A Practical View of the Similarity and Differences Among the Impaired Driver States in Legal Driving

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Abstract. Detection and intervention of various impaired driver states have been intensively studied with corresponding technologies widely implemented in modern vehicles. Different algorithms are proposed to detect certain states or conditions, with intervention means like driver alerts or vehicle active safety features being developed and optimized accordingly. However, there lacks a unified view of all of these different driver states. In order to support the development of vehicle systems, this study tries to compare the commonly-seen impaired driver states in terms of their detection features as well as the effects on degraded driving performance. A meta-analysis is conducted to identify the overlapping and disjoint spaces among them from the angle of the vehicle design. The research finds some answers about the driver behavior and environment features that the vehicle system shall pay attention to and the degraded driving performance that the vehicle shall prepare for, when impaired driving happens in different ways in the reality.

Keywords: Impaired driver states · Driver state sensing · Feature detection · Degraded driving performance

1 Introduction

Impaired driving is a commonly used term of abnormal driving states in recent years with the rapidly development of automated vehicles, which means operating a vehicle while under the influence of sleepiness, distraction, or mind wandering and so on. Since impaired driving states can significantly reduce drivers' visual scanning capability and cognitive process of concentrating on the driving tasks, they are main causes of vehicle crashes. When happening, drivers will not be able to grip the steering wheel or step on the brake pedal in time during some emergency situations. Thus, the impaired driver states will affect the driving safety with degraded driving performance on the road. Considering the complexity in this area, impaired driver states in this paper are limited to those happening during legal driving like mind wandering, angry, fatigue, distraction

C. Stephanidis et al. (Eds.): HCII 2020, LNCS 12429, pp. 207–220, 2020.
https://doi.org/10.1007/978-3-030-59987-4_15

and drowsiness, which can link the occurrence of many potential road accidents with higher risks.

The research on driver distraction began in early 1990s, when inattention caused by cell phones were proved to have huge impact on drivers' capability of responding to the critical driving conditions. The 100-Car Naturalistic Driving Study found that almost 80% of all crashes and 65% of all near-crashes involved driver distraction [1]. Based on police reports, the US National Highway Traffic Safety Administration (NHTSA) conservatively estimated that a total of 100,000 vehicle crashes each year are the direct result of driver drowsiness [2]. These crashes resulted in approximately 1,550 deaths, 71,000 injuries and $12.5 billion in monetary losses [3]. Reference [4] reported that lane departure was dramatically greater while driver has mind wandering as well as a narrow visual attention. For angry driving state, drivers tend to be more aggressive with faster speed and less headway distance while following the lead vehicle [5]. Meanwhile, driver fatigue is one of the major implications in transportation safety and accounted for up to 40% of road accidents [6]. Therefore, the above five impaired driver states can interfere with driving tasks affecting divers' concentration, reaction time, and capability to maintain adequately direct attention to the critical scenarios in legal driving.

Since drivers may intentionally or unintentionally make mistakes while driving on the roadway due to different types of impaired driving states, in-vehicle driver state sensing (DSS) systems are currently equipped and utilized in some level 2 or higher level automated vehicles to monitor human driving status and provide the corresponding information to the automated driving system. Through the DSS systems, drivers' driving behaviors can be detected based on visual features, which mainly involve eye tracking, head movement, and facial expressions. By analyzing these features, the system can accurately estimate driver status and determine whether the driver is capable to control the vehicle. If drivers are in any types of above-mentioned impaired driving status, the control authority will be transferred from human to the machine. Thus, the DSS is critical to future autonomous vehicles due to its importance of transition process from auto-control to manual-control.

Different methods are proposed to detect certain impaired driver states in the literature for driver alerts or other vehicle active safety features accordingly. However, there lacks a unified view of all these different driver states. The isolated studies of these driver states and the theoretical comparisons among them, provide limited guidance in developing vehicle systems to efficiently intervene impaired driver states in practical situations involving dynamic and complex states. This paper will mainly focus on the commonly-seen impaired driver states happening in legal driving, and generate a practical view of the similarity and differences among them in terms of the detection features and negative effects on driving performance. A meta-analysis will be conducted to identify general abnormal driver states, and then compare their detection features as well as the reported effects in degrading driving performances. The main outcomes of the paper are the most important features the driver state sensing system should pay more attentions and what are the potential degraded driving performances the automated system needs to be prepared when impaired driving occurs on the road.

2 Common Impaired Driver States

To control the research scope, this paper excludes the impaired driver states for illegal driving conditions like drug or alcohol. Medical concerns are also not included. After excluding these conditions, this section summarizes impaired driver states that are widely investigated in the literature. For each state, commonly used definitions and ground-truth measurements are discussed.

2.1 Fatigue

Fatigue is an impaired driving states happened in normal driving because of feeling overtired, with low energy and a strong desire to sleep, which interferes with safe driving activities. Fatigue generally happens with the following three potential root causes: lifestyle factor, physical health conditions, and mental health issues. For driving purpose, fatigue generally means that the driver possesses the deficient functions of physiology and mentality after a long driving time. During the driving process with fatigue, the skills and response time will decline with higher risk levels comparing with the normal driving status. The current installed in-vehicle driver state monitoring system can detect fatigue by capturing the grip strength of steering wheel, eyelid movements, Electrocardiogram (ECG) or driver visual features, such as yawning [6–9].

2.2 Drowsiness

Drowsiness is commonly known as people feeling abnormally sleepy or tired during the daily life. It can lead to some related symptoms, such as fatigue, forgetfulness or falling asleep at inappropriate times. Similar to fatigue, multiple reasons may cause drowsiness, which can range from mental health and other lifestyle factors to some serious medical situations. Although "Fatigue" and "drowsiness" are usually confused and interchangeably, they are significantly different. Fatigue generally refers to the feeling of tiredness or exhaustion, drowsiness specifically means the precise state right before sleep. Therefore, fatigue can result into drowsiness, or we can say drowsiness is the relevant aspect of fatigue during driving. Since we have no control during this time period, the vehicle may have higher risk levels than fatigue from a driving safety perspective. The DSS also has the ability to detect drowsiness by capturing drivers' eye blink, facial features, and questionnaires and so on [10–15].

2.3 Distraction

Driver distraction (DD) is defined as an activity performed by a driver that diverts the attention away from the primary activity (vehicle longitudinal and lateral control) potentially leading to safe driving degradation. It appears due to some event, activity, object, or person within or outside the vehicle, which compels or induces the driver's attention away from the primary task [16]. Thus, it is a significant cause of fatal accidents. Distraction has also been extended by Regan et al. [17], adding the similar concept of driver inattention, which means insufficient or no attention to critical activities for safe driving toward a competing activity. Driver distraction is commonly classified into 3 categories, namely manual distraction, visual distraction and cognitive distraction. The detection methods for driver distraction have been widely studied, using eye and head movement, vehicle dynamics and assessment questionnaires and so on [18–23].

2.4 Angry

Angry is another risk factor for driving in recent years due to high-intensity and high-paced life. According to [5], drivers tend to be more aggressive with faster speed, less headway distance while following the front car in an angry state. Greater deviations in lateral position and acceptable shorter turning radius were also observed when driver is angry. Thus, it is also a significant factor can lead to fatal traffic collisions. From research point of view, angry driving is different from "road rage". Road rage is one of the extreme type of aggressive driving, which intends to commit a criminal behaviors, such as intentionally colliding pedestrian and using weapons to harm other drivers. The angry driving state discussed in this paper includes speeding, changing lanes without signaling and so on. All illegal driving states and behaviors will not be considered. Nowadays, eye movement data and braking pressure are generally used to detect angry drivers since they scan a narrower area and brake harder to compensate for the delay of initial braking when in an angry state [24–26].

2.5 Mind Wandering

Mind wandering is also called task unrelated thought, which is the experience of attention and thoughts not maintaining on the original single task for a relative long time period, and it is specifically dangerous when people are engaged in task requiring concentration and attention, such as driving. Texting, reading or talking to other people are all possible causes for driver mind wandering. Drivers will not be able to take an appropriate actions when facing with critical conditions since the brain cannot process both task-relevant and task-irrelevant sensing information in detailed way. Lane deviation and speeding were possibly two significant degrade driving performance from mind wandering [26]. Variables of vehicle speed, lateral position deviation and hazard response time are some commonly applied features for detecting driver mind wandering [27,28].

3 Methodology

By using the key words of each impaired driver sates, a number of research papers were found, which contain papers and reports following the PRISMA meta-analysis guidelines including: title, abstract, methods, results and discussion and so on [10]. All the papers being included consist of conference papers, journals, book chapters, and some other works that can satisfy all the following rules:

- The paper had to be published within 2010 and 2020.
- It had to be revolved around the impaired driving states; mind-wandering, fatigue, drowsiness, anger, and distraction.
- With-in the study it needs to mention degraded driving performances that the impaired state may cause and discuss the measurable features that were used to conduct the study.

Figure 1 demonstrates the selection process of papers for consideration in this meta-analysis. A total of 197 papers were collected initially according to the search results using the keywords of all the impaired driver states. For studying the detection features of these impaired driver states, 135 papers that contain the measurable features were kept, with 26, 54, 10, 33, 12 papers were used for impaired driver state of distraction, drowsiness, angry, fatigue, and mind wandering, respectively. For studying the degraded driving performance, similar criteria was applied which excludes illegal driving states and requires degraded driving performance measurements in the studies, and 32, 19, 15, 23, 16 papers were utilized in the meta-analysis for different impaired driver states as previous.

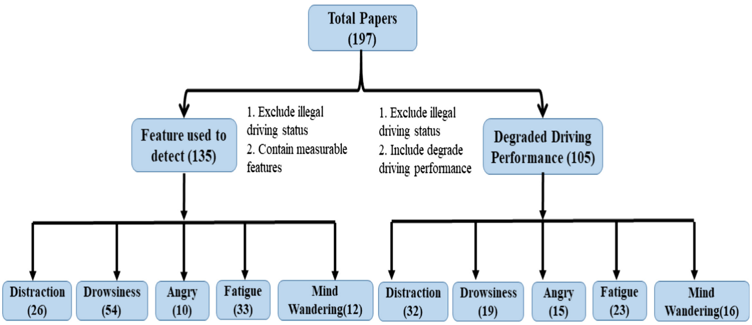

Fig. 1. Selection of publications included in the meta-analysis.

3.1 Detection Features

Although there are many publications about impaired driving states and their detection methods, there is not a uniform and commonly agreed set of features to be collected and used. Several features very often overlapped and mixed with other driver states, such as drowsiness and distraction. The methodology of how we explore this issue will be introduced in the following sections.

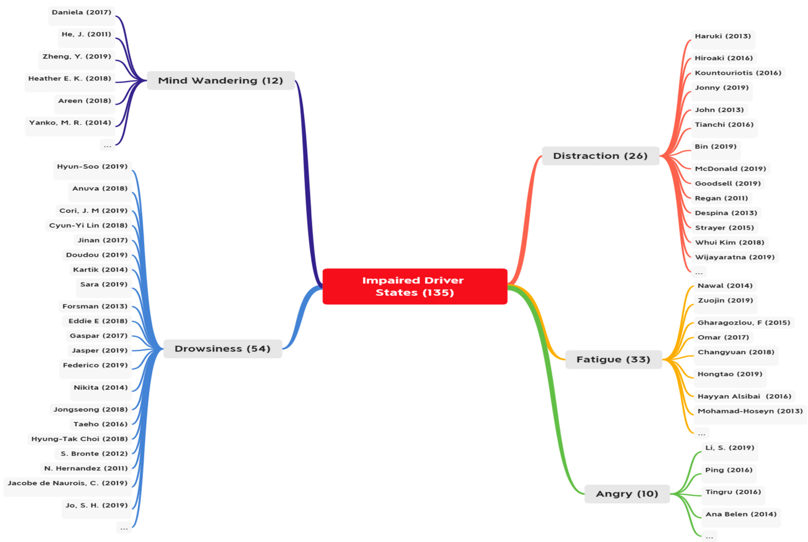

Fig. 2. Data collection methods used in the feature selection for detecting impaired driver states.

Data Extraction. Depicted in Fig. 2, 135 reference papers were selected for meta-analysis of feature detection, with 78 common features extracted from the literature over decades of research. Specifically, all the measurable features can be separated into five categories: Vehicle-performance Feature, Psychological feature, Subjective feature, Human-behavior feature and Other features. The Fig. 3 depicts all the categorized 78 features with their corresponding index, which have been separated into five categories as follow.

1. Vehicle-performance Feature - mainly focus on the vehicle driving information on the road. Moreover, five additional small groups were divided for better representations. 1). Vehicle longitudinal dynamics include the features of describing vehicle moving information along the longitudinal direction, and features as use of brake pedal and headway distance were considered in this group; 2). Vehicle lateral dynamics include the features of describing vehicle moving information along the lateral direction, and features as vehicle lateral position and lane deviation were discussed; 3). Steering wheel includes the variables of describing human steering maneuvers while driving, and features of steering wheel acceleration and steering wheel movement were taken into considerations; 4). The road properties containing vehicle driving environment were also utilized for detection such as lane width and road curvature and so on; 5). Vehicle lane change frequency and total number of cars the ego vehicle passes are features in the group of other related features.

2. Psychological feature - a feature of the mental life of a living organism, which is critical for detecting drivers with impaired driving states. This kind of feature will reflect the cognition and reaction time of drivers in some emergency situations. Blood pressure and electrocardiogram were two commonly used features to recognize the impaired driver states.
3. Subjective feature - a feature of subjective report or designed questionnaires. For example, a common used questionnaires for detecting driver drowsiness is Karolinska Sleepiness Scale (KSS) [29], which is listed in Fig. 3;
4. Human-behavior feature - this type of feature is influenced by a number of factors from human behavior, and these factors also belong to several categories. In this meta-analysis, six following categories were taken into account. 1). Eye features are used in many research papers, which include eye tracking, eyelid movement and blink frequency and so on. 2). Face features were also applied by using computer vision algorithms with face orientation and facial morphological. 3). Driver mouth status is also a critical and effective way to detect abnormal driving status. The most commonly used two features are mouth opening and yawning. 4). As the largest organ of the body, human skin has many information reflecting driver mental states and healthy conditions, such as nervous with sweating and drowsiness with fever. Thus, the skin conductance level can be used to detect these two types of impaired driver states. 5). Body skeleton features include all of the bones, cartilages, and ligaments of the body, and can generate driver movement through muscles. 6). The last category is time information of driver, such as continuous driving time and braking reaction time. These variables are also a supplemental features to help estimate the impaired driver states.
5. Other features - excluding from all above categories, there are still some features we need to collect for the evaluation of driver status. Several driving activities were labeled in some learning methods for better predicting the distracted driving behavior, such as texting and talking. Some researchers also did capture the lightning conditions to describe the driving environment and detect the abnormal driver states.

Data Analysis. In order to better understand current trends of feature selection for detecting impaired driver states, the frequency of 78 extracted features being used in the studies were calculated and compared. Since each category has different numbers of papers, the usage frequency of detection was computed by dividing the frequency number over the total paper number of each impaired driver state.

Furthermore, some features were individually utilized to detect one specific abnormal driver state, but some features were shared to use for detecting at least two of the impaired driver states. All shared features will be collected and connected to the five impaired driver states with usage frequency.

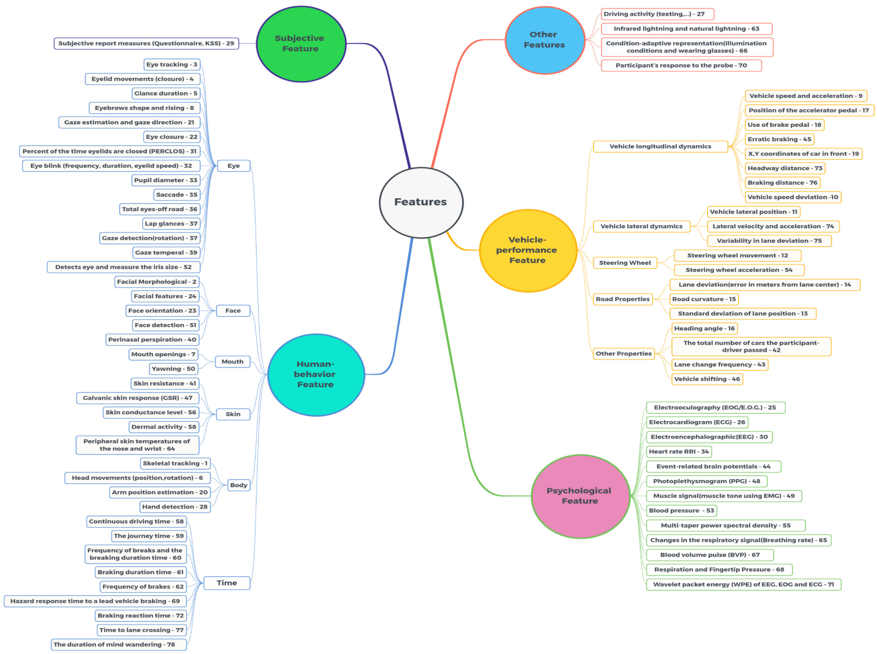

Fig. 3. Feature collection used for detecting impaired diving states.

3.2 Degraded Driving Performance

When conducting the study there are various impaired driving states that can occur. From this we evaluated five impaired driving estates categorized as distraction, drowsiness, mind wandering, anger and fatigue and the correlation to degraded driving performances. Presented in Fig. 4, 105 references were selected for a meta-analysis.

Data Extraction. Throughout the literature, there were common outcomes for the impaired driving states. The outcomes can be broken down into four main categories: speed, lane position, headway and reaction time. Figure 5 illustrates the results of the impaired driver state degraded driving performance and the number of findings in the research papers. Based on the research papers the four subsequent categories are defined, as follows.

1. Speed - Evaluating the study baseline speed and then the speed the driver was going when they recorded the impairment driving state, determines if there was an increase or decrease speed.
2. Headway - Increase and decrease in headway relates to the distance between the driver's car and the car in front of it. If there is less distance between the driver's car and the car in front, it is considered a decrease in headway. If there is more distance between the driver's car and the car in front, then it would be considered an increase.

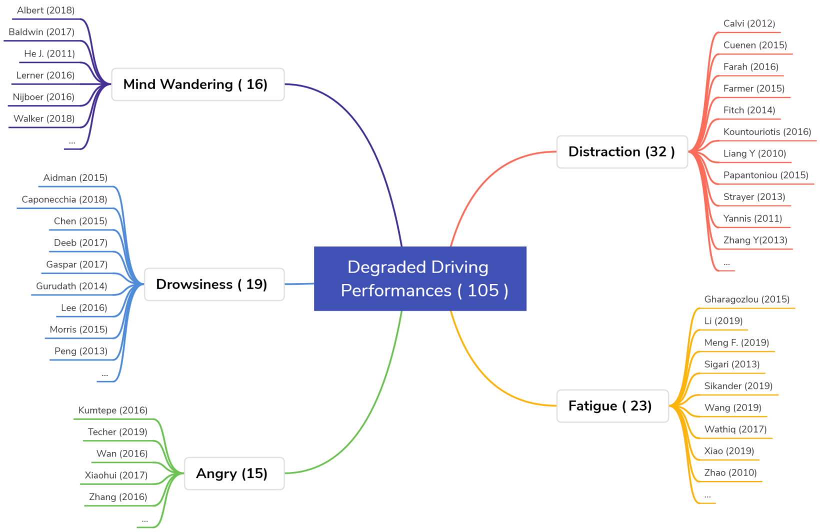

Fig. 4. Data collection methods used in the degraded driving performance for detecting the impaired driver state.

3. Reaction time - Relates to the amount of time a driver responds to the situation. The increase in reaction time indicates the additional amount of time to react.
4. Lane position - Increase and decrease in lane position refers to how often drivers will change lanes. When lane position increases, the driver will demonstrate changing lanes more frequently.

Data Analysis. 105 papers were analyzed in investigating the common occurrences of the impaired driving state in relation to degraded driving performance. The study revealed four different degraded driving performances: reaction time, headway, speed and lane position.

4 Results

This section consists of two parts, one is the analysis results for detection features and the second one is effects on driving performance. For detection features, the usage frequency of each feature was calculated, and the shared features with the corresponding weights was also generated. For effects on driving performance, the impaired driver states mapping with the degraded driving performance was demonstrated.

4.1 Detection Features

A total of 78 features were extracted and summarized in Fig. 5. As can be seen in the segment bar chart, different colors represent for different impaired driver states, and the feature usage frequency for detecting each abnormal driver states was accumulated. The six most commonly utilized features can be clearly obtained from the results as below:

1. Feature Index 10 - Vehicle speed deviation
2. Feature Index 31 - Percent of the time eyelids are closed (PERCLOS)
3. Feature Index 13 - Standard deviation of lane position/lane detection
4. Feature Index 4 - Eyelid movements (closure)
5. Feature Index 14 - Lane deviation (error in meters from lane center)
6. Feature Index 12 - Steering wheel movement

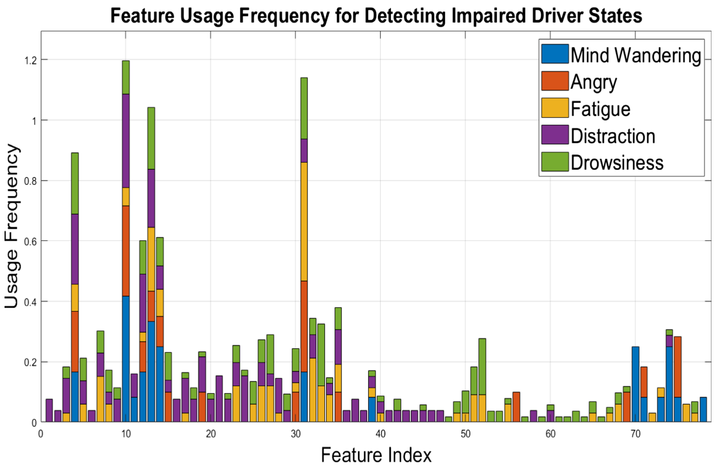

Fig. 5. Feature Usage Frequency for detecting the impaired driver state.

Shared features were also collected and shown in Fig. 6. In this paper, shared features are defined for features that can detect at least three abnormal driver states. Thus, a total of 23 features were shared to detect impaired driver states among all 78 extracted features. In the figure, the common features were connected to the related impaired driver states with the usage frequency; The number of shared features for detecting each impaired driver state are 10 for angry, 23 for drowsiness, 23 for distraction, 20 for fatigue, and 8 for mind wandering. Different colors of connection lines show different groups of shared detection features with usage frequency. The detailed descriptions of each shared features are listed in Fig. 3.

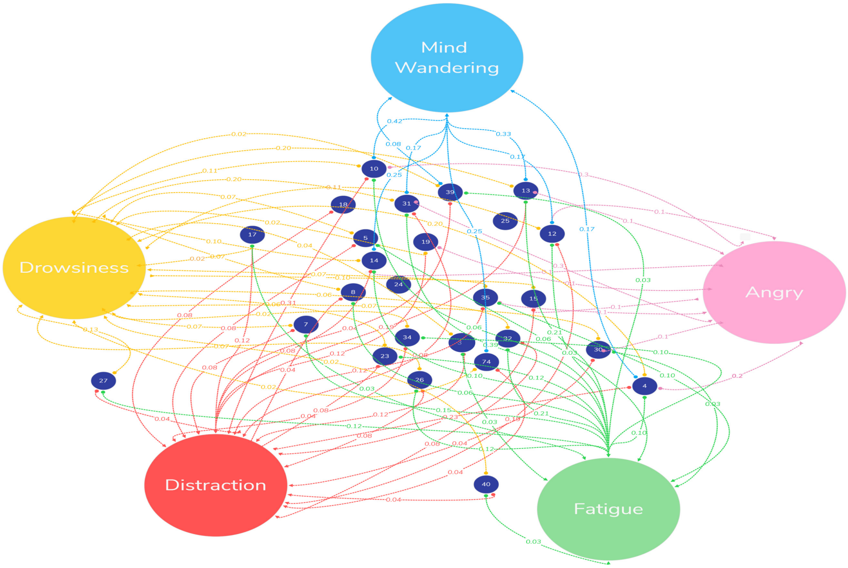

Fig. 6. Feature Usage Frequency for detecting the impaired driver state.

4.2 Effects on Driving Performance

Figure 7 illustrates the connections among impaired driver states and degraded driving performances. There were certain degraded driving performances and

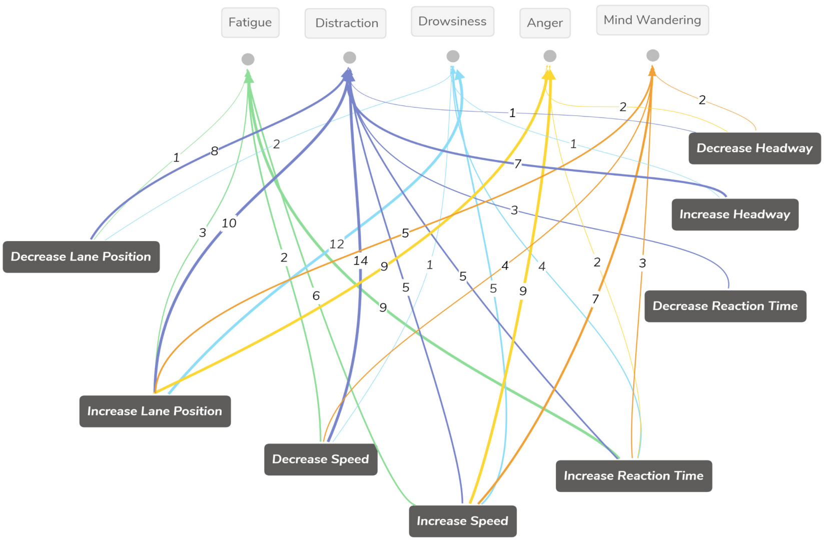

Fig. 7. Results of the impaired driver state with the degraded driving performances

impaired driving states that had higher numbers than others. Distraction has been shown to decrease a driver's speed in fourteen papers and increase lane position in ten papers. Fatigue has been associated to increase the drivers' reaction time in nine papers. Lane position increases when a driver is drowsy according to twelve papers. Anger degraded driving performance consists of an increase in speed in nine papers and an increase in lane position in nine papers.

5 Conclusions and Discussions

In this study, a comprehensive literature is conducted to summarize the widely-studied impaired driver states, common detection features corresponding to these states, as well as the effects of these driver states on driving performance. A total of 197 papers were reviewed. The results give some answers about when certain impaired driving state happens in different ways in the reality, what features the vehicle system shall pay attention to and what may be the corresponding driving performance degradation.

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