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An improved braitenberg policy for object tracking

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Abstract. In vision-based unmanned vehicle tracking of moving vehicles, it is difficult to achieve accurate tracking of motorized vehicles with conventional fixed-parameter PID controllers due to their varying speeds and changes over time. To generate control signals for the systems and move the controlled object, the PID controller performs calculations based on percentage, integral, and derivative data. This is the discrete PID controller method. In this paper an improved tracking method, the Braitenberg policy, is proposed and a series of experiments are conducted in Simulink. The experimental results verify that the method can achieve stable tracking in simple environment for both general and extreme cases. The method can be used for future experiments for both general and extreme cases. The method can be used for future experiments in more scenarios. Braitenberg policy provides stronger and more stable tracking performance in extreme cases compared to conventional PID control. The algorithm provides more opportunities for tracking research and a small idea for the integration of multiple algorithms.

Keywords: braitenberg vehicle, control policy, object tracking, PID controller.

1. Introduction

Tracking technology has applications in multiple fields such as aerospace, traffic monitoring, autonomous driving, video surveillance, computer vision, augmented AR, and so on. In the aerospace field, motion model tracking can be used to track the motion status of spacecraft, satellites or drones for navigation, orbit control and mission planning [1]. In the field of traffic monitoring, the color characteristics of vehicles are detected and tracked to achieve traffic flow statistics, traffic violation detection, and other functions [2]. In the field of autonomous driving, deep learning tracking is widely used to achieve tracking and recognition of targets such as vehicles, pedestrians, and traffic signs by analyzing and predicting sensor data in real time using deep learning models [3]. Various methods have been used to achieve tracking such as color, feature point, motion model or deep learning based tracking methods. Some of the suggested methods are as follows.

Tracking that is based on color: Tracking that is based on color makes use of object color information, which is typically processed in the HSV color space. This approach is straightforward and simple to use [2].

Tracking based on feature points: This technique tracks targets like SIFT, SURF, ORB, etc. by using algorithms for feature point identification and matching. The suggested approach is sensitive to changes in occlusion and lighting but somewhat robust to changes in object shape and texture [4].

Motion model-based tracking: Using motion models like the Kalman filter, particle filter, etc. This technique tracks objects across a series of frames. This approach works well in scenes where objects move continuously, but it fails in scenes where objects move intermittently or when there is significant occlusion [1].

Deep learning-based tracking: As deep learning has grown, target tracking techniques based on deep learning have likewise become more and more popular. Typical techniques include YOLO, Siamese network, Faster R-CNN, and others [5]. The suggested approach produces good results and is resistant to changes in the shape, texture, illumination, and occlusion of objects. However, a significant amount of training data and computational power are needed [3].

Braitenberg vehicles with tracks can be created in software or manufactured physically utilizing robotic components. They offer a straightforward yet effective method for investigating and simulating the connection between sensor inputs and motor outputs in the context of tracking behavior [6].

However,the tracking of target vehicles and obstacle avoidance by driverless vehicles remains a task that needs to be constantly developed at the present time. Based on this, this study provides a method using braitenberg vehicles that can perform stable tracking of a single moving target, has some robustness, and exhibits smooth trajectories and relatively modest errors even in the most extreme circumstances.

2. Braitenberg vehicle principle

The braitenberg vehicle can alter how its sensors and actuators are connected to produce different target tracking behaviors [7]. For instance, if the connection between the sensor and the actuator is set up to be proportional, the actuator will respond to the stimulus in line with the stimulus when the sensor detects it, leading to the behavior known as object following [8]. It can enable object tracking by identifying the location and motion of the object if the braitenberg vehicle's sensors are configured as a camera or a sensing device like the Li DAR. In response to a signal generated by the sensor when an object is in proximity to it, the actuator is prompted to track the object.

3. Braitenberg tracking policy

3.1. Tracking principle of distance sensor

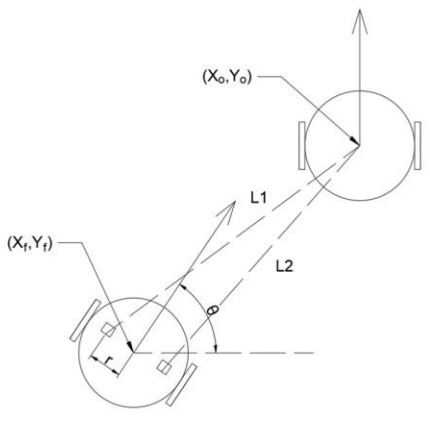

Figure 1. Determine the distance of the individual distance sensors from the center of the target vehicle.Shown on figure 1, the coordinates of the center of the tracking vehicle are (X_f, Y_f). The angle between the tracking vehicle's direction of motion and the horizontal direction is theta. the coordinates of the two distance sensors can be calculated as (X_f-rsinθ, Y_f+rcosθ) and (X_f+rsinθ, Y_f-rcosθ), respectively. According to the Cartesian distance formula, L_1 and L_2 can be found respectively.

The distance sensor calculates the collected data and returns the distance between the sensor and the target. The collected data is packaged into an array containing the coordinates and angles of the robot.

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In the figure 1, the distances are L1 and L2, and the angles are Theta. This distance is used as an input to the control strategy. L1 is the distance between the distance sensor on the left side of the tracking vehicle and the target vehicle. L2 is the distance between the distance sensor on the right side of the tracking vehicle and the target vehicle. r is the distance of the distance sensor from the center of the vehicle. The location of the center of the target vehicle is set to (Xo,Yo), and the location of the center of the tracking vehicle is set to (Xf,Yf). From this, the distance formulas for L1 and L2 can be derived.

$$L_1 = (X_o - X_f + r\sin\theta)^2 + (Y_o - Y_f - r\cos\theta)^2$$
$$L_2 = (X_o - X_f + r\sin\theta)^2 + (Y_o - Y_f - r\cos\theta)^2 \quad (1)$$

3.2. Tracking principle of braitenberg policy

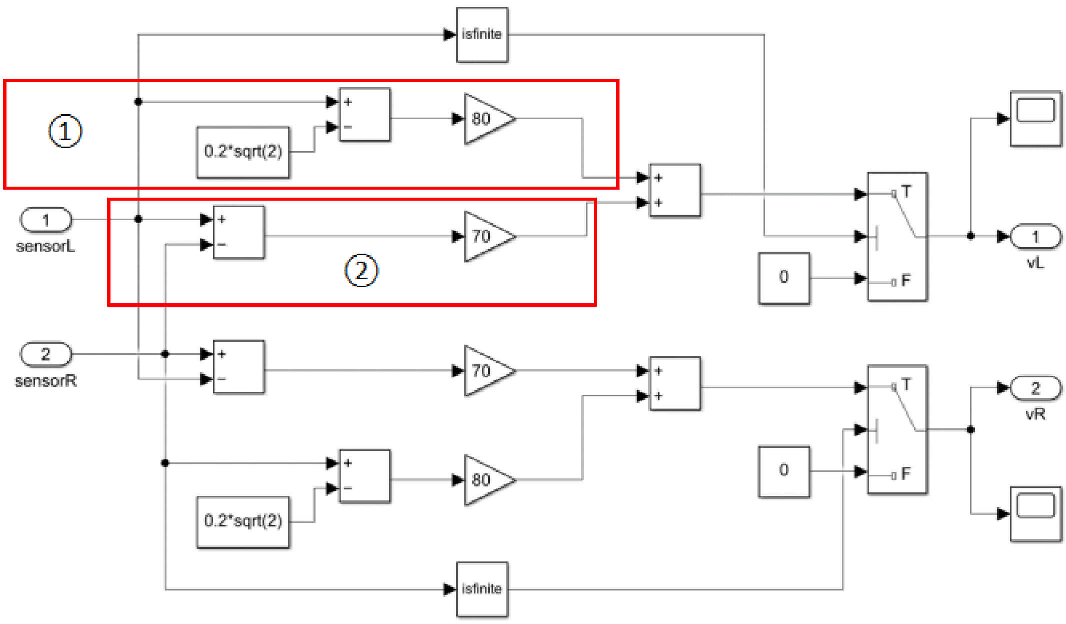

Figure 2. Braitenberg policy simulated in simulink.

The strategy is to build and experiment in Simulink. Shown on figure 2 the two distances are the policy inputs and the outputs are two independent speeds for each wheel. For the connected networks, they are divided into two parts. One is to reduce the following distance by proportional calculation, and the other is to respond to the change of the distance sensor according to the difference between the two distances. The final policy outputs the speeds of the two wheels of the vehicle separately.

① When the tracking vehicle can realize the tracking perfectly, the speed of its two wheels is equal to the speed of the two wheels of the target vehicle. In addition, the tracking vehicle is directly behind the target vehicle, so the shortest distance between the sensor and the target vehicle is 0.2×sqrt2. And after 80 times gain, can ensure that the tracking car quickly follows the target vehicle.

② When the distance output of the left and right sensors is different, the angle of the following vehicle must be adjusted quickly. The plus or minus of the difference between L1 and L2 can determine the direction of the angle change of the following vehicle. The gain of the difference can make the tracking vehicle change the angle quickly to complete the tracking of the target vehicle.

4. Simulation experiments

4.1. Environment

The first step is to set up the environment needed for the experiment. Shown on figure 3, establish a Cartesian coordinate system so that the position of all objects in the environment can be expressed in coordinates. There are two moving vehicles in the environment, one of which is the target vehicle and the other is the tracking vehicle. There are obstacles in the environment.

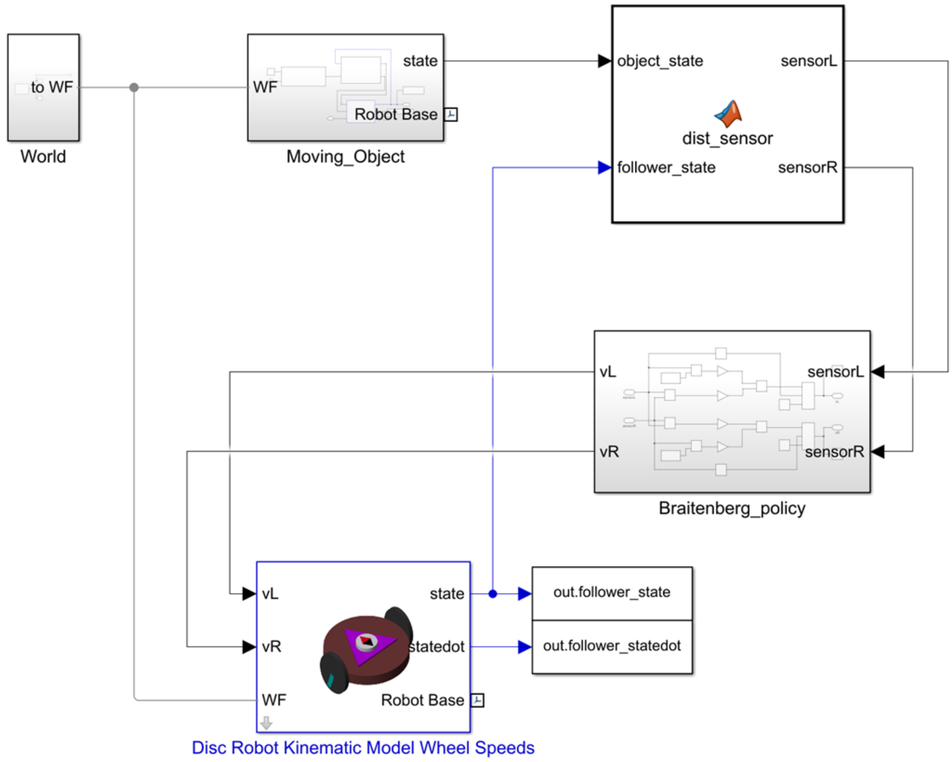

Figure 3. Overall model construction and environment.

4.2. Moving object

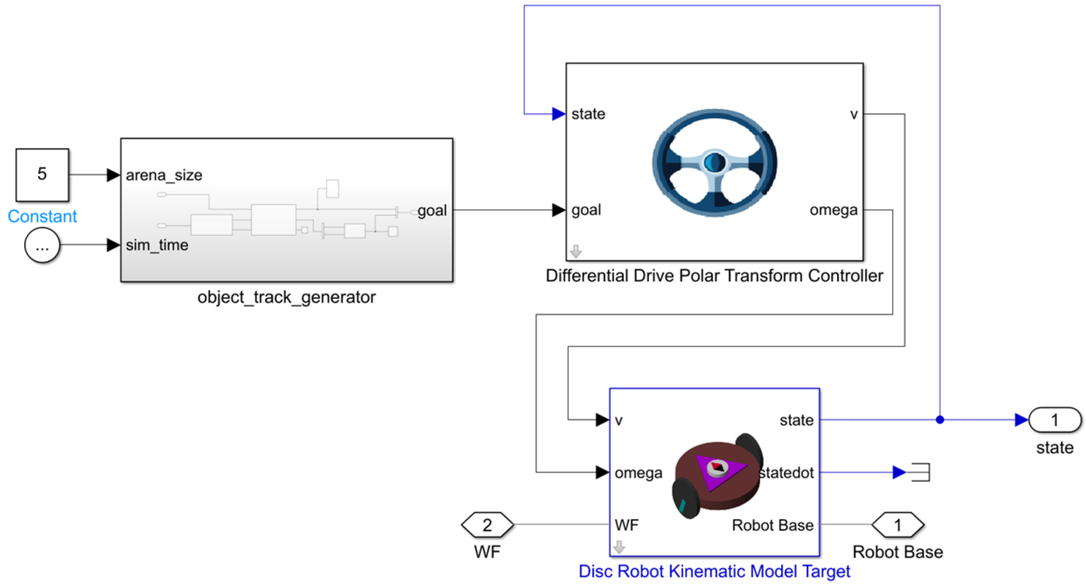

Figure 4. The motion model is the target vehicle. In order to be able to make the target model able to move anywhere, the differential polar transformation controller was built specifically for it.

Shown on figure 4, another disk robot is the moving object; it is controlled by a differential polar transformation controller and constructs the target's trajectory using a B-spline polynomial trajectory. The function may determine the robot's target by providing the coordinates of randomly dispersed locations. By altering the coordinates, different trajectories can also be applied, and this can be used to evaluate the approach to make sure it operates in all circumstances.

4.3. Comparison of PID and BV

4.3.1. PID

In order to create the system's control signal and move the controlled object, the PID controller performs calculations based on percentage, integral, and differential data. This is the discrete PID controller's formula [9].

$$\mathrm{u}(k)=K_p\{e(k)+\frac{T}{T_1}\sum_{j=0}^{k}e(j)+\frac{T_d}{T}[e(k)-e(k-1)]\} \tag{2}$$

e (k) is the difference of the KTH sampling point; T is the sampling period of the controller.

4.3.2. The adjustment rule of PID control

Kp, Ki, and Kd must adhere to the adjustment law.

Kp ought to be high whenever the value of e is high. For improved tracking performance, Kd should be smaller on the other hand. Ki should also be set to zero in order to prevent integral saturation and severe overshooting.

When e is a median value, Kp, Ki, and Kd ought to be moderate for quick response, but Ki ought to be tiny for slight overshoot.

To improve steady-state performance for low values of e, K p and Ki should both be increased. Ki should be kept moderate to prevent oscillations around the corresponding static values and to take the system's anti-interference capability into account [10].

5. Result

5.1. Simulation results of the proposed policy

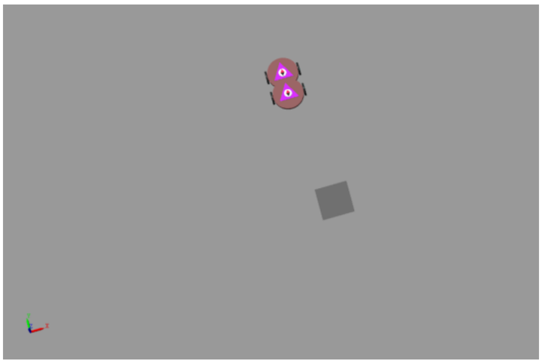

Figure 5. The vehicle tracks well and avoids static obstacles.

The figure 5 depicts the vehicle's target tracking behavior. Although there is initially a distance between the two cars. The follower responds rapidly and maintains a constant proximity to the target.

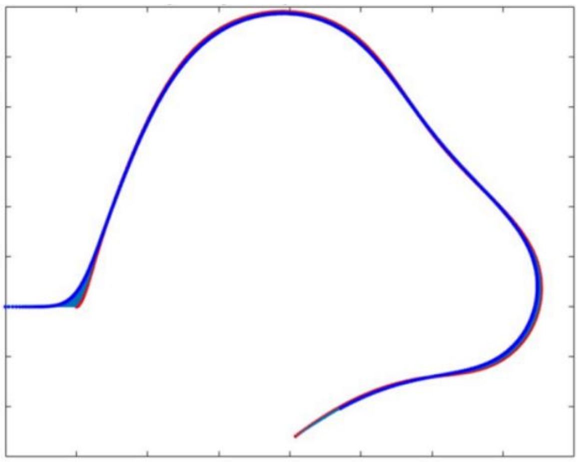

Figure 6. Trajectory of object and follower. The blue track is for the target vehicle and the red track is for the tracking vehicle.

The two vehicles' paths are displayed in the figure 6. It is capable of performing well when following, whether it is stable tracking or long-distance chase. The gap between the two vehicles will grow though when it turns or accelerates.

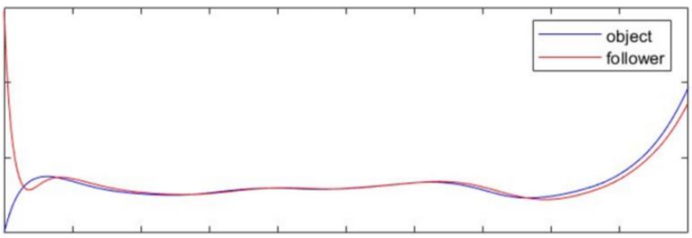

Figure 7. Speed of the object and follower.

The tracking vehicle is stable to follow the target vehicle, shown on the figure 7.

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5.2. Comparison with PID

To test whether the Braitenberg policy works, a robot with a PID controller is also created for comparison, shown on the figure 8.

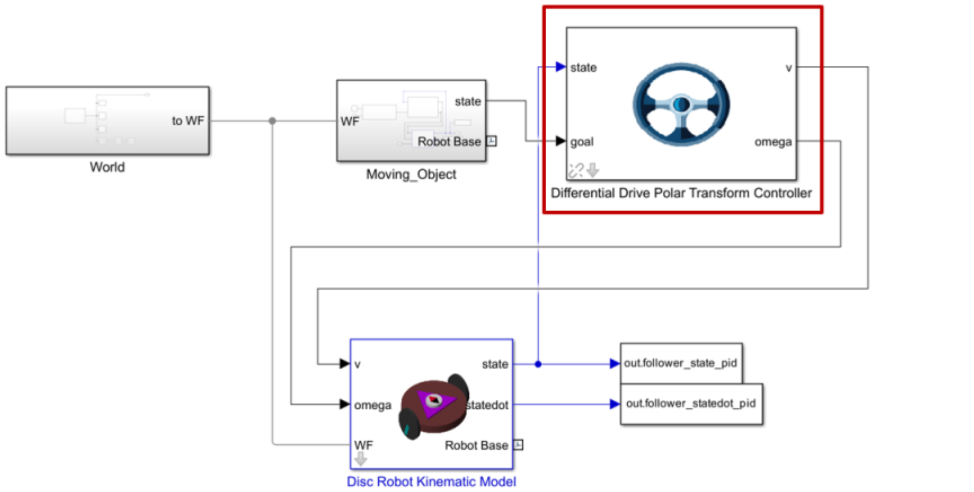

Figure 8. A PID controller is newly built on the tracking vehicle.

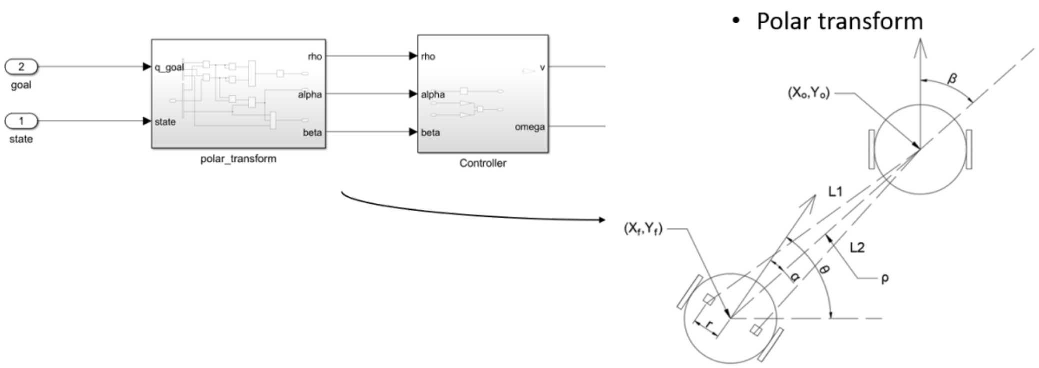

Figure 9. The target information and state information of the target vehicle are transformed in polar coordinates, and the three parameters obtained are used as the input of the PID controller, and then the behavior of the tracking vehicle is controlled.

The identical surroundings and trajectory used to evaluate the Braitenberg policy are employed when the robot follows the target. To operate the robot, the differential drive model incorporates a PID controller. As seen in the figure 9, the target and state are put via a polar coordinate transformation inside the module to yield the three parameters rho, alpha, and beta. The controller sets Ki and Kd to 0.01 and 0.1 and controls the velocity using PID with rho as Kp. It adds up to the sum times the gain, which is more akin to a proportional control.

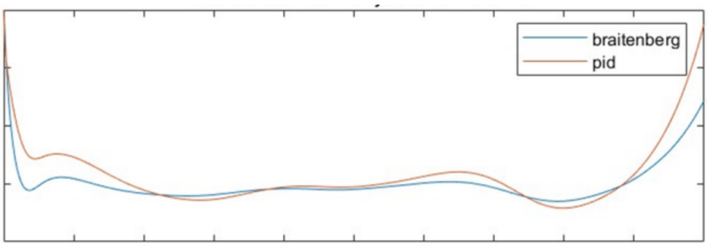

Figure 10. The distance between the target vehicle and the tracking vehicle under different algorithms.

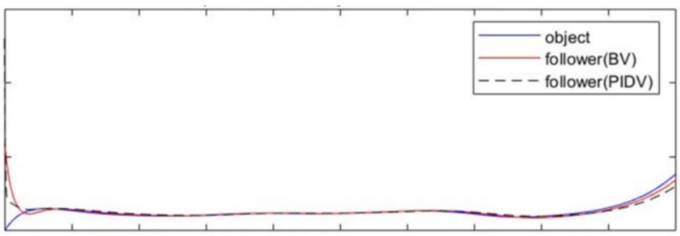

Figure 11. Speed of object and follower.

The simulation findings are discussed in relation to a number of different factors. The PID controlled cars and the Braitenberg strategy are contrasted in the first. As seen in the figure 10 and 11, the two vehicles perform comparable target tracking functions based on their trajectories. The graphs compare the tracking distances of BV and PID vehicles from a statistical perspective. The target tracking vehicle using the BV approach may be shown to have slightly more consistent tracking performance, a quicker response time, and a closer tracking distance in extreme situations. Another benefit of BV in this application is that it can substantially avoid the conflict that PID-controlled vehicles always experience between faster reaction and excessive overshoot.

6. Conclusion

In this study, the method of braitenberg policy is proposed, and the tracking of moving vehicles is accomplished by using simulink simulation. After the braitenberg policy experiment and the comparison with PID, the effectiveness of the method is verified, and it can realize good and stable tracking for the target vehicle in a simple environment, and it has very good robustness.

Future study can examine the applicability, benefits, and drawbacks of algorithms like PID controllers and britenberg rules in various contexts and applications. To further enhance the system's performance and robustness, more control methods and approaches may be added concurrently.

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