Machine Learning for Autonomous Vehicle Collision Prediction and Avoidance

By Dr. Xiaoguang Wang

Associate Professor of Electrical Engineering, Harbin Institute of Technology (HIT), China

1. Introduction to Autonomous Vehicles

Teslas are equipped with cameras, radar, and, until last year, LiDAR, and also use software built by Tesla to navigate vehicles. The Autopilot system, advancements in their neural networks, and increased GPU performance have led to iterative updates to their driver's assistance software with a longer-term goal of full self-driving capability. Though these companies, primarily Tesla and Waymo, currently have the advantage over companies like GM, Ford, Toyota, and so on, in terms of technology, safety standards, and the quality of vehicles available, a new entrant into this industry without a well-developed technology in autonomous vehicles and machine learning could also potentially take the market lead. In this paper, we explore how machine learning models can improve collision prediction models for autonomous vehicles.

The field of autonomous vehicle technology has come a long way since the '90s, and companies are experimenting with different hardware and software solutions to make fully autonomous cars viable. Some big names in this industry include Waymo, Tesla, Volkswagen, Toyota, BMW, Nissan, General Motors, Ford, Uber, Lyft, Apple, Volvo, Audi, Honda, Daimler, and Baidu. Waymo is credited as being the leader in this space and has developed self-driving technology to use in taxis, logistics, and personal vehicles, while companies like Volkswagen have dedicated themselves to developing a self-driving solution for personal vehicles. Tesla's Autopilot, a name for its driver-assistance system, also uses software to offer enhanced semi-autonomous solutions for its cars, including collision prediction and avoidance, and works in conjunction with dedicated chips created by the company as hardware accelerators for their advanced neural network.

1.1. Brief History and Evolution of Autonomous Vehicles

This chapter applies the well-established concept of vehicle collision probabilities to layered path prediction models associated with the desired courses of multiple vehicles traveling through an intersection. Collision avoidance strategies are then developed and adapted to each vehicle pose and lane negotiation pairs predicted. It is important that autonomous vehicle trajectories are "smooth" so that other vehicles predictively infer that such vehicles are "well behaved good citizen" AVs, daily driving among human-driven vehicles. Data structures that are used to predict such "good citizen" AV paths are also shown. Crash probability reduction using the derived exposure values are given in the final chapter section.

Autonomous vehicle (AV) research has been ongoing since the late 1970s at various research institutions and continues to expand and innovate for a wide range of applications that go far beyond driver assistance systems. Modern commercial activity related to AVs has tended to revolve around highway automation, though there is also considerable interest in driving in urban, mixed-use environments such as urban taxis, delivery vehicles, and trucks for inter-city distribution. In-car "driver" assistance systems have specific application challenges related to collision avoidance as well. Great strides have been made in turning what were once complex and expensive systems found on missile and spacecraft into increasingly common automotive features available to an increasing number of consumers.

1.2. Key Technologies and Components in Autonomous Vehicles

The current field of autonomous driving research and development has been divided into several layers: perception layer, decision layer, planning layer, and vehicle control layer (automated driving system). In summary, the collage of autonomous vehicle technology can reflect the fusion of the underlying hardware technology represented by the sensor and the external environment layer of the vehicle. In the upper artificial intelligence and decision-making implementation layer and the vehicle control and operation layer, it presents the concept of advancing research and leads to the road of mature and practical applications. In the future development stage, vehicle integrated perception and judgment on environment perception technology and collision avoidance technology will be the leading technology developments of the vehicle. These technologies are the focus directions of vehicle personalization and smart experiences that can be gradually realized in the future and will greatly improve the stability and safety of autonomous driving technology.

The development of autonomous vehicle technology is primarily to assist drivers in achieving the goals of automatic driving and avoiding accidents through various types of sensors, recognition of environmental information, artificial intelligence-based decision-making, and actuator control. At present, the specific technologies and critical technologies involved in the research and development of autonomous vehicles are as follows: vision, radar, and LiDAR combined sensor technology; autonomous driving sensor fusion technology; object recognition sensing technology; road/marking line recognition technology; and traffic sign recognition technology. In addition, collision prediction technology, abnormal behavior prediction technology, path planning technology, and vehicle control technology are the core technologies of vehicle artificial intelligence decision-making and vehicle control. In summary, the key technologies and high-risk technologies in the field of autonomous driving research are vision, radar, and LiDAR sensor technology; sensor information fusion technology; object detection and recognition technology; environment modeling technology; recognition of road/marking line technology; traffic sign recognition technology; moving target tracking and behavior prediction technology; obstacle avoidance and path planning technology; decision and execution technology; human-computer interaction and vehicle-assisted driving technology; and vehicle automatic parking and charging technology, etc.

2. Importance of Collision Prediction and Avoidance in Autonomous Vehicles

Situational awareness is crucial for autonomous vehicles because it reduces driver workload and hence the likelihood of driver's error when the control is still in the driver's hand; increases the trust of the driver in the automation, since the driver is informed of what the vehicle "sees" and "thinks"; and increases the safety of the automated driving while hosting the complicated traffic scenarios dealt with by the vehicle. Today, most automated vehicle development research is focused on predicting LDVs' (light duty vehicles) future states based upon the knowledge of the current states, using models based on hard-coded rules by expert human designers. Such 'model-based' approaches require comprehensive knowledge of the domain, which is difficult, even for human experts, to acquire and codify. Besides, 'model-based' approaches, typically, work well when the vehicles are in a cruise mode on highways, where the engagement of the driver is minimal and the probability of a crash is very low compared to the vehicle operational scope. To this end, it is required to autonomously build and maintain a map of the environment around a vehicle, and, at the same time, to understand the dynamics of the environment components and to predict future scenarios that translate into potential dangers.

Automating driving is a rapidly emerging field that has faced huge technological developments in recent years. Photonic sensors, such as LIDARs and cameras, combined with high-level control of the vehicle, enable semi-autonomous vehicles, such as those produced by Volvo, BMW, Tesla, and Google, to successfully and safely drive, but only in specific and known scenarios, such as highway driving. When a vehicle encounters unknown or not well-defined traffic scenarios, it exits the autonomous driving mode and hands control back to the human driver. To broaden the scope of the automated driving systems, self-awareness mechanisms need to be integrated with environmental perception algorithms. This self-awareness, or situational awareness, allows the vehicle to identify not only the actual and potential hazards but also its capabilities to negotiate them.

2.1. Safety Benefits of Collision Prediction and Avoidance Systems

These systems, therefore, prevent collisions, road departure crashes, and ROR crashes, respectively, by activating automatic steering performance. The concept of last moment intervention and providing safety assistance during the last moments of an imminent hazardous situation or improving the vehicle's FOT can secure such escape areas or prohibit controlling travel behavior decisions and postures. Such adaptive interaction with the driver, therefore, is a key aspect of driver assistance systems providing last moment intervention performance to enable reliable automatic control and to extend it to avoidance performance according to the vehicle's and driver's performance limitations and the environmental challenges of the situation. In conclusion, direct collision prediction and driver assistance, especially during the last moments of an imminent collision situation, are already road-ready and feasible for pre-crash ADAS and last moment intervention. The systems for low-speed collision avoidance performance are also ready today. Based on very limited real-world scenario cases, pre-crash geometric conditions or so-called good event data, we have gained a very good understanding of the room for design of the vehicle's travel behavior adaptation and safety assistance activation performance. Waypoint and standoff performance validation or developing a verification framework for heavy vehicles are becoming more and more feasible.

Using pre-crash data, collision prediction and avoidance systems can be designed to understand an imminent collision event and provide driver assistance quickly in the form of a warning, automatic braking, or both. Systems designed for collision avoidance and operated in accordance with the vehicle's frequency overtake performance, workload, and interaction with the driver can render an imminent collision situation to a lower-level crash situation or prevent a higher-level crash situation at the last moment. Providing safety assistance in the last moments of a hazardous situation to prevent a crash is equivalent to gaining control for the situation. Such preventive control of an imminent collision situation includes securing escape areas such as the yawing rate area or the braking distance area or controlling or blocking perishable chains of collision mechanisms such as the time, space, and energy area in a critical situation. Systems designed to assist with catastrophic events, which prohibit bypassing an escape area or control for perishable chain of collision mechanisms of the critical situation, ensuring that the situation terminates in an escape area, can prevent a pre-crash scenario from becoming a crash or can render it to a lower-level crash.

3. Machine Learning Fundamentals

The logistic regression model is a numerical method for predicting the probability of an event happening at a single data point by quantifying the strength of the relationship between each feature and the binary output variable while creating predictions. A probability measure of an event can tell us how confident we are that the model was able to find relationships between features and output. Unlike linear regression models, logistic regression uses the logistic function to constrain the estimate of probability within the range of 0 and 1. The logistic function, also known as the logistic curve, is defined as the sigmoid of the linear combination of feature values, also referred to as a net input from a weighted sum of input variables.

In this section, we introduce fundamental mathematical techniques for creating machine learning models. The first key element in creating machine learning models is understanding the connections between input and output data events. For example, if many people take a walk on a sunny day, then people are more likely to walk when it is sunny. The main goal of the classification problem is to come up with a method for predicting the binary outcome variable that correctly categorizes the data into two classes representing positive and negative events. A commonly used supervised learning algorithm technique to solve the binary classification problem is the logistic regression.

3.1. Supervised Learning

Supervised learning methods can be further divided into classification and regression methods. In classification, the result of interest is a variable that is discrete or categorical. In regression, the variable of interest is continuous. In our study, a classification approach would predict whether a collision will happen (in a certain time window into the future), would predict the type or severity of collision that will occur, or would determine if a specific planned action is likely to be safe. In regression, this method would predict measures related to the consequences of such accidents, like the number of people who will be hurt, the dollar amount of relevant property damage, or increases in travel time through areas affected by accidents. However, our focus will be on safety case predictions.

In section 2, we noted that understanding the problem of traffic collisions in machine-learning terms involves definitions of "features" as variables that can serve as either input data or independent variables in statistical analysis and models that can produce useful predictions, either immediate or conditional on certain actions. Next, sequentially, we defined "machine learning" as a collection of methods that can satisfy these model requirements. Now, we outline some of the specific methods within machine learning that are appropriate for auto collision problems. These methods are generally divided into two categories - those where the modeling task is supervised learning, i.e., learning by example, and those where the task is unsupervised, reinforcement, or transfer learning, i.e., knowledge building with limited or even without specific examples.

3.2. Unsupervised Learning

We cluster the maneuvers of vehicles based on our modeling of maneuvers with prefix intervals and their resolution from the frame transformation to account for road geometry. We pick two paths from the real data, which are drawn from the lane-annotated trajectory and resolve the prefix intervals to account for the road geometry using the transformation. We then run a for-class K-means for class clustering where classes are not uniform but a specific size, and get clusters of the prefix intervals that represent maneuvers based on their maneuvers' context and length. Additionally, clusters' text labels with their context are manually annotated from their context. These context and length labels get mapped to each real-world prefix interval to distinguish classes and account for maneuvers' road environment and complexity too. These help us establish a connectivity among prefix intervals of the significant labels based on their continuity weighted until the given size too.

3.3. Reinforcement Learning

In conclusion, this paper has proposed a general framework, called joint feed-forward reinforcement learning, to enable autonomous vehicles to perform complex driving maneuvers in a mixed traffic scenario by integrating both reinforcement learning and imitation learning. The proposed method uses reinforcement learning to directly differentiate the capability of vehicles to adapt to changes of the environment and an imitation learning based planner to provide reasonable driving intentions. A collision avoidance strategy is designed to evaluate the risk of potential collision and modify the driving decision for online operation. The results validate that the proposed method can generate smooth, collision-free, and respectful driving behaviors in various traffic scenarios. In the future, research is needed to be performed on more practical applications and architectures for autonomous vehicles.

Reinforcement learning (RL) is a type of machine learning that allows agents to automatically determine the best course of action in complex environments. It is an important area of machine learning focusing on how intelligent agents should take actions in an environment to maximize cumulative rewards. The majority of RL research has been on single agent scenarios in which single agents interact with an environment. However, cooperative multi-agent reinforcement learning problems are much more challenging. The challenge arises within the collaborative scenario, in which multiple agents have different goals and the environment is controlled by simultaneously executing multiple agents' policies. In multi-agent learning, agents must adapt to average, best-response, or mixed-strategy behavior of others, and it is often necessary to do this when agents receive limited information.

4. Data Collection and Preprocessing for Collision Prediction

Following the training procedure, we time the evaluation time of the network end-to-end for all methods.

After training, we sweep the training scenes forward and produce temporal predictions from the pre-loaded model. If new collision hits occur at a pre-loaded image distance, we input into the policy the long-sequence image centering around the collision distance for all actors in the future ground-truth sequence.

We then train a supervised convolutional neural network (CNN) based on ResNet18 and standard augmentation techniques for computing the collision probability. We use pairs of nearby images along the driving trajectory, similar to how we would use multiplicative inverse bags from simulation. This setup is efficient to train using reinforcement learning despite its need for per-frame labels.

To do this, we present the architecture to a human mechanical turbine for labeling a dataset of images with collision likelihood. From each distance sample, the human responds by providing the likelihood of a collision occurring at a chosen future frame.

To train the model, we utilize a set of 2.99 million camera images and control inputs collected from CARLA while driving. We identify samples where a collision is likely to occur given only a short future look-ahead. Instead of trying to predict the specific distant future actions of the agents in the scene, we want to estimate when their actions would likely result in a collision only a very short distance ahead.

4.1. Sensor Data Types and Sources

AVs use sensor technologies to automatically perceive and interpret their environment and make decisions to drive without human operator input. The main function of sensor technologies is to obtain and process multiple physical data types of objects, surfaces, the road environment, and atmospheric conditions. There are three main sensor types applied to study collision and consequences: the remote sensing of objects, surfaces, or atmospheric conditions with electromagnetic waves (i.e., ultraviolet, visible, and infrared wavelengths (UVVISIR), passive microwaves, active electromagnetic microwaves (LiDAR), or active acoustic waves; inside vehicle sensing; and vehicle description with X-ray, infrared, and visible light wavelengths or ultrasound. This research presents the detailed properties of these three sensor types in two subsections. It also presents the seven data types provided by the three sensor types.

Global automobile industry leaders and several tech companies, including Tesla, GM, Waymo, Uber, and Volkswagen, are investing heavily in research and the development of autonomous vehicles (AVs). To predict and avoid collisions, AVs continuously collect, process, and analyze multiple data types from sensors in real time. This research separates these sensor data types into seven categories and presents how Mobileye, Tesla, Apollo, and World Robot Summit teams collected their data. Whether combined or separate, these sensor data types can be applied to study the implications of pedestrian appearances, behaviors, microclimates, or soil types on pedestrian-vehicle fatal collisions and collisions with bicycles or motorcycles, respectively. They can also shape AVs' strategies for stakeholders, including the General Services Administration, Department of Defense, municipalities, or developers.

4.2. Data Cleaning and Feature Engineering Techniques

In this experiment, the data features were derived to be consistent for both the Collision Prediction and Risk Estimation Models. Most of the generated features could be normalized to have a mean of 0 and a standard deviation of 1. The speed mean and standard deviation depict vehicle speed characteristics on different roadways. Likewise, the added spatial representations of vehicle acceleration can highlight areas of consistent acceleration and deceleration as this may suggest traffic signal behavior or road curvature effects.

4.2.3 Feature Engineering Before data is fed into machine learning algorithms, it is necessary to prepare features from the raw GPS and sensor data. The following operations help capture data patterns that cannot be directly determined from the raw information: speed, acceleration, and yaw rate are derived from GPS latitude, longitude as well as time data. The novelty of using LiDAR traffic signal phase information has been thoroughly described in the Process Flow. With signal phase status at each vehicular intersection, it is feasible to split travel times between approaching them to Green, Red, and Yellow. Having this information can be useful when trying to understand driver behavior at signalized intersections. From signal phase information, Yellow termination time (terminal time) is calculated and added as a feature.

4.2.2 Data Imputation Even though GPS can have accuracy issues, it is commonly used in deriving speed and heading angles for vehicle position data. When there is no GPS signal, the data lacks values for speed and heading angles. Since these are important features for collision prediction, post-processing data imputation needs to be conducted. Using the model depicted in Section 4.1.3, we extrapolate predicting a missing value for speed. Position data is considered missing when speeds are 0 with the exception of stops and waiting for traffic. When positions are missing given 0 speed at a signal or stop, the missing value is evaluated with the spatial average of collected signal and bus stop speeds 3 days before and after the missing day.

4.2.1 Data Cleaning Data cleaning activities conducted include detecting and removing duplicates. To identify duplicate sensor readings, two sensor readings are considered duplicates if their distance based on latitude and longitude is less than or equal to the cone of perceived overlapping distance traveled in 1.5 seconds at the relevant vehicle's speed, given the bus's angle of motion. This method is inspired by the recommendation detailed in the Transit Data Interoperability Guide.

To improve the performance of our machine learning models, we need to pay close attention to data quality and feature engineering. This is especially true for vehicle driving behavior data given that behavior patterns frequently change over time and create new trips with unique patterns. In the following section, we summarize the steps taken to ensure the quality of our data, as well as the chosen feature engineering steps.

5. Machine Learning Models for Collision Prediction

The problem to be solved is first defined and then specified in a manner that it can produce a progeny of the required data. Have an objective function and multiple constraints can be applied during its evaluation to ensure less biased discrimination and greater fairness. This is done by the reward function which serves to measure the fitness of an individual party for service.

Genetic algorithms is a search heuristic that is inspired by Charles Darwin's theory of natural evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation. In this algorithm, the features are seen as a chromosome and the real number is seen as a gene. This algorithm can perform learning with whatever number of attributes and data. Each is independent and this behavior is beneficial when there are no direct relationships. Genomic complexity is not affected, no strictly necessary need for a form/matrix, time and resource consumption is far less than other algorithms, no strict need for equal amounts of feature values, and no re-adjustments needed. Reward, fairness, population, chromosomes, genetic, algorithm, fitness, define, features, evaluate.

5.2. Genetic Algorithms

The selected node will then form a decision to the subset attribute in response to the most significant entropy. It will lead the subset to be partitioned.

The Risit is the main portion where there are multiple results and the answer is one of them. The C5.0 is an advanced version of ID3. Another version of decision tree is the Classification and Regression Trees (CART) used for both classification and regression. The construction of a decision tree is completed in 3 phases. It's done dealing with the concepts of entropy and information gain. First, determine if the dataset contains any differing values. If the answer is no, create a leaf node for the decision tree and assign it the class majority for the subset. Otherwise, calculate the best question to ask on the current set of attributes: device, questions, entropy, dataset, features, example. InfoGain(Attribute, dataset): for each value v of Attribute, calculate the entropy.

Decision trees (DT) is a non-parametric, supervised learning method primarily used for classification, but can also be adapted for regression tasks. This method involves partitioning the dataset into subsets that contain instances with similar values. The decision trees algorithm iteratively applies binary tests until the best value to be placed in a node is found.

5.1. Decision Trees

5.1. Decision Trees

The process of loading these modules and coming up with a decision tree for node-level binary classification is completed through the two lines of code in Listing 5.1. The decision tree can then be used to make predictions through the use of the command "clf.predict(X_test)". Here, "clf" is a "DecisionTreeClassifier" instance we have already created using the module, while "X_test" is a matrix of evaluated test inputs to be used for prediction. The parameters defining the structure of the decision tree are of particular interest. First is the parameter "min_samples_split" which sets a requirement on the minimum number of training data items needed to branch a decision tree node. If a breaking point is to be declared, it is then equal to this parameter setting. A decision tree for node-level binary classification is trained to the level of our training data uncertainty. Note that a setting for minimum samples per node can also be implemented using the option "min_samples_leaf". Other parameters in the module "tree" may also be of interest in order to minimize tree height or to control overfitting and to adjust the size and number of trees built.

The Decision Tree learning algorithm is readily available in the Python scikit-learn module under the package name "tree". "Tree" is a general class for decision trees and its functionality can be used to build both classification and regression trees based on the input parameters. However, in order to both minimize tree height and obtain the best-performing decision trees, we use "DecisionTreeClassifier" and "DecisionTreeRegressor" instead, which are specialized decision tree classes exclusively designed for performing classification and regression tasks, respectively.

5.2. Random Forests

The Random Forests classifier can process a large number of input features, while handling linear, quadratic, and even simpler terms. The bottom line is that the process is robust as long as attributes do not carry highly correlated information. Moreover, trees built with Random Forests can handle both numerical and categorical data, which means it can handle different types of information. Thus, Random Forests deliver good generalization performance and are robust to noise, capable of handling with high-dimensional spaces, can perform well on small sample sizes without causing overfitting.

The Random Forests algorithm is one of the simplest and yet most powerful among multiple classifiers present in the machine learning toolbox. The reason for its strength is attributed to its ability to allow the generalization process both the training stage and run-time stage. Therefore, the inherent overfitting problem faced by a number of classification algorithms is less severe in the case of Random Forests algorithm.

The data involves real-world trajectories of pedestrians walking on streets and sidewalks. Both the individual trajectories are represented as a sequence of Euler angles in the form (t, yaw, pitch, roll, x, y, z, boxsize). We also provide the Hawkes and Random Forest model we used to predict whether pedestrians on a particular trajectory will collide with an AV during a particular time interval. The features include all distances to the AV, derived from the AV's GPS location at the time. The time-to-collision (TTC) signal is present for all features. We also include other features derived from TTC, such as whether the pedestrian is facing the AV, whether the Tound the AV, and whether the TTC is increasing or decreasing as well.

Our feature space contains the readouts from every sensor, route distance and time, and cumulative distance. With these features, we trained the model. Our models were all binary, classifying trajectories as collisions or no-collisions. Our code is made available to the public, however, as of this writing, the data itself is not publicly available.

5.3. Support Vector Machines

The principle behind SVMs is to undertake data classification or regression by producing the optimal division of the data in a feature space such that the gap between data of the two different classes is established as maximum. This is demonstrated in Fig. 4. The middle division line (dashed line) is not the optimal decision boundary in which the two different classes are recognized but not yet clearly divided. The decision boundary that maximizes the gap between the two classes is the solid line. The samples are the support vectors that lie at the edge of each class. The solid line is defined by the set of support vectors. The maximum margin hyperplane is used to classify data by fitting the largest amount of data between several classes in the input feature space. The dimension of the margin is determined by evaluating the closest distance between each data point and the decision boundary, which is also known as the point distance. The larger the smallest point distance is, the larger the margin can be. The hyperplane is defined mathematically as w T Xi + b = 0, where Xi is each sample data point and w is the orthogonal unit vector to the margin. Although some data points might not be linearly separable, SVMs become useful by transforming the data nonlinearly into higher dimensions and classifying data there.

Support Vector Machines (SVMs) are a set of supervised learning methods used for classification, regression, and outlier detection. The advantages of support vector machines are: effective in high-dimensional spaces, still effective in cases where the number of dimensions is greater than the number of samples, and using a subset of training points in the decision function (called support vectors). The advantage of this function is that it is fully defined by the support vectors and is often independent of the number of dimensions of the feature space. Disadvantages of support vector machines: if the number of features is much greater than the number of samples, the method is likely to provide poor results, and SVMs do not directly provide probability estimates which are then calculated using an expensive five-fold cross-validation.

6. Evaluation Metrics for Collision Prediction Models

In the absence of actual accidents, we try to design a simple and efficient supervised training schema to be able to model the hypothesis of proximity of obstacles using sensors.

We suggest in this chapter that a good way to address the generality and evaluation issue is to develop as many useful operations as possible to work on our sensor data inside the hypothesis schema using the uninterpreted function "black-box" models or short and well-understood white-box machine learning models. Take collision prediction as an example: although the issue is paramount and impacts traffic safety, the number of actual traffic incidents is low.

We saw in chapter 2 that the number of sensors present in the self-driving car can be very large, leading to very complex machine learning models with millions of parameters. In addition to the issue of the need for the generality of the model, the evaluation of such systems is also a very hard and important issue.

We study a fairly simple model for this prediction using machine learning methods and show that, although our classification model is not as accurate as we would have hoped, we can gain most of the potential reduction in false alarms through introducing a short time delay between the collision risk prediction model and the collision avoidance model.

An important feature of self-driving cars is the ability to predict a potential collision with another vehicle or pedestrian, in order to apply full braking power to avoid the collision (or at least mitigate its consequences). Good prediction models for collision risk, therefore, should be key components of the technology stack of self-driving cars.

6.1. Accuracy

However, this model reduces the time-to-collision measurement, TMC, achieved using the source of Mean and Standard Deviation features. The reduction of the achieved TMC was separated by the distance travelled by the SPOT_OBJECT Motion in relation to the EGO-Motion. In particular, our model extended the time-to-collision evaluation for a depth equal to 2 units for a distance value up to ≈70 m between the SPOT_OBJECT and the EGO. Finally, the comparison between the used machine learning models allowed to improve even the accuracy of the prediction model.

The accuracy of the proposed prediction model is higher than that obtained in the work reported in when using both the sliding window and the time-to-collision techniques, which are considered state-of-the-art. Moreover, the accuracy of the proposed is even higher when using the sliding window technique and the SHTP dataset. The improvement is mainly achieved by taking simultaneous Ego-Motion and Spot-Object Motion variables as input to the designed extended convolutional neural network model. In particular, the accuracy increased significantly when using the designed time-to-collision computation technique. This improvement offers the possibility to measure the temporal variation of the time-to-collision since it takes as parameter the current data window knowledge. Here, the current window represents a time instant of front-view images as the source of Ego-Motion and Spot-Object Motion.

6.2. Precision and Recall

Precision and recall are another thorough approach to evaluating the performance of classification models. Precision and recall are calculated by dividing the true positive results and false positive results, and the true positive and true negative. Recall is the ratio of correctly predicted positive observations to the actual positives in the data. The question recall is trying to answer is: When the actual value is positive, how often is the prediction correct? Recall is also known as sensitivity or true positive rate. Precision is the ratio of the correctly predicted positive observations to all predicted positive observations. The question precision is trying to answer is: Based on our predicted positive prediction, how often is it correct? F1-score, also known as F-score or F-measure, is a weighted average of precision and recall. F1-score reaches its best value at 1, and worst at 0. F1-score is the harmonic mean of precision and recall. The F1-score is a good way to show that a classifier has a good value for both recall and precision.

6.3. F1 Score

Recall and F1-score are different even if precision is the same for both. In the event of imbalanced datasets, when classifying fraud detection, churn prediction, bankruptcy prediction, etc., F1-score should be used and a precision-recall curve should be examined. It allows you to evaluate and judge the success of machine learning models. In imbalanced datasets, a high F1-score value should be sought, which corresponds to high true positive and low false positive values for classification models. A higher F1-score means a better trade-off between precision and recall. Reason: it is included in the calculation of confusion matrix, precision, and recall. Its value ranges from 0 to 1, where 0 means precision and recall zero, while 1 means both values of precision and recall are one. Both values are multiplied by the F1-score and I added them. The F1-score ensures that the model's entire range of thresholds is captured in different ways.

The value "squaring the precision and recall" was made intentionally for the following reasons: it adds more weight to lower precision and recall values, making it difficult for machine learning models to get higher F1-scores using imbalanced data. In addition, implementation and interpretation are the same as the recall score. F1-score should be used in all imbalanced datasets and scenarios.

The F1-score or F1-measure is a metric to measure a model's accuracy for imbalanced classification scenarios. This method combines both precision and recall into a single measure. The F1-score calculates the balance between the model's precision and recall across the entire range of decision thresholds (cut-off levels).

7. Challenges and Limitations in Collision Prediction Models

Collision prediction models with perception sensors seem to be harder to build and also much less reliable than models built from maps. While being essential in the control pipeline used in decision making, models based only on perception suffer from a lack of effectiveness. Moreover, unexpected model failures lead to potential risks that are hard to quantify. The necessity to upgrade retroactively in order to keep prediction models on the edge signals the limits of these models physically and empirically. We have various limitations and preconditions that we might not necessarily be aware of when using only machine learning as the method of choice. These limitations are entirely transferable and determine the result of the prediction. Some additional, learning-specific challenges were also considered.

Subsequently, we show the power of collaboration and the importance of knowledge of the behavior and decisions of other traffic agents during the development between the models for prediction and the role of prediction in decision making. We then explore human driving behavior to set boundaries for prediction models, as well as the inherent errors in perception sensors.

The assumption that driving is adversarial, regardless of the behavior of surrounding vehicles, poses a challenge to safety as a fundamental requirement. Making decisions requires predicting the future. The present work outlines existing paradigms in traffic prediction for collision prevention and avoidance, focusing on the limitations of paradigms that use only perception sensors for prediction.

7.1. Data Imbalance

Random futhest oversampling technique (RFOT) is used whose core idea is to randomly select a subset from the majority class, and putting the selected subsets in the same class and then cluster the data, marking all the instances of the same cluster within the majority class. Support Vector Machine with Gaussian decoder (SVMSMOTE) is also used which used kernel transformation function on original data and then apply the standard SMOTE on transformed data. Clustering references based oversampling considerations (CRO) is based on two steps, first step is to carry out select k representative cluster center by clustering approach, and then in the second step more samples from original data points. After that solutions different typical classification algorithms including SVM, MLP, KNN and Adaboost, and pruning-based logic learning ensemble algorithms like Naïve Bayes, Maximum Likelihood Chi-squared and Gama hill-climbing decision stump can be implemented. Expensive Cost-sensitive trees, decision table and Adaboost algorithm Hold are also used. Different learning evaluation values, confusion matrix, and receiver operator characteristic and precision-recall curve are utilized to test the performance of above listed classification algorithms. The experiments are based on three different datasets, which are collected from NGSIM vehicle trajectory dataset.

As a first preprocessing step, a number of potential collision samples are identified based on the crash group and timestamps of ego lane-change crash data from the NGSIM trajectory dataset. A trajectory feature set was then derived for each potential collision sample based on its context data, including information about the vehicle's interaction with its surrounding vehicles rather than specific vehicle's sensor data. The learning features have multi-level hierarchical structures, and are dynamically selected for each vehicle based on the vehicle's relative behavior, which is personal, interaction-induced, and trajectory-context-aware. Multiple level properties, ranging from vehicle information to trajectory contexts data, are considered when selecting the proper learning features, including attributes and behavior features, close international vehicle behavior, local/relative vehicle's behavior, and historical vehicle behaviors. Then, under the features context, a set-up is established to consider all the potential collision samples and unbalance our datasets as well.

7.2. Adversarial Attacks

In this section, we deal with the issue of adversarial attacks, i.e., the capability of creating specific stimuli and making their classification be altered. This issue is crucial in our setup because similar real-life, photorealistic perturbations could be passed off as natural, not really intentional images. Indeed, network internals and generally behaviors remain widely unexplored. We naturally rely on Keras Adversarial Modeling library implementation, optimizing over an initial dataset of collisions directed to specific output targets, baits. It is important to notice that the model's weights remain constant, then the trained discriminator is strong in their hyperplanes approximation. Our generated images are considered adversaries if the discriminator does not consider them as real examples (i.e., p(Real Image) < 1). We consider standard errors well described in the literature, such as random/pgd/uniform noise. A potential meaningful extension interesting to deeper study is creating malicious inputs in order to directly influence controller decisions through adversarial examples or attacks with a certain kind of features, bounds, by which the current class and the generated outputs are both compliant with the required steering angle.

8. Real-World Applications of Collision Prediction and Avoidance Systems

Since the machines that are learning to categorize driving scenarios are being implemented into autonomous vehicles, applications are also emerging regarding choices of ethics and liability in regards to the actions of the autonomous vehicles in the context of a crash event. Google's self-driving car project goals are based on the need to save people from their own bad habits. According to their report, "Research shows that human drivers are very often the cause of accidents themselves, making driving errors like not paying attention, being too close to the car in front, or braking too late. Indeed, in the United States, vision and perception failure account for 24% of all critical reasons for accidents, while decision errors or mistakes account for 18%. In both cases, inattention was a major cause. Such high percentages could be drastically reduced by leaving the care entirely to software technologies, avoiding human errors for at least 96% of the critical reasons behind the accidents (78% + 18%)."

We have explored many of the algorithms, sensors, and supporting hardware that go into predictive collision avoidance systems. But what are some real-world applications of this technology? Some of the first iterations of these systems can be seen in current vehicles for driver assistance. Predictive software applications have also begun to be implemented into areas other than vehicle collision prevention. Traffic flow prediction for intersection assistance systems has the potential to prevent intersection collisions and also help to move traffic along faster. There are other applications in non-traffic areas that use the same base machine learning algorithms to inform action choice, speed prediction, and location prediction in different fields. These same technologies can also be implemented in security checks and disaster response in buildings, as well as disaster recovery, search and rescue tasks, and agricultural uses, particularly for yield and work planning.

8.1. Case Studies in the Automotive Industry

The first part of the chapter is interested in the acceleration and motion modeling of both leading vehicles and emergency vehicles (EV) in order to predict their future movements (on complex urban traffic) in case of collisions. The second part of the chapter describes our machine learning approach for the AV-automatic collision prevention. Various machine learning algorithms are tested and compared in order to design the best predictor for EV-AV collision, and a discrete event simulator model is used to validate it. Our tests have been made on artificially created and real traffic data with satisfactory results. AV automatic collision prediction and avoidance are major challenges for intelligent transportation management and for the successful implementation of AV in the future transportation system.

There is a great interest in the development of autonomous vehicles (AV) by numerous research centers and companies. Many players are involved in this domain, and all have their own methodologies according to each one's convictions. A complementary examination of these different theories could be very helpful for better understanding of the AV problem. Some significant trends can be extracted from these numerous studies, characterizing the way each different working team is managing the transportation environment. Such an approach can be useful for setting up intelligent transportation systems able to manage mixed traffic flows.

9. Ethical and Legal Implications of Autonomous Vehicle Collision Prediction

In this chapter, we provide some background about AV collision predictions in the context of autonomous vehicle (AV) technology from an ethical and legal perspective. We motivate the need for locally interpretable, simple representations of complex classifiers. If a pedestrian incorrectly anticipates that the AV will yield him the right of way, he might walk in front of it. Depending on the speed and control systems of the AV, it might not be possible to safely stop before a collision occurs. In that case, the pedestrian would have no opportunity to correct his choice and continue walking. To more safely interact with such dynamic systems, pedestrians would need reliable information about the AV's operation.

EPICC is a machine learning approach that accurately predicts potential pedestrian-collision hotspots for a self-driving vehicle. The approach dynamically adjusts to ensure generalization across cities and uses attention mechanisms to understand the importance of sensory inputs. The importance of this work has led to an exploration to better understand and optimize for improving generalization across data sources. Intercity-hotspot-collecting policies are analyzed for their influence on the appearance of data sampling-induced discrepancies. Policy implications are discussed. Measures for softening prediction-induced biases and potential options left to vehicle designers are explored. In critical systems, simple and computationally-efficient models can reduce design complexity and directly address issues, while explaining the model's rationale to stakeholders. In contrast to global post-hoc explanations, the intersect class model gives local explanations by detecting which sensory inputs had strong influence on prediction without any invasive model modifications.

9.1. Liability and Responsibility Issues

When all of the car's driving functions are carried out by automated systems, the driver is merely the supervisor and the operator. With such a degree of automation, the condition of the driver is not material as the driving function is not required. The control of the vehicle is undertaken by the car. When the driving functions are no longer equally distributed and there is a preliminary stage to emergency intervention, the role of the driver as supervisor and the operator of the vehicle gives way to the innovation of the vehicle. As autonomy becomes greater, the operator's possibility of exerting a direct (real-time) control function diminishes. With high level autonomy, the control function is no longer to be found in the driver, but in the vehicle, which is, in this case, the real driver. The operator has now become the passenger.

One final key area requiring thorough analysis and thought from an AT standpoint is the attribution of responsibility and liability in the event of an accident. The role played by the system could be key in determining who, if anyone, should be held responsible and financially accountable for the consequences of the accident. This could be particularly pertinent in cases where the introduction of AT elements is gradual and happens in the context of mixed traffic flows in which the vehicle's level of autonomy varies over time. For instance, a responsibility shift could be brought on at the moment drivers are allowed to disengage fully from the driving task.

10. Future Directions and Emerging Trends in Machine Learning for Autonomous Vehicles

We aimed to provide an extensive review of the application of conventional machine learning techniques and state-of-the-art AI technologies in collision modeling and advanced topics in AV safety modeling and analysis. We have reviewed methods of big data (BD) modeling, zero-inflated modeling, various sensors/technologies, and software/hardware platforms for automatic vehicle-vehicle-centered safety modeling.

In this book, we have reviewed a variety of machine learning methods for collision avoidance and collision prediction for autonomous vehicles. We have provided insights into effective methods, software, and hardware requirements for AI-based collision avoidance and collision prediction for autonomous vehicles. The model performance metrics are provided for users to evaluate how well the model predicts. We have identified various key emerging technologies and research challenges in AV safety.

Finally, we also review various key emerging technologies and research challenges in AV safety.

In this section, we discussed the various future research directions and emerging trends in machine learning-based collision avoidance and collision prediction for autonomous vehicles. Some of the future research directions include: multimodal datasets, public AV fleets data, robustness to sensor noise, temporal uncertainty, safety guarantees, human verification, RNN/transformer-based models, domain generalization methods, and enhanced algorithms.

In this chapter, we have reviewed the relevant literature on collision prediction and collision avoidance methods for autonomous vehicles using machine learning algorithms. We have also identified various research challenges.

10.1. Explainable AI

The noise, outliers and missing features/latent factors present in the data should be carefully filtered. The Noise and Outliers present in data would significantly reduce the performance of the AI model. The outliers present in the Model's decision output should also be removed. For instance, if the model predicts the distances d1, d2,...dn from its different sensors and think of stopping within time T, the model's maximum limit of the distance covered cannot be more than n*t where n is the number of sensors used. Any prediction more than that threshold is a clear outlier. There is a fair deal of feature engineering that transforms the data points in such a way that we get a better explanation. Statistical techniques can be used as a latent factor in improving the model.

As shared earlier, AI models should be more explainable. The prediction and policy decisions of the model can be interpretable by explanation methods like SHAP, LIME. In contrast, we cannot get explanations for decisions from predominantly used algorithms like CNN. Also, we cannot apply some techniques that are used at certain stages of the Machine Learning Model. For instance, we can only apply techniques like Fourier analysis at the output of the neural network. Again, it is hard to uncover relationships between specific Input-Output pairs (Features and Classes) by just using confusion matrix of the model. AI models used in a real-world scenario should be simple and interpretable.

11. Conclusion

While our results represent a step forward in the state-of-the-art for data-driven traffic conflict prediction, they merely scratch the surface of learned traffic models. To further validate our approach, future work should explore a wider variety of traffic conflict types, simulate even more sequences, and test on an even wider variety of real-world examples. It is our hope that the open source nature of our platform will enable industry, standards bodies, and academics to collaborate quickly for the greatest benefit. AV designers using these data-driven models to set perception parameters should follow industry standards and guidelines to ensure system robustness and reduce the risk of unanticipated failure.

In this work, we demonstrate that deep learning methods can be used to detect traffic conflict using only raw image input and minimal processing for sensor fusion. These networks were trained on hundreds of thousands of individual traffic conflicts in simulation and have shown the ability to generalize to real-world recorded data. These results set a new state-of-the-art and demonstrate the potential for data-driven methods to exceed physical models for this task. Our approach has implications on the future of how AVs are designed, specifically on the role traditional perception can play.

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