Annual Reviews in Control 000 (2018) 1–11

Contents lists available at ScienceDirect

Annual Reviews in Control

journal homepage: www.elsevier.com/locate/arcontrol

Vision article

Trajectory planning and tracking for autonomous overtaking: State-of-the-art and future prospects

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A R T I C L E I N F O

Article history:
Received 4 September 2017
Revised 19 February 2018
Accepted 20 February 2018
Available online xxx

Keywords:
Autonomous vehicles
Overtaking
Trajectory planning
Trajectory tracking
Connected vehicles

A B S T R A C T

Trajectory planning and trajectory tracking constitute two important functions of an autonomous overtaking system and a variety of strategies have been proposed in the literature for both functionalities. However, uncertainties in environment perception using the current generation of sensors has resulted in most proposed methods being applicable only during low-speed overtaking. In this paper, trajectory planning and trajectory tracking approaches for autonomous overtaking systems are reviewed. The trajectory planning techniques are compared based on aspects such as real-time implementation, computational requirements, and feasibility in real-world scenarios. This review shows that two important aspects of trajectory planning for high-speed overtaking are: (i) inclusion of vehicle dynamics and environmental constraints and (ii) accurate knowledge of the environment and surrounding obstacles. The review of trajectory tracking controllers for high-speed driving is based on different categories of control algorithms where their respective advantages and disadvantages are analysed. This study shows that while advanced control methods improve tracking performance, in most cases the results are valid only within well-regulated conditions. Therefore, existing autonomous overtaking solutions assume precise knowledge of surrounding environment which is not representative of real-world driving. The paper also discusses how in a connected driving environment, vehicles can access additional information that can expand their perception. Hence, the potential of cooperative information sharing for aiding autonomous high-speed overtaking manoeuvre is identified as a possible solution.

Contents

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https://doi.org/10.1016/j.arcontrol.2018.02.001
1367-5788/

1. Introduction

Modern cars are equipped with various sensors and electronic systems to reduce the workload of a driver by providing emergency assistance (e.g., ABS, traction control, stability control, etc.), ADAS (e.g., cruise control, lane keeping, crosswind assistance, blind spot detection, etc.), and navigational assistance (e.g., trip planning, route selection, regular traffic update, etc.). However, the next generation of intelligent vehicles are expected to have increased capabilities which allow automated manoeuvring in various driving scenarios (Eskandarian, 2012; Gordon & Lidberg, 2015). Overtaking is one of the most common driving manoeuvre and any vehicle capable of end-to-end autonomy must have the ability to determine if, when, and how to perform this driving task.

Overtaking is a complex driving task as it involves both lateral and longitudinal motions of an overtaking vehicle (subject vehicle) while avoiding collisions with a slower moving vehicle (lead vehicle) (Milanés et al., 2012). Additional complexity arises due to different environmental conditions (e.g., road legislations, visibility, weather, etc.) and diversity of road-users (e.g., small cars, buses, trucks, etc.) (Vanholme, Gruyer, Lusetti, Glaser, & Mammar, 2013). Typically, an overtaking manoeuvre is considered successful on proper completion of three sub-manoeuvres namely, (i) lane change to overtaking lane, (ii) pass lead vehicle(s), and (iii) lane change back to original lane (Petrov & Nashashibi, 2014). The lane change sub-manoeuvre which indicates the start and the end of an overtake can be classified under two categories; (i) Discretionary Lane Change (DLC) and (ii) Mandatory Lane Change (MLC) (Moridpour, Rose, & Sarvi, 2010). A DLC sub-manoeuvre is performed when the immediate traffic situation in the faster lane is deemed to be better than the current lane and thus, the lane change is performed in anticipation of an improvement in the immediate driving conditions. On the other hand, an MLC submanoeuvre is performed due to compulsion arising from traffic rules (e.g., stalled vehicle, need to follow desired route, etc.). Moreover, the lane change to return back to the original lane can also be either DLC or MLC based on traffic conditions in each lane, legislation, etc. thus, transforming an overtaking manoeuvre into a complex task of dynamically choosing the best driving lane based on (i) legislation, (ii) driving intentions, and (iii) instantaneous traffic situation. This inference that the choice of lane is affected by both; (i) driving intention, and (ii) neighbourhood traffic conditions was verified in Toledo, Koutsopoulos, and Ben-Akiva (2003) using an integrated model (combining MLC and DLC) for lane changing behaviour based on gap acceptance (lead and lag gap). Therefore, it is noted that due to the dynamic nature of driving environments (i.e., traffic conditions in original and fast lane, speed limits, road conditions, etc.) overtaking is not standardised manoeuvre and thus, each overtaking manoeuvre in real-world scenarios is unique. This uniqueness arises from variations in number of overtaken vehicles, duration of overtake, relative velocity between concerned vehicles, distance between concerned vehicles, etc (Baber, Kolodko, Noel, Parent, & Vlacic, 2005; Hegeman, Brookhuis, & Hoogendoorn, 2005; Kesting, Treiber, & Helbing, 2007; Motro et al., 2016; Shamir, 2004; Thiemann, Treiber, & Kesting, 2008; Vlahogianni, 2013; Webster, Suzuki, Chung, & Kuwahara, 2007). For an autonomous vehicle, feasibility of an overtaking manoeuvre is evaluated on the basis of safety based on subject vehicle's states as well as surrounding information leading to a discrete outcome for making tactical decisions (i.e., either perform lane-change or do not perform lane change) which form a part of planning and decision making process. A variety of techniques for decision making are available in literature with (i) multi-level decision trees (Claussmann, Carvalho, & Schildbach, 2015), (ii) probabilistic weighted comparison of concurrent goals (Ardelt, Coester, & Kaempchen, 2012), and (iii) higher award seeking Markovian Decision Process algorithms (Ulbrich & Maurer, 2015) being among the prominent methods.

A schematic representation of an overtaking manoeuvre is shown in Fig. 1 with each sub-manoeuvre labelled with roman numerals. As discussed above, the lane change back to the original lane depends on the traffic conditions and thus both possibilities are depicted in the schematic. Despite the innumerable variations present due to the factors discussed above, overtaking manoeuvres can be classified under the four categories listed below (Hegeman et al., 2005):

- Normal: The subject vehicle approaches the lead vehicle and waits for a suitable opportunity to perform the manoeuvre.
- Flying: The subject vehicle does not adjust its longitudinal velocity and is directly able to overtake the lead vehicle.
- Piggy backing: The subject vehicle follows a preceding vehicle as they both overtake the lead vehicle.
- 2^+: The subject vehicle overtakes two or more lead vehicles in a single manoeuvre.

For the aforementioned scenarios, the duration of a completed overtake has been found to be in the range of 5.4 to 12.5 s (subject to dynamic nature of the surrounding traffic and environment) using recording the trajectories of vehicles on typical European highways (Jong, Park, Chao, & Yen, 2016; Kanaris, Kosmatopoulos, & Ioannou, 2001; Khodayari, Ghaffari, Ameli, & Flahatgar, 2010; Milanés et al., 2012; Valldorf & Gessner, 2005; Vlahogianni, 2013; Wan, Raksincharoensak, Maeda, & Nagai, 2011). Performing an autonomous overtaking manoeuvre based on any of scenarios mentioned above within a given time range requires accurate information of surrounding environment, traffic, and weather conditions along with sophisticated sensing and perception, planning, and control systems (Chu, Lee, & Sunwoo, 2012). The surrounding environment of a vehicle is populated by different features; (i) permanent (road and lane limits), (ii) slowly changing (e.g., temporary speed limits, road works, traffic density, etc.), and (iii) fast changing (surrounding vehicle velocity, position, heading, etc.). A modern day vehicle uses a host of on-board sensors to discern the environment and the placement of an on-board sensor suite used to perform this task can be seen in Fig. 2. The information from these sensors is combined and used for tasks such as; (i) classify objects, (ii) track stationary and moving obstacles, (iii) identify safe driving zones, etc. Currently, there are some production vehicles that utilise vehicle-to-everything (V2X) information to provide updates on permanent (e.g., road and lane limits, road inclination, etc.) or slowly changing features (e.g., temporary speed limits, road works, traffic updates, etc.) of surrounding environment via a combination of cellular data and Local Dynamic Map (LDM) updates. However, despite an elaborate sensor suite and first generation V2X communication systems the capabilities of the contemporary autonomous vehicles is limited to low-speed overtaking. This is due to limitations such as; (i) range of sensors, (ii) blind spots, (iii) small timescales for predicting motion of traffic participants, (iv) sensor imperfections, and (v) possible V2X network outages. The combination of one or more of these limitations result in significant uncertainty while planning complex highway manoeuvres (e.g., overtaking) which span several seconds at high-speeds (Aeberhard et al., 2015; Son, Kim, Lee, & Chung, 2015). Moreover, unless all the traffic participants are connected and autonomous the uncertainty arising from predicting the motion of traffic vehicles cannot be brought down to negligible levels even with the advent of perfect on-board sensors and/or V2X communication network. Thus, predicting the motion of traffic participants for risk assessment forms a vital part of manoeuvre planning and this domain has witnessed a lot of research and a large number of techniques are present in literature. The different methods for motion planning for intelligent