IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 10, Issue 03, March 2023 https://www.ijirae.com/archives

Stanley Controller based Autonomous Path planning and Tracking in Self-Driving Cars

Sanjay S Tippannavar*
Department of Electronics and Communication Engineering,
JSS Science and Technology University, Mysuru, India
Sanjayu2345@gmail.com
Yashwanth S D
Assistant Professor, Department of ECE,
JSS Science and Technology University, Mysuru, India
yashwanth@sjce.ac.in
R Harshith
Department of Electronics and Communication Engineering,
JSS Science and Technology University, Mysuru, India
rharshith2697@gmail.com
Sourab Jain
Department of Electronics and Communication Engineering,
JSS Science and Technology University, Mysuru, India
Sourab.jain.01@gmail.com

Publication History
Manuscript Reference No: IJIRAE/RS/Vol.10/Issue03/MRAE10080
Research Article | Open Access | Double-blind Peer-reviewed | Article ID: IJIRAE/RS/Vol.10/Issue03/MRAE10080
Received: 04, March 2023 | Revised: 14, March 2023 | Accepted: 19, March 2023 Published Online: 31, March 2023 Volume 2023 | Article ID MRAE10080 https://www.ijirae.com/volumes/Vol10/iss-03/01.MRAE10080.pdf
Article Citation: Sanjay,Yashwanth,Harshith,Sourab(2023). Stanley Controller based Autonomous path planning and Tracking in self-Driving Cars. IJIRAE:: International Journal of Innovative Research in Advanced Engineering, Volume 10, Issue 03 of 2023 pages 40-48 https://doi.org/10.26562/ijirae.2023.v1003.01
BibTeX sanjay2023stanley
Academic Editor-Chief: Dr.A.Arul Lawrence Selvakumar, AM Publications, India

Abstract: Autonomous systems have the ability to replace human-performed tasks like personal assistants in residential or commercial settings. Self-driving cars, which have shown potential, are one area of significant interest in AI. This may include anticipating the activities and goals of people, such as pedestrians, as well as those of other vehicles. The creation of high-resolution images and sophisticated obstacle-clearing manoeuvres at high speeds are other developments. Increased highway safety and better use of travel time are only two of the many advantages of autonomous cars. In order for automated steering to retain the best trajectory despite changes in the road's conditions, lateral steering control is a critical component of autonomous cars. This study aims to investigate the use of a dynamic bicycle model and Stanley controller as a route tracking method, as well as the use of sensors to identify objects and lanes on the way. Discussion will also include the outcomes of MATLAB and SIMULINK tests performed to evaluate these approaches.
Keywords: Autonomous systems, Path Planning, Stanley Controller, Self-driving car, MATLAB, image processing, 3D Simulation, Safety, AI, Machine learning, Dynamic Bicycle Model.

I. INTRODUCTION

A technique for producing control actions using geometry-based PTC is the Stanley controller, sometimes referred to as the Hoffman controller. Instead than considering the vehicle's overall orientation, the method concentrates on how the front wheel is oriented in relation to the reference trajectory. The architecture of this approach does not need a look-ahead distance, unlike the PPC controller. This method was developed and used by the DARPA Grand Challenge 2005 winner. In Figure 1's picture, the geometry of the Stanley controller is shown. The diagram in Figure 1 shows the separation between the front axle and the reference point (el), as well as the angle between the direction of the vehicle and the tangent at the reference point (alpha). The needed steering angle may be calculated with this geometry by using the formula;

$$\delta(t) = \alpha + \tan^{-1}\left[\frac{ke_l(t)}{v(t)}\right]$$

Where; The equation includes both the adjustable factor (expressed by "k") and the vehicle's speed (represented by "v"). Asymptotic stability is ensured by the controller, which takes vehicle velocity into account while producing control actions. for non-zero speeds and steering angles between 0 and 2. In expressing steering laws, steering angle limitations are taken into account.

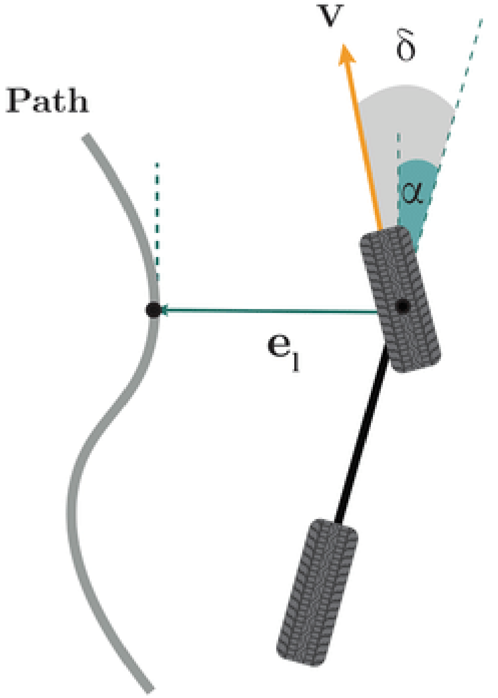

Fig.1. Stanley controller's geometry applied to a bicycle model.

$$\delta(t)=\begin{cases}\alpha+\tan^{-1}\left[\dfrac{ke(t)}{v(t)}\right] & \text{if } \left|\alpha+\tan^{-1}\left[\dfrac{ke(t)}{v(t)}\right]\right|<\delta_{max};\\ \delta_{max} & \text{if } \left|\alpha+\tan^{-1}\left[\dfrac{ke(t)}{v(t)}\right]\right|\geq\delta_{max};\\ -\delta_{max} & \text{if } \left|\alpha+\tan^{-1}\left[\dfrac{ke(t)}{v(t)}\right]\right|\leq\delta_{max}.\end{cases}$$

- While the requirement of 0 max /2 is satisfied by the magnitude of both the maximum and lowest steering angle, max. The value of the tuning parameter has a big impact on how well the controller works. In research by Snider, the Stanley controller was implemented with various k values, and its effectiveness was assessed in a variety of driving circumstances. At large values of k, the controller performed well; but, beyond a certain threshold, it destabilised. It should be observed that the Stanley controller's control law **[2]** places more emphasis on regulating the position of the front wheel than it does the orientation of the whole vehicle. Hence, a revised model suggestion was made **[4]**. The new regulation generated control actions by taking into consideration both the rate of steering angle and error caused by yaw variations;

$$\delta(t)=\alpha+\tan^{-1}\left[\frac{ke(t)}{v(t)}\right]+k_\theta(\dot{\theta}_{ref}-\dot{\theta})+k_\delta\dot{\delta}$$

The reference yaw angle is shown as θref, the actual yaw angle is shown as, and the tuning-dependent parameters are θ , and kθ, kδ and k. It has been noticed that a collection of certain criteria could only be useful for particular driving situations and cars. An adaptive approach was suggested to overcome this problem, which would allow the gain settings to be adjusted in response to changing road conditions and vehicle speeds.

II. RECENT WORKS

The combined-slip effect, wheel dynamics, and tyre force nonlinearities for driver-assistance systems are all taken into account in this research to propose a unique integrated control framework that combines concurrent vehicle lateral stabilisation and path tracking. The designed slip-aware receding horizon control system uses active front steering and brakes as actuators and incorporates longitudinal slip dynamics into the prediction model to account for the loss of cornering forces.The controller keeps track of tyre capacities and normal forces, corrects the driver's input, and modifies wheel torques and steering to ensure safe route tracking (like lane-keeping) performance while stabilising the car within its handling parameters. The capacity to manage multiple vehicle actuator systems due to its more precise prediction model is the developed slip-aware driver assistance controller's key benefit **[1]**.

This study suggests a force-driven switching MPC path tracking control method that syncs up active front-wheel steering with an outside yaw moment. The rear tyre dynamics are first described by modelling a linear time-varying tyre using the affine approximation linearization approach. Moreover, vehicle dynamics is modelled in order to forecast vehicle states across the prediction horizon. The system prediction model is then used to support the proposal of a force-driven switching MPC control approach. The maximum tyre lateral force and the zero-point moment approach, respectively, are used to limit the vehicle's lateral stability and rollover stability. The findings indicate that under conditions of normal speed, the maximum lateral deviation and course deviation are respectively lowered by 42.86% and 2.89%. In conditions of limited speed, the maximum lateral position deviation and course deviation are respectively lowered by 30.6% and 10.25% **[2]**.

In this work, a tyre force distribution rule is suggested, and a route tracking control technique based on comprehensive model predictive control (MPC) is developed. In the controller model, a UniTire tyre model with coupled slip conditions is constructed to characterise the coupling and significant nonlinearity of tyre dynamics. In addition, the Taylor expansion is used to linearize the nonlinear controller model, and a linear time-varying MPC controller is created to enhance the system's real-time performance. The findings demonstrate the clear benefits of the suggested approach in terms of route tracking performance, lateral stability, and traffic efficiency **[3]**.

The coordinated control system for the lateral stability of autonomous vehicles is proposed in this paper and is based on state estimation and path tracking. It helps to improve the path-tracking capability while also preserving the stability of autonomous vehicles operating in complex and dynamic road environments. The vehicle parameters are first estimated using an extended Kalman filter observer. Finally, a model for adaptive preview time is created for the accuracy of path tracking based on the single-point preview theory. Sideslip angle and yaw rate, two crucial variables for lateral dynamic stability control, are taken into account while building the direct yaw-moment controller, and the single-wheel braking technique is used to appropriately distribute the excess yaw moment to a specific wheel **[4]**.

The most recent developments in LOS guidance for AMV route following are summarised in this study. An AMV's route following using a kinematic model is given first, along with a control goal. After that, a thorough study of the main LOS guideline laws for route following is conducted. After that, expanded LOS guidance regulations for coordinated route following of many AMVs follow. In order to follow the course of both single and many AMVs, LOS guidance has made significant advancements. This study gives a summary of such advancements. It outlines some of the LOS advice literature in terms of its categorization, approach, and features. Also, five future paths are highlighted, including collision-free LOS advice, LOS guidance for 3-D CPF of many AMVs, shared LOS guidance, powerful anti-disturbance LOS guidance, and RL-based LOS guidance **[5]**.

In this research, a hierarchical dynamic drifting controller is proposed to enable integrated control of vehicle drifting and typical cornering movements, allowing the vehicle to operate both inside and outside of the stability limits and improving the vehicle's handling limitations on the general route. First, the dynamic drifting inverse model is recommended in order to fully use tyre forces during drifting and typical cornering situations. The development of two MPC-HDDC and LQR-HDDC hierarchical dynamic drifting controllers, as well as the development of two route tracking controllers based on MPC and LQR, are presented. The results of the ECU hardware-in-the-loop platform's testing of the real-time performance of the two controllers and the algorithms' adaptability show that the recommended algorithms are practical and efficient in terms of route tracking and manoeuvring stability **[6]**.

III. METHODOLOGY

Here, the path tracking mechanism has been focused on mainly two models;

A. Kinematic Bicycle Model:

The following equations provide the mathematical representation of the nonlinear continuous-time kinematic bicycle model inside an inertial reference frame;

$$\begin{aligned}
\dot{x} &= v\cos(\psi+\beta) \\
\dot{y} &= v\sin(\psi+\beta) \\
\dot{\psi} &= \frac{v}{l_r}\sin(\beta) \\
\dot{v} &= a \\
\beta &= \tan^{-1}\left(\frac{l_r}{l_f+l_r}\tan(\delta_f)\right)
\end{aligned}$$

The kinematic bicycle model shown in Fig. 2 is used to explain the mathematical equations that describe a vehicle's motion inside an inertial reference frame. These equations use the coordinates x and y for the centre of mass, for the inertial orientation, and v for the vehicle's speed. The letters lr and lf, respectively, stand for the separations between the front and rear axles from the centre of mass. The angle denotes the speed at which the centre of mass is currently moving with respect to the longitudinal axis of the vehicle. The variable a stands in for the acceleration of the centre of mass, which is parallel to its velocity. The rear and front steering angles, denoted as r and f, respectively, serve as the system's control inputs; r is often set to zero since most cars lack the capacity to perform rear steering. Given that only two parameters must be determined, this model's benefit is its ease of application (lf and lr). This property enables the use of standardised control systems or route planning algorithms for a variety of vehicles with various wheelbase sizes.

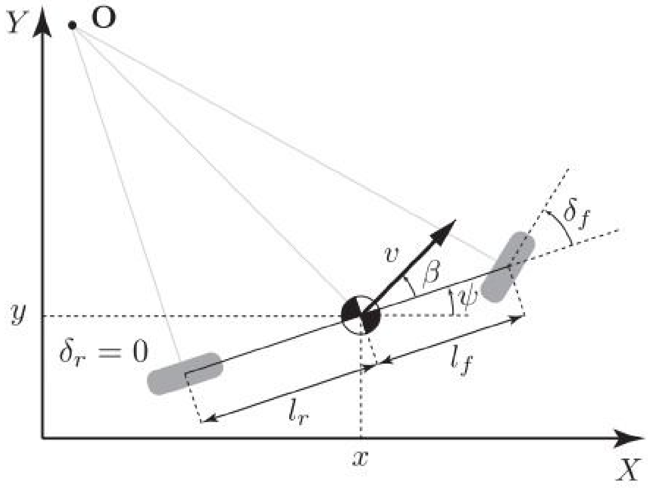

Fig.2. Kinematic Bicycle Model

B. Dynamic Bicycle Model:

Similar conceptualizations for the orientation angle and inertial position are used by the bicycle model, which incorporates dynamic concepts, as its kinematic counterpart. Differential equations serve as the model's mathematical representation in this instance;

$$\begin{aligned}
\ddot{x} &= \dot{\psi}\dot{y} + a_x \\
\ddot{y} &= -\dot{\psi}\dot{x} + \frac{2}{m}\left(F_{c,f}\cos\delta_f + F_{c,r}\right) \\
\ddot{\psi} &= \frac{2}{I_z}\left(l_f F_{c,f} - l_r F_{c,r}\right) \\
\dot{X} &= \dot{x}\cos\psi - \dot{y}\sin\psi \\
\dot{Y} &= \dot{x}\sin\psi + \dot{y}\cos\psi,
\end{aligned}$$

In the equations above for the dynamic bicycle model, the terms X, Y, and are used to denote the lateral and longitudinal speeds in the reference vehicle's frame of reference and the rate of change of yaw, respectively. These equations also incorporate m, which stands for the vehicle's mass, and Iz, which stands for the yaw inertia. Moreover, f, Fc, and r reflect the forces acting on the lateral tyres of the front and back wheels, respectively. The following is how the linear tyre model defines Fc,i:

$$F_{c,i} = -C_{\alpha_i}\alpha_i,$$

For i in Fc,i ,{f, r}, is dependent on the slip angle of tire(αi) and the stiffness due to cornering of tire (Cαi).

1. Defining a vector of Waypoints:
   Using a programme called Driving Scenario Designer, a vector comprising waypoints is constructed and saved in.mat format.
2. Interpolating and smoothening the reference position and orientation:
   Refining the reference with regard to direction and location and removing any undesirable variations is essential for the Stanley controller to be implemented successfully. The raw waypoint vector sample points have a tendency to form a lumpy trajectory, thus interpolation is used to achieve this.
3. Defining a reference velocity profile:
   In order to create the reference velocity profile, velocityProfile.mlx employs three alternative methods: the conventional trapezoidal profile, a trapezoidal profile affected by the radius of the curvature and a trapezoidal profile, and friction defined by maximum acceleration and velocity.
4. Tuning the controller:
   In order to increase the controller's accuracy, it is essential to keep critical parameters at proper values, such as position gain for forward motion and feedback gain for yaw rate and steering angle.

A simplified three-dimensional depiction of a two-axle vehicle with a fundamental drivetrain and powertrain serves as the foundation for the vehicle dynamics model in this reference application. It is taken from the example "Scene Interrogation with Camera and Ray Tracing" and uses a trapezoidal velocity profile to compute the required velocity. The scenario's waypoints are given in a mat file that was produced from the Driving Scenario Designer. After the acceleration, steering, and deceleration instructions have been produced, the Stanley controller will next follow the reference trajectory. Moreover, a 2D graph of the vehicle's movements is shown by the model. The block diagram of the proposed model is depicted in Fig. 5.

Fig.3. Waypoints for Double Lane Road.

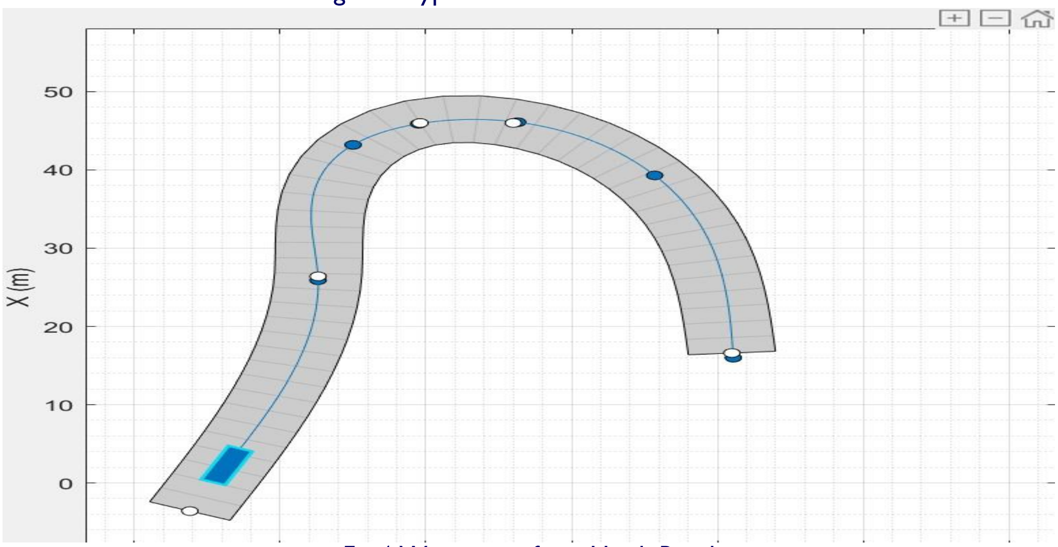

Fig.4.Way points for a Hook Road

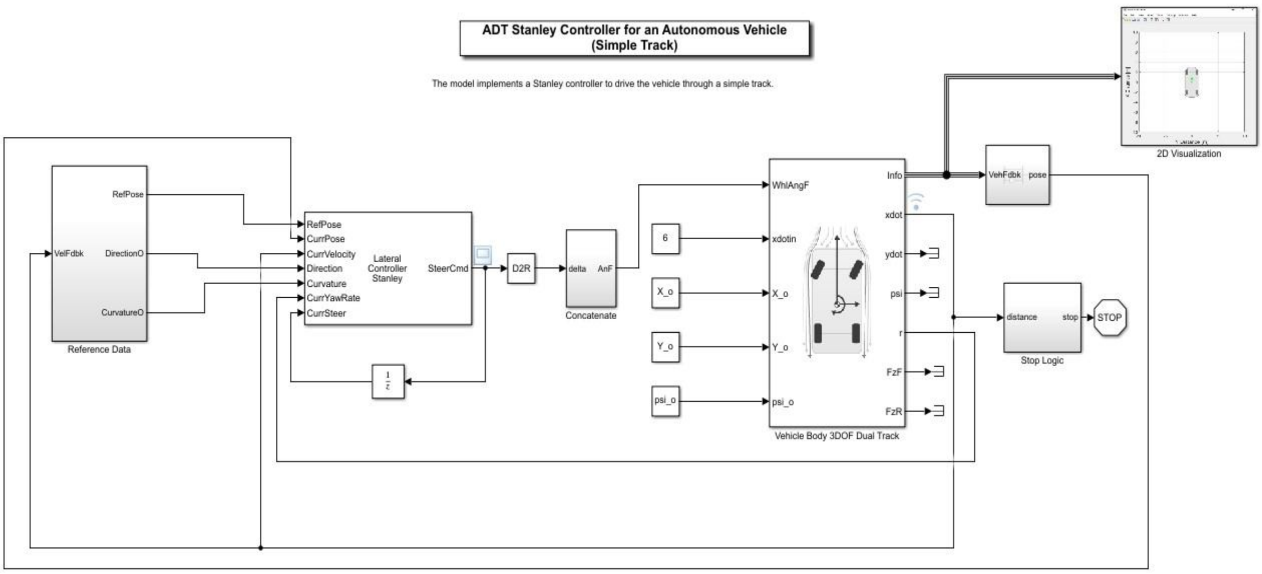

Fig.5. Simulink Model of the proposed system.

The Stanley block Lateral Controller determines the steering angle, expressed in degrees, required to move a vehicle from its present location to a reference position that integrates dynamic and kinematic models. Parking lots are a good example of a low-speed condition where the kinematic model excels, whereas high-speed circumstances where inertial effects are more pronounced benefit from the dynamic model. The vehicle model also takes into account a number of characteristics that define its dynamics. The controller's goal in computing the steering angle is to reduce the present errors in angle and position with respect to the reference position. When the direction parameter is set to 1, which indicates that the vehicle is moving forward, the error with respect to position is calculated as the lateral distance between the front axle centre and the path's point of reference, and the error with respect to angle is the front wheel's angle in relation to the reference path.

IV. RESULTS AND DISCUSSIONS

On diverse roads, such as hook roads and double-lane roads, experimental results were achieved by altering the vehicle's speeds. The various gains of the Stanley controller's crucial parameters, including as the yaw rate, forward and reverse position vectors, and other parameters, are adjusted to the proper values to provide the vehicle with the most precise control possible.

A. Hook Road:

The outcomes of the proposed model for a hook road is depicted in Fig. 6, 7 & 8. By varying the velocities and different gains the important parameters of the Stanley controller is verified.

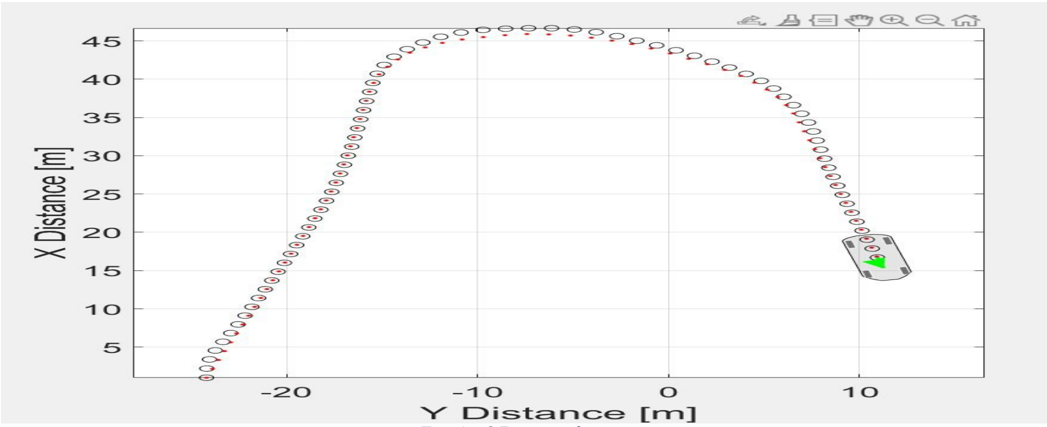

Fig.6. 2D simulation.

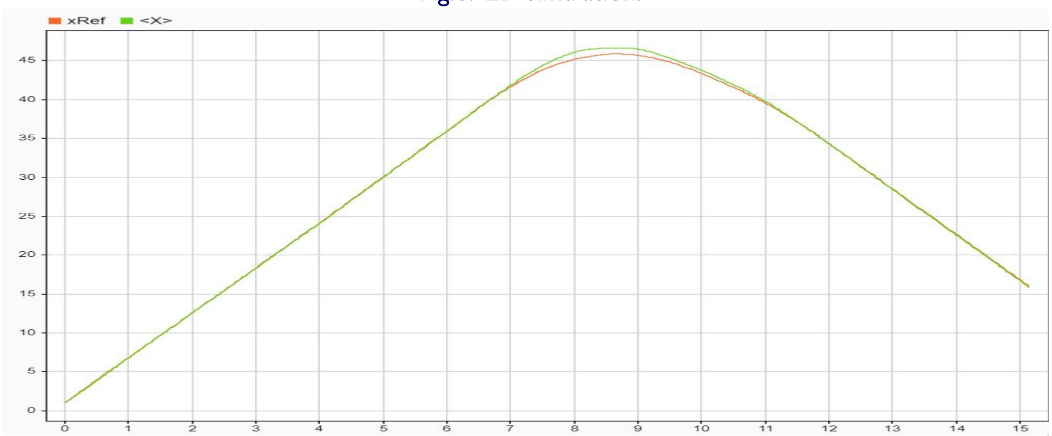

Fig.7. Xref V/s X.

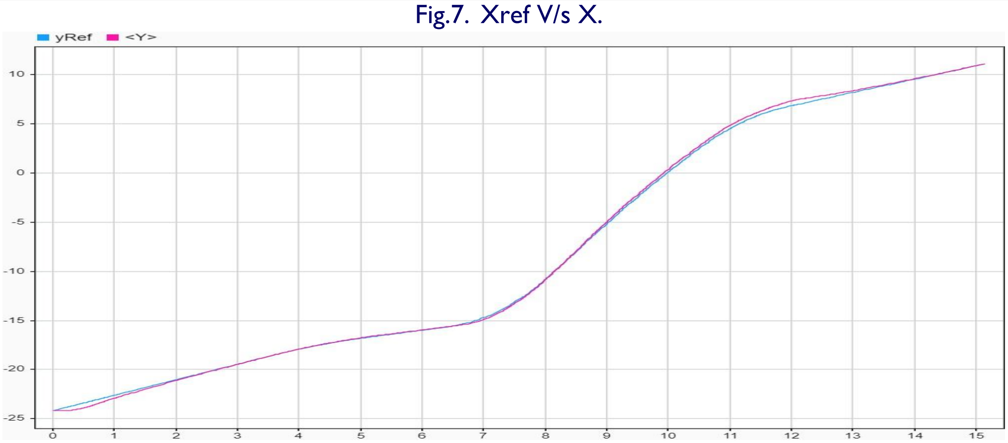

Fig.8. Yref V/s Y.

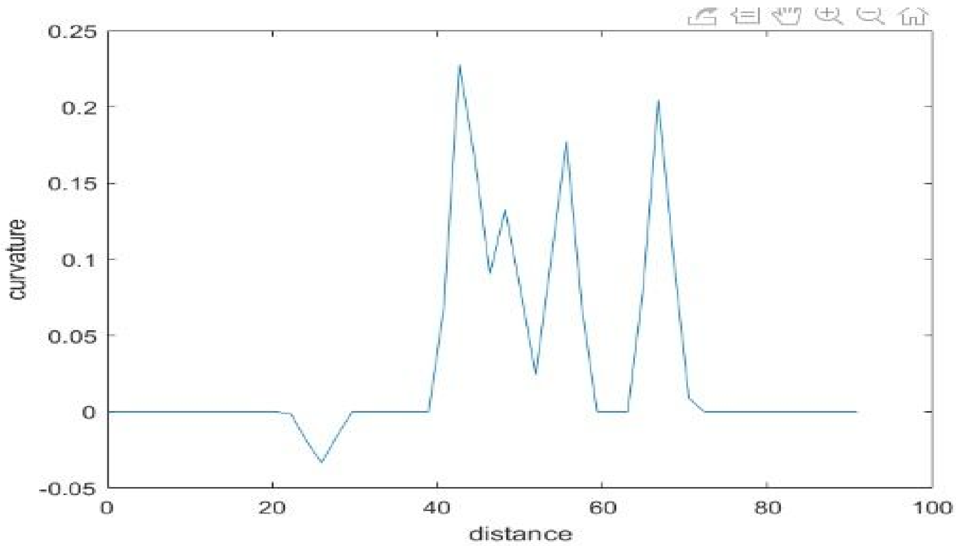

Fig.9. Curvature Vector.

B. Double Lane Road:

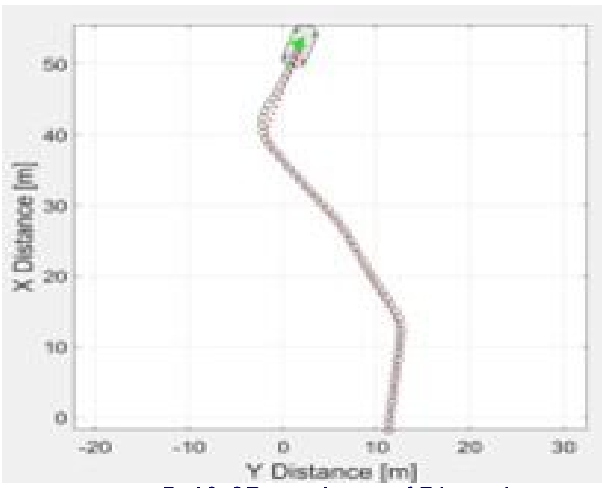

Fig10. 2D simulation of DL road

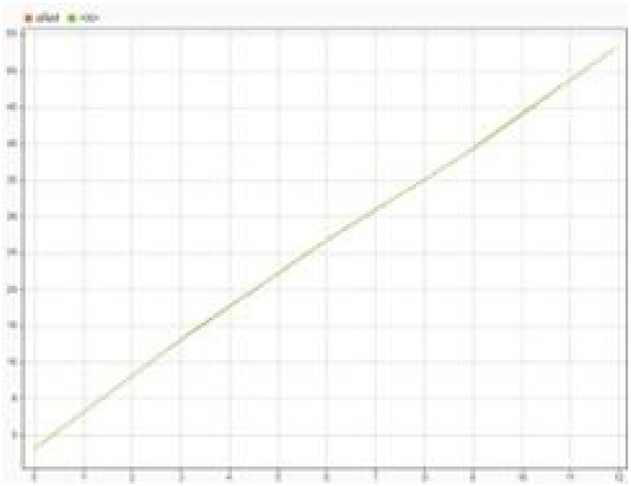

Fig11. Xref V/s X of DL road.

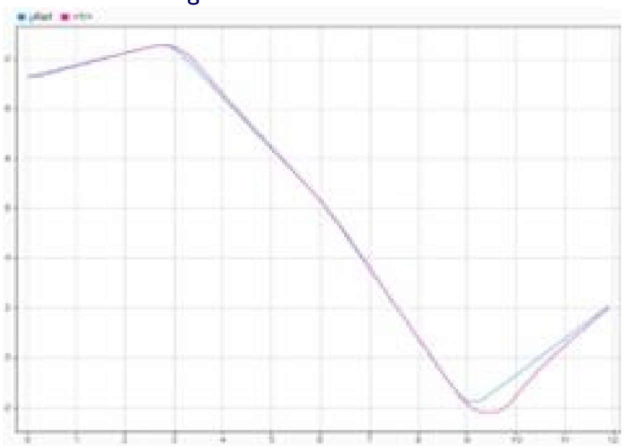

Fig.12.Yref v/s Y of DL road.

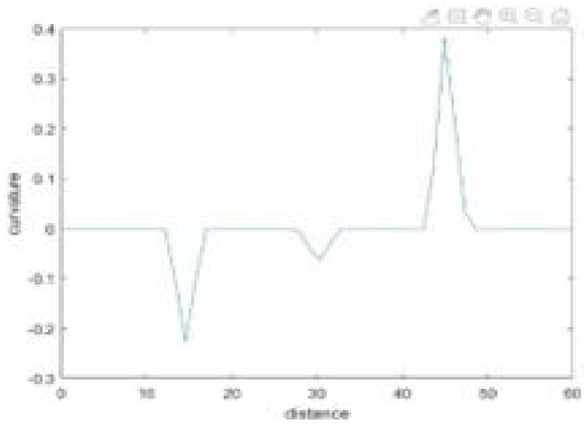

Fig.13.Curvature vector of DL road.

We upgraded the automobile with front and rear cameras as well as a radar sensor. Together, these sensors are able to identify things and offer crucial data for traffic management. The cameras record high-resolution pictures and movies that enable us to recognize and follow nearby cars, people, and other things. We may use the extra information the radar sensor offers about the distance and speed of objects to assist us make judgements about braking, acceleration, and steering in the moment. Combined, these sensors provide the automobile a thorough understanding of its surroundings, enhancing both its safety and effectiveness for traffic management. In order to improve traffic flow and lessen congestion on the roads, the data gathered from these sensors may also be utilised for traffic analysis and forecasting.

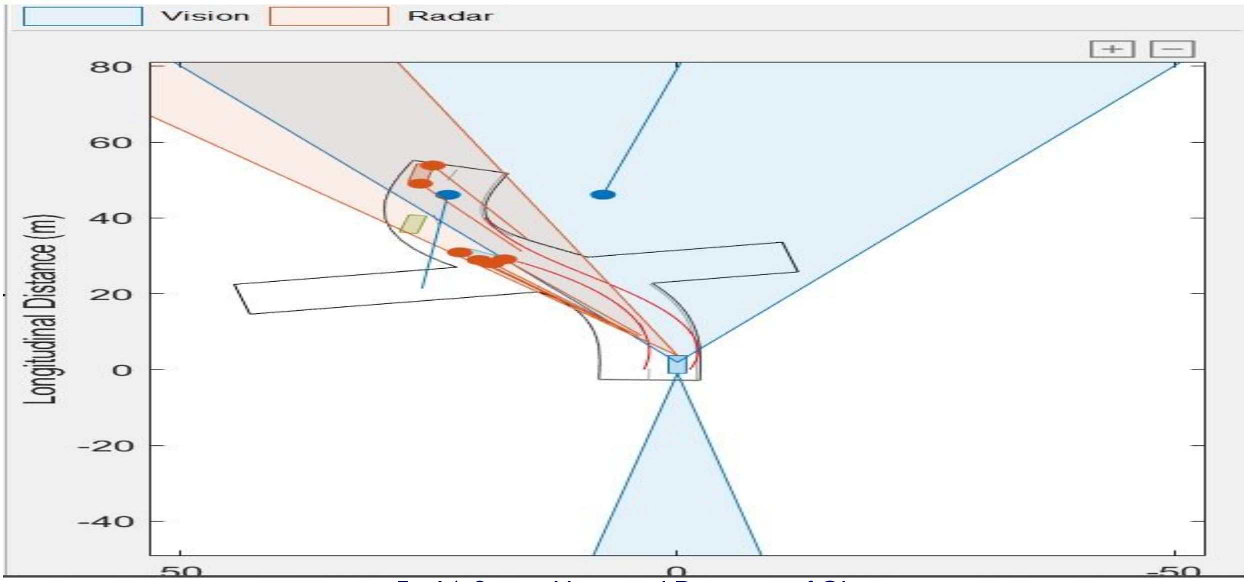

Fig 14. Sensor Vision and Detection of Object.

Fig.15. 3D simulation of the proposed work

V. CONCLUSIONS

In conclusion, the Stanley controller has shown to be an effective tool for autonomous vehicle navigation when used with the dynamic cycling model. The Stanford Artificial Intelligence Laboratory's controller uses a dynamic model to correctly and successfully steer a vehicle across challenging terrain. To anticipate a vehicle's future trajectory and make the necessary modifications, this model takes into consideration the characteristics of the vehicle, such as its speed and steering angle. The Stanley controller has been put to the test in a variety of situations, and in each one it has shown to be a very reliable and useful navigational tool. Even in the face of barriers and other unforeseen factors, the controller's capacity to precisely forecast the vehicle's trajectory and make appropriate modifications in real-time enables smooth and safe navigation. The vehicle also has sensors and radars built in to recognize lanes and other things, such as bicycles, vehicles, and people.

REFERENCES

1. John M. Guirguis, Sherif Hammad, and Shady A. Maged Ain Shams University, Cairo, Egypt International Journal of Mechanical Engineering and Robotics Research Vol. 11, No. 7, July 2022 "Path Tracking Control Based on an Adaptive MPC to Changing Vehicle Dynamics". https://doi.org/10.18178/ijmerr.11.7.535-541
2. Liu, Z. Yang, Z. Huang, W. Li, S. Dang and H. Li, "Simulation Performance Evaluation of Pure Pursuit, Stanley, LQR, MPC Controller for Autonomous Vehicles," 2021 IEEE International Conference on Real-time Computing and Robotics (RCAR), 2021 https://doi.org/10.1109/rcar52367.2021.9517448
3. V. K, M. Ambalal Sheta and V. Gumtapure, "A Comparative Study of Stanley, LQR and MPC Controllers for Path Tracking Application (ADAS/AD)," 2019 IEEE International Conference on Intelligent Systems and Green Technology (ICISGT), 2019 https://doi.org/10.1109/icisgt44072.2019.00030
4. Ahmed AbdElmoniem, Ahmed Osama, and Shady A Maged, International Journal of Advanced Robotic Systems 2020"A path-tracking algorithm using predictive Stanley lateral controller". https://doi.org/10.1177/1729881420974852
5. Amer, N.H., Zamzuri, H., Hudha, K. et al. Path tracking controller of an autonomous armored vehicle using modified Stanley controller optimized J Braz. Soc. Mech. Sci. Eng. 40, 104 (2018) https://doi.org/10.1007/s40430-017-0945-z

6. S. Xu and H. Peng, "Design, Analysis, and Experiments of Preview Path Tracking Control for Autonomous Vehicles," in IEEE Transactions on Intelligent Transportation Systems. https://doi.org/10.1109/tits.2019.2892926
7. N. H. Amer et al., "Adaptive Trajectory Tracking Controller for an Armored Vehicle: Hardware-in-the Loop Simulation," 2018 57th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE), 2018 https://doi.org/10.23919/sice.2018.8492544
8. S. S. Tippannavar, E. A. Madappa and R. S. B, "Automatic Accident Alert System – Early Accident Prediction and Warning for the consumers," 2022 IEEE 2nd Mysore Sub Section International Conference (Mysuru Con), Mysuru, India, 2022, pp. 1-6, https://doi.org/10.1109/mysurucon55714.2022.9972367
9. S. S. Tippannavar, S. B. Rudraswamy, S. Gayathri, S. P. Kulkarni, A. Thyagaraja Murthy and S. D. Yashwanth, "Smart Car - One stop for all Automobile needs," 2022 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), Greater Noida, India, 2022, pp. 54-59, https://doi.org/10.1109/icccis56430.2022.10037715
10. Sanjay,Yashwanth,Megha,Shachee (2023). LC2BS – Low cost secondary Braking System implemented using Arduino and Motor Speed Control Mechanism, International Journal of Innovative Research in Advanced Engineering, Volume 10, Issue 02 of 2023 pages 18-23 https://doi.org/10.26562/ijirae.2023.v1002.02
11. S. S. Tippannavar, S. D. Yashwanth, M. P. Madhu Sudan, K. M. Puneeth, B. N. Chandrashekar Murthy and M. S. Vinay Prasad, "Analysis Of Performance of different Control Techniques on Anti-Lock Braking System," 2022 International Conference on Disruptive Technologies for Multi-Disciplinary Research and Applications (CENTCON), Bengaluru, India, 2022, pp. 35-40, https://doi.org/10.1109/centcon56610.2022.10051207
12. S. S. Tippannavar, K. M. Puneeth, S. D. Yashwanth, M. P. Madhu Sudan, B. N. Chandrashekar Murthy and M. S. Vinay Prasad, "SR2 - Search and Rescue Robot for saving dangered civilians at Hazardous areas," 2022 International Conference on Disruptive Technologies for Multi-Disciplinary Research and Applications (CENTCON), Bengaluru, India, 2022, pp. 21-26, https://doi.org/10.1109/centcon56610.2022.10051203