Control of an Intelligent Vehicle (Robot) System

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Abstract**--** This research concerns the control of an intelligent vehicle (robot) swarm. A formal engineering design synthesis methodology based on evolutionary computations which are common to encounter when design and optimization of distributed control systems such as intelligent vehicles are considered. The efficacy of the evolutionary design synthesis method is validated through multiple different case studies. More importantly, this automatic design synthesis method shows great potential to handle more complex design problems with a large number of design variables and multi-modal noise involved, where a good hand-coded solution may be very difficult or even impossible to obtain. Based on driver reaction time experimental results, new warning and overriding criteria are proposed in terms of the new measure, and the performance is analyzed statistically in terms of two typical sample pre-crash traffic scenarios.

Keywords**--** *Intelligent Vehicle, Design, Robot, Control*

I. INTRODUCTION

Various levels of simulation of traffic systems with different vehicle models and driver models have been published previously. Each simulation model has its own characteristics and specific target application background. Conversely, different models have been developed for various design requirements and research purposes. Miniature autonomous mobile robots share important characteristics with simple biological systems: robustness, simplicity, small size, flexibility, and modularity. Each individual is rather simple with limited local sensing and actuating capabilities, while as a group they can accomplish difficult global tasks in dynamic environments, without any external guidance or centralized control [1].

Design and control of such an intelligent vehicle (robot) swarm are difficult mainly because their group behavior is an emergent property of their mutual interaction and their interaction with the environment. The robot swarm becomes a distributed dynamical system due to independent parallel actions of different individuals [2]. Since the robots only have partial perceptions based on crude and noisy sensors, limited computational capabilities and energy budget, managing the robots to solve a global task under such constraints presents significant technical challenges. This is especially true because human intelligence is specialized in individuals and centralized control, instead of the collective intelligence shown in nature. Vehicle and driver behavior modeling is the core of the microscopic traffic models. Traditionally, vehicle and driver behavior modeling is classified into two major types of models, which are concerned with longitudinal and lateral motions of the vehicle, respectively. The longitudinal vehicle control models are concerned with the vehicle's longitudinal dynamics, while the lateral vehicle control models relate to the vehicle steering behaviors.

Evolutionary robotics [3] is a new and promising technique for automatic design synthesis of control strategies for autonomous robots in a distributed control system, especially for miniature robots. Inspired by nature, evolutionary robotics makes use of tools such as neural networks and evolutionary computation algorithms.

In this research, a more generic class of vehicle and driver models is desirable, therefore multiple levels of simulation models with different trade-offs of model complexity and reasonable simulation time are implemented.

II. MULTI-LEVEL SIMULATION AND MODELING OF INTELLIGENT VEHICLES

The development of advanced intelligent vehicle technologies that improve traffic safety demands multiple levels of dynamical vehicle models and human driving behavior models. These models can serve as useful tools in analytical investigations and simulations of the effects of the proposed sensor and control systems. The simulation time complexity usually increases as the model complexity and accuracy increase, hence different trade-offs between the two factors have to be made under different situations and requirements.

In general, traffic simulations can be divided into microscopic and macroscopic simulations.

The macroscopic traffic flow simulations are usually concerned with global characteristics of the overall traffic flow, such as the average vehicle speed and the traffic flow density, where individual vehicle behaviors are usually not modeled [4]. Most macroscopic models are based on the continuity equation and related to particle physics and gas kinetics [5]. Since intelligent vehicles are considered in this thesis, the entire vehicle models discussed here falls into the microscopic traffic simulation category.

Vehicle simulation models can be divided into several categories. The simplest vehicle model is the point model, where vehicles are only represented by moving points without any details of the vehicle. The embodied vehicle simulation models characterize different levels of details of the vehicle model, which usually contains a three-dimensional (3D) representation of specific vehicle modules, such as vehicle body and wheels. The kinematic embodied vehicle simulation model only describes some kinematic characteristics of the simulation, such as the vehicle position, speed, wheel speed, etc. While the dynamic embodied vehicle simulation can simulate certain dynamic scenarios, such as applying a driving/braking torque, friction force and wheel slip, body roll and pitch, or wind effects, etc. In addition, noise can be added to all different levels of vehicle simulation to simulate actuator and environmental noise effects.

On the other hand, driver models also play an important role in microscopic traffic simulation. In fact, most traffic simulation systems are focused on driver behavior modeling, such as car-following, lane-keeping, and lane-changing, etc. Different methods are applied to try to obtain realistic human driving behavior models.

III. VEHICLE SIMULATION

Three different levels of vehicle simulation models are implemented for different research application requirements. The principle here is to keep the models as simple as possible with only the necessary characteristics.

The simplest vehicle models are point models, where each vehicle is simply represented by a moving point and all details of vehicle dynamics are ignored. The advantages of point models are their simplicity and fast simulation. No specific simulator is needed and basic numerical analysis can be performed efficiently. However, the disadvantage is that they only simulate ideal situations and are not easy to view graphically. To make point simulations more realistic, probabilistic models are introduced to the point models, where the motions of the points can be modeled with certain probabilistic distributions.

To have an animated graphic interface of the simulation, a kinematic embodied simulation is introduced, where each vehicle consists of several modules, such as the vehicle body and wheels as well as on-board sensors, with certain shape defined for each module, and certain relative position and simple joints (motion constraints) defined between modules. The simulation could run either with or without noise, i.e., under ideal situations.

To simulate more realistic vehicle dynamics effects, a dynamic embodied simulation is implemented, where customized physical properties of each module can be defined and more complex joints are introduced. The simulation time complexity increases as additional features are introduced into the simulation, and the appropriate level of model complexity necessary and sufficient for a certain research purpose must be carefully chosen.

A. Theoretic Models

Under theoretic conditions, the point movements are governed by fundamental kinematic equations, as shown below:

$$v(t) = v_0 + \int_0^t a(t)dt \qquad (1)$$

$$R(t) = R_0 + \int_0^t v(t)dt \qquad (2)$$

Here, $a(t)$, $v(t)$, and $R(t)$ are the point's acceleration, velocity, and position time histories, respectively, with v_0 and R_0 representing its initial velocity and position, respectively. Hence the $v(t)$ and $R(t)$ of a point can be computed from the above equations given its $a(t)$, v_0, and R_0.

On the other hand, given the distance between two points, their relative velocity and acceleration, it is easy to compute when they would collide assuming certain acceleration histories $a_1(t)$ and $a_2(t)$ and when the following vehicle needs to brake to avoid a potential collision. The collision is defined here when two points are within a certain distance D from each other. In other words, the vehicle can be considered to have a safety disk with center at the point and diameter D, as shown in Figure 1.

It can be noted here that even with a simple theoretic vehicle model, the driver model part that decides the acceleration profile $a(t)$, could be complex and highly stochastic in nature, which makes the whole simulation and subsequent analysis a non-trivial task.

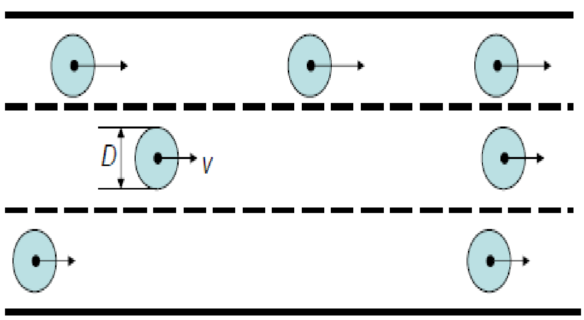

Figure 1: Sample Point Vehicle Models with Speed *v* and Collision Disk with Diameter *D* Moving on a Three-lane Highway

B. Rule-based Model

A heuristic approach to implementing a driver model is to control the vehicle by a series of logical commands according to driver preferences and sensor measurements as well as vehicle model responses updated in real time. Simple driver behaviors can be easily implemented this way, and some control parameters and thresholds need to be hand-tuned or evolved to get desirable behaviors.

For example, the car-following behavior can be implemented following the logic scheme shown in Figure 2, where vH and vL are current speeds of the host vehicle and the lead vehicle, respectively, ε is a small positive constant speed buffer, and Rmin is a positive constant distance parameter. The blocks "Accelerate" and "Decelerate" could be further expanded to implement more realistic car following behaviors, which could refer to the Helbing model or be hand-tuned through trial and error. Although the logic scheme shown in Figure 2 seems simple, it could take considerable time and effort to fine tune the parameters to get desirable and realistic car-following behaviors. The three different rotational motions of the vehicle body are pitch, yaw, and roll, as shown in Figure 3, which are also simulated by the dynamic embodied vehicle model through ODE. We are going to simulate the force and observe its behaviour.

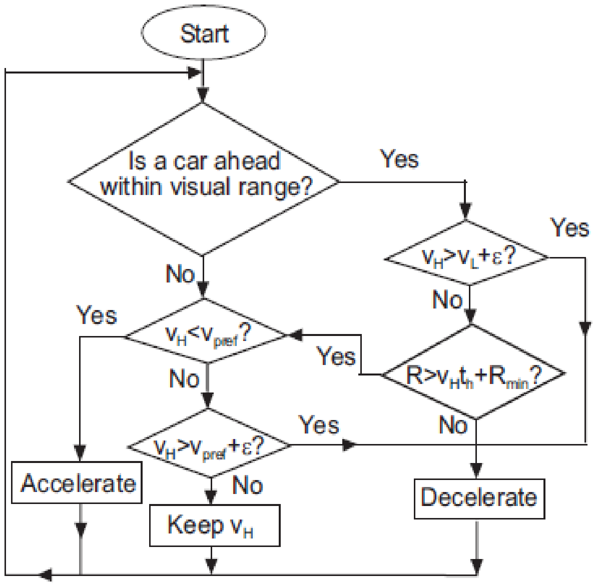

Figure 2: The Logic Scheme of a Simple Car-following Behavior

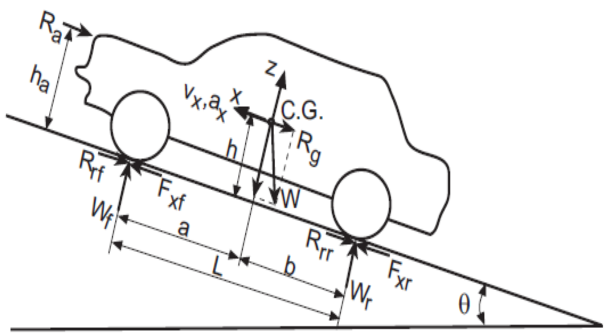

Figure 3: Significant Forces Acting on a Two-axle Vehicle

IV. RESULT

Figure 4 shows the time histories of the three angles under a sample vehicle driving scenario, where the vehicle drove along alternate straight and curved roads and changed lanes regularly. First the vehicle accelerated on a straight road from static to its preferred speed (61 mph) for the first 12 s, during which only the pitch angle was a non-zero value, since the dynamic weight transfer effects due to acceleration caused the vehicle to pitch backwards. Then the vehicle entered a clockwise curve at time 37 s, before which it reduced its speed, and exited this curve at time 76 s, after which it resumed its preferred speed. It also went through a counter-clockwise curve from time 106 to 145 s, with similar speed control as before. In addition, the vehicle changed lanes at time 22, 44, 68, 89, 112, 136, and 158 s, respectively. Note that the yaw and roll angles changed dramatically due to the lane changes, while the roll angle followed the steering angle changes quite closely, especially on straight roads. Moreover, the magnitude of the pitch and roll angles depends on the elasticity and damping characteristics of the suspension system, which are adjustable vehicle model parameters to fit real car experimental data.

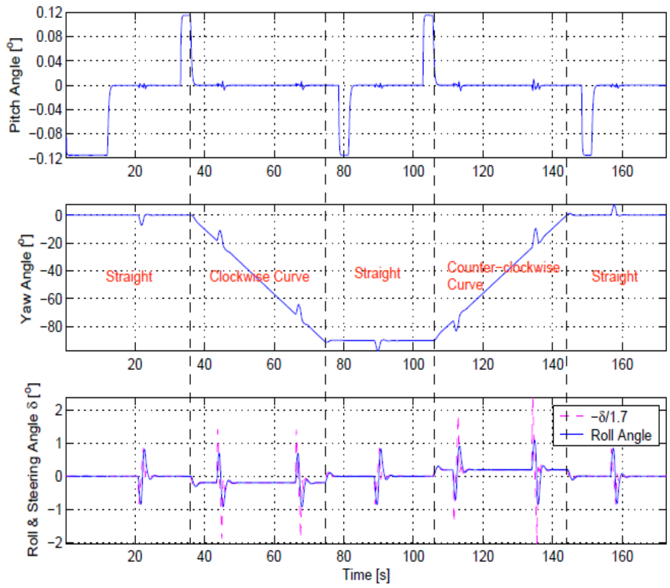

Figure 4: The Simulated Vehicle Pitch, Yaw, and Roll Motions with Steering Angles

CONCLUSION

The evolutionary algorithm is applied to automatically synthesize controllers for autonomous robots in a noisy simulation environment. The evolutionary design synthesis methodology is validated again in the framework of two case studies concerned with collective robotic inspection of 2D regular structures as well as driver behavior modeling. In addition, the evolutionary design synthesis method also appears to be able to deal with the noise in fitness evaluation efficiently and adapt to the collective task nature well in terms of the collective robotic inspection case study.

In the future, the same methodology can be applied to more complex and realistic problems such as collective robotic inspection of 3D irregular space structures and/or jet propulsion systems as well as development of more complex and realistic driver behavior models. Implementation and verification of evolved controllers with real robots would also be meaningful.

References

[1] Alm, H. and Nilsson, L. (1994), “Changes in driver behaviour as a function of hands free mobile phones—A simulator study”, *Accident Analysis and Prevention*, 26(4):441– 451.

[2] Bishop, R. (2005), “Intelligent vehicle R&D: A review and contrast of programs worldwide and emerging trends”, *Annales des T´el´ecommunications*, 60(3–4):228–263.

[3] Modjtahedzadeh, A. and Hess, R. A. (1993), “A model of driver steering control behavior for use in assessing vehicle handling qualities”, *Transactions of the ASME: Journal of Dynamic Systems, Measurement, and Control*, 115(3):456–464.

[4] Antonsson, E. K. and Cagan, J., (Eds.) (2001), *Formal Engineering Design Synthesis*, Cambridge University Press, Cambridge, U.K.

[5] Bakker, E., Nyborg, L., and Pacejka, H. B. (1987), “Tyre modelling for use in vehicle dynamics studies”, SAE Technical Paper No. 870421.

[6] Wong, E. and Litt, J. S. (2004), “Autonomous multi-agent robotics for inspectionand repair of propulsion systems”, In *Proceedings of AIAA First Intelligent Systems Technical Conference*, number AIAA-2004-6364, Chicago, IL.

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