electronics

MDPI

Article

Recognition of Lane Changing Maneuvers for Vehicle Driving Safety

Yuming Wu [1], Lei Zhang [2,*], Ren Lou [3] and Xinghua Li [4]

1 Department of Physics, Shanghai University, Shanghai 200444, China
2 Department of Traffic Information and Control Engineering, Tongji University, Shanghai 200092, China
3 Zhejiang Scientific Research Institute of Transport, Hangzhou 310023, China
4 College of Transportation Engineering, Tongji University, Shanghai 201804, China
* Correspondence: reizhg@tongji.edu.cn

Abstract: The increasing number of vehicles has caused traffic conditions to become increasingly complicated in terms of safety. Emerging autonomous vehicles (AVs) have the potential to significantly reduce crashes. The advanced driver assistance system (ADAS) has received widespread attention. Lane keeping and lane changing are two basic driving maneuvers on highways. It is very important for ADAS technology to identify them effectively. The lane changing maneuver recognition has been used to study traffic safety for many years. Different models have been proposed. With the development of technology, machine learning has been introduced in this field with effective results. However, models which require a lot of physical data as input and unaffordable sensors lead to the high cost of AV platforms. This impedes the development of AVs. This study proposes a model of lane changing maneuver recognition based on a distinct set of physical data. The driving scenario from the natural vehicle trajectory dataset (i.e., HighD) is used for machine learning. Acceleration and velocity are extracted and labeled as physical data. The normalized features are then input into the k-nearest neighbor (KNN) classification model. The trained model was applied to another set of data and received good results. The results show that based on the acceleration features, the classification accuracy of lane keeping (LK), lane changing to the left (LCL) and lane changing to the right (LCR) is 100%, 97.89% and 96.19%.

Keywords: lane changing maneuver; acceleration; HighD; k-nearest neighbor classification (KNN)

Citation: Wu, Y.; Zhang, L.; Lou, R.; Li, X. Recognition of Lane Changing Maneuvers for Vehicle Driving Safety. *Electronics* **2023**, *12*, 1456. https://doi.org/10.3390/electronics12061456

Academic Editor: Rameez Asif

Received: 25 January 2023
Revised: 20 February 2023
Accepted: 15 March 2023
Published: 19 March 2023

1. Introduction

As the number of vehicles increases worldwide, traffic conditions are more and more complex in terms of safety. On 23 December 2005, a grave rear-end collision occurred on a highway in Beijing, China. Twenty-four people died in this collision. Forty people died in Senegal because of a traffic accident on 8 January 2023. According to the World Health Organization (WHO), approximately 1.3 million people die each year as a result of road traffic crashes. Between 20 and 50 million more people suffer non-fatal injuries, with many incurring a disability as a result of their injury.

Emerging autonomous vehicles (AVs) have the potential to significantly reduce crashes [1]. Driven by cutting-edge technologies such as sensor technology and artificial intelligence, the development of AVs has entered a new stage. There are different paths for AVs to develop. Among them, the advanced driver assistance system (ADAS) has received widespread attention. With advanced sensors and intelligent video systems, ADAS alerts the driver to potential traffic hazards or even takes over control to prevent a collision. Lane keeping and lane changing are two basic maneuvers on the road. In comparison with lane keeping maneuvers, lane changing maneuvers present more dangers and risks to traffic safety. It is also more likely for lane changing maneuvers to lead to traffic accidents. In the U.S., the percentage of fatal accidents associated with lane changing increased from

18% to 23.6% from 2005 to 2014 [2]. Traffic data in recent years also show that 23.91% of traffic accidents are caused by lane changing [3]. In order to avoid traffic accidents caused by lane changing maneuvers and improve traffic safety, it is very important for ADAS technology to effectively identify vehicles' lane changing maneuvers.

Research has examined various aspects of lane change maneuvers, including lane change frequency, speed, acceleration, headway and steering angle during lane changes [4,5]. They are used together as inputs for models in most cases. However, the cost of all the equipment needed to detect all these features, such as sensors, is high. Moreover, the cost of AV platforms is one barrier to large-scale market adoption which impedes AV development [1]. Although it is believed that devices such as sensors will be more affordable in the future, it is also worth considering a new method to achieve similar results using less data.

Connected vehicles (CVs) will allow for the analysis of individual drivers' behavior with their proliferation on the road. However, since CV market penetration is currently low, researchers can only observe the behavior of a small sample of drivers in a traffic stream, which may not be representative of all drivers. By using archived high-resolution vehicle trajectory data, this study develops a framework for recognizing lane changing maneuvers based on single physical data. To build a feasible framework, this study first reviews lane changing maneuver studies in the past. Driving scenarios from real-world trajectory datasets are examined next. Then, the method of data extracting and processing is described. The algorithm and the establishment of the model are also described in detail. The results are then presented and discussed. The last section provides the conclusions.

2. Literature Review

Analysis of driving trajectories is one of the heated topics in the field of traffic safety. Mauriello et al. explored driving behavior on horizontal curves of two-lane rural highways based on a driving simulator experiment. Six major classes and twenty-one sub-classes were defined [6]. In addition, their study pointed out that driving trajectories are a promising surrogate measure of safety as highlighted by the correlation between the trajectories identified as dangerous and the radii of the curves. Another study analyzed driving trajectories with little lane discipline [7]. By studying lateral distance-keeping behavior, lane keeping behavior and the lateral behavior of vehicles, the article explored the non-lane-based behavior of traffic. The researchers also compared lateral clearances of various vehicle types in the study.

Lane keeping and lane changing are maneuvers that commonly happen in driving trajectories. Galante et al. studied lane keeping by analyzing the mean and standard deviation of lateral position [8]. They demonstrated several effective treatments which were strongly advised to be tested on the real road. Wonho Suh et al. developed an index related to lane keeping named Deviation of Lateral Placement (DLP) which represents a driver's steering behavior along a given section of highway [9]. The index was able to demonstrate a vehicle's overall lateral stability. Among the studies on lane changing, some researchers have used lateral position and vehicle heading angle to study lane variation [10]. They created a new ADAS system to support drivers when overtaking cyclists.

Lane changing maneuvers' recognition has been used to study traffic safety for many years. Many studies have focused on this area to test new theories, improve the accuracy of lane change identification and reduce traffic accidents. The Gipps decision method model based on logic rules was the first to be proposed [11]. However, this model was too idealistic to be applied in practice. Researchers have optimized and improved the classical model from different aspects and built new models, such as MITSIM and CORSIM [12,13]. Other models have also been proposed by researchers. One group of researchers built an integrated lane changing model combining a sine function and a constant velocity migration function [14]. A multilevel analysis model of vehicles' longitudinal and lateral acceleration during lane change was established as well [15]. Other researchers set up a safe lane-change model based on a quintic polynomial trajectory [16].

With the development of technology, researchers used new methods to analyze lane change maneuvers. Machine learning was proven to be useful for estimating, classifying and predicting lane changing maneuvers. Using steering wheel angle and angular velocity as inputs to an HMM model, researchers developed an algorithm for recognizing lane changes [17]. Based on their method, the accuracy of lane change left (LCL), lane change right (LCR) and lane keeping (LK) classifications was 84%, 88% and 94%, respectively. Other researchers established a decision model of an autonomous lane change by analyzing the influencing factors of autonomous lane change [18]. Additionally, with the help of a support vector machine (SVM), they solved the multi-parameter and nonlinear problems. Another RVM model used 200 sensor signals [19]. It was able to classify a driver's intentions three seconds before the actual lane change occurred. With long short-term memory networks (LSTM) and deep belief networks (DBN), researchers modeled both lane keeping and lane changing [20]. Compared with the classical model, this model could accurately estimate both lane keeping and lane change maneuvers. The model had higher lane-change prediction accuracy as well. Though all these methods have achieved good results, none of them have used a distinct set of physical data as input.

Meanwhile, vehicle status data are also derived from a variety of sources. Researchers used different methods to obtain naturalistic driving data (NDD). One group of researchers developed a data collection platform called POSS-V (PKU Omni Smart Sensing - Vehicle) to collect real human driving data in urban street scenarios [21]. The POSS-V included GPS/IMU, a steering angle sensor and a panoramic camera. Other researchers made use of UAVs to collect natural driving-track data [22]. A fixed-base driving simulator was also utilized by researchers [23]. Compared with collecting data individually or using virtual data, it is more convenient and efficient to use datasets from the real world. Both NGSIM and HighD [24], two high-resolution natural vehicle-trajectory datasets, had a good effect on machine learning [25,26]. However, among the lane-changing maneuver recognition models which were based on a dataset, a distinct set of physical data was not used as the input for machine learning. Therefore, the study aims to build a machine-learning model to identify vehicle lane change maneuvers which are based on a distinct set of physical data from the HighD dataset.

3. Driving Scenario

3.1. HighD Dataset

This study makes use of the driving scenario from the HighD trajectory dataset [19]. Using drone videography, the HighD dataset collected naturalistic vehicle-driving data on German highways. The dataset consists of 60 recordings from six locations (labeled 1–6) over 16.5 h with a frame rate of 25 Hz. Four-lane and six-lane highways with hard shoulders on the outer edges and dividing medians are included in the dataset. Data are recorded on highways without a speed limit or with a limit of 120 km/h and 130 km/h. Data collection took place between 8:00 a.m. and 7:00 p.m. on weekdays. The dataset contains 110,000 vehicles (81% cars and 19% trucks). They cover a total distance of 45,000 km. A total of 11,000 lane changes are recorded in it and 5600 of them were visible. The researchers of the HighD dataset also applied algorithms and post-processing to retrieve the position, velocity and acceleration in the x and y directions. Vehicle ID and lane ID are contained in the dataset as well.

Compared to the well-known NGSIM dataset, the HighD dataset not only contains more data but also has higher diversity. What is more, false collision and unrealistic values in the NGSIM dataset led the study to the HighD dataset.

3.2. Data for Study

In the study, only the No. 36 data file in the dataset is used to train for the recognition model. The No. 36 data are recorded in position 1. The data include 2543 vehicles (1955 cars and 588 trucks). A total of 372 vehicles performed lane changes. All the record data in No.36 are used for training. The simultaneous presence of cars and trucks in the dataset helps capture driver behavior in real-world mixed traffic. The highway in the video has six lanes. This is demonstrated in Figure 1.

Figure 1. Highway of No.36 data.

4. Methodology

This study focuses on establishing a method of lane changing recognition based on physical data. The process can be divided into two parts: data extraction and processing, and machine learning. The study analyzed the process of lane changing maneuvers. Combined with the logic from other researchers, the study extracted vehicle lane change trajectory data from the dataset. At the same time, the study labeled the lane change direction on data by lane ID. Features were then extracted and normalized. The study set up a k-nearest neighbor (KNN) classification model for lane-changing maneuver recognition. The introduction of KNN and the reason to utilize it are declared soon afterward. At the end of this section, the model is established step by step.

4.1. Data Extraction and Processing

In order to identify vehicle lane change maneuvers through machine learning, the study needed to extract and process lane change data from the dataset.

According to the characteristics of lane change maneuvers, the study divided the process of vehicle lane change into four stages:

1. Intention generation: The driver decides to change lanes according to the driving environment (following distance, etc.);
2. Land changing preparation: The vehicle is ready to change lanes. It approaches the line of the target lane. The moving distance which is perpendicular to the road (lateral direction or y-axis) increases;
3. Lane change: The driver starts to change lanes to the left or right. The vehicle passes the lane line and enters an adjacent lane;
4. End of lane changing: The vehicle moves away from the lane line. The moving distance perpendicular to the road reduces. The vehicle follows the new lane normally.

Figure 2 shows four stages of vehicle lane changing process.

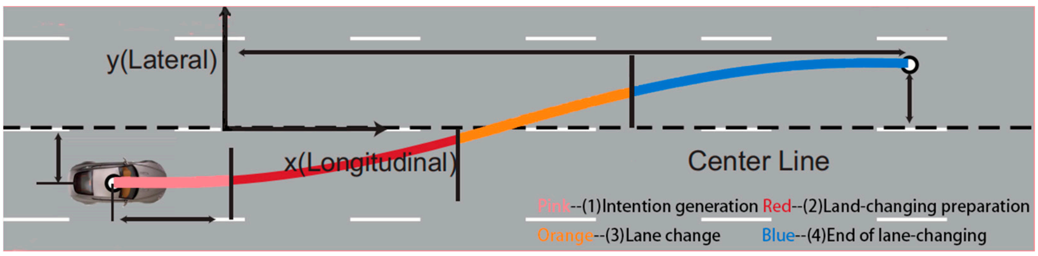

Figure 2. Lane changing process.

The dataset contains vehicle ID and matched lane ID. In that case, when the vehicle ID remains the same but the lane ID changes, there will be a lane changing maneuver. If both vehicle ID and lane ID remain the same, there will be a lane keeping maneuver. The data which share the same vehicle ID and lane ID will be extracted directly as the lane keeping maneuver data. The logic from other researchers is introduced to extract the lane changing data. A lane change begins and ends when the longitudinal moving distance of the vehicle is less than 0.1 m within 10 frames [22]. Based on this logic, the study extracts the lane changing data from the dataset. Therefore, the lane changing data extraction method in the study is as follows:

1. According to the vehicle ID and lane ID, the study determines the trajectory data with lane keeping maneuvers or lane changing maneuvers in the dataset;
2. If the maneuver is lane keeping, all the data with the same ID will be extracted;
3. If the maneuver is lane changing, only the data on which the longitudinal moving distance of the vehicle is less than 0.1 m within 10 frames will be extracted;
4. Velocity and acceleration are extracted as the most basic physical data.

Figure 3 shows the lane changing data that will be extracted from the dataset. All the data in the list with red borders are extracted as lane changing data because their lane ID changed and their longitudinal moving distance is more than 0.1 m within 10 frames, as shown in the list with blue borders.

frame	id	laneId	xVelocit	yVelocit	xAccelera	yAccelera	x	y	frontSigh	backSight	preceding	preceding	following	leftPrece	leftAlong	leftFollo	rightPrec	rightAlor	rightFoll	width	height	dhw	thw	ttc
167	7	3	-34.24	-0.65	0.26	-0.09	52.16	7.41	53.76	358.62	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
168	7	3	-34.23	-0.65	0.26	-0.09	50.79	7.38	52.35	360.04	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
169	7	3	-34.22	-0.66	0.26	-0.09	49.43	7.36	50.93	361.45	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
170	7	3	-34.21	-0.66	0.26	-0.09	48.06	7.33	50.02	362.36	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
171	7	3	-34.2	-0.66	0.27	-0.08	46.67	7.3	48.51	363.88	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
172	7	3	-34.19	-0.67	0.27	-0.08	45.3	7.28	47.14	365.2	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
173	7	3	-34.18	-0.67	0.27	-0.08	43.92	7.25	45.78	366.5	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
174	7	3	-34.17	-0.67	0.27	-0.08	42.55	7.22	44.42	367.87	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
175	7	3	-34.16	-0.67	0.27	-0.08	41.19	7.2	43.05	369.23	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
176	7	3	-34.14	-0.68	0.28	-0.08	39.82	7.17	41.69	370.6	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
177	7	3	-34.13	-0.68	0.28	-0.08	38.46	7.14	40.32	371.96	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
178	7	3	-34.12	-0.68	0.28	-0.08	37.09	7.12	38.96	373.33	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
179	7	3	-34.11	-0.68	0.28	-0.08	35.73	7.09	37.59	374.69	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
180	7	3	-34.1	-0.69	0.28	-0.08	34.36	7.06	36.23	376.06	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
181	7	3	-34.09	-0.69	0.28	-0.08	33	7.03	34.87	377.42	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
182	7	3	-34.08	-0.69	0.29	-0.08	31.64	7.01	33.55	378.73	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
183	7	3	-34.07	-0.69	0.29	-0.08	30.28	6.98	32.14	380.15	0	0	9	0	0	20	0	0	19	4.85	1.92	0	0	0
184	7	2	-34.05	-0.7	0.29	-0.07	28.91	6.95	30.72	381.56	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
185	7	2	-34.04	-0.7	0.29	-0.07	27.56	6.93	29.46	382.83	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
186	7	2	-34.03	-0.7	0.29	-0.07	26.2	6.9	28.09	384.19	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
187	7	2	-34.02	-0.7	0.29	-0.07	24.84	6.87	26.68	385.61	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
188	7	2	-34.01	-0.71	0.29	-0.07	23.48	6.84	25.37	386.92	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
189	7	2	-34	-0.71	0.29	-0.07	22.12	6.81	24	388.28	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
190	7	2	-33.98	-0.71	0.29	-0.07	20.76	6.79	22.64	389.65	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
191	7	2	-33.97	-0.72	0.3	-0.07	19.4	6.76	21.27	391.01	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
192	7	2	-33.96	-0.72	0.3	-0.07	18.04	6.73	19.91	392.38	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
193	7	2	-33.95	-0.72	0.3	-0.07	16.69	6.7	18.6	393.69	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
194	7	2	-33.94	-0.72	0.3	-0.07	15.32	6.67	17.18	395.11	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
195	7	2	-33.92	-0.73	0.3	-0.07	13.96	6.64	15.82	396.47	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
196	7	2	-33.91	-0.73	0.3	-0.07	12.6	6.61	14.5	397.79	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
197	7	2	-33.9	-0.73	0.3	-0.07	11.23	6.58	13.09	399.2	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
198	7	2	-33.89	-0.74	0.3	-0.07	9.87	6.55	11.72	400.57	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
199	7	2	-33.88	-0.74	0.3	-0.07	8.52	6.52	10.36	401.93	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
200	7	2	-33.86	-0.74	0.3	-0.07	7.16	6.49	8.99	403.29	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
201	7	2	-33.85	-0.74	0.3	-0.07	5.82	6.46	7.68	404.61	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
202	7	2	-33.84	-0.75	0.3	-0.07	4.48	6.44	6.37	405.86	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
203	7	2	-33.83	-0.75	0.3	-0.07	3.13	6.41	5.05	407.11	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
204	7	2	-33.82	-0.75	0.3	-0.07	1.78	6.38	3.64	408.52	0	0	19	0	0	9	0	0	0	4.85	1.92	0	0	0
1	8	7	31.65	0	0.17	0	139	25.95	271.04	141.38	30.34	4	10	3	0	11	0	0	14	7.18	2.5	138.21	4.36	105.49
2	8	7	31.66	0	0.18	0	140.16	25.95	269.73	142.7	30.34	4	10	3	0	11	18	0	14	7.18	2.5	138.15	4.36	104.7

Figure 3. The extracted partial lane-changing data.

After extraction, the study labels the lane change direction on data by lane ID. It is important to note that the vehicles in the dataset are traveling in different directions. Figure 4 shows the lane ID in a different location [27]. The number of lane IDs is in order from top to bottom. The vehicle which drives on the upper road lane directs to the negative x-axis direction as demonstrated in Figure 1. On the contrary, the vehicle on the lower road drive directs in the positive x-axis direction. Therefore, on the upper road, when the lane with a small ID changes to the lane with a large ID, the vehicle changes lanes to the left. In contrast, on the upper road, such a situation means lane changing to the right. Hence the data are labeled as 'LCL' (lane change to left), 'LCR' (lane change to left) or 'LK' (lane keeping).

Location ID ⟶	1	2	3	4	5	6
velocity Limit [km/h]	120	–	130	–	–	–
Upper Road	LANE ID					
Lane 0 (acc. lane)	–	–	–	–	–	2
Lane 1 (right)	2	2	2	2	2	3
Lane 2	3	3	3	3	3	4
Lane 3	4	–	4	4	–	5
Lower Road	LANE ID					
Lane 1 (right)	8	6	8	8	6	9
Lane 2	7	5	7	7	5	8
Lane 3	6	–	6	6	–	7

Figure 4. Lane ID.

Meanwhile, the study extracts the features of vehicle trajectory data and normalizes them for KNN model training. Driving profiles of data are mostly similar whether it is lane keeping or lane changing. The study chooses several representative profiles as features of vehicle trajectory data. The maximum value, average value, skewness and kurtosis of acceleration and velocity are extracted in the x and y directions from speed and acceleration, respectively. They are shown in Equations (1)–(4).

$$MAX = \max(a) \tag{1}$$

$$Mean = \frac{a_1 + a_2 + \cdots + a_n}{n} \tag{2}$$

$$Skewness = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} [(\frac{x_\mathrm{i} - \mu}{\sigma})^3] \tag{3}$$

$$\text{Kurtosis} = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} [(\frac{x_\mathrm{i} - \mu}{\sigma})^4] \tag{4}$$

μ represents the mean value and σ represents the standard deviation.

All four sets of features need to be normalized. If the original features vector is $\{(x_{i1}, x_{i2}, \ldots, x_{in})\}_{i=1}^{m}$, then the normalized features vector will be $\{(x'_{i1}, x'_{i2}, \ldots, x'_{in})\}_{i=1}^{m}$, as shown in Equation (5).

$$x'_{ij} = \frac{x_{ij}}{M_j} \ \ M_j = \max_{i=1,2,\ldots,m} x_{ij} - \min_{i=1,2,\ldots,m} x_{ij} \tag{5}$$

In that case, the study obtains the two groups of normalized speed features and acceleration features as two different inputs for the model.

4.2. KNN

Currently, many algorithms are used in the identification and prediction of lane change maneuvers. The HighD dataset used in this article has a large amount of data. Therefore, the study adopts a simple and effective algorithm, k-nearest Neighbor algorithm, which is suitable for supervised learning.

K-nearest neighbor algorithm is a nonparametric statistical method mainly used for classification and regression. The KNN algorithm is one of the simplest algorithms in all machine learning algorithms. It is a lazy learning algorithm. Furthermore, this instance-based algorithm is very simple and effective. Given a training set D and a test object $z = (x', y')$, the algorithm computes the distance $d\ (x', x)$ between z and all the training objects $(x, y) \in D$ to determine its nearest neighbor list by majority-voting rule as shown in Equation (6). A high-level summary of nearest neighbor classification is shown in Figure 5 [28].

$$y' = \underset{v}{\text{argmax}} \sum_{(x_i, y_i) \in D_z} I(v = y_i) \tag{6}$$

Input: D, the set of k training objects, and test object $z = (\mathbf{x}', y')$

Process:

Compute $d(\mathbf{x}', \mathbf{x})$, the distance between z and every object, $(\mathbf{x}, y) \in D$.

Select $D_z \subseteq D$, the set of k closest training objects to z.

Output: $y' = \underset{v}{\text{argmax}} \sum_{(\mathbf{x}_i, y_i) \in D_z} I(v = y_i)$

Figure 5. The k-nearest neighbor classification algorithm.

Then, the KNN classification model of this study is established step by step.

1. Input: The normalized features such as maximum value, average value, skewness and kurtosis from horizontal and vertical directions (i.e., x and y directions) are obtained through data extraction and processing. They are the input for the model as shown in Equation (7).

$$X_{Input} = (x_{MAX}, y_{MAX}, x_{Mean}, y_{Mean}, x_{\text{Skewness}}, y_{\text{Skewness}}, x_{\text{Kurtosis}}, y_{\text{Kurtosis}}) \tag{7}$$

A group of the normalized lane-keeping speed features and a group of the normalized lane-changing acceleration features are shown in Figure 6. They are samples of input;

xvelocity max	xvelocity max	xvelocity mean	yvelocity mean	xvelocity skewness	yvelocity skewness	xvelocity kurtosis	yvelocity kurtosis	label
1. 298997511	0. 075783272	1. 201627282	0. 621068984	45. 74205352	0. 183670041	30. 6134963	0. 165586795	LK
xaccleration max	xaccleration max	xaccleration mea	yaccleration mea	xaccleration skewnes	yaccleration skewnes	xaccleration kurtosi	yaccleration kurtosi	label
0. 347336382	2. 14626995	0. 140952087	1. 24077555	0. 203729898	0. 219144398	0. 018761728	1. 916855823	LCR

Figure 6. Two samples of input.

2. Distance: KNN model needs to calculate the distance between the test object and all the training objects. The study uses Euclidean distance to measure the absolute distance between two sample points in multidimensional space as Equation (8) showed. Thanks to the normalization, the Euclidean distance will not be dominated by variables with a wide range.

$$L = \sqrt{\sum_{n=1}^{N} (X_{Input1} - X_{Input2})^2} \tag{8}$$

3. K value: After obtaining the distance, the KNN algorithm selects K training objects that are closest to the test object for classification based on the majority-voting rule. Choosing an appropriate K value is important. If the K value is too small, the model will become complicated and overfitting. On the other hand, if the K value is too large, the approximate error will increase. In the study, the value of K is determined by cross-validation. Figure 7 shows partial values of K and cross-validation accuracy;

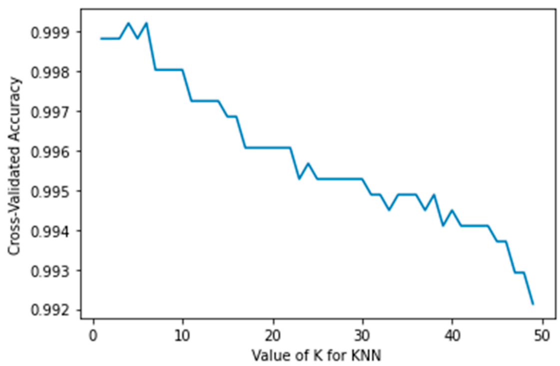

Figure 7. Partial values of K and cross-validation accuracy.

4. Training and Validating: A dataset was split in 80:20 proportions for model training and accuracy testing. The trained model is then tested on another set of data.

5. Results

Because of the HighD dataset's diversity, the study tested the trained model on other data from the dataset. The model in the study shows good lane keeping and lane change recognition ability. In the case of lane change, considering only speed or acceleration, the recognition accuracy of the model is 100%. Meanwhile, the model can identify 324 out of 332 lane change trajectories by acceleration only. Considering only speed, 315 lane change trajectories are recognized by the model. Table 1 demonstrates the accuracy rates of lane keeping recognition and lane change recognition when only speed and acceleration are considered. In addition, a combination of lateral acceleration and lateral velocity, which is often used by researchers, is introduced for comparison.

Table 1. Accuracy of lane keeping and lane change identification.

Input	Lane Keeping (LK)	Lane Changing (LC)
Only acceleration	100%	97.59%
Only velocity	100%	94.88%
Lateral acceleration and velocity	100%	100%

It can be seen that models can accurately identify the lane keeping maneuver in all three cases. In the recognition of the lane changing maneuver, the model with a combination of lateral acceleration and lateral velocity is still very accurate. The model with acceleration and the model with speed achieve fine results as well. Among all the features of the input, skewness seems to have a good effect in distinguishing lane change from lane keeping maneuvers. In lane keeping data, the normalized value of x acceleration is from 0.002777 to 6.478679, with a mean of 0.727666. The normalized skewness value of y acceleration is from 0.014515 to 1.143730, with a mean of 0.156184. In contrast, in lane changing data the normalized value of x acceleration is from 0.000068 to 2.649308, with a mean of 0.399693. The normalized skewness value of y acceleration is from 0.014888 to 1.333985, with a mean of 0.508121. Such a difference can be clearly seen in Figure 8.

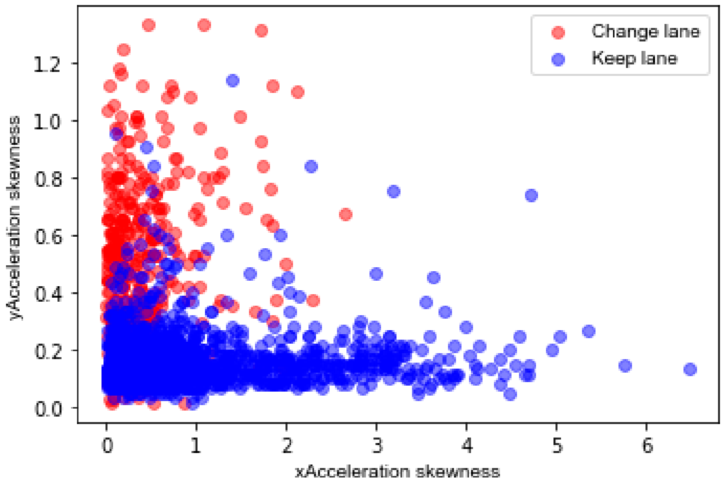

Figure 8. Skewness of acceleration.

In addition, the study also explores the model's identification accuracy of lane change direction. This is demonstrated in Table 2.

Table 2. Accuracy of lane-change direction identification.

Input	Lane Changing to Left (LCL)	Lane Changing to Right (LCR)
Only acceleration	97.98%	96.19%
Only velocity	36.91%	51.08%

In the identification of lane change direction, a model with acceleration can still maintain excellent accuracy. Such a result proves that the model proposed in the study can feasibly identify lane changing maneuvers with only one distinct set of physical data. With only velocity, the model is unable to recognize lane changing direction. The reason is that the features selected in the study do not show an obvious difference between LCL and LCR when only speed is considered.

Therefore, with only acceleration, the model can effectively and accurately identify lane changing and lane keeping maneuvers. Lane changing direction can also been recognized by this model. The model with velocity is able to identify lane changing and lane keeping maneuvers as well. However, further research is needed for the model with velocity to recognize lane changing direction.

6. Conclusions

Traffic conditions are more and more complex in terms of safety with the number of vehicles increasing worldwide. Several researchers have studied driving trajectories. Lane keeping and lane changing are two basic maneuvers of driving trajectories on the highway. They are discussed in many articles. It is one of the keys for AVs and their ADAS to recognize lane keeping and lane changing maneuvers in order to reduce crashes on the road. Over the years, different models have been proposed in the field of lane change recognition. Moreover, with the development of technology, machine learning has been introduced to this field with good results. However, these studies have ignored the possibility of recognizing highway lane-maneuvers based on a distinct set of physical data. This study could reduce the costs which hold back the development of autonomous vehicles before the appearance of an affordable AVs platform.

By utilizing a driving scenario from the HighD dataset, the study proposes a model for lane change identification based on physical data. The study focuses on the identification of lane changing maneuvers of vehicles through a distinct set of physical data such as acceleration or speed. Moreover, the study goes further. Lane-changing direction recognition is also added to the model.

Then, the driving scenario is briefly introduced. The HighD dataset and the data file used for training are also presented. The methodology is proposed next. The study analyzes the characteristics of vehicle lane change maneuvers. Lane changing trajectory data in the dataset is extracted based on vehicle ID and lane ID, and the logic comes from other researchers. These data are labeled with lane changing directions. Four features of physical data are extracted and normalized subsequently. Considering the labeled data and simplicity, the study chose supervised KNN algorithms, which are often used for lane change recognition and prediction. The KNN algorithms and model established are described in detail.

Due to the diversity of this dataset, the study uses another set of data from the HighD dataset to validate the model. The result is fine. With acceleration or velocity, the model's accuracy in recognizing lane keeping and lane changing is close to or higher than 95%. The model with speed does not perform well on lane-changing direction recognition. However, the performance of the model with acceleration is still excellent. The model's accuracy of recognizing lane changing direction is higher than 96%.

Nevertheless, the presented research is not without limitations, and there is the possibility for study to develop. The speed and acceleration in the HighD dataset are not captured directly by sensors. They are retrieved by algorithms and post-processing. Besides velocity and acceleration, steering angle and other physical data are also worth studying for lane changing recognition. The SVM model and LSTM model are expected to be introduced. They will upgrade the study's model to be more precise and practical. The model of this study is looking forward to being validated by data from real-world sensors as well.

Author Contributions: Conceptualization, L.Z.; methodology, Y.W.; software, Y.W.; validation, Y.W., L.Z., R.L. and X.L.; formal analysis, Y.W.; investigation, Y.W. and L.Z.; resources, Y.W.; data curation, Y.W.; writing—original draft preparation, Y.W.; writing—review and editing, Y.W., L.Z., R.L. and X.L.; visualization, Y.W.; supervision, L.Z.; project administration, L.Z.; funding acquisition, L.Z. All authors have read and agreed to the published version of the manuscript.

Funding: The work was also sponsored by the Key R&D Program of Zhejiang Province, China (No. 2021C01011).

Data Availability Statement: The data are not publicly available due to the data provider's request for confidentiality of the data and results.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Fagnant, D.J.; Kockelman, K. Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers and Policy Recommendations. *Transp. Res. Part A Policy Pract.* **2015**, *77*, 167–181. [CrossRef]
2. Kim, I.-H.; Bong, J.-H.; Park, J.; Park, S. Prediction of Driver's Intention of Lane Change by Augmenting Sensor Information Using Machine Learning Techniques. *Sensors* **2017**, *17*, 1350. [CrossRef]
3. Chen, T.; Shi, X.; Wong, Y.D. A lane-changing risk profile analysis method based on time-series clustering. *Phys. A Stat. Mech. Its Appl.* **2021**, *565*, 125567. [CrossRef]
4. Schmidt, K.; Beggiato, M.; Hoffmann, K.H.; Krems, J.F. A Mathematical Model for Predicting Lane Changes Using the Steering Wheel Angle. *J. Saf. Res.* **2014**, *49*, 85.e1–90. [CrossRef]
5. Sun, D.J.; Elefteriadou, L. Lane-Changing Behavior on Urban Streets: An "In-Vehicle" Field Experiment-Based Study: Lane-Changing Behavior on Urban Streets. *Comput.-Aided Civ. Infrastruct. Eng.* **2012**, *27*, 525–542. [CrossRef]
6. Mauriello, F.; Montella, A.; Pernetti, M.; Galante, F. An Exploratory Analysis of Curve Trajectories on Two-Lane Rural Highways. *Sustainability* **2018**, *10*, 4248. [CrossRef]
7. Bangarraju, V.S.H.; Ravishankar, K.V.R.; Mathew, T.V. Analysis of Lateral Distance Keeping Behaviour in Mixed Traffic Conditions with Little Lane Discipline. *Int. J. Traffic Transp. Eng.* **2016**, *6*, 431–443. [CrossRef]
8. Galante, F.; Mauriello, F.; Pernetti, M.; Rella Riccardi, M.; Montella, A. Effects of Traffic Control Devices on Rural Curve Lateral Position. *Transp. Res. Rec.* **2022**, *2676*, 162–180. [CrossRef]
9. Suh, W.; Park, P.Y.-J.; Park, C.H.; Chon, K.S. Relationship between Speed, Lateral Placement, and Drivers' Eye Movement at Two-Lane Rural Highways. *J. Transp. Eng.* **2006**, *132*, 649–653. [CrossRef]
10. Brijs, T.; Mauriello, F.; Montella, A.; Galante, F.; Brijs, K.; Ross, V. Studying the Effects of an Advanced Driver-Assistance System to Improve Safety of Cyclists Overtaking. *Accid. Anal. Prev.* **2022**, *174*, 106763. [CrossRef]
11. Gipps, P.G. A Model for the Structure of Lane-Changing Decisions. *Transp. Res. Part B Methodol.* **1986**, *20*, 403–414. [CrossRef]
12. Ahmed, K.I. Modeling Drivers' Acceleration and Lane Changing Behavior. Ph.D. Dissertation, Department of Civil and Environmental Engineering, MIT, Cambridge, MA, USA, 1999.
13. Ratrout, N.T.; Rahman, S.M.; Box, K. A comparative analysis of currently used microscopic and macroscopic traffific simulation software. *Arab. J. Sci. Eng.* **2009**, *34*, 121–133.
14. Yang, Z.; Qi, Z.; Huang, Y. Research on free Lane Change Trajectory Planning of Intelligent Vehicles. *J. Chongqing Jiaotong Univ. (Nat. Sci. Ed.)* **2013**, *32*, 520–524.
15. Ouyang, K.; Wang, Y.; Li, Y.; Zhu, Y. Lane Change Decision Planning for Autonomous Vehicles. In Proceedings of the 2020 Chinese Automation Congress (CAC), Shanghai, China, 6–8 November 2020; pp. 6277–6281.
16. Liu, Y.; Wang, Y.; Wang, X.; Tao, C. A Model for Safe Lane Changing of Connected Vehicles Based on Quintic Polynomial Trajectory Planning. In Proceedings of the 2022 7th International Conference on Intelligent Informatics and Biomedical Science (ICIIBMS), Nara, Japan, 24–26 November 2022; pp. 51–55.
17. Jin, L.; Hou, H.; Jiang, Y. Driver Intention Recognition Based on Continuous Hidden Markov Model. In Proceedings of the 2011 International Conference on Transportation, Mechanical, and Electrical Engineering (TMEE), Changchun, China, 16–18 December 2011; pp. 739–742.
18. Liu, Y.; Wang, X.; Li, L.; Cheng, S.; Chen, Z. A Novel Lane Change Decision-Making Model of Autonomous Vehicle Based on Support Vector Machine. *IEEE Access* **2019**, *7*, 26543–26550. [CrossRef]
19. Morris, B.; Doshi, A.; Trivedi, M. Lane Change Intent Prediction for Driver Assistance: On-Road Design and Evaluation. In Proceedings of the 2011 IEEE Intelligent Vehicles Symposium (IV), Baden-Baden, Germany, 5–9 June 2011; pp. 895–901.
20. Zhang, X.; Sun, J.; Qi, X.; Sun, J. Simultaneous Modeling of Car-Following and Lane-Changing Behaviors Using Deep Learning. *Transp. Res. Part C Emerg. Technol.* **2019**, *104*, 287–304. [CrossRef]
21. Yao, W.; Zhao, H.; Davoine, F.; Zha, H. Learning Lane Change Trajectories from On-Road Driving Data. In Proceedings of the 2012 IEEE Intelligent Vehicles Symposium, Alcal de Henares, Spain, 3–7 June 2012; pp. 885–890.
22. Zhao, L.; Xu, T.; Zhang, Z.; Hao, Y. Lane-Changing Recognition of Urban Expressway Exit Using Natural Driving Data. *Appl. Sci.* **2022**, *12*, 9762. [CrossRef]
23. Wissing, C.; Nattermann, T.; Glander, K.-H.; Hass, C.; Bertram, T. Lane Change Prediction by Combining Movement and Situation Based Probabilities. *IFAC-PapersOnLine* **2017**, *50*, 3554–3559. [CrossRef]
24. Krajewski, R.; Bock, J.; Kloeker, L.; Eckstein, L. The HighD Dataset: A Drone Dataset of Naturalistic Vehicle Trajectories on German Highways for Validation of Highly Automated Driving Systems. In Proceedings of the 2018 21st International Conference on Intelligent Transportation Systems (ITSC), Maui, HI, USA, 4–7 November 2018; pp. 2118–2125.
25. Mahajan, V.; Katrakazas, C.; Antoniou, C. Prediction of Lane-Changing Maneuvers with Automatic Labeling and Deep Learning. *Transp. Res. Rec.* **2020**, *2674*, 336–347. [CrossRef]

26. Ahmed, I.; Karr, A.F.; Rouphail, N.M.; Chase, R.T.; Tanvir, S. Characterizing Lane Changing Behavior and Identifying Extreme Lane Changing Traits. *Transp. Lett.* **2022**, 1–15. [CrossRef]
27. Kruber, F.; Wurst, J.; Chakraborty, S.; Botsch, M. Highway Traffic Data: Macroscopic, Microscopic and Criticality Analysis for Capturing Relevant Traffic Scenarios and Traffic Modeling Based on the HighD Data Set. *arXiv* **2019**, arXiv:1903.04249.
28. Wu, X.; Kumar, V.; Ross Quinlan, J.; Ghosh, J.; Yang, Q.; Motoda, H.; McLachlan, G.J.; Ng, A.; Liu, B.; Yu, P.S.; et al. Top 10 Algorithms in Data Mining. *Knowl. Inf. Syst.* **2008**, *14*, 1–37. [CrossRef]