Highly-Safe Intelligent Vehicle Based on Trajectory Prediction

Master's Thesis
修士論文

Highly-Safe Intelligent Vehicle Based on Trajectory Prediction

（軌道予測に基づく高安全知能自動車に関する研究）

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Contents

Chapter 1

Introduction

We all depend heavily on transport in our everyday lives. However, ever-increasing road traffic generates serious social problems: congestion of road networks and urban areas, damage to the environment and to public health, energy waste and, above all, accidents [1]. Many people die every year on roads and many more are injured. Fortunately, advanced information and automation technology can now be incorporated into onboard "Highly-safe intelligent vehicle", offering new solutions to today's transport problems.

A highly-safe intelligent vehicle is an automobile with artificial intelligence (or "AI") functionality. As automation technology has progressed, especially in the decades after the invention of the integrated circuit, more and more functions have been added to automobiles, relieving the driver of much of the mundane moment-to-moment decision making that may be regarded as having made driving carefully [2]. Highly-safe intelligent vehicle clearly improve traffic safety if they are extensively taken into use, many of them effectively reduce the number of fatalities and injuries, will become more common in future. A highly-safe intelligent vehicle has some "smart" features: adaptive cruise control, advanced automatic collision notification, automatic parking and so on. The advanced automatic collision notification can help drivers prevent or avoid traffic accidents, benefit significantly from an accurate prediction of the trajectory of the vehicles which near it. Trajectory prediction can help drivers to:

- Maintain a safe speed
- Keep a safe distance
- Avoid overtaking in critical situations

- Avoid collisions with road vehicles

Until now, in our lab, proposals of vehicle trajectory prediction have been investigated for road environment where obstacles are static. That is to find a trajectory to avoid collision with static obstacles in given road environment. In this thesis, dynamic obstacles position changes as time in given road environment. Therefore, it is need to consider dynamic obstacles' future trajectories. Here, we use driver 's intention to predict target vehicle's future trajectory in road environment. If target object was a ball or something without intention, it is possible to predict trajectory according to calculation of physical laws, and predicted trajectory is considerably accurate. However, in the case of trajectory prediction of vehicle with intention, trajectory prediction is very different from the former mentioned according to physical laws and intention influence. Therefore, it is required to estimate intention at first.

As driver 's intention can not be estimated by camera and sensor, it is necessary to predict road environment information, vehicle information and some information which can be observed at first. Then intention is forecasted according to prediction model that includes the observed information. Observed information is used to estimate the information which can not be observed.

Generally, inference technique is well known to solve such a problem. As a kind of graphical model of inference technique, Bayesian network is adopted in this thesis. Bayesian network is directed acyclic graph whose nodes represent random variables in the Bayesian sense: they may be observable quantities, latent variables, unknown parameters or hypotheses [3]. Edges represent conditional dependencies; nodes which are not connected represent variables which are conditionally independent of each other. Each node is associated with a probability function that takes as input a particular set of values for the node's parent variables and gives the probability of the variable represented by the node.

In this thesis, inference system is structured by Bayesian network for predicting trajectory of highly-safe intelligent vehicle.

To predict trajectory of vehicle, it is necessary to estimate driver 's intention which determines future trajectory [4]. It is need to define probability variables from information observed in road environment. However, there are various information including road environment information, traffic rule information and much information in road environment, it is very difficult to define all the information as nodes of Bayesian network. To solve the problem, the proposal that one road environment corresponds to one Bayesian network is proposed. The problem about vehicle position, speed and coordinate setting is complex when define nodes of Bayesian network according to road environment. Then, in a given road environment, method about modeling road environment is proposed. So vehicle position and speed can be defined easily, probabilistic variables of intention nodes can be set easily too. In case of single intention node, the total conditional probabilities would be considered, so the complexity of combination of conditions would increase. To solve the problem, hierarchical Bayesian network is proposed. The result is that relationship between nodes become simple.

In the case that there is more than one vehicle near target vehicle, their motions affect each other, interaction problem arises. So it is impossible to predict their trajectories respectively. To solve the problem, in this research, approximation prediction method is proposed. That is, we consider front vehicle as the vehicle which gives largest effect to target vehicle. The most important information is future information of vehicle in front position of target vehicle, except front vehicle, the information of other neighborhood vehicles is also used. Based on this method, the approximate prediction Bayesian network can be constructed and interaction problem can be solved.

For a certain Bayesian network, the research on learning of the probability with the condition of each node improved. The statistic data for learning is necessary. In this thesis, the image processing method is proposed for acquisition of statistic data. When a road environment is given, corresponds to it, the image processing proceeds through fixed camera. Based on this design, statistic data can be obtained by simple two-dimensional image processing. And learn the conditional probability of nodes according to acquired data, then the simulation based on conditional probability can be used to check the constructed Bayesian network's accuracy.

This thesis summarizes the contents mentioned above, and composed by 5 sections shown below.

Section 1 introduces background, purpose and abstract.

Section 2 discusses the basic consideration about trajectory prediction of highly-safe intelligent vehicle. The necessity of trajectory prediction is mentioned firstly. Then, as a method which can solve prediction problem of uncertainty, the Bayesian network including probabilistic inference and probabilistic model is discussed. In addition, to solve interaction problem in the case where more than one vehicle nears target vehicle, approximate prediction is also discussed.

Section 3 discusses two methods of Bayesian network construction for two cases. In the first case, only one vehicle is running in road environment. In the other case, multiple vehicles are running together.

Section 4 discusses experimental evaluation of vehicle trajectory prediction for two situations. In situation one, only one vehicle runs in road environment. According to this situation, a simple two-dimensional image processing is used for acquisition of statistics data need by Bayesian network construction. Next, learning the node of probabilistic inference based on obtained data, probability is calculated to check accuracy of Bayesian network. In situation two, multiple vehicles run together in road environment. According to this situation, a simulation is made for experimental evaluation.

Section 5 summaries the entire contents of this thesis and discusses future work.

That is the outline of the thesis.

Chapter 2

Fundamental Consideration on a Highly-Safe Intelligent Vehicle with Vehicle Trajectory Prediction

As an example of "Highly-safe intelligent vehicle" that supports safe driving, alarm system can predict danger in driving, warm driver to avoid traffic accident and safe many lives.

Generally, because the real-world motion is much slower than the computation, it is possible to predict real-world motion [5]. For example, in a crossroad with traffic signal, we suppose that highly-safe intelligent vehicle want to turn right, while target vehicle is coming close to highly-safe intelligent vehicle (Figure 2.1). If signal was yellow, target vehicle will slow down and stop at stop line or go ahead and turn right, there are two possibilities. If highly-safe intelligent vehicle turns right without prediction about target vehicle, alarm system would be late for crash avoidance. Therefore, to know future movement of target vehicle, it is necessary to predict future trajectory of target vehicle.

Although it is essential to estimate driver 's intention which determines future trajectory for vehicle trajectory prediction, it is impossible to observe information of intention directly by camera and sensor. Inference and prediction based on observation of road environment is required. However, there is road information, traffic rule information and target vehicle information in road environment.

It is impossible to observe all the information, anyway, uncertainty exists. As a method to solve that kind of problem, probabilistic inference is well known.

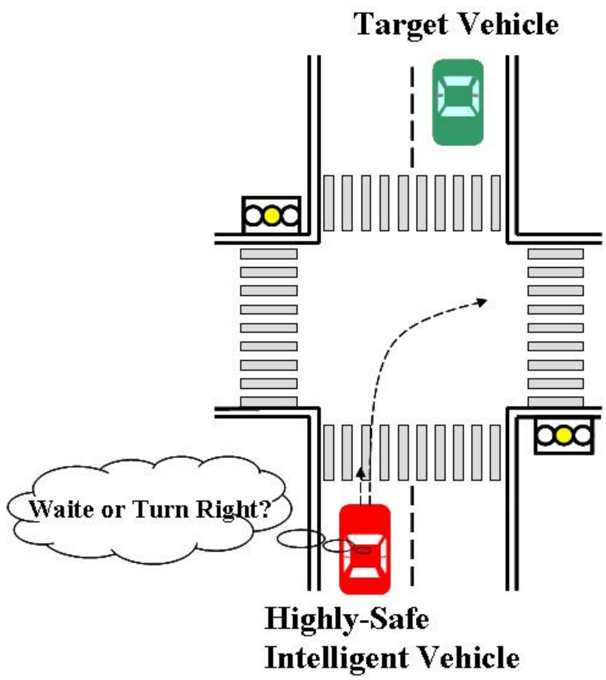

Figure 2.1: Example of forecast in crossroad

This process of computing the posterior distribution of variables given evidence is called probabilistic inference. The posterior gives a universal sufficient statistic for detection applications, when one wants to choose values for the variable subset which minimize some expected loss function, for instance the probability of decision error. In observation problem of dynamic environment with uncertainty, it is unusual to get enough information, so probabilistic inference is considered as a very effective method.

Difficulty of problem description and complexity of inference calculation are appeared when large-scale inference problem is inferred. Therefore, a kind of graphical model, modeling of Bayesian network is used to solving those problems [6]-[8]. A Bayesian network, belief network or directed acyclic graphical model is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG) [3]. For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases.

Formally, Bayesian networks are directed acyclic graphs whose nodes represent random variables in the Bayesian sense: they may be observable quantities, latent variables, unknown parameters or hypotheses. Edges represent conditional dependencies; nodes which are not connected represent variables which are conditionally independent of each other. Each node is associated with a probability function that takes as input a particular set of values for the node's parent variables and gives the probability of the variable represented by the node. In Figure 2.2, node A, B, C, D, E, F, G, H present events, between them there are several causal relationships which are based on dependence relationship presented by edges. For example, the edge between event B and F means a relationship

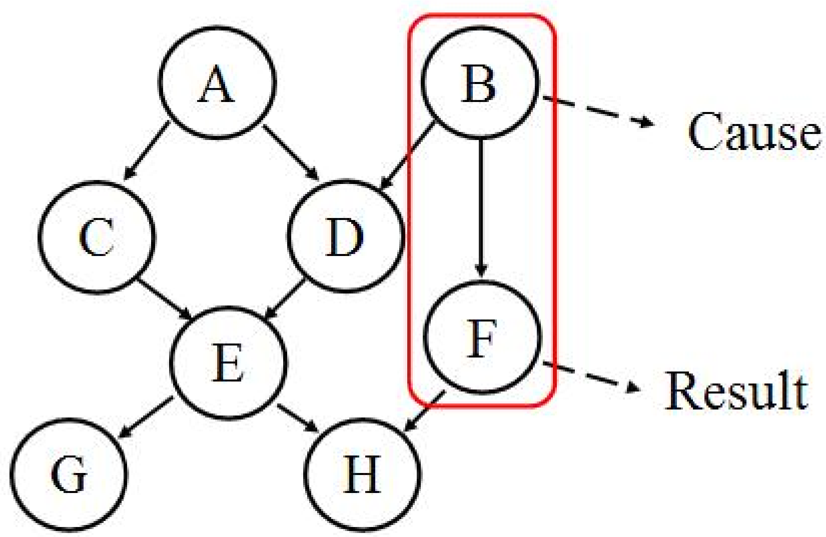

Figure 2.2: Bayesian Network

that means probability of event F is depend on probability of event B, event B is cause, even F is result. The probabilities of them can be presented by P(B) and P(F) respectively. Conditional probability is the probability of event F, given the occurrence of some other event B. Conditional probability is written P(F|B), and is read "the (conditional) probability of F, given B" or "the probability of A under the condition B". Conditional probability can be indicated by conditional probability table (CPT).

To understand clearly, I make a simple example for Bayesian network. Suppose that rain could cause grass to be wet. The situation can be modeled with a Bayesian network (Figure 2.3). All three variables have two possible values, T (for true) and F (for false). The model can answer questions like "What is the probability that it is raining, given the grass is wet?" by using the conditional probability formula and summing over all nuisance variables:

$$P(R = T \mid G = T) = \frac{P(R = T, G = T)}{P(G = T)} = \frac{P(G = T \mid R = T) P(R = T)}{\sum_{R \in \{T,F\}} P(G = T, R)}$$

$$= \frac{0.9 \text{ x } 0.4}{0.9 \text{ x } 0.4 + 0.2 \text{ x } 0.6} = \mathbf{0.75}$$

where the names of the variables have been abbreviated to G means Grass wet and R means Rain.

The Bayesian network offers several advantages over alternative modeling approaches. The most important of these advantages are:

1. Decision theory As Bayesian networks are models of the problem domain probability distribution, they can be used for computing the predictive distribution on the outcomes of possible actions. This means that it is possible to use decision theory for risk analysis, and choose in each situation the action, which maximizes the expected utility. It can be shown that in a very natural sense, this is the optimal procedure for making decisions [9].

2. Consistent, theoretically solid mechanism for processing uncertain information Probability theory provides a consistent calculus for uncertain inference, meaning that the output of the system is always unambiguous. Given the input, all the alternative mechanisms for computing the output with the help of a Bayesian network model produce exactly the same answer.

3. Smoothness properties Bayesian network models have been found to be very robust in the sense that small alterations in the model do not affect the performance of the system dramatically. This means that maintaining and updating existing models is easy since the functioning of the system changes smoothly as the model is being modified. For sales and marketing systems this is a crucial

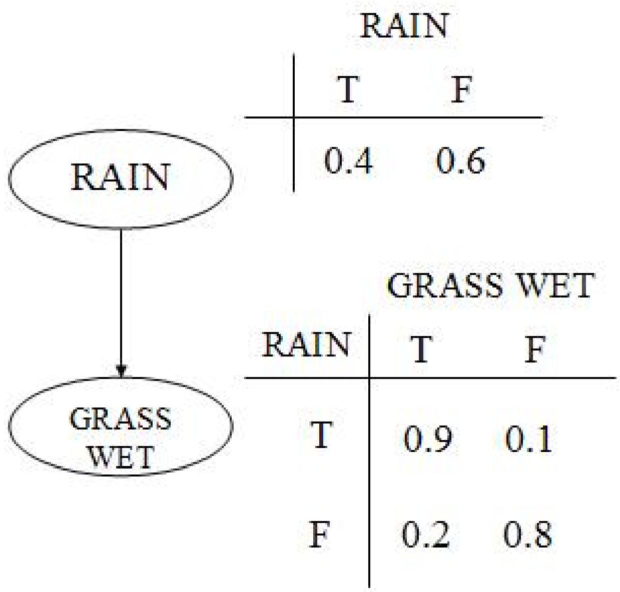

Figure 2.3: A simple example of Bayesian Network

characteristic, as these systems need to be able to follow market changes rapidly without complex and time consuming re-modeling.

In Bayesian network, missing data is marginalized out by integrating over all the possibilities of the missing values. Probability distributions of the node of inobservance can be calculated by inputting the information which has been observed.

Chapter 3

Vehicle Trajectory Prediction Based on Bayesian Network

3.1 Modeling of Road Environment

There are many kinds of road environment for vehicle running such as a crossroad. Therefore, it is necessary to build an individual Bayesian network for each kind of road environment. One of the hierarchies in a driver 's intention corresponds to selection of a labeled road region as shown [4]. The crossroad is divided into labeled road regions based on inside lane districts in Figure 3.1.

All the road environment models are stored in advance in the estimation system. During the real-time inference for the estimation, the road environment under which the vehicle is running is recognized by vision sensors and the subsequent image processing. Then, the matching between the recognized environment and one of the models is done. Selecting one of the models, probabilistic reasoning can be started using the corresponding Bayesian network. Target Vehicle Intelligent Vehicle where Vision Sensors are mounted!

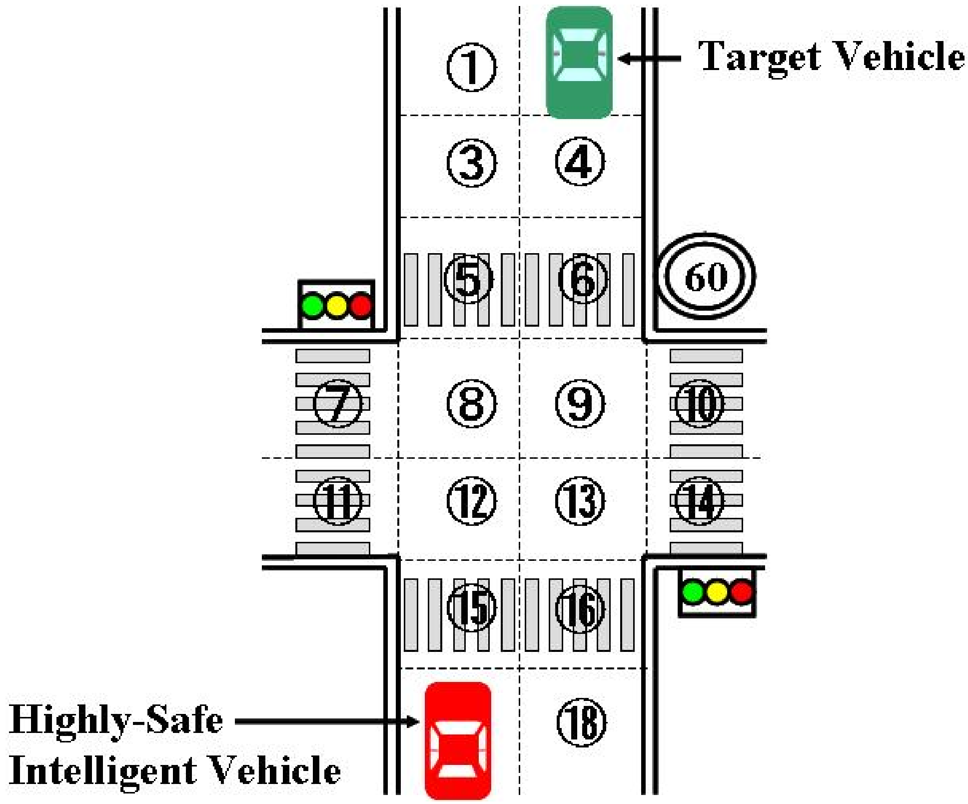

Figure 3.1: Road environment model of crossroad

3.2 Bayesian Network Construction

3.2.1 One Bayesian Network corresponds to One Road Environment

There are a variety of road information, traffic rule information and vehicle information in a general traffic environment. Road information includes two-lane road, four-lane road, T-junction, crossroad and so on. Traffic rule information includes traffic signal, limit speed, one way road, no right turn and so on. Predicted target vehicle information includes present position, present speed, winker, brake lamp and so on. Moreover, information on various obstacles also exists.

For constructing Bayesian network which can correspond to any road environment, it is need to define all road environment information as nodes of Bayesian network. However, it is extremely difficult to enumerate such a large amount of information completely. Thus, as a method to solve this problem, the proposal that one Bayesian network corresponds to one road environment is given.

Based on this proposal, it is possible to define information of one road environment as nodes of Bayesian network. Nevertheless, according to position of target vehicle, same road environment and traffic rule information can lead to different effect on future trajectory. For example, even at the same crossroad, before target vehicle enter the crossroad, traffic signal will give a large effect to future trajectory of target vehicle. However, after entering crossroad, target vehicle will come out as soon as possible, traffic signal hardly affect future trajectory of target vehicle. Then, we suppose Bayesian network is constructed according to position of target vehicle, the relationship between nodes of traffic rule information and nodes of intention, causal relationship of each node can be presented precisely.

Every kind of road environment and constructed Bayesian network corresponds to them are put into memory in advance, real-time prediction flow is shown as below:

1. According to camera and sensor, the present road environment is recognized.

2. Recognized road environment is matched with Bayesian network memorized in memory, the Bayesian network corresponds to road environment is selected.

3. To selected Bayesian network, the value of observed evidence node is set, and probabilistic inference is inferred.

3.2.2 Hierarchized Bayesian Network

Modeling of Bayesian network about problem of vehicle trajectory prediction is described.

First, define information of road environment which can be observed as nodes. For example: traffic signal, present position of target vehicle, speed, winker and so on. Similarly, define information of driver 's intention which can not be observed as nodes. Then, directed edge is presented as causal relationship between nodes. Origin of edge presents cause, head of edge presents result. For instance, the situation that before vehicle entering crossroad, according to traffic signal the vehicle will enter or not is given. In this case, traffic signal is cause, the intention about entering or not is result, edge direction is from "traffic signal" to "intention about before entering crossroad vehicle will enter or not". Similarly, in accordance with relationship between nodes of other road environment information and intention nodes, Bayesian network is constructed.

In modeled road environment shown in Figure 3.2, problem point and resolu-

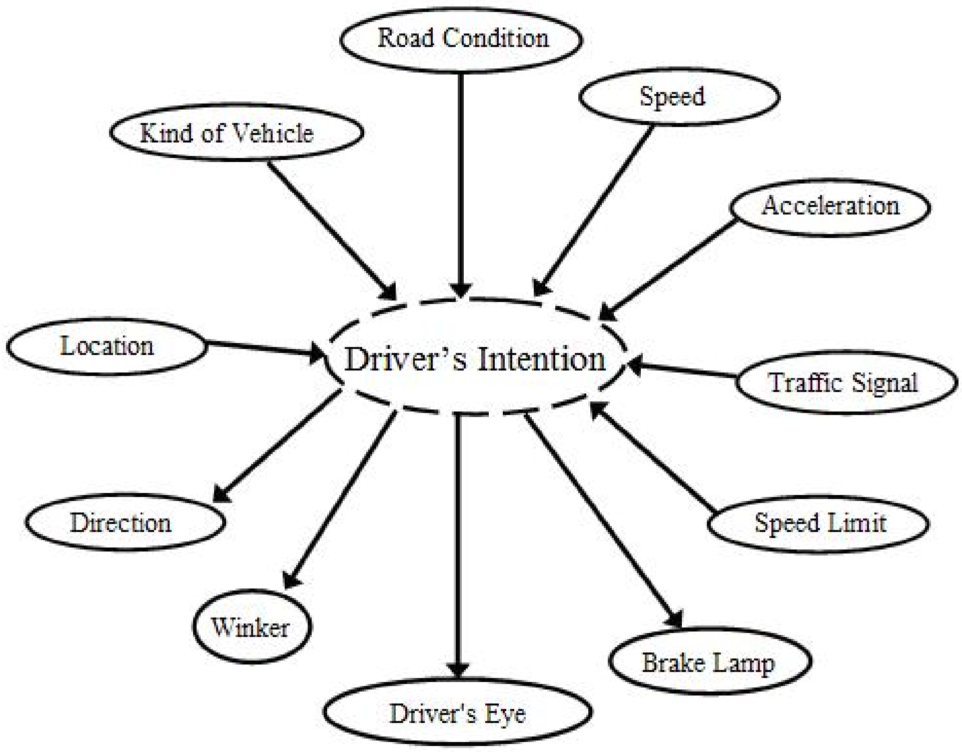

Figure 3.2: Bayesian network which includes single intention node

tion are presented to construct Bayesian network for estimating driver 's intention.

In this case that intention node is single node without hierarchized driver 's intention, Bayesian network looks like Figure 3.2. The nodes made by Bayesian network present the means shown in below.

Nodes which can be measured

- Vehicle information (position, direction, speed, acceleration, kind of vehicle, winker, brake lamp, driver 's eye)
- Traffic rule information (traffic signal, limit speed)

Nodes which can not be measured

- Driver 's intention

As shown in Figure 3.2, the network looks like a star. Therefore, for probabilistic inference, it is required to consider all of the conditional probabilities, then the problem that calculation complexity increases arises. To solve the problem, the proposal of hierarchizing Bayesian network is suggested.

Information of destination of prediction target vehicle is used in road environment, intention is hierarchized as 3 levels.

- Level 1: Intention on Destination
- Level 2: Intention on Trajectory until the Vehicle reaches Destination
- Level 3: Intention on Acceleration until the Vehicle reaches Destination

Concept about hierarchizing from a rough level to a detailed level is considered, the intention on destination is the roughest level. If destination is decided, because it is general to decide intention on trajectory until the vehicle reaches destination, the detail level is intention on trajectory until the vehicle reaches destination. Similarly, if trajectory is decided, because vehicle 's acceleration is selected along trajectory, the detail level is intention on acceleration until the vehicle reaches destination. Based on the same consideration, the causal relationships between hierarchized intention nodes are decided (Figure 3.3).

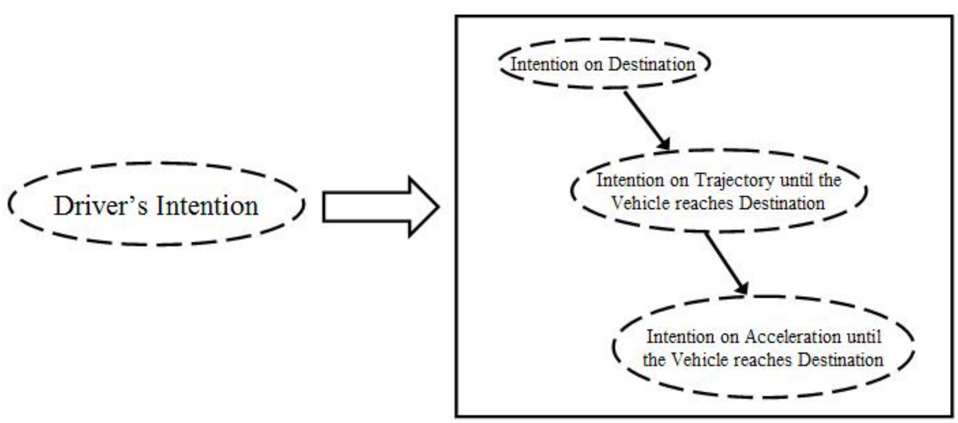

Figure 3.3: Process for hierarchizing single intention

The prediction results are position and acceleration until target vehicle reaches destination in interval Δ t, 2 Δ t, 3 Δ t$\cdots$n Δ t. Then prediction is repeated in interval Δ t, forecast result updates each time until target vehicle reaches destination. Therefore the precise forecast result can be acquired.

Forecast consideration for single intention and hierarchized intention are shown in Figure 3.4 and Figure 3.5 respectively.

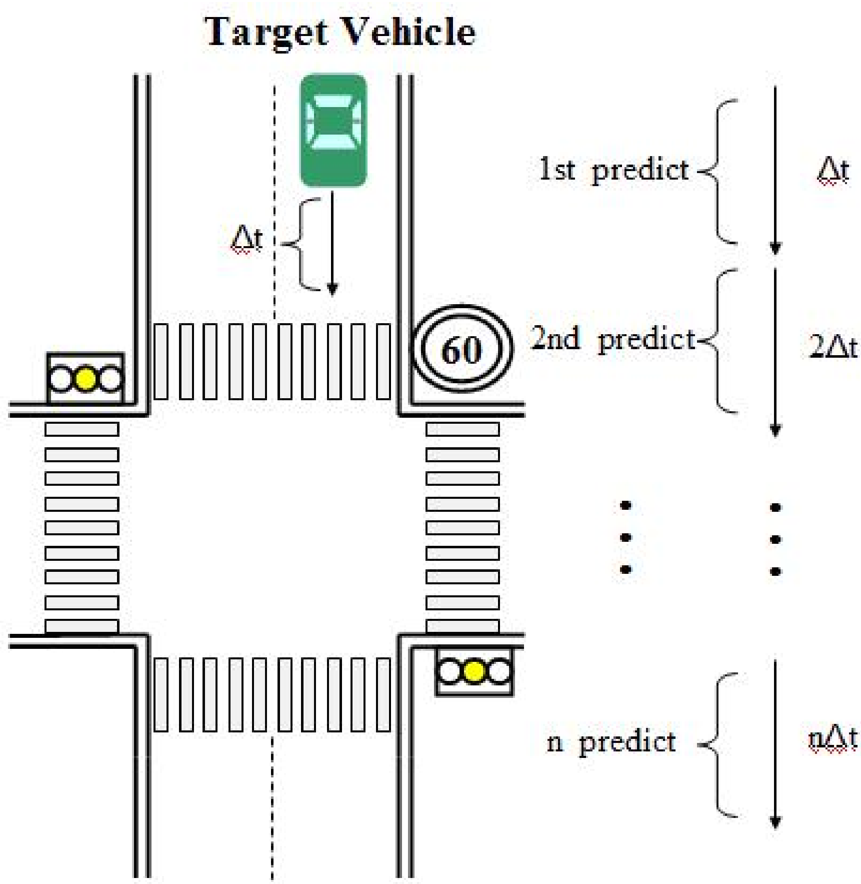

Figure 3.4: The situation for single intention Estimation

According to 3-level intention nodes, environment information which can be observed and these relationships between them, Bayesian networks as shown in Figure 3.6 and Figure 3.7 are constructed respectively for two cases where target vehicle enters crossroad or not.

On the basis of 3.2.1, causal relationships are different according to position

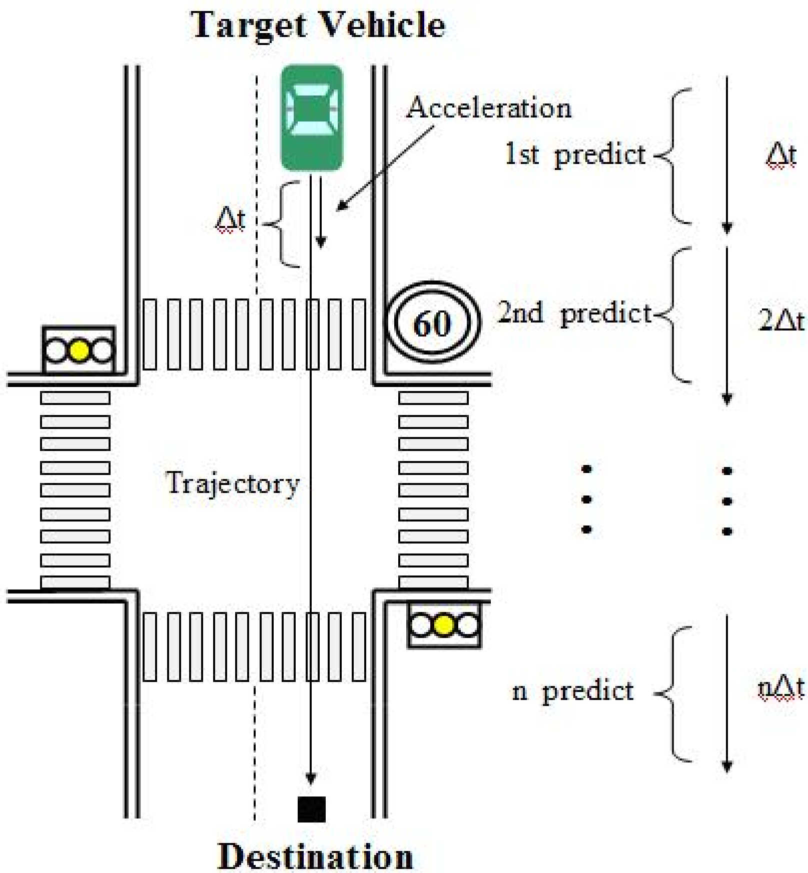

Figure 3.5: The situation for hierarchized intention Estimation

of target vehicle. Therefore, according to the case where vehicle enter crossroad or not, the network constructions which present causal relationship respectively in Figure 3.6 and Figure 3.7 are different.

In addition, the case that target vehicle enter crossroad or not is important for prediction. For that, 3-level intention mentioned above and the node which presents vehicle enters crossroad or not are added, network is constructed.

Compare Bayesian network using hierarchized intention nodes with Bayesian network using single intention node, evidence nodes do not point to one intention node. In each level intention, there are only causal relation nodes and edges. For example, in Figure 3.7, cause of "Intention on Destination" is the result of "Present Position" and "Present Direction", and cause of "Winker" is not all the intention, but the result of "Intention on Destination".

So, the causal relationships of nodes become detail. Thus, for probabilistic inference, only essential conditional probability can be pay attention. The result is, prediction accuracy does not only increase, but calculation complexity of inference also reduces.

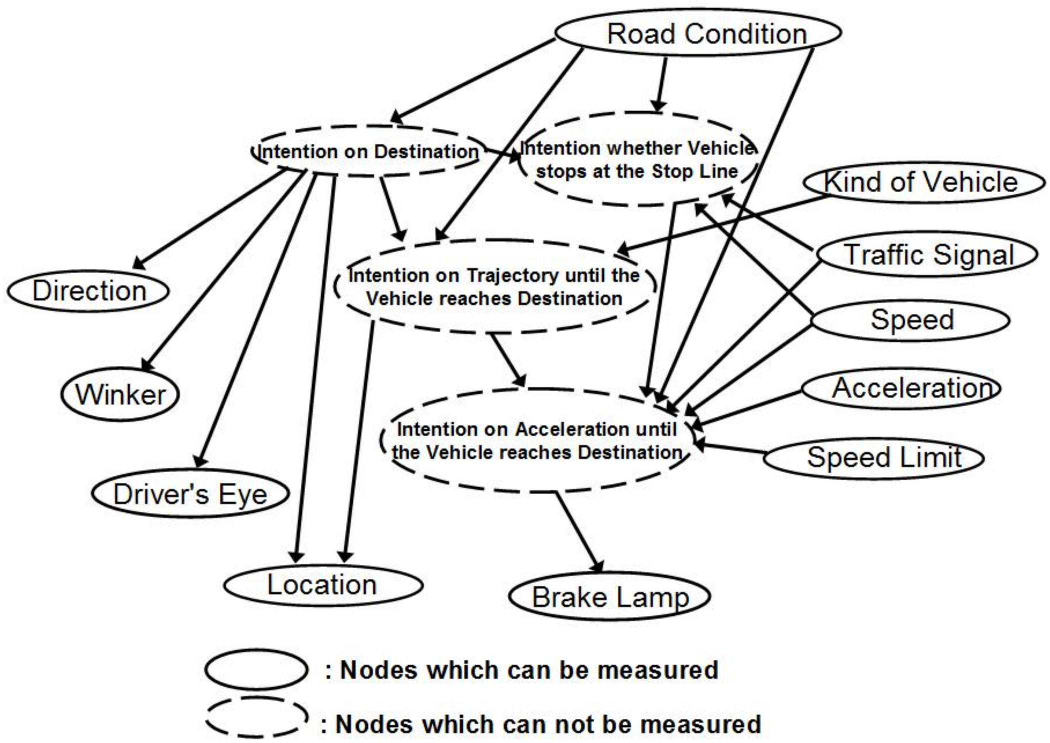

Figure 3.6: Bayesian network using hierarchically defined intentions(Before the vehicle enters a crossroad)

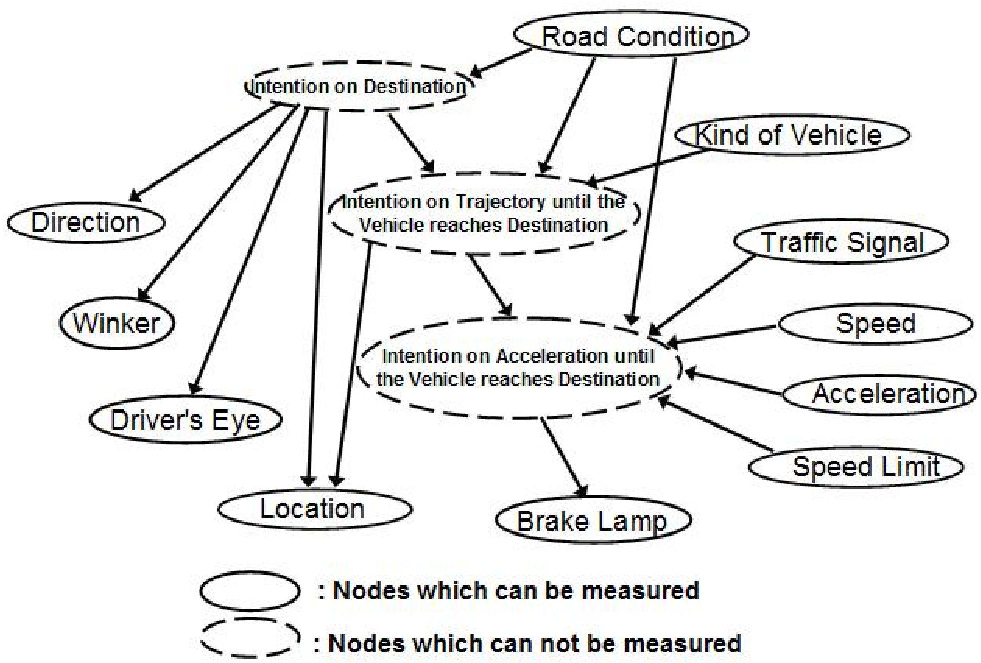

Figure 3.7: Bayesian network using hierarchically defined intentions(After the vehicle enters a crossroad)

3.3 Bayesian Network Construction for the Case where Multiple Vehicles are running around a Target Vehicle

Until now, we considered only the case where only a single vehicle exists in the road environment. In practical situation, multiple vehicles are running in road environment as shown in Figure 3.8, and vehicles influence their motions each other. We discuss a model for the environment where there are multiple vehicles around a target vehicle.

Generally, when a driver is driving a vehicle, he usually predicts future trajectories of neighborhood vehicles which depend on drivers' intentions of neighborhood vehicles. In contrast, drivers of neighborhood vehicles also predict future trajectory of this vehicle. In other words, Vehicles' motions depend on drivers' intentions affect each other. An interaction problem arises. For example, in Figure 3.9, motions of vehicle A and B affect each other. So it is impossible to predict a vehicle 's future trajectory in the case where multiple vehicles are running together. In this thesis, an approximate prediction method is proposed to solve this interaction problem.

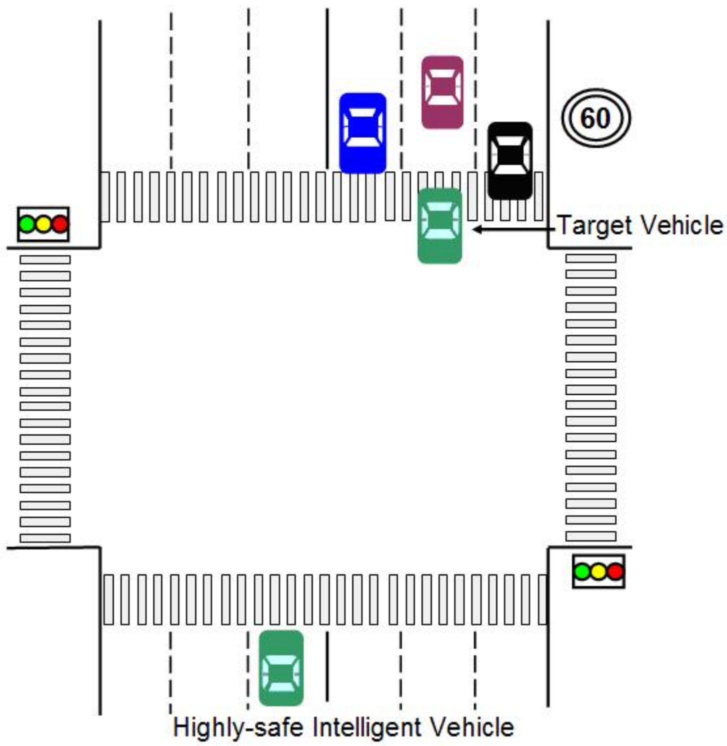

Figure 3.8: The case where multiple vehicles are running around a target vehicle

The proposal is that, the future trajectory, direction and speed of neighborhood vehicle which is in front of target vehicle are considered to be the most influenced factors for target vehicle; the present trajectory, direction and speed of the other neighborhood vehicles are considered to be ordinary influenced factors for target vehicle. From experience, it is well known that in neighborhood vehicles, the largest influence to target vehicle is from front neighborhood vehicle. Because front vehicle and target vehicle stay at same lane, and they have same running direction, driver of target vehicle will change movement of target vehicle according to movement of front vehicle based on safe consideration. And the driver of front vehicle does not need to pay attention to target vehicle. Because if there are some accidents between them, target vehicle would take full respon-

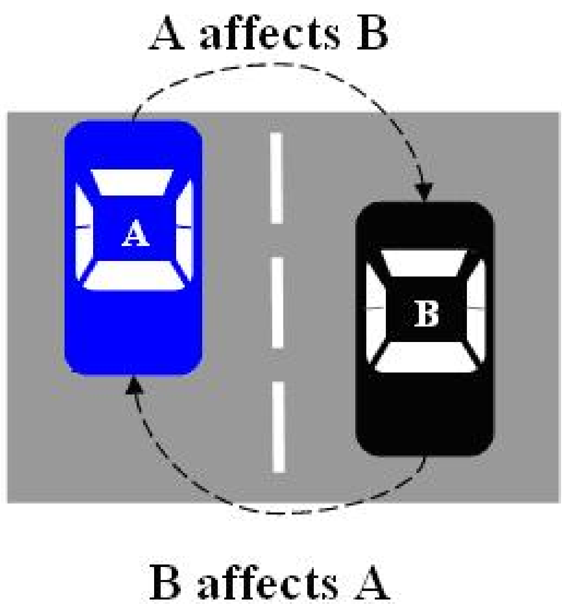

Figure 3.9: Motions of vehicle A and B influence each other

sibility according to traffic rule. Therefore front vehicle can affect target vehicle, but target vehicle can not affect front vehicle. Therefore there is no interaction problem between target vehicle and front vehicles. Except front vehicle, the other neighborhood vehicles are also considered. we only consider about their present information, for example: present speed, present accerleration and etc. These present information can be observed, not depend on motions of neighborhood vehicles. So interaction problem is solved completely.

Let us estimate the trajectory of the target vehicle using the information of the neighborhood vehicles of NE, E, SE, S, SW, W and NW regions as shown in Figure 3.10.

If there is no vehicle in the region S at the front of the running direction, we can estimate the trajectory of the target vehicle using the Bayesian network of Figure 3.11. Present direction, present locations and speeds are used as the information of neighborhood vehicles.

If there is a vehicle in the region S at the front of the running direction, we firstly estimate the trajectory of the vehicle located in the road region S using the Bayesian network of Figure 3.11. Then, using the information of both the estimated future trajectory/speeds of the vehicle in the road region S, and the present vehicle locations and speeds in the regions of NE, E, SE, SW, W and NW, we can estimate roughly the target vehicle trajectory using the Bayesian network of Figure 3.12.

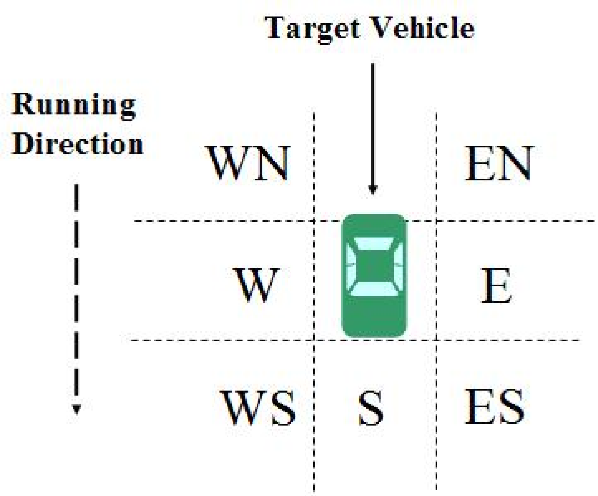

Figure 3.10: Vehicles around a target vehicle which must be considered for estimation

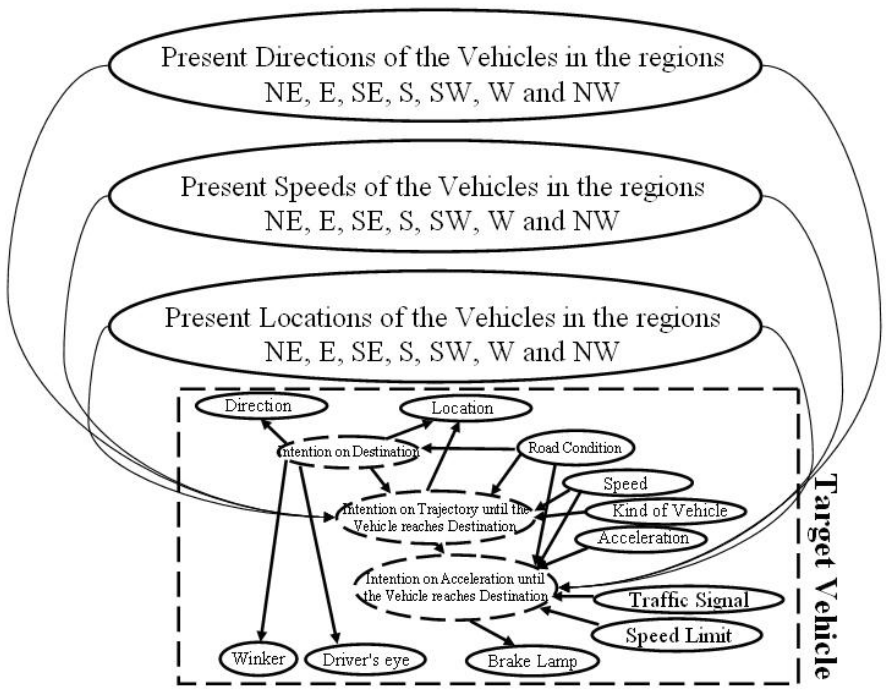

Figure 3.11: Bayesian network for a target vehicle in a case where there is no neighborhood vehicle in the region S

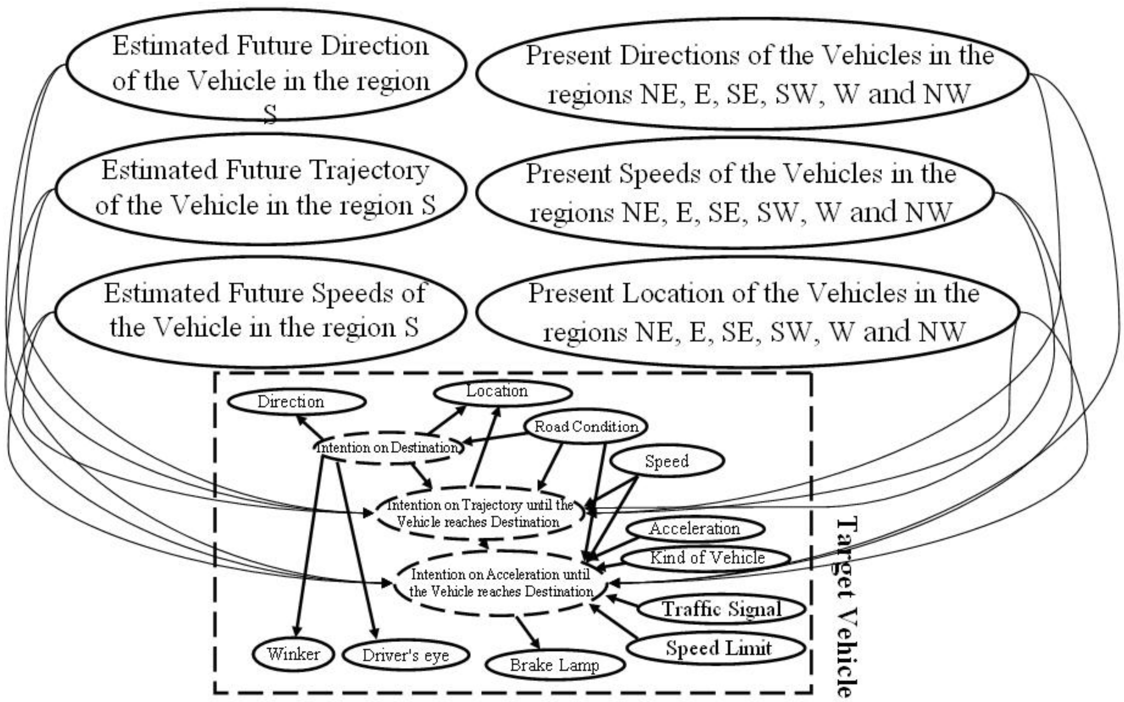

Figure 3.12: Bayesian network for a target vehicle in a case where there is a neighborhood vehicle in the region S

Chapter 4

Experimental Evaluation of Vehicle Trajectory Prediction

4.1 Image processing for acquisition of learning data

4.1.1 Vehicle Extraction

The Bayesian network for target vehicle in the case where no vehicle nears it has been constructed in chapter 3 (Figure 3.4, Figure 3.5). This construction method can be summarized simply. First, define information which can be observed as nodes. Similarly, define driver 's intention which can not be observed as node. Then hierarchize driver 's intention, define each level as nodes. Next, define causal relationship as directed edge. Nodes connected to origin of edge are cause nodes, the nodes connected to head of edge are result nodes.

It is difficult to decide probabilities of Bayesian network nodes by people. It is difficult to ensured precise conditional probabilities presented by causal relationship of nodes by human feeling. Recently, the research on learning of conditional probability from statistic data is improved. In this section, image processing method is proposed for acquisition statistic data. In the case with same setting, because vehicle moves with camera and sensor, three-dimensional image processing is essential. In this thesis, image processing method is proposed based on a given road environment with fixed camera (Figure 4.1).

In highly-safe intelligent vehicle system, road environment is recognized ac-

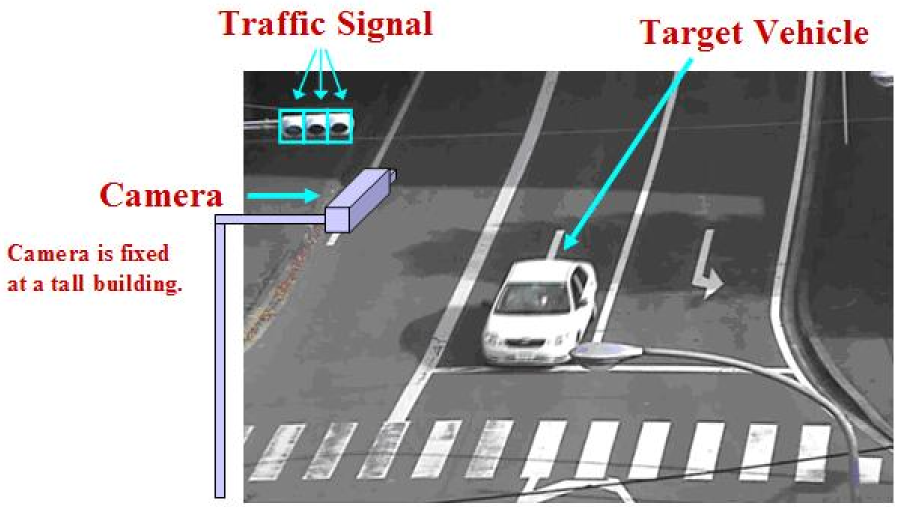

Figure 4.1: A given road environment with fixed camera

cording to camera and sensor fixed on vehicle. Based on simple two-dimensional image processing, statistic data also can be acquired. Detailed illustration is written as below. Road environment for acquisition of statistic data is shown in Figure 4.2. According to this road environment where no vehicle nears target vehicle, statistic data is acquired.

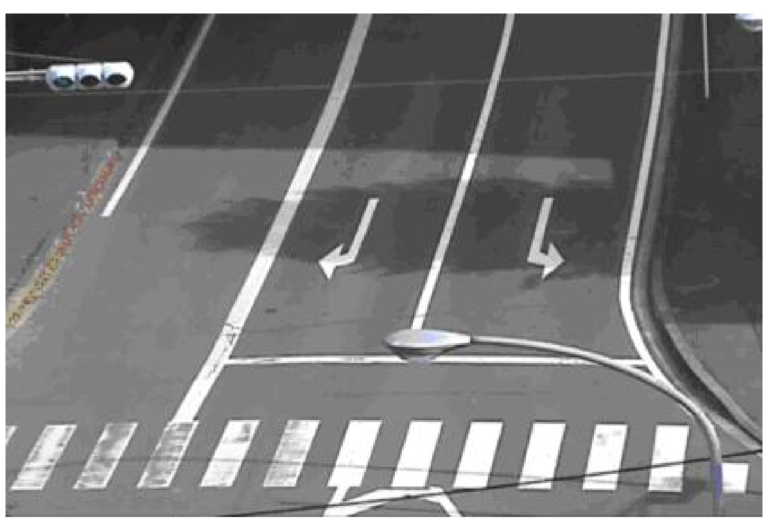

Figure 4.2: Road environment (static background)

Probability inference is inferred for estimating driver 's intention which determines future trajectory of vehicle in Figure 4.3.

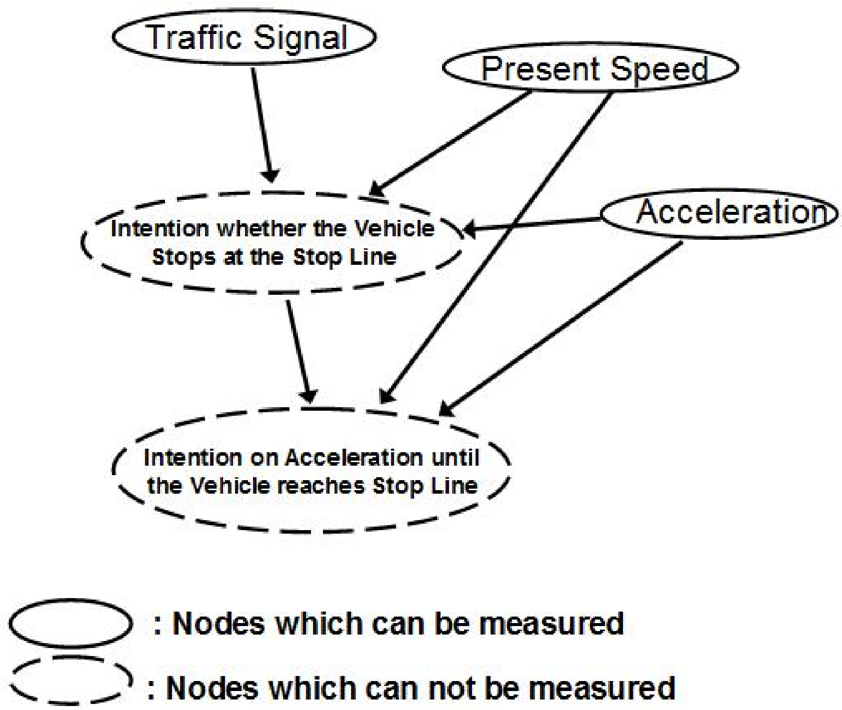

Figure 4.3: Bayesian network for probability inference

In this Bayesian network, traffic signal, present position of target vehicle, present speed, acceleration and driver 's intention (intention whether the vehicle stops at stop line, intention on acceleration until the vehicle reaches the stop line) are acquired by two-dimensional image processing.

(1) Detection of information on the traffic signal sign. Because the traffic signal sign is located at some fixed region in the input image, we can easily detect the color information of blue, red and yellow. This is done by a RGB feature pattern.

(2) Extraction of the vehicle location by subtraction technique. Because the road background has already been known, we can get a difference image by subtracting the value of pixels which have the same coordinates between the static background and background with vehicle. Firstly, modeled static background in

Figure 4.4 can be acquired according to method of modeling static background proposed in chapter 3 as shown in Fig 4.2. Static background is separated into some regions based on traffic lane, and marked by numbers.

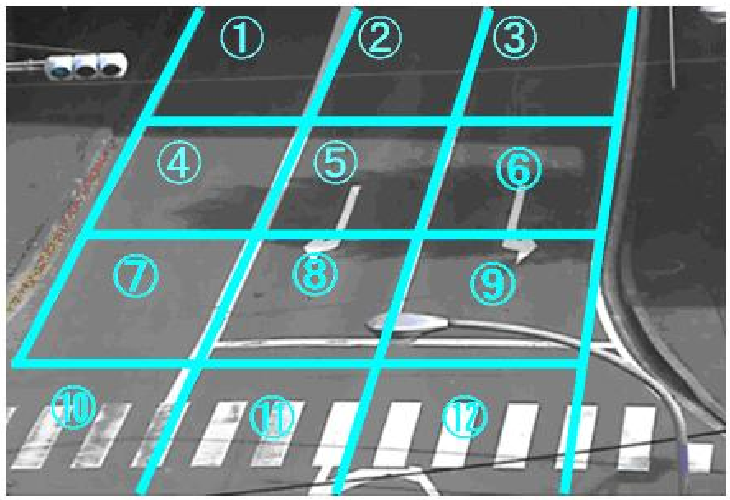

Figure 4.4: Modeling static background

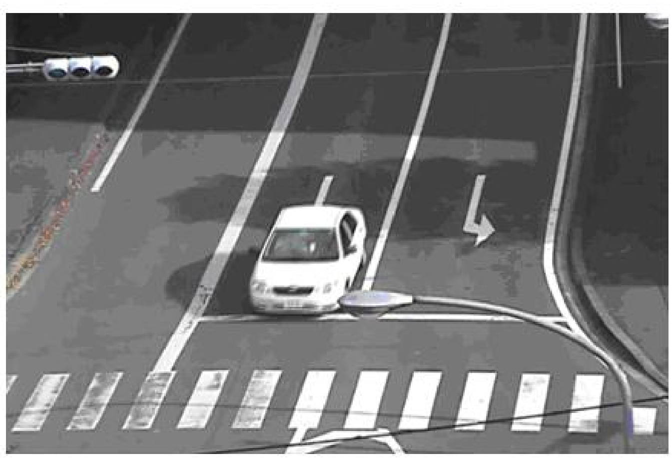

Figure 4.5: Background with vehicle

In a background with vehicle (Figure 4.5) where there is only one vehicle, the number of vehicle position is necessary to be requested. First, because the road background has already been known, after changing backgrounds into black and white images, we can get a foreground image by subtracting the value of pixels which have the same coordinates between static background and background with vehicle. The different parts are non-zero pixels marked by white color, the same parts are zero pixels marked by black color (Figure 4.6).

In Figure 4.6, only using subtraction technique, the almost part is gray color that between white color and black color, so vehicle could not be recognized clearly. Therefore, after using subtraction technique, it is need to use threshold to extract vehicle which is only composed of white color and black color.

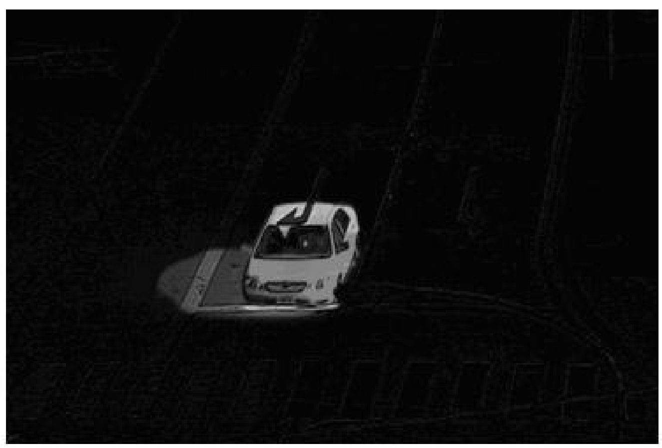

Figure 4.6: Foreground where vehicle be recognized hardly

How to get the threshold that is a problem. First, I use histogram to find threshold from experiment in which bus, taxi, jeep and sedan are analyzed [10] [11]. These histograms are shown as Figure 4.7 which indicates pixel peak is from 0 to 50 of the common point in histograms. So I choose 50 as threshold to separate vehicle from background. I made an algorithm based on threshold 50: If value of pixel of foreground is more than 50, 255 is given to the pixel; if not, 0 is given to pixel. Pixel 0 means white color, and pixel 255 means black color. The algorithm is expressed as below:

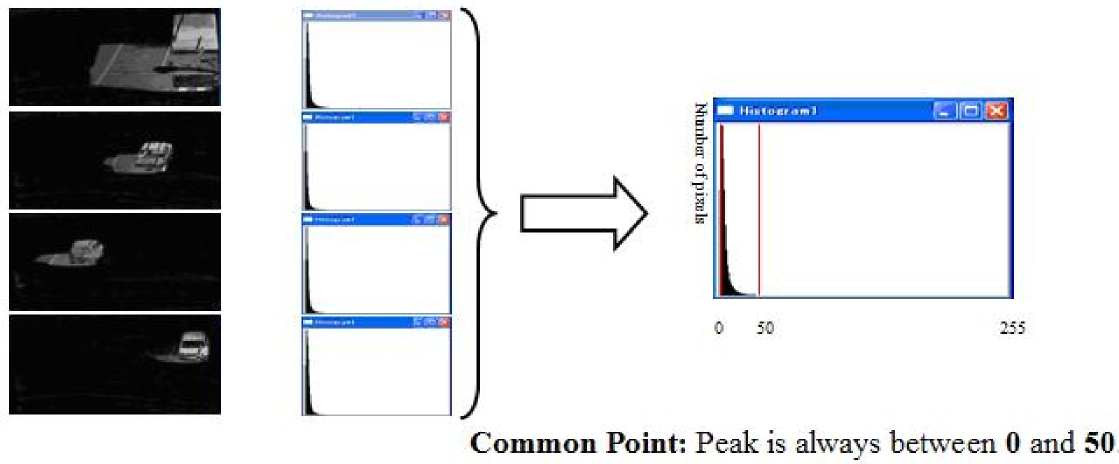

Figure 4.7: The common point between histograms of bus, taxi, jeep and sedan

Pixel $\leq 50 (Threshold) Pixel = 0$

Pixel > 50 (Threshold) Pixel = 255

and applied in image processing with threshold 50 as shown in Figure 4.8.

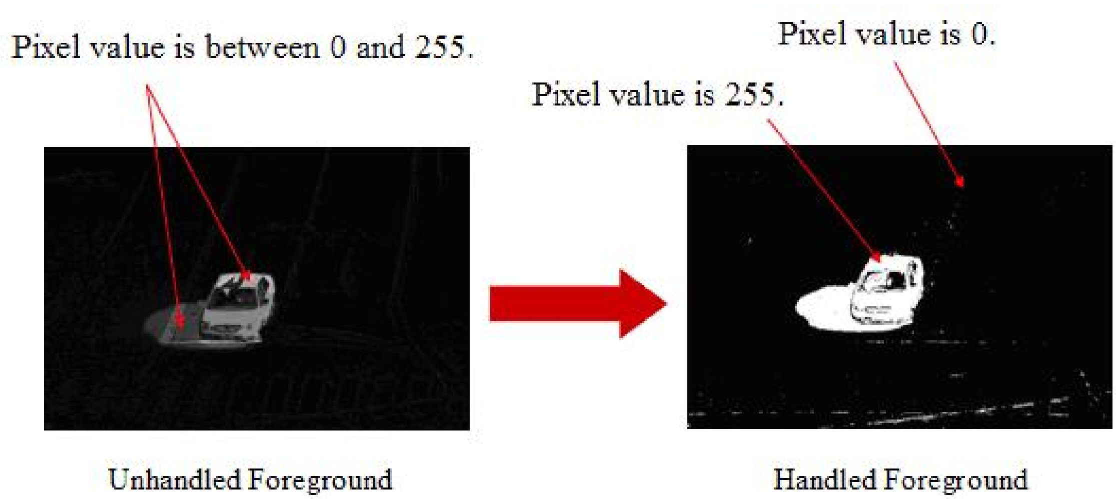

Figure 4.8: The procedure from unhandled foreground to foreground after image processing with threshold

(3) Detection of the speed and acceleration. Similarly, the speed and acceleration of a target vehicle are detected based on the difference image between two input images at different times. Let the vehicle location at time t1 and time t2 be x1 and x2, respectively. The speed is calculated simply as: (x2-x1)/(t2-t1). The acceleration can be also calculated from the speed information at two different times.

(4)Detection of the driver ’s intention The driver ’s intentions can not be detected at real time, but off-line monitoring process makes it possible to get the driving history. Therefore, the intention is acquired by the trajectory and speed pattern of the target vehicle.

4.1.2 Removal of Vehicle Shadow Influence

(1) Analysis for a shadow of a target vehicle If there is a vehicle shadow, we need to consider the removal of its influence. Because a target vehicle moves together with its shadow at the same speed, the shadow is identified as a part of the target vehicle by special image processing. The HSV (Figure 4.9) color space representation is introduced to remove the shadow of a target vehicle [13]. Because Saturation and Value in a shadow region are different from those of the same region without a shadow, we can make separation of vehicle and shadow regions using this property [13]-[15]. For an example, the minimum and maximum of Saturation and Value in Figure 4.10 are 0 and 255, respectively. In the shadow region, Saturation concentrates around 44. However, Saturation concentrates around 20 in the same region without a shadow. Similarly, the difference of Value is 41.

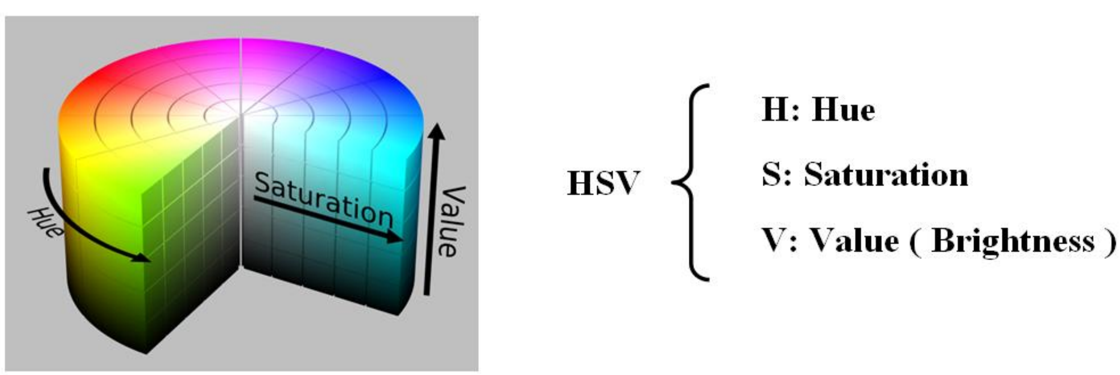

Figure 4.9: HSV cylinder

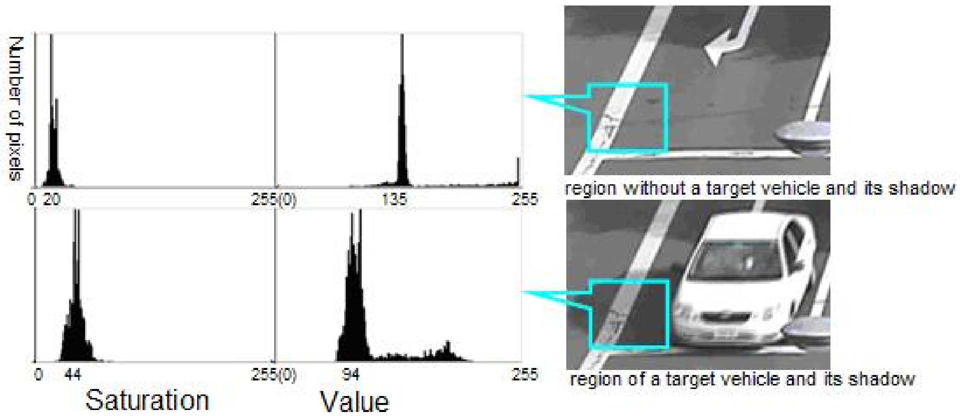

Figure 4.10: Histograms of Saturation and Value in a shadow region and the region without shadow

(2) Shadow extraction Based on the property of a shadow region, we can separate the shadow region from a vehicle region. Then, we mask the shadow region with blue color for understanding clearly in Figure 4.11 (b). A shadow mask SMK is defined for each pixel at the coordinate (x, y) defined as follows:

$$\mathrm{SMK}\ (x, y) = \begin{cases} 0 \quad \text{if} & Ts1 < (\ Ss\ (x, y) - NSs\ (x, y)\ ) < Ts2 \\ & \text{and} \\ & Tv1 < (\ Sv\ (x, y) - NSv\ (x, y)\ ) < Tv2 \\ 255 \quad \text{otherwise} & \end{cases}$$

where Ss, Sv are Saturation and Value of at (x, y) in a shadow region respectively. Similarly, NSs and NSv are those in the same region without a shadow, respectively. According to many experimental results, the Saturation difference between shadow and non-shadow regions is usually distributed between Ts1 and Ts2. Similarly, the Value difference between shadow and non-shadow regions is usually distributed between Tv1 and Tv2. If the two conditions are satisfied, 1 is given to SMK (x, y). That means the pixel (x, y) becomes black as shown in the example of Figure 4.11 (d).

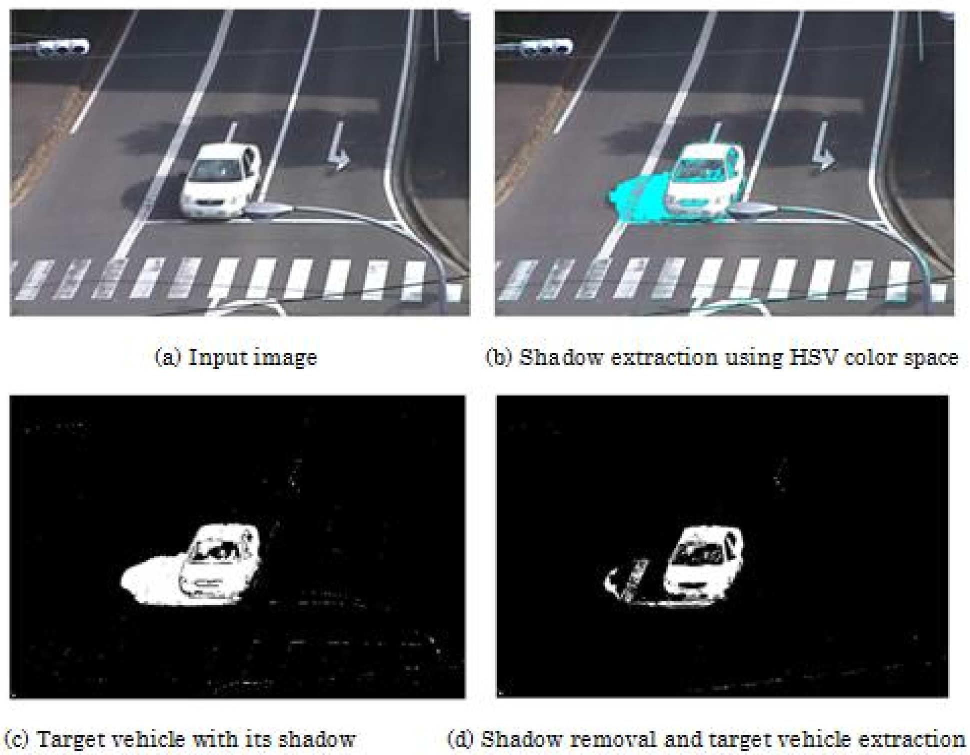

Figure 4.11: Process of shadow extraction

4.2 Probabilistic inference for the driver 's intention estimation using Bayonet

Using the conditional probability distribution acquired by the above learning, probabilistic inference for some input condition is done using a program package of Bayesian network Construction System (BayoNet) [16]. The traffic signal sign is blue, the speed of a target vehicle is 0-30 km/h, and the acceleration is between 0 m/sec and 5 m/sec. The vehicle will not stop at stop line. The inference result is shown in Figure 4.12. The probability distribution of the driver 's intention seems to be reasonable in this road environment.

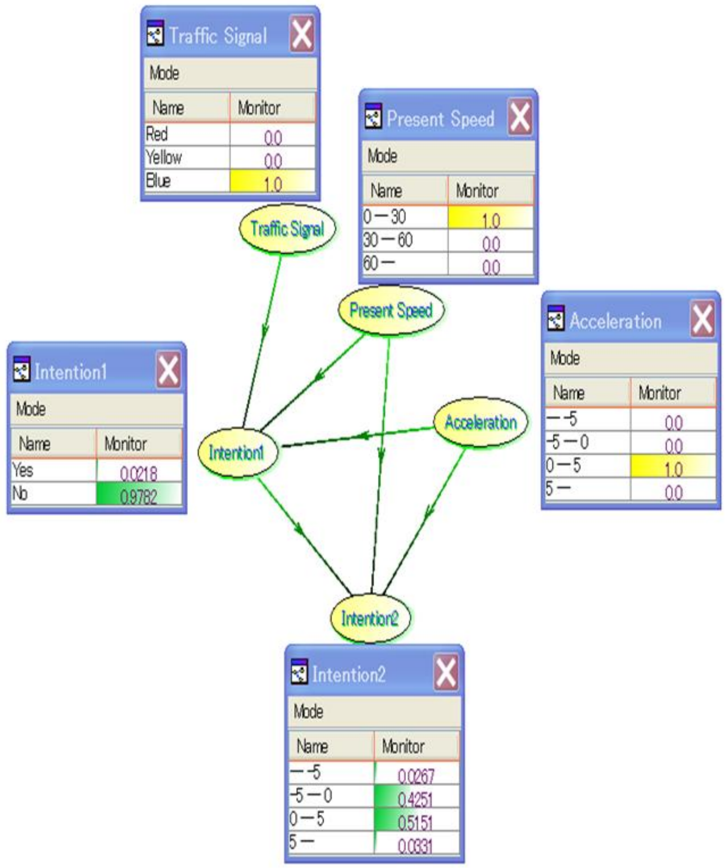

Figure 4.12: Example of probabilistic inference with Bayonet

4.3 Simulation of Vehicle Trajectory Prediction in the Case where Multiple Vehicles are running around a Target Vehicle

In this section, a simulation of vehicle trajectory prediction in the case where multiple vehicles are running around a target vehicle is made based on the method of Bayesian network construction mentioned in chapter 3 (Figure 3.11, Figure 3.12). Figure 4.13 gives an example of a very simple road environment for simulation of vehicle trajectory prediction in the situation that two vehicles are running on the same lane in one way road. Trajectory, speed, vehicle winker, brake lamp and distance between target vehicle and front vehicle are considered in this situation. Driver of target vehicle changes movement of target vehicle based on prediction about future trajectory and speed of front vehicle. We can express this relationship using Bayesian network in Figure 4.13.

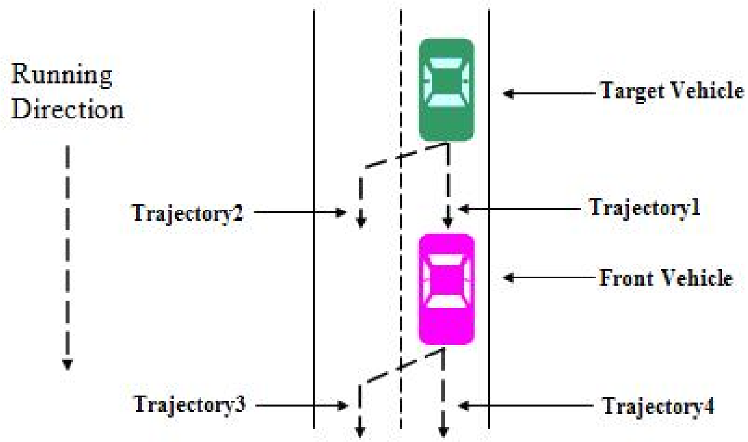

Figure 4.13: The situation that two vehicles are running on the same lane in one way road

Bayesian network in Figure 4.13 includes two sub-Bayesian networks which include Bayesian network of front vehicle and Bayesian network of target vehicle respectively. Two causal relationships are between nodes " Estimated Future Trajectory of Front Vehicle ", " Estimated Future Speed of Front Vehicle " and node " Intention on Future Trajectory of Target Vehicle ". The common point is that both of them have winker, brake lamp and intentions on trajectory and speed. Based on Bayesian network in Figure 4.14, a simulation is made by Bayonet as shown in Figure 4.15. Input information and output information is shown in table 4.1 and table 4.2 repectively.

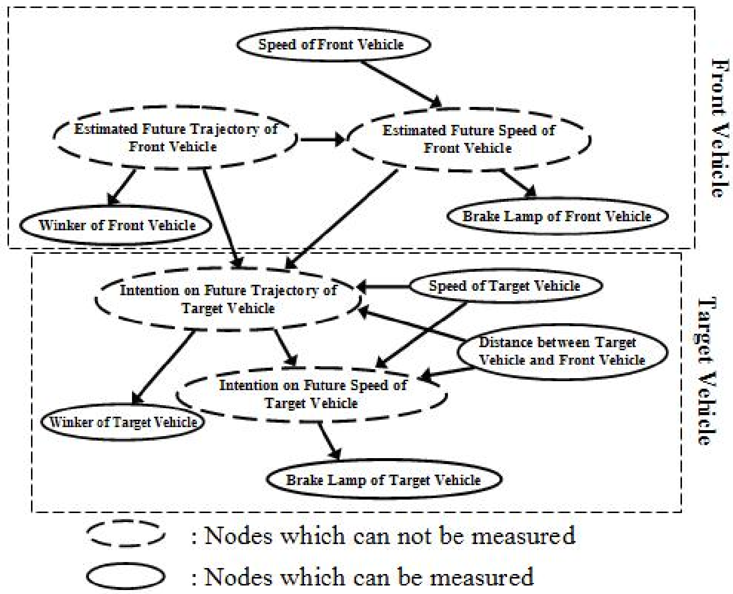

Figure 4.14: Bayesian network for the situation in Fig 4.13

Table 4.1: Input information of simulation

Speed of Front Vehicle	0-30km/h
Brake Lamp of Front Vehicle	Off
Winker of Front Vehicle	On
Distance	0-20m
Speed of Target Vehicle	30-60km/h
Brake Lamp of Target Vehicle	Off
Winker of Target Vehicle	Off

Table 4.2: Output information of simulation

Intention1	Trajectory 3 (99%)
Intention2	0-30km/h (40.54%) 30-60km/h (34.78%) 60km/h- (24.68%)
Intention3	Trajectory 1 (99.01%)
Intention4	0-30km/h (89.92%)

Intention1: Estimated Future Trajectory of Front Vehicle

Intention2: Estimated Future Speed of Front Vehicle
Intention3: Intention on Future Trajectory of Target Vehicle
Intention4: Intention on Future Speed of Target Vehicle
Distance: Distance between Target Vehicle and Front Vehicle

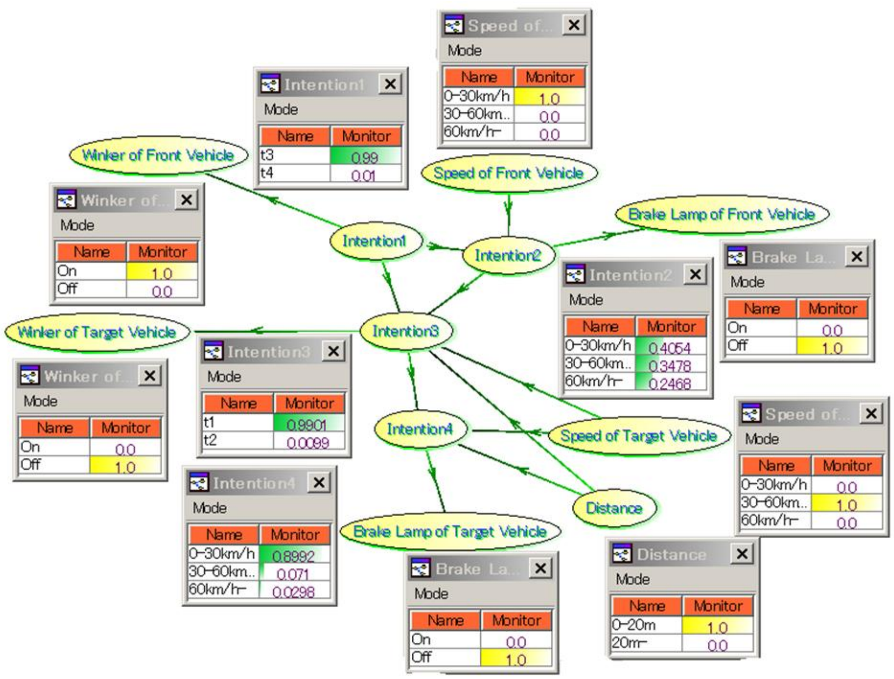

Figure 4.15: Simulation based on Bayesian network in Figure 4.14

Chapter 5

Conclusion

The concept of model-by-model Bayesian network construction and hierarchy of driver 's intention has been discussed for reasonable trajectory estimationin in two situations: In situation one, only one target vehicle is running in road environment. In situation two, multiple vehicles are running together in road environment. There still remain some future problems:

(1) In general road environment, it is important to build an integrated Bayesian network so that common sub- Bayesian network components between many different road models are shared as many as possible. Because such a Bayesian network will be of large scale, an inference engine implemented by the recent VLSI technology is required to be developed.

(2) In practical situation, recognition of road environment and vehicle information using vision sensors mounted on an intelligent vehicle is essential based on 3-D image processing technology.

(3) Not only vehicles but also the other moving objects such as pedestrians must be included for the trajectory estimation in road environment.

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