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Drowsiness Detection by the Systems Dynamic Approach of Oculomotor Systems

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ABSTRACT

literature shows that blink rate, blink duration, and percentage of eye closure (PERCLOS) are the indicators of drowsiness, but the quantification of these parameters, inter-individual differences, and scientific or the physiological validation of the results have not been addressed. This study attempts to resolve these problems by the systems dynamic approach by modelling the oculomotor system. Autoregressive model of the EOG blink signatures during active and drowsy states are used to approximate and model the system. The impulse response of the active blink signal shows under damped response with the damping ratio of 0.61-0.75, (p<0.0005), and drowsy blink signal shows a critically damped behavior with the damping ratio of 1, (p<0.0005). It is clinically correlated that the continuous bombarding of the neuronal impulses from the brain acts as the stimulus for the blink. Hence, during the drowsy phase, the response of the oculomotor system is sluggish (damping ratio is high), thus causing increased blink duration.

KEYWORDS

Blink Features, Drowsiness, Oculomotor System

1.INTRODUCTION

Drowsy driving is fatal and causes irreparable losses. The U.S.National Highway Traffic Administration has found that 100,000 crashes that happen every year are because of drowsiness at the wheel. Drowsiness has contributed to 15550 deaths, 71,000 fatal injuries, and $12.5 billion monetary losses (World Health Organization, 2009).The AAA Foundation for Traffic Safety estimates that 21 percent of the crashes that occur every year are due to the ‘driver fatigue’ (National Highway Traffic Safety Administration, n.d.). The national sleep foundation has reported that every year 60 percent of adult drivers have been under drowsiness while driving, and 37 percent of drivers had fallen asleep (Asleep at the Wheel, 2010). The main culprits causing drowsiness are prolonged periods of driving, driving alone, night time driving, driver’s anxiety or stress. However, most disappointing factor is that this cause was never pinpointed as a reason for the accidents, since many of the case reports highlight rash driving, alcoholism, and manmade mistakes. With the advent of technology, it is possible to detect drowsiness well before, an accident and prevent the lives. Research on these lines called for a greater focus on designing and development of non-intrusive solutions for detection of drowsiness.

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Detection of drowsiness involves identification of certain parameters from the subject or the vehicle. Based on these, the existing methodologies are categorised into Subjective measures, Behavioural measures, Vehicle-based parameters, and Physiological parameters.

Subjective measures of the drowsiness are the driver's general assessment of the mental status based on a scale Karolinska Sleepiness Scale (KSS) (Dong et al., 2011; Sahayadhas et al., 2012). This method uses general feedback from the driver to give the ratings from 1-9, in which the ratings of 5-9 indicate high Blink duration, large steering wheel corrections, yawning (Ingre et al., 2006). Subjective measures are correlated with the physiological data collected such as EOG and EEG (Hu & Zheng, 2009; Portouli et al., 2007). Subjective assessment is not possible to implement in real-time scenario.

Behavioural measures of the driver include the change in the position of the head, pupil diameter, blink duration, yawning, gaze, which are monitored by several sensors (Dong et al., 2011; Sahayadhas et al., 2012). One method uses Eye tracker employing one or multiple cameras to monitor the pupil and the line of vision of the driver in the vehicle. This device continuously tracks the eyelids, and if the eyelids are closed for more than a pre-defined limit, an alarm rings to alert the driver (Husar, n.d.). A Non-intrusive real-time image acquisition system with efficient image processing algorithm was developed to detect the vigilance level by Eye, Gaze, Face and Pose tracking (Ji & Yang, 2002). These methods (Bergasa et al., 2006; Husar, n.d.; Ji & Yang, 2002) have a limitation as a camera cannot be used under the poor illumination conditions. PERCLOS the Percentage closure of the pupil over time is measured in many studies (Abe et al., 2011; Lexus LX Driver Monitoring System, n.d.; McKinley et al., 2011; Seeingmachines Driver State Sensor, n.d.) and is commercially available as Seeing Machine and Nexus. These technologies employ High Definition IR camera to capture the eye and apply efficient image vision technologies to find the PERCLOS. Several other methods have used yawning and position of the head as the criteria (Murphy-Chutorian & Trivedi, 2010; Nature, n.d.; Smith et al., 2003; Xue et al., 2009).

Vehicle-based parameters include the Steering Wheel Movement (SWM), Standard Deviation from the Lane Position (SDLP), pressure on the accelerator, clutch, brake, and grip force on the steering wheel (Dong et al., 2011; Sahayadhas et al., 2012). One method uses non-intrusive Accelerometer sensors to find the Steering Wheel Movement (SWM) to assess the Standard deviation from the Lane position (SDLP) (Liu et al., 2009). This study found that the deviation in the Steering Wheel Angle is more than 5 degrees as the driver tends to manipulate more corrections in the steering to cover the SDLP during the drowsiness. However, this study has limitations concerning the real-time implementation because the vibrations of the vehicle could result in generating noise of the SWM. Detection of SDLP involves employing a camera (Bergasa et al., 2006; Fairclough & Graham, 1999; Ji & Yang, 2002; Liu et al., 2009; Otmani et al., 2005; Ruijia et al., 2009; Sommer et al., 2010; Thiffault & Bergeron, 2003) which is, hard to implement in real-time under poor illumination conditions.

Physiological measures of the drowsiness include Heart Rate Variability (HRV), Respiration Rate, Power within the EEG (Electroencephalogram), EOG (Electroocculogram) blink characteristics, Power within the EMG (Electromyogram) signal (Dong et al., 2011; Sahayadhas et al., 2012). EOG signal is used widely to detect the Rapid Eye Movements (REM) and Slow Eye Movements (SEM) from the Blink signal by placing a pair of electrodes on the eyeball (Hu & Zheng, 2009; Khushaba et al., 2011; Kurt et al., 2009). However, the EOG Blink signal is only an indicator of drowsiness and cannot help to quantify these parameters in real-time. A study reports that HRV also varies when a driver progresses from the 'awake' to the 'drowsy' stage. The LF/HF ratio decreases as the increase in the parasympathetic dominance over the sympathetic dominance of the autonomic nervous system during the drowsiness (Guosheng et al., 2010; Patel et al., 2011). Many studies have used EEG signal as a strong indicator of drowsiness since the neuronal activity decreases during the transition of 'active' to 'sleep' states of a driver (Akin et al., 2008; Fu et al., 2012). It is found that the Beta activity decreases and Theta activity increases when a person is in a transition from active to sleep mode. Several signal processing techniques such as FFT, Power spectrum, DWT, Entropy are used to derive such features as Power within the Beta, Delta to identify drowsiness. These features are