A MICROSCOPIC DRIVER ATTENTION ALLOCATION MODEL

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ABSTRACT

Misallocating attention has been considered the most likely cause of crashes. The acquisition of incomplete or unusable information leads to insufficient comprehension of the current driving environment. Thus, a functional mechanism for attention allocation is a critical issue in crash prevention. Researchers have conducted several field studies to analyze attention allocation from an aggregate perspective. However, only a few characteristics of attention allocation can be extracted. This study proposes a driver attention allocation model from a microscopic perspective to explore the driver attention allocation problem and clarify how drivers allocate attentions. This study treats the continuous process of attention allocation as successive choices of their focal point, and derives the probability of choosing specific focal point using a discrete choice model. A set of hypothetical data was generated for numerical analysis to illustrate the appropriateness of the proposed attention allocation model. Although this study only adopts hypothetical data and simple scenarios, the results show that the proposed model can reveal the mechanisms of eyesight shifting for information gathering, and have the potential to be an effective tool for safety evaluation.

Keywords: attention allocation, focal point, discrete choice model.

INTRODUCTION

To understand roadway crashes, researchers have worked on mining aggregated crash data to extract crash patterns (Chang and Yeh, 2007; Elvik, 2003; Wong and Chung, 2007a; 2007b; 2008a; 2008b; 2010; Wong et al., 2010). However, a crash-prone driver driving in a crash-prone scenario with risky behavior does not always lead to crashes. In fact, most crashes are preventable under dangerous situations, as long as the surrounding traffic is properly observed and adequate maneuvers are successfully executed (Wong and Chung, 2010; Wong et al., 2010). This phenomenon suggests that there is still a missing link between crash patterns and crash occurrences. The key element seems to rely on the understanding of drivers, especially the attention allocation process while driving. Thus, to illuminate the causality and the inherent nature of crashes, this study explores crashes from the perspective of drivers' attention allocation.

Misallocating attention has been considered as the most likely cause of crashes (Brown et al., 2000; Chan et al., 2010; Di Stasi et al., 2009, McKnight and McKnight, 2003; Olson et al., 2009; Underwood, 2007; Underwood et al., 2003a). Continuous information searching is a key step in comprehending, anticipating, and reacting to tasks or events (Endsley, 1995). The acquisition of incomplete or unusable information will lead to insufficient comprehension of the current driving environment. To drive safely, drivers must pay attention to multiple information sources to make informed driving decisions. However, one's attention resources are limited (Kahnemen, 1973). Each driver has a central processor that determines the policy of attention allocation and divides their mental resources within the limits of their mental capacity. As a result, the problem of divided attention may degrade one's ability to detect potential threats (de Waard et al., 2009; Marmeleira et al., 2009). Misallocating attention may distract someone with useless information, causing them to miss important information. Thus, a functional policy for attention allocation without mental resource misallocation is a critical issue in driving safety.

Policies for attention allocation are the keys to distinguishing experienced drivers from novices (Konstantopoulos et al., 2010). Experienced drivers have better knowledge of driving tasks, and are more likely to make better decisions (Borowsky et al., 2010; Martens and Fox, 2007; Nabatilan, 2007; Underwood et al., 2002). On the other hand, novice drivers, who have immature mental models and limited rules of attention allocation, usually fail to allocate attention to surrounding area, and focus only on limited targets in front of the vehicle (Chan et al., 2010; Martens and Fox, 2007; Underwood, 2007; Underwood, et al., 2002; 2003a; Konstantopoulos et al., 2010). Nevertheless, unanticipated hazards and surprising events that may seriously harm driving safety can appear frequently. As a result, novices may commit more driving errors due to attention allocation failure (Chan et al., 2010; Martens and Fox, 2007).

Quantifying the policy of attention allocation is essential to evaluating driving safety. Researchers have conducted several field studies to observe the proportion of time that drivers spend on particular objects or areas under various conditions (Borowsky et al., 2010; Konstantopoulos, 2010; Levin et al., 2009; Nabatilan, 2007; Underwood et al., 2003a). Under normal conditions, the frontal areas attract the most attention (Levin et al., 2009; Nabatilan, 2007; Underwood, 2007; Underwood et al., 2003a). In addition to focusing on the frontal side, drivers occasionally allocate attention to their surrounding areas to maintain situational awareness (Crundall et al., 2006). However, shifting attention away from the frontal area increases driver uncertainty, which urges drivers to shift their attention back to the front (Brown et al., 2000; Underwood et al., 2003a). Instead of using single point or area as the focal point, Underwood et al. (2003a) analyzed driver attention allocation through scan paths, which contain multiple and sequential fixation points. This approach enables the in-depth study of attention allocation and provides more clues regarding drivers' strategies of situational awareness.

Another approach to analyze the attention allocation process is to evaluate the allocation policy through its overall variety and flexibility (Chapman et al., 2002; Hosking et al., 2010; Nabatilan, 2007). A well-trained driver maintains a high variance of eyesight fixation. Rather than saccade eyesight randomly, experienced drivers are able to direct their eyesight around the vehicle on the basis of clues obtained from the environment (Borowsky et al., 2010). This enhances their situational awareness and allows continuous observations for potential threats. However, attention allocation strategies become less variant when facing hazardous objects, which drivers invariably pay close attention to (Hosking et al., 2010).

Other than analyzing attention allocation based on the perspective of time proportion, several researchers have attempted to compile computational models to predict the probability of choosing focal point under various conditions. The SEEV model divides the contributing factors of attention allocation into four constructs: salience, effort, expectancy, and value (Wickens et al., 2003a; 2003b; Horrey et al., 2006). “Salience” represents the conspicuity of information that determines whether drivers can easily identify and extract those stimuli from the background information. “Effort” characterizes the distance (or the difference of visual angle) between different sources of information. Larger spans of visual angles may inhibit the scan path owing to the greater mental effort they require. “Expectancy” represents the expectation of information appearance that drivers must collect. Areas that are expected to have more wanted information attract higher levels of attention. Finally, “Value” symbolizes the relevance and importance of information. The higher the value of an information source, the more attention it will attract.

The SEEV model provides a good framework for attention allocation research, as it comprises four major contributing factors. However, the model in Horrey et al. (2006) was originally designed for simple tasks containing only few information sources, such as outside the vehicle and in-vehicle tasks. Several difficulties appear when applying the concept of SEEV model to a real driving environment, which contains complex focal points. First, the SEEV model only utilizes four constructs which were presented in the form of ranking order (namely one to three). More manifest measurements of the four constructs are required to clarify how drivers shift attention during dynamic and complex driving tasks. Second, the obtained probability reflect only the probability of choosing specific focal point. Therefore, to analyze the attention allocation process from a more microscopic perspective, an attention allocation model that can reflect eyesight fixation and saccade is needed.

Modeling attention allocation is a major step in identifying the external information perceived and driver reactions. Recognizing the critical role of attention allocation in driving safety, this study proposes a driver attention allocation model from a microscopic perspective. A discrete choice model to determine the probability of selecting focal point with specific attributes is developed. It will allow us to observe and represent the real-time behavior of shifting eyesight for driving information acquisition. Thus, a framework of the driver attention allocation model with its contributing factors based on the concept of SEEV model is developed firstly in the following section. A set of hypothetical data is then generated for a numerical analysis to illustrate appropriateness of the proposed model.

DRIVER ATTENTION ALLOCATION MODEL

Before we can develop a driver attention allocation model, it is necessary to clarify the issue of “where to allocate attention.” The following section classifies the complex driving environment into several focal points based on the concept of vehicle driver’s domain (Wong and Huang, 2010).

Focal Points

In real driving tasks, there are countless potential focuses that may attract drivers' attention, including objects on-road, off-road, or in-vehicle. It is therefore technically unpractical to conduct analysis at this level of detail. From the viewpoint of operational feasibility, an appropriate approach is to classify the potential focal points into several groups based on their characteristics. Thus, objects within the area of interest, which is treated as a focal point, should produce similar maneuvers. This section characterizes the focal point based on two dimensions. The first dimension is the vertical distance between focal points and the subject vehicle, which is classified as the vehicle driver's domain. The second dimension is the lateral location of the focal points.

The vehicle driver's domain is a driver's conceptual area in which external objects may appear to interact with the subject vehicle and degrade driving safety. To prevent collisions, drivers must allocate their attention within the vehicle driver's domain to gain information for driving maneuver. This study only discusses conscious visual attention; information is completely effective and successfully perceived when being attended to. In line with Underwood et al. (2003a), this study divides the interested area into three sub-domains from near to far. These domains are the critical domain, reaction domain, and perception domain. A vital aim of defining these three domains is to simplify the alternatives of eyesight fixations. Objects located in different domains should attract different levels of attention and activate different reactions due to varying levels of risk. Closer threats induce greater risk of collision and require more attention.

The perception domain reflects the relatively distant area in which a driver has plenty of time to perceive stimuli there. Drivers usually only maintain situational awareness against objects located in the perception domain. Immediate technical tasks, such as changing speed or direction, are not necessarily made when objects are situated in this area. The reaction domain is the area in which objects are determined as threats to safety that drivers must pay close attention on and in which drivers must react to any stimuli appearing. Objects inside this area will attract a higher level of attention. Technical tasks will be activated to prevent collisions. The third domain is the critical domain, which represents a safety boundary; drivers must secure this area and prevent objects from entering it. Although drivers do allocate attention to the critical domain, crashes are not preventable if threats appear inside this domain. Immediate technical tasks must be performed if the threats to safety are close to the critical boundary or inside the critical domain. The development and detailed discussion of a vehicle driver's domain is beyond the scope of this study. Interested readers are referred to Wong and Huang (2010).

Another advantage of adopting vehicle driver's domain is to simplify the complex interaction of factors in locating driver's eyesight fixation. Different settings of contributing factors, such as a driver's reaction capability under different psychological and physiological conditions, individual intention, weather, and speed, may create different results of attention allocation. By adopting the concept of the vehicle driver's domain, it is possible to represent the complex interaction of various factors based on the size and shape of the three proposed domains, even though each domain's size and shape may change with the driving environment and driver status. Therefore, in modeling attention allocation, the problem is reduced to derive the probability of choosing specific domain without the concern of different drivers' characteristics.

The second dimension for characterizing focal point is the lateral location. This study adopts a simplified scenario. Drivers were assumed to drive on a divided four-lane freeway without interferences of intersections. In this scenario, threats would appear on either the same lane or the adjacent lane when looking forward. Moreover, drivers are able to observe the rear traffic by looking the mirror and to collect information via roadside signs. Therefore, mirror and roadside are two alternatives included in attention allocation. Combining the vehicle driver's domains and their relative location generates eight focal points (F_1 *to* F_8).

F_1: The critical domain on the same lane
F_2: The reaction domain on the same lane
F_3: The perception domain on the same lane
F_4: The critical domain on the adjacent lane
F_5: The reaction domain on the adjacent lane
F_6: The perception domain on the adjacent lane
F_7: Mirror
F_8: Roadside

Model Specification

Driver attention allocation is a continuous process of choosing targets and information searching. However, the decision to select focal point is made in drivers' sub-consciousness on the basis of experience and training. The purpose of this study is to capture the mechanisms of driver attention allocation.

This study proposes a probability based model that utilizes a discrete choice model to analyze the attention allocation process from a microscopic perspective. Thus, the continuous process of attention allocation must be converted into discrete counterparts and treated as successive focal point choices. The resulting probability of choosing focal point must reflect the fact that a driver would fixate and maintain fixation on one focal point for a while, then shift eyesight to another focal point. Instead of allocating attention randomly, a proper policy of attention allocation should direct driver's eyesight based on cues from driving tasks and the surrounding environment. Therefore, contributing factors of dynamic traffic and driving tasks must be considered. Identifying the contributing factors of attention demand and evaluating the extent of their effect can provide an in-depth understanding of the mechanisms involved in driver attention allocation.
This study further categorizes attention into two types to make it easier to model. The first type is spare attention. This can be regarded as the level of attention allocated without any interference, such as vehicles or other objects on road. Spare attention reflects the areas of drivers' concerns over safety against intended maneuvers and does not vary with dynamic traffic flow. The second type of attention is motivated attention. This is a feature-based attention involving the attributes of each object, which attract different levels of attention. Combining the spare attention and motivated attention, the attention demand function of each focal point is defined as

$$A_{i,j,k} = Spare_{i,j,k} + Motiv_{i,j,k} + \varepsilon_{i,j,k} \tag{1}$$

where $A_{i,j,k}$ is the attention demand function of shifting attention from focal point i to focal point j at time stage k, $Spare_{i,j,k}$ is the attention demand resulting from spare attention related factors, $Motiv_{i,j,k}$ is the one from motivated attention related factors, and $\varepsilon_{i,j,k}$ is the error term.

The "expectancy" and "effort" constructs in the SEEV model form the basis of spare attention. Different intended maneuvers, headings, and diverse future trajectories create distinct areas of interest and allocation patterns. Equation (2) define spare attention, which contains $Asc_{i,j}$ and $Time_{i,k}$.

$$Spare_{i,j,k} = Asc_{i,j} + \beta_{TIME,i} \cdot Time_{i,k} \tag{2}$$

$Asc_{i,j}$ is the constant term of shifting attention from focal point i to focal point j, and should reflect the attention demand without motivation from other vehicles on roads. The alternative specific constants include two dimensions of spare attention. The first dimension is the intrinsic attention demand, which reflects the attractiveness of each focal point under specific maneuver intentions. Drivers usually fixate their sight on, and pay attention to, the direction of current moving trajectories. This implies that a greater risk of conflicts may arise when other vehicles appear on future trajectories. Different maneuver intentions create different future trajectories and induce unique expectations of threat that drivers must pay attention to. For example, when driving forward, drivers allocate more attention to the far area of the current lane (Levin et al., 2009; Nabatilan, 2007; Underwood, 2007; Underwood et al., 2003a). On the other hand, drivers pay attention to the adjacent lane and rear of the vehicle when attempting to change lanes (Salvucci and Liu, 2002; Underwood et al., 2002). This study treats maneuver intentions as exogenous factors that are not included in the attention demand function. Instead, the alternative specific variables in Eq. (2) represent the attention demand of each focal point under the given maneuver intention. In our current hypothetical case, the drivers' intention is to drive forward and keep on lane. Moreover, instead of shifting attention randomly, drivers allocate their attention based on the function of the previous focal point (Underwood et al., 2003a). In other words, the second dimension of the constant is the different conditions of previous focal point. To extract the scan path of a driver's shifting attention around the vehicle, the proposed model includes eight sub-models that respectively represent the given conditions of focal point in the previous stage. If scan paths exist, the calibration results of alternative specific constants among the eight sub-models should be different and show distinct patterns of eyesight saccades from one focal point to another. The scan path method can also reveal the effects of "effort" on shifting eyesight across the field of view.

The other element of spare attention is the enduring time, the number of time stages a driver fixating on the same focal point. The probability of choosing same focal point in the second time stage will be the highest among all the alternatives, and will decrease with the time that a driver has fixated on a particular focal point. $Time_{j,k}$ is the time that a driver has spent on focal point j before time stage k. This time should have a negative effect on the probability of the same focal point being chosen; that is, the probability of shifting attention away to other focal points increases over time.

The second type of attention demand is motivated attention, which reflects the “value” and “salience” of objects or vehicles within each area of interest. Equation (3) presents the motivated attention demand, which is explained in detail in the following.

$$Motiv_{i,j,k} = \beta_{F,i,j} \cdot F_{j,k} + \beta_{Dc,i,j} \cdot Dc_{j,k} + \beta_{Lc,i,j} \cdot Lc_{j,k} + \beta_{Sc,i,j} \cdot Sc_{j,k} + \beta_{Co,i,j} \cdot Co_{j,k} \quad (3)$$

Like the construct of “value” in the SEEV model, threats that are more relevant and important to driving tasks and safety motivate more attention demand (Kahnemen, 1973; Martens and Fox, 2007; Underwood et al., 2003a; ; 2003b). To minimize the likelihood of possible crashes, drivers tend to fix their eyesight on threats with a higher level of risk. In this study, the “value” of each threat is determined by the location of vehicles and their maneuver states. $F_{j,k}$ is a dummy variable for whether the focal point j is occupied by other vehicles or objects at the time stage k. Threats existing within the vehicle driver’s domain imply the existence of objects that drivers may run into. Hence, drivers must pay more attention to threats that induce a higher risk of colliding with subject vehicles. For example, threats that are closer to the subject vehicle are expected to attract more attention due to the shorter time for crash prevention. Threats located in adjacent lanes induce less crash risk than those in the same lane, provided that the subject vehicle is not changing lanes.

In addition to the existence of a threat, vehicles on road with different maneuver induce different levels of crash risk. The maneuvers considered in this study include deceleration and lane change of a vehicle within the driver’s domain. The associated dummy variables of vehicle in focal point j corresponding to speed decrease and lane change at time stage k are $Dc_{j,k}$ and $Lc_{j,k}$, respectively. Drivers should pay more attention to threats maneuvering toward the subject vehicle’s moving trajectory, such as a frontal vehicle decreasing speed or vehicle in an adjacent lane changing lanes in the driver’s frontal area. The results of these value related variables can be treated as perceived risk levels for threats in specific locations and specific maneuvers.

The other contributing factor of motivated attention is the “Salience” of the threat, which represents the demand induced by orientation reaction. This variable reflects the ease with which drivers can identify the stimuli from traffic flow and induce involuntary transitions of attention. This study analyzes two orientation reactions. The first orientation reaction is $Sc_{j,k}$, which represents an object located in focal point j changing its maneuver state in time stage k. Drivers perceive and store the characteristic of current traffic condition in their memory, then use the obtained information to allocate attention and drive (Underwood et al., 2003b). Changes in the maneuver states of other vehicles are events that break the current stable pattern of traffic flow and are therefore more easily noticed by drivers. Upon encountering new stimuli and events, drivers must be able to identify the latest maneuver threats, update memory, evaluate the threat to safety, and apply a new attention allocation policy (Kahnemen, 1973). For non-threatening objects, drivers still have higher chances of shifting attention to vehicles that simply brake, change lanes, or appear. Objects are generally ignored if they pose no significant threat. $Sc_{j,k}$ contributes to the attention demand only when a maneuver is initiated. After the initial state changes, the additional demand disappears and the new maneuver state of corresponding vehicle is updated. The attention demand will be determined by $Dc_{j,k}$ and $Lc_{j,k}$ until the end of the maneuver.

The second orientation is the $Co_{j,k}$, which represents the additional attention attracted by a complex threat located in focal point j in time stage k. A threat with unusual behavior and exterior can be viewed as a complex threat that is relatively easy to identify. The determination of the complexity depends on the traffic conditions in different situations. Provided that the behavior and exterior of a vehicle is different from others, it can be determined as a complex threat. For example, drivers will pay more attention on ambulances or aggressive vehicles, yielding to avoid potential conflicts. Moreover, heavy vehicles, such as trucks and buses, are unique in size among other vehicles and easier to be identified.

By assuming the error term $\varepsilon_{i,j,k}$ is independent and identically distributed, the probability of choosing focal point j at time stage k ($\Pr_{i,j,k}$) can be derived using Eq. (4). The maximum likelihood method can then be used to estimate the model parameters with the likelihood function shown in Eq. (5)

$$\Pr_{i,j,k} = \exp\left(A_{i,j,k}\right) \Big/ \sum_{j} \exp\left(A_{i,j,k}\right) \tag{4}$$

$$L = \prod_{k=1}^{K} \prod_{j=1}^{J} \left(\Pr_{j,k}\right)^{f_{j,k}} \tag{5}$$

where K is the number of time stages (number of samples), and $f_{j,k}$ is a dummy variable indicating whether the focal point j is chosen in time stage k.

The output of the driver attention allocation model is the probability of choosing a specific target as the focal point under certain traffic conditions and intended maneuvers. Given the driver's previous focal point, this probability can be further expanded into the form of a transition matrix that determines the probability of shifting eyesight from one focal point to another. This makes it possible to analyze attention allocation from a microscopic perspective.

NUMERICAL STUDY

The purpose of this numerical study is not to investigate real driving behavior, but to illustrate the appropriateness of the proposed choice-based driver attention allocation model. Thus, a set of hypothetical data was generated for demonstration. To be effective, working with hypothetical data, which is generated based on certain rules and characteristics, can effectively show how the model works and how its results can be applied. The model estimation results should be able to recover the rules and parameters of data generation.

Simulation Data Generation

The basic process of shifting attention around a vehicle is to fixate on one focal point for a while, and then shift to another. Thus, two types of parameters must be identified. The first parameter is the fixation duration for each focal point. The second parameter is the probability of shifting eyesight from one focal point to another. This study treats the process of attention allocation as successive choices of next focal point. Therefore, the continuous data of attention allocation must be transferred into discrete counterparts for every 250 milliseconds. Figure 1 shows the data generation procedure, where, to make things simple, only spare attention is considered and the motivated attention is ignored. The three outputs of data generation used to calibrate the proposed attention allocation model include the focal point chosen in time stage k ($F_{j,k}$), the enduring time of fixating on each focal point ($Time_{i,k}$), and the focal point chosen in the time stage k - 1 ($Prev_k$).

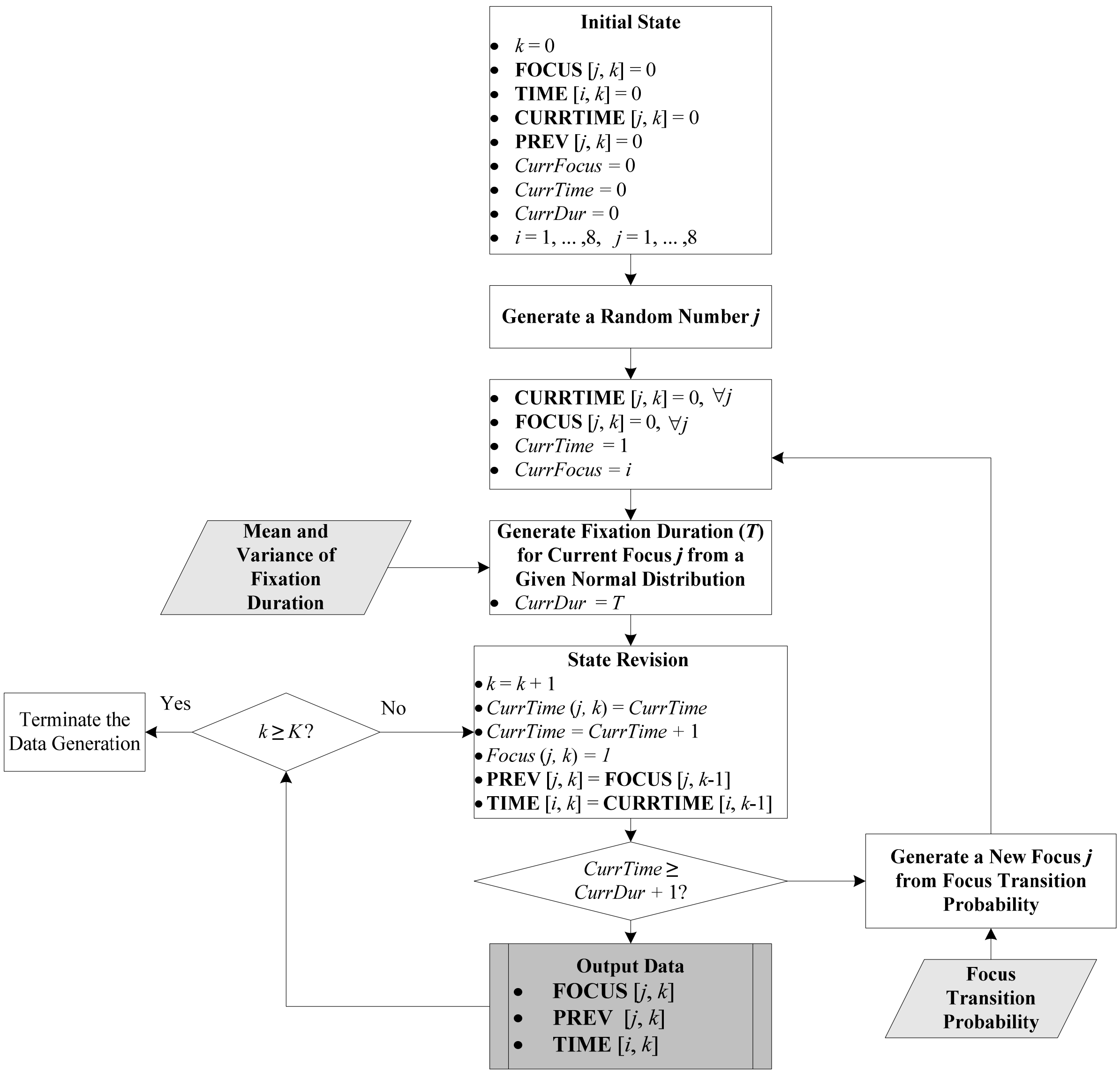


Figure 1 Data generation procedure

The duration of fixating each focal point (T) was randomly generated from normal distribution. Under normal conditions, the mean fixation duration of each focal point is between 400 ms to 700 ms, which is approximately 1.5 time stages to three stages in this study (Chapman et al., 2002; Konstantopoulos et al., 2010; Underwood, 2007; Underwood et al., 2002a; Underwood et al., 2002b). When driving in a demanding situation with heavy traffic, the sampling rate of each fixation will be higher due to psychological pressure. This means that the fixation duration would be shorter than normal conditions, which is about 400 ms to 500 ms (Chapman et al., 2002; Underwood et al., 2002b). When driving in hazardous situations in which accidents may occur, the mean fixation duration would increase significantly to one second since drivers must pay close attention to hazardous objects (Underwood, 2007).

Table 1 summarizes the mean and standard deviation of fixation duration based on previous research (Chapman et al., 2002; Konstantopoulos et al., 2010; Underwood, 2007; Underwood et al., 2002a; Underwood et al., 2002b). Since the attention attracted in different focal points is not identical, the mean fixation duration was set between 1.5 time stages to three time stages (375 ms to750 ms). Among the focal points, the perception domain of the current driving lane attracts most drivers' attention (Levin et al., 2009; Nabatilan, 2007; Underwood, 2007; Underwood et al., 2003a). Therefore, the mean duration of fixating on F_3 was set as three time stages. In contrast, drivers pay less attention to perception domain of the adjacent lane (F_6), and critical domains of the current driving lane (F_1) and adjacent lane (F_4). Drivers usually glance at these areas and then quickly shift their attention to other focal points. Therefore, the mean durations of F_1, F_4, and F_6 were set as 1.5 time stages. In addition, glancing at mirrors and roadside signs requires more effort to identify the object in the mirror and the message on the sign. Previous research shows that drivers spend an average of 400 ms to 650 ms glancing at roadside signs and mirror (Crundall et al., 2006; Kiefer and Hankey, 2008; Underwood et al., 2002a). Therefore, the mean duration of mirror and roadside sign was set to two time stages.

Table 1 Parameters for data generation

Origin Focal Point	**Fixation Duration (250 ms)**		**Probability of Focal Point Transition (%)**							
	Mean	Std.	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
F_1	1.5	0.75	0	5	70	5	5	5	5	5
F_2	2	1	7	0	50	7	15	7	7	7
F_3	3	1.5	2	30	0	2	30	32	2	2
F_4	1.5	0.75	5	5	40	0	10	5	30	5
F_5	2	1	6	20	40	7	0	6	15	6
F_6	1.5	0.75	8	8	45	8	8	0	15	8
F_7	2	1	5	5	70	5	5	5	0	5
F_8	2	1	5	5	70	5	5	5	5	0

When drivers finish the fixation on current focal point and the enduring time reaches T, they choose a new focal point. Instead of shifting attention randomly, they exhibit some patterns of shifting attention. Table 1 illustrates the probability of shifting attention from one focal point to another in the data generation process. The parameters must reflect the mechanisms of attention allocation. The hypothetical driver in this study was assumed as an experienced driver who fits the "normal driving pattern." This simulation considers no particular intention, such as looking for road sign. Figure 2 shows the three types of scan paths considered in this study. Each block in Figure 2 represents a focal point that a glance of eyesight fixation can cover. The arrows between two blocks represent the origin and destination focal point of scan paths.

The first type of scan path confirms that the frontal area dominates attention allocation. Drivers usually focus on the farthest point of the current driving lane (F_3). Since the driving task discussed in this case study is driving forward without changing lanes, F_3 dominates the attention allocation process. Shifting attention away from this focal point will increase the risk. Therefore, drivers will have higher probability to shift attention back to F_3 after shifting away. Hence, seven paths originated from other seven focal points to F_3 were created. The second type of scan paths shows the attention demand of neighboring transition. Considering that the invested effort increases with the distance between two consecutive focal points, drivers tend to allocate attention in neighboring areas. This study considers six neighboring transition paths. The third type of scan paths represents the attention allocation for roadside areas, and acquiring information from road signs. In this study, drivers do not have intention to search roadside actively for information. However, roadside areas are occasionally fixated due to neighboring transition. Since the driver was assumed to drive on the inner lane, the three focal points on adjacent lane (F_4 to F_6) are closer to the roadside than other focal points. Therefore, the three scan paths of neighboring transition from adjacent lane to roadside (F_7) are generated.

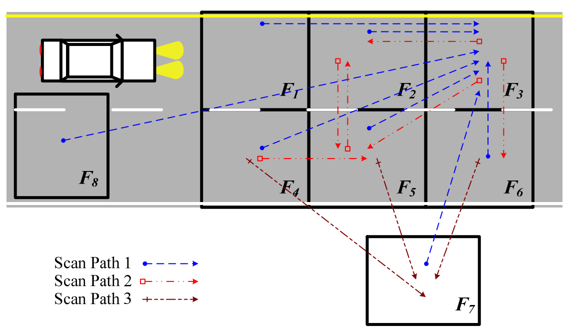
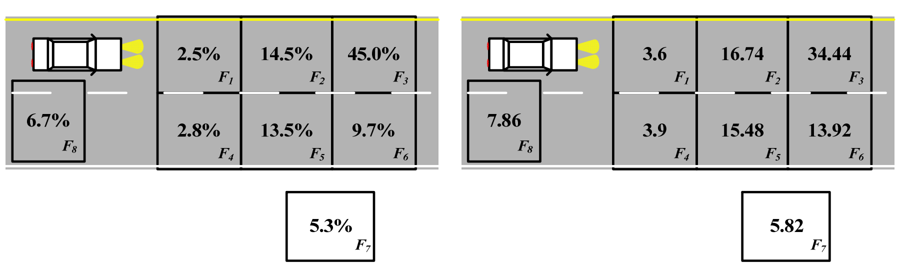


Figure 2 Hypothetical scan paths

In total, 8,001 samples were generated. The first sample was removed due to data unavailability for the previous focal point. The average duration of one fixation is 590.1 ms, which is within the reasonable range obtained from previous studies. Figure 3 illustrates the time percentage and frequency of the hypothetical driver's attention allocation. As shown in Figure 3a, the farthest area of current driving lane attracts the most attention. Meanwhile, drivers paid the least attention to the area closest to the vehicle. The proportion of time spent on each focal point, including the length of fixation duration and probability of transition, fits well with the general driving behavior. Figure 3b shows that the number of fixation (101.67 per minute) was similar to the results of Underwood et al. (2003a).



(a) Percentage of time of eyesight fixation (b) Number of fixation per minute

Figure 3 Statistics of eyesight fixation

Model Estimation

Based on the generated data set, a multinomial logit model was calibrated by adopting NLOGIT 3.0. Eight sub-models of shifting attention from the eight focal points were also calibrated. Each model contained eight alternative specific constants, where the constant of choosing same focal point was set to zero for parameter calibration, and one generic variable (enduring time of fixating on current focal point). Table 2 presents the estimation results. To illustrate the applicability of the proposed attention allocation model, the estimation results should be consistent with the hypothetical characteristics of the generated data, including the fixation duration and the transition probability among focal points. The two major outcomes of model estimation are the alternative specific constants and parameters of enduring time.

Table 2 Estimation results of attention allocation model

Models \ Alternatives	Estimated Coefficient								
	Alternative Specific Constant (*Asc*)								Generic Variable
	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	*Time*
Model 1: F_1 as the Previous Focal Point	**0**	-6.67	-3.35	-6.16	-6.16	-5.98	-6.38	-5.37	-2.68
Model 2: F_2 as the Previous Focal Point	-5.43	**0**	-3.02	-4.99	-4.09	-4.96	-4.75	-5.08	-1.34
Model 3: F_3 as the Previous Focal Point	-7.51	-3.94	**0**	-6.42	-3.86	-3.78	-6.72	-6.02	-0.77
Model 4: F_4 as the Previous Focal Point	-5.33	-5.58	-3.23	**0**	-4.82	-5.91	-3.67	-5.73	-2.26
Model 5: F_5 as the Previous Focal Point	-6.06	-4.24	-3.54	-5.80	**0**	-5.18	-4.29	-5.56	-1.43
Model 6: F_6 as the Previous Focal Point	-5.32	-5.23	-3.34	-4.92	-4.90	**0**	-4.42	-5.04	-2.18
Model 7: F_7 as the Previous Focal Point	-5.17	-5.62	-2.96	-5.22	-5.62	-5.62	**0**	-5.86	-1.40
Model 8: F_8 as the Previous Focal Point	-5.82	-5.95	-3.12	-5.82	-5.60	-5.95	-5.82	**0**	-1.55

A unique characteristic of the proposed model is that it treats continuous attention allocation as a discrete and consecutive process of focal point. To be effective, the proposed model should be able to reflect both eyesight fixation and saccade. Fixating on one focal point can be presented by the attention demand of choosing repeatedly the same focal point. Table 2 shows that the constants of choosing the same focal point were set to zero (such as the constant of choosing F_1 in Model 1) and other constants were all negative. This indicates that the probability of maintaining fixation on the same focal point was higher than transiting to other focal points. Hence, drivers would fixate on the current focal point in the next stage. In contrast the estimated parameters of time ($Time_i$) suggest enduring time in the model has a negative effect on the attention demand of staying in current focal point. The probability of maintaining fixation on current focal point keeps decreasing with time. Eventually, a driver's eyesight will transit to other focal points.

In addition to eyesight fixation, the scan paths of shifting attention around the driving environment can be extracted through the model estimation. The estimated coefficients of constants represent the relative level of attention demand for each focal point. In Model 1, in which F_1 was chosen in the previous stage, the constant of F_3 is higher than those of other focal points. In other words, there is a scan path of shifting attention from F_1 to F_3. Table 2 shows that the model is able to capture the three types of hypothetical scan paths hypothesized in Figure 2. Consistent with the first type of scan path, the estimation results show that the attention of choosing F_3 as the new focal point is the highest despite the attention demand of choosing to stay at the current focal point. This indicates that F_3, the farthest area ahead, dominates the attention allocation. Drivers tend to shift attention to F_3 after shifting eyesight to other focal points. The second type of scan path represents the neighboring transition. Take Model 3 for example, the demand of shifting attention from F_3 to F_2, F_5 and F_6 are the highest despite of F_3 itself. The third type of scan path is the attention allocated to roadside areas, searching for signs. Estimation results show that the attention demands shifting from F_3, F_2 and F_5 to F_7 are higher than the minimum level of respective models.

Model Performance

Based on the model estimation, Table 3 presents the transition probability of simulated attention allocation policy, the probability of focal point transition after different durations. Take F_3 for example; the probability of maintaining fixation on the same focal point is 87 %. After paying attention to F_3 for 1.25 seconds (five time stages), the probability of maintaining attention on the current focal point drops to 24 percent. At the same time, the probability of shifting attention away to F_2, F_5, and F_6 increases. The lowest part of Table 3 shows the transition matrix when the enduring time is infinite and the probability of focusing attention on the current focal point is close to zero. It shows the scan paths in which higher probability of shifting attention from specific focal pointcan be identified. For example, the probability of shifting attention from F_1 to F_3 is 71 %, which is higher than those of other focal points when enduring time is infinite. This suggests that the scan path of shifting attention from F_1 to F_3 exists.

Table 3 Focal Point transition matrix for various enduring durations (%)

***Time$_i$* = 1**	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
F_1	**58**	1	30	2	2	2	1	4
F_2	1	**73**	14	2	5	2	2	2
F_3	0	4	**87**	0	4	4	0	0
F_4	3	2	21	**54**	4	1	13	2
F_5	1	5	9	1	**77**	2	4	1
F_6	3	3	18	4	4	**59**	6	3
F_7	2	1	16	2	1	1	**76**	1
F_8	1	1	16	1	1	1	1	**77**
***Time$_i$* = 5**	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
F_1	**0**	3	71	4	4	5	3	9
F_2	4	**1**	49	7	17	7	9	6
F_3	1	21	**24**	2	23	25	1	3
F_4	6	4	45	**0**	9	3	29	4
F_5	3	20	40	4	**1**	8	19	5
F_6	6	7	45	9	9	**0**	15	8
F_7	7	5	67	7	5	5	**1**	4
F_8	5	4	71	5	6	4	5	**1**
***Time$_i$* = ∞**	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
F_1	**0**	3	71	4	4	5	3	9
F_2	4	**0**	49	7	17	7	9	6
F_3	1	28	**0**	2	30	33	2	3
F_4	6	4	45	**0**	9	3	29	4
F_5	3	20	40	4	**0**	8	19	5
F_6	6	7	45	9	9	**0**	15	8
F_7	7	5	68	7	5	5	**0**	4
F_8	5	4	71	5	6	4	5	**0**

The duration that drivers spend on one focal point at each fixation is an important measurement of attention allocation. Equation (6) derives the mean duration by observing the probability of maintaining fixation on current focal point.

$$T_j = \sum_{Timej=1}^{\infty} Time_j \cdot \left(P_{j,Timej-1} - P_{j,Timej}\right) \tag{6}$$

T_j is the estimated duration of focal point j. $Time_j$ is the number of time stages during which drivers remain fixated on current focal point. $P_{j,Timej}$ is the probability of maintaining fixation on focal point after continuously fixating on the current focal point for $Time_j$ time stages. $P_{j,Timej}$ - $P_{j,Timej}$ is the percentage of samples that shift attention away from focal point j at the instance of $Time_j$. Table 4 shows the probability of maintaining fixation on focal point j after different enduring times. Take F_1 for example; the initial probability of fixating on F_1 is 100 % when $Time_1$ equals zero, and the probability of fixating on F_1 is 58.15% when $Time_1$ equals one. Thus, 41.85 % of the samples fixate on F_1 for one time stage before shifting to other focal points.

Table 4 Probability of maintaining fixation on focal point *j* under different enduring time

Focal Point	Enduring Time Spend on Focal Point *j*																Estimated Duration
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
F_1	100.0	58.15	8.71	0.65	0.04	0	0	0	0	0	0	0	0	0	0	0	1.68
F_2	100.0	72.65	41.01	15.39	4.54	1.23	0.32	0.09	0.02	0.01	0	0	0	0	0	0	2.35
F_3	100.0	87.02	75.73	59.21	40.32	23.91	12.76	6.37	3.07	1.45	0.68	0.32	0.15	0.07	0.03	0.01	4.03
F_4	100.0	54.40	11.07	1.28	0.14	0.01	0	0	0	0	0	0	0	0	0	0	1.67
F_5	100.0	76.80	44.11	15.84	4.29	1.06	0.25	0.06	0.01	0	0	0	0	0	0	0	2.42
F_6	100.0	58.79	13.85	1.78	0.20	0.02	0	0	0	0	0	0	0	0	0	0	1.75
F_7	100.0	76.35	44.38	16.47	4.65	1.19	0.30	0.07	0.02	0	0	0	0	0	0	0	2.43
F_8	100.0	77.38	42.07	13.36	3.17	0.69	0.15	0.03	0.01	0	0	0	0	0	0	0	2.37

Table 4 summarizes the estimated duration of each focal point. In line with the hypothesis of data generation process, F_1, F_4, and F_6 are the focal points with the shortest duration, which are between 1.67 to 1.75 time stages. The second groups of focal points includes F_2, F_5, F_7, and F_8, which have estimated durations ranging from 2.35 to 2.43 time stages. F_3 is the focal point with the longest duration, and has an estimated duration of 4.03 time stages. These estimated duration results are slightly higher than the parameters in data generation due to rounding generated fixation duration away from zero in data generation.

The most important advantage of the proposed approach is its ability to evaluate an attention allocation policy from multiple dimensions in a single model. Previous studies used fixation duration (Chapman et al., 2002; Konstantopoulos et al., 2010; Underwood, 2007; Underwood et al., 2002a; Underwood et al., 2002b), proportion of time spent on a particular target (Borowsky et al., 2010; Konstantopoulos, 2010; Levin et al., 2009; Nabatilan, 2007; Underwood et al., 2003a) and scan path (Brown et al., 2000; Underwood et al., 2003a) to present an attention allocation model. However, those measurements are usually analyzed and discussed separately. This study analyzes attention allocation by adopting discrete choice analysis and providing a transition matrix of shifting eyesight from one focal point to another. The probability of choosing focal point is a function of previous focal point and duration. Providing only the proportion of time spent on a specific object cannot reflect fixation and saccade simultaneously. Same value of average percentage of attention may be the results from very different behaviors and induce different level of crash risks. For example, short glance with high frequency and less frequent glance with long duration can produce same average time spent on one target. The two scenarios imply different strategies and may result in different risk of crashes. Therefore, analyzing attention allocation from a microscopic perspective can help gain deep insight into driving behavior and crash occurrence.

CONCLUSIONS

Although researchers have conducted many studies on crash pattern analysis, the nature of crashes remains unclear without a further exploration of driver involvement in crashes. Driving is a continuous process of collecting information and making decisions. The frequent occurrence of crashes caused by failing to note road conditions indicates a serious problem in attention misallocation. Malfunction of attention allocation may result in improper information collection, increasing the risk of crashes. Hence, understanding the mechanisms of driver attention allocation is a key step in exploring the nature of crashes and preventing them from happening.

Rather than using a macroscopic approach, such as the proportion of time spent on a particular target, this study proposes a microscopic driver attention allocation model that treats continuous attention allocation as a discrete and successive process of choosing next focal point. A major characteristic of the proposed model is that it presents the behavior of fixating eyesight on specific object and the saccade process. Fixation duration and focal point transition probability are the two major indices of attention allocation. Considering either one of these measurements provides only partial insights into driver attention. Besides, using a macroscopic approach cannot reflect the heterogeneity of focal point under a variety of conditions. This study illustrates the microscopic transition process of shifting attention from one focal point to another under intended maneuver and driving tasks.

Since the proposed approach is statistically based, various contributing factors can be adopted to derive the probability of choosing specific target as the focal point. This study utilizes the SEEV model while incorporating dynamic changes of traffic flow. The original SEEV model analyzes the process of shifting attention between a few targets by adopting salience, effort, expectancy, and value as measurements of attention demand. However, more measurements of the four construct are required for complex driving environments. This study classifies the numberless potential focal points into eight alternatives. Moreover, two major types of attention, which are spare attention and motivated attention and their related measurement are adopted in the driver attention allocation model.

By using a hypothetical dataset, the appropriateness and performance of the proposed model is tested. The hypothetical driver in this study drives in a divided four-lane highway without interference from other vehicles, objects, or intersections. That is, only spare attention is considered for illustration. Results show that the proposed model can successfully reproduce the attention allocation process hypothesized in the simulated data. In addition, the results also can reveal a driver's potential scan paths. Even though the results are derived from the simulated data, outcomes of the attention allocation policy indicate that exploring attention allocation from a microscopic perspective can provide greater insights into driving behavior. It allows a deeper analysis by evaluating the contribution of each factor to attention demand. Nevertheless, further research using field data is necessary to validate the proposed model.

Constructing the attention allocation model could clarify the mechanisms of shifting eyesight for information gathering. The proposed model can be an effective tool to compare different attention allocation strategy under different situations, such as novice drivers versus experienced drivers, various intended maneuvers, or different levels of external information availability. However, attention misallocation does not always induce crashes. There is currently no clear linkage between attention allocation and crashes. Several research used variance or standard deviation of focal point as an safety index of an attention allocation model (Chapman et al., 2002; Hosking et al., 2010; Nabatilan, 2007). For example, Borowsky et al. (2010) suggested that experienced drivers maintain high variance of eyesight fixation and are able to observe surrounding traffic in a more flexible pattern. However, this approach can only explain the pattern diversity of one's attention allocation policy without clarifying the connection between flexibility and safety. Even though the high variance of an attention allocation strategy means more information sources can be observed, it may imply wasting time on unnecessary focal points. Meanwhile, low flexibility suggests that only a few focal points are observed, and several important focuses are ignored. Therefore, a risk index that connects attention allocation policy and risk of crash is necessary to evaluate the effects of an attention allocation policy on safety. The issue of building the connection between attention allocation policy and safety is vital and worthy for future research.

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