The Lateral Control of Autonomous Vehicles: A Review

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***Abstract*—Human need safety, comfort, and speed in driving-requirements that can be fulfiled by autonomous vehicles that enable drivers to avoid obstacles and maintain a safe distance from other motorists. These function are executed through lateral vehicle control, which has been the subject of considerable research. The current research was aimed at providing a comprehensive review and description of previous investigations that implemented both conventional and innovative lateral control methods, such as proportional-integral-derivative control, fuzzy logic, artificial intelligence, neural networks, genetic algorithms, and combined approaches. The evaluated studies were also classified into two categories, namely simulation and experimental research that used real-world tools. The paper concludes with a recomendation to use an alternative method called direct inverse control. Which is a modification of neural network-based control. This method is advantageous because it uses output/input feedback, thereby effectively functioning in unpredicable terrain. This feature is highly suitable because autonomous vehicles are non-linear system.**

***Keywords*—lateral control, intelligent controller, autonomus vehicle**

I. Introduction (*Heading 1*)

Human have become highly mobile beings, thus developing travel needs that can be satisfied through the use og autonomous vehicles. Such automobiles can be reliable means of transportation under guaranted safety, comfort, and speed. Rhey can detect environmental conditions, such as the pressence and speed of other road users, bends or turns, and obstacles. Autonomous vehicles can also tun well. Even eithout intervention from drivers. These advantages have driven research and decelopment on these innovations. Autonomous vehicles are manuvered mainly through longitudinal and lateral control. Longitudinal control involves the regulation of the speed, which enables the maintenance of a safe distance between two vehicles and thereby prevents collision. Lateral control always maintains the direction of the vehicle to match the specified trajectory[1], [2]. The lateral control of autonomous vehicles is the focal subject if this study, in which several such methods that were implemented by previous researchers were reviewed. These approaches include proportional-integral-derivative (PID) control [3]–[6], fuzzy logic [7], [8], neural networks (NNs) [9], genetic algorithm (GAs)[10], and a combination of categories [11], [12] ,namely, software simulation-based research and experimentation grounded in real-world tools. The paper concludes with a discussion of opportunities for lateral control of autonomous vehicles. Specifically, the authors recommend the use of direct inverse control (DIC), which provides feedback from output to input units, thereby efectively handling nin-linear systems. In a DIC system, the output unit, chich comes in the lateral errors, which are the inputs. The prediction of uncertainies and environment difficulties is a problem that must be solved by an autonomous vehicle-a function that is faciliated by DIC. This latereal control method is therefore suitable for maneuvering non-linear systems such as autonomous vehicles.

II. Vehicle Model

The general charactersitics of vehicles are performance, handling, and ride quality. Performance refers to the effectiveness of a vehicle to accelerate, decelerate, and avoid objects. Handling pertains to the ability of a vehicle to respond to driver interactions. Ride quality is the capacity of an automobile to interact with environmental factors, such as routes, road types, road surfaces, and traffic conditions [13].

Fig. 1 shows the coordinate system that underlies the movement of a vehicle. The center of gravity, which is sometimes referred to as the point of gravity, is the midpoint of the axes (x, y, and z) of the movements in the direction of the x-axis. Lateral motion (right-left turn) and yaw motion are movements toward the y-axis. Vertical motion (oscillating up-down) and pitch motion are movements in the direction of the z-axis [14], [15].

Vehicles of low speeds can be simulated assuming that the speed on each wheel toward the wheel. When speed increases, however, such simulation cannot be accomplished. In this situation, lateral car movements must be reflected in a dynamics model. Fig. 2 shows the two degrees of freedom (DOF) of a bicycle model, where Y is the vehicle position, and ψ denotes the vehicle yaw angle, which is the second DOF.

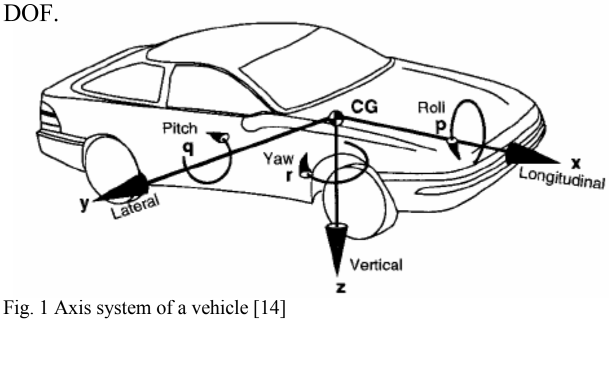

Fig. 1 Axis system of a vehicle [14]

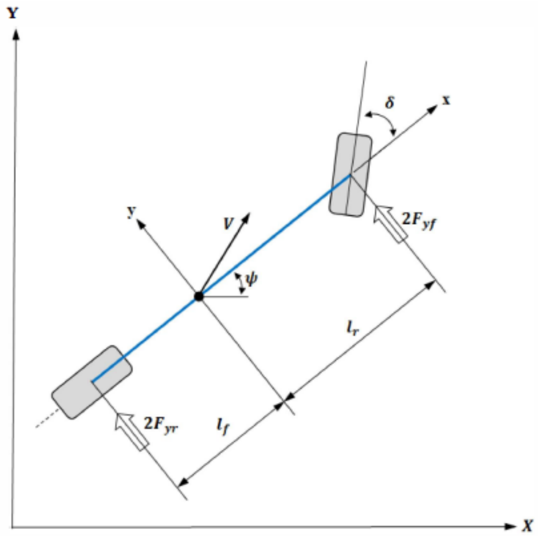

Fig. 2 lateral Dynamics model of a vehicle [16]

The state-space model for lateral dynamics is given as follows:

$$\begin{bmatrix} \dot{y} \\ \ddot{y} \\ \dot{\psi} \\ \ddot{\psi} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & a_{22} & 0 & a_{24} \\ 0 & 0 & 0 & 1 \\ 0 & a_{42} & 0 & a_{44} \end{bmatrix} \begin{bmatrix} y \\ \dot{y} \\ \psi \\ \dot{\psi} \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{2C_{af}}{m} \\ 0 \\ \frac{2C_{ar}}{I_z} \end{bmatrix} \delta \quad (1)$$

$$a_{22} = -\frac{2(C_{af} + C_{ar})}{mV_x}$$

$$a_{24} = -V_x - \frac{2(l_f C_{af} - l_r C_{ar})}{mV_x}$$

$$a_{42} = -\frac{2(l_f C_{af} - l_r C_{ar})}{I_z V_x}$$

$$a_{44} = -\frac{2(l_f^2 C_{af} + l_r^2 C_{ar})}{I_z V_x}$$

where C_{af} is cornering stiffness of front tires, C_{ar} denotes the cornering stiffness of rear tires, I_z refers to the yaw moments of inertia, I_f represents the distance from the corner of gravity to front tores, and I_r indicates the distance from the center of gravity to rear tires [16].

III. Lateral Control System

Lateral control presents the core problem of minimizing a vehicle's deviation from a desired lane and keeping it on the desired lateral displacement of a reference lane. Simple linear bicycle models with two DOFs are widely used in research simulations [17]–[19].

Conventional PID control is used to regulate double-track changes, for which the control parameters needed, namely, Kp, Ki, and Kd, are identified using MATLAB-Simulink. ISO 3833 [20] is used to define the types of passenger cars used by motorists. The results of a study showed that at a moderate speed (two speed levels: 50 and 90 km/h), maneuvers in a double-lane-change test can improve [3].

The other PID method, adaptive PID, was used in bicycle modeling involving the installation of two 4-core computers and sensors in a 1.6 L Tiggo3 sport utility vehicle (SUV) [21]. The results indicated that vehicles controlled in this manner exhibit enhanced stability and adaptability. In another research, automobiles with lengths of 4.8 and 1.85 m were equipped with several sensors, whose steering system was run via a computer [22]. At a distance of 7.5 m between the two cars, their speeds reach 2.5 km/h. This study achieved favorable and robust control in both simulations and experiments.

Many advantages are obtained through control based on fuzzy logic. Fuzzy controllers were used in the lateral control of two autonomous Berlingo Citroen cars [23], [24], to which speed control and steering conditions were applied. The vehicles were also equipped with a color camera sensor, a high-resolution global positioning system (GPS), and several other sensors whose data were then processed using a PC. Driving by humans was successfully simulated. Path selection, acceleration and vehicle overtaking were simulated with an autonomous vehicle that was controlled through fuzzy logic [23].

The autonomous vehicle In2Bot requires a charge-coupled device (CCD) and 3 Lidar to function as effectively as possible [25]. The determination of membership functions and rule bases influences the success of using fuzzy logic, which also commonly involves trial and error and relying on one's expertise. Genetic algorithms (GA) are used by researchers to ascertain optimization [26], [27]. Fuzzy GA, for example, was implemented in a Citroen C3 Pluriel mass-production vehicle to regulate the lateral control of the automobile [28]. The system created for this experiment had angular and lateral errors as input. The distance between the car and a desired line was regarded as a lateral error, whereas the angle between the car and a reference line was denoted as an angular error.

Fuzzy GA was also used to operate autonomous vehicles at relatively high speeds in special test trajectories [29]. The experiment involved operating the vehicles in a manner similar to how a human would have driven them. A desired steering position was the output. In [30], a motor was mounted on a steering wheel to exercise control related to a desired position. The study found that on a straight paved path, a vehicle can be properly controlled at a speed of 10 to 15 km/h. However, when this strategy is applied to a cornering path, the quality of resultant control diminishes [28], [29].

Steering under symmetrical control is a typical treatment in the application of fuzzy logic. The distance between the right and left directions is considered the same in determining membership functions, but this condition does not hold on an actual highway. For example, a car that runs slowly should stay on the left lane so that it can be overtaken by a car that runs fast. Another method classified under fuzzy logic is the Mamdani system, which involves adopting input lateral errors and angular errors [31]. Here, the membership function consists of four or five variables, and the steering system is the output. The center of mass is applied in defuzzification.

Lateral control entails keeping an automobile on a desired path and requires information such as lateral error, yaw rate, and steering angle. In such control measure, a reference path serve as a benchmark. Neural networks (NNs), which are also adopted as a means of lateral control, come in various forms, one of which is feedforward NN [32], which uses three neurons and three parameters to simplify network structure. It can execute control in three ways: inverted pendulum control, ball-and-beam system-based control, and lateral vehicle control. A desired predetermined point can be achieved after the training of a GA chromosome. Lateral control can likewise be solved via an NN method through simulations of driver behaviors in an autonomous vehicle. In this regard, two types of control are written in C, namely, backpropagation and adaptive resonance theory [33]. Finally, the feedforward multilayer NN was used to address lateral control [34], for which simulations and real-world experiments generated good results.

With Monte Carlo evaluation, the simulation of FRC optimization for a fuzzy controller yields optimal results. The same is true in real-world experiments [35]. Researchers likewise established model-free longitudinal and lateral control of vehicles [36]. Using using a Peugeot 406, researchers collected data and incorporated these into a model, whose inputs were longitudinal and lateral movements and outputs were driving/braking torque and steering wheel angle. The model was used in a MATLAB simulation. Other simulations involve models with 10 DoFs, which exhibit efficient control, and feature the use of pro-SiVIC (simulation of vehicles, infrastructure, and sensors) and RTMaps.

Another study in which a real SUV was used is[37], with the researchers equipping the vehicle with a 3D laser scanner that detects the conditions surrounding the SUV. PI control was implemented to reduce tracking errors, and a path tracker and primitive driver were incorporated as components of the lateral control system.

MATLAB R2013a simulation was carried out in [38] to examine the non-linear systems in autonomous vehicles. The vehicle parameters were established in the transfer function, which served as a dynamic model of vehicles. Furthermore, the second-order system was based on system control and controlled auto regression and moving average. After all the parameters were satisfied, a PID NN was constructed. The PID value, expressed in parameters Kp, Ki, and Kd, was satisfactorily identified through backpropagation PID control. The results of the simulation reflected real-time and robust control.

Lateral control on a highway is grounded in vehicle control intended to maintain distance between cars and allow lane switching. Such control is maintained, and its strength persists with various types of vehicles. In [39], researchers conducted a simulation using a fuzzy multimodel controller and derived good control. The other advantages of the research are related to control under variations in load imposed on cars, the moment of inertia, and the position of a wheel during cornering.

Using vehicles that are commonly used in the community, such as a Citroen Berlingo van, researchers tested an autonomous system. They employed fuzzy logic in calculating a position from the steering wheel targeted at any time. On this basis, classical control was adopted to reach the initial target. The results of the GPS- and AI-based analysis reflected excellent control, as evidenced by the ability of the system to mimic driver behavior and the minimal error rate.

Using an algorithm, Youla–Kucera-based simulations involving Renault ZOE electric cars were carried out [40]. Good lateral control was obtained, especially for tracking trajectories and changes. In [41], a modified Fiat Palio was used in an exploration of longitudinal and lateral control. The algorithm used for lateral control was a cubic Bezier curve. Testing with MORSE simulation software and experiments in two campus trajectories showed good control outcomes.

Hydraulic power steering system has begun to be abandoned by being replaced by electrical power steering (EPS). EPS systems are widely used especially for heavy vehicles [42]. Difficult installation, energy waste, high prices, lack of security are the reasons the hydraulic system is not used anymore [42]–[44]. Lane keeping systems are studied for EPS applications with sliding control mode [45]. Disturbances can be overcome when there is a fast steering angle change by using this mode, where the EPS model used is second order. Research of Nonlinear Steering Wheel Angle on the EPS approach to lateral control was carried out with EPS hardware-in-the-loop (HIL) simulation. The self is obtained by installing a spring on the steering output. But it does not explain the strength of the spring or its variations because real road conditions can vary [46].

Linear control is used to vehicle control with lane changes under stable conditions. But the reality often happens is not according to that matter. Therefore, research [47] uses a reset controller design method to overcome this. CarSIM is used to validate the control system, which begins by creating a dynamic model that is equipped with external disturbance. Zero crossing, fixed reset band, and variable reset band are the three main things studied.

Linear Quadratic Regulator (LQR) H is used to control upper control. The results of upper control were compared with conventional LQR, then verified with HIL. The results obtained by LQR H are better than conventional LQR. The software used is the Matlab simulink and LabVIEW from National Semiconductor. Logic threshold is applied to the motor steering control for the lower controller. Haval H7 is the real car used for this study [48].

Comparison between pure pursuit, Stanley, and a simplified Kinematic steering control is done for lateral control. By using the Renault Zoe ZE which is controlled automatically via a predetermined path. The C ++ and ROS programming languages are used for environmental simulations. The kinematic controller has an advantage compared to other controls at high speeds. Pure pursuit and kinematic excel in vehicle stability, whereas only kinematic control is suitable for passenger comfort [49].

Lateral control is applied to Tucson (Hyundai Motor) which has been equipped with a camera sensor. The algorithm used in this study is the Kalman Filter robust muti-rate, the problem of losing images while the camera on a car can be overcome with this system, so that the yaw rate can be reduced by ripple [50].

The previous studies reviewed in this work are summarized in Table 1. In addition to the use of algorithms such as fuzzy logic and NNs, models or software including C programming language, MATLAB, robot models, or certain types of actual cars were employed in these works.

TABLE I. COMPARISON OF LATERAL CONTROL METHODS USED IN PREVIOUS STUDY

Algorithm/ Method	**Model/Software**	**Simulation**	**Experiment**	**Reference**
PID	MATLAB/Sim	Yes	No	[3]
	Corollary	Yes	No	[4]
	Jetson TK-1 & Daewoo	Yes	Yes	[5]
	Fiat Linea	No	Yes	[6]
	Real car	No	Yes	[22]
Adaptive PID	Tiggo3	Yes	Yes	[21]
Fuzzy	Citroen B	Yes	No	[23]
	In2Bot	Yes	Yes	[25]
		Yes	No	[24]
	veDYNA	Yes	No	[7]
	CarSim Matlab	Yes	No	[8]
Neural networks	CarSim Matlab	Yes	No	[9]
	C language	No	Yes	[33]
	Mobile-Rbt	Yes	Yes	[34]
GA	C Language	Yes	No	[10]
Fuzzy PID	ROS	No	Yes	[11]
	Citroen B	Yes	No	[30]
BPNN PID	MATLAB	Yes	No	[38]
Model-free	MATLAB Peugeot 406	No	Yes	[36]
Adaptive pure pursuit	SUV Car	No	Yes	[37]
Fuzzy GA	Citroen C3	Yes Yes	Yes Yes	[28] [31]
Iterative fuzzy GA	Citroen C3	No	Yes	[39]
FRC - Fuzzy GA	Monte Carlo evaluation	Yes	Yes	[35]
Multimodel and fuzzy	MATLAB	Yes	No	[39]
NN-GA	MATLAB	Yes	Yes	[32]
Youla–Kucera	Renault Zoe	Yes	Yes	[40]
Bezier curve	Fiat Palio MORSE	Yes	Yes	[41]
Sliding Mode Control	EPS HILS	No	Yes	[45]
Nonlinear SWA	Matlab/Simulink EPS HILS system	Yes	Yes	[46]
Reset Controller	CarSIM	Yes	No	[47]
LQR	Matlab, LAbVIEW, Haval H7	Yes	Yes	[48]
Kinematic Controller	Renault Zoe C++, ROS	Yes	Yes	[49]
Multi-rate Control	Tucson Hyundai	No	Yes	[50]

IV. FUTURE PROSPECTS

NNs are a collection of simple neuron systems that are primarily designed to recall system knowledge. After being trained, NNs can mimic mathematical models of non-linear systems. A type of NN that is simple but reliable is multilayer perceptron. Meanwhile, backpropagation can be used to update NN, but this method, unfortunately, exhibits diminished performance in recalling mathematical models. This deficiency is attributed to disadvantages such as low convergence speeds and easy trapping in the local minimum [51]. The review conducted in this work revealed that no researchers have used DIC control, which can resolve the aforementioned weaknesses.

DIC involves two core processes: forward modeling and inverse modeling [52]. Fig. 3 illustrates an approach to training forward modeling with NN placement parallel to a plant. The weight of NNs obtained from errors changes because of the inequality between the plant and the model. Fig. 4 presents a block diagram of inverse modeling, which does not entail parallel connection to a plant. Ascertaining the internal conditions of a plant and performing an error calculation as regards the output of an inverse model (between the output of the plant and the desired output) are difficult. Therefore, direct models are not connected in series to a plant. A simple solution is to link inverse model series to a plant. The block diagram of this system is shown in Fig 5. The DIC inputs are angular and lateral errors, which are obtained from the steering wheel of a vehicle.

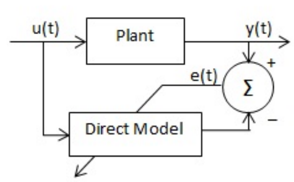

Fig. 3. Forward modelling

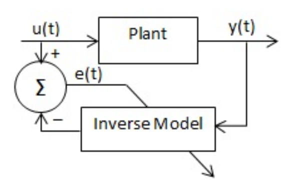

Fig. 4. Inverse modelling

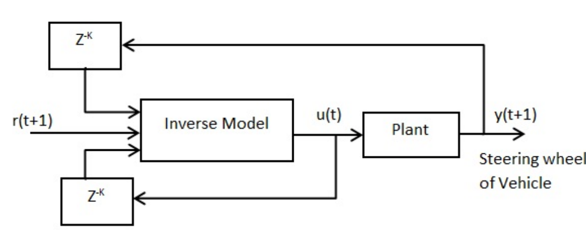

Fig. 7. Direct inverse control of a lateral system

V. CONCLUSION

This study comprehensively reviewed the literature on lateral control in autonomous vehicles. Table 1 summarizes the examined studies. As can be seen, researchers carried out software simulations and direct experiments in laboratories as well as in the field or highways. The control methods used in these works are PID control, fuzzy control, NNs, GAs, and various combinations of approaches. An alternative to these approaches is DIC, whose advantage is its ability to overcome a range of shortcomings observed in NNs. This control method is also very compatible with autonomous vehicles with non-linear systems. DIC is a valuable option as uncertain and changing conditions are challenges that confront autonomous vehicles.

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