Elastic Bands to Enhance Vehicle Following

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Abstract— **The vehicle-following principle has been widely used in several intelligent-vehicle applications. Adaptive cruise control systems, platooning systems, and systems for stop-and-go traffic employ this principle: The ego-vehicle follows a leader vehicle at a certain distance.**

The vehicle-following principle comes to its limitations when obstacles interfere with the path between the ego-vehicle and the leader vehicle. We call such situations dynamic driving situations.

This work introduces a planning and decision component to generalize vehicle following to situations dealing with non-automated interfering vehicles in mixed traffic.

As a demonstrator we employ a car that is able to navigate autonomously through regular traffic being longitudinally and laterally guided by actuators controlled by a computer. This paper focuses on lateral control for collision avoidance.

Previously, this autonomous driving capability was purely based on the vehicle-following principle: The path of the leader vehicle was tracked. To extend this capability to dynamic driving situations, a dynamic path planning component is introduced. Several driving situations are identified that necessitate responses to more than the leader vehicle.

We borrow an idea from robotics to solve the problem: Treat the path of the leader vehicle as an elastic band that is subjected to repelling forces of obstacles in the surroundings. This elastic band framework offers the necessary features to cover dynamic driving situations. Simulation results show the power of this approach. Real-world results obtained with our demonstrator validate the simulation results.

Keywords— **Intelligent vehicle, computer vision, robotics, stereo vision**

I. Introduction

Collision avoidance has been the subject of extensive research both in the field of robotics and intelligent vehicles. A tremendous benefit is assessed for reducing collisions with automated systems in regular traffic [1]. The detection capabilities of vision-based intelligent vehicles are mature enough to perform such a task (see e.g. [2]).

For lateral vehicle guidance, vision-based lane following is a promising and well-tested strategy. However, lane following relies on lane markings and tends to fail in cluttered scenes and in urban areas. Hence, a popular approach for automated vehicle guidance is to follow a leader vehicle both longitudinally and laterally. This intuitive behavior comes to its limitations when other traffic participants interfere with the leader vehicle's path. Dynamic path modification becomes necessary. These dynamic driving situations motivated the work of this paper.

How is this paper organized? Section II gives an overview of related work both in the field of intelligent vehicles and robotics. In Section III the elastic band framework is introduced. Section IV describes the necessary adaptations to the elastic band framework in order to tune the avoidance behavior towards that of human beings. The selection of the leader vehicle is explained in Section V. Results are detailed in Section VI. Conclusions and future work comprise the final Section.

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II. Related Work

A. Potential Field Approaches

The most prominent idea for collision avoidance are artificial potential fields (e.g. [3], [4]). The obstacles are modeled as potentials and the gradient of the superimposed potential field yields the direction command for the mobile robot. Potential fields are an elegant way to model obstacles and can be analyzed globally. A formal verification of the obstacle avoidance behavior is feasible.

Generalized potential fields depend not only on distance to obstacles and can therefore determine irrelevant obstacles pointing away from the ego-path. This method was first applied to velocity-dependent potentials in [3].

A popular approach to avoid local minima, i.e. trapping situations, in potential field applications is the use of harmonic potentials (see e.g. [5], [6]).

B. Approaches Using Physical Models

Other physical models besides potential fields are also popular for collision avoidance.

An alternative approach to the potential field methods is presented in [7], where analogies of this problem to hydro mechanics problems are shown. Fluid dynamics equations are used. The fluid starts at the starting point towards the goal point and obstacles obstruct the flow. From the resulting flow field the planned path can be computed.

In [8], an approach to behavioral control of robots is described that uses the model of dynamical systems. The path for navigation and obstacle avoidance is generated solving dynamical differential equations. The approach is rather time-consuming due to the necessary relaxations.

Quinlan and Khatib present an approach to obstacle avoidance that uses the model of an elastic band for a robot (see e.g. [9]). The elastic band framework is used for our application. An initial path has to be supplied. This path is modeled as an elastic band that is subjected to forces, exerted by obstacles which are represented as potential fields. This approach has also been extended to non-holonomic mobile robots [10].

Other approaches often include rule-based systems or systems executing behavioral patterns. These systems are not covered here due to space limitations.

C. Approaches for Intelligent Vehicles

A potential field application in driver assistance applications is described in [11]. On force-control basis, also vehicle dynamics can be taken into account and combinations of different drive-assist systems are feasible. Simulation results are presented.

A completely autonomous car with obstacle avoidance capability is presented in [12]. The application of potential fields to determine the risk yielded oscillatory behavior in overtaking situations. As a consequence, behavioral patterns were implemented for obstacle avoidance maneuvers.

A very interesting approach both for robotics and intelligent vehicles applications is presented in [13]. In contrast to the other approaches presented here, obstacle avoidance is performed in configuration and in velocity space. Constant velocity is assumed for all obstacles. However, this constraint is not always met.

III. Elastic Bands

A. Introduction to Elastic Bands

The original elastic band approach for collision avoidance was proposed by Quinlan and Khatib [9]. Similar physical properties are used for snakes in computer vision [14]. An initial, feasible path must be delivered by a path planner. This path is dynamically modified by treating the path as an elastic band that is able to change its shape. The starting and end points are kept fixed. The total energy of the elastic band is minimized yielding smooth paths. Forces acting on the elastic band are computed by taking the gradient of the potential energy at discrete path points. The repelling forces on the elastic band are produced by obstacles in the vicinity of the path. In total, three types of forces are acting on the elastic band. These forces are described in the following sections.

B. The Internal Contraction Force

The elastic band is modeled as a series of particles with a series of springs in between in the discrete case. See Figure 1 for a representation of an elastic band. Hooke's law would suggest a force proportional to the amplitude of the displacement. However, with defining zero as the unstrained state, the internal force would become larger as the length of the elastic band increases. This would yield an avoidance behavior which depends on the length of the elastic band which is undesirable. Hence we follow Quinlan's approach and let the internal potential be independent of the path length. This normalized force ensures the same avoidance behavior independent of the band length.

C. The External Force

The external force is due to obstacles that are modeled as potentials in the scene. Any potential shape that repels the elastic band from obstacles is conceivable. We decided to use Quinlan's position dependent potential [15] superimposed by Krogh's velocity-dependent potential [3]. The gradient of this potential, $\vec{f}_{ext}$, yields the external force. Details on the external force follow in Section IV-E.

D. The Constraint Force

The elastic band potentially reduces its internal energy by moving particles along the elastic band. This is an undesired property since the band might thin out at some parts. To constrain the motion along the elastic band, a constraint force $\vec{f}_{constr}$ is introduced along the direction of the elastic band.

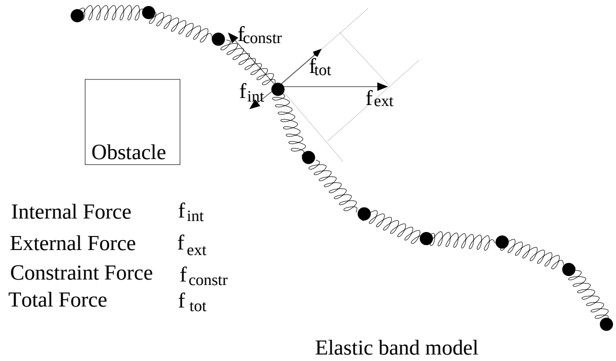

Fig. 1. Representation of an elastic band as a series of particles with springs in between.

E. The Elastic Band Algorithm

The elastic band is simulated with reduced dynamics since only the equilibrium state is of interest for obstacle avoidance. For every time step, the algorithm is repeated. The path is represented by particles $\vec{q}_i$ and these particles are subjected to the total force

$$\vec{f}_{tot} = \vec{f}_{int} + \vec{f}_{ext} + \vec{f}_{constr}. \tag{1}$$

With our pseudo-static simulation, the particles are moved along the total force to the new position

$$\vec{q}_{i,new} = \vec{q}_{i,old} + \alpha * \vec{f}_{tot}(\vec{q}_i). \tag{2}$$

Higher order terms beyond particle acceleration are neglected here. This procedure represents a very simple gradient descent method performing Euler integration of the underlying partial differential equations with a constant step size. Applying this procedure iteratively yields an approximately linear convergence and proved to be sufficiently fast for our real-time application. The new configurations are recomputed until the total force of all configuration points is sufficiently small, i.e. until the force equilibrium is reached.

In the original elastic band approach, the moving procedure is supplemented with a procedure of adding and removing particles in order to maintain a collision-free path at all times (see Section IV). So-called bubbles model the available free space around a configuration. Adding particles becomes necessary when two adjacent bubbles do not overlap anymore. Bubbles are circles with a radius of the minimum distance to the closest obstacle for our two-dimensional case.

IV. Adaptations for Vehicle Following

A. The Basic Idea

The elastic band approach is adapted to the vehicle-following scenario here. The path of the leader vehicle constitutes the initial path. Obstacles in the environment exert forces on the band and move it into a final configuration. This is the path the ego-vehicle tracks subsequently. There are configurations where the final path is still infeasible in contrast to the original elastic band approach. In order to find these configurations, a final clearance check along the envisioned ego-vehicle path is performed. If the clearance check fails, the autonomous driving mode is switched off and the driver has to take over the control of the vehicle manually.

Driving situations that necessitate this dynamic modification of the leader vehicle path are

- passing a cyclist or pedestrian along the road while following a leader vehicle, or
- driving too close to parking cars due to the smaller size of the leader vehicle, or
- driving around a car that comes to a stop slightly inside the road intersection, or
- driving around a pedestrian that moved one step into the road.

Many more scenarios can be identified. In addition, further extensions of the autonomous driving capability of such a vehicle definitely need this dynamic path planning component.

B. The Sensor System

Our range sensor delivers a list of objects in the scene. We use a calibrated stereo camera system to obtain 3D information of the car's surroundings. However, the elastic band algorithms in this paper are applicable to any sensor delivering range data with a "suitable" angular resolution.

The calibrated stereo camera system delivers 3D measurements of significant points resulting in a sparse 3D point cloud (less than 500 3D measurements). The significant points of the left image are matched in the right image by correspondence analysis along the epipolar line similar to [16].

To extract objects from 3D measurements, we apply a spatial clustering method to all 3D points except the ones on or below the ground. Here we assume a constant orientation between the camera system and the flat road.

We match objects from different frames by requiring them to be close together in space. This procedure works well for small scene changes between consecutive frames. We assume a flat environment and use only the x and z coordinates of the objects for collision avoidance.

One object corresponds to one clustered 3D point cloud projected to the x-z-plane represented by its convex hull for collision avoidance purposes. A convex hull of a set of points is defined as the smallest convex polygon containing the points. In our algorithm, the convex hull represents the outline of an obstacle, which is better suited than a rectangular description such as a bounding box.

The relative velocities of the objects w.r.t. the ego-vehicle are computed based on the center of the obstacles bounding boxes using an extended Kalman filter. One of the extracted objects is the leader vehicle supplying the initial path. The other detected objects constitute obstacles.

C. Efficient Distance Computation

The distance of the ego-vehicle path to the obstacles is the most important quantity for the determination of the external force. Since the distance is computed thousands of times in one cycle, it is of uttermost importance to compute it fast.

If the ego-vehicle path is not influenced by the potential generated by the bounding box of the obstacle, no refined distance computation is necessary and the distance between the bounding boxes is sufficient. The algorithm described below is only necessary for obstacles being close to the ego-vehicle. This coarse to fine strategy saves a significant amount of computation time.

In our approach the distance computation between a rectangle (our ego-vehicle) and a convex hull (obstacle) is reduced to a distance computation between two line segments. The ego-vehicle's orientation is parallel to the tangent on the elastic band. When the ego-vehicle and the obstacle do not intersect, the distance is computed from all points of the ego-vehicle to all obstacle points. The points with the minimum distance are taken and the distance of the two adjacent line segments on both sides is computed subsequently. Thus, a total of four line-segment-to-line-segment distance computations is necessary.

The distance between the obtained obstacle line segments and the ego-vehicle line segments is computed using Lumelsky's algorithm [17]. This algorithm is about five times faster than the straightforward approach.

D. Modifications to the Original Elastic Band Approach

The vehicle-following application of the elastic band framework differs from the original idea in the following ways:

- The initial path cannot be guaranteed to be collision free. Since the initial path is created by the path of the leader vehicle, changes in the scene might have occurred since the leader vehicle has passed. It is possible that another traffic participant has approached that path in the meantime. In addition, the leader vehicle might be smaller in width than the autonomous vehicle and might have chosen a path very close to an obstacle.
- The equilibrium position of the configuration particles is the leader vehicle path. We want the autonomous vehicle to follow exactly this path in the absence of obstacles. Hence the internal forces of the initial configuration receive an offset yielding zero in the absence of obstacles. In the original approach, the elastic band was assumed to have zero length and would always collapse to a straight line in the absence of obstacles.
- The concept of bubbles of free space disappears automatically by allowing initial trajectories that are not collision free. By giving up on the bubble concept we need an additional algorithm to reassure a collision-free path after the equilibrium position has been found. This is done by geometrically checking for overlaps along the final configuration of the elastic band. The procedure of adding and removing particles becomes superfluous as well.

• A regular car is an intrinsically non-holonomic vehicle. The original algorithm applies only to holonomic robots. This limitation has not been explicitly taken into account. Hence the paths created by the elastic band could be infeasible for non-holonomic cars. Since uncertainties in the 3D measurement of objects and uncertainties in the vehicle control require additional slack around the planned path, this is not considered a serious problem. In addition, the non-holonomic constraint also applies to the leader vehicle and is reflected in the leader vehicle path. Work on elastic bands for non-holonomic vehicles has been presented in [10].
• In regular traffic situations, lane markings are also used for vehicle guidance. The lane markings are detected and are also modeled as virtual obstacles with repelling forces pointing away from the lane boundaries towards the lane center. Lanes are modeled as polygons so the same distance computation algorithm as for obstacles is used.
• The external force of the elastic band must be shaped to comply with natural driving behavior. Drivers keep more distance from obstacles at high speed than at low speed (e.g. parking situations). Therefore, a velocity-dependent potential shape must be used. This is detailed in the following section.

E. The Potential Shape for the Obstacles

We have experimented with a lot of potential shapes and came to the conclusion that potentials with limited reach best model human driving behavior. Usually, events and objects further away than a certain distance from our planned path do not have an impact on our actually driven path.

The original approach for elastic bands is designed for mobile robots that rarely exceed 2 m/s. So a position-dependent potential is sufficient. We modified this approach in a way that the effective reach of Quinlan's potential, d_{eff}, becomes a function of velocity as well. In addition, we superimpose a velocity-dependent potential, introduced by Krogh [3]. Since we already know an initial path, only obstacles close to that path are considered.

When an obstacle is unavoidable for or inside a particle of the elastic band, a maximum force is exerted towards a direction, where obstacle clearance is obtained on the shortest way. Details on how to find this direction are presented in [18].

F. Control with the Elastic Band

The result of the elastic band algorithm is a path that has to be tracked. Considering the leader vehicle path as the initial path to be tracked, the elastic band framework delivers a modified path. Path tracking is performed by selecting a path point at a certain lookahead distance. This path point is approached taking vehicle kinematics into account (see [19] for a detailed description.).

Since the elastic band algorithm operates statically on the current scene snapshot and is re-run at every time step, no connection between the elastic band results from one frame to another exist. Sudden changes in the controller input might cause an oscillatory behavior. Hence, a low-pass filter is applied to the resulting desired steering angle delivered by the elastic band path.

V. Leader Vehicle Selection

In the standard vehicle-following approach, a planning and decision module selects the leader vehicle and sends the leader vehicle position to the controller. A leader vehicle is initially selected by projecting the planned corridor forward using the current steering angle and the first vehicle to intersect with this corridor is the leader vehicle.

The elastic band framework can be integrated easily using a path-based approach for vehicle following [19]. Only the leader vehicle path has to be exchanged with the elastic band path. The longitudinal control is implemented in such a way that we follow the leader vehicle at a safe distance. The elastic band algorithm only affects the lateral control.

The corridor to be searched for the leader vehicle becomes the corridor around the elastic band path. Hence, when small intersections with an obstacle occur, the elastic band algorithm bends the path in such a way that no intersection with the obstacle occurs. As a safety measure the bent of the elastic band path is monitored and when deviations beyond a certain threshold occur, the control is returned to the driver. Although the elastic band is still feasible in such a case, the behavior of the ego-vehicle would already be far from that of a typical vehicle-following system.

VI. Results

A. Simulation Results

The initial verification of the implemented algorithms was performed in an off-line environment, where only a snapshot of a scene was analyzed. Parameter tuning was performed in this environment.

In Figure 2 a situation is shown, where the leader vehicle is slightly driving out of lane and other cars drive to the left and right. Hence a slight path modification to the right occurs due to the obstacles and also slightly due to the lane markings with the elastic band algorithm. Obstacles are modeled as rectangles for simplicity. The equilibrium state is found within 18 iterations.

B. Real World Results

B.1 Real World Results without Lateral Control

We integrated our elastic band framework in the basic vehicle-following system. Computing the modified path runs in real-time without much optimization. With our current parameterization, the elastic band finds its equilibrium state within 20 iterations for most situations.

Figure 3 shows a typical traffic scene with counter traffic on the left and a parked obstacle (a dredger) on the right.

The leading vehicle drove very close to the dredger (see initial path in Figure 4) and has a smaller car than our research vehicle. Hence following the initial path brings

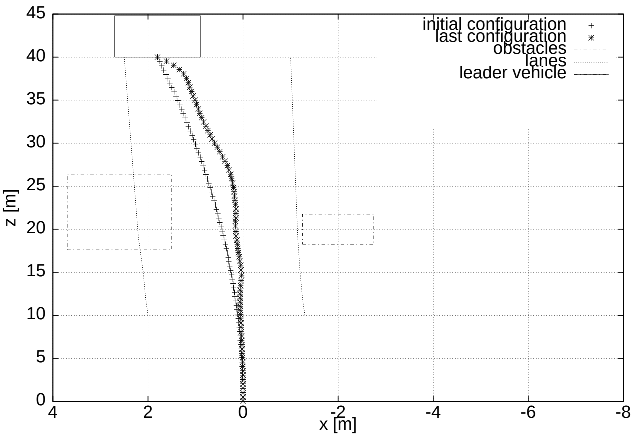

Fig. 2. Simulation result of the elastic band algorithm (bird view) utilizing both lanes and obstacles.

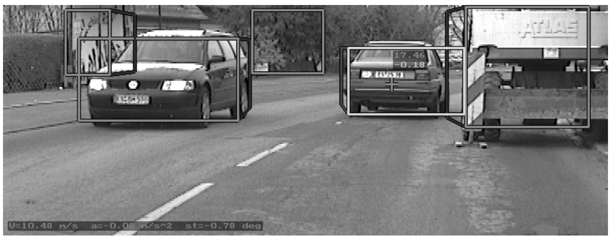

Fig. 3. Traffic scene with a dredger at the right side of the street and with counter traffic.

us dangerously close to the dredger. The elastic band approach yields the dashed path in Figure 4 which avoids the dredger and keeps a safety distance from the car on the left at the same time. Lane markings were not used here.

B.2 Real World Results with Simulated Obstacles

Collision avoidance maneuvers are dangerous to conduct in the real-world. It is not safe to interfere with a car's path when it moves. Maneuvers with especially little clearance to obstacles are critical. So we decided to perform some of these maneuvers in simulation first.

Experiments have been conducted using the elastic band path as input to the lateral control. Results using simulated obstacles in the research vehicle are described in the following.

Above simulation results encouraged us to perform test in our demonstrator, a Mercedes Benz E-class 420. It is equipped with electronic gas, brake, and steering wheel enabling autonomous motion. On-board sensors deliver vehicle velocity and steering angle that are used to integrate the ego-motion for ego-position estimation. This is necessary to determine the leader vehicle path [19].

We simulated obstacles in the research vehicle to test the algorithm safely. The experiments can be reproduced exactly this way. Figure 5 shows a scene, where the leader vehicle drives straight. Another vehicle in the right lane recognizes an obstacle ahead and starts to change its lane. When recognizing the autonomous vehicle it brakes but overlaps slightly with the other lane. The ego-vehicle

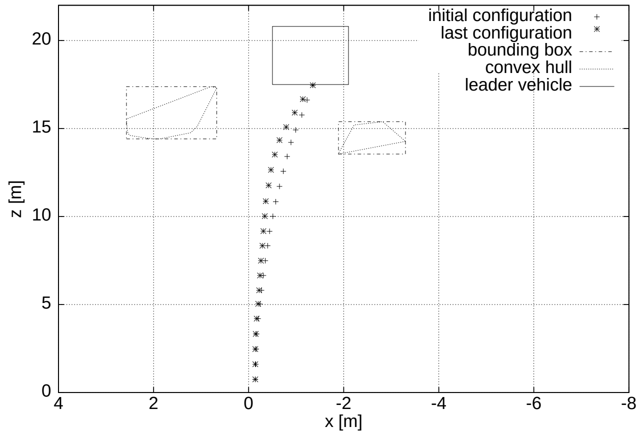

Fig. 4. Bird view for the dredger scene. The leader vehicle is located at the end ($z = 17.5m$) of the path and smaller than the ego-vehicle.

avoids this obstacle by performing a swerve maneuver. The desired path as output from the elastic band algorithm is depicted in a dashed line. Note that the ego-vehicle does not follow exactly the elastic band path due to non-holonomic constraints and due to the simple controller design.

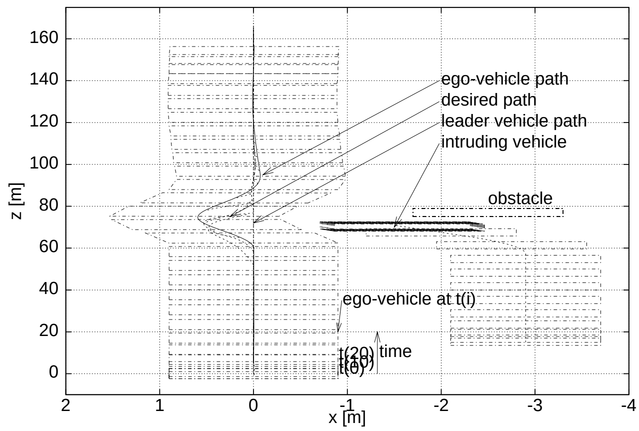

Fig. 5. Bird view for a situation where a car slightly enters the driving corridor which necessitates a swerve maneuver. The ego-vehicle and the leader vehicle drive at $8m/s$ and they are about $18m$ apart.

B.3 Real World Results Using Stereo Vision

After extensive tests with simulated obstacles, we performed avoidance maneuvers with real image processing data in the research vehicle. In our chosen scenario, a human as a thin leader vehicle runs on a straight path at about $5m/s$. A cardboard box is located next to that path. The ego-vehicle has to avoid the box while following the human. Figure 7 shows the deviation between leader vehicle and ego-vehicle path. The deviation increases at the cardboard box location due to the avoidance maneuver. Figure 6 shows a snapshot of the scene. The depicted corridor is the corridor modified by the elastic band algorithm. In a simple vehicle-following scenario, the car would have touched the cardboard box.

Fig. 6. Avoidance scene with a human as a leader vehicle passing close to a cardboard box on the left. Due to the larger width, the ego-vehicle performs a swerve maneuver to avoid the box. The elastic band path is depicted projected to the ground. The leader vehicle and the ego-vehicle are about $12m$ apart.

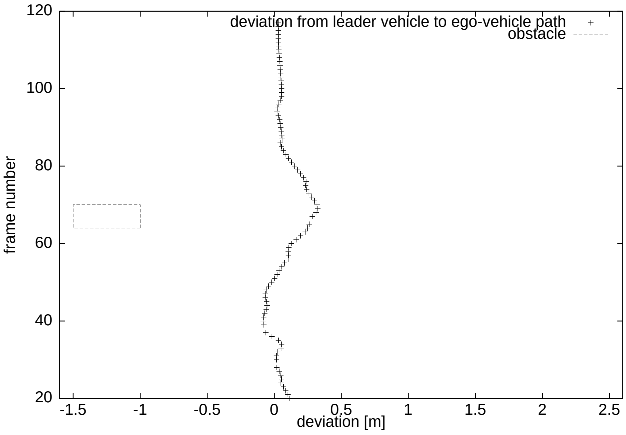

Fig. 7. Deviation plot for the scene in Figure 6. The frame number roughly corresponds to the z position in the global reference frame (constant velocity assumed). Compared to the image data, the cardboard box location is depicted in the graph. Assuming the leader vehicle path runs along the z axis at $x = 0$, the deviation curve also shows the path of the ego-vehicle.

We performed further tests in real traffic using the elastic band framework. The desired avoidance maneuvers were properly performed in all encountered dynamic situations.

VII. Conclusions and Future Work

In this paper a dynamic collision avoidance component for the standard vehicle-following approach has been introduced. The elastic band framework is used to modify the initial path of the leader vehicle.

Modeling human driving behavior requires a lot of context knowledge that has to be represented as a rule base in some way. However, we consciously skipped that step and tried to model human driving behavior with a physical model in order to keep things intuitive and to analyze global properties of the planned path.

The results show, that for standard vehicle-following situations, no modification is necessary. In dynamic situations, the intuitive obstacle avoidance behavior is achieved. Computation time measurements show that real-time performance is achieved without much optimization effort.

By considering the leader vehicle, all obstacles in the scene, and lane markings, an intelligent fusion of lane-following and vehicle-following behavior has been achieved.

An interesting future area of research is the choice of the lateral controller to follow the elastic band path. In the intelligent vehicle community, lateral vehicle guidance is often achieved performing lane following. A lot of robust lateral controllers have been presented for that task (e.g. [20]). These controllers could be used to track the elastic band path by treating that path as a lane center.

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