi-modality fusion-based preceding vehicle trajectory estimation and leader waypoints management. Higher velocities and shorter inter-distances are obtained by applying the developed longitudinal and lateral navigation control method.

Algorithm 1 Reading Horizon Control [33]

Measure: The current state vector z
Calculate: u and z for $[t, t + t_f]$
Apply: $u = \bar{u}$ for the period $[t, t + \delta]$
Update: $t \leftarrow t + \delta$
Return: Start of Size/shape Switching Algorithm

Algorithm 2 Size Switching [33]

Measure: The current state vector z
Update: d as αd
Calculate: u and z for $[t, t + t_f]$
Apply: $u = \bar{u}$ for the period $[t, t + \delta]$
Update: $t \leftarrow t + \delta$
Return: Start of Size/shape Switching Algorithm

Algorithm 3 Shape Switching (Graph Not Changed) [33]

Measure: The current state vector z
Update: d
Calculate: u and z for $[t, t + t_f]$
Apply: $u = \bar{u}$ for the period $[t, t + \delta]$
Update: $t \leftarrow t + \delta$
Return: Start of Size/shape Switching Algorithm

Jond *et al.* [35] implemented a formation control objective to drive multiple agents for obtaining a pre-defined constraint on their states with a proposed method incorporating

Algorithm 4 Shape Switching (Graph Changed) [33]

Measure: The current state vector z
Update: D, W, d
Calculate: u and z for $[t, t + t_f]$
Apply: $u = \bar{u}$ for the period $[t, t + \delta]$
Update: $t \leftarrow t + \delta$
Return: Start of Size/shape Switching Algorithm

a quadratic performance index using graph theory [33]. The multi-agent system dynamics are applied as a controllable linear system. The solution of the control law is a nonlinear function of the graph Laplacian matrix and formation of desired distance vectors. Algebraic Riccati equation solution leads to a solution matrix a receding horizon control law in a closed form. A control structure including four algorithms based on closed-form control to handle formation size/shape switching is developed, as shown in Fig. 6. Initially, the convoy follows Algorithm 1. The convoy needs to tune its shape due to obstacles. The convoy also needs to tune its size for any change in the vehicle number. According to the received signals from an external observer or a decisionmaker, the vehicle that is equipped with sensors selects a control mode at each sample time. The control loop stops when the formation control objectives are met. The simulation results of this study indicate efficiency of the proposed solution.

Formation control in an autonomous convoy refers to adjusting the vehicle control inputs to form and maintain a predefined shape and moving configuration. Platooning is a linear formation that mostly considers the longitudinal coordinated control of vehicles [36]. Mohamed-Ahmed *et al.* [37] designed a coupled longitudinal and lateral control method for autonomous convoying using nonlinear predictive control, aiming to track a trajectory. This method enables controlling a convoy using accessible information and following a leader's path while keeping a safe distance between vehicles in the convoy to eliminate any possible collisions. The proposed nonlinear model controls different components. Accelerating and braking wheels control the longitudinal motion of the convoy vehicles. The steering angle is responsible for lateral motions.

The nonlinear control method proposed in [37] provided precision in performance with trajectory tracking of lateral convoy motions. It is also robust when the parameters are not accurately calculated. The control rule ensures a safe distance between vehicles to eliminate any possible collision using longitudinal control while the convoy moves with a similar leader velocity. Accumulation of the convoy tracking error is negligible using the proposed control method. Kato *et al.* [38] developed a new multi-lane platooning method for maximizing safety of cooperative autonomous vehicles on highways. A predefined number of vehicles (up to 5) is engaged in a convoy, including the leader. Using a multi-lane group control method, the level of safety improves as a vehicle collaborates with other vehicles in the same lane

TABLE 1. A summary on autonomous convoying techniques in several published studies.

Paper	Year	Implementation	Ground	Vehicle	Objective	Features / Comment	Affiliation*
[16]	2009	Demonstration	On- & off-road	Robot	Development of a vision-based robotic follower system	One of the best works during the time of its publication. The approach has common limitations of tracking algorithms that rely only on the visual.	Defence R&D, Canada
[17]	2004	Military test	On- & off-road	Robot	Development of both 1) Perceptive follower and 2) Delayed follower.	The perceptive follower stays close to the leader, The Delayed follower follows previously recorded path.	Thales Land & Joint Systems, France
[18]	2003	Simulation	On-road	Truck	Development of both 1) Perceptive follower and 2) Delayed follower.	They have demonstrated several issues of long vehicles in the simulation environment.	University of Illinois, USA
[34]	2003	Demonstration	Highway	Car	Laser based autonomous lateral vehicle following control.	As they are using laser, their algorithm is robust against light fluctuation.	University of California, Berkeley, USA
[20]	2015	Demonstration	On-road	Car	Autonomous convoy driving in absence of light.	Uses internal navigation system (INS), camera, and LiDAR. Capable of estimating the relative 3D position and orientation, the velocity and the steering angle of the leader.	University of the Bundeswehr, Munich, Germany
[21]	2014	Design	On- & off-road	Any	Autonomous convoy with several capabilities: 1) Updating parameter model 2) Processor, memory, communication interface. 3) Set of instructions.	No demonstration or simulation in this work. Only the system design.	Neya Systems, USA
[22]	2017	Demonstration	Terrain	UGV**	A practical real-time leader's path following control system.	A robust work. Many capabilities were demonstrated. System Framework, Waypoints Management, Pose Estimation, Data Fusion, Obstacle Avoidance, Inter-Distance Control, etc.	China North Vehicle Research Institute, China
[25]	2013	Demonstration	On- & off-road	Car	Robust method for vehicle tracking with a monocular camera.	They present a template-based solution using different features to estimate a 3D vehicle pose.	University of the Bundeswehr, Munich, Germany
[26]	2015	Design	Any	Any	Efficient communication between the leader and the follower.	No demonstration or simulation in this work. Only the system design.	GM Global Technology Operations, USA
[30]	2008	Simulation	Any	Any	Modeling of a two-vehicle convoy. Proving concepts with equations and simulations.	Detailed mathematical modeling. Assuming that the leaders' position, linear/angular velocities are known to the follower. There might be uncertainty in real scenarios.	Technical University of Sofia, Sofia, Bulgaria

* Affiliation of the first author.
** Unmanned Ground Vehicles.

as well as neighboring lanes. Marjovi *et al.* [39] developed a technique where a convoy of autonomous vehicles adapts to the path on a road, and different vehicles can join or leave the convoy using a complex messaging system. However, the convoy fails to adapt to changes in terms of road shapes and impacts from other vehicles. Both longitudinal and lateral convoy algorithms are coordinated, since they are necessary for different vehicle maneuvers, including adaption to road shapes, lane changes, as well as maneuvering and overtaking operations [40].

Many researchers apply various multi-agent system-based algorithms in formation control of autonomous convoys. The formation control approaches include vision-based leader-follower [41], heterogeneous line formation using virtual-structure [42], distributed graph-based control [35], and behavior-based methods [43]–[46]. The leader-follower formation control method for autonomous convoying is one of the most popular methods. However, in case of loss of the leader vehicle, the entire convoy formation fails. To solve this issue, a leaderless formation control mechanism was proposed by Jond *et al.* [33]. Using an optimal formation control strategy for structuring a leaderless autonomous convoy, each agent has the same role in the group. The control problem of an autonomous convoy is modeled in terms of linear dynamics. The convoy formation control problem is studied under the receding horizon Linear Quadratic (LQ) optimal control framework. The LQ modeling approach to formation control is used because of the analytic tractability of LQ problems. Using the proposed method [33], the formation control objective to drive multiple agents for obtaining a pre-defined constraint on their states is implemented by applying a quadratic performance index with graph theory [47].

The study in [5] proposed a tracking control method of a convoy of autonomous vehicles to avoid any possible collisions while following a pre-defined path. A coordinate transformation method is used to transform the position errors with respect to each of two consecutive vehicles in a convoy. Transformation is performed from the earth-fixed frame of two consecutive vehicles into their relative position and angle errors to fulfill the predefined transient and steady-state constraints. Using the pre-determined performance method, a nonlinear transformation is used for transforming the constrained relative position and angle errors and achieving an unconstrained kinematic error equation. A new kinematic controller is developed to meet the transient and steady-state performance conditions without causing collisions and controller singularities. Moreover, the Dynamic Surface Control method is applied for simplifying the controller design of the convoy at the dynamic level by applying a first-order filter. An adaptive neural network is employed to keep robustness of the control system against model errors, noise, and disturbances. The Lyapunov theory is exploited to confirm stability of the control system. The overall controller performance for the convoy, including several autonomous vehicles, is tested and validated in a simulation environment, and efficiency of the proposed method is confirmed. A graph-based distributed control approach in a coordinate system parallel to the path was proposed for controlling heterogeneous vehicles aiming to form multi-lane convoys [35]. Every vehicle in the convoy keeps a local graph with information received from close vehicles while the required distances between vehicles are calculated dynamically. This permits quick adaptation to the variations in vehicle numbers and their locations. Through the implemented distributed mechanism, the vehicles in the convoy can collaboratively change lanes. The formation velocity through this method is fixed, and does not satisfy the shifting necessities for various traffic conditions.

The potential field approach is one of the main methods that create corresponding repulsive and potential fields for obstacles, road maps, and target locations. This is a useful approach to model the driving area, measure risk in the driving environment, and enhance the obstacle avoidance capability. A smooth track without any collisions is planned through the potential field approach while keeping the vehicles close to the initially planned path. Gautam *et al.* [48] developed a novel technique for a group of multiple robots to establish a chain form from the beginning position to the end position by combining the A*(A-star) algorithm. The technique performs path planning based on a static map and the potential field technique to avoid collisions with obstacles. Huang *et al.* [49] applied a combination of the potential field technique and model predictive control (MPC), instead of the gradient descent technique, for optimal path planning and vehicle control. However, the potential field-based techniques do not consider speed planning, which is a significant factor in autonomous driving, owing to limitations of the convoy line length, long-distance communication, and incremental time delay in the traditional configuration of vehicle platoons can cause instability. According to Gao *et al.* [50], distributed graph and potential field offer an effective approach to multi-lane convoy control. The formation changes its strategy using a distributed graph algorithm to enhance adaptability, obstacle avoidance capability, and stability in various traffic conditions. The potential field approach is applied to build the traffic field model, measure the driving environment risk, and enhance the obstacle avoidance capability to complete motion planning. A double-layer controller for distributed vehicle control is implemented. The higher layer is in charge of path planning and speed planning, and the associated layer formation is a graph model for the road map, with the consideration of obstacles. The lower layer is a tracking control layer that performs lateral and longitudinal control. This layer uses vehicle kinematics to conduct speed control and path tracking for the vehicles. Validated in a simulation environment, the results show efficiency of the proposed method, which possesses better capacity and stability while considering unknown vehicle numbers that can communicate with each other locally.

III. CAPABILITIES OF A SUCCESSFUL FOLLOWER VEHICLE

According to our literature search, a successful follower vehicle requires the following capabilities.

A. FOLLOW THE LEADER VEHICLE

The first requirement of a successful follower vehicle is the ability to track and trail the leader vehicle. There can be a desert of vast plain land without any obstacles and traffic rules. The most rudimentary follower vehicle needs to follow the leader vehicle in situations with no obstacles in the path and no traffic rules.

An example of such a simple follower robot can be toy robots following or tracking a colorful ball [51]. In 1998, Sony Corporation [52] developed a toy dog named AIBO, which can track pink or yellow balls. No hard rules like road boundaries, traffic signals, and fear of major accidents exist in their demonstration.

B. FOLLOW THE LEADER VEHICLE IN INTERSECTIONS

Even a naive autonomous vehicle should be able to follow another vehicle in a straight path with a zero steering angle. A robust autonomous vehicle should not fail to follow the leader vehicle in intersections. The follower vehicle needs to stay within the road while turning in the intersection. Moreover, a long follower vehicle needs a certain maneuver for turning.

When a vehicle convoy transverses along a path in a city, it is expected to encounter traffic lights, which can cause the follower vehicle to lose the leader vehicle. As such, the follower vehicle needs to be able to join the convoy after separation. Several researchers have developed robust follower techniques and applied them in simulation environments [53] or real-world conditions [54].

C. COLLISION AVOIDANCE CAPABILITY

Many researchers have prescribed a separate collision avoidance module for an autonomous system [55], [56]. A follower module can fail to consider details of the road, other vehicles, landmarks, and pedestrians, leading to potential accidents. A dedicated emergency module can help the vehicle to avoid many undesired incidents [54].

D. PEDESTRIAN AVOIDANCE CAPABILITY

An autonomous vehicle needs to detect pedestrians and other moving obstacles. As an example, the autonomous vehicle needs to detect and wait when a pedestrian crosses a road. Another scenario is when a person stands on the side of a road for a long time, the autonomous vehicle needs to detect and avoid the pedestrian [57].

E. CONSIDERATION OF STANDING AND MOVING VEHICLES

An autonomous vehicle needs to travel through different types of roads. One possible scenario is the detection and understanding the condition of a vehicle near the corner of a road. Since there is a possibility for a parked vehicle to appear at the corner of a road, the autonomous vehicle needs to know whether another vehicle is moving or otherwise. If it is a slow-moving vehicle, the autonomous vehicle also needs

FIGURE 7. Negotiation between vehicles at an intersection: An autonomous follower truck needs to detect other vehicles at an intersection and negotiate with them (Photograph taken during a project demonstration with the Australian Army).

FIGURE 8. Driving on a dirt road: An autonomous convoy needs the capability of operating on not just quality tarred roads but also dirt roads without markings (Photograph taken during a project demonstration with the Australian Army).

to detect the movement of that vehicle for planning its own maneuverability [54], [58].

F. ABLE TO NEGOTIATE IN INTERSECTION

The negotiation capability of an autonomous vehicle at an intersection is critical. Based on the position of other vehicles, the autonomous vehicle needs to decide. However, negotiating at the intersection is the task of the leader vehicle. A follower vehicle does not need to negotiate at an intersection unless it is separated from the leader vehicle by traffic signals [59], [60]. Fig. 7 presents a scenario of an intersection, where an autonomous truck needs to negotiate with another vehicle.

G. ABIDING ROAD CONVENTION

An autonomous follower vehicle needs to obey road conventions of a country. Depending on the regulations of a country, vehicles travel either on the left or right lanes. As such, an autonomous vehicle needs to consider vehicles coming in the opposite direction. Road conventions are also required while overtaking other vehicles or allowing overtaking by other vehicles [61], [62].

H. IDENTIFYING OVERTAKING VEHICLES

When a convoy of vehicle transverses along a road, its speed can be slow and a vehicle may want to overtake the convoy.

The message pertaining to existence of such a vehicle has to be conveyed from the follower vehicle to the leader vehicle. Moreover, all follower vehicles should not confuse the overtaking vehicle as an obstacle [54], [63]. In addition, heavy autonomous vehicles do not change lanes frequently. So, the convoy of autonomous vehicles needs to consider the overtaking vehicle can appear either from the left or right lane.

I. LENGTH OF A VEHICLE CONVOY

A vehicle convoy can consist of many autonomous trucks. Companies have demonstrated convoys of up to ten trucks. When a vehicle overtakes, another vehicle from the opposite direction can appear [54]. The vehicle convoy can face a change with respect to the road width during the course of traveling. The overtaking vehicle can come to the same lane as that of the vehicle convoy. The relevant follower vehicle should give way for the vehicle to enter the lane. The overtaking vehicle can start another attempt later. As such, the follower vehicle needs to keep communicating with the leader vehicle with respect to maneuverability of the overtaking vehicle. The follower vehicle can adjust and maintain an appropriate distance when the overtaking attempt commences again.

J. SENSING THE ROAD PROPERLY

An autonomous vehicle needs to sensorise a road properly. When a road has multiple lanes, the autonomous vehicle needs to detect the available lanes. The algorithm and sensor systems have to be robust enough to detect the road scene under varying weather conditions, presence of other vehicles and pedestrians, or occlusions that can degrade detectability of the road conditions [64].

K. DRIVING ON DIRT ROADS

A vehicle convoy can be useful for sending goods to rural and remote locations, which may not have painted roads. In many contested conditions, autonomous trucks need to travel on dirt roads or mountainous tracks [65]. The implementation of a robust autonomous convoys in such conditions is beneficial. Fig. 8 depicts an autonomous convoy travelling on a dirt road.

L. NIGHT OPERATIONS

A robust autonomous vehicle needs the path following capability, even in the absence of light. Night operations can be under lit or unlit conditions [54]. As such, night operations of an autonomous vehicle need the assistance of information from multiple sensors. Choi *et al.* collected GPS, LiDAR, stereo, thermal image, and RGB stereo images to produce a combined data set for night operations of autonomous vehicles [66].

M. DYNAMIC REROUTING

Typically, an autonomous vehicle performs a rough path planning before starting its journey. Due to obstacles and potential hazards, the vehicle needs to dynamically change

FIGURE 9. Proof of autonomy by lifting hands by a driver (who takes over vehicle control only during emergencies) while the military truck moves on a dirt road (Photograph taken during a project demonstration with the Australian Army).

its routes when the initially planned path is unavailable [67]. The capability of dynamic routing, which is the process of selecting an optimal path given the current traffic conditions, is therefore crucial in autonomous convoying.

N. CONSIDERATION OF THE VEHICLE LENGTH

Research studies on autonomous cars attempt to narrow the vehicle length, since the driving seat is not required. However, in autonomous convoying with trucks, the vehicle length is a key concern [68] because maneuverability, speed limits on intersections, and overtaking considerations are different.

O. BOTH FORWARD AND BACKWARD MOVEMENTS

A follower vehicle may need to perform a backward movement in unforeseen situations. Any blockade on the road can cause the entire autonomous convoy to move in the backward direction until the leader vehicle reaches a previous intersection. Many goods loading and unloading spots are located at the end of a road. Backward driving is different for long vehicles due to the jack-knife effect [69]. This backward movement capability needs to avoid collision with objects, pedestrians, and other vehicles. Therefore, a follower vehicle needs the ability to move in a backward direction on straight roads, bent roads, intersections, and other conditions robustly, efficiently, and safely.

P. ROBUST COMMUNICATION

A robust and secure short-range communication capability among autonomous vehicles is important. Communication should not be affected by other vehicles or any malicious intrusions. Ucar *et al.* [70] proposed a visible-light hybrid communication-based platoon using the front light of the follower vehicle and the tail light of the leader vehicle. The IEEE 802.11p radio frequency communication technology is also adopted, in order to produce a secure communication system.

Q. PROOF OF AUTONOMY

As autonomous convoying is in its infancy, companies keep a driver at the driving seat of the follower vehicles. This scenario raises the question whether the follower vehicles can move autonomously. As shown in Fig. 9, drivers raise their hands from the steering wheel to prove that the follower vehicle moves autonomously. The driver's duty is to take over control of the vehicle during emergencies [54].

IV. R&D ON AUTONOMOUS TRUCK CONVOYING IN DIFFERENT INDUSTRIES

According to our literature search, the following industries are significantly contributing towards R&D on autonomy and autonomous convoying of trucks.

A. AUTONOMOUS MOBILITY APPLIQUÉ SYSTEM (AMAS) BY LOCKHEED MARTIN

The AMAS Leader-Follower mode links a large fleet of vehicles together as a cohesive convoy. As a result, the follower vehicles can operate without a person in the driver's seat [54]. Lockheed Martin conducted a military user assessment in Carolina in the summer of 2014, and demonstrated driver-assist capabilities in December 2015. The recent solution can perform leader-follower convoying with consideration of moving obstacles and presence of small cars in the middle. These capabilities have been evaluated in both urban and rural environments and low-light conditions. As indicated in the AMAS report, current challenges include barriers and obstacles, rights of way, dynamic re-routing, 4-way intersections, pedestrian traffic, emergency braking, and negotiation in a traffic circle.

Although Lockheed Martin has achieved great progress in convoy autonomy, there exists some confusion in their demonstrations. Negotiation with pedestrians and other vehicles in intersections is still challenging for humans. Humans struggle to decide which vehicle should go first. However, autonomous vehicles can solve this issue through communications. When a human dummy approaches, the truck can move on the other side of the road, or the truck can wait until the dummy crosses the road. Lockheed Martin has not disclosed any clear margin between these two decisions.

B. LOCOMATION

A Missouri-based truck company, namely Locomation, has started a multi-year program on human-guided autonomous convoying. According to the American Trucking Association, in 2018, trucks transported 11.5billion tons of freight and made nearly 800 billion USD in revenue. The demand for autonomous convoying technologies has increased due to COVID-19. Locomation announced that they are working with Wilson Logistics to transport cargo using autonomous trucks, e.g., covering more than 400 miles between Oregon and Idaho in each journey [71]. The company has investigated the use of autonomous follower trucks to deliver goods with less human involvement. This solution also minimizes air drag and optimizes fuel efficiency [72]. Fig. 10 presents an air-drag minimization scenario.

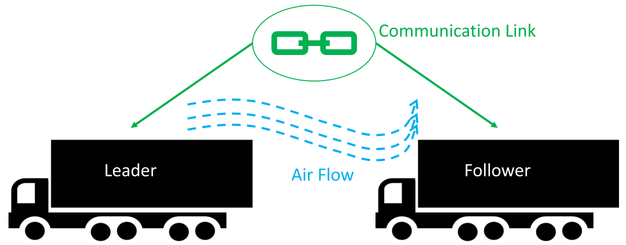

FIGURE 10. A follower truck follows the leader truck in leader-follower autonomy. The requirement of a driver is reduced by almost 50% and the fuel cost is reduced by 8%. The reason of reduction on fuel consumption is a lower air drag in the follower truck. This picture is drawn according to the description of the Locomation convoy in [71].

Vehicles share data on steering angle, acceleration, speed, and the degree of brake and throttle applied. Locomation trucks use an intricate system of radar, lidar, and cameras to observe the surroundings. To avoid blind spots, the trucks are well-equipped with a range of sensors. A place behind the driver's seat is suggested for the driver of a follower truck to rest and sleep after activating autonomous operations. Currently, a driver sits on the driver's seat when automation is enabled. In the future, drivers can leave the seat to take a rest. According to Avi Geller, the CEO of Maven Machines, a comprehensive management system for the fleet is required, as the vehicles are becoming more sophisticated. In the next five years, the driver assistance features may eventually become standard in industries. Locomation has received about 5.5 million USD of funding from different sources. A plan to add the third truck is in place. If they can add the third truck, the driver requirement can be reduced to about 33%. Locomation currently evaluates their autonomous convoying system at the Transport Research Center in Perry.

Many economic issues related to autonomous truck convoying need to be considered. As an example, issues such as whether the driver of the follower truck should be paid during his/her rest period, equal payment for both active and inactive drivers, etc. need to be addressed.

The steps of achieving semi-autonomy are as follows:

- Two drivers sit in different trucks. They start the journey, cross the surrounding urban/busy area with manual driving.
- Then, one truck takes the lead and the other follows.

- Truck drivers can change rules. Trucks can interchange their position, and the leader truck driver can take a rest while the follower truck driver takes over the driving duty.

C. EUROPEAN TRUCK MANUFACTURERS

Volvo is currently evaluating autonomous garbage collection trucks in urban environments [73]. In addition, multiple manufacturers, which include Iveco, MAN, Scania, Volvo Group, DAF, and Daimler [74], have established plans to demonstrate multi-brand autonomous truck convoying on European roads from 2018 to 2022.

D. GOOGLE

A Google spinoff, i.e., Waymo, made use of autonomous trucks to deliver goods to the data centres of Google in Atlanta in 2018 [75]. Currently, they are planning to extend their services to Texas and Mexico, due to commercial potentials. The company conducts test and evaluation in Huston, Dallas, and El Paso. In Mexico, the company perform tests in the southern part of the country. In June 2019, Waymo engaged 13 robotic experts, including Boris Sofman, former CEO and co-founder of Anki, to provide expertise to the company.

E. NATIONAL ROBOTICS ENGINEERING CENTER (NREC) AT CARNEGIE MELLON UNIVERSITY

NREC provides innovative robotic solutions [76]. Recently the center is working on a cargo unmanned ground vehicle. Several capabilities on unmanned ground vehicles have been established, as follows:

1) Vehicles must have instantaneously switching capability among normal, remote, and autonomous driving.
2) Vehicles must be aware of other moving vehicles, vehicles in a convoy, and moving pedestrians.
3) Vehicles should drive safely in varying conditions including the presence of smoke, dust, snow, and rain.
4) Vehicles must navigate robustly with respect to any visual degradation of the path caused by a previous vehicle or any previous event.
5) Vehicles must be capable of operating in different environments, such as open country, mountains, villages, and cities.

An autonomous vehicle requires a good perception capability pertaining to visual objects and their speed. Several planning mechanisms are also necessary, namely:

1) Local planning: generating a short-term trajectory based on recent information to help the autonomous vehicle in lane-following and obstacle avoidance;
2) Global planning: computing the shortest path based on the available global map;
3) Speed planning: setting the autonomous vehicle speed based on the road condition and visibility.
4) Traffic planning: interacting with traffic and other moving obstacles near the road.

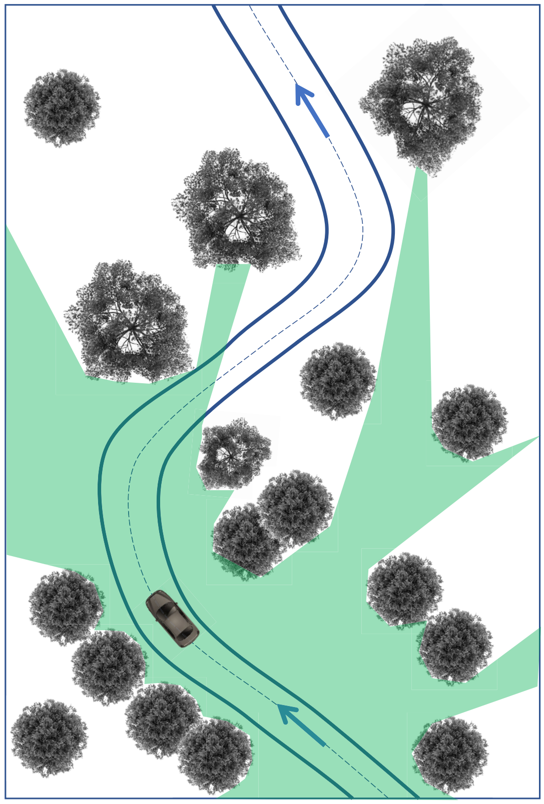

FIGURE 11. Road area, vehicle, and obstacles are merged into a single map (drawn according to the information from NREC [76]). White and green regions represent previously and newly re-explore areas in the map, respectively. An existing map for initial path planning, is required and recent changes of information in the map are helpful in obstacle avoidance and rerouting.

5) Learning: applying machine learning to improve performance.

A local map containing information on previously established areas and newly explored areas is crucial. Fig. 11 depicts a visualization on sensor and map fusion. In Fig 11, the green areas of the map is newly explored regions through sensors, which are merged with previously recorded areas in the map.

F. BAE SYSTEMS

According to a recent report, key vendors in military autonomy are BAE Systems, Elbit Systems, Lockheed Martin, Northrop Grumman, Polaris Industries, and RUAG Group [77]. BAE System is one of the top companies in the business of land artilleries. The company has demonstrated autonomous battlefield unmanned ground vehicles to the Australian Army. However, documents on autonomous convoying capabilities developed by BAE Systems are unavailable publicly.

G. MILITARY RESEARCH IN AUTONOMOUS CONVOYING

Many research areas started with initial sponsorships for defense and exploration purposes. As an example, Shannon's theory and related techniques were heavily sponsored by the space exploration industry in the 1960s. The benefits of these research studies have now been extended to many current compression algorithms [78]. Similarly, while R&D on airplane was initiated by military forces in its early stage [79], air travelling now brings benefits to everyone.

In 2018, the US Army planned to deploy seventy self-driving trucks for supply chain activities, with human supervision in 2020 and full autonomy by 2022 [80]. A human driver is engaged to operate the leader vehicle, while unmanned follower trucks should not lose the leader vehicle in the absence of a clear vision due to rain, snowfall, dust, etc. While humans are very good at driving in such situations, the use of computer vision for autonomous driving is still in its infancy which can fail to act properly in noisy environments. In contested environments, the follower trucks need to consider shell holes, rocks, trees, rubble etc., as well as to recognise animals, pedestrians, and other vehicles.

The US Army is confident in the development of computer vision. The technology can remove manpower from becoming the front-line troops, therefore maximising safety of soldiers. The US Army planned to investigate ten Oshkosh M1075 PLS (Palletized Loading System) trucks and convert 60 more vehicles to self-driving vehicles by 2020 [80].

Note that the leader-follower convoy concept of the US Armay is not in a full autonomy setting. Full autonomy in a convoy of vehicles is expected in 2022. The experiments from 2020 to 2021 are based on the leader-follower combination, where humans are present in the driver seat to handle emergencies. While identifying an optimal path or a moving direction is not difficult, travelling with robust obstacle avoidance capabilities is a great challenge. Autonomous vehicles are not free from accidents, but their performance can be better than humans in the future.

Autonomous vehicles in cities rely on the use of GPS for navigation. Due to hostile terrains or network jammers that can block the reception of GPS signals [80], military research studies utilise an internal navigation system (INS). The INS consists of an accelerometer, gyroscope, and computer algorithms. These algorithms face higher uncertainty [81] when traveling a long distance. Therefore, military robots need to calibrate their estimations from landmarks. Humans also do similar calibrations when travelling without GPS signals. By observing a landmark, humans become certain with respect to distance travelled thus far and the remaining journey. The crucial part of off-road autonomous vehicle navigation is the combined outputs from radar, camera, and lidar. GPS signals serve as a support means, whenever available. The computer algorithms in a leader vehicle are used to detect landmarks and compute the locations and dimensions of landmarks. Information on landmarks is transmitted to follower vehicles. A good INS system can reduce the required number of landmarks. The INS system in US Army vehicles is very accurate, which has only ten centimeters of error after traveling 100 meters. As such, only few calibrations are required, and the number of required landmarks is also low [82]. The combination of INS and landmarks allows a follower vehicle to follow the path taken by the leader vehicle, even after one month. This raises a question on the requirement of a human driver. According to the US Army, a human driver is still needed to handle situations with barriers and bushes that can cause safety issues.

V. ADVANCED AUTONOMOUS CONVOYING METHODS

While humans are good at controlling vehicles, approximately 90% of road casualties are due to human errors. Moreover, recent advancement in technology has brought higher capabilities that surpass human capabilities. Machines can sense a large number of information, and take collaborative decisions within seconds [83]–[85]. Therefore, researchers introduce advanced methods by combining a range of sensors and computational intelligence to develop new autonomous driving technologies.

A. MULTI-AGENT COLLABORATION

Multi-agent-based solutions are important in tackling problems that need collaborative effort. In Fig. 12, two players (denoted by red squares) collaborate to capture (i.e., occupy) the blue square that can change its location dynamically. Grey regions denote walls. Squares can move only in black regions. Capturing the blue square by one player (one red square) is difficult. An efficient collaborative strategy by two players can reduce the number of movements required to occupy the blue square.

Recently a collaborative Artificial Intelligence (AI) model was applied to bring the grandmaster level performance in the game StarCraft II [86]. StarCraft II is an online strategy game. Players need to build a troop of soldiers, construct buildings, and fight with opponents. In the game, the AI agent learns by imitating human players. When a human defeats the AI agent, the strategy of the human is learned [87]. Multi-agent collaboration is based on the consideration of uncertainties associated with the target. These uncertainties vary from situation to situation [88]. It is possible to derive mathematical formulations for small games, as shown in Fig. 12. Training of neural networks by imitating humans is effective for complex games. However, trial and error are not possible during real wars. Multi-agent collaboration is possible in a small part of a war. We anticipate large-scale multi-agent collaborations [89] in real wars when a significant percentage of troops can operate autonomously.

As research in autonomous convoying is in its early stage, multi-agent collaboration is yet to be investigated by companies. Currently, a vehicle needs a human drive to start and end a journey. In the future, it is expected for a vehicle to reach its loading/unloading location autonomously. The vehicle chooses its position in a convoy autonomously with multi-agent collaboration strategy for successful loading/unloading activities.

There are several futuristic academic research on autonomous convoying based on multi-agent collaboration. A recent paper proposed rules for automotive platoons [91].

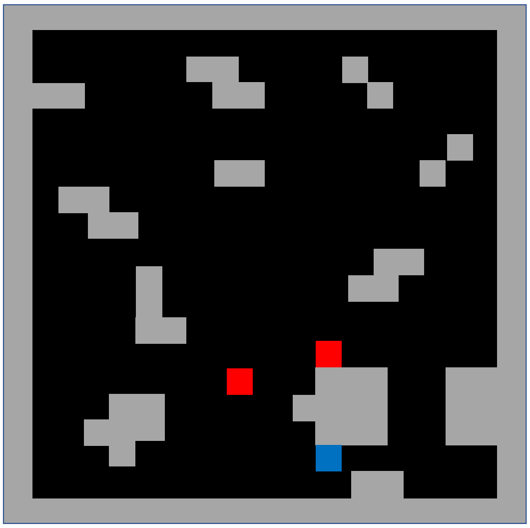

FIGURE 12. An example of multi-agent collaboration (redrawn from an image in Google DeepMind [90]). The objective is for two players (red squares) to collaborate and capture the blue square that can change its location dynamically.

A vehicle can join a convoy either at the end or in the middle position with different control strategies. The joining procedure is as follows:

1) A non-member vehicle sends a joining request to the leader vehicle.
2) If a vehicle joins a convoy at the rear position, the leader vehicle sends back an agreement, provided that the maximum convoy length is not reached.
3) If a vehicle joins a convoy in the middle position, e.g. in front of vehicle Y, the leader vehicle sends an ''increase space'' command to vehicle Y, and the new vehicle receives an agreement
4) Changing lanes to join a convoy is a manual procedure performed by a human driver. Upon receipt of an agreement, the joining vehicle changes its lane.
5) Once the vehicle is in the correct lane, its automatic speed controller is enabled to approach the preceding vehicle.
6) When the vehicle is close enough to the preceding vehicle, its automatic steering controller is enabled, and an acknowledgment to the leader vehicle is sent; and, finally,
7) The leader vehicle sends a ''decrease space'' command to vehicle Y, and when the leader vehicle is informed that spacing has returned to normal, it replies to the acknowledgment message.

The leaving procedure is:

1) A convoy member sends a leaving request to the leader vehicle and waits for an authorisation.
2) Upon receipt of a 'leave' authorization, the vehicle increases its space from the preceding vehicle.
3) When the maximum spacing is achieved, the vehicle switches both its speed and steering controller to 'manual' and changes its lane; and, finally
4) The vehicle sends an acknowledgment to the leader vehicle.

Several research groups also proposed simulators for automated platooning [92], [93].

B. ROAD SEGMENTATION

A road segmentation model takes an image of a road and provides a binary classification output for every pixel. In the training data, the image pixels are labeled as road and non-road. Multilabel semantic segmentation models are employed to segment various objects in the image. Through multilabel semantic segmentation, an estimation of both the drivable surface and objects on that surface can be obtained. The drivable surface includes all pixels with respect to the road, parking spots, lane markings, crosswalks, and even rail tracks. Objects on that surface can be other vehicles, pedestrians, animals, etc. With the information on the drivable surface, an autonomous driving system constructs an occupancy grid. The occupancy grid is constructed by projecting several points of the LiDAR, or RADAR point cloud on the visual image. The random sample consensus (RANSAC) algorithm is a popular method to robustly fit a drivable surface plane model even with erroneous semantic segmentation [95]. The occupancy grid construction algorithms work well on flat road surfaces. The occupancy grid helps an autonomous vehicle to move with collision avoidance capability.

Researchers have also developed road segmentation algorithms based on different types of input data. The most common approach is road segmentation on RGB images [96], [97]. Recently, methods for segmenting roads with LiDAR and RADAR data have also been developed [98]–[101]. There are several road segmentation data sets that exist in multiple forms. Since many new road segmentation methods yield different results, it is difficult to predict which combination works the best in the future. In a KITTI challenge [102], the best results use both image and depth information. Several studies indicate the presence of depth information increases segmentation efficiency [103]–[105]. Fig. 13 presents an example of a road segmentation method where both RGB image and depth information are considered, in accordance with the study in [94].

C. FUSION

Data fusion techniques can be broadly classified into three categories [106]: (i) state estimation, (ii) data association, and (iii) decision fusion. Data, sensors, and decisions fusions are performed for visualization, reliability, and further processing of information.

1) ALGORITHM AND DATA FUSION

In real-world applications, no sensor information is error-free. Moreover, detection or classification models are subject to errors. Assume that the first detection system has a success probability of $P(S_1)$. As such, the probability of failure in the i^{th} detection system becomes:

$$P(F_i) = 1 - P(S_i). \tag{1}$$

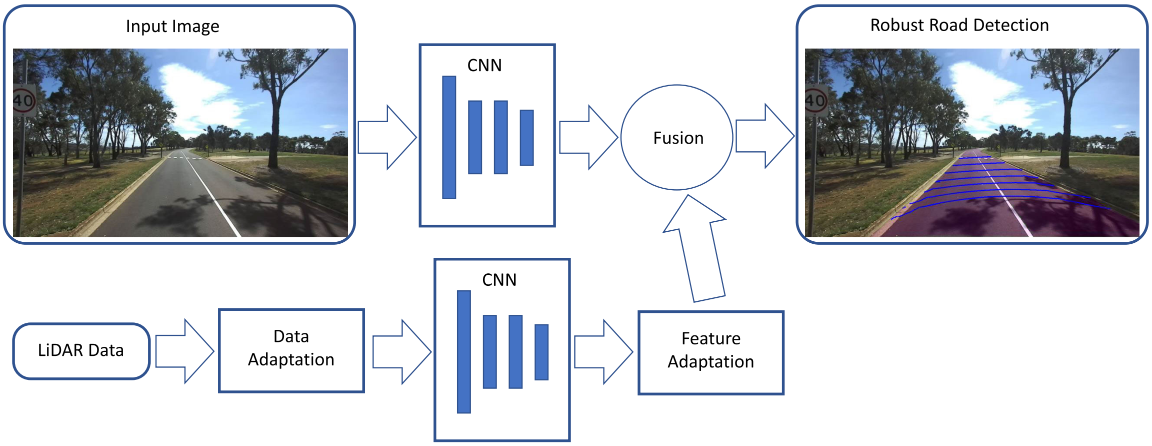

FIGURE 13. Based on [94] , a robust road detection method that incorporate the convolutional neural networks (CNNs) can be developed to combine camera and LiDAR images [94] (Photograph taken during a project demonstration).

Assume that two sensors or algorithms are fused together, and they are independent of each other. Their combined probability of failure is:

$$P(F_1 \cap F_2) = P(F_1) \times P(F_2). \tag{2}$$

The probability of success from both systems is also in a multiplicative form:

$$P(S_1 \cap S_2) = P(S_1) \times P(S_2). \tag{3}$$

However, when the system is used for ensuring safety or detecting obstacles, the outcome from one algorithm or system is considered as the correct detection. The detection success probability from any two sensors or algorithms can be written as follows:

$$P(S_1 \cup S_2) = 1 - P(F_1 \cap F_2). \tag{4}$$

Their combination does not bring success when both of them fail. Combining with Eqn. (2), Eqn. (4) can be written as:

$$P(S_1 \cup S_2) = 1 - P(F_1) \times P(F_2). \tag{5}$$

Therefore, the equation for getting detection success from the fusion of N systems becomes:

$$P(S_1 \cup S_2 \ldots \cup S_N) = 1 - \prod_{i=1}^{N} P(F_i). \tag{6}$$

As $P(F_i) < 1$, multiplying any number with $P(F_i)$ decreases the value, i.e., $P(F_1) \times P(F_2)$ is smaller than both $P(F_1)$, and $P(F_2)$. Therefore, $P(S_1 \cup S_2)$ is greater than both $P(S_1)$, and $P(S_2)$. We can conclude that the probability of success increases with fusion of sensors or algorithms. Moreover, one sensor or computation utility may not work at a certain time. The presence of multiple sensors or algorithms can provide information that allows a greater degree of autonomy in such situations.

Besides detections, algorithms provide prediction of numeric quantities, e.g. steering angle, desired vehicle speed, etc. The mean or median value of numeric quantities can be utilised for further processing. While one prediction system can easily be subject to incorrect outcome, the probability of all prediction systems being incorrect is lower [64]. Moreover, domain experts know the input range of different sensors. They can develop algorithms to select an optimal sensor-algorithm combination under different situations.

2) SENSOR FUSION

Although it is possible to achieve semi-autonomy with single image sensor, such a system may fail in the absence or fluctuation of light condition [107]. Uncertainties exist in information solicited from the environment, sensors, algorithms, and controllers [108], [109]. Therefore, a robust autonomous vehicle is equipped with a range of sensors to minimise uncertainties associated with perception.

The concept of sensor fusion is developed for optimal information processing in multisensory environments [110]. A paradigm of sensor fusion is human perception in food tasting scenarios. Humans perceive food through our eyes, nose, and tongue. Information from all sensors helps a human to identify the underlying ingredients. There are several motivations for sensor fusion, e.g. to accommodate partial or total failure of sensors as well as limited coverage and precision that cause uncertainty. Sensor fusion enables a system to act correctly, in the event of noisy information from certain sensors.

Sensor fusion allows the creation of an internal map that contains various detected objects with different confidence levels. Different sensors have different resolutions and ranges, and they cover different regions. As such, sensor fusion brings benefits pertaining to accurate position, orientation, and situational awareness [111]. There are three general types of sensor fusion: competitive, complementary, and cooperative. In competitive sensor fusion, each sensor derives an independent measurement. A decision is taken based on individual outputs. Competitive sensor fusion brings higher accuracy. In complementary sensor fusion, sensors are combined to provide a more complete definition [112], e.g. images from two cameras can be combined to have a better area coverage. In cooperative sensor fusion, multiple sensors derive combined information that cannot be achieved from using just single or fewer sensors, e.g. understanding 3D structures from multiple image sensors [113]–[115].

Sensor fusion is becoming popular in autonomous driving [116]. An autonomous vehicle uses several sensors, which include camera, radar, LiDAR, odometer, global positioning system (GPS), infrared (IR) devices. Information from a camera is usually useful in the presence of light. However, a change in lighting condition or any painting on the road can cause errors when the detection algorithm relies on images only. Radar and LiDAR are useful in detecting objects under dim conditions. However, it is difficult to classify objects based on radar and LiDAR signals. An internal map and odometer information can potentially help recognise nearby landmarks, even in the absence of light. The combined information from sensors reduces uncertainties of the perceived environment and improves the confidence of autonomous driving [117]–[120].

Sensor fusion can be used to build an occupancy map by combining signals from different sensors, e.g. in indoor navigation [121]. The first stage of building an occupancy map is to transform and combine data. A 2D image from a camera is different from radar or LiDAR data [122]. Therefore, transformation from the image coordinate to robot coordinate through mapping is required [122]. The second stage is combining the information to enhance robustness. Information from various sources (e.g. image sensor, radar, sonar, etc.) is combined using competitive, complementary, or cooperative sensor fusion methods. Algorithms are applied to the combined data for safe navigation. Indeed, sensor fusion makes the information more reliable and reduces the chance of a collision or failure [123]. Obstacles in the occupancy map is generally made larger, in order to prevent potential collisions by autonomous agents [122].

Sensor fusion is a growing field in military applications. The market of military sensor fusion is predicted to grow to 756 million by 2029 [124]. Indeed, sensor fusion has been deployed in various military equipment in several countries, which is useful in target detection, combat vehicles, enemy identification, weapon systems, etc. Combining GPS data with information from an odometer, magnetic compass, gyroscope, and map results in a more accurate occupancy map [125]. Both the position and orientation information of an equipment is required when navigating under dim conditions. Identifying the positions of other moveable objects is important in autonomous convoying, e.g. other vehicles, peoples, enemies, or animals in specific locations. Currently, leading companies that develop military sensor fusion technologies are General Dynamics, Esterline Technologies, Safran Group, BAE Systems, Lockheed Martin Corporation, Honeywell International, and Kongsberg Gruppen [126].

D. FUEL AND SPACE EFFICIENCY

Fuel and space efficiency can potentially be achieved through a carful platooning strategy. Recently, Locomation demonstrated that minimization of air drag can lead to higher fuel efficiency. Researchers have also proposed several advanced techniques for efficient air drag control [127]–[129] and road space utilisation [130]–[133]. Both fuel and space efficiency can also be achieved through efficient traffic signaling [134]–[136]. It is envisaged that extensive research from industries to improve fuel and space efficiency will emerge in the near future.

E. MODULAR VS END-TO-END APPROACHES

There are two popular approaches to autonomous driving [137], [138]: modular and end-to-end methods. Fig. 14 presents an end-to-end approach. Autonomous vehicles use multiple sensors for ensuring a successful operation, e.g. infrared (IR) sensor, LiDAR, RADAR, ultrasonic, odometer, camera, etc. Besides sensors, autonomous vehicles have dedicated short range communication (DSRC), internal navigation system (INS), map, and global positioning system (GPS) to improve sensing of the environment.

The modular approach is widely applied in industries [139], with the advantage of ease of implementation [140]. An accident can occur due to a fault in a sensor or an algorithm. The algorithm may work with one or more faulty sensors. Several algorithms are applied for autonomous driving in the modular approach, e.g. algorithms for traffic signal detection [141], pedestrian detection [142], road segmentation [143], steering angle prediction [144], speed prediction [145], and path planning [146]. When the sensor readings and recent predictions are recorded, it becomes easy to investigate and improve the performance of different modules.

The end-to-end approach can potentially bring good performance with sufficient samples and proper training methodology [147]. Many researchers anticipate that the end-to-end approach will become better with the advancement in AI [148].

F. FUTURE OPPORTUNITIES FROM AI

AI is a fast-growing research domain, and an immense improvement in AI methodologies can be observed in the last decade [149]–[151]. AI provide smart solutions to many existing problems, which has brought new research dimensions [152]–[154]. With the help of AI, a novice user can develop prediction models. The advent of transfer learning models yield good performance with reduced computation loads and smaller data sets [155]. Recent advancements in DeepFake have caused difficulty in distinguishing real and fake video clips by humans. Successful autonomous driving requires many calibrations [156], [157], e.g. slight differences between the odometer reading and the actual distance traveled by a vehicle normally exist [158], [159]. In this case, fusing sensor information or adjusting sensor readings requires calibrations [160]. Neural networks have been used as a useful

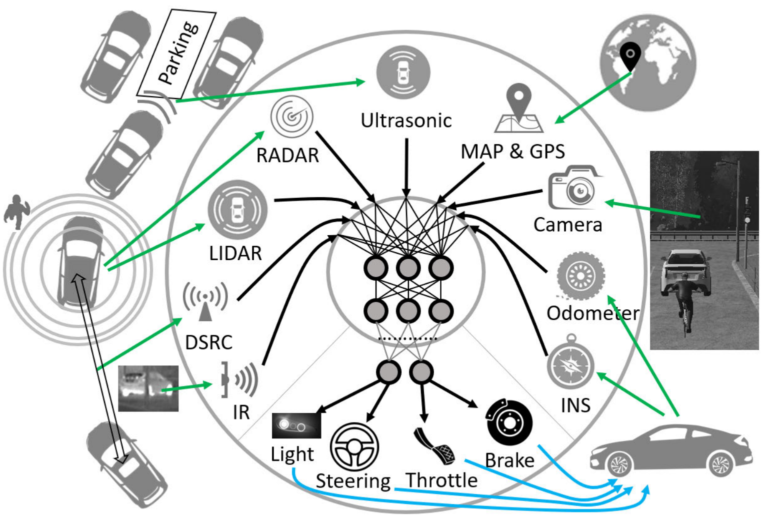

FIGURE 14. Sensor fusion with an artificial intelligence (AI) model for end-to-end autonomous driving, where the AI model receives information from different sensors and predicts the relevant outputs.

method for such calibrations [161], which benefit R&D in autonomous convoying.

VI. CONCLUSION

Autonomous convoying is a rapidly growing research field to date. Convoying with a fleet of autonomous vehicles requires the consideration of many aspects. This survey has provided important information on autonomous convoys to facilitate future R&D activities. We have analyzed current methods and techniques associated with autonomous convoying, covering tracking and control mechanisms, characteristics of a good follower vehicle and related real-world scenarios. This literature also has presented current R&D initiatives of different industries and future possibilities. As the technology of autonomous convoying is in still its early stage, many research activities are funded by the military at this moment. Successful implementation of a fully autonomous convoy can potentially enable transporting goods to remote places without human involvement. Indeed, it is envisaged that logistic and supply chain activities to help people in rural and remote locations with greater efficiency without endangering life become possible through realization of autonomous convoying in the future.

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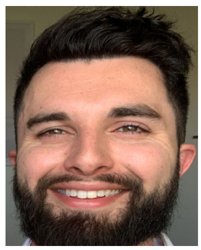

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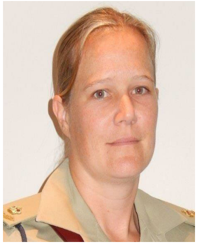

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