Automotive Safety:

Preventing Road Accidents Using Tiredness Detection Methods

osmitau

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About us:

Osmitau Technologies is currently building **Teyered**: a hybrid solution for drowsiness detection powered by machine learning.

By embracing state-of-the-art machine learning techniques and advanced statistical methods, **Teyered** aims at improving vehicle safety by detecting drowsiness with a personalized, versatile, and accurate system.

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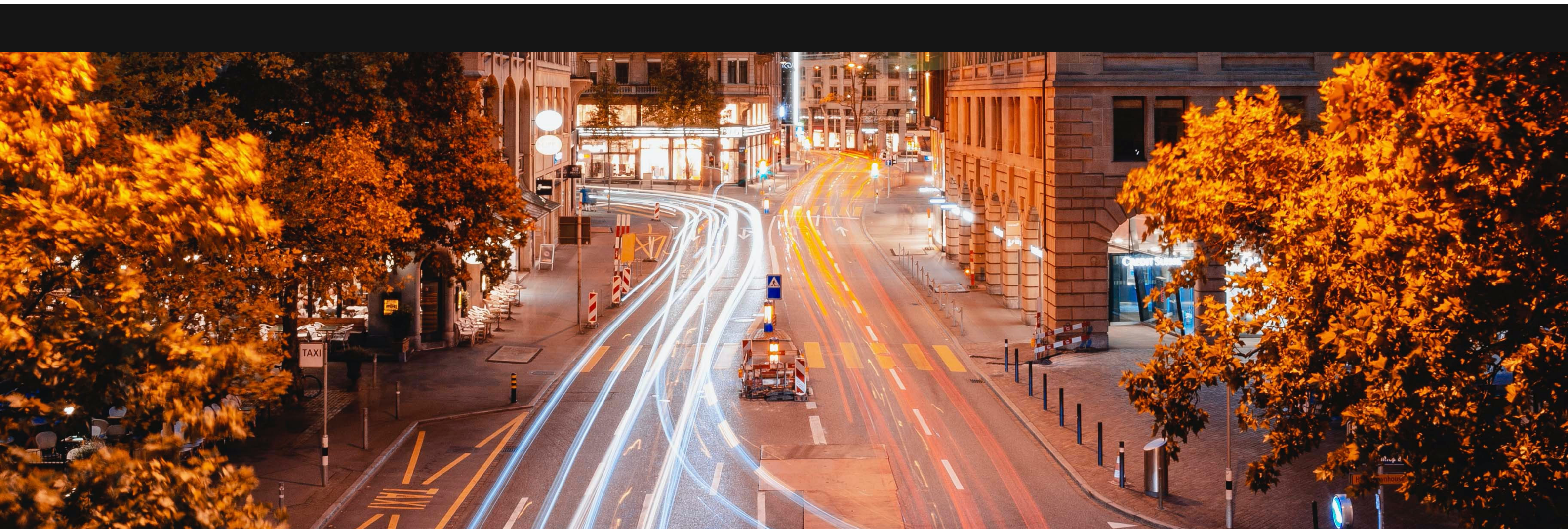

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Introduction

Safety is the most essential priority while driving with US drivers considering safety the most influential point when purchasing a car[1]. One of the major factors reducing safety for both drivers and pedestrians is drowsiness behind the wheel. It has been demonstrated to severely impair driving performance. On average, tired drivers perform worse than alcohol-intoxicated individuals with a blood alcohol concentration of 0.05%[2]. Drowsiness is also the main cause of about 17% of fatal traffic accidents[3].

In the US alone about $671 Billion worth of goods per year are transported by 15 million trucks[4]. The monetary loss due to crashes has been growing steadily since 2013. In 2016, crashes involving large trucks and busses leading to property damage, injury and fatalities, amounted to a total loss of $134 Billion[5]. Predicting dangerous levels of tiredness and preventing crashes and accidents offers an opportunity to produce safer vehicles that in turn will increase their value to potential car buyers.

This white paper analyses the current research available on patterns of drowsiness that can lead to vehicle accidents, as well as current and future solutions to the problem.

1. Drowsiness

Drowsiness is the tendency of an individual to fall asleep. There are three main phases of sleep: awake, Non-Rapid Eye Movement (NREM) sleep and Rapid Eye Movement (REM) sleep[6]. NREM can then be subdivided three stages by using brain waves data from electroencephalograms (EEG):

- Stage 1: Awake to Asleep transition (drowsy)
- Stage 2: Light Sleep
- Stage 3: Deep Sleep

Drowsiness-related accidents show recurring characteristics. They occur primarily late at night (0:00 AM – 7:00 AM) or in the early afternoon (2:00 PM

– 4:00 PM). Usually, there are no signs of vehicle defects or breaks usage and the weather conditions are generally good with clear visibility[7]. Multiple studies[8] [9] have identified the monotony of the road environment as a possible trigger for drowsiness. Moreover, signs of drowsiness based on the drivers' performance can be observed within 20-25 minutes of driving[8].

Additionally, the European Road Safety Observatory identified the lack of sleep, time spent on a task, monotony of the road and the internal body clock, as main sources of drowsiness that can lead to fatal accidents[10].

2. Measuring Drowsiness

Drowsiness detection systems typically attempt at detecting the early stages of NREM. They generally consist of a device that is embedded in the vehicle and monitors the driver. The device captures data in the form of pictures from a camera or sensors such as steering wheel sensors. The data is then processed and analyzed by an algorithm to measure the drowsiness level. This process can be repeated multiple times for a certain length of time `t` Figure 1.

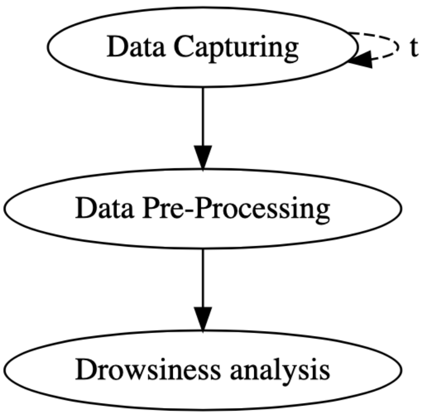

Figure 1: A diagrammatic representation of the drowsiness analysis process. When data is recorded, it is then pre-processed and used for drowsiness analysis. The process is usually repeated over time (dashed line labeled `t`).

This process is adapted in different ways depending on the type of data being collected, which is either: subjective, vehicle-based, behavioral or physiological.

2.1 Subjective Measures

Subjective measures involve the driver's assessment of their alertness level. The Karolinska Sleepiness Scale (KSS) is a nine-point scale and it is the most widely used scales to describe drowsiness[11]. Each rating of the KSS has an associated description as shown in Table 1.

Rating	Description
1	Extremely alert
2	Very alert
3	Fairly alert
4	Alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy but no effort to keep alert
8	Sleepy some effort to keep alert
9	Very Sleepy, great effort to keep alert, fighting sleep

Table 1: The Karolinska Sleepiness Scale (KSS) with descriptions for each rating.

The KSS has been used to monitor the driver's drowsiness level in driving simulations and compared to other sources of data such as EEG data[12] or Lane Position data[13].

The results, however, were mixed and they largely depend on the driver's consistency in the self-assessment. This method may not be consistent between different drivers and may also fail to capture sudden changes in drowsiness levels due to microsleep events. An additional limitation it is difficult to inquire about the driver while driving on a real road, and in addition to being a source of distraction, it may indirectly alert the driver, affecting their drowsiness level[7].

2.2 Vehicle-Based Measures

Vehicle-based measures aim at determining the drowsiness level via the interaction between the driver and the vehicle. These usually involve sensors such as steering wheel sensors or lane position sensors.

Steering Wheel Sensors

These sensors measure the change in the angle of the steering wheel. There are two main phases of drowsiness that can be detected with steering wheel sensors:

- **Phase 1**: Early-stage drowsiness where the driver is unable to smoothly control the vehicle, with large maneuvers to correct the vehicle position. This usually results in zigzag driving and has been reported by multiple research. Studies[14][15]
- **Phase 2**: The dozing off phase. The driver stops reacting to feedback from the road, therefore the steering sensors have a flat and constant value which is usually combined with an increased lateral position[15].

Typically, these two phases alternate each other in drowsy individual, right before a crash (Figure 2)

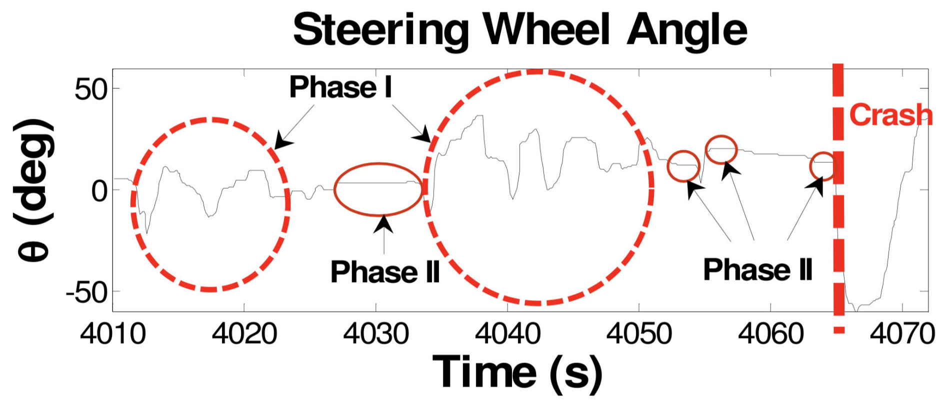

Figure 2: Steering wheel angle patterns in a 5 km drive simulation. There are two main phases: Phase 1 characterized by large changes in steering angles and Phase 2 with rather constant values.[15]

Other measures that can be calculated from steering sensors are the Standard Deviation of Angular Velocity (SDAV) of the steering wheel and the proportion of STeering wheel movements EXceeding Three degrees (STEX3). These are highly correlated to Psychomotor Vigilance Tests and the KSS scale.[16]

These sensors work optimally with steering angles between 0.5° - 5.0° and they are also relatively easy to install on vehicles. Steering wheel metrics, however, are too dependent on roads with specific geometries and may be affected by the vehicle kinetics in particular environments. Additionally, monotonous roads such as straight roads, provide little to no variation to be detected which may result in drowsiness not being detected. Steering wheel sensors may also fail to detect changes in relatively straight roads or highly trafficked roads, which are among the roads with the highest number of accidents.[15]

Lane Position Sensors

Lane position sensors involve a combination of an external camera and lane-tracking algorithms to calculate the position of the vehicle with respect to the lanes.

Patterns that can be calculated from this type of data are Standard Deviation of Lane Position (SDLP)[17], Lateral Lane Position[18] and the Frequency of Abnormal Lane Deviation[19]. In their research, Ingre et al.[17] found a significant correlation between the KSS scale and both the SDLP (Figure 3) and the blink duration which is also discussed in the next section.

Limitations of this method include the dependency on road marks for lane detection, lighting and weather conditions[7].

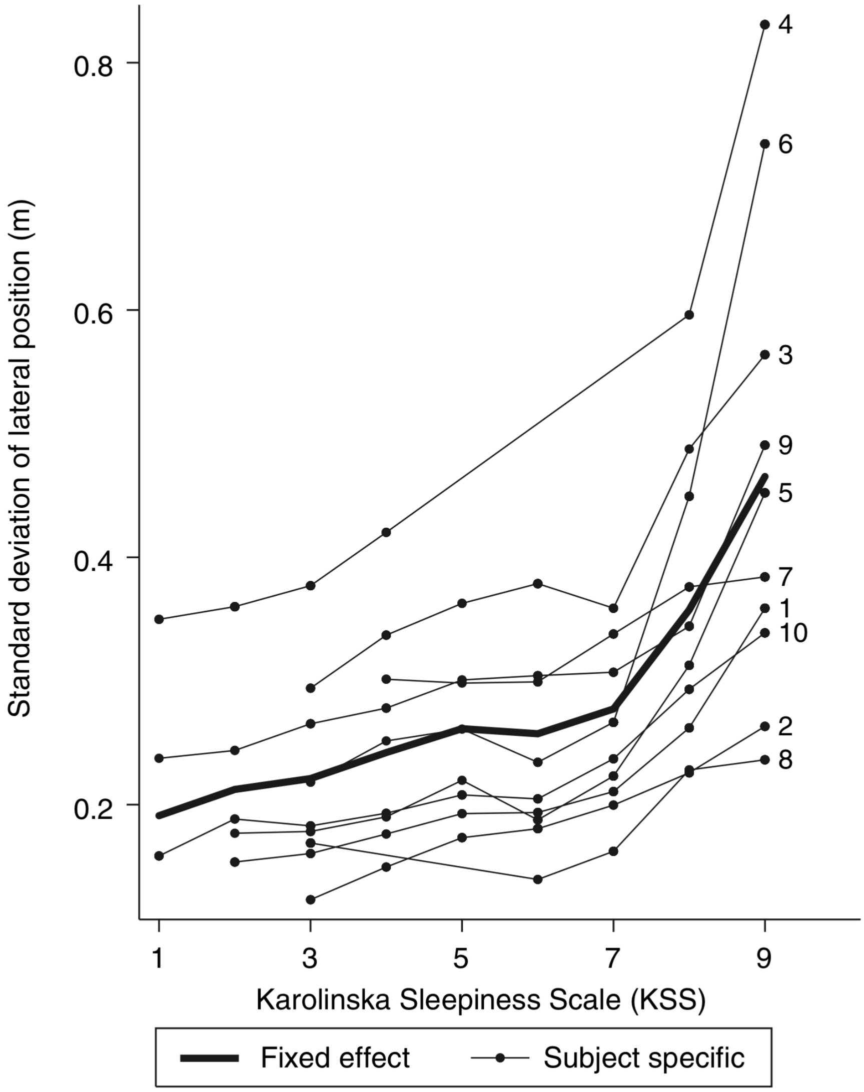

Figure 3: A positive correlation between the Standard Deviation of Lane Position (SDLP) and the Karolinska Sleepiness Scale (KSS) (n = 20). The estimated fixed effect (thick) shows a peak in drowsiness (KSS 8-9) between SDLP of 0.36 and 0.40[17].

2.3 Behavioural Measures

Behavioral measures attempt at identifying behaviors associated with drowsiness. They usually rely on a camera that records the driver's face. A set of features is extracted from the pictures which can be correlated to drowsiness (e.g. eyes closed for a prolonged period of time). The majority of the features are obtained from the mouth, eyes, or head as a whole.

Mouth Features

Yawns are the most common mouth features correlated with drowsiness. This is usually measured as the degree of mouth openness which will vary if the driver is normal, drowsy or just talking[20].

Eyes Features

Eyes, and more specifically blinking, have been studied extensively for drowsiness detection. The most commonly used approach is PERCLOS, the PERcentage of eyes CLOSure over a time period and is very effective in drowsiness detection[7]. A more recent study by Trutschel et al.[21] however, challenged the effectiveness of PERCLOS and commercially available PERCLOS-based systems. In a trial with three commercial systems, PERCLOS had a higher error rate in drowsiness detection of about 10% compared to EEG data. This has been associated with episodes of microsleep events where drivers are asleep with their eyes open which PERCLOS fails to address.

Alternative eye features correlated with drowsiness include the Average Eye Closure Speed (AECS), Blink Frequency and Duration and pupil diameter. Additionally, eye gaze can also be extracted to verify whether the driver is looking at the road ahead[20].

Head Features

Drowsy drivers seem to sway their heads, increase nodding, scratch their faces more frequently and more prone to rotate their heads to the left to relieve tension on the neck. The head position can also be used to calculate the slouching and posture adjustment frequency. The features involving rotations are quantifiable with available face detection methods. Other behaviors like scratching may be harder to quantify and may not be consistent across different individuals.[15]

Once these features are extracted, a threshold is set to classify the driver as drowsy or not. Given that most of these features rely on a temporal dimension, they tend to perform better when used for a longer period[22].

The main limitation of behavioral approaches is the camera as it is significantly affected by light conditions. This has partially been minimized by the addition of an infrared camera[7]. However, the systems may still be sensitive to sudden changes in illumination or dust accumulating on the camera sensor which may affect the feature detection steps.

2.4 Biological Measures:

Biological measures focus on detecting significant changes in physiological signals as measured by electrocardiogram (ECG), electroencephalogram (EEG), electro-oculography (EOG), surface electromyogram (sEMG)[23].

EEG has been studied extensively, as it detects brain waves related to sleep[20]. Drowsiness is usually correlated with an increase of a continuous signal of α and θ waves compared to β waves, detectable over a time period of choice with the formula:

$$\frac{\Delta\alpha + \Delta\theta}{\Delta\beta}$$

Although very accurate, EEG measurements are very invasive, consisting of electrodes in contact with the skin[23]. Nonetheless, it has been very useful to evaluate other patterns of drowsiness such as Standard Deviation of Steering Wheel Angle and Lateral Lane Position[24].

2.5. Hybrid measures

Theoretically, combining information about the driver's physical state and driving performance should improve the confidence of the detected fatigue[23]. Hybrid measures consider multiple patterns of drowsiness, such as the ones previously outlined, to refine the confidence of the prediction.

As an example, Eskandarian and colleagues analyzed driving data from 20 subjects over two days. The study identified correlations between PERCLOS, Steering Wheel Angle, Lateral Displacement of the vehicle and vehicle crash accidents. A neural network model trained on all of these patterns achieved a larger accuracy with lower false-positive signals compared to just considering one pattern[15].

Machine learning models are therefore suitable candidates for drowsiness detection solutions for three main reasons: personalization, accuracy, and versatility.

- **Personalization:** Unlike many patterns of tiredness described earlier such as PERCLOS, machine learning does not rely on specific values to determine the drowsiness. Instead, machine learning can *learn* drowsiness-specific patterns on a driver-to-driver basis, taking into account variations in the individuals.
- **Accuracy:** Additionally, machine learning models can improve their accuracy as more data from the driver is obtained compared to other algorithms. Their great versatility also allows them
- **Versatility:** Due to their modular architecture, machine learning models allow for multiple sources of data to be used, as in the case of Eskandarian and colleagues Additionally, this allows adaptation to data from new sensors that may be developed in the future.

In terms of drawbacks, machine learning models generally take longer development time, as they need to be trained with appropriate datasets and require hyperparameters tuning. Additionally, even high-accuracy machine learning models tend to have black-box properties, meaning it may be hard to understand exactly how they reached their conclusions. Finally, high-accuracy models are usually resource-intensive which means they require high computational power to be trained.

3. Proposed Solution

Osmitau Technologies is tackling these problems to create a hybrid solution called Teyered, powered by machine learning:

- **Development Time**: Osmitau's team has had extensive experience in the fields of machine learning and data analysis, working at companies such as IBM, JPMorgan, and Amazon. They take care of the development for you.
- **Explainability**: Teyered does not uniquely rely on off-the-shelf black-box models. It exploits advanced statistical methods to extract relevant patterns from drivers' data and couples them with an advanced prediction model to determine the drowsiness state of the driver.
- **Computational Power:** Osmitau takes care of the computational resources required for training the system by using the best high-performance cloud computing platforms provided by Google (GCP) and Amazon (AWS). This approach guarantees fast training times and the immediate availability of resources.

4. Conclusion

Truck and bus accidents resulted in a loss of $134 Billion in 2016 only, which includes property damage, injury and fatalities[5]. More than 40% of accidents involving commercial vehicles occur due to drowsiness[25] and it manifests itself in several detectable patterns that are used in current drowsiness-detection systems. The patterns most correlated with drowsiness involve vehicle sensors such as steering wheel angle and driver's behavior such as blinking rate. Other physiological indicators such as EEG waves, although accurate, are invasive to the driver but can be used as a baseline to validate other potential signs of tiredness.

Nevertheless, the most accurate methods for drowsiness detection involve the use of multiple patterns as an input to the predictive system into a hybrid solution. This can be done using a statistical method with a fixed drowsiness threshold, an adaptive black-box machine learning or a combination of the two.

Find out more

You can find out more about our company and our services at

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We offer consulting services for AI and Machine Learning and can help you tackle complex problems that require optimal solutions.

Osmitau is aiming to release Teyered in early 2020. You can join our newsletter by clicking HERE (we don't spam, unlike the big guys).

Or you can email us at hello@osmitau.com.

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Notice:

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