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Lane Change Detection of Surrounding Vehicles in Dashcam Videos: A Synthesis of Methods and Challenges for Future Research

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Abstract

Lane change events are a critical focus for road safety research. Detecting the lane-changing or cut-in behavior of surrounding vehicles using dashcam video has significant potential for supporting driver behavior monitoring and timely interventions during such events. However, as this field has not yet been systematically reviewed in a dedicated literature survey, researchers often face the challenge of manually filtering through many studies with overlapping keywords to identify relevant work. To address this gap, after investing significant efforts to seek the target studies of this specific domain, this paper presents a detailed review of each recent novel study from 2019. These existing approaches were also innovatively categorized into two main directions: direct model inference and logical inference based on lane marking. Each category is analyzed to highlight the shared characteristics and key differences, offering researchers a clearer understanding of the field's current landscape. Based on the analysis, several shared limitations specific to each direction were identified, and some open challenges that need to be solved by future research were proposed from both practical application and road safety perspectives. These include the heavy reliance on manually annotated data during preprocessing, the prevalent focus on evaluating algorithms only on event-specific video clips, and the lack of connection from detection methods to road safety research, among others. Addressing these issues is critical for advancing this field and strengthening its connection with real-world safety considerations.

Keywords: lane change; cut-in; surrounding vehicle behavior; dashcam video

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1. Introduction

Lane change events are a critical focus for road safety research due to their significant role in traffic accidents. Studies of Fitch et al. (2009); Lee et al. (2004) have shown that improper lane changes contribute to 4–10% of all crashes, with factors such as driver distraction, turn signal usage, and gap misjudgment playing key roles. According to Shawky (2020), crash data analysis from 2010 to 2017 indicates that abrupt lane changes were responsible for approximately 17.0% of all severe accidents, while tailgating contributed to 11.2% of these incidents. Hence, the development of lane change detection techniques is significant for road safety improvement. From the individual driver's perspective, such techniques can be helpful to design experiments for evaluating the driver’s action and creating driver behavior profiling during the detected nearby vehicle’s lane change, e.g., eye movement tracking, reaction behavior evaluation. In addition, the surrounding vehicle’s lane change behavior can cause an abrupt decrease in headway and then be mistakenly recognized as tailgating behavior. Hence, these techniques are helpful to differentiate real tailgating from tailgating resulting from lane changes.

Liang et al. (2023) stated that previous traditional methods utilize physical variables from various sensors to detect lane change behavior, such as speed, acceleration, heading angle, yaw angle, and distances. As mentioned by Rocky et al. (2024), with the rise of deep learning, dashboard cameras have been increasingly acknowledged in academic research as an affordable and widely available tool for vehicle accident analysis, as they are now prevalent in most vehicles. Therefore, it becomes popular to utilize the scene's semantic information and visual features from dashcam videos to perform detection of dangerous lane change behaviors. CNN, LSTM, Two-Stream Networks, 3D video action recognition models, and Vision in Transformer models were gradually applied to this area and achieved better and better performance in the studies of Izquierdo et al. (2019a), (2021); Fernandez-Llorca et al. (2020); Biparva et al. (2022); Liang et al. (2023); Nalcakan and Bastanlar (2023a); Raja Mohamed et al. (2025); Chao et al. (2025). In addition to their research applications, dashcams are also becoming integral components in commercial driver safety products in regions where their use is permitted, as mentioned in the study of Ordonez and Englehardt (2024). Common use cases include providing objective evidence during accidents to expedite insurance claims and determine fault, as in the study of Hsu et al. (2020). Several insurance companies even offer premium discounts to drivers who install dashcams, recognizing their role in promoting safer driving. Moreover, dashcams are increasingly used in video-based telematics systems, which combine video data with driving analytics to monitor driver behavior, detect risky events, and offer feedback or coaching, such as in the study of Kumagai et al. (2023). This evolving field presents a promising future application area for lane change detection and other behavior analysis methods developed in academic research, bridging the gap between laboratory advances and real-world safety solutions.

However, the existing literature review, such as the one from Song and Li (2022), is relatively outdated and too broad, and does not cover the most recent advances in this specific domain of detecting surrounding vehicles' lane change events based on dashcam videos. Researchers working in this field often have to invest considerable effort in filtering out a large number of articles that, while related in appearance, differ in focus. These include studies on self-lane changes, works centered on roadside surveillance video rather than dashcam footage, and overly broad reviews on autonomous driving or intelligent automation, such as the one from Zakaria et al. (2023), etc.

To address this issue and facilitate future research in this significant domain, this work provides a synthesis of recent methods specifically targeting the detection and prediction of surrounding vehicles' lane change behaviors from dashcam videos. Furthermore, a comprehensive analysis of their respective advantages and limitations was conducted, and several promising research directions were proposed to help further development in this area, especially from practical application and road safety aspects.

2. Problem formulation

This study focuses on research conducted from 2019 to the present that utilizes dashcam video as the primary data source. Studies based on roadside surveillance footage, surrounding vehicle trajectory data, LiDAR, or other sensor modalities were excluded from consideration. The research targets explicitly the detection and prediction of behaviors, namely, lane changes, cut-ins, and lane keeping, of surrounding vehicles located in front of the ego vehicle. The goal is not to analyze the ego vehicle's behavior, but rather to assess how the driver in the ego vehicle perceives and potentially reacts to the actions of surrounding vehicles. This distinction is important, as it aligns with applications focused on driver behavior analysis and situational awareness, setting this work apart from most existing studies that primarily concentrate on ego vehicle behavior analysis.

The literature review begins in 2019, as this marks a clear shift in the field toward using appearance-based features and deep learning methods in behavior prediction, especially from dashcam perspectives. This shift is also highly related to the publication of the PREVENTION dataset from Izquierdo et al. (2019b). According to Fernandez-Llorca et al. (2020), most previous approaches relied heavily on physical and handcrafted features, instead of the visual cues from dashcam videos. They also emphasized that the number of earlier studies utilizing visual cues is surprisingly low, especially considering that humans can detect lane changes by using only visual cues.

3. Literature search

In this study, relevant literature was retrieved from 2019 through Scopus, Springer Link, IEEE Xplore, and Google Scholar. During the search process, keyword combinations such as “surrounding vehicle,” “lane change detection,” and “video” were employed. Where possible, search filters were applied to restrict results to Engineering and Computer Science fields, and only English-language journal articles and conference papers were considered.

However, due to the high similarity of keywords across related fields, for instance, "lane change" appears frequently in both surrounding vehicle and self-lane change studies, it was difficult to fully distinguish relevant literature based on keywords alone. Therefore, extensive manual screening was conducted based on abstract reading and keyword searching to exclude studies focused on self-lane change behavior, roadside monitor videos, trajectory-based predictions, LiDAR and other sensor modalities, lane detection, autonomous vehicles, and advanced driver assistance systems, as well as general review papers in these areas. This manual curation ensured that the final selection of literature remained highly aligned with the focus of this study: the automatic recognition of surrounding vehicles’ lane change behaviors based on dashcam video data.

4. Lane change maneuver inference methods

Cut-in behaviors refer to lane changes where a vehicle moves from an adjacent lane into the ego lane. Since cut-in detection is a specific case of lane change detection, existing lane change detection algorithms can also be applied to identify cut-ins. Therefore, these methods are also included in this section for introduction and analysis. Given that various studies exist, they are classified into two directions based on their methods to better conclude their advantages and disadvantages: 1. Direct model inference, and 2. Logical inference based on lane marking.

4.1. Direct model inference

Most studies in this research area align with this direction. In this context, direct model inference involves training machine learning or deep learning models, such as a CNN or sequence-based network, to directly classify driving behaviors from input data (e.g., images or video frames), without relying on hand-crafted rules or intermediate reasoning steps. For lane change detection, driving behaviors are typically categorized into three classes: no lane change, left and right lane change. For cut-in detection, behaviors are generally classified into two categories: cut-in (when a vehicle merges into the ego lane) and lane-pass (when a vehicle continues in its own lane without merging). Apart from the initial studies, which used a series of famous image classification CNN models for behavior classification based on one input image, most studies adopted models that can accept a sequence of features or frames as input and then output the behavior classification, e.g., LSTM, video action recognition models, because of their capability of capturing both spatial and temporal features.

The PREVENTION dataset is the most widely used benchmark in this direction. It comprises 356 minutes (corresponding to 540 km of driving) of data recorded in 2018 by three different drivers in both urban and highway settings, using a suite of sensors (LiDAR, radar, and cameras). The authors also provide extensive post-processed annotations for surrounding vehicles, including vehicle bounding box (Bbox), unique vehicle IDs, trajectories, lane-marking delineations, and detailed lane-change behavior labels. Each behavior label contains the target vehicle ID, the lane change direction, the start-frame, mid-frame, end-frame, and whether the turn indicator was activated.

These behavior labels are commonly utilized as prior information to prepare event-specific video clips for experiments in this research direction.

To begin with, in the study by Nalcakan and Bastanlar (2023b), LSTM models were implemented for cut-in behavior classification. The authors used vehicle detection and tracking models to obtain each vehicle’s Bbox and track them in the event-specific video clips of cut-in and lane-pass events. The tracked time-series Bbox sequence of the target vehicle defined the input of LSTM models to classify the cut-in or lane-pass behaviors. The PREVENTION dataset and BDD-100K dataset of Yu et al. (2020) were both used for model training and testing. However, only the PREVENTION dataset provides the required target vehicle ID and lane change behavior's start and end frame indexes for preparing event-specific video clips. Hence, the authors manually labeled the required prior information on the BDD-100K dataset.

Moreover, following this work, Nalcakan and Bastanlar (2023c) proposed another framework based on contrastive representation learning to detect cut-in behavior from video clips. The encoder network 3D-ResNet was trained in a self-supervised fashion with contrastive loss and then fine-tuned with cut-in/lane-pass labeled datasets. Instead of using original video frames, the input was a more straightforward image sequence where each image only included the segmentation masks of surrounding vehicles and the ego lane. The vehicle masks were obtained using Detectron2 by Wu et al. (2019), while the ego-lane segmentation method was not introduced. So, the performance of ego-lane segmentation is unknown, though it is actually significant for the following behavior classification step’s accuracy. Target vehicle identity was no longer needed for this method because the input includes all surrounding vehicles’ segmentations, instead of only the target vehicle. Consequently, it is impossible to identify which vehicle is performing the cut-in behavior because the output of the trained model is just a classification label based on the scene's representative image sequence.

Subsequently, Nalcakan and Bastanlar (2023a) enumerated two previous approaches for the lane change detection task, instead of cut-in detection. As mentioned before, one is to input the Bbox sequence into the LSTM model, and the other utilizes self-supervised contrastive video representation learning. The predictions from two branches on the target vehicle’s event-specific feature or frame sequence were ensembled using soft voting and weighted sum strategies to form the final decision.

Izquierdo et al. (2019a) explored two approaches, simple CNN, GoogleNet & LSTM, to achieve lane-change intention prediction on dashcam videos from the PREVENTION dataset. Detecting lane-change behaviors from a video needs a sequence of frames to provide the vehicles’ movement features to the models. However, the simple image classification CNN model takes only one image as input. Hence, the authors changed the input image’s three channels to contain three elements: a grayscale scene image, a target vehicle's motion history, and other vehicles' motion histories. The motion history here means that a series of detected vehicles’ contours are temporally integrated into one frame. In the second method, GoogleNet by Szegedy et al. (2015) was utilized to extract features from the input vehicle region-of-interest (ROI) to generate feature vectors for each frame. A time-series sequence of feature vectors of the vehicle ROI crop with its Bbox coordinates, representing the vehicle’s location on the frame, was input into an LSTM model for behavior classification.

This revealed two potential improvements: the implemented CNN model was too simple, and the prior information, such as the identification of the target vehicle in the video clip, needed to be labeled in advance. Hence, following that work, Izquierdo et al. (2021) conducted a follow-up study to address these issues. Several famous CNN models with higher capability and accuracy were implemented, including AlexNet, GoogleNet, SqueezeNet, and ResNets. Furthermore, to automate target vehicle identification in each frame, a Target Selection Method was introduced. This method systematically selects each detected vehicle as the candidate target and encodes its motion trajectory into the blue channel of the image. Since the model must process the same scene multiple times, once for each vehicle being evaluated as the target, the overall computational load of the pipeline is significantly increased.

Subsequently, the researchers started to focus on using video action recognition models in this area. Fernandez-Llorca et al. (2020) implemented two video action recognition models: Disjoint two-stream convolutional networks and spatiotemporal multiplier networks. A sequence of ROI images of a target vehicle and corresponding dense optical flow were used as inputs for the models' spatial and motion streams for behavior classification. The authors also explored two other video action recognition models using similar pipelines in the study of Biparva et al. (2022).

Liang et al. (2023) explored seven 3D CNN action recognition models in the study for this lane change detection task on the PREVENTION dataset. With these models, two pipelines were proposed to utilize only the appearance feature from video frames, named RGB+3DN and RGB+BB+3DN. RGB+3DN only accepts a sequence of pre-processed video frames as input to the 3D CNN modes for behavior classification. RGB+BB+3DN was inspired by the study by Izquierdo et al. (2019a). It took advantage of video frames combined with Bboxes as the input, where the red channel encodes the scene appearance in grayscale, the green channel highlights the Bbox of the target vehicle, and the blue channel represents the Bboxes of other surrounding vehicles. While RGB+3DN achieves 84.79% accuracy, the RGB+BB+3DN pipeline achieved a classification accuracy of 99.33% at the cost of a prior information requirement, the target vehicle identity. However, it is important to note that the two approaches used different datasets for training and testing, and the RGB+BB+3DN's dataset is only 17.85% the size of the RGB+3DN's dataset.

With the development of Vision in Transformer, Raja Mohamed et al. (2025) explored tackling lane change detection tasks by using Video Vision Transformers. Similar to previous methods, a sequence of 25 pre-processed video frames, including Bboxes generated for all surrounding vehicles, is input into the model for behavior classification.

In addition, Chao et al. (2025) implemented Multi-Scale Three-Stream 3D ResNets, which extract the target vehicle's centralized ROI image sequence, optical flow sequence, and depth map sequence from event-specific video clips as input for lane change event classification. A data filtering procedure was introduced to remove unreasonable samples with tiny and distorted aspect ratios in the PREVENTION dataset. During model evaluation, it was noted that Non-Lane-Change events accounted for over 85% of the test set. Although the overall accuracy reached 90.94%, the recall was 54.74%.

4.2. Logical inference based on lane marking

The methods in this direction depend heavily on the lane markings and vehicle Bboxes detected by deep learning models. These detected elements serve as key semantic features for interpreting the driving scene. Logical inference, in this context, refers to rule-based reasoning applied to each frame of dashcam video, rather than relying on model-driven classification over a sequence of features or frames. This approach tracks the relative movement of surrounding vehicles with respect to lane markings and infers behavior based on pre-defined spatial and temporal patterns. Although this direction has some notable advantages, e.g., no need for target vehicle identification and event-specific video preparation, this direction has not received sufficient attention in the research community.

Zhang et al. (2022) implemented an improved version of Mask R-CNN by He et al. (2022) to detect the Bbox of vehicles, and used a method of Van Gansbeke et al. (2019) to detect left and right ego-lane's lane markings. The accumulated change rate of the angle formed between the target vehicle's Bbox and the detected ego lane's nearby lane marking was calculated over time to determine the lane-changing behavior. However, the authors stated that the algorithm was developed assuming that the ego-vehicle was stable without obvious lateral movement and the driving area was a straight section instead of curves. In addition, their paper also introduces a conceptual confusion, because the authors stated that their purpose is to detect lane change behavior, although the algorithm described in the paper seems to be only able to detect cut-in behaviors.

In addition, Bian et al. (2022) utilized vehicle detection and tracking models to obtain the location of surrounding vehicles and assign each of them an individual ID. Meanwhile, lane marking key points generated from the lane detection model of Qin et al. (2020) were used to define the ROI in front of the ego-vehicle to determine the tracking vehicles' relative position to the ego lane. A status descriptor including 'keep', ' follow', and 'cut-in' was utilized to define the relative position. The transitions among these three statuses were used to distinguish cut-in and cut-out. A dataset named "Cut-in Maneuver of Surrounding Vehicles" was introduced and used for performance assessment, but was unfortunately not published for other researchers to utilize and validate.

The content above mainly summarizes the techniques employed by various methods. Hence, Table 1 presents a comparison of their accuracy on the PREVENTION dataset. However, it is valuable to note that although all methods use the same public dataset, the training set and test set of each method were selected, processed, and used differently. Therefore, it is not right to judge whether a method outperforms another method just based on the listed accuracy.

Table 1. Performance comparison of various methods on the PREVENTION dataset. Accuracy values marked with "(Cut-in)" correspond to the cut-in task; all others refer to the lane change task by default.

Method	Accuracy	Method	Accuracy	Method	Accuracy	Method	Accuracy
Nalcakan and Bastanlar (2023b)	97.99 (Cut-in) 94.84	Izquierdo et al. (2019a)	67.0 74.4	Biparva et al. (2022)	90.98 91.94	Chao et al. (2025)	90.94
Nalcakan and Bastanlar (2023c)	91.60 (Cut-in)	Izquierdo et al. (2021)	86.9	Liang et al. (2023)	84.79 99.33	Zhang et al. (2022)	94.5 (Cut-in)
Nalcakan and Bastanlar (2023a)	94.25	Fernandez-Llorca et al. (2020)	90.3 91.94	Raja Mohamed et al. (2025)	85.0	Bian et al. (2022)	91.35 (Cut-in)

5. Discussion

Overall, the research trajectory in the first direction (direct model inference) has evolved from the initial use of simple CNN models to increasingly complex approaches that explore various video action recognition models and embed manually annotated prior information from datasets into the input preprocessing stages. Commonly, the target vehicle identity is needed as prior information and embedded in the input in the form of a Bbox or contour of a particular vehicle to help the models focus on the target vehicle and improve their classification performance. Furthermore, even if this prior information is not needed, the models either need to make an inference on each vehicle in turn at the price of computational cost, or can only output a classification result of the input frame sequence without indicating which vehicle performed that behavior and what is the start and end frame of that behavior, which are necessary to send warnings to drivers. Moreover, as the PREVENTION dataset already provided the start and end frames of each lane change event, this information was always utilized to cut the complete videos to prepare many event-specific video clips as the input feature or image sequence to the models. However, in practice, obtaining this prior information requires considerable time-consuming manual labeling work. These facts make it considerably difficult to implement these studies into real-world applications. In addition, the obtained decent performance on well-prepared event-specific video clips cannot guarantee the same performance on full-length videos, which contain many scenarios not included in these models’ training and testing processes.

In the second direction (logical inference based on lane marking), some common shortcomings can be found in the works. Although lane marking detection is the algorithm's most crucial element, neither paper discusses the details of this critical part, e.g., its accuracy and stability. The failure or incorrect detection of lane markings will affect the angle calculation between Bbox and lane markings and also result in a wrong status descriptor in the aforementioned algorithms. In particular, the lane marking might be blocked by the surrounding vehicles, which is still a challenge for many lane marking detection algorithms. Furthermore, the performance assessments were conducted on the author’s own datasets instead of public ones. Bian et al. (2022) conducted an ablation study to compare the performance if the lane detection model is deployed in the pipeline. However, after replacing the lane detection model with a fixed ROI, the accuracy was still high, up to 85.48% on average. While the reported accuracy is impressive, it would be valuable to assess the dataset's quality and difficulty level further. Making the dataset publicly available would enable the research community to validate the algorithm's performance, facilitate comparisons with existing approaches, and encourage further improvements.

There are also some common drawbacks in the works of both directions. Most of the works in both directions do not analyze the reasons for the failures of their algorithms. A simple report of accuracy, recall, and precision scores is insufficient for readers to understand the algorithms’ limitations, robustness, and potential optimization directions. This is more challenging for the work in the first direction because the deep learning models are like black boxes and lack explainability. Furthermore, although the initial purpose for performing lane change detection is to improve road safety, the existing studies have not considered how to implement the techniques in real-world applications to improve road safety. For example, identifying if the detected lane change event can pose potential risks to the ego vehicle, whether the lane-changing vehicles use turn indicators, or how the ego driver's eye and head movements respond during lane change events could extend existing studies. Moreover, the project codes, model weights, and extra data annotations of previous works seem rarely fully open to the public. If road safety researchers want to implement the methods to solve some road-safety-related questions, the barriers to code reproduction, model retraining and testing, data preparation, and reannotation seem to make it too hard to start.

The publication of the PREVENTION dataset significantly promoted the comparison and development of the algorithms in this research domain. Especially, the lane change event annotations served as a remarkable basis for data preprocessing, performance evaluation, and saved a considerable amount of efforts of researchers on manual labelling. However, it also has some issues. The provided lane marking annotations are not given in the camera coordinate system, requiring coordinate transformations. Furthermore, some lane change events are missed in the annotations. This issue was rarely mentioned by previous studies because most existing works conduct experiments on event-specific video clips rather than evaluating model performance on full-length videos. Additionally, some annotated lane change events in the dataset are either unrelated to the ego lane or occur at a considerable distance from the ego vehicle, thus having little impact on the driving safety of the ego vehicle. It would be better to make additional labels to distinguish such events from safety-related events. Moreover, the videos in this dataset seem slightly homogeneous; they lack diversity in challenging conditions such as low resolution, nighttime, rainy weather, overcast environments, and different camera angles. Consequently, methods developed based on this dataset have not been evaluated for accuracy under these challenging conditions. In addition, the dataset primarily focuses on highway scenarios. It remains unclear how the models perform in non-highway environments, where challenges such as high traffic density, congestion, unclear or occluded lane markings, intersections, and turns are prevalent.

To conclude, considering the problems above, it can be proposed that future research in this area could focus on the following interesting challenges:

- Eliminate the requirement of target vehicle identity during data preprocessing.
- Eliminate the requirement of behaviours' start and end labels to generate a vehicle’s corresponding event-specific video clips as input for the models. Actually, this challenge means that no matter the duration of the video, the algorithm can still process the video well.
- Robustness and accuracy, i.e., adaptation to different scenarios, e.g., different dash cameras, installation places, shooting angles, weather, light conditions, and so on.
- The identification of the lane-changing vehicle and also the determination of the start and end frames of each event, instead of just outputting a classification label for an input feature sequence.
- Highlighting the lane-changing vehicle in advance for warning drivers. This challenge means the algorithm can somehow detect the behavior before the lane-changing vehicle completely enters the ego lane in real-time, instead of just summarizing the occurrence of the behavior.

In summary, ideally, given a video of arbitrary length, the algorithm should be able to accurately identify all vehicles that perform lane change or cut-in maneuvers, along with the corresponding start and end frames of each event, without requiring additional information or manual annotations.

6. Conclusion

This paper presents a comprehensive review of recent studies focused on detecting lane change behavior of surrounding vehicles using dashcam video. It introduces a novel classification of current approaches into two main categories: direct model inference and logical inference based on lane marking. In particular, it also highlights the widespread reliance on prior information in direct model inference methods and the lack of empirical validation on public datasets in logical inference-based approaches. These limitations were analyzed in depth based on the proposed classification and may provide valuable insights for guiding future research. Finally, several open challenges are outlined from the perspectives of real-world deployment and road safety, aiming to encourage the development of more reliable and practically applicable solutions in this field.

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