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Dynamic driver fatigue detection using hidden Markov model in real driving condition

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ABSTRACT

Driver's states in successive time slices are not independent, especially, fatigue is one of a cognitive state that is developing over time. Meanwhile, driver fatigue is also influenced by some corresponding contextual information at a certain time. In such case, classifying driving state at each time slice separately from it in before and after time slices obviously has less meaning. Therefore, a dynamic fatigue detection model based on Hidden Markov Model (HMM) is proposed in this paper. Driver fatigue can be estimated by this model in a probabilistic way using various physiological and contextual information. Electroencephalogram (EEG), Electromyogram (EMG), and respiration signals were simultaneously recorded by wearable sensors and sent to computer by Bluetooth during the real driving. From these physiological information, fatigue likelihood can be achieved using kernel distribution estimate at different time sections. Contextual information offered by specific environmental factors were used as prior of fatigue. As time proceeds, the posterior of fatigue can be gotten dynamically by this HMM-based fatigue recognition method. Based on the results of the method in this paper, it shows that it provides an effective way in detecting driver fatigue.

1. Introduction

Driver fatigue is a constant occupational hazard for drivers, which is the major cause of road accidents and has implications for road safety (Jap, Lal, Fischer, & Bekiaris, 2009; Pylkkonen et al., 2015). According to statistics, highway traffic accidents accounted for the total number of accidents in 11.09% (Li, Liu, Yuan, & Liu, 2010). Besides driver fatigue, many other reasons can also cause traffic accidents, such as unsafe lane change maneuvers (Hou, Edara, & Sun, 2015; You et al., 2015), overloading, illegal parking, illegal overtaking, and driving over-speed. The driver fatigue is the largest contributor to the highway traffic accidents, which has been estimated to be involved in 2%–23% of all crashes (Yang, Mao, Tijerina, & Pilutti, 2009). Due to the difficulty of assessment the exact number of fatigue-related collision, these numbers are still conservative estimation.

The highway with the wide and flat pavement, few spatial references, and high traffic speed provides monotonous driving environment. All vehicles follow their respective lanes, moving in orderly fashion on the highway with high speed. Long duration of driving in this monotonous traffic environment require drivers' sustained attention for long periods (Ting, Hwang, Doong, & Jeng, 2008). It is inevitably accompanied by a decrease in alertness and results in performance decrements and a higher risk of accidents (Eugene, Carolyn, Kayla, & John, 2015). Moreover, great decrement of driver performance can be markedly influenced by two physiological factors – circadian rhythm and sleep quality (Ferguson et al., 2012; Sahayadhas, Sundaraj, Murugappan, & Palaniappan, 2015). Great proportion of fatigue-related accidents occur between the hours of 2–6 a.m. and 2–4 p.m. approximately (Williamson & Friswell, 2011). During these two time periods, driver's body easily get into natural drowsiness, which increase the chance of crashes. Meanwhile, sleep quality plays a critical role in driver's behavior. Sleep deprivation can cause essentially degradation of all aspects of functions, including cognitive processes, attention and focusing, vigilance, physical coordination, judgment, awareness and decision making, communication, and numerous other parameters (Al-Sultan, Al-Bayatti, & Zedan, 2013; Ji, Lan, & Looney, 2006). Many previous studies noted that sleep deprivation almost have the same hazardous effects as drunk driving (Williamson & Feyer, 2000).

Over the past several decades, the fatigue detecting technology has been the widespread hope in the prevention of fatigue related accidents (Shen, Li, Ong, Shao, & Wilder, 2008). Up to now,

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researchers have developed several different types of fatigue detection technologies. According to the features used for fatigue recognition, there are four main categories technologies based on different features as contextual features, physiological features, driver's performances, and the combination of aforementioned features.

1) Contextual features technologies: from different point of views, this kind of methods include,
   (i) driver-related: personality, sleep quality, circadian rhythm, and physical condition.
   (ii) vehicle-related: noise, seating comfort degree, and temperature;
   (iii) road-related: monotony of road, density of vehicles, and the number of lanes.

   Questionnaire is always used for collecting such contextual features. Context-based technologies are perhaps the easiest method by which the extent of driver fatigue can be investigated from these features by some statistical methods.

2) Physiological measures: driver fatigue may be presented on some physiological features, such as features from EEG, EMG, ECG (electrocardiogram), respiration, and many other physiological signals (Khushaba, Sarath, Sara, & Gamini, 2011; Sun and Xiong, 2014). EEG features can reflect the ongoing brain activity and give abundant information on human cognitive states directly. Rogado et al. developed a driver fatigue recognition system based on Heart rate variability (HRV) from Electrocardiograph (ECG) during driving period because ECG is also found that it contains lots of fatigue relevant information. EMG features were used by Hostens et al. under high level monotonous driving condition (Hostens & Ramon, 2005). Besides these physiological signals, respiration can contribute some fatigue related information. The methods based on physiological signals have been regarded as the most accurate and objective fatigue recognition method.
3) Performance-related methods: fatigue can result in some typical fatigue-related behaviors, such as reaction time, eye blinking frequency, eye-closure rate, throttle/brake input, steering angle, vehicle speed, lane deviation (Son, Yoo, Kim, & Sohn, 2015), gear changes (Yang, 2007), head nodding, and grasping position of driver's hand on steering wheel (Di Stasi et al., 2012; Minin, Benedetto, Pedrotti, Re, & Tesauri, 2012). Based on imaging processing or other measurement methods, the changes of these different features can be monitored to infer driver fatigue. The main drawback of these methods is that their accuracy depends on the individual characteristics of the vehicle and its driver (Jo, Lee, Kang, Kim, & Kim, 2014).
4) Methods based on combination of aforementioned features: these integrated methods can take the advantages of the three previous methods, meanwhile, try to avoid the disadvantages of them.

The previous three methods focus only on a certain aspect, therefore they may lead to inaccurate results easily. First, in the technologies based on contextual features, drivers can evaluate their efficiency decline during driving. Self-feedback plays an important role in subjective measurement and may be affected by subject's will and consciousness (Declerck, Boone, & Brabander, 2006). On the one hand drivers easily overestimate their driving abilities, and on the other hand they also incline to underestimate the risk of accidents. Sleepiness is such a powerful biological signal that it can happen in an uncontrolled and spontaneous way (Ji et al., 2006). Most of us have experience that sometimes we felt so drowsy that we fell asleep suddenly even when we were driving (Morris, Pilcher, & Switzer, 2015). In fact, in National Sleep Foundation's 2005 Sleep in America poll, 60% of adult drivers – about 168 million people – admit they have driven a vehicle while feeling drowsy in the past year, and more than one-third, (37% or 103 million people), have actually fallen asleep while driving. National Highway Traffic Safety Administration conservatively estimates 100,000 police-reported crashes being the direct result of driver fatigue each year. This results in an estimated 1550 deaths, 71,000 injuries, and $12.5 billion in monetary losses. Therefore, methods only relay on drivers' self-report cannot always reflect real objectivity. Second, studies of performance-based techniques cannot prove that these abnormal behaviors are exactly relevant to driver's drowsiness state. Vehicle type, driver experience, driving conditions (Ueno, Kaneda, & Tsukino, 1994), and some other factors can also result in those abnormal behaviors. Third, some validation criteria used for fatigue recognition were based on the image processing techniques. Although there is great value for fatigue detection, many of these features were reported that they may vary in different driving conditions (Lin et al., 2006). There are still some moments when a driver still looks awake with wide open eyes but does not process any information (Renner & Mehring, 1997).

Therefore, fusing as many features as possible is a better way to get an accurate inference (Chen & Meer, 2005) and make fatigue recognition more reliable. Physiological features, as mentioned above, contribute significantly to fatigue recognition because a person usually has little control over them, which makes they could provide reliable and objective source of information to determine person's fatigue (Conati, 2012). Methods based on fused physiological features are perhaps the most accurate, valid and logical method (Ji, Zhu, & Lan, 2004). Ji et al. developed fatigue detection model fusing contextual and physiological features by a static Bayesian network (Ji et al. 2004). However, in driver's fatigue recognition, the dynamic character of features should be considered. Therefore, Li and Ji proposed a dynamical fatigue detection model based on dynamic Bayesian network in their further study (Li and Ji. 2005). The physiological features were utilized by Ji et al. are all based on driver's face expression information gotten by image processing technology. Many studies had shown that face expression features work well in detecting driver's fatigue. However, on one side these visual features are vulnerable to lights and it increases the difficulty in accurate recognition, on the other side the face image data have much larger size than physiological signals, this requires the algorithm has higher computation speed. Based on these studies, Yang et al. involved EEG and ECG in constructing a probabilistic driver's fatigue detection model by dynamic Bayesian network to enhance the reliability of fatigue detection (Yang, Lin, & Bhattacharya, 2010). These studies created a kind of new thoughts in the driver's fatigue detection research.

Based on this kind of new thought given in previous studies, we constructed a dynamic fatigue detection model based on Hidden Markov Model. We developed this approach in the following ways: (i) the previous studies were based on the simulated driving condition, and we built the fatigue inferring method under the real driving condition, which makes these kind of method more reliable. (ii) to avoid the limitation of visual features, we utilized three physiological features from EEG, EMG and respiration signals. And these data acquisition were collected in wireless way. This is one of the differences from Yang' work. (iii) we combined static Bayesian and dynamic Bayesian (HMM) to estimate the driver's fatigue at initial time and following time periods. And we analyzed the posteriors of fatigue by local and global contexts involving in HMM. (iv) by feature fusion, we can infer the fatigue states more reliable and make the fatigue detection model as the 3-layer HMM. This makes the fatigue inferring by combining more information and meanwhile the model is still with simple structure.

The purpose of this research is to establish an objective, reliable, and real-time model to detect and monitor driver fatigue,