Artificial Potential Field Simulation Framework for Semi-Autonomous Car Conception

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***Abstract** – Artificial potential field is investigated to provide a high level of synergy between driver and semi-autonomous vehicle. This article presents a framework developed to test the performances of this approach. Stand-alone performances of this system is tested for a lane keeping and cruise control application. Performances are promising and future development is discussed.*

***Keywords:** Artificial potential field, Autonomous car, Simulation, Human-machine interface.*

Introduction

Autonomous cars are one of the next major innovations in the field of car manufacturing. Such technology represents a real revolution, especially regarding safety, labor organization and town planning [Eug13].

However, driving is a difficult task to automatize due to its highly dynamic nature and the variety of situation in which it can be exercised. Therefore, most of the time, autonomous driving is approached in a progressive way.

However, autonomous vehicles initially designed to operate under specific condition can rarely be adapted to operate in less specific situations. Also, autonomous vehicles only handling some situations require an autonomous-to-manual transition so a human driver can take over controls when leaving the autonomous system comfort zone. And partially autonomous vehicles able to execute only some specific part of the driving task need to be assisted by a human operator at all time.

In both cases, a good cooperation between driver and autonomous car is required. Whether it is to share vehicle control or to switch between autonomous and manual driving, the driver needs to understand the intentions of the autonomous system quickly and correctly.

In pursuit of a solid base for polyvalent autonomous vehicle development, as well as for efficient human-computer interaction, this work explores the use of artificial potential field method applied to autonomous driving technology by proposing an architecture for autonomous vehicle low-level control.

Theoretical background

Artificial Potential Field (APF) is a method used to make robots navigate in an environment containing obstacles [Kha86, Oku86]. Originally, this method was developed to control robotic arms in real time by means of force fields. Those fields were designed to attract the robot into the desired place and to keep it away from any obstacles at the same time as seen Fig. 1.

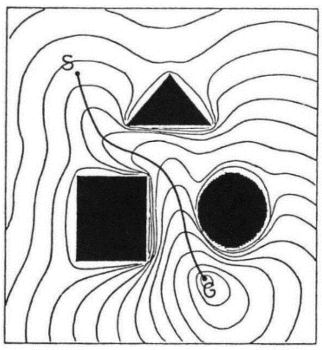

Figure 1. Contour plot of an artificial potential field and trajectory of a robot guided by it. Black polygons represent obstacles. The point named S is the starting position and G is the goal. The trajectory is obtained by a gradient descent procedure along the field. Figure from Okutomi's work [Oku86]

APF method differs from classic motion planning technique due to its reactive nature contrasting with traditionally more proactive methods. For this reason, APF method requires no preliminary computation to run. Therefore, environment modification or dynamic obstacles do not have significant impact on performances which gives the APF method an edge over classic motion planning for highly dynamic environments.

Classic APF guidance is based on two types of fields. Attractive field attached to the goal and repulsive field attached to obstacles. Once generated, those fields are summed up together in order to generate the global guidance field used for the robot navigation. The field generated by this operation is then used to apply guidance forces to the robot using gradient descent. The force obtained by this process can be applied as acceleration setpoint to control the robot.

Even if the APF approach is better suited for holonomic robots, it can be adapted to autonomous driving problems. Semsar-Kazerooni applied some of the APF method to create an automated cruise control enhance with platooning capability [SK16]. In this system, longitudinal distance between vehicles was maintained by a specific artificial potential field.

APF technology was also used to produce racing artificial intelligence. By mixing multi agent system with artificial potential field method, Uusitalo managed to build an efficient autonomous racing car system even if purely reactive [Uus11].

Wolf implement an autonomous system able to drive on the highway [Wol08]. This also proves APF method can provide strategic decision-making up to a certain limit.

Research question

The reason behind focusing on APF guidance come from the similarities between APF and human cognition models. This has been theorized by Gibson [Gib38] as shown by Fig. 2 and confirmed by Fajen [Faj03a, Faj03b]. This parallel between cognition and guidance fields makes APF a good candidate to realize a semi-autonomous vehicle easy to empathize with.

In order to experiment with this hypothesis, a test environment is required. Our question of research is related to the creation of a simulation framework able to handle complex dynamic model and various field representation of the different obstacles. This framework also needs to run real time to enable human-in-the loop testing.

Our proposed architecture integrates the APF method in a way shown in Fig. 3. Important entities are extracted from the environment and translated in terms of potential field. Those fields are then merged together to obtain the final guidance field.

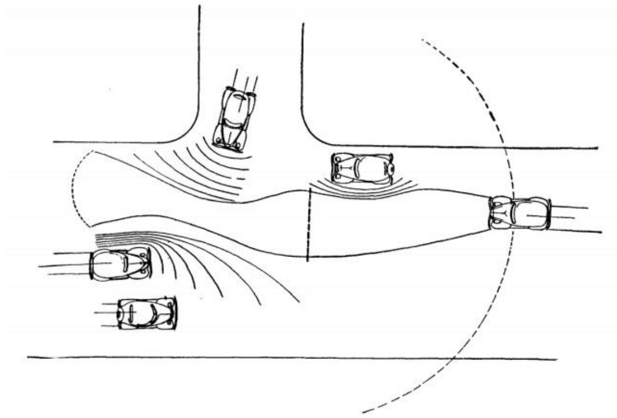

Figure 2. A field of safe travel at a traffic intersection. An attempt to represent how proximity to other vehicles trajectories affect our own driving behavior. Illustration from Gibson's work [Gib38].

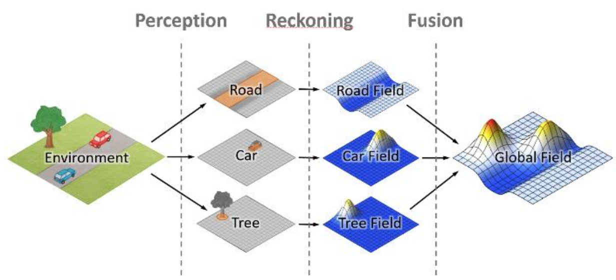

Figure 3. Illustration of the global potential field computation workflow. This includes perception, reckoning and fusion phases.

On top of the APF generation is built a control loop designed to interact with the car and the driver as shown Fig. 4. This system is responsible for converting forces into commands for the vehicle as well as interacting with the driver.

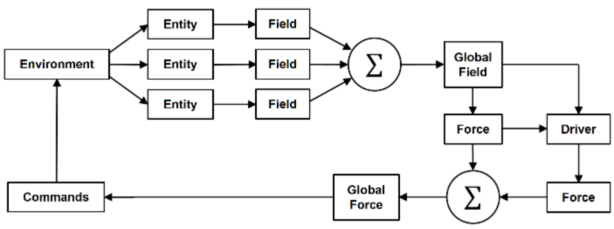

Figure 4. Illustration of the main interactions between the different parts of the framework.

Development

In order to illustrate the internal functioning of the framework, a simple implementation example is shown in this section. The situation considered here implies a sole autonomous vehicle which aims to maintain speed while staying in the middle of the lane. Implementation is made using the modular driving simulation software SCANeR studio (version 1.6).

In this context, the only obstacle that needs to be considered is the edge of the current lane. Because this is a simulation, all the information about the environment is directly accessible, thus reducing the perception task to extracting the road geometry through the SCANeR API. Fig. 5 show what the information extracted during the perception process can look like.

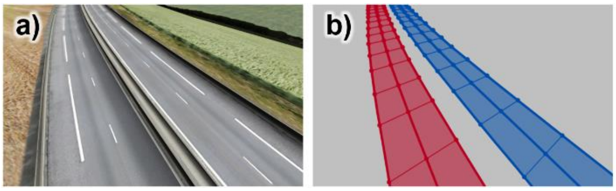

Figure 5. SCANeR graphic layer (a) and road logic extracted (b) side by side.

Classic obstacle fields are attached to the edges of lanes in order to push the vehicle back toward the center of the road. Those fields are defined by Eq. 1.

$$U_o(\vec{X}) = \begin{cases} \frac{1}{2}\eta\left(\frac{1}{\rho(\vec{X})} - \frac{1}{\rho_0}\right)^2 & if\ \rho(\vec{X}) \leq \rho_0 \\ 0 & if\ \rho(\vec{X}) > \rho_0 \end{cases} \quad (1)$$

η is a constant which is used to modulate the field intensity. With $\vec{X}$ being the robot position in space, $\rho(\vec{X})$ represents the distance between the robot and the obstacle. ρ_0 is the limit radius of the repulsive field area of effect. Beyond this distance, the obstacle doesn't interact with the robot anymore. Details about those fields can be found in [Kha86].

Fusion of the different fields is done by summing up all fields obtained in the previous step.

In order to calculate the force required, the guiding field is then sampled at multiple locations under the vehicles and inclination is determined through planar least square regression.

An additional artificial friction force is also introduced to limit oscillations. This force is also responsible for cruise control. Artificial friction is defined by Eq. 2.

$$\vec{F_f}(\vec{V}) = \mu(\vec{V_0} - \vec{V}) \quad (2)$$

$\vec{V}$ is the current velocity of the vehicle. $\vec{V}_0$ is the nominal velocity of the road. This nominal velocity is oriented in the same direction as traffic and its value is the speed required by the driver. μ is a constant used to modulate the intensity of the force. The sum of the artificial friction force with the previously computed lane keeping force gives the global force to apply to the vehicle.

Control is achieved through a reverse control maps. Those maps give controls to apply for a given system status and acceleration setpoint. Reverse control maps are generated by benchmarking the vehicle performances prior to the experiment. As an example, throttle reverse map is shown Fig. 6.

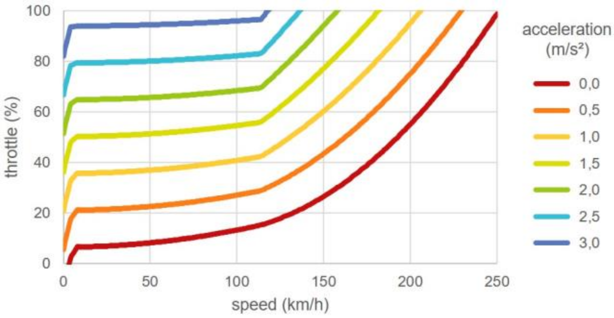

Figure 6. Throttle reverse control map.

Results and Discussion

Tests were conducted on a terrain used to validate some autonomous vehicle capabilities. It consists of a four-lane highway displaying a succession of curves with a radius of curvature of 400m. The road layout is shown Fig. 7.

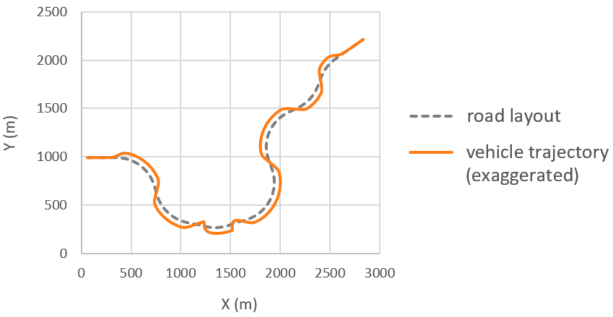

Figure 7. Road layout used for the test and vehicle trajectory obtained. Lateral shifting is magnified (150x) to show the effects of road curvature on the trajectory.

The vehicle behaves as intended for a wide range of parameters. However, extreme setups can lead to some erratic behavior. Insufficient artificial friction leads to system instability resulting in oscillations and eventually lane departures. A small field area of effect leads to violent force variations and unpredictable behavior. The same phenomenon is observed if the repulsion gain is too low.

As an example of "normal" behavior, following results are obtained for a required speed of 100 km/h and with gain parameters η and μ both set to 10. The obstacle effect radius ρ_0 is set to 3 meters and forces are computed by regression over 4 points placed in the corners of a 30 cm square around the vehicle center of gravity.

In this setup, vehicle speed is maintained within 1% of the requested speed and acceleration never rises above 2 m/s². At the corners, the vehicle shifts toward the outside as if centrifugal force was pushing it as shown Fig. 7. This is because the chosen obstacle field profile doesn't take speed into account.

This issue might be reduced or negate by the use of dynamic potential fields adapting shapes according to the relative velocity between the vehicle and the obstacle. An example of a dynamic potential field can be found in [Par08]. A maximum of 40 cm offset was recorded as shown Fig. 8. Considering that lanes are 3.7 m wide, this lateral shifting is somewhat acceptable even if not desired.

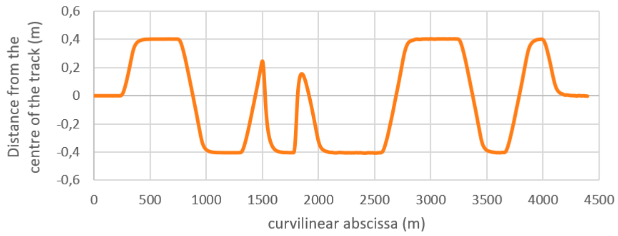

Figure 8. Lateral shifting along the track.

The framework and its implementation don't create any noticeable perturbation in regard to the APF method. Reverse control maps performed extremely well by keeping acceleration within 0.1% of the setpoint despite being an open loop controller. However, the dynamic model used was fairly simple and more complex ones might impact control performances. The whole system was running in real time at 100 Hz on a laptop without any performances issue. This frequency was sufficient for the tested situation but more complex environment and haptic feedback may require higher execution speed.

Conclusion and Perspectives

This work lays the foundations of an architecture which aims to provide a new approach for autonomous vehicles conception based on human machine cooperation and artificial potential fields. Stand-alone performances in simple situations are promising and more exhaustive testing are on the way including in depth parametric exploration and testing of other artificial potential field profiles.

Corresponding development of the human-machine interface is also in progress starting with real time graphical representation of the global guiding field. In addition to being an efficient tool for designing potential fields, it might be an intuitive way to convey the intentions of the autonomous system to the driver in addition to force feedback. If future human experimentations confirm this hypothesis, the architecture described here will take on its full significance as an efficient and user-friendly paradigm.

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