Model-Based Trajectory Prediction for Autonomous Driving

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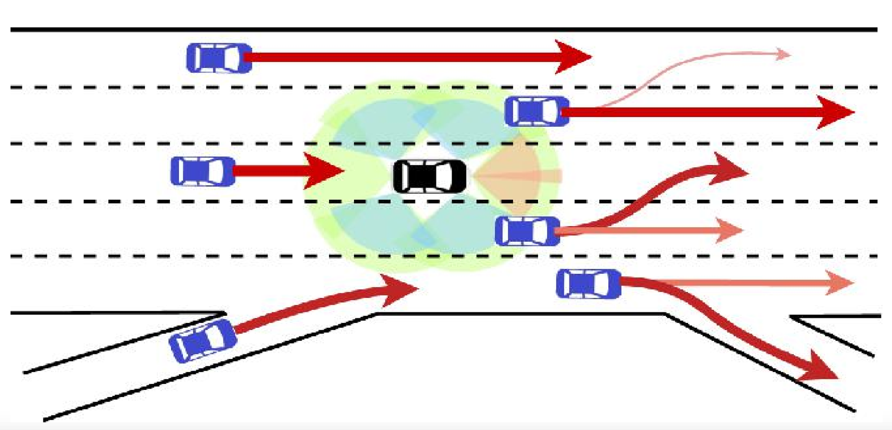
Introduction and Motivation

Environmental sensing and interpretation is essential for autonomous driving, the major tasks involved include target detection, classification, object tracking, and trajectory prediction. The goal of this research is to develop algorithms for trajectory prediction in highway scenes. In order for the autonomous vehicle to plan safe trajectories as it navigates, predicting trajectories of nearby objects is necessary for enhanced motion planning, decision making, and risk assessment.

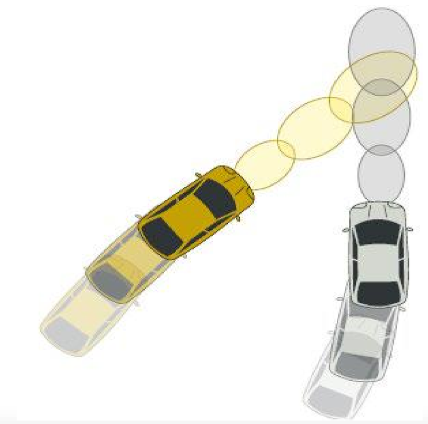
In order for trajectory prediction to occur, target detection and tracking must happen first, where sensors such radars, cameras, and LIDARs are used to detect targets to obtain noisy measurements such as the target's position. These measurements are then fed into a multi-target tracker to estimate the state of a target, the state includes the position, velocity, acceleration, etc. Afterwards, given the state estimate and estimated trajectories of each target (also known as tracks) from the tracker, the goal is to predict each target's future trajectory.



Model-Based Prediction

In model-based strategies, state estimation algorithms such as the well-known Kalman Filter (KF), Extended Kalman Filter (EKF), and Unscented Kalman Filter (UKF) are widely used. These filters require the mathematical model of the vehicle maneuver to be specified, examples include constant velocity, constant acceleration, constant turn, etc. As shown in the figure below, the ellipses represent the covariance in the predicted positions, which is what these filters provide. However, a limitation associated with using these methods is that one model is not sufficient to represent all maneuvers.

Therefore, a state estimation algorithm known as the Interacting Multiple Model (IMM) estimator is utilized in this research since this strategy can take multiple motion models to represent different maneuvers. The IMM is widely used for tracking maneuvering targets. In this work, the IMM is also used to identify the different maneuvers of a vehicle such as lane-keeping and lane-changing, which is useful information for trajectory prediction.

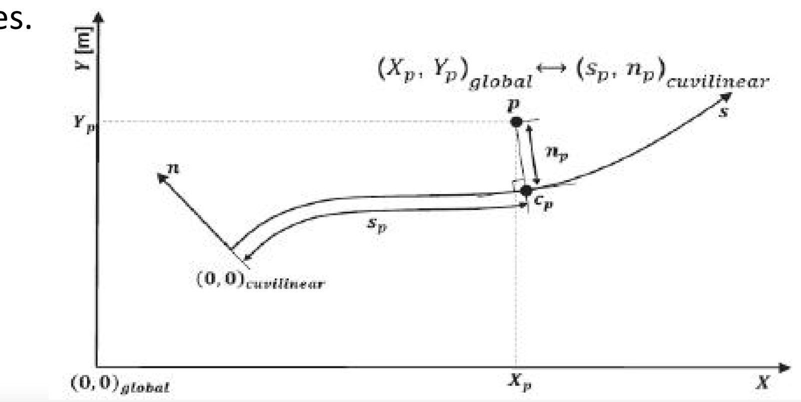


Using Road Geometry in Prediction

Target-tracking is typically performed in Cartesian coordinates, a disadvantage with this is that the Cartesian plane gives no restrictions on the direction of vehicle motion. In other words the car can move in any direction, which is not the case in highway driving conditions. Therefore, a coordinate system known as the Curvilinear Coordinate System (CCS) is utilized.

The CCS constrains the vehicle's motion to be within the roadway boundaries. One axis of the CCS gives the distance traveled by the car, denoted as s_p in the figure below and the other axis gives the minimum lateral distance to the roadway curve, which is n_p . The s-axis in this figure is a roadway curve, which can be obtained from lane-markings detected by cameras or from a roadway map database.

In this work, target-tracking and trajectory prediction is performed in the CCS to make it easier to identify lane-changing and lane-keeping maneuvers and to ensure predicted trajectories lie within the road boundaries.



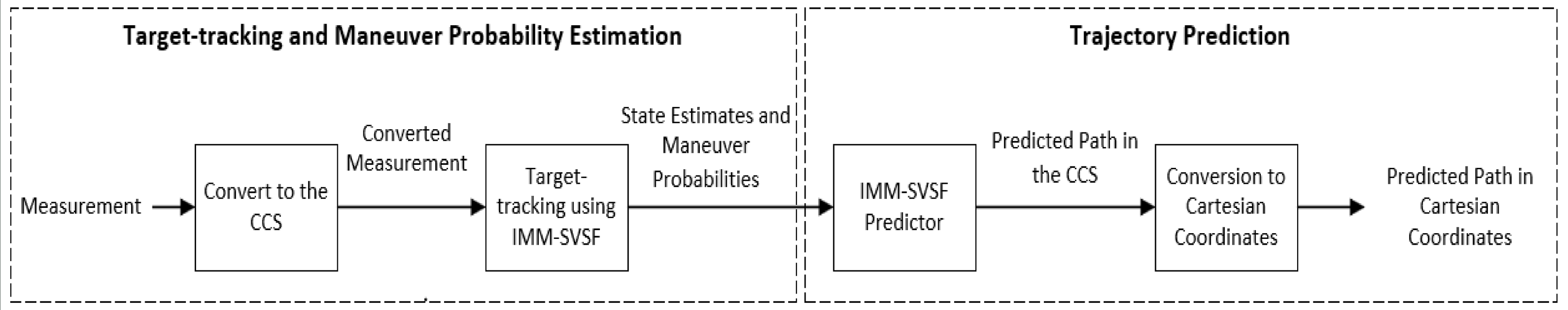
Proposed Approach

A more recently developed state estimation strategy known as the Smooth Variable Structure Filter (SVSF) has been used in the proposed approach. It is combined with the IMM estimation technique, hence, forming the IMM-SVSF. The proposed strategy consists of two stages:

1. Target-tracking to estimate the current state of the vehicle and to obtain probabilities of different maneuvers
2. Trajectory Prediction

Multiple motion models are used by the IMM to represent maneuvers such as lane-changing, lane-keeping, and velocity-tracking (driving to a specific velocity).

In this study, the measurement of the vehicle position is given in Cartesian coordinates, this is then converted to the position in the CCS, which is used by the IMM-SVSF tracker to estimate the vehicle's state and compute probabilities of each maneuver. The maneuver probabilities, state estimates, and motion models are utilized to obtain the predicted trajectory in the CCS.



Experimental Results

A public dataset known as the HighD dataset was used to assess the performance, this dataset was obtained from using Unmanned Aerial Vehicles (UAVs) to obtain video recordings of vehicles on highways. This dataset provides the position of the vehicles, which is what the IMM algorithms use as a measurement for target-tracking and prediction.

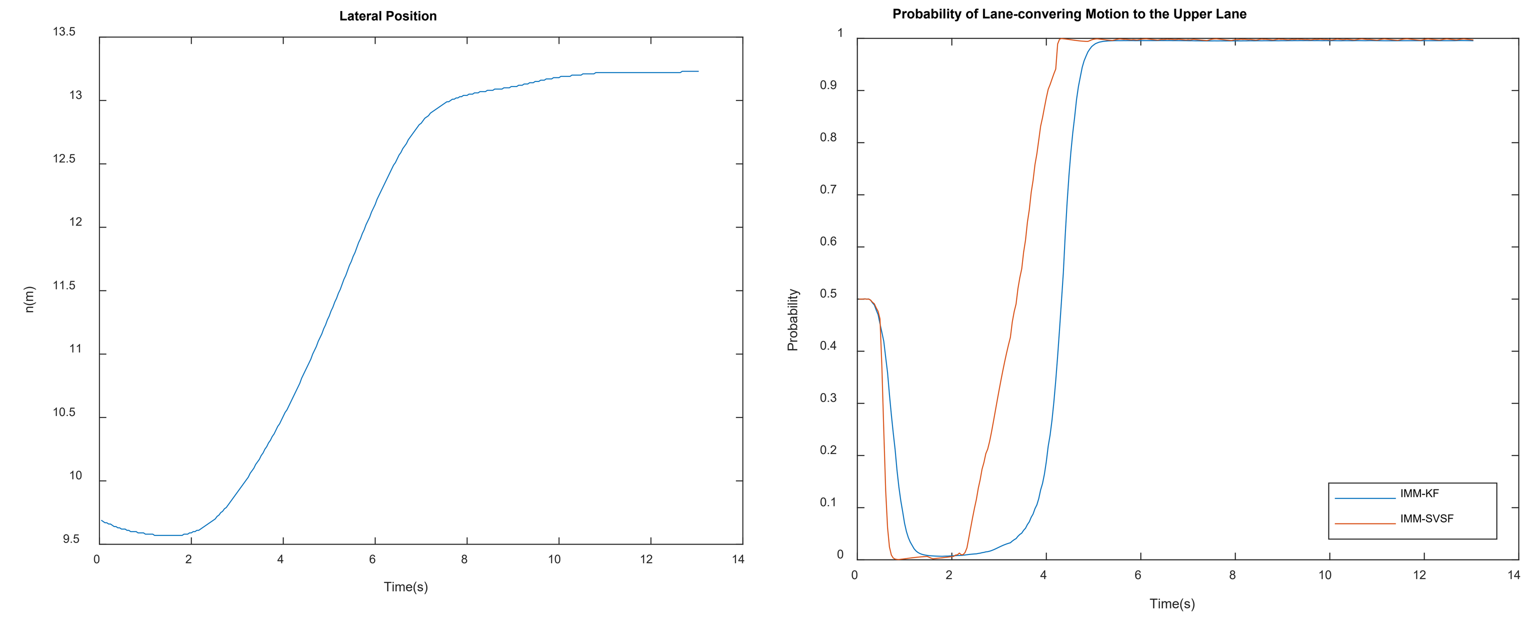
- Once a vehicle is seen in the video for 0.5s, its trajectory is predicted with a horizon of 7s.
- The relative prediction error refers to the square root of the squared error divided by the distance travelled by the car in the 7s prediction horizon, which is multiplied by 100.

	Position Prediction RMSE (m)		Relative Position Prediction Error (%)		Velocity Prediction RMSE (m/s)	
Prediction Horizon Time (s)	IMM-KF	IMM-SVSF	IMM-KF	IMM-SVSF	IMM-KF	IMM-SVSF
1	0.4182	0.3188	0.13	0.12	0.5401	0.4520
2	1.0416	0.8671	0.33	0.31	0.7419	0.6788
3	1.8385	1.6193	0.57	0.54	0.9497	0.9079
4	2.8166	2.5753	0.86	0.82	1.1483	1.1190
5	3.9674	3.7155	1.20	1.16	1.3239	1.3024
6	5.2695	5.0125	1.6	1.54	1.4781	1.4623
7	6.7037	6.4468	2.03	1.97	1.6203	1.6091

Maneuver Recognition

The performance of both strategies are also analyzed in terms of maneuver identification. The lateral position of one vehicle from the HighD dataset that performs a lane-change is shown below. The maneuver probability is used to identify the maneuver through quantifying the chance of it.

As illustrated by the maneuver probability plot below, the IMM-SVSF identifies the lane-converging maneuver to the upper lane earlier than the IMM-KF by approximately 0.7s. This is attributed to the SVSF's greater robustness against modelling errors and stability, allowing state estimation error to converge faster, which results in earlier maneuver recognition.



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