ENPM661 Project 5 Phase 2 - Intro

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I. INTRODUCTION

A. Motivation

In 2018, 36,560 people were killed in motor vehicle crashes. Of these fatalities, 10,511 (28.75%) were due to alcohol impairment [1]. 9 out of 10 (94%) serious roadway crashes occur due to human behavior [2], [3]. While there has been a downward trend in traffic fatalities over the last 40 years due to vehicle improvements like airbags, seat belts, and electronic stability control [1], there could be significant further reduction in vehicular fatalities with the integration of computer assisted driving and the phasing out of human drivers in favor of autonomously driven cars. The development of reliable autonomous vehicles is an important area of research in robotics, with vast life-saving potential. This field spans many complex sub-disciplines, often including perception, planning, controls, machine learning, and tremendous data processing, often at high speed and in real time. As ENPM661 is primarily a planning course, our focus will be on a small slice of the planning aspect of autonomous cars.

B. Background

Testing new autonomous vehicle algorithms in the real world can be both expensive and dangerous, especially when human occupied vehicles are nearby. If an experimental autonomous car is going to fail, it's safer for it to fail in a low risk setting, and not at high speed on a highway surrounded by unsuspecting human drivers. For this reason, autonomous cars must be tested with close human supervision, and usually in controlled, sequestered settings. According to the Bureau of Transportation Statistics, in 2017, vehicles drove over 5.5 million miles on US highways [4]. Experimental autonomous vehicles can only be driven comparatively short distances in their controlled environments, which limits their exposure to but a slim slice of the multitude of diverse road conditions and driving experiences that human driven cars face. Furthermore, car manufacturers only have finite human resources to devote to the supervision and testing of new autonomous cars, and they also have financial capital tied into each physical vehicle they build and test [5]. To test and train autonomous vehicles in necessarily large numbers and over millions of miles of varied road without risking product or human lives, many companies are turning towards simulation. In simulation, an arbitrarily large number of cars can be driven through greatly varied situations, offering companies a safe venue to test their algorithms and strategies and train their autonomous driving intelligences [5]. The more conditions that can be explored digitally, the better the physical car will be able to fare in the varied conditions of the real world [6].

The goal of this project is to implement an advanced driver-assistance system (similar to what is found in L2 autonomous cars like Tesla) that renders a car capable of autonomously navigating a straight road at a predefined speed without hitting other cars. The problem will first be framed as a moving car on a road with stationary obstacles, such as parked cars and road obstructions. Time permitting, we will expand our solution to work with dynamic obstacles, such as vehicles moving at constant velocities (which may differ from our car's velocity). Finally, if time permits, we will expand the solution to work with highly dynamic systems - cars that can change lanes and move with varying speed.

Accordingly, this project will be an original research project, as we implement our own search algorithm approach to this particular problem. Later, we will compare our results with other similar works from existing literature related to path planning and autonomous vehicles.

Due to the prohibitively high cost of the requisite hardware (multiple vehicles with advanced sensor suites and sophisticated instrumentation that enables user-defined control signals on a real road) and legal obstacles surrounding autonomous vehicles, this project will be a simulation of an autonomous vehicle driving in a straight road with other vehicles. There is therefore no real hardware requirement

besides the minimal computer specification requirements for our simulation software(s).

C. Literature Review

It is clear from our literature review both that planning is a vital component of car autonomy and also that RRT (and it's variants) are a popular solution for many aspects of such a problem. RRT has been used for path planning for parking [7], [8],

Collision avoidance is obviously a paramount element of autonomous car operation. Multi-agent RRT has been used for this purpose to plan to avoid collisions between two objects [9]. Time based RRT (TB-RRT) has been used for the exact opposite problem - planning rendezvous for two dynamic systems objects [10]. While rendezvous (also known as collisions) are avoided at all costs in the vehicular world, this TB-RRT approach, in which each node specifies a specific state at a specific time [10], may prove to be useful for planning collision avoidance trajectories for highly dynamic systems.

Other non-RRT related planning algorithms for autonomous vehicles are also popular in recent (and semi-recent) literature, such as the use of A* with numeric non-linear optimization to path plan parking lot and U-turn navigation for an autonomous vehicle in an unstructured environment[11]. However, it seems that most recently, RRT and its variants have dominated the autonomous car path planning space.

There are a growing number of RRT variants, and it is clear that this is an active area of research. A bidirectional variant of RRT known as RRT-Connect converges faster than standard RRT and produces a more optimal solution[12]. RRT*-Smart, which uses intelligent sampling and path optimization has faster convergence than RRT or RRT* [13]. Local and global pruning of RRT* results via line of sight path shortening can dramatically reduce the total path from a solution, improving its optimality [14].

II. METHOD

A. Car Model and Dynamics

The car we are modeling is a front wheel steer (FWS), rear wheel drive (RWD), 4 wheeled vehicle utilizing Ackerman steering. This setup was chosen to closely mirror the steering dynamics of a real car. Physical cars move with non-holonomic motion, so it is important that our simulator replicate this behavior.

Figure 1 defines our key car dimensions. We'll be using the notation in this diagram [15] for the duration of this paper.

For simplicity, we assume that the two front wheels must remain mutually parallel. Therefore, we only have one wheel angle δ. We also define C, the vehicle's center of mass, to be in the physical center of the vehicle, and therefore:

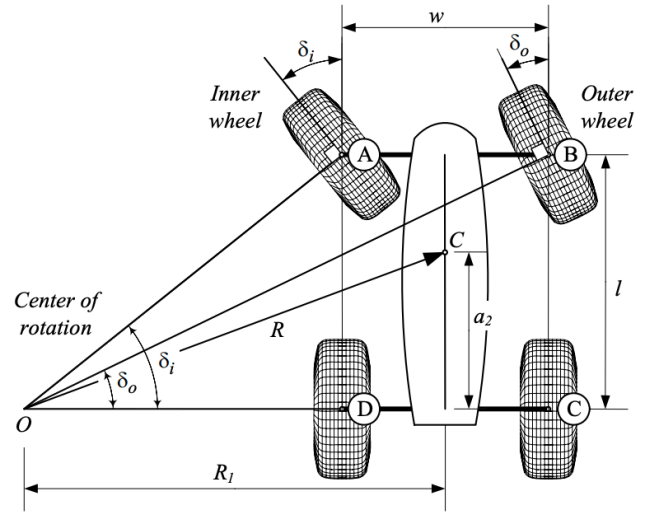$$a_2 = \frac{l}{2} \qquad (\text{II.1})$$

Fig. 1: A front-wheel-steering vehicle and steer angles of the inner and outer wheels.[15]

Figure 2 adds additional information - the speed of the rear wheels for RWD. Without loss of generality, we'll assume that the two rear wheels are actuated at equal speeds:
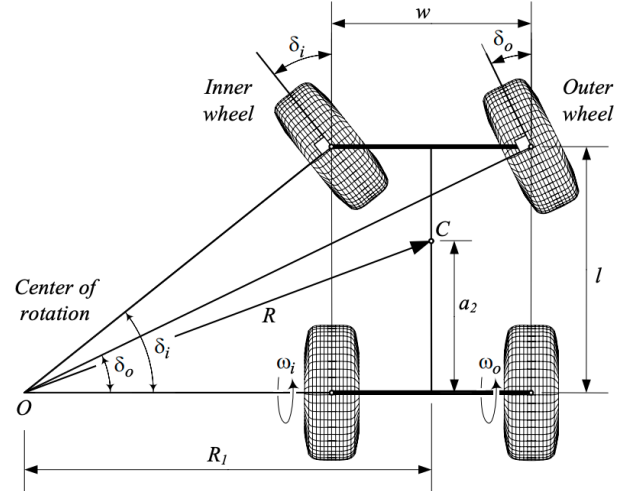
$$\omega_i = \omega_o = \omega \qquad (\text{II.2})$$

Fig. 2: Kinematic condition of a FWS vehicle using the angular velocity of the inner and outer wheels.[15]

The turning radius about O is [15]:

$$R = \sqrt{a_2^2 + l^2 cot^2(\delta)} \qquad (\text{II.3})$$

By simple trigonometry, we define a new angle α, which is the angle between R_1 and R (Figure 3):

$$\alpha = sin^{-1}(\frac{a_2}{R}) \qquad (\text{II.4})$$

R_1, the horizontal distance between C and O (Figure 1) is:

$$R_1 = Rcos(\alpha) \qquad (\text{II.5})$$

The yaw rate, or angular velocity, of the vehicle can be defined as follows [15]:

$$r = \frac{R_w \omega}{R_1 + \frac{W}{2}} \tag{II.6}$$

From the car's perspective, as the car turns, it drives out an arc with radius R. The angle the car subtends as it travels $d\theta$ is a function of the vehicle's yaw rate r and the time it has to move dt (Figure 3):
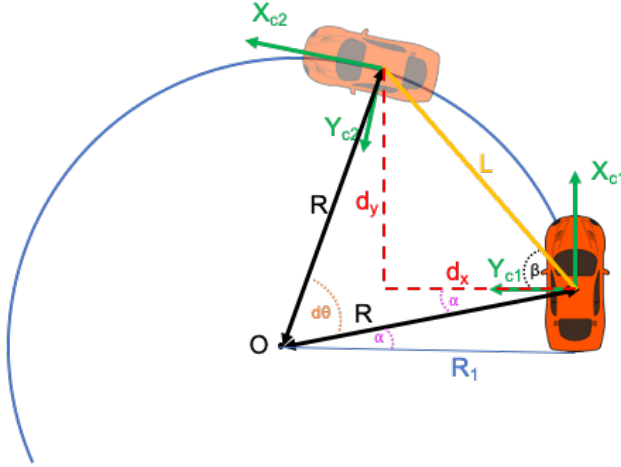
$$d\theta = r \cdot dt \tag{II.7}$$

Fig. 3: Diagram showing the car motion (relative to the car frame) which defines our geometric variables

Figure 3 displays the motion of the car (in the car's reference frame) as it moves through it's arc. L is the shortest Euclidean distance between the start position and end position; a chord of the circle of movement, defined by R and $d\theta$:

$$L = 2R sin(\frac{d\theta}{2}) \tag{II.8}$$

We're interested in finding d_x and d_y, the components of the displacement of the car in the car's reference frame. Note that the center of rotation O also moves with the car. This d_x and d_y exclusively measure the displacement of the car relative to O and do not yet account for the motion of O. d_x and d_y are in directions coincident with X_{c1} and Y_{c_1}, the car's initial direction vectors, and not aligned with the global X_w and Y_w coordinate system. We will later compensate for the initial angle of the car in the world frame, but for now we can work with just the car frame without loss of generality. Since Y_{c1} is defined to be parallel to R_1, we know the angle between R and Y_{c1} must also be α. The triangle ΔRLR must be an isosceles triangle.

$$2(\beta + alpha) + d\theta = 180° \tag{II.9}$$

Rearranging to solve for β:

$$\beta = \frac{180° - d\theta}{2} \tag{II.10}$$

We now have enough information to compute the components of the displacement of the car:

$$d_x = Lsin(\beta) \tag{II.11}$$

$$d_y = Lcos(\beta) \tag{II.12}$$

We need to compensate for angle θ of the car as well as the motion of O as the car moves. The component of d_x and d_y in the X_w direction is:

$$d_{x_w} = d_x cos(\theta) + d_y cos(\theta) \tag{II.13}$$

Similarly,

$$d_{y_w} = d_y sin(\theta) + d_x sin(\theta) \tag{II.14}$$

The center of rotation O moves as a function of the car's forward velocity v, the car's angle θ, and the time it has to move dt:

$$O_x = vcos(\theta)dt \tag{II.15}$$

$$O_y = vsin(\theta)dt \tag{II.16}$$

Finally, the new position of the car can be computed as follows:

$$x_f = d_{x_w} + O_x \tag{II.17}$$
$$x_f = d_x cos(\theta) + d_y cos(\theta) + vcos(\theta)dt \tag{II.18}$$

$$y_f = d_{y_w} + O_y \tag{II.19}$$
$$y_f = d_y sin(\theta) + d_x sin(\theta) + vsin(\theta)dt \tag{II.20}$$

$$\theta_f = \theta + d\theta \tag{II.21}$$

B. Simulation

We are building a highway driving simulation in Pygame. This simulation features a horizontally scrolling top-down view of a four lane highway (Figure 4) and the cars upon it.
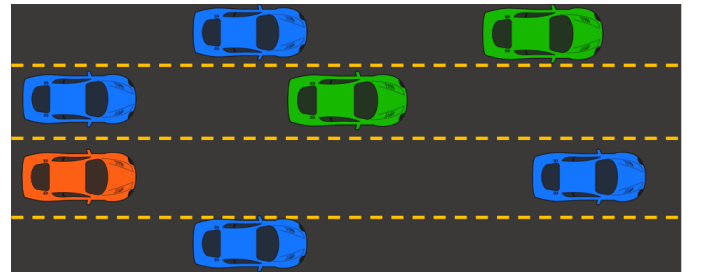

Fig. 4: Sample image from the Pygame simulation

Figure 4 shows a sample image from our Pygame simulation. Our car is shown in orange. Blue cars are disabled or damaged vehicles, serving as stationary obstacles, and can be generated randomly or at predefined locations. Green cars are other highway drivers that travel in their own lane at a constant speed (which may or may not be the same as the default speed of our car). These cars serve as dynamic obstacles. To reduce the complexity of this situation, green
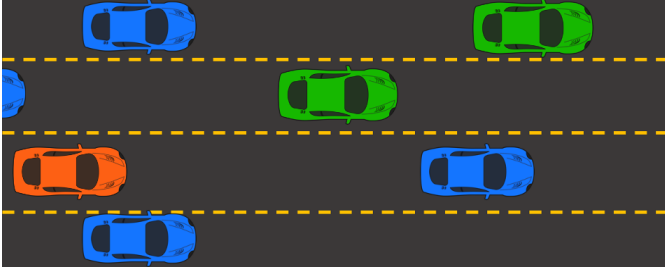
Fig. 5: Sample image from the Pygame simulation at some time later.

cars will be free to pass through any blue car in their path and are not expected to expend any effort attempting to avoid obstacles. For increased challenge, the speed of the green cars may later change with time. Figure 5 shows the simulation at a slightly later time. The orange and green cars have continued to move forward at the same pace, and so appear in the same location on screen. The blue stationary cars have not moved, and so appear to have slid to the left on the screen.

C. RRT

While the environment that car is navigating is initially assumed to be static (i.e. the obstacles are stationary), the ultimate goal of this project is to implement dynamic planning that simulates driving on a real highway.

Therefore, the planning algorithm for the proposed system is going to be rapidly exploring random tree (RRT) [16], a sampling-based method that tends to offer better performance by sacrificing optimality, which is not a requirement in our application. Efficiency, on the other hand, is of paramount importance since the planner needs to be invoked every time the current motion plan becomes invalid and thus, RRT is very suitable for the nature of this problem. The main intuition behind the performance boost gained by sampling-based planners is that by randomly sampling the configuration space, they generate fewer nodes that encode the connectivity of the space compared to grid-based alternatives.

The inputs to our RRT algorithm are the start configuration q_s, goal configuration q_g, and the configuration space C, which is constructed by processing the localization information coming from the car's sensors. The algorithm comprises the following steps:

1) Initialize the road map graph G with the start configuration q_s.
2) Randomly sample k configurations from a bounded region centered around q_s.
3) Find the closest vertex q_n in G to the sample q_{rand} using any distance metric (such as Euclidean) defined on C.
4) Call any local planner that incorporates the differential constraints on the car motion to produce a feasible obstacle-free trajectory from q_n to q_{rand}. The endpoint q_r of the trajectory doesn't necessarily coincide with q_{rand} but will be as close as possible to it.

5) Add q_r as a vertex in G.
6) Connect the edge from q_n to q_r.
7) Repeat Steps 3 through 6 for each configuration in the k samples.
8) Repeat Steps 2 through 7 until the goal configuration q_g is reached.
9) Once the car has reached q_g, define a new $q_s = q_g$ and a new q_g at the edge of the car's sensing range.
10) Repeat steps 2 through 9 until the car reaches the final goal.

III. References

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APPENDIX

A. Definitions

According to SAE J3016[17][2], there are 6 relevant tiers of autonomy for vehicles:

0) **No automation** - the driver is fully responsible for all vehicular operation under all circumstances
1) **Driver Assistance** - Vehicle is controlled by the driver, but some driving assist features may be included in the vehicle design
2) **Partial Automation** - Vehicle has combined automated functions, like acceleration and steering, but the driver must remain engaged with the driving task and monitor the environment at all times.
3) **Conditional Automation** - Driver is a necessity, but is not required to monitor the environment. The driver must be ready to take control of the vehicle at all times with notice.
4) **High Automation** - The vehicle is capable of performing all driving functions under certain conditions. The driver may have the option to control the vehicle.
5) **Full Automation** - The car is fully responsible for all vehicular operation under all circumstances. No human driver is necessary for any portion of operating the vehicle

RRT - Randomly exploring Random tree

FWS - Front Wheel Steering, a common steering method for cars in which only the front two wheels can be angled. The rear two wheels remain parallel to the car chassis

RWD - Rear Wheel Drive, a common driving method for cars in which only the rear two wheels are powered. The front two wheels are free to spin but not connected to the engine.

AWD - All Wheel Drive, a common driving method for cars in which all 4 wheels are driven by the engine.

B. Important Variables

R_1 - the distance between the center of mass (C) of the vehicle and the Center of Rotation (O). This distance is parallel to the rear wheel axle. See Figure 1. Not to be confused with R, R_w, or r.

R - the radial distance from the center of mass (C) to the Center of Rotation (O). Not to be confused with R_1, R_w, r.

R_w - the radius of the wheels, in meters. Not to be confused with R, R_1, or r.

r - the yaw rate (or angular velocity) of the vehicle, in rad/s. Not to be confused with R, R_w, or R_1.

C - the center of mass of the car, defined to be the physical center of the vehicle

l - the distance between the front and rear axles of the car. See Figure 1.

a_2 - the distance between the rear axle and the center of mass (C). See Figure 1. Defined to be $l/2$. Not to be confused with α

α - the angle between R_1 and R. Also the angle between Y_{c1} and R. See Figure 3. Not to be confused with a_2

W - the distance between the left and right wheels. See Figure 1. Not to be confused with ω.

ω - the angular velocity of the rear wheels, in rad/s. Not to be confused with W

$d\theta$ - the angle subtended by the car as it rotates through it's arc. See Figure 3. Not to be confused with θ

θ - the angle of the car, defined in degrees as positive in the counter clockwise direction. $0°$ is the car facing horizontally to the right. Not to be confused with $d\theta$.

β - the angle between Y_{c1} and L. See Figure 3

X_c - the X direction of the car frame. This is always the direction of forward motion for the car (regardless of it's world orientation). See Figure 3. Not to be confused with X_w.

X_w - the X direction of the world frame. This is defined to be horizontal to the right. Not to be confused with X_c.

Y_c - the Y direction of the car frame. This is always the direction to the left of the car (regardless of it's world orientation). See Figure 3. Not to be confused with Y_w.

Y_w - the Y direction of the world frame. This is defined to be vertical, with positive Y in the downward direction. Not to be confused with Y_c.

C. Graphics Sources

Orange, blue, and green car graphics from http://clipart-library.com/overhead-car-cliparts.html