

Fully Automated Reverse-Parking System for a Level 3 Autonomous Heavy-Duty Vehicle

**Tarek Kabbani^a, Pouria Sarhadi^a, Ersun Sozen^b, Berzah Ozan^b, Emrah Kinav^b,
Ahu Ece Hartavi^{a*}**

^aDepartment of Mechanical Engineering Sciences, Centre of Automotive Engineering, University of Surrey,
Guildford, GU2 7XH, UK.

^bFord Otosan, Akpınar Mah Hasan Basri Cad No 2, Sancaktepe, Istanbul, 34885, Turkey.

a.hartavikarci@surrey.ac.uk

Abstract

Autonomous vehicles have the potential to be a game-changer for road transportation due to benefits they have offered. However, it is expected that highly autonomous trucks possibly hit the roads before the passenger vehicles. Even though functionality that enables different levels of autonomy exists, there are still challenges that need to be overcome to implement automation successfully. Hence, the test coverage needs to be enhanced, and critical scenarios should be tested before the implementation phase. In this paper, in the framework of an EU funded project TrustVehicle, a fully self-reverse parking system for a tight docking space with the limitations on the: i) number of manoeuvres, and ii) direction of motion is proposed for a heavy-duty vehicle. The system consists of two key components, which are: a novel artificial potential field-based trajectory planner, and a well-matched precise trajectory tracking controller. The planner part of the system has an embedded reference vehicle model to consider the non-holonomic vehicle behaviour during the trajectory generation, and a feedback to make the control scheme more robust. This enables the generation of a more realistic trajectory that is trackable by the controller. To evaluate the effectiveness of the algorithm, several test cases are selected ranging from tight parking to relax parking conditions. The results have shown that the proposed system, generates feasible trajectories and tracked with high precision, showing a promising performance for real-world experiments.

Keywords: Heavy-Duty Vehicle, Artificial Potential Field, Trajectory Planning, Trajectory Controller

1- Introduction

Heavy-duty vehicles are the backbone of road freight transport, since more than 70% of freight is transported over land by these vehicles. Recently, manufacturers have started to devote significant effort to enhance the autonomy level of these vehicles [1], [2]. This mainly due to the fact that the advantages of automation include, but not limited to, increased safety, reduced emission, reduced energy consumption as well as enhanced driving comfort [28]-[30]. Among these, parking is considered as one of most challenging manoeuvre specifically for articulated heavy-duty vehicles due to its complexity, being most time consuming, most anxiety inducing experience, as well as being root causes of low speed accidents. To overcome these challenges, fully automated reverse parking has become one of the choices of research in current autonomous vehicle development. In this context, self-parking problem can be defined as *finding a feasible obstacle free trajectory that the vehicle can follow starting from a given initial posture to a final one within the available space.*

Studies in the current literature in the field is more focused towards the use of path planning techniques [13], skilled-based methods [4], and path following controllers as discussed in [5]. However, for autonomous driving (AD) in semi-structured environments trajectory planning (TP) should be the preferred solution rather than path planning [6]-[910]. Because of the major differences between them [3]. Different way of constructing the TP algorithms also have been also discussed in the studies [3][18] [19],[20],[21],[25]. Some of these studies have preferred to use an integrated approach [23], [24], whereas other researchers have considered the problem separately.

Trajectory tracking techniques are also proposed in the literature, which have discussed the challenges of reverse motion and implementation [12], [13] . In [12], non-minimum phase behaviour of front steering vehicles with the front sensors are analysed and an innovative mechanism to overcome this issue is presented. In [13], nonlinear controllers are proposed and implemented. Three different lateral controllers for backward driving are compared in [14]. The problem is more investigated in [15]. One of the highly cited trajectories tracking technique, which is based on a nonlinear transformation between the vehicle pose and trajectory is introduced in [16].

In this study for planning artificial potential field technique is selected due to its simplicity. The method's well known limitation is the local minima that can cause the vehicle to stop. To mitigate this problem, the potential field environment must be designed carefully [11]. The method has been successfully implemented for passenger vehicles as in [10] and [22]. It is also implemented to a single-trailer system in [9] for a parking scenario with the use of 'Ghost walls' to restrict the entry trajectory of the parking bay to a single point.

This paper presents a novel artificial potential based fully automated reverse parking system of a heavy duty vehicle for a tight parking space with limitations on number of manoeuvres and direction of motion. The method presented have extended and adopted the approaches proposed in [9], and [10] in a way to overcome the specific challenges of the test scenario considering the non-holonomic behaviour of the vehicle. The paper is organized as follows. Vehicle dynamics model is presented in Section 2. In Section 3 reverse parking and main building blocks of the fully automated reverse parking system is described. Artificial potential based trajectory planner is given in Section 4, whereas trajectory tracking controller is discussed in Section 4. In Section 5 simulations' results are presented to demonstrate the effectiveness of the proposed system. Finally, Section 6 concludes the paper with some remarks.

2. Vehicle Dynamics Model

An accurate full vehicle mathematical expressions is required to represent the vehicle behavior to design fully-reverse parking system for a HDV, since it is quite complex and challenging (Fig.1). This is mainly due to the fact that: i) existence of nonholonomic constraints, that limit the possible directions of motion, even in the absence of obstacles, and ii) reduced degree of freedom at the inputs of the system, which will be addressed later in Section 5. Specifically, it is also required to integrate potential field forces to produce feasible trajectories. Therefore, to model the HVD a well-known bicycle model, which is extended to *hybrid*-kinematic model is used [3].

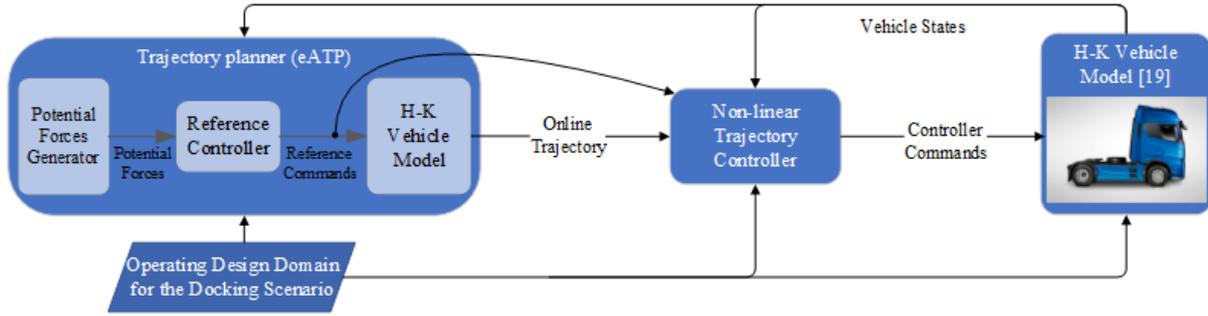


Figure 2: TrustVehicle fully-automated reverse parking solution main building blocks [27]

Moreover, the limitations dictated by the operating design domain together with the other requirements are applied to the TP as shown in Fig.2. Parking bay environment is simply configured as a tight rectangular parking lot, but it is designed in a way that the size is easily configurable.

4- Attractive-Repulsive Artificial Potential Field

The artificial potential field technique is used to generate the required forces to orient the truck towards the goal while avoiding the collision with parking boundaries. Two types of potential fields are used, one of which is set for the goal point and other to direct the vehicle and avoid collision. Attractive potential field is used for a goal point, whereas repulsive field are assigned to the parking bay and lot boundaries. Once the required forces are defined, they are summed and transferred to the reference vehicle frame. Afterwards, longitudinal and lateral forces are projected on the hybrid-kinematic model of the vehicle to produce the required velocity and steering angle.

4.1. Potential Force Generator

Goal field is defined by uniting both conical and parabolic functions as follows

$$U_G(Q_{t,tp}) = \begin{cases} \frac{1}{2}k_G\rho_{t,g}^2 & \rho_{t,g} \leq d_c \\ d_c k_G \rho_{t,g} - \frac{1}{2}k_G d_c^2 & d_c < \rho_{t,g} \end{cases} \quad (2)$$

where d_c is a fixed distance to the goal where the conical field changes to parabolic, k_G is the goal field gain and ρ is the Euclidean distance between the look ahead point and the goal point (x_g, y_g) . The aim is to apply first steep force using the conical function while at relatively far distances from the goal point, and then produce a smooth and gradual reduced force while vehicle approaches the goal point using parabolic function.

Imaginary walls, which are repulsive type potential fields, are also defined. This is firstly because to stop the vehicle from crossing boundaries of that specific parking lot. Secondly, to align the vehicle within the parking bay.

4.2. Reference controller

A reference controller is used to transform the generated potential forces to the input references for the embedded reference vehicle. In this context reference velocity v_{ref} is calculated proportionally to the longitudinal potential force $F_{x,t}$ derived from the generated artificial potential field, as in

$$v_{pot} = k_v(F_{x,t}) \quad (3)$$

where k_v is a constant that influences both the longitudinal motion and accuracy of the goal position. Once the vehicle approaches the final position, $F_{x,t}$ starts to diminish reference velocity tends towards

zero.

To define the lateral motion, TP should also determine the reference steering angle δ_f . Therefore, first the resultant force is used to determine a reference yaw angle ψ_{pot} . Using the single-track model and Ackerman steering [7], the steering angle needed to achieve the reference yaw angle is assumed to be determinable. The steering angle δ_{pot} is calculated based on the known values of yaw angle. The potential total forces $(F_{x,t}, F_{y,t})$ acting on the embedded reference vehicle is defined by first taking the sum of forces of the goal F_G and imaginary walls components (F_{GW}, F_B) as follows

$$F_T = F_G + F_{GW} + F_B \quad (2)$$

It is important to note that those components along with the total force are calculated on the look ahead point $Q_{t,lp}$. The look ahead point with coordinates (x_{lp}, y_{lp}) is set to be with a fixed distance l_p from the truck position to increase the steering ability of the vehicle. Furthermore, the forces in are expressed in the inertial reference frame. The rotation matrix in Eq.3 is used to transform F_T into force F_t acting in the truck reference frame, which is centred at the middle of the rear axle of the vehicle.

$$F_t = \begin{bmatrix} F_{x,t} \\ F_{y,t} \end{bmatrix} = \begin{bmatrix} \cos(\psi_t) & \sin(\psi_t) \\ -\sin(\psi_t) & \cos(\psi_t) \end{bmatrix} \begin{bmatrix} F_{x,T} \\ F_{y,T} \end{bmatrix} \quad (3)$$

where ψ_t is the yaw angle of the actual vehicle and $F_{x,t}$ and $F_{y,t}$ are the longitudinal and lateral forces, namely the x,y components of the F_T . Similarly, $F_{x,T}$ and $F_{y,T}$ are the x, y components of F_T in the inertial reference frame.

5- Trajectory Tracking Controller

Trajectory control (TC) designed in a way that it can track time-varying reference postures P_{ref} with two inputs: the longitudinal speed and the steering angle. This means that even though the controlled variables have 3 degrees of freedom manipulation parameters are two. Therefore, it is assumed the desired posture is generated based on a vehicle model that considers the non-holonomic constraints. By implementing the flatness condition and the nonlinear control theory, a well-posed stable trajectory tracking technique can be developed as in [15]. This technique is adopted here to develop the trajectory tracking algorithm of the truck. The only difference between the robotic model used in [1] and the truck model in (1) is in the yaw equation of the vehicle deduced from Ackermann steering. Then the input vector $[v_c \ \delta_c]^T$ that enables the truck posture $P_t = [x_t(t) \ y_t(t) \ \psi_t(t)]^T$ to track the reference P_{ref} . Is calculated. Based on these a posture error vector $P_e = P_{ref} - P_t$ is defined as:

$$P_e = \begin{bmatrix} x_{te} \\ y_{te} \\ \psi_{te} \end{bmatrix} = \begin{bmatrix} \cos \psi_t & \sin \psi_t & 0 \\ -\sin \psi_t & \cos \psi_t & 0 \\ 0 & 0 & 1 \end{bmatrix} (P_{ref} - P_t) = T_e (P_{ref} - P_t) \quad (6)$$

where T_e is the tracking transformation matrix. The derivative of the posture error vector also can be written as [16]

$$\dot{P}_e = \begin{bmatrix} \dot{x}_{te} \\ \dot{y}_{te} \\ \dot{\psi}_{te} \end{bmatrix} = \begin{bmatrix} \omega_t y_{te} - v_t + v_{ref} \cos \psi_t \\ -\omega_t x_{te} + v_{ref} \sin \psi_t \\ \omega_{ref} - \omega_t \end{bmatrix} \quad (7)$$

According to the Eq. 6 and 7, the reference input vector $[v_{ref} \ \delta_{ref}]^T$ is used to solve the differential equations of error. According to Lyapunov stability theory, it is proven that the Eq.10 can ensure stable

reference tracking [16]

$$\begin{aligned} v_c &= v_{ref} \cos \psi_{te} + K_x x_{te} \\ \omega_c &= \omega_{ref} + v_{ref} (K_y y_{te} + K_\psi \sin \psi_{te}) \end{aligned} \quad (8)$$

Subsequently, the controller steering output can be calculated by

$$\delta_c = a \tan \left(\frac{L_t \omega_c}{v_c} \right) \quad (9)$$

The availability of feedforward input signals from the proposed TP makes the tracking control approach developed suitable for implementation.

6- Simulation Results

In this section, simulation results for the parking algorithm that integrates the TP and controller together with the Ford Otosan F-Max vehicle model are presented [26], [27]. To evaluate the performance of the proposed system firstly eight test cases are defined, which are listed in Figure 3. Then the location of the parking lot and bay are defined by setting the coordinates. The parking lot dimensions are set to $80\text{m} \times 36\text{m}$ while the parking bay size is set to $3.8\text{m} \times 16\text{m}$. Then goal point is at the centre of the parking bay is set. Before the testing process, the potential field parameters k_G , d_c , $k_{GW,1}$ and $k_{GW,2}$ are tuned. The gain to calculate the reference velocity is also set. Afterwards, the trajectory controller parameters are tuned as $K_x = 0.2$, $K_y = 1$ and $K_\psi = 0.2$.

Based on these parameters generated trajectories for all of eight test cases are shown in Figure 3 (upper-right). It is important to note that the centre of mass is used instead of the rear axle position for illustration purposes in the figures. Results have shown that the planner successfully produces the trajectories for each defined test case to guide the vehicle to the goal point.

In the lower-left hand side of the Fig.3 the total longitudinal and lateral potential forces generated by the artificial potential fields for the test case 1 are shown. Even though these forces are virtual but their relation to the velocity and steering angle could be observed. In lower-right hand side of Fig.3 also the output signals are given for test case 1. Those signals include real and embedded reference vehicle yaw angle, velocity and the steering angle. The values of those signals are almost identical for both vehicles.

To assess the performance of the developed algorithm in that relevant scenario, also Key performance indicators (KPIs) are defined. These KPIs are the final position error between goal and trajectory denoted as $e_{c,n} = Q_{c,n} - Q_g$ and the final yaw angle error given by $e_{\psi,n} = \psi_{g,n} - \psi_{t,n}$. Figure 3 (Upper-left) provides the KPI values for the defined test cases that demonstrates the successful parking with low final position error together with the desired final orientation

Test Case	$Q_i(\text{m}, \text{m})$	$\Psi_i(^{\circ})$	$e_{c,n}(\text{m})$	$e_{\psi,n}(^{\circ})$
1	(53, 10)	0.0	0.02	0.47
2	(53, 10)	-10.0	0.04	0.34
3	(53, 10)	10.0	0.01	0.24
4	(31, 10)	180	0.02	0.47
5	(42, 10)	-90	0.002	0.03
6	(42, 10)	-60	0.03	0.54
7	(53, 5)	-20	0.01	0.26
8	(31, 5)	160	0.002	0.02

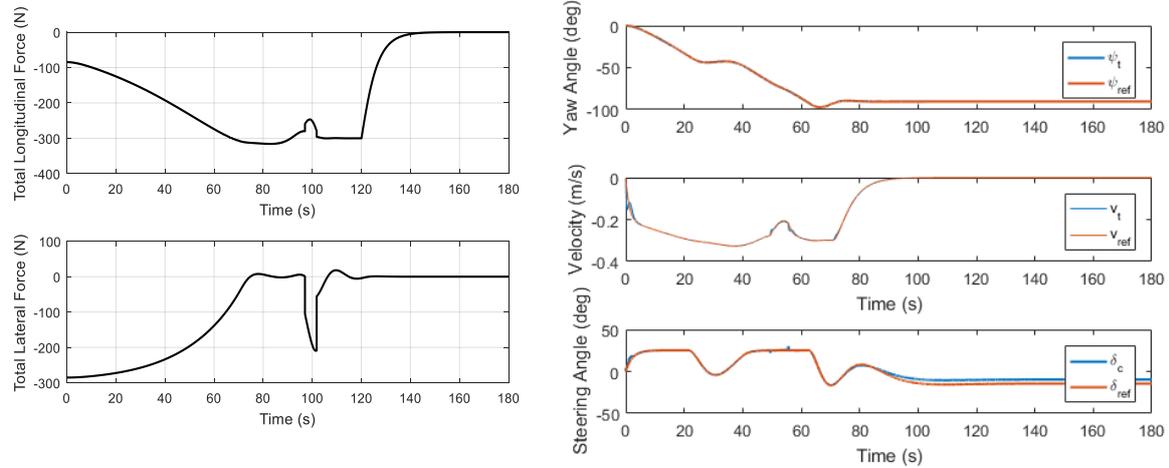


Figure 3: Configurations and KPIs of the eight test cases (Upper-Left), their generated paths (Upper-Right), Test case 1: Longitudinal and Lateral potential forces (Lower-Left), Test case 1 real and embedded reference vehicle velocity and steering angle (Lower-Right)

7- Conclusion

In this study, two main autonomous driving functions have been presented for a fully automated reverse parking of a heavy duty vehicle, which are: a trajectory planner based on the artificial potential field and a non-linear trajectory tracking control algorithm. The developed algorithm is designed for a single-maneuvre fully autonomous reverse parking and based on the attractive and repulsive artificial potential field. The forces are defined both to define the goal point and the boundaries of the parking bay and the lot to guide the truck from the initial posture to the goal posture. The main advantages of the proposed technique depend on the consideration of physical limitations of the vehicle while being real-time implementable. The method has been tested in various tight and relaxed simulation scenarios and results analysed by several KPIs. The obtained results demonstrate a proper performance by a confidence level of less than 1 cm in distance and 1° in the heading. These results demonstrate that the proposed autonomous parking algorithm can be taken into consideration for the next implementation phases. In the future, the proposed algorithm will be implemented on the Ford-Otosan F-max heavy-duty Truck.

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