Microscopic Simulation of Vehicular Traffic on Congested Roads

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Abstract

In this work a microscopic traffic interaction model is simulated as a distributed set of autonomous agents, each of which controls its own vehicle and responds to the actions of other agents. Both navigating along a road as well as static and dynamic obstacle avoidance are achieved by applying nonholonomic robot motion constraints on a a potential field model. Dynamic effects are controlled by constraining the turn direction to lie within a dynamically defined cone (maximum turn depends on current velocity). Each reactive agent has a set of primitive behaviours. It also has a set of beliefs regarding its own behaviour and the behaviours of other vehicles in the system.

1 Introduction

Modeling vehicular interactions, difficult enough in the simplest of circumstances, is made more complex by the variability in vehicle and driver characteristics typical of uncontrolled road access. Pedestrians, trucks, automobiles, and non-motorized vehicles, share the same road area and negotiating a path requires a good understanding of the behaviour typical of the other types of vehicles.

A popular approach for simulating multi-entity interactions is based on distributed agent architectures [30]. Here, the behaviour of a mobile robot may be controlled by a set of schemas based on potential fields [1], where the parameters of the field is affected by environmental stimuli. The potential field approach is very popular in path planning, and is increasingly used in modeling nonholonomic systems such as vehicles ([29, 25, 24, 7]). In this work a 3-dimensional C-Space (x, y, θ) is constructed dynamically for each vehicle, and paths are found directly (without search) using potential field interactions in this space. The nonholonomicity is modeled by permitting continuous motions over a range of angles instead of a set of discretized models. Vehicle dynamics is handled by constraining the range of possible motions as a function of velocity. Anticipated behaviour of other vehicles is modeled through a projective potential field where the vehicles are projected to their likely future positions. Particular agent characteristics , e.g. aggressiveness, speediness, lateral-position-on-road, can be formulated in terms of the parameters of the potential field.

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2 Modelling the System

2.1 Vehicle Model

The vehicle is modeled as a convex polygon $\mathcal{A}$ with midline RF, where R and F are the midpoints of the rear and front axles. The steering angle ϕ is the angle between the velocity at F and the axis RF. When the vehicle moves, the point R describes a curve that must be tangent to the main axis of the vehicle, thus generating a nonholonomic constraint of the form :

$$-\dot{x}.\sin\theta + \dot{y}.\cos\theta = 0$$

where x,y is the position at mid-rear-axle R, and θ is the angle between the vehicle axis RF and the global frame.

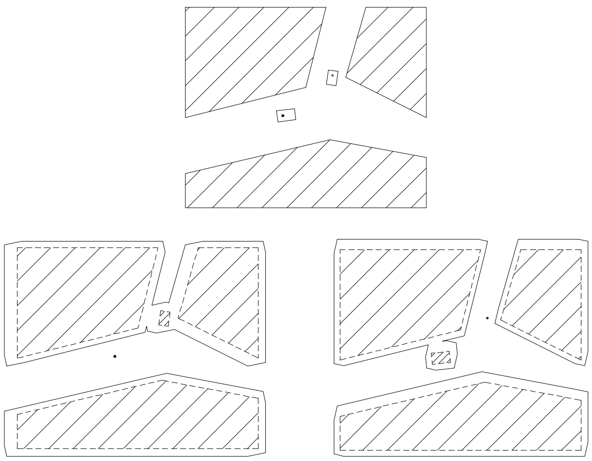

Figure 1: *Configuration Space* Θ*-slice for a given Road Geometry* The grown areas are those x, y configurations which result in a collision with the road for the given θ. Each vehicle dynamically computes its own C-space slice treating the other objects (as known to it), as obstacles (two lower figures.

2.2 Potential Field Model

The model considers driver behaviour and all considerations of the near future are projected into the current instant. Since global search is not used, a potential field based approach that returns instantaneous decisions is preferable.

The basic potential field gradient in the current model is of the form k/r^n explained. The strategy applied in the "Two-car Model" is to assign micromotion to one vehicle at a time alternately. In certain situations, kike when two vehicles approach eachother on a collision course certaon anomalous behaviour is noticed owing two the formation of some local minima. SUch problems are however sorted out by using a projective look - ahead technique.

2.3 Modelling the Driver Behaviour

The action of each vehicle and its driver is based on the current situation and its own belief regarding other agents' behaviour and this is reflected in its own parameter set.This mechanism is stimulus-response type in nature.

2.3.1 Driver Aggressiveness

The driver aggressiveness criteria is typically represented as an index (μ) in a scale of 1-100. A more aggressive driver is assigned with a higher value of μ .This value is also dependent on the type of the vehicle. In this model, aggressiveness has no independent effect on the velocity with which the vehicle is travelling. It plays a key role when the vehicle has to yield to other vehicles, while taking turns or while braking.

d_{cr} is a rapidly decreasing function of μ in the form:

$$d_{cr} = |\vec{v}_{rel}| . \left[\text{BrakingTime} \times \text{SafetyFactor} \times \left(1 - \frac{b}{\mu^2} \right) \right]$$

where, $\vec{v}_{rel}$ is the relative velocity of travel, *Braking Time* is a parameter related to the driver characteristics and b is a global constant. The global *Safety Factor* is thus reduced by the factor (1 - $\frac{b}{\mu^2}$). Hence, the car having a lower μ may deviate from the track earlier in order to give room for the more aggressive driver. Also the shadow potential constant (E_{shadow}) is dependent upon the aggressiveness (μ_c) of the driver, as well as $\vec{v}_{rel}$, estimated size of the approaching vehicle (S_o) and the estimated aggressiveness (μ_o) of the approaching driver:

$$E_{shadow} \propto \frac{|\vec{v}_{rel}| .B(S_o)}{\mu_c .B(\mu_o)}$$

where, index $B(\ )$ indicate the output from the Belief function. This E_{shadow} is further modulated by k_shadow.

The aggressiveness index (μ) is also used while the vehicle is turning or braking. A more aggressive driver will use a shorter braking threshold (d_{th}) and the braking force (F_{br}) will be greater:

$$F_{br} \propto \mu$$
$$d_{th} \propto \frac{1}{\mu}$$

2.3.2 Belief functions

Currently the model has belief functions for estimating the aggressiveness of the other driver. An ad hoc multiplier has been used to estimate sizes, but no psychological validity is claimed for any of these functions. However, belief functions modulate the driver's entire knowledge of the world: the other systems as well as his own.

Modelling belief is an extremely complicated process. Koller [15] has constructed a "belief network" for analysing symbolic traffic flow explaining features like lane changes in a highway traffic simulation.

2.4 Modes of Travel : Normal (in Segment) Motion, Turning and Goal Reaching

Different travel modes are used due to varying effect of the goal along with the driver attitudes. A route planner decomposes the route of each vehicle into track segments and returns the track list. At the road junctions the vehicle switches from one segment to another. This mode is called Turning. At the Goal Reaching mode the vehicle travels in the last track segment and nears the final goal. The normal mode is used while travelling in a single track segment. For the turning operation the driver has to reduce the vehicle velocity and then shift the target from the current goal to the next. The velocity during turning is purely a function of the current potential field gradient subject to the kinematics and dynamics of the vehicle. The effect of discretisation into steps of length $|\vec{v}| .\Delta t$ needs to be taken into account and thus d_{turn} becomes:

$$d_{turn} = |\vec{v}| .\Delta t. \left[\sum_{i=1}^{n} \cos(i.\phi_{max}) - \cot\alpha \sum_{i=1}^{n} \sin(i.\phi_{max}) \right]$$

where, ϕ_{max} = maximum steering angle attainable at velocity $\vec{v}$, $n = \lfloor \frac{\alpha}{\phi_{max}} \rfloor$ and $\alpha \neq 0^{\text{th}}$.

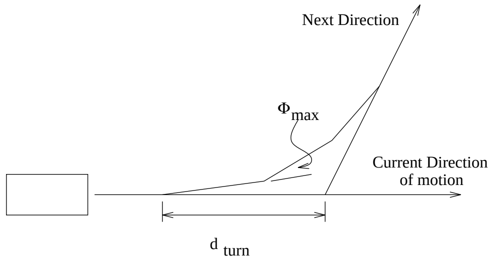

Figure 2: *The Switching of the Goal during Turn:* When a vehicle navigates, it takes an element from the track list as its current goal direction. At distance d_turn before the current goal, depending upon its ability to steer, the vehicle shifts the goal to the next element from the list.

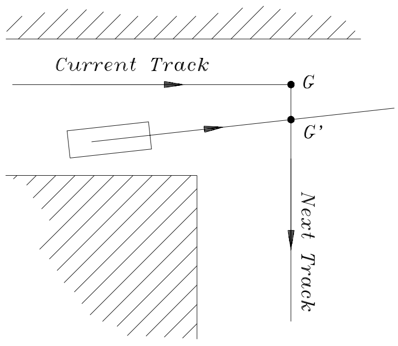

Figure 3: Locating the virtual goal on turning

2.4.1 Goal Reaching Mode

Deceleration before reaching the goal is necessary, otherwise the gradient near the goal is infinite and the vehicle will shoot past the goal at tremendous speed. In

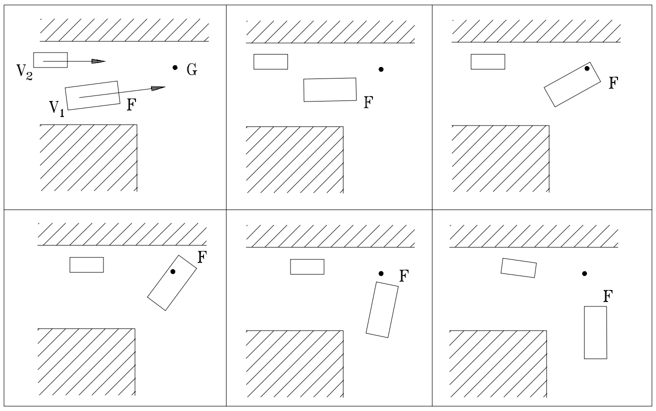

Figure 4: *Backing up during Turning:* V_1 backs up at the road junction because it has deviated from its original track in reaction to V_2 at the cross-road (the front of the vehicle is marked F).

this mode the vehicle speed has slowed down so that it stops near about the final target. Depending upon the current velocity, goal distance and the field gradient the driver alters the velocity taking into account the vehicle's braking ability.

3 Implementation and Results

3.0.2 Road and Vehicle Geometry

The input data is read from several files containing road, track, and vehicle data.

The **Road data** structure contains the physical configuration of the fixed obstacles i.e., the road edges in the global coordinate frame (the coordinate frame of the workspace).

The **Track data** structure holds information about the road segment connectivity in the form of a vertex list of the tracks.

The orientation of each track is computed and included in the data structure. This information is used, for example, when the vehicle switches its goal (at a turn).

The **Vehicle data** consists of:

1. Geometry: i.e. coordinates of the vertices of a convex polygon in a local coordinate frame. This frame is placed at the midpoint of the vehicle's rear axle.

2. Technical specifications: Maximum car speed, engine power, braking power and the maximum steering angle.

3. The driver data structure: This contains potential field parameters that influence the driving.

3.0.3 Results

We now present several trial runs are presented for different situations.

1. Longitudinal Distance: A measure of the distance between the vehicles measured along the axis of the track.

2. Lateral Deviation: This reflects the distance between the vehicles measured in a direction orthogonal to the track axis.

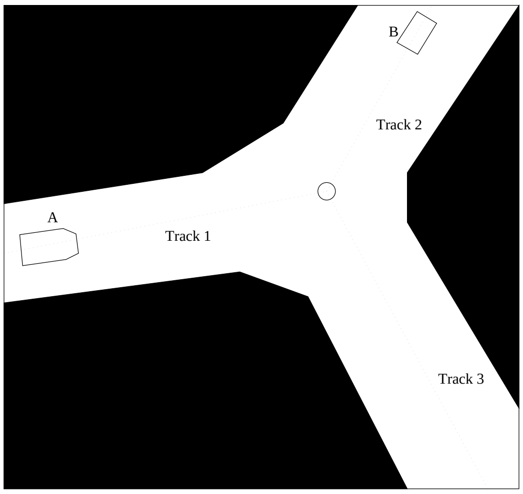

Figure 5: *Inputs:* Road geometry, Start, Goal, and Track geometry. Vehicle A starts as shown, and moves along Tracks 1 and 2 while B moves along Tracks 2 and 3.

Wherever meaningful, we also present Time vs. Lateral Deviation and Time vs. Longitudinal Distance plots. Sharp deflections in these curves reflect sudden avoidance maneuvers etc. In each instance, a brief analysis is presented to support and explain the observation(s). (The time resolution for the outputs = 0.1 seconds.)

3.1 Single vehicle in motion

In this case, only one vehicle is in action. It moves on a narrow road and during the course of motion, it has to take a turn.

Analysis

The car is moving on a narrow road. The starting point is right at the centre of the road. Soon it moves to the left to its steady state configuration. It continues to keep to the left even after taking the turn.

3.2 Vehicles crossing - Wide road

Two cars are moving in opposite direction on a broad road. The cars approach one another, yield and move away.

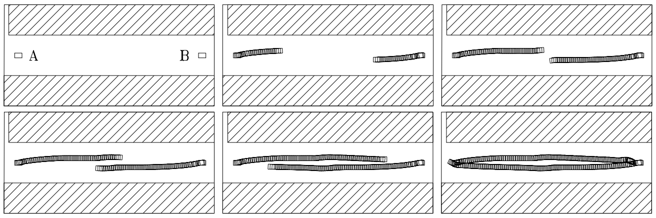

Figure 6: *Simulation: Two vehicles in wide road.* Two vehicles cross each other comfortably on a wide road.

3.3 Vehicles crossing - Narrow road

Two cars are moving in opposite direction in a narrow road. The cars approach one another, yield and move away. (see Figure 8 and Figure 9).

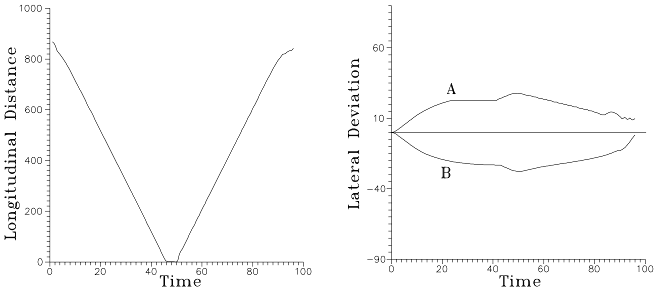

Figure 7: *Characteristic Curves: Two vehicles in wide road* The longitudinal distance (along track length) and lateral deviation (perpendicular to track length) are plotted against time. Lateral Deviation increases but not too sharply, when the two vehicles are within lookahead distance.

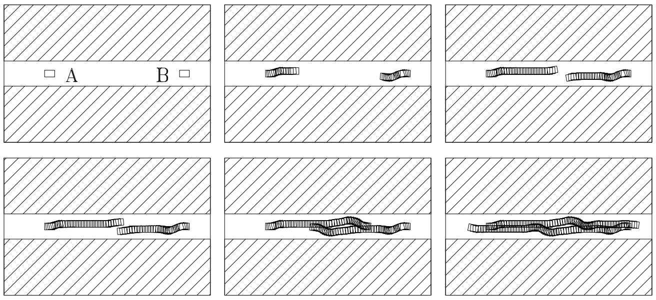

Figure 8: *Simulation - Two vehicles in narrow road* The jump to the sides is sharper.

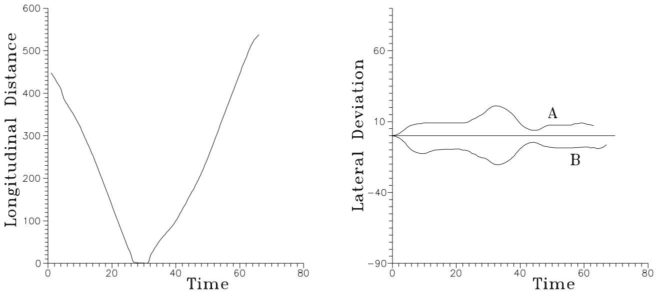

Figure 9: Characteristic Curves - Two vehicles in narrow road

3.4 Truck overtaking a Car

A car is moving on the road. A truck approaches it from behind and overtakes the car. Both vehicles continue to move on in the same direction.

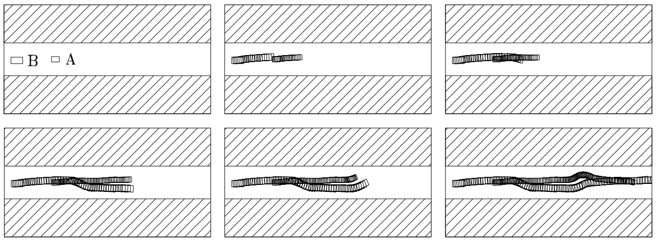

Figure 10: *Simulation - Truck overtaking a car.*

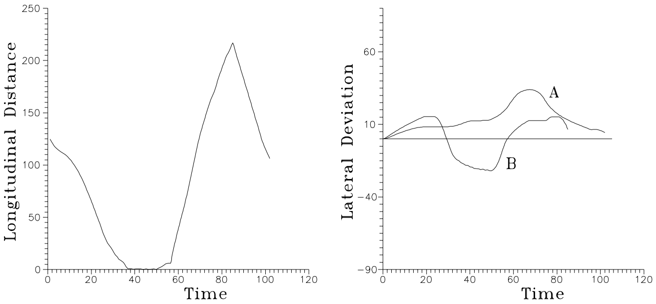

Figure 11: Characteristic Curves - Truck overtaking a car.

3.5 Vehicles Crossing - Unequal Aggressiveness Analysis

When car(B) and bus(A) approach each other B deviates a bit earlier since the car driver is less aggressive. As can be seen Figure 12 and Figure 13, the deviation of A is less than that of B.

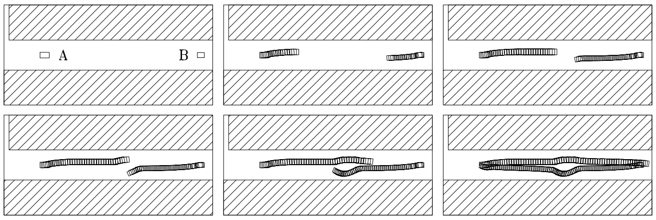

Figure 12: Simulation - Two vehicles of unequal Aggressiveness

5(a) The Vehicle and Driver Characteristics.

4 Conclusion

The current work replaces conventional path-planning schemes involving explicit search. This is done by local decisions using potential field and driver behaviour based models. The results presented in section 3.0.3 depict the suitability of the current work in modelling two vehicle interaction over a wide range of situations associated with congested roads with several turns and crossings.

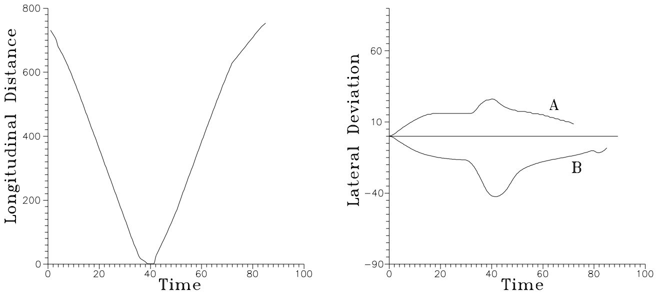

Figure 13: Characteristic Curves - Two vehicles of unequal Aggressiveness

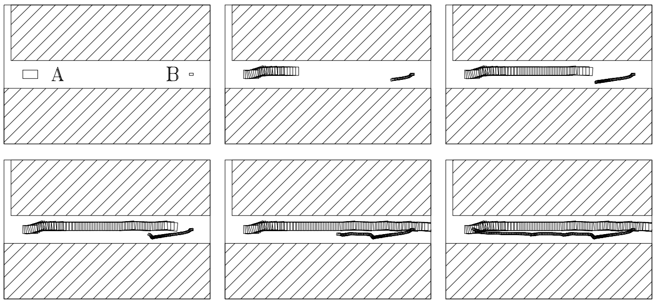

Figure 14: Simulation - A Rickshaw crossing a Truck

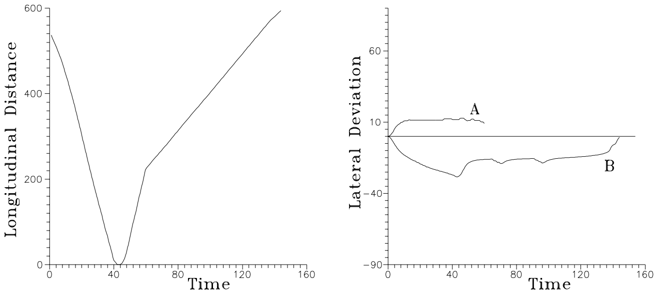

Figure 15: Characteristic Curves - A Rickshaw crossing a Truck

Purely potential field based models cannot execute preplanned motion sequences such as parking or "U" turning in narrow roads. However, these can be done by search based algorithms [20]. On the other hand, a purely search-based model is inefficient in handling conflicting dynamic situations. Thus, a trade-off between the two approaches is probably required. Such a model will use potential fields and in certain field characteristics it will also utilise some predefined set of possible actions - a feature of search-based algorithms.

However, the model presented in this thesis is elementary in nature and is based on potential field only. Further work needs to be done to model more complex and conflicting traffic situations. Some of the issues for future research can be:

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