Adjacent Vehicle Collision Warning System using Image Sensor and Inertial Measurement Unit

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ABSTRACT

Advanced driver assistance systems are the newest addition to vehicular technology. Such systems use a wide array of sensors to provide a superior driving experience. Vehicle safety and driver alert are important parts of these system. This paper proposes a driver alert system to prevent and mitigate adjacent vehicle collisions by proving warning information of on-road vehicles and possible collisions. A dynamic Bayesian network (DBN) is utilized to fuse multiple sensors to provide driver awareness. It detects oncoming adjacent vehicles and gathers ego vehicle motion characteristics using an on-board camera and inertial measurement unit (IMU). A histogram of oriented gradient feature based classifier is used to detect any adjacent vehicles. Vehicles front-rear end and side faces were considered in training the classifier. Ego vehicles heading, speed and acceleration are captured from the IMU and feed into the DBN. The network parameters were learned from data via expectation maximization(EM) algorithm. The DBN is designed to provide two type of warning to the driver, a cautionary warning and a brake alert for possible collision with other vehicles. Experiments were completed on multiple public databases, demonstrating successful warnings and brake alerts in most situations.

Categories and Subject Descriptors

I.4.8 [**Image Processing and Computer Vision**]: Scene Analysis—*Object recognition, Sensor fusion*

Keywords

Driver Assistance System; dynamic Bayesian network; Expectation Maximization; inertial measurement unit; vehicle detection

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1. INTRODUCTION

Advanced driver assistance systems (ADAS) are an active research area in recent years. Various algorithms have been developed to aid drivers on-road to keep them alert for possible collisions and assist them in driving safely by proving superior guidance. Safe and accurate ADAS systems are crucial due to the frequency of collisions caused by distracted drivers. Statistics shows that approximately 60% of rear-end collisions can be avoided if the driver had additional warning [1]. According to the U.S. Census Bureau, there were approximately 10.8 million motor vehicle accidents in 2009 alone, and 35,900 deaths were reported from road accidents [2]. Among those, about 40% of the deaths were caused by motor vehicle crashes. Drivers' delay to recognize or estimate possible collisions is a major cause of these accidents. Even a half second prior warning can significantly reduce the amount and severity of accidents. These observations point to the need of a system that can alert and warn the driver appropriately.

With the advent of inexpensive vision sensors, accurate inertial measurement units (IMUs), lidar, and radar scanners, robust driver assistance systems and fully autonomous vehicles have become a goal for near future. Collision avoidance is an important area in driver assistance as well as in autonomous driving. Detecting nearby vehicles and providing appropriate warning to the drivers remains a challenging research area [3]. Many researchers have been working in the area of driver alert and awareness; therefore, multiple systems have been proposed to detect and track vehicles on-road and monitor the driver's behavior [4]. Some researchers have tried to monitor the driving behavior and facial reaction [5] , while others have tried to identify different objects such as pedestrians and traffic signs and provide driver awareness based on the vehicle's state [6]. Some researchers have focused in solving simple tasks, such as predicting turning behavior and lane change collision avoidance. Using only one sensor modality, such an awareness system can be ineffective. Almost all the proposed methods have used multiple modalities to achieve robust performance.

This paper proposes an on-road adjacent vehicle collision warning system. The method incorporates a multi-vehicle detection system based on a histogram of oriented gradient (HOG) features trained with AdaBoosted classifier and on-board vehicle IMU measurement unit. A dynamic Bayesian network integrates all the measurements to provide correct warnings to driver. The proposed method is tested on real driving databases with varying road and weather conditions.

The rest of the paper is constructed as follows. A background study of the related area is discussed in Section 2. Section 3 explains the proposed method, including the introduction of the DBN model, extraction of IMU data, vehicle detection module and parametrization of the DBN model using EM. Section 4 describes the experimental results and limitations of the model. Section 5 discusses future direction of our research work.

2. RELATED WORK

The start of 21st century has seen automakers introduce several safety features like adaptive cruise control (ACC), dual-stage front air bags, and antilock brakes. Automakers are currently pursuing research to introduce other advanced features like collision warning and avoidance systems. Several researchers have implemented methods using various modalities to raise awareness and provide warnings to driver. Research topics include monitoring driver's behavior through face detection, eye tracking, drowsiness and fatigue detection and several other driver monitoring methods. Other researchers focused on searching the surrounding environment for any possible collision or abnormal driving by nearby vehicles. Both of these research are crucial for developing safety warning system for vehicles.

Sun et al. [7] proposed a context-awareness model for smart cars. The model accurately captured several elements of contextual information such as turn left and right, drive constantly and lane change. A petri net model is introduced for context awareness, with transition probabilities for different situations. Rakotonirainy [8] described a real-time contextual aware system, capturing information, from the surrounding that is then later reasoned with Bayesian network. The network can predict the future states of the vehicle based on both reliable and unreliable information but was unable to give information about current condition of the driver. Lee et al. [9], developed a system to map captured images to global co-ordinates to monitor driving behavior. Using a hidden Markov Model (HMM), they were able to deduce four driving forms. Tsu-Tian et al. [10] demonstrated a multi-sensor fused system to create a collision maneuver warning system on a embedded platform. Matthias et al. [11] proposed a dynamic Bayesian network to model a situation-aware driver assistance system. Their approach laid an architecture to fuse information from inter-vehicle and intra infrastructure-to-vehicle network connectivity. Mitrovic [12] proposed a method using a HMM to accurately recognize driving events such as turns, curve and turns on roundabout. Eren et al. [13] proposed to determine driving behavior using only a smart-phone. They used mobile sensor data with Bayes classification to determine risky or safe driving pattern.

The integration of sensors in the context of collision avoidance with vehicles, has multiple methods. The sensors can be categorized as, active or passive. Active sensors include sonar, radar, ladar/lidar, accelerometers and global positioning system (GPS), and passive sesnors include infrared and vision camera. Kalman filter, Bayesian network, sequential Monte Carlo and their variants are some of the methods to fuse these sensors. Using a vision sensor, the detection may be performed using a single camera or multiple camera setup. Sivaraman and Trivedi [14,15] and Mukhtar et al. [6], provided a comprehensive idea on the state of the vehicle detection, collison avoidance and behavior analysis framework. HOG [16], Gabor [17,18] and Haar-like features [19] are well represented in visual-based model whereas, optical flow [20], 3D point clustering and stixel are approaches in motion-based method. Shadow, symmetry and edge features are also used as vehicle cues. Li et al. [21] provided a system for rear-end vehicle collision avoidance using mobile device sensors. It monitors the driver's reaction to detected vehicles taillights and provides warning or passive safety. The detection of vehicles can be divided into two parts, visual and motion based. van Leeuwen and Groen [22] presented a method to detect midrange, distant and passing vehicles without any knowledge of distance of the road. The passing vehicles were detected using temporal difference and projected motion.

3. FRAMEWORK

The goal of this project is to provide warning to the driver about adjacent vehicles on-road and provide brake alert to driver in case of probable collision. The first step is to capture the IMU data and process the data to obtain velocity, heading and acceleration. The second step is to detect nearby vehicles on-road using a HOG feature based AdaBoosted classifier. Finally, all the processed data is fused in a dynamic Bayesian network to issue the probabilities of warning and brake alert. The information used to build the DBN model are:

- Vehicle heading
- Vehicle speed
- Vehicle acceleration
- Detected vehicle's position with respect to the ego vehicle - Left, Middle or, Right

The IMU data is processed to acquire the heading, speed and acceleration of the ego-vehicle, and nearby vehicles are detected using a image classifier. Warnings are issued based on heading, speed, and detected vehicle's position; brake alert is issued based on speed, acceleration and current warning status.

3.1 Driver Alert System

The driver alert system provides warnings to the driver based on the position of detected vehicles in the image frame and the ego-vehicle's motion characteristics. The captured data from the IMU and camera can provide multitude of possible combinations to derive warnings. In addition to the available data, the different states may be unobserved. The information may be incomplete due to sensor error or, failure to meet input threshold. An accurate and efficient driver alert system requires fusion of different type of contexts, observable and unobservable. A dynamic Bayesian network (DBN) was implemented to provide warnings. DBN is a directed acyclic graph that represents the conditional independence between a set of nodes. It can handle incomplete and uncertain states with probabilistic inference upon receiving evidences. It consists of a set of nodes that represent the states and a set of directed edges representing the independence or dependence between variables. It can be

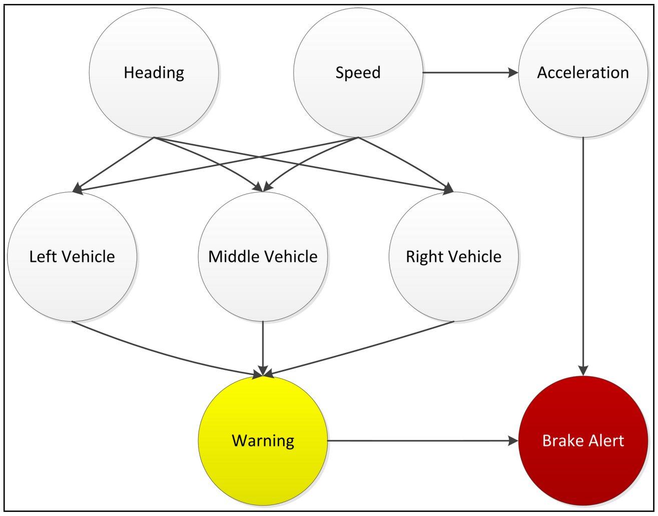


Figure 1: The dynamic Bayesian network model

represented as a set of static Bayesian networks with simple temporal features [23] [24]. Figure 1 represents the proposed model.

The vehicle alert system has two possible nodes, warning and brake alert. Warning situation includes existence of nearby vehicles and high speed driving. Brake alert is for situations of a possible collisions with nearby vehicles due to high speed or abnormal acceleration. The various situations considered in the system can be summarized below:

- Vehicles coming from a blind spot or passing vehicles pose a bigger threat than vehicles that are in front. The driver's focus is mostly towards the forward road and existing front vehicles. The passing and side vehicles are out of the driver's view. So, warnings about the vehicles existing in the sideways can help the driver.
- If the vehicle's heading is towards the existing vehicles and its acceleration is higher than usual, then there is a possible collision with the vehicle. In this situation it is necessary to issue a brake alert to driver.
- The brake alert may be removed if the driver decreases its acceleration or the existing vehicle goes out of the possible collision distance.
- If the vehicle is heading and speeding towards the existing vehicles, then a warning is issued to the driver.

The decision to provide the warning is based on the IMU data, (heading, speed and acceleration), and adjacent vehicle position, (left, middle and right) with respect to the ego vehicle. The proposed model is shown in Figure.1. The nodes and their corresponding states are listed below:

- Heading - Leftward, Straight and Rightward
- Speed - Low and High
- Acceleration - Decreasing and Increasing
- Detected position of vehicle with respect to driver. The corresponding nodes are,
  - Left - False and True.
  - Middle (in-front of the vehicle) - False and True.
  - Right - False and True.
- Warning - False and True.
- Brake Alert - False and True.

A further description of the nodes and their different states will be provided in the following sections.

3.2 IMU Data processing

IMUs are commonly used to navigate aircraft, including unmanned aerial vehicles (UAVs) and spacecraft, satellites and landers. It is a self-contained system that generally consists of three accelerometers and three gyroscopes that provide three acceleration and three angular velocity components. It may be used to determine both position and orientation of an object by integrating acceleration and angular velocity from IMU measurements. The accuracy and reliability of IMUs have enabled it to be widely used in navigation and maneuvering application.This section describes the process of acquiring the three inputs: heading, speed and orientation.

The gyroscope of an IMU provides information about the angular velocity of the ego-vehicle. These signals can be processed to estimate the current orientation of the vehicle [25], such as three angle measurements, pitch, yaw and roll. The yaw angle is used to determine the current heading of the ego vehicle. Knowing the direction of movement with respect to other vehicles' position helps dictate warning to drivers. Vehicle heading are categorized in three directions as described earlier: Straight, which indicates no change of driving direction; leftward or rightward, which may indicate vehicles intention of lane change or taking left or right turn. While vehicles can go reverse, it is not considered here as typical highway and street driving. The yaw_t is the yaw in radian units at time instant t, and ranges between $-pi$ to $+pi$. A zero value means heading is towards east, positive value indicates angle in the counter clockwise direction. The current value is compared with average of the past values to calculate the change in direction. A value between -1 to $+1$ indicates a forward direction and a value greater than 2 indicate a leftward and less than -2 for rightward direction. The following condition was used in calculating the direction,

$$Heading = \begin{cases} Left, & \text{if } yaw_t \ > 2 \\ Straight, & \text{if } |yaw_t| < 1 \\ Right, & \text{if } yaw_t \ < -2 \end{cases} \qquad (1)$$

where,

$$yaw_t = yaw_t - \frac{1}{3}\sum_{i=1}^{3}(yaw_{t-i}).$$

If the conditions are not met in any of the three cases, the evidence from input is not provided to the DBN model.

Speed limits vary with respect to the location such as residential, business, city and freeways. Current focus is on residential and city roads, so in our proposed method we wanted to distinguish between driving in a residential and city roads. We looked at the data for several states in the USA and other countries, and we found out that residential area speed limit ranges from 10-30 mph, and in urban city roads, the speed ranges from 35 to 55 mph. The following equation is based on these assumptions and categorizes the vehicle speed as either low or high speed.

$$Speed = \begin{cases} Low, & \text{if } {v_t^f}^2 + {v_t^l}^2 \leq 625; \\ High, & \text{if } {v_t^f}^2 + {v_t^l}^2 \geq 1225. \end{cases} \tag{2}$$

Here, *speed* is regarded low if it is less than 25 mph and high if it is greater than 35 mph. Generally, an IMU does not provide vehicle speed data, but it can be estimated [26]. The captured data from the IMU unit were, v_t^f-forward velocity, and v_t^l-leftward velocity; both measurements are parallel to earth-surface, at time t. The units are in miles per hour.

Vehicle acceleration is another measurement that provides information of possible collision if the ego vehicle moving faster towards an adjacent vehicle. Acceleration, coupled with the heading and speed provides the DBN the required data to issue warnings in an appropriate manner. We obtain the average difference between acceleration rather than the instantaneous difference. The IMU unit provides acceleration in three axis directions. In this case, two data classifications were considered for calculating the acceleration, forward acceleration, a^f, and leftward acceleration, a^l (negative if rightward). The acceleration units used was $(m\backslash s^2)$. Increasing acceleration indicates the buildup of speed possibly due to driver's intent or downhill road. Decreasing acceleration indicates the slowing in case of braking or uphill road. This helps DBN decide the outcome of possible warnings.

$$Acceleration = \begin{cases} Decreasing, & \text{if } a_t^f < -1 \vee a_t^l < -1 \\ Increasing, & \text{if } \left|a_t^f\right| > 0.8 \vee \left|a_t^l\right| > 0.8 \end{cases} \tag{3}$$

where,

$$a_t^f = \tfrac{1}{3} \sum_{i=0}^{2} a_{t-i}^f - \tfrac{1}{4} \sum_{i=1}^{4} a_{t-i}^f$$
$$a_t^l = \tfrac{1}{3} \sum_{i=0}^{2} a_{t-i}^l - \tfrac{1}{4} \sum_{i=1}^{4} a_{t-i}^l.$$

The process to give evidence from the IMU to the DBN nodes are described here. If the conditions are not met in any of the cases, evidence from the input is not provided to the DBN model.

3.3 Vehicle Detection

Vehicle detection using vision has become an integrated part of ADAS systems. Recent image-based classification algorithms are efficient and popular in real-time applications [15]. The detection module recognizes vehicles from the front and side view of the ego-vehicle. Vehicles look different from these view points, so the training of the classifier includes both front-rear end and side views of a vehicle.

A HOG feature based AdaBoosted classifier was used in detecting vehicles on-road. HOG features are previously used in vehicle detection studies [15]. It was developed by Dalal and Triggs [16], and is a image descriptor defined from a set of gradient orientation histograms extracted over a patch in the image. The patch is a small region of image, and over each patch the intensity gradients or edge direction are computed. A histogram of the edge orientation is collected to form the feature vector.

The training database included images from several public databases and Craigslist vehicle images. There were approximately 2000 positive and 5000 negative images collected for training. We included 80% image data for training and 20% for testing purposes. Figure. 2 shows several output of the vehicle detection module is shown.

Figure 2: Results of on-road vehicle detection

Figure 3: Vehicle position

After detecting vehicles, the position of vehicles in the image frame is determined by extracting regions for left, middle and right vehicles. These regions are created based on the heading information provided by yaw estimation to locate the position of the detected vehicles with respect to the ego vehicle. The image is divided in three parts, evenly based on the width of the image frame. The center part is used as the heading or middle region for the vehicle, if the heading angle (yaw) is zero. It is shifted toward the left or right according to the heading angle of the ego vehicle. The position of the detected vehicles is decided by the heading region. If the bounding box of the detected vehicle is inside the heading region, then the vehicle is in the middle position. If it's position is to the left of the heading region then the vehicle is in the left position. Similar rules are defined for the right region. The vehicle's position with respect to the ego-vehicle will provide information to the DBN to process collision probabilities. In Figure. 3 shows the three regions where the green region is the region for middle vehicle.

3.4 Network Parameterization

The network parameterization step finds the probabilities of the root nodes and conditional probabilities of the child nodes of the network. All of the nodes in the network and their possible states have been specified. Acquiring the correct probability for each node is important for the network performance. A DBN model can be parameterized in several ways and primarily Maximum Likelihood Estimate (MLE) and expectation–maximization are used for parameter learning of the Bayesian network. In Bayesian estimation, the goal is to compute a full posterior over the parameters. The MLE or Maximum A Posteriori (MAP) method provides a point estimate that maximizes the likelihood function. If the data of the model is partially observed as in models with hidden variables, then the EM algorithm can be used to learn the parameters.

The EM algorithm was used to obtain the parameters for the DBN. The EM algorithm iteratively determines the MLE of the model that describes the distribution of a given incomplete data set. Before EM, partially observed parameters of the model were provided. It was difficult to obtain such data for collision warning system. Therefore, information from published work in this area and other related studies related to it were adapted to the system to parameterize the network properly [27–29]. The training data included both random parameters and observed cases obtained from the literature study. These observed parameters were based on the real world conditions and their corresponding warning probabilities.

In EM, the E-step is performed first, and involves the determination of the complete data log-likelihood constrained by the incomplete or partially observed data. The M-step is then performed for the estimated completed data log-likelihood. The maximized estimations are used in the repeated EM steps until a predefined convergence or constraints are met. Bayes net toolbox for Matlab [30] was used to design the network and perform EM operations. Multiple runs were completed with randomized initial points, and the best performance were achieved by the probability table shown in Figure. 4. Now, the trained DBN model can be used to issue warning and brake alert based on the evidences received from the IMU and vehicle detection. Since the IMU and camera have different sampling rate, the IMU data closest to the image frame time was chosen as the corresponding data.

4. EXPERIMENT AND RESULTS

Our experiment was completed on several public databases that included both camera and IMU data. A significant amount of vehicle images were used for HOG classifier training. The performance of the vehicle detector was evaluated on several public databases including the TME Motorway Dataset [31], Lisa Vehicle Detection Dataset [3] and KITTI database [32], the Málaga Stereo and Laser Urban Data Set [33]. We have considered both front, back and side faces of vehicles in our database. Moreover, we have considered only personal vehicles such as sedans and SUVs in our design of the classifier. For this reason, large trucks and heavy duty vehicles are mostly unrecognized in the images. In future work, we intend to cover all major classes of vehicles. Both the DBN and vehicle detection performance are discussed here.

Database	Front vehicle	Side vehicle
KITTI	78.6	81.7
Lisa Vehicle Detection	73.1	78.3
Málaga Stereo and Laser Urban Data Set	76.5	80.6
TME Motorway Dataset	77.3	79.1

Table 1: Average precision of Vehicle detection

4.1 Vehicle Detection Performance

Vehicle detection is the major component in the DBN for providing warning. Without an robust and accurate system, it will fail to provide appropriate warnings. The HOG feature based classifier has shown effective performance in pedestrian detection [16]. The evaluation procedure involved gathering different road and weather condition scenarios. The database included roads with no vehicle and sometimes very few vehicles on-road. Therefore, we captured several 3 to 5 minute segments from the database where there are 2-5 vehicles present. A total of 14 segments from the mentioned database were acquired. The classifier training procedure were performed using Matlab libraries. Performance measurement was done using average precision (AP) metric.

The average precision of vehicle detection is shown in Table 1. Both front and side vehicle detection perfomance is included in the table. Our performance shows that our classifier was able to detect on average, more than 75% of vehicles on-road. The performance can be improved by reducing the false positives. This can achieved by adding motion information to verify detected vehicles.

4.2 DBN Performance

The DBN was evaluated under various situations to determine whether it provides the appropriate warning and brake alert on time. The performance of the system required gathering ground truth from the database and creating corresponding warning and brake alert. The databases had vehicle location and size labeled, but unfortunately the selected databases provided no ground truth for any sort of safety or warning system. So out of the evaluated videos, a small set was annotated and used as ground truth. It had labeled vehicle location provided by the corresponding database. The heading, speed and acceleration were gathered from the IMU, and situations such as high speed, high acceleration, stationary vehicle label in each frame were added. There were in total 30 minutes of video (45000 frames), labeled manually based on several possible required warning and crash situation. The warning and brake alert performance result were estimated using failure rate criteria. This simple criteria can be explained by the failure rate over time duration t given by,

$$\lambda(t) = \frac{f(t)}{R(t)}$$

where $f(t)$ is the number of failures to provide corresponding warning or alert over the time duration t, and $R(t)$ is the total occurrence of warning or alert over the time duration t.

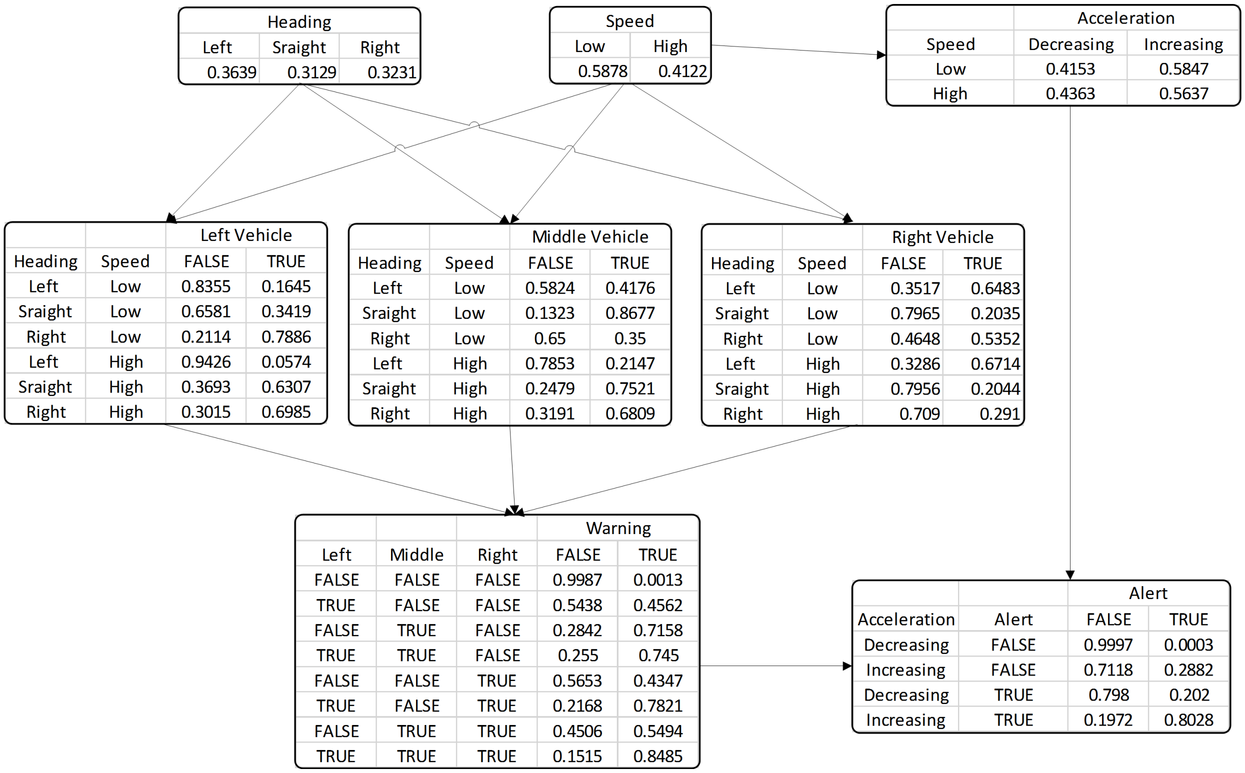


Figure 4: The priors and conditional probabilities for the DBN model

Several cases were considered and examined in the test condition. Cases such as vehicle heading, speed, acceleration and detected vehicle's position were included. The results can be seen in the Table 2. Separate failure rates for warning and alert were calculated. Hidden states means IMU data generated unobserved conditions in the DBN. Warning are issued when there is an adjacent vehicle and the speed is high towards the vehicles. If the vehicles accelerates further towards the vehicle, a brake alert is provided. In the Figure. 5 several warning and alert cases are shown with the corresponding results from the DBN. The results show our system performs well in detecting vehicles and issuing warnings to the driver with low failure rate. Although the brake alert had higher failure rates than the warning, it can be improved by providing more information about surrounding vehicles, such as distance to the detected vehicle and minimum distance from ego-vehicles to prevent collisions and relative speed measurements.

Cases				Failure Rate	
Heading	Speed	Acceleration	Vehicles detected	Warning	Brake Alert
Straight	Low	Hidden	Yes	5%	N/A
Straight	Low	Increasing	Yes	3%	22%
Straight	High	Increasing	No	6%	N/A
Straight	Hidden	Decreasing	Yes	5%	13%
Right	High	Hidden	Yes	8%	26%
Right	Low	Increasing	Yes	4%	17%
Left	Low	Increasing	Yes	3%	17%
Left	High	Increasing	No	4%	N/A
Left	High	Decreasing	Yes	9%	19%

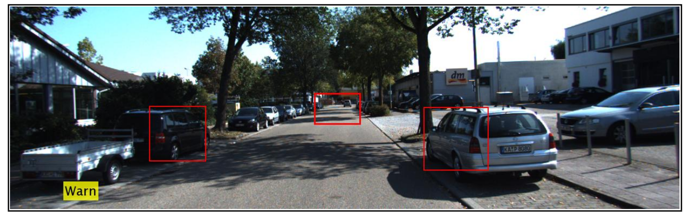
Table 2: Performance of the Vehicle Alert System. N/A in brake cases means no brake is needed in those situation and Hidden means the values were unobserved in DBN.

5. CONCLUSION

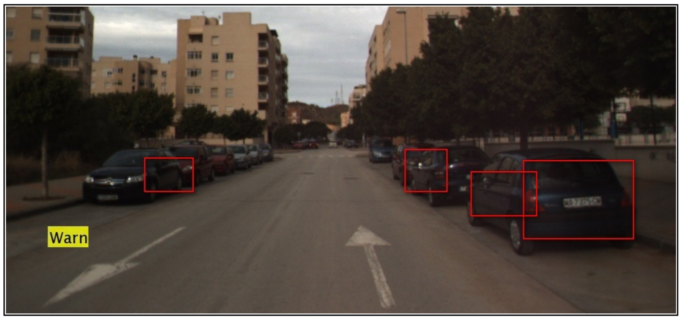
This study introduces a framework to alert drivers about surrounding vehicles and current driving behavior. The final output of the system is estimated by a dynamic Bayesian network that requires an IMU sensor and a camera. The system detected nearby vehicles, and ego vehicle's speed, heading and acceleration. The network was able to provide suitable warning to the driver of adjacent vehicles and alert the driver in the case of potential collision. Experiment results showed a good performance in generating these warnings. Warning were issued with a very low failure rate and alert were generated in 80% of test cases.

Future work will improve performance using additional sensor modalities, such as radar and lidar sensors. Vehicle-to-vehicle communication could also provide information about nearby vehicle speed and turning intention. This would require a more sophisticated DBN setup. Sensor reliability and uncertainty were also an issue in the design. These parameters can be incorporated in the future designs. One key issue is the lack of suitable open training data for collision avoidance. Expectation Maximization could be improved with a more complete training data for the Bayesian network. Another avenue of future work will focus on gathering such data. Vehicle detection performance can be improved using a convolutional neural network (CNN). This work could also be extended to include detection of pedestrians and traffic signs. ADAS will be an active research area for the coming years. This work in vehicle safety can mitigate life-threating crashes.

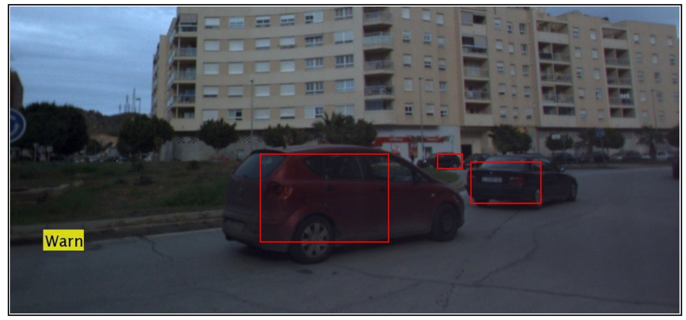
No Warning, as no vehicles and low speed



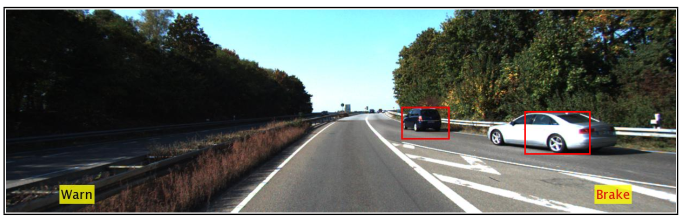
Warning Issued, as adjacent vehicles detected



Warning issued, as adjacent vehicles created a possible collision



Warning issued, a high acceleration was found in an right turn.



Both Warning & Brake Alert are issued, as high acceleration with adjacent vehicles created a possible collision situation

Both Warning & Brake Alert are issued, a high acceleration was found in an abrupt left turn.

Figure 5: Several results of the DBN alert system

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