Automatic driving lane change safety prediction model based

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Autonomous driving (AD) technology promises to enhance traffic safety and driving efficiency. The key to this improvement is the accurate trajectory prediction of surrounding vehicles. This paper presents an artificial intelligence model using LSTM networks that surpass traditional methods in long-term trajectory prediction ensuring both smooth and safe lane changes. The research highlights the various challenges that AD currently faces in adapting to dynamic traffic environments specially with executing lane changes. AD technology is divided into several modules which can be represented as: perception, decision-making, planning and control. The key challenges are managing dynamic traffic environments and ensuring safe maneuvers during lane changes.

The model of human lane change execution is data-driven and requires extensive training data. While others studies and researchers have applied the K-nearest neighbor algorithm or two-layer Backpropagation (BP) for predicting lane change trajectories. These techniques have limitations like restricted data usage and the oversight of temporal dynamics. To tackle these limitations, the model uses LSTM neural networks which have demonstrated higher accuracy in this field. However, rule-based lane change models lack robust mathematical descriptions and lead to a multitude of trajectory curve equations that have no consensus on the best equation and significant errors that can occur in kinematic models. The LSTM (Long Short-Term Memory) model is used to address the dynamic changes in the time scale of vehicle driving behavior, which contains time-continuous information. The model proposed good simulation results for lane change intention recognition. Their LSTM neural network train a safe lane change prediction model for autonomous vehicles that enable long-term storage of safe lane change memory. The LSTM network is trained and tested using a high dimensional dataset. Also, it contains information extracted via Vehicle-to-Vehicle (V2V) technology to predict the motion trajectories of surrounding vehicles.

The core architecture of the LSTM network is composed of several cell structures, each with three control gates: input gate, forget gate and output gate. The input gate determines what information is updated to the cell state using activation functions like sigmoid or tanh. The forget gate controls whether to retain or delete the hidden cell state from the previous layer. At the end, the output gate decides what information from the cell state should be outputted also by using the activation functions mentioned previously.

For lane change planning, they use a cubic polynomial curve which is adopted to avoid overly complex parameter solving while ensuring continuous acceleration during vehicle driving. For collision avoidance, they use the "Gipps" model a classic vehicle safety distance model which is improved by incorporating vehicle body length as a constraint condition for the cubic trajectory curve. This ensures the safety of the lane change process by detecting and predicting the driving state of surrounding vehicles.

The experiments involved building two driver scenarios based on high-dimensional datasets to verify and evaluate the proposed LSTM-MPC algorithm. The algorithm was compared with the MPC algorithm which use a constant velocity prediction and NIO network prediction which focus more on driving safety and efficiency metrics such as RAI (Risk Assessment Index) and collision avoidance speed. The LSTM-MPC algorithm shows better performance in both scenarios with lower risk.

In conclusion, this article proposes a safe and efficiency way for predicting lane changes. It addresses the flaws of old and current models by integrating methods with real-time data analysis and risk assessment leading to improvements in both driving safety and system efficiency. This work offers a safer methods for autonomous vehicles in the future.