Collision Avoidance in dynamic environments applied to autonomous vehicle guidance on the motorway

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Abstract

This paper discusses an approach to automatic vehicle guidance on a motorway with the intention of avoiding collisions. The autonomous vehicle should be able to manage the tasks of a driver. Therefore it has to manage complex traffic situations in real time.

Environment information is provided by several vision sensor modules and stored in a central dynamic database. A system view of the environment is generated by data fusion and data interpretation based on data stored in the dynamic data base that represents the current scene. This system view is transformed into a riskmap *representation which integrates information about the street, the relative position and speed of obstacles and traffic signs.*

The riskmap is an egocentric map of potentials reflecting the risk at a certain position in the environment. These potentials are interpreted as charged points repelling the vehicle which is intepreted as an electron within an electric field. The field intensity vector that is computed for the map center is then taken to determine the required values for velocities in longitudinal and lateral direction which are passed to a lower level controller.

In order to achieve "humanlike" behaviour, each riskmap is built according to a driver model and a vehicle model.

1 Introduction

For the pilot of an airplane the autopilot has become a very useful assistant. A similar technological support for the driver of a passenger car is conceivable. During a long journey on the motorway, the attention of a human driver is not always high enough. Therefore the small number of critical situations occurring during the journey can cause accidents. The traffic on the motorway is less complex compared to city traffic. Therefore this domain has been chosen to demonstrate the feasibility of autonomous driving. In the following sections such a system will be discussed.

The basic tasks are lane keeping and staying at a given velocity. The autopilot has to adapt to the situation that it is confronted with. It has to keep safe distances to other traffic participants, to overtake if necessary and to follow traffic regulations.

This paper presents a method that realizes the behaviour control level of such an autopilot. It is designed in a way that enables the autonomous vehicle to cope with almost any traffic situation.

2 The Electric Field Model

The approach presented here follows the artificial potential field method for autonomous mobile robots [KHA85, KRO84, KT86, SD92]. A potential field approach has also been presented for automatic guidance of ships [M88]. In contrast to the static environment of an autonomous mobile robot, the environment of a car on the motorway is dynamic. Furthermore driving on a motorway implies adaptation to traffic regulations, vehicle dynamics, and driver intentions apart from the path finding task of a robot. The human driver takes this knowledge into account during his information processing.

The *electric field method* consists of two parts. First, the representation of the environment as an egocentric map of potentials reflecting the risk at a certain position in the environment. Second, the evaluation

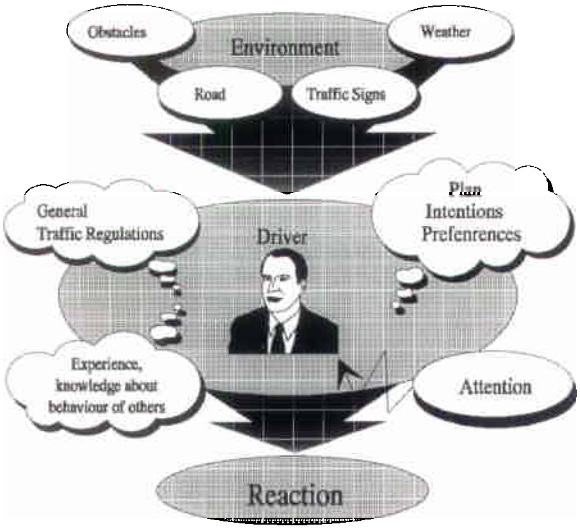

Figure 1: *The human driver perceives environment information mainly by vision. This information is processed to generate reactions with the use of knowledge about behaviour of traffic participants and about traffic regulations. Furthermore the driver's intentions and plans influence his reactions. When building an autonomous vehicle this information processing scheme is adapted.*

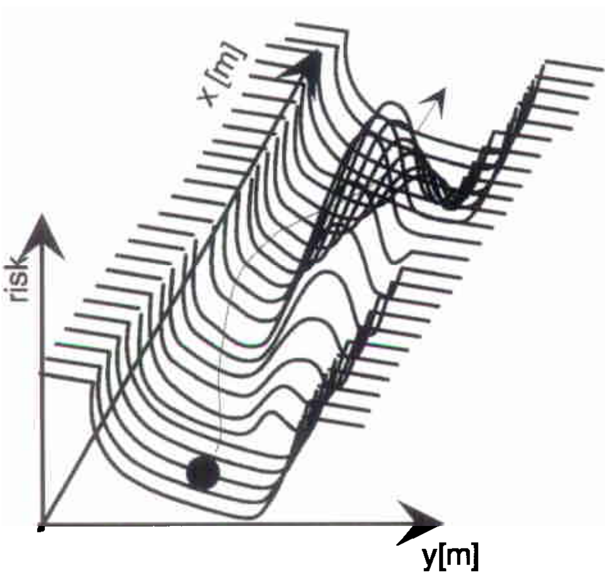

Figure 2: *This potential field shows a simple traffic scenario with an obstacle ahead and a road with two lanes. The forces generated by the electric field guide the vehicle along the indicated trajectory.*

of this map by interpreting the potentials as charged points repelling the vehicle which is interpreted as an electron in this model. The forces that take effect on the virtual electron are mapped onto nominal values for velocities and accelerations passed to low level algorithms for longitudinal and lateral control of the vehicle. Figure 2 shows the principle of the electric field approach.

During construction of the risk map, a driver model and a vehicle model are taken into account. The information processing performed by the autonomous vehicle is intended to be 'humanlike'. Visual information passes a filter mechanism that relies on background information classifying objects according to their danger potential. If an object is regarded as dangerous it becomes the stimulus for a reaction. In a similar way, knowledge about traffic regulations influences vehicle behaviour. Especially traffic signs are regarded as stimuli for domain concurring behaviour.

Both the classification and the reaction differ from driver to driver. By exchanging the underlying driver model the autonomous vehicle is able to adapt to the driver type. The reaction does not only depend on the driver but also on the vehicle. The dynamics of the car are assumed to be known. Therefore they are treated as constraints on the autonomous vehicle's behaviour.

2.1 System Overview

Before explaining any details, this section should give an overview of the system in which the described method is embedded as the behaviour control module.

The input data is provided by a number of video based sensor modules.

- A *Road Tracker* module gives information about the street, its curvature, its number of lanes and the current position of the autonomous vehicle.
- *Obstacle Detection* modules detect and track other cars around the autonomous vehicle and determine their velocities, their distances and their relative positions.
- A *Traffic Sign Recognition* module detects and classifies traffic signs.

All these modules work in real time and communicate via a *dynamic database*. This database carries symbolic data describing the current situation and the state of the autonomous vehicle.

Within a system cycle the behaviour control module reads data from the dynamic database and transforms it into a set of partial risk maps for the road, for obstacles and for the driver's intention. Then these maps are combined to a single one. A force vector is determined by interpreting the map as an electric field. This force vector is transformed into nominal values for longitudinal and lateral control which are passed to a vehicle control module via the dynamic database. The vehicle control module has direct access to vehicle actuators.

2.2 Electric Field

The environment of the autonomous vehicle is represented as an egocentric map. Each coordinate is interpreted as a charged particle. To each coordinate (i,j) of the map charged with L(i,j) the directed field force $E_{AV(i,j)}$ is determined by

$$E_{AV(i,j)} = L(i,j) \cdot \frac{(i,j)}{(\sqrt{i^2+j^2})^3}. \quad (1)$$

The force vector for the map center is then determined by

$$E_{AV} = \sum_{i,j} E_{AV(i,j)}. \quad (2)$$

The force vector E_{AV} is used to determine the acceleration and direction of the autonomous vehicle.

2.3 Potential Field

The method used to determine vehicle movement seems to be very simple at the first glance. However, the main task is not the force vector computation but the *construction* of the potential field. The way how the potential field is constructed for autonomous driving on a motorway will be discussed in this section.

2.3.1 Representation of the Road

Assuming that there are no obstacles present in the current scene, the only task of the autonomous vehicle is to keep the lane. For simplification we start by focusing on the lateral forces.

The attractive point for the vehicle is the lane center. Small offsets are tolerated by generating low potentials. If the vehicle drifts towards the lane markings higher potentials are generated, always considering the vehicle dynamics. Apart from the position of the vehicle, its velocity and direction are taken into account.

Approaching the borderlines of the road is regarded as extremely dangerous. Therefore the potentials are chosen much higher than those which avoid the leaving of a lane.

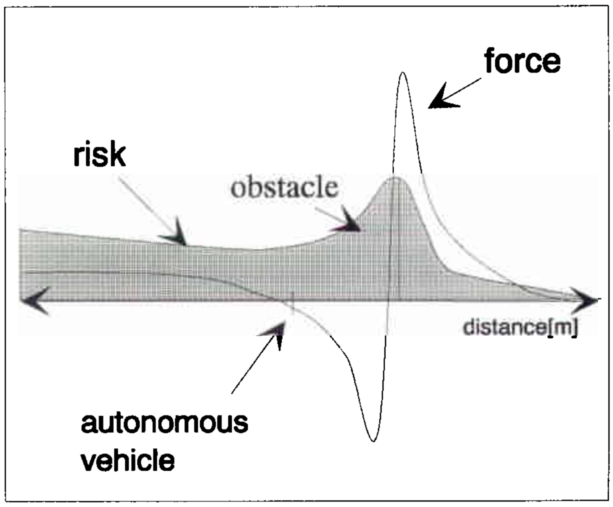

Figure 3: *The above image shows the profile of a longitudinal cut through the potential field and the associated forces. In the underlying scene there is an obstacle in front of the autonomous vehicle which is represented by a hill. The height and ascent of the hill correspond to the relative speed of the obstacle. The autonomous vehicle moves at a lower speed than the desired travel speed. This is represented by a sloping set of potentials along the street. The negative force value at the position of the autonomous vehicle causes the vehicle to decelerate.*

2.3.2 Representation of the Driver's Intention

The driver is able to set a desired speed[1]. If the current velocity is too low, higher potentials are generated behind the vehicle. This invokes forces that accelerate the vehicle. Accordingly the vehicle can be decelerated by generating a higher potential in front of the car.

2.3.3 Representation of Obstacles

Many potential field approaches represent obstacles as hills sloping towards the the obstacle borders. Krogh and Thorpe [KT86] describe obstacles based on position and direction of the steered vehicle. The obstacle representation described here follows this approach.

The higher the probability of a collision the higher the risk associated with the involved obstacle is chosen. Every obstacle that is considered as a risk generates longitudinal and lateral reactions of the vehicle. An obstacle in front invokes repelling potentials that

[1] It is possible to add a navigation component to the system. The driver's task is then reduced to input the destination and the time for the journey.

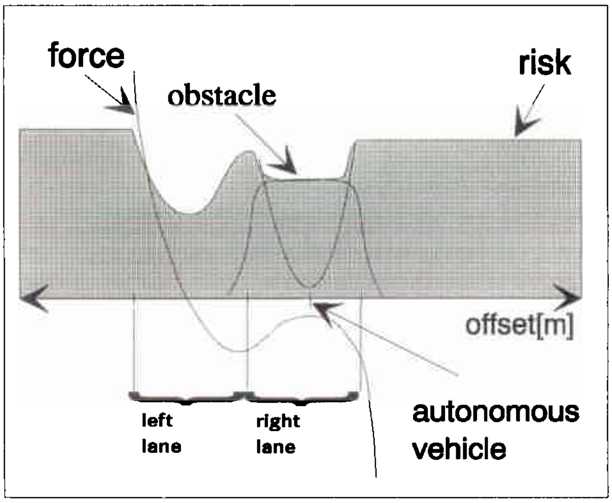

Figure 4: *The above image shows the profile of a lateral cut through the potential field and the associated forces. The autonomous vehicle moves on a road with two lanes. An obstacle on the right lane "fills the right valley". This induces a negative force value at the position of the autonomous vehicle which makes the vehicle move to the left.*

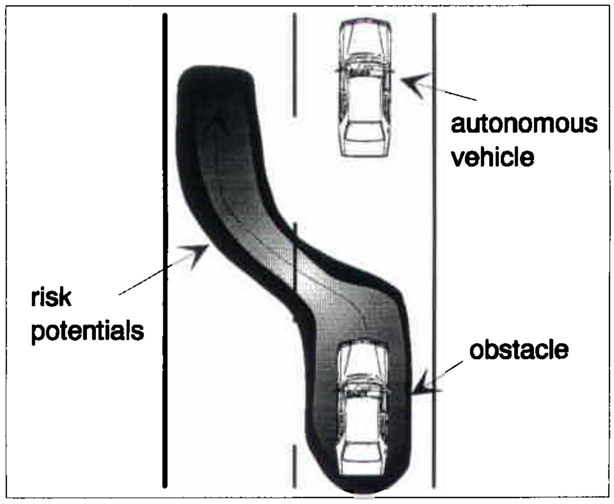

Figure 5: *The assumption that a vehicle approaching from behind intends to overtake leads to the above representation.*

force the autonomous vehicle to decelerate and keep a safe distance. The same obstacle induces potentials that make the autonomous vehicle change lanes to overtake it. The figures 3 and 4 show how the electric field generates forces which are used to guide the vehicle.

The information about which distance to keep stems from a driver model and a traffic regulations knowledge base. This knowledge base also gives information about the preferences of the virtual driver. If the autonomous vehicle approaches an obstacle it can react by changing lanes or decelerating.

When passing an obstacle the reaction on it depends on the direction in which the autonomous vehicle moves. If both cars move in parallel, no reaction is necessary. Yet, if the lateral distance is less than the distance requested by the virtual driver, an obstacle hill is created.

To improve reactions on other traffic participants knowledge about their behaviour is used. If a vehicle approaches from behind, it is assumed that it will change lanes to overtake. Therefore it is not necessary to accelerate to avoid a collision. The potentials generated by this approaching vehicle follow its assumed future trajectory (see figure 5). This reduces the repulsion from behind. On the other hand this representation of the approaching vehicle keeps the autonomous vehicle from overtaking another obstacle in front.

2.3.4 Representation of Traffic Regulations

Up to now potentials have been associated with risks. A traffic regulation is not a concrete risk but a domain constraint. Traffic regulations can either be of permanent validity or indicated by traffic signs. One of the permanent regulations is the precept to drive on the rightmost lane[2]. When driving on a motorway with more than one lane, potentials are set onto the left lanes to make the vehicle move towards the rightmost lane. These potentials are so low that any kind of obstacle generates higher ones. This allows automatic overtaking.

There are different ways to realize an overtaking prohibition on the right side of an obstacle[3]. The autonomous vehicle can be forced to change lanes and place itself behind the obstacle or it can be told to decelerate to avoid passing.

A speed limit indicated by a traffic sign is treated comparable to the driver's intended speed (see 2.3.2).

If a traffic sign is detected that forbids overtaking, potentials are set onto the left lane that hinder the vehicle to overtake. Furthermore, the 'hill' of an obstacle ahead is expanded to the left lane to keep the autonomous vehicle from passing it.

[2]The precept to drive on the rightmost lane is valid on the German Autobahn.

[3]On the German Autobahn right overtaking is not allowed.

2.3.5 Partial Field Fusion

The sections above discuss how to generate the partial potential fields for a number of possible events and domain constraints. These partial potentials have to be combined to a single representation to react correctly on every possible combination of risks.

As remarked when discussing 'right driving', there are different weights for partial potential fields. To distinguish between emergency reactions, preventive actions, driver's intentions and traffic regulations, they are associated with a set of weights. These weights are part of the driver model.

How can a weighting of partial potentials be realized? First of all the partial potential fields are normalized by subtracting the potential at the origin of the coordinate system from the field potentials.

During the combination phase, the generated partial potential fields are shifted up relative to their weight. Then they are combined with a maximum function. Finally the resulting potential field is normalized again. It should be noted that any partial potential field is created and valid if and only if the underlying stimulus is found in the current traffic scene.

2.4 First Results

The method described above has been implemented on a PC and on a transputer system. First results are taken from a simulation environment. In this environment the autonomous vehicle demonstrated accurate behaviour. Apart from lane keeping, distance keeping and overtaking it solved dangerous situations caused by manoeuvers of other vehicles.

With the help of some simplifications made on the complex theoretical model the system is running on PC in real time. This was achieved by reducing the potential field to a set of peaks. The loss of exactness was tolerable for simulation.

3 Conclusion

Regarding the target as an attractive pole and the environment as repelling charges, an electric field forces a charged particle on a trajectory that leads to the goal whenever there is an accessible path. What we get is a local operator for a global path. Decuyper and Keymeulen [DK92] present another approach leading to a similar local operator based on a fluid dynamics metaphor.

The representation of the environment is rather complicated. As we intend to present a passenger car guided by the system described above, our main task is to find a way to reduce complexity while keeping a high level of accuracy.

The system presented here is an approach that draws a direct link between behaviour decision and vehicle guidance. Its reactions are continuous in contrast to the discrete states of an automat. The principle of composing the reaction on a scenario of a number of reactions on single events makes it capable of dealing with unknown situations.

The next step will be the expansion of the method by a planning component that detects critical situations in advance which helps to model more 'human-like' behaviour. To improve the behaviour of the autonomous vehicle it is planned to consider the interdependencies of different stimuli and reactions.

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