Control System For Low-cost Autonomous Vehicle Using ESO and Lyapunov-based Control

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***Abstract*—This paper is concentrating on designing a control system to handle a low-cost autonomous vehicle. There are many shortcomings in this system such as time-delays, sensor noise and nonlinearities that cannot be modelled with equations. In real experiments, the performances of this vehicle are recorded by data and diagram which quantifies the shortcomings of this system. With these results, two problems are founded which are the research objectives of this paper. One is the uncertainty in this system, which makes it hard for a linear controller to stabilize this system. The other is that there are nonnegligible time-delays in the front wheel motor, and it can resist disturbance. To solve these problems, a Lyapunov-based method is applied to design a nonlinear tracking controller. Meanwhile, an Extended State Observer (ESO) is designed to solve the problems of the front wheels. The control system is tested in simulation and real vehicle, whose results prove the correctness and feasibility.**

***Index Terms*—Lyapunov-based, Extended State Observer, vehicle control, nonlinear control, stability**

I. Introduction

Control system design for autonomous vehicle is an important topic for the rapidly developing autonomous driving technology nowadays. This problem can be very easy if the vehicle is equipped with high-performance devices while it can be really hard when the devices are low-cost ones. There will be non negligible time-delays and disturbances in low-cost devices and the limited computility will make it hard to deploy advanced algorithm in this system. This paper is mainly about designing and testing a control system for a kind of low-cost autonomous vehicle.

Many control methods are proposed for autonomous driving, PID controller is the most common used one whose biggest advantage is model-free. However, it does not work well in nonlinear system especially those with disturbances. In [1], an adaptive PID controller is proposed to control an underwater vehicle. Sliding Mode Control (SMC)[19-20] and fuzzy control [2][13] are also effective method for autonomous vehicle. Optimal control is a popular control algorithm in recent years, since the computility of the hardware is greatly improved. Linear Quadratic Regulator (LQR) and Model Predictive Control (MPC) are two essential optimal controller that are widely used in robots, autonomous vehicles, quadrotors and the numerous successes prove their effectiveness. In [5], the authors gives out a comparison between PID, LQR and MPC and they point out optimal control is a better solution for modern control system, but there are still many problems to be solved. For a low-cost autonomous vehicle, the limited computation resources will make the algorithm unable to perform well. The nonlinear controller needs less computation resources, and more importantly, the vehicle kinematics model is nonlinear[9-10][14-15]. Lyapunov-based method, also known as backstepping method, is a controller designed based on Lyapunov stability theory. Some typical Lyapunov-based method are proposed to control mobile robots and underwater vehicle [16-17] and it is proved that this method can tackle the non-linearity in the system. In [11], the authors design a Lyapunov-based controller to stabilize a drone which is a complex nonlinear system. For a low-cost vehicle with poor hardware performance, there are many nonlinearity and uncertainties in the model. It is very difficult to model the system accurately, so in the actual research, we hope to design a simple and effective control algorithm. Therefore, Lyapunov-based method is a good choice.

On the other hand, the autonomous driving control system is a hierarchical system. The actuator is the motor, the high-level controller gives the steering angle and velocity, and the low-level controller needs to generate current to control the motor. Therefore, this problem is not only about designing a high-level nonlinear controller, but also deigning a low-lever motor controller. The motor control model is very complex, but the main goal is not to study the motor model, so the model-free method is more suitable. Active Disturbance Rejection Control (ADRC) is a model-free method which can also handle the disturbances. It is applied in speed control of a DC motor in [3] and the authors study ADRC in simulation. One of the most important subsections of ADRC is ESO which regards the disturbance as an extended state value. ESO-based method is an useful tool to tackle uncertainties [7], so it is chosen to control the motor in our system.

Hence, a hierarchical system is designed in this paper to control a low-cost vehicle with various limitation. The main contribution of this research is proposing a solution to the real

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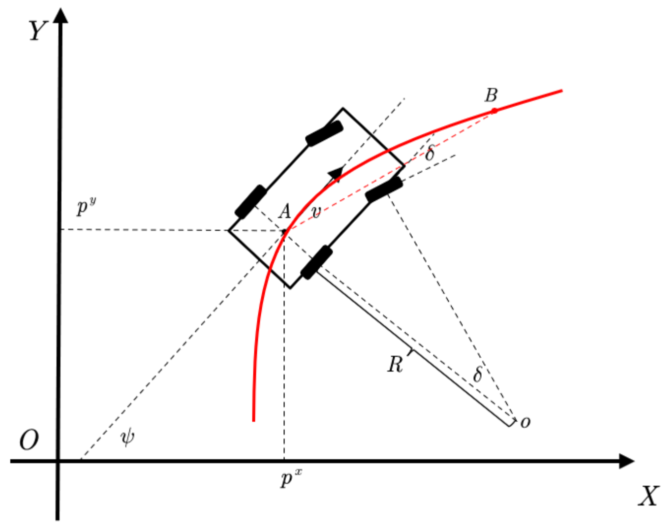


Fig. 1. This figure includes the kinematics model of the autonomous vehicle and that of the trajectory tracking problem.

vehicle control problem. The system modeling process will be introduced in the next section. The high-level and low-level design will be introduced in Section III and Section IV. The detailed introduction of experiments is arranged in Section V. Finally, the conclusion and analysis will be given out in Section VI.

II. System Modeling

The classical Ackermann Turing Model is chosen to describe the vehicle‘s movement. Using $\mathbf{x} = (p^x, p^y, \psi)^T$ to represent the position and orientation of the car with the fact that all states variable in this system are considered in the World Coordinates. On the other hand, $u = (v, \delta)^T$ is used to represent the control inputs of this system. Equation (1) is the system model derived based on the kinematics.

$$\begin{bmatrix} \dot{p^x} \\ \dot{p^y} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} \cos\psi \\ \sin\psi \\ \tan\delta/l \end{bmatrix} v \tag{1}$$

Fig 1 is the illustration of this system in which point A is the center of the rear wheels, the red line is the reference trajectory and the state variables $\mathbf{x}$ and u are also marked in this figure. It is also worth noting that point o is the turning center and R is the turning radius. Point B is the target tracking point on this trajectory which only gives out the desired positional data (p_r^x, p_r^y). With the planning module, the desired pose ψ_d can be obtained. Using (p_r^x, p_r^y, ψ_r) to represent the reference states of the vehicle and the tracking error is $e = (p^x - p_r^x, p^y - p_d^y, \psi - \psi_r)^T$ so that the following controller designing is based on this.

III. High-level Controller

Lyapunov Stability Theory is an important theory for analyzing system stability. The theory points out that the system is stable as long as there is a positive definite energy function for the system and the derivative of it is negative definite. The energy function is the so-called Lyapunov Function which is usually a linear quadratic one. If given the Lyapunov and the system model, then the control law can be derived from them. Namely, this control law satisfies the Lyapunov stability condition, so the it can stabilize the system. In the following contents, define $z = (z_1, z_2, z_3)^T = (p^x, p^y, \psi)^T$ and $u = (u_1, u_2)^T = (v, \delta)^T$. In that way, the system is changed into:

$$\begin{aligned} \dot{z}_1 &= u_1 \cos z_3 \\ \dot{z}_2 &= u_1 \sin z_3 \\ \dot{z}_3 &= u_1 \tan u_2 / l \end{aligned} \tag{2}$$

Accordingly, the desired state is z_d, and the tracking error can be written as $e_i = z_i - z_{id}$ $(i = 1, 2, 3)$. For $z1$, if e_1 converge to 0, the system tend to be stable. Deign the first Lyapunov function:

$$V_1 = \frac{1}{2} e_1^2 \tag{3}$$

Obviously, $V_1 \geq 0$, if the derivative of it $\dot{V} \leq 0$ the subsystem is stable according to the Lyapunov Stability Theory.

$$\dot{V}_1 = e_1 \dot{e}_1 = e_1 (\dot{z}_1 - \dot{z}_{1d}) = -k_1 e_1^2 \leq 0 \tag{4}$$

in which k_1 is a positive constant. In other words, $\dot{z}_1 - \dot{z}_{1d} = -k_1 e_1$. As a result, there is

$$\dot{z}_1 = u_1 \cos z_3 = -k_1 e_1 + \dot{z}_{1d} \tag{5}$$

Similarly, for z_2 there is an another Lyapunov function V_2 and there is:

$$\begin{aligned} V_2 &= \frac{1}{2} e_2^2 \\ \dot{V}_2 &= e_2 \dot{e}_2 = e_2 (\dot{z}_2 - \dot{z}_{2d}) = -k_2 e_2^2 \leq 0 \end{aligned} \tag{6}$$

Similarly, k_2 is a positive constant and there is another equation:

$$\dot{z}_2 = u_1 \sin z_3 = -k_2 e_2 + \dot{z}_{2d} \tag{7}$$

From (5) and (7), it can be found that $(u_1 \sin z_3)^2 + (u_1 \cos z_3)^2 = u_1^2$, so that

$$u_1^2 = (-k_1 e_1 + \dot{z}_{1d})^2 + (-k_2 e_2 + \dot{z}_{2d})^2 \tag{8}$$

In that way, we obtain the velocity controller u_1:

$$u_1 = \sqrt{(-k_1 e_1 + \dot{z}_{1d})^2 + (-k_2 e_2 + \dot{z}_{2d})^2} \tag{9}$$

For steering controller u_2, the Lyapunov function can be designed in the same way with

$$\begin{aligned} V_3 &= \frac{1}{2} e_3^2 \\ \dot{V}_3 &= e_2 \dot{e}_3 = e_3 (\dot{z}_3 - \dot{z}_{3d}) = -k_2 e_3^2 \leq 0 \end{aligned} \tag{10}$$

then there is an equation similar to (5) and (7):

$$-k_3 e_3 + \dot{z}_{3d} = \frac{u_1 \tan u_2}{l} \tag{11}$$

so that the steering angle control law u_2 can be derived as:

$$u_2 = \arctan\left[\frac{l}{u_1}(-k_3 e_3 + \dot{z}_{3d})\right] \tag{12}$$

Besides, the velocity and angle constraints must be taken into account,

$$-5 \leq u_1 \leq 5, -45^\circ \leq u_2 \leq 45^\circ \tag{13}$$

In sum, the nonlinear controller that can be deployed on the real vehicle is:

$$\begin{cases} u_1 = \sqrt{\left(-k_1 e_1 + \dot{z}_{1d}\right)^2 + \left(-k_2 e_2 + \dot{z}_{2d}\right)^2} \\ u_2 = \arctan\left[\frac{l}{u_1}\left(-k_3 e_3 + \dot{z}_{3d}\right)\right] \\ -5 \leq u_1 \leq 5, -45^\circ \leq u_2 \leq 45^\circ \end{cases} \tag{14}$$

Accordingly, the Lyapunov function satisfies:

$$\begin{cases} V = \frac{1}{2}e_1^2 + \frac{1}{2}e_2^2 + \frac{1}{2}e_3^2 \geq 0 \\ \dot{V} = -k_1 e_1^2 - k_2 e_2^2 - k_3 e_3^2 \leq 0 \end{cases} \tag{15}$$

The selection of k_1, k_2, k_3 is another important problem, which will be discussed in the next section.

IV. Low-level Controller

In the former section, the steering angle δ is derived. The actuator of the vehicle steering control system is the motor of the front wheel. Fig 1 shows the signal response of the real vehicle which shows the open-loop performance of this motor. This figure shows that there are significant time-delays and disturbance.

After that, in another experiment u_2 is directed sent to the motor for comparison. In this case, the results show that the system cannot accurately track this signal. Therefore, it is necessary to deign a low-level controller to improve the performance of the motor. The output u_2 from the high-level controller can be treated as the input of the low-level controller. In addition, there is only an angle sensor in the motor which means we cannot design a multi-loop controller to stabilize the angular velocity. Therefore, designing an observer is taken into account.

A. ESO

There are three typical problems that should be tackled in this low-level controller: (1) The accurate system model of the motor is unreachable. (2) There is only a first-order angle feedback. (3) Time-delays and disturbance, so it will be hard to design a model-based controller. As a result, model-free controller is taken into account to solve this problem. PID controller is a classical solution, but it can reject the disturbance in this system. What‘s more, it cannot tackle the time-delays in this motor. ESO is a good choice since it takes the disturbance into account and there can be some treatment to handle the time-delays. Fig 2 is the illustration of the entire control system.

Since controller‘s output can influence the torque of the motor, this system can be regarded as a second-order system with an unreachable system model f:

$$\begin{cases} \ddot{x} = f\left(x, \dot{x}, t\right) + bu_l + w \\ y = x \end{cases} \tag{16}$$

in which x is the angle of the steering motor , and accordingly $\dot{x}$ is the angular velocity and $\ddot{x}$ is the angular acceleration. Meanwhile,b is the input matrix with the low-level controller‘s output u_l, w is the unknown system disturbance and y is system feedback. For the real vehicle, y is the value given by the motor encoder.

In the flowing content, let $x_1 = x$, the system equations can be rewritten as:

$$\begin{cases} \dot{x}_1 = x_2 = \dot{x} \\ \dot{x}_2 = \ddot{x} = f\left(x, \dot{x}, t\right) + bu_l + w \\ \ y = x_1 \end{cases} \tag{17}$$

If w is regarded as a new extended state variable x_3, there is

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 + bu_l \\ \dot{x}_3 = \dot{f}\left(x, \dot{x}, t\right) + \dot{w} \\ y = x_1 \end{cases} \tag{18}$$

Formulate a Linear Extended State Observer (ESO), which can be used to estimate the real-time disturbance,

$$\begin{cases} \dot{\hat{x}} = a\hat{x} + bu_l + \beta\left(y - \hat{y}\right) \\ \hat{y} = \hat{x} \end{cases}$$
$$\begin{cases} \dot{\hat{x}}_1 = \beta_1\left(y - \hat{x}_1\right) + \hat{x}_2 \\ \dot{\hat{x}}_2 = \beta_2\left(y - \hat{x}_1\right) + \hat{x}_3 + bu_l \\ \dot{\hat{x}}_3 = \beta_3\left(y - \hat{x}_1\right) \end{cases} \tag{19}$$

where β is the observer gain and $\hat{x}$ is the estimated state. Discretization can be done to make ESO more suitable for computation, the final form of it is as follow:

$$\begin{aligned} \xi_1\left(k\right) &= x_1(k) - y(k) \\ x_1(k+1) &= x_1(k) + h\left(x_2(k) - \beta_1\xi_1\right) \\ x_2(k+1) &= x_2(k) + h\left(x_3(k) - \beta_2 \ \mathrm{fal}\left(\xi_1, \alpha_1, \theta\right)\right) \\ x_3(k+1) &= x_3(k) - h\beta_3 \ \mathrm{fal}\left(\xi_1, \alpha_2, \theta\right) \end{aligned} \tag{20}$$

in which h is the time step length and the nonlinear function $fal\left(e, \alpha, \theta\right) = \begin{cases} \frac{e}{\theta^{1-\alpha}} & |e| \leq \theta \\ |e|^\alpha sgn\left(e\right) & |e| > \theta \end{cases}$ and e is the tracking error of each state and α is the constants of this function with ξ as the boundary of e. $sgn\left(\cdot\right)$ is the symbolic function.

B. Control Law

The desired signal of the low-level control system is δ, and the signal consists of discrete step signals. The instantaneous errors may damage the motor, so it is necessary to smooth the signal. In addition, noises are involved in the signal so that a filter is also needed. Tracking Differentiator (TD) is an effective signal synthesizer, and differential signal can be calculated for a given angle signal. For the steering control system, the smooth angle signal and angular velocity signal can be calculated with the desired front wheel angle.

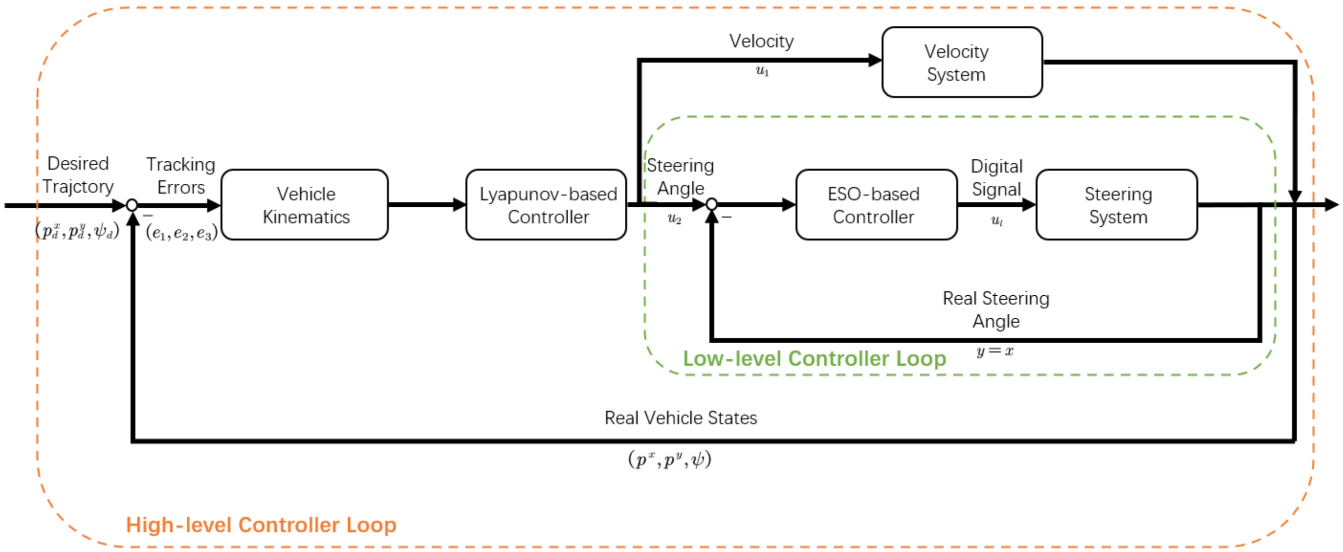


Fig. 2. This diagram shows the structure of the entire control system. The high-level controller is a nonlinear controller based on Lyapunov stability theory, and the low-level controller is a motor controller based on ESO. This paper mainly focuses on the practicability, so we give the detailed control system design method as much as possible in the article.

Let $\delta(k)$ be the input signal of TD, v_1 is the angle signal and v_2 is the angular velocity signal,

$$\begin{cases} v_1(k+1) = v_1(k) + hx_2(k) \\ v_2(k+1) = v_2(k) + hfhan(v_1(k) - \delta(k), v_2(k), r, h) \end{cases} \tag{21}$$

in which $fhan(\cdot)$ is the fastest synthesis function and there are

$$\begin{cases} d = rh, d_0 = dh \\ y = x_1 + hx_2, a_0 = \left(d^2 + 8r|y|\right)^{1/2} \\ a = \begin{cases} v_2 + (a_0 - d)/2, |y| \\ v_2 + y/h, |y| \le d_0 \end{cases} \\ fhan = -\begin{cases} ra/d, |a| \le d \\ rsgn(a), |a| > d \end{cases} \end{cases} \tag{22}$$

In (21), r is the velocity factor which can influence the tracking velocity and h_0 is the filtering factor which can reduce the overshoot in TD.

With TD and ESO, the input and feedback are solved, then the final control law is:

$$\begin{cases} u_0 = \beta_1 fal(e_1, \alpha_1, \theta) + \beta_2 fal(e_2, \alpha_2, \theta) \\ u_l = u_0 - x_3(k)/b \end{cases} \tag{23}$$

in which b is the feedback factor. This controller can be regarded as a nonlinear PID controller taking the disturbances into account. It can be leveraged to control system whose system model is unknown like the steering control system of this low-cost vehicle. In the next section, the simulation and real vehicle experiments will be introduced with details.

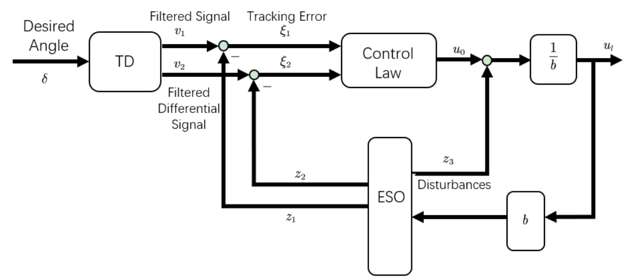


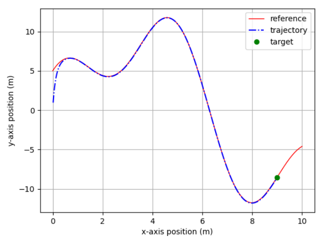
Fig. 3. Structure of low-level controller. Due to the poor equipment performance of low-cost vehicles, a model free controller is designed to improve the performance of the steering system.

V. Experiment

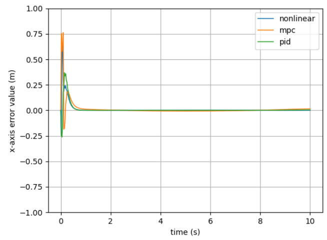
In this section, simulation and real vehicle experiments will be introduced. The simulation of the high-level controller is to track the trajectory generated by a trigonometric function. At the same time, the comparison test with the previous MPC algorithm and PID algorithm is carried out. The low-level algorithm simulation object is a nonlinear system. Because the model of the steering motor cannot be established, the simulation about the low-level control algorithm is only the validation.

A. Simulation

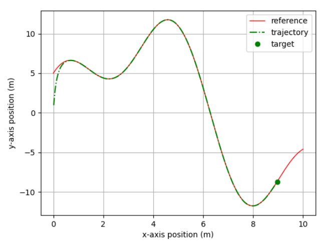
The simulation experiment was completed on a laptop computer with I7 CPU, Nvidia RTX 2080s, and Windows 10 system. In addition, the performance of this computer is similar to that of industrial computers on real vehicles. This nonlinear algorithm together with MPC and PID is tested in



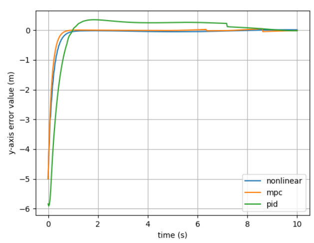
(a) Nonlinear control



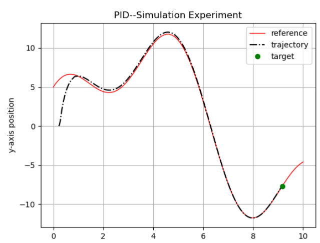
(b) x-axis comparison



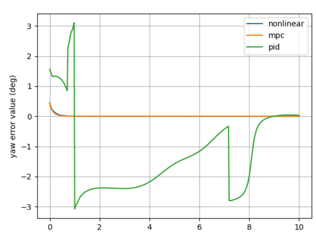
(c) MPC



(d) y-axis comparsion



(e) PID controller



(f) yaw comparsion

Fig. 4. Simulation results in which it can be found that the nonlinear algorithm performances as the MPC and both of them are better that PID.

this experiment, and the results of x-axis, y-axis and yaw-axis are compared to prove the effectiveness of the nonlinear control algorithm. The reference trajectory is $y = \sin(x/20) + 0.5\cos(x/8), x \in [0, 10]$ with the initial state $(0, 0, 0.5)^T$ and simulation time $dt = 0.1s$. The feedback factor of nonlinear control algorithm is $(k_1, k_2, k_3) = (2.4, 1.8, 0.96)$ and the parameter matrix $Q = Q_{Np} = diag(1, 1, 1.5)$ and $R = diag(1.2, 1.5)$ while for PID $(k_p, k_d, k_i) = (2, 0.05, 10)$. Fig 5 contains all the simulation results, sub figure (a),(c),(e) are results from Lyapunov-based method, MPC and PID while the remaining are the comparisons of x-axis, y-axis, yaw-axis. It can be seen from the tracking results that the performance of nonlinear algorithm is almost the same with that of MPC which can be also concluded from (d) and (f) that the tracking error can quickly converge to 0. However, it can be found in (b) that the x-axis errors of MPC algorithm cannot converge 0. The desired pose of the vehicle is generated according to the trajectory curvature which is not accurate, and the calculation burden of MPC is much heavy, so this result does not mean that MPC performances poorly. As for PID, it can be found

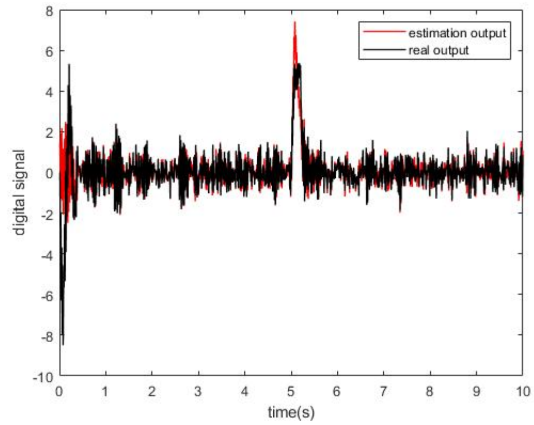


Fig. 5. Noise tracking result of the ESO-based algorithm in which red line stands for the estimation noise and the black line stands for the real output of the ESO.

in (e),(f) that it performances much worse that the other two ones.

In general, the nonlinear algorithm performances as well as MPC in simulation. The calculation burden of MPC is really heavy, and the computational resources required by nonlinear algorithms are much less than that of the optimal control algorithms. In the simulation, the time for the two algorithms to complete the experiment is recorded. The nonlinear algorithm takes 27 seconds, while the MPC takes 47 seconds. This means that the nonlinear algorithm can consume much less computing resources than MPC on the premise of ensuring the same effect, which will help reduce the cost of the vehicle system.

As for the low-level controller, the accurate model of the steering model is not the concerning topic so the simulation is set to test the noise tracking capacity of the ESO-based algorithm. Generating a series of random noise and using TD and ESO to estimate and adjust the output. Finally, the results are shown in Fig 5 in which it can be found the real output is also the same with the estimation one after some iterations.

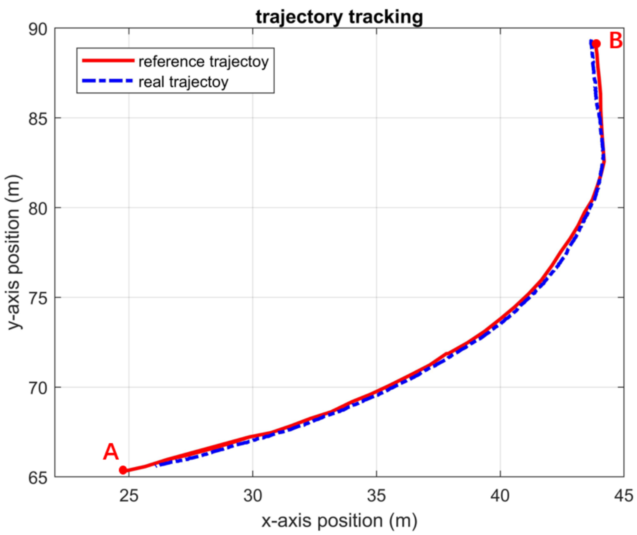
Up to now, all the modules in this system is tested in simulation, the most important result of the procedure is that there is no theoretical error in this system which means it can be deployed on real vehicle.

B. Real Vehicle

In the real vehicle experiment, the experimental scene is that the vehicle passes through a narrow curve, the reference trajectory is the global trajectory planned by Astar algorithm, and the positioning information is given by the laser radar. The trajectory result can be seen in Fig 6, it can be found that the vehicle can track the reference trajectory well, which means that the vehicle can pass the curve smoothly in the real world. In addiction, the velocity and pose angle data are shown in Fig 7 that the vehicle can track the velocity and angle signal.

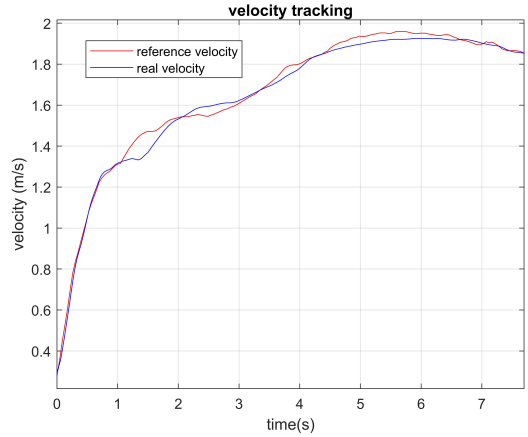
In order to verify the effectiveness of ESO-based algorithm, the results of the steering motor in open-loop condition are recorded which is shown in Fig 8. Sub figure (a) is the open-

(a) real vehicle experiment scence

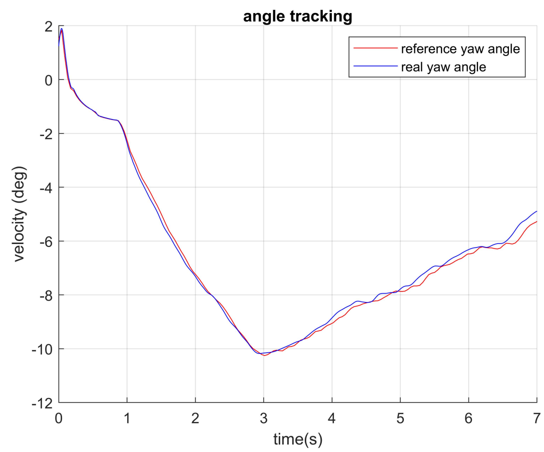


(b) trajectory tracking result

Fig. 6. Velocity and angle tracking result, the red lines are the reference value and the blue lines are the real values. These two lines almost coincide which means it can track the trajectory well. It is worth mentioning that this trajectory is generated online with Astar algorithm.



(a) velocity tracking



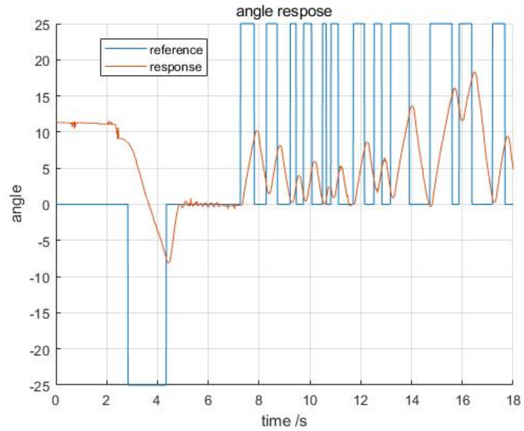
(b) angle tracking

Fig. 7. Velocity and angle tracking result, the red lines are the reference value and the blue lines are the real values. It takes around 20s to finish this experiment, these to sub figures show the data in the first 7 second in which the car is speeding up and adjust the pose angle quickly.

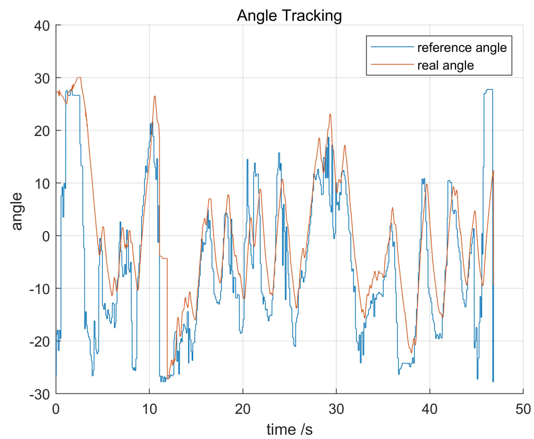
loop response of the steering motor, tt can be seen from the figure that when a series of step signals are sent to the motor, due to friction and time delays, the response speed of the front wheel is very slow and it is difficult for it to track the reference signal. In engineering, it means the force of the motor is not enough, so it is necessary to design a low-level controller to improve its performance. As for (b), it is the results when only the high-level controller is deployed on this vehicle, it can be found that though the nonlinear algorithm can improve the performance of the steering motor, there are still noise and time-delays in this system. Compare Fig 8 with Fig 7, it can be concluded that the low-level controller can greatly improve the steering motor which is an encouraging result that can prove the effectiveness of the entire system.

VI. Conclusion

In this paper, a hierarchical control system containing a high-level nonlinear controller and a low-level ESO-based controller is designed to control a low-cost autonomous vehicle. The open-loop response results show that the mechanical and electronic performance of the vehicle are poor, which means that the control system must be able to compensate the limited hardware performance with algorithm and software. The high-level controller is based on Lyapunov Stability theory which can guarantee the system stability while the low-level controller is based on ESO. In general, this is a nonlinear control system. The high-level algorithm is a new trajectory tracking algorithm which has almost the same performances with MPC, but requires much less computational resources. In other words, this algorithms suits this kind of low-cost vehicle better can it can be realized much easier than MPC on the real vehicle. As for the low-level controller, it is essentially a solution in engineering, which means its practical value is much higher than academic value. The experimental results clearly prove that the performance of the vehicle performances much better after using this control system.



(a) open-loop responses of the steering motor



(b) angle tracking result without low-level controller

Fig. 8. Velocity and angle tracking result, the red lines are the reference value and the blue lines are the real values.

Frankly, the proposed control system in this paper can be a engineering solution for a low-cost autonomous vehicle with limited hardware performances which is the main contribution of this paper. There are various kinds of low-cost autonomous vehicle which means there are different shortages in each kind of vehicle. However, the core challenge is to using algorithm to solve hardware limitations. The accurate model of the steering motor is still a unsolved problem, and the data-driven method is a good idea to handle this kind of problem. As a result, more data-driven method or learning-based control will be taken into account to improve this hierarchical control system.

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