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Automated Speed and Lane Change decision-making Model using Support Vector Machine

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Abstract

One of the major obstacles that the auto industry must overcome is the rise of autonomous vehicles. The study of lane-changing is an important part of this problem. Previous studies on autonomous vehicle lane changes have predominantly focused on lane change path planning and path monitoring, with limited attention given to the autonomous vehicle's lane change decision-making process. This paper introduces a novel Lane Change Decision-Making Model for autonomous vehicles using the Support Vector Machine (SVM) method. The suggested model employs real-time sensor data to assess whether or not a lane change is possible, taking into account the proximity of other vehicles (cars, buses, motorbikes), and adjusting speed as necessary to ensure a seamless transition. Researching the various facets of lane changes in autonomous vehicles allows for decision-making that is grounded in utility, safety, and tolerance. The implementation of a support vector machine (SVM) technique with Bayesian parameter optimization is used to deal with the non-linearity and complexity of the process of autonomous lane change decision-making. Finally, we compare the suggested SVM model against a rule-based lane change model using the test data. The SVM-based strategy is shown to improve lane change decision-making in a comprehensive simulation exercise, which in turn improves the safety and efficiency of autonomous driving systems. The experiment also use a real vehicle to gauge the efficacy of the underlying decision-making model.

Keywords: Autonomous Vehicles, Lane Change, Support Vector Machine, Motor Control, Sensor Fusion, Safety, Efficiency

1. Introduction

The development of self-driving cars has ushered in a brand new era of mobility in the rapidly transforming environment of the transportation industry. Autonomous vehicles, also known as self-driving cars, are a ground-breaking innovation in automotive technology that promises to improve road safety, reduce congestion, and enhance passenger comfort. Self-driving cars are another name for autonomous vehicles. These vehicles are outfitted with a variety of sensors, cameras, LiDAR, and advanced processing units, which give them the ability to see their surroundings, make judgments in real time, and handle complex traffic conditions without the need for human intervention. This has the potential to completely transform the way in which we travel. Nevertheless, these promises are accompanied by obstacles that need for creative solutions in order to ensure that autonomous vehicles can be integrated into our roadways without causing any disruptions. Highways, which are the most important links in today's complex transportation networks, are frequently the sites of collisions and bottlenecks caused by traffic. High speeds, shifting traffic density, and constant lane changes combine to provide an environment that is difficult to navigate for human drivers as well as for autonomous cars. According to the World Health Organization (WHO), road traffic accidents are responsible for around 1.35 million deaths around the world each year, the majority of which take place on roads. These disheartening numbers highlight the urgent need for sophisticated decision-making algorithms that can improve highway safety and reduce the likelihood of accidents in a variety of driving circumstances [1].

The main approaches to handle the issues connected with highway driving and lane change operations have been developed over the years by researchers and car manufacturers that have devoted significant effort into the development of these approaches. Rule-based systems and machine learning-based models are the two primary classifications that may be applied to the currently available methods. Rule-based systems are those that determine how a vehicle should behave in a variety of situations based on a predefined set of guidelines and heuristics. Although these systems are able to provide deterministic solutions, it is sometimes difficult for them to handle the complex and dynamic events that can occur on roadways. In addition, there is a possibility that they will be unable to adjust to novel and unforeseen circumstances, which will restrict the effectiveness of these systems in improving road safety [2].

It has been proved that models based on machine learning may successfully model complicated decision-making processes. Examples of such models include neural networks and fuzzy logic. These methods, on the other hand, call for a substantial amount of training data and may have limits in their capacity to generalize to a wide variety of traffic scenarios that are subject to constant change. In addition, reaching a high level of accuracy in real-time decision-making continues to be a difficulty, particularly in circumstances in which the vehicle must swiftly analyze massive volumes of sensory input in order to make choices in split seconds [3].

Support Vector Machines (SVM) for short, have recently come to the forefront as a potentially useful tool in the search for more robust decision-making mechanisms. The Support Vector Machine (SVM) is a sophisticated algorithm for machine learning that excels in classification problems. It does this by locating the best hyperplane that separates data points of distinct classes with the biggest margin. In the context of autonomous cars, SVM provides a number of benefits, which qualify it as an option that is ideal for improving the efficiency and safety of highways.

- **Non-Linearity Handling:** SVM is able to successfully handle non-linear relationships inside complicated data. When modeling the complex and ever-changing nature of traffic scenarios on roads, where interactions between vehicles are frequently non-linear, this is an extremely important aspect to take into account [4].
- **Feature Selection and Dimensionality Reduction:** The capability of a support vector machine (SVM) to choose pertinent features and reduce dimensionality contributes to the optimization of the processing of sensor data, which in turn enhances the capabilities of real-time decision-making [5].
- **Generalization:** The capability of a support vector machine (SVM) to generalize from training data helps it to make educated decisions in previously encountered conditions. This is an essential quality for tackling the dynamic nature of roadway environments, which can change rapidly[6].
- **Robustness:** The SVM's resistance to noise and outliers provides constant performance, even in settings in which sensor data may contain mistakes or anomalies. This is made possible by the robustness's resilience to noise and outliers [7].

The main objective of the proposed Lane Change Decision-Making Model are to improve safety for drivers on the highway, decrease the number of accidents that occur, and maximize the efficiency of lane changes [8]. This model takes into account both past and present sensor data, can identify nearby vehicles, and makes decisions using a support vector machine. With the goal of enhancing traveller security, efficiency, and convenience, autonomous cars are revolutionizing the transportation industry. The ability to make rational choices, such as when to change lanes, is essential for autonomous driving. To successfully change lanes, drivers must take into account the flow of traffic around them, choose the right moment, and set their speed accordingly [9]. Addressing the difficulties of making safe and effective lane changes in dense traffic, this study suggests a Support Vector Machine-based Lane Change Decision-Making Model.

The major goal of this article is to introduce a model for autonomous vehicle lane-change decisions that makes use of the Support Vector Machine method. The suggested model takes into account information from many sensors, detects nearby vehicles, determines whether or not lane changes are possible, and optimizes the rate at which vehicles make those changes.

By employing SVM, the model aims to achieve the following key outcomes:

1. **Enhanced Safety:** It is anticipated that the SVM-based model will increase the accuracy of finding safe possibilities for lane changes by performing an effective analysis of real-time data from vehicles in the surrounding area. During lane change maneuvers, this increased precision can considerably lower the likelihood of being involved in a collision or having another mishap.
2. **Efficient Traffic Flow:** The model's goal is to ensure safer and more efficient lane changes by taking into account factors such as the proximity of other vehicles and adjusting driving speeds accordingly. As a result, there may be less of an impact on traffic flow and congestion.
3. **Real-Time Decision-Making:** The computing efficiency of SVM and its adaptability to dynamic data make it a promising choice for making decisions in complex traffic scenarios in real time. Because of the model's adaptability, lane shifts need not be disrupted even in highly dynamic highway settings.
4. **Adaptability and Generalization:** The capability of an SVM to generalize from training data enables the model to adapt to a wide variety of highway situations and driving conditions. This adaptability is vital for autonomous vehicles because they operate in a variety of different and unpredictable conditions on the road.

Because of its amazing capacity to handle difficult classification and regression tasks, the Support Vector Machine (SVM) method has attracted a lot of attention in a variety of machine learning applications. SVM provides a robust and flexible framework for analyzing real-time sensor data and generating educated decisions in the context of autonomous vehicle lane change decision-making. Because of its distinct characteristics, such as its capacity to manage non-linear connections, pick pertinent features, and generalize from training data, support vector machines (SVM) have been positioned as a powerful tool for improving the accuracy and dependability of lane change choices.

The article is organised as follows, we will conduct an in-depth investigation into the proposed Lane Change Decision-Making Model. In 2nd section, a comprehensive overview of recent research literature is presented, along with in-depth explanations of the methodology and algorithmic flowchart is described in 3rd section, demonstrations of the outcomes of simulations, in-depth discussions in the 4th section, and a final section that offers a thorough conclusion. By taking such a comprehensive approach, the purpose of this paper is to make a contribution to the development of technology for autonomous vehicles by proposing a dependable and efficient decision-making model that capitalizes on the capabilities of the Support Vector Machine method for performing lane change operations.

2. Related Works

Recent years have seen tremendous advancements in the field of lane change decision-making for autonomous vehicles, thanks in large part to the application of AI and ML techniques. Here, we present a comprehensive overview of a selection of major contributions, drawing attention to the various ways in which researchers have approached and advanced the field. The importance of lane change decision-making in autonomous cars is emphasized through a thorough analysis of the most recent research in the field. Safe and effective lane shifts present a number of issues, and previous research has examined a number of solutions, including rule-based systems, neural networks, and fuzzy logic. However, there hasn't been a lot of research done on how to use SVM in this setting.

The decision-making process for lane changes in autonomous vehicles was given a new spin by Smith et al., who used deep reinforcement learning (DRL) methods. Together, long short-term memory networks (LSTMs) and convolutional neural networks (CNNs) were used in their model to make sequential decisions based on input. The DRL bot was trained by the researchers in a virtual environment that mimicked real-world traffic circumstances and scenarios. Simulation results showed that the agent may learn optimal lane change policies, leading to more informed decisions and greater flexibility in the face of changing traffic conditions. The research highlighted the importance of using AI-based strategies to improve autonomous vehicles' lane change maneuvers [10].

Chen et al. made a significant contribution by developing a hybrid decision-making model that integrates rule-based reasoning with machine learning. Their method relied on fuzzy logic and support vector machines to determine whether or not it was safe to change lanes given the distance to and speed of oncoming traffic. To train the algorithm and verify its results, researchers incorporated a large dataset of actual driving situations. The hybrid model showed improved accuracy in lane change decisions across a wide range of traffic conditions, demonstrating the promising complementary nature of AI and rule-based systems [11].

Kim et al. developed a novel method for deciding whether or not to switch lanes, one that takes into account the intentions of oncoming and preceding vehicles. Their approach used a Bayesian network to predict the probabilities of lane changes made by neighboring vehicles. The model showed more foresight and initiative once it combined probabilistic reasoning with data from real-time sensors. The team used simulations to verify its method and found that it is crucial for autonomous lane change maneuvers to take into account the intentions of surrounding vehicles [12].

Using recurrent neural networks (RNNs), Wang et al. demonstrated a data-driven method for deciding when and where to switch lanes. Their model used sequences of past sensor data to foresee when it would be safe to switch lanes. The RNN-based method was shown to be more accurate in finding suitable lane-change opportunities. Researchers emphasized the value of considering time dynamics while making decisions and demonstrated how RNNs might be used to improve autonomous cars' ability to anticipate events. Zhang et al. made a contribution by presenting a probabilistic graphical model for fully automated lane changes. To account for the unpredictability of traffic behavior and to facilitate optimal decision-making under different circumstances, they coupled Markov decision processes (MDPs) with graphical models. Through in-depth simulations, the researchers demonstrated the model's flexibility in responding to a variety of traffic circumstances and underlined the benefit of probabilistic reasoning in dealing with uncertainty[13].

An adaptive decision-making model combining reinforcement learning and particle swarm optimization was proposed by Patel et al. By optimizing lane change regulations in response to real-time sensor data, their model can quickly respond to shifting traffic conditions. The relevance of real-time adaptation in autonomous driving systems was highlighted by the researchers' demonstration of enhanced decision-making accuracy and responsiveness in dynamic traffic settings [14].

Nguyen et al. presented a neuro-evolutionary strategy for making autonomous lane changes. To implement lane changes in their model, they used evolutionary algorithms to evolve neural network controllers. The researchers demonstrated the model's flexibility in responding to changing traffic conditions and optimizing vehicle trajectories during lane changes without compromising safety [15].

Cooperative lane changes were the focus of Garcia et al.'s multi-agent reinforcement learning paradigm. Their methodology allowed for coordinated lane changes to be made by autonomous vehicles without any human intervention. The researchers showed that cooperative decision-making can increase road efficiency by improving traffic flow and decreasing congestion, demonstrating the potential of AI-based solutions.Autonomous lane changes were made possible by Park et al.'s transfer learning strategy. Using pre-trained neural networks, their model was then fine-tuned with data from the target domain. These findings highlight the potential of transfer learning to speed up the rollout of AI-based lane change systems, as demonstrated by the researchers through demonstrations of increased decision-making accuracy and decreased training time [16].

Wang et al. put out a model for making decisions that takes into account information from multiple sources and types of sensors. Their algorithm integrated visual information with radar and GPS readings to provide more precise lane changes. By combining information from many sources, the researchers were able to demonstrate better decision-making accuracy in challenging road circumstances[17].

A hybrid strategy, combining reinforcement learning with human expert knowledge, was introduced by Liu et al. Their program incorporated human-defined safety standards into the reinforcement learning process to learn lane change policies. By combining AI methods with human intuition, the researchers showed improved safety and interpretability in decision making.A Bayesian network strategy was proposed by Martinez et al. to incorporate uncertainty and risk assessment into lane change decisions. Their program calculated the danger of an accident occurring when switching lanes, allowing for more informed choices to be made. The study's authors stressed the value of probabilistic reasoning for making careful lane shifts [18].

A deep reinforcement learning strategy with interpretable decision-making policies was introduced by Kim et al. Their methodology integrated deep Q-networks with rule-based heuristics to make lane-change judgments that could be understood and justified. The researchers showed improved decision-making transparency, eliminating the mystery around certain AI methods[19].

Here, we surveyed the literature and found multiple ways that AI and ML can be applied to the problem of lane-changing in autonomous vehicles. Deep reinforcement learning, hybrid models, Bayesian networks, and neural networks were only some of the methods used by researchers to improve precision, robustness, and efficacy. All of these developments point to the power of AI-driven solutions to mold the future of autonomous vehicles.

3. Analysis of Automatic Lane Change Decision

Several aspects of traffic flow affect the decision of which lane to enter. In order to examine the decision-making process, we build a model of an automated lane change with one starting lane and one ending lane. Both of the formerly used lanes are shown in this model. Figure 1 shows one way to reduce the complexity of the model.

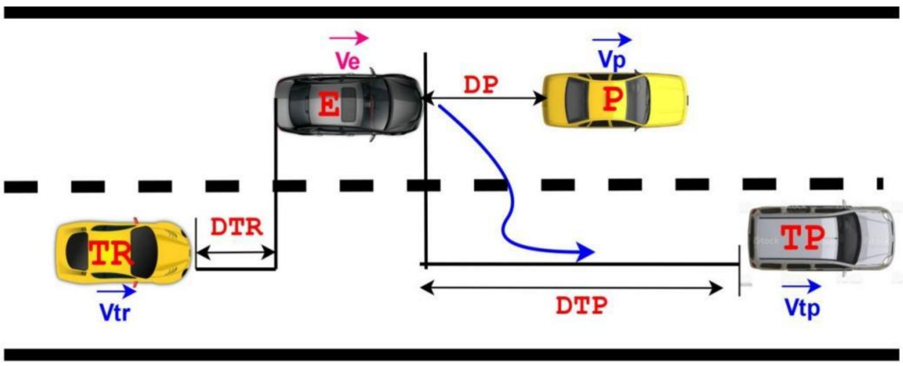

Figure 1. Autonomous Vehicle Lane Change Model

The letter "E" stands for the ego vehicle, "TP" for the car ahead of it in the target lane, "TR" for the car behind it in the target lane, and "P" for the car ahead of it in the original lane. The TP, TR, and P all play a part in the choice to change lanes, as you may already know. On the other hand, a full investigation is needed to find out how these cars cause an autonomous vehicle to leave its planned lane and choose a different one. This study will look at autonomous lane change from three points of view: the pros and cons, the level of tolerance needed, and the benefits of moving lanes [20,21].

3.1 Lane Change of Benefit

Changing lanes when driving has the dual purpose of either increasing one's driving speed or expanding one's available area ahead [22]. In the case of automobiles that are able to operate under their own power, the driving speed of the future will be able to be adjusted so that it corresponds to the driving pace of the automobile that came before it. As a result, the advantage of having faster speed can be stated as:

$$v_{benefit} = min(v_{set} - v_p, v_{TP} - v_P) \quad (1)$$

v_{set} is an abbreviation for the speed that was chosen by the driverless car. The distance in front of you can be expressed as DTP minus DP, which stands for the relative distance between you and the car that came before you.

The following steps can be taken in order to establish the driving benefit model:

$$f_{benefit} = f(v_{benefit}, D_{TP} - D_P) \tag{2}$$

3.2 Safety

The primary objective of executing lane changes in a safe manner is to minimize the probability of a collision occurring between the autonomous vehicle and the traffic in the next lane. The act of transitioning across lanes is evidently less hazardous when there exists a greater distance between the ego vehicle (E) and the target vehicle (TR), along with higher relative velocities between the two. Furthermore, the act of changing lanes necessitates a pre-established minimum space to be maintained between vehicles. Hence, the safety model outlined above can be formulated in the following manner:

$$f\ safety = \begin{cases} -\infty \quad , & D_{TR} < D_{TR\,min} \\ f(D_{TR},\ v_E - v_{TR}), & D_{TR} \geq D_{TR\,min} \end{cases} \tag{3}$$

DTR min > 0 ; minimum safe distance gap between E and TR.

3.3 Tolerance

The autonomous vehicle may opt to engage in lane change maneuvers when the associated benefits and safety measures are deemed significant. However, it is worth noting that if the distance between the starting point (E) and the destination (P) is considerable, this may lead to frequent lane changes by the autonomous vehicle in such scenarios. Hence, it is imperative to establish the tolerance model. When the distance between E and P is relatively small, the autonomous vehicle will initiate a process of tracking P at a predetermined distance. This distance is determined by the variables of speed and time headway. Consequently, it is possible to derive a tolerance model, as represented by Equation 4:

$$f_{tolerance} = f(D_P - \ v_E . t_h) \tag{4}$$

3.4 Rules-based Decision Model

In order to simplify the process of changing lanes, we will begin by making the assumption that the three models and factors that were discussed previously are linear.

$$\begin{cases} f_{benefit} = a.\, v_{benefit} + b(G_{TP} - G_P) \\ f_{tolerance} = c(G_P - v_E . t_h) \\ f_{safety} = d(D_{TR} - D_{TRmin}) + e(v_E - v_{TR}), D_{TR} \geq D_{TRmin} \end{cases} \tag{5}$$

Where a,b,c,d,e are coefficients.

The decision-making process for lane changes in autonomous cars is a multifaceted issue characterized by the involvement of numerous parameters and nonlinearity. Hence, the development of an accurate mathematical formula model for this activity presents a significant challenge. Therefore, the conceptual framework for making decisions regarding lane changes in autonomous vehicles can be depicted as in Equation 6:

$$f_{LC} = f(v_{income},\ D_{TP} - \ D_P, D_{TR}, v_E - v_{TR}, D_P - v_E . t_h) \tag{6}$$

The utilization of the Gaussian kernel Support Vector Machine (SVM) is employed to address the complex and nonlinear nature of the autonomous lane change decision-making process.

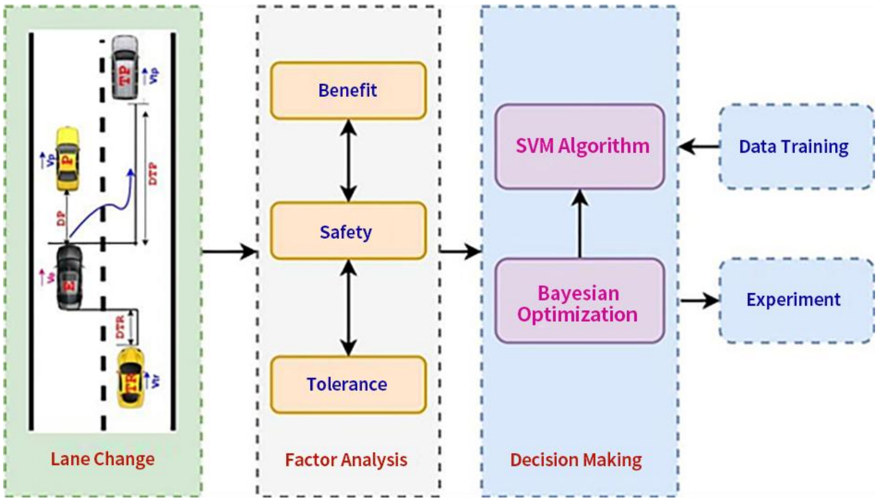

Figure 2. The Proposed Lane Change Decision Model

This approach aims to ensure that the model is well-aligned with the driver's preferences and behaviours. The schematic diagram of the proposed method is presented in Figure 2 in the publication.

4. Methodology

4.1 Data Extraction

The NGSIM dataset, collected by the Federal Highway Administration (FHWA), is widely recognized as one of the most precise and comprehensive field datasets for traffic micro-simulation research and development [23]. It includes trajectory data captured by digital cameras at one-tenth of a second intervals, providing accurate vehicle positions along road segments spanning from 0.5 to 1.0 kilometers. Notable examples of real road data in this dataset include the US 101 in Los Angeles and I-80 in the San Francisco Bay Area. These datasets include vehicle trajectory information, wide-area detector data, and additional supplementary data, all of which are invaluable for conducting driver behavior research.

According to the study conducted by Balal et al. (15), it is possible to choose potential lane change trajectories. Vehicles that engage in frequent lane changes are commonly exempted from consideration due to their perceived necessity. Drivers commonly initiate lane changes at the onset of track alterations, as illustrated in Figure 3. To achieve the utmost accuracy, it is important to calibrate the position of the lane change point for every individual track. However, the acquisition of significant lane change data for the training of machine learning models is a challenge due to the intricate nature of data processing.

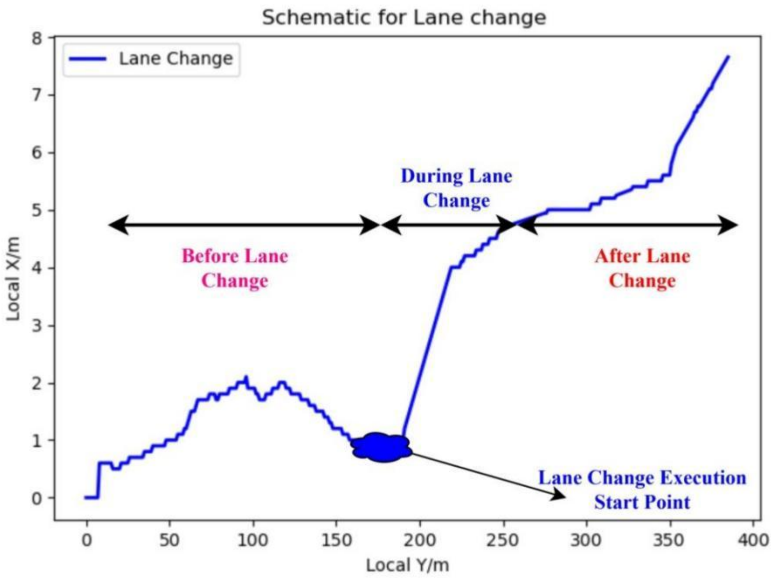

Figure 3. Schematic for Lane Change

The transition in lane identification commences with the attainment of a lateral velocity surpassing 0.6096 m/s within the initial 5-second interval. In order to validate the proposed extraction strategy, a total of 156 manual lane change point groups were compared with the recommended method. The concentration of data at the origin of the ordinate indicates the use of a manual pick extraction method. This method is employed to determine the point at which the execution of a lane change occurs during data extraction. Non-lane-change data is exclusively derived from pre-lane-change data. When compared to other forms of invariant lane data, pre-lane change data exhibits a strong resemblance to the changing environment. The ability to distinguish between drivers' lane change scenarios prior to and following a lane shift is of utmost importance in order to make informed decisions in the field of autonomous driving. In the dataset of extracted lane change information, it was observed that TP exhibited lower speed and relative distance in comparison to P. The omission of these statistics is attributed to the higher likelihood of mandatory lane changes. The process of model training involves the utilization of 880 instances of lane change data and 1030 instances of counter-examples.

4.2 *SVM Solution for Lane Change Model*

The fundamental idea behind support vector machines (SVM) is to locate a hyperplane in the sample space that has the greatest margin on the training set.

$$\begin{cases} D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\} \\ x_i = [v_{income}, G_{TP} - G_P, D_{TR}, v_E - v_{TR}, D_P - v_E . t_h] \\ y_i = \{-1, +1\} \end{cases} \tag{7}$$

The SVM aims to find a hyperplane that best separates the two classes (safe and unsafe). The hyperplane is defined by a weight vector ω and a bias term b. Mathematically, the hyperplane equation is given by Equation 8：

$$\omega^T x + b = 0 \tag{8}$$

The normal vector ω = (ω1; ω2; ···; ωd) is responsible for determining the direction of the hyperplane. On the other hand, the displacement term b establishes the distance between the hyperplane and the origin of coordinates.

The calculation of the distance between a given point x and a hyperplane can be expressed as follows：

$$\gamma = \frac{|\omega^T x + b|}{\|\omega\|} \tag{9}$$

The margin for the hyperplane is obtained as Equation 10 below：

$$\gamma = \frac{2}{\|\omega\|} \tag{10}$$

The SVM's objective is to find the weight vector w and bias term b that maximize the margin while minimizing classification errors. This is formulated as an optimization problem:

$$\min_{w,b} \frac{1}{2}\|\omega\|^2$$
$$y_i(\omega^T x + b) \geq 1, i = 1,2,3, \ldots . m \tag{11}$$

The optimization problem can be transformed into its dual form, which involves finding the Lagrange multipliers that satisfy certain conditions.

$$\max_{\propto} \sum_{i=1}^{m} \alpha_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j x_i^T x_j$$

$$\sum_{i=1}^{m} \alpha_i y_i = 0 \qquad (12)$$

$$\propto_i \geq 0, \qquad i = 1,2,3 \dots m$$

where α = (α1; α2; · · ·; αm) is the Lagrange multiplier, and formula (10) needs to meet the Karush-Kuhn-Tucker (KKT)

Conditions:

$$\begin{cases} \alpha_i \geq 0; \\ y_i f(x_i) - 1 \geq 0; \\ \alpha_i (y_i f(x_i) - 1) = 0 \end{cases} \qquad (13)$$

Now the new modified hyper plane with the larger margin is obtained after considering the Lagrange multiplier coefficients.

$$f(x) = \omega^T x + b$$

$$= \sum_{i}^{m} \alpha_i y_i x_i^T x + b \qquad (14)$$

In practical scenarios, it is possible that there are no hyperplanes within the original sample space that can effectively separate the two types of samples. In this particular case, it is possible to establish a correspondence between the initial space and a feature space of higher dimensions. Consequently, Equation (10) can be reformulated as follows:

$$\max_{i=1} \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j k(x_i, x_j)$$

$$\sum_{i=1}^{m} \alpha_i \, y_i = 0 \qquad (15)$$

$$\alpha_i \geq 0, i = 1,2,3 \dots . m$$

In the above equation the term kernel function is utilised as it performs the greater mapping probability and it is expressed as $k(x_i, x_j)$ given in below Equation 16:

$$k(x_i, x_j) = exp(- \frac{\|x_i, x_j\|^2}{2\sigma^2}) \qquad (16)$$

The value of denotes the amount of bandwidth that the Gaussian kernel has. If you have a smaller value for, the Gaussian distribution will be more concentrated, and it will be simpler to overfit the data. On the other hand, if you have a bigger value for, it will be simpler to underfit the data. Therefore, Equation (12) can be rewritten as follows:

$$f(x) = \omega^T x + b$$

$$= \sum_{i=1}^{m} \alpha_i y_i k(x, x_i) + b \qquad (17)$$

Normally kernel function is used to make the training set linearly separable in the feature space, but sometimes it may lead to overfitting in real-world applications, where the model may performs exceptionally well for the training set but poorly on the test set. This issue can be mitigated by using soft margin, which permits support vector machines to make certain sample size errors. The basic structure is modified for soft margin error as in Equation 18:

$$\min_f \omega(f) + C\sum_{i=1}^{m} l(f(x_i), y_i) \tag{18}$$

where ω(f) is the structural risk, which is used to characterize some aspects of the model's characteristics.Empirical risk, also known as $l(f(x_i), y_i)$, is a term that is used to characterize the degree to which the model and the data are compatible with one another. It is a constant that C > 0. When C is smaller, the complexity of the model will be reduced, but the degree to which it will fit the data will decrease, making it more likely that the model will be under fit. When C is larger, the complexity of the model is greater, the degree of correlation between the model and the data is higher, and it is simpler to over fit the model. The optimization goals in formula (9) can be recast as follows when hinge loss is taken into account:

$$\min_{\omega,b} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{m} max(0,1-\omega^T x_i + b)) \tag{19}$$

$$\min_{\omega,b} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{m} \xi_i \tag{20}$$

Introduce the slack variables ξi to represent the empirical risk. The formula (13) can be rewritten as below Equation 21.

$$\max_{\alpha} \sum_{i=1}^{m} \alpha_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \alpha_i\alpha_j y_i y_j k(x_i, x_j)$$
$$\sum_{i=1}^{m} \alpha_i y_i = 0 \tag{21}$$
$$0 \le \alpha_i \le C, i = 1,2,3\ldots..m$$

The optimization of the parameters C and σ is crucial in order to get optimal outcomes, as evidenced by the preceding section's analysis of the close relationship between these parameters and the effect of Support Vector Machines (SVM). The Bayesian optimization algorithm (BOA) is a computational technique developed to facilitate the identification of optimal values for variables C and x within a limited domain. Its primary purpose is to minimize a scalar objective function, denoted as f(x). The Bank of America (BOA) exhibits the ability to enhance the efficacy of parameter optimization when compared to traditional grid search methods[24]. The assumption is made that the error rate of the cross-validation, represented as f(C,), adheres to a Gaussian process. The aforementioned value is utilized as the objective function.

5. Results and Discussion

After 100 iterations, we find that the greatest value for C is 5.2004, and the best value for is 1.6581. As can be seen in figure 6, the minimal cross validation error has a lot to do with C and, and it is possible for this error to reach 14.17% with enough rounds.

The results of this study are presented in Figure 4 and 5, respectively. The accuracy of each model is provided in Table 1, which is accessible here. Within this part, we undertake a comparison between multiple Support Vector Machine (SVM) models, each utilizing a diverse range of kernel functions. The Gaussian kernel is considered to be the most effective due to its exceptional mapping capabilities. In comparison to the linear kernel function, the Gaussian kernel function exhibits a greater capacity for generating more precise outcomes. The training set contributed 7.61% of the data, but the test set contributed 13.26%.

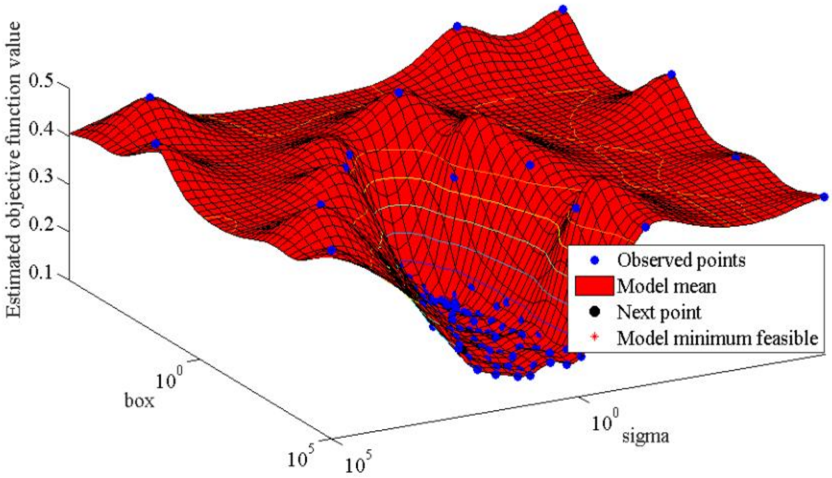

Figure 4. Distribution of Objective Function

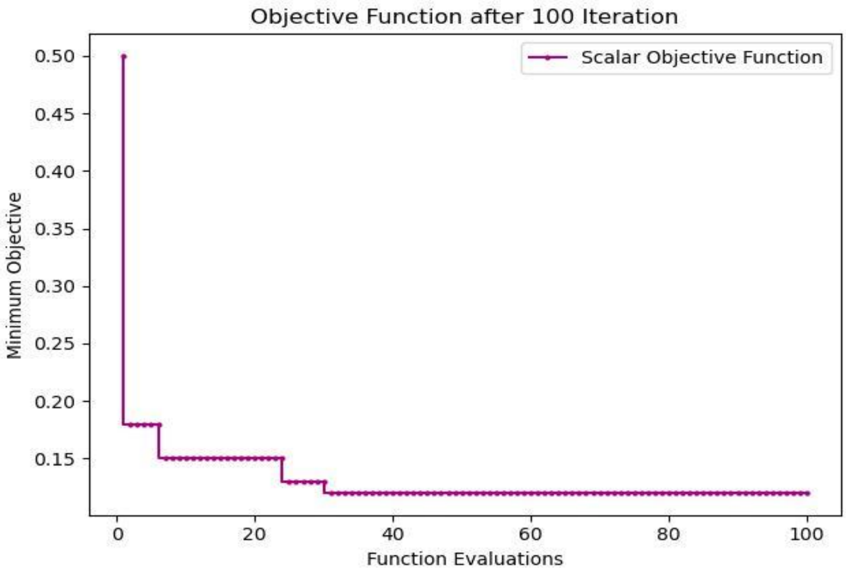

Figure 5. Minimum Objective Function after 100 Iteration

BOA Gaussian SVM, an improved version of the original Gaussian kernel SVM, achieved an accuracy of 85.33 percent on the training set and 86.2 seven percent on the test set. With an accuracy of over 70%, rule-based models also fare fairly well. Because this is actual information, there are undoubtedly many mistakes in it, thus achieving this degree of precision is a big deal.

Table 1. Accuracy Prediction from Various SVM Algorithm

Algorithm	**Accuracy**			
	Training Set	Test Set	True Positive	False Negative
Linear SVM	76.2%	71.28%	68.98%	73.78%
Polynomial SVM	81.96%	81.35%	79.96%	82.78%
Gaussian SVM	83.25%	84.45%	88.54%	80.97%
BOA Gaussian SVM	85.45%	86.49%	87.43%	86.26%
Rules based	75.68%	73.29%	62.35%	85.35%

There is a substantial disparity between the precision of true positives and the precision of false negatives in the test dataset of the rules-based model. The genuine positive accuracy is observed to be 61.31%, but the false negative accuracy is found to be 85.19%. This observation highlights the tendency of the rules-based model to exhibit excessive caution when making lane change decisions, hence failing to effectively emulate the habitual nature of lane change decisions made by actual drivers. The close proximity of the true positive and false negative rates (87.43% and 86.27%, respectively) in the BOA Gaussian SVM model indicates a substantial ability to accurately represent drivers' decision-making patterns.

The purpose of vehicle verification is to evaluate the precision of the BOA Gaussian SVM model. The experimental vehicle utilized in this study is the Zhongtong bus, specifically the LCK6105GZ model. The diverse array of sensors and assistance technology that have been integrated into the vehicle. The aforementioned technologies encompass the Mobileye system, millimeter wave radar, mobile station GPS, AutoBox dSPACE, and inertial navigation unit.

Due to the inherent challenges in obtaining accurate data regarding the vehicles present in the target lane during the course of the experiment, it has been decided that the target lane would remain unoccupied during the duration of the study. At the commencement of the experiment, the autonomous vehicle proceeds along a linear trajectory at a pre-established velocity of 28 kilometers per hour, while the preceding vehicle, denoted as P, maintains a consistent speed of 10 kilometers per hour, positioned 150 meters ahead of the experimental vehicle, referred to as E. The results of the trials are illustrated in Figure 6, 7, and 8. At the 20-second mark, point P is situated at a distance of 52 meters from point E. It is at this juncture that point E initiates the activation of its acceleration control (ACC) mode, resulting in a deceleration of its speed.

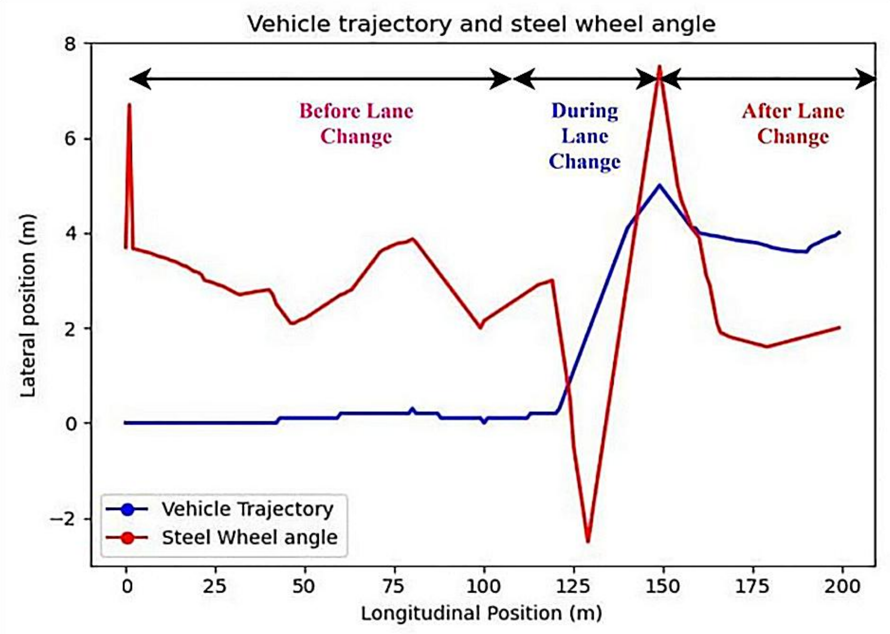

Figure 6. Vehicle Trajectory and Steel Wheel Angle

Figure 7. Vehicle Trajectory and Steel Wheel Angle of Both Ego Vehicle and Preceding Vehicle

When the timer hits 29.5 seconds, the car has reached a speed of 18 kilometers per hour, and the distance between them is 18 meters. At this point, the BOA Gaussian SVM lane change decision-making model comes to the conclusion that a lane change should take place. After that, the driverless car makes the lane change without incident, and the speed of the car gradually increases until it reaches the desired speed of 28 kilometers per hour.

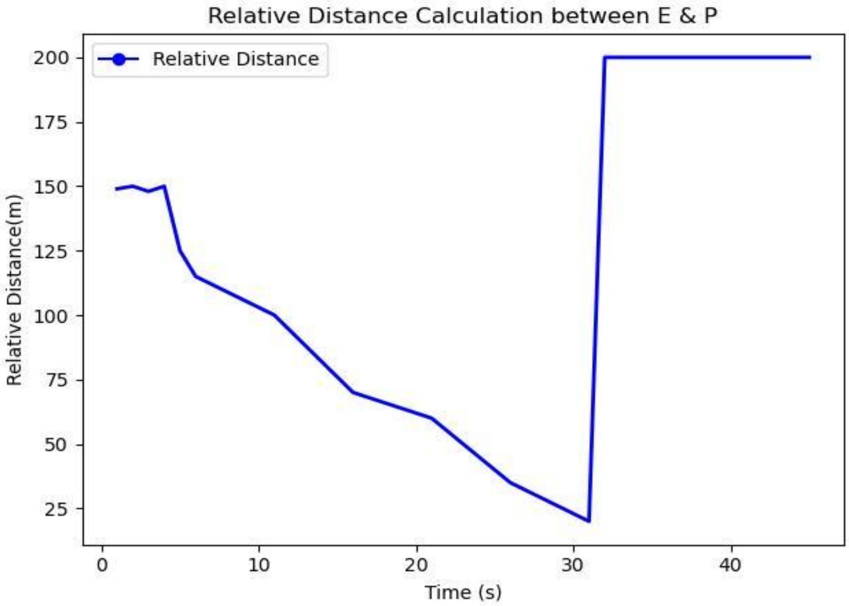

Figure 8. Relative Distance

In instances where there are no obstructions present in the vehicle's path, the target speed vset is adjusted to match the speed of point P. Additionally, the radar's maximum detection range, which spans 204.7 meters, is configured to correspond to the distance separating points E and P. The presence of Figure 9 and 10 illustrates this phenomenon. The experimental results offers ubstantiation for the accuracy and validity of the BOA Gaussian SVM lane change decision-making model.

6. Conclusion

The primary topic of this study is the quandary of autonomously determining lane change judgments. An autonomous lane change model is produced in the first step of the approach by first doing an analysis of the lane change process. This step is followed by further development of the model. We presented linked features that have an effect on autonomous lane changes based on an investigation of the advantages, safety, and tolerance of lane changes. Specifically, we looked at how these factors interact with one another. Following this, this study developed a Gaussian-SVM-based autonomous lane change decision model using Bayesian Optimization Algorithm (BOA). This model is designed to address the complex challenges associated with the lane change process, which involve multiple parameters and nonlinearity. Simulation and testing done on real automobiles are used to evaluate the model that has been provided in order to determine whether or not it is feasible. This paper proposes a novel model for deciding when and whether to switch lanes. However, due to the intricacy of actual traffic and road conditions, the viability of the model needs to be further investigated before it can be used.

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