Drowsiness Detection for Life-Saving – A Hidden Continuous Monitoring System for use in Road Vehicles

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Abstract: *These days, driver monitoring and fatigue detection are challenging issues, since road accidents mostly occur, due to human errors. In the first part of this paper, methods for drowsiness detection possibilities are introduced. After that, a supervision system is presented, in the form of an incremental hierarchical fuzzy inference system. In the first level of the system, camera-based drowsiness level estimation is carried out using simple independent variables: blinking per minute, respiratory level and the position of the head. Drowsiness is determined on a scale of 0…5. At the second level, the supervision is managed. Based on the drowsiness level and the relative distance, the required action of the system is defined using intervention in the braking system of the vehicle. This system can be a potential foundation to create a simultaneous operating supervision system, for highly automated vehicles, to improve driver state monitoring and road safety.*

Keywords: road safety, drowsiness detection, driver monitoring system, highly automated functions, road vehicles, fuzzy logic, hierarchical fuzzy system

1 Introduction

Driver drowsiness is a major contributor to road traffic accidents, posing significant risks to drivers, passengers and others on the road. Globally, “drowsy driving” is estimated to account for 20–30% of road crashes, with the National Sleep Foundation reporting that it is responsible for approximately 21% of fatal crashes annually in the United States, resulting in an estimated 6400 deaths each year [8]. Drowsiness—defined as a state of sleepiness or reduced alertness during inappropriate situations—can severely impair driving performance, even over short periods. This impairment, primarily due to fatigue, significantly affects attention, reaction time, and decision-making abilities [9]. The National Highway Traffic Safety Administration (NHTSA) estimates that distracted driving contributes to about 8% of all fatal crashes. This means that drowsiness remains a distinct and critical factor in road safety [10]. These statistics underscore the urgent need for effective countermeasures to reduce drowsiness-related accidents and fatalities [11].

In response, extensive research has focused on the development of Driver Drowsiness Detection (DDD) systems. Advances in machine learning and deep learning have enabled the creation of various methods to detect and predict drowsy states in real time, aiming to reduce accident rates and improve road safety [12]. However, drowsiness is a complex, multifactorial phenomenon influenced by physiological, behavioral, and environmental factors, making accurate and robust detection difficult. This complexity necessitates comprehensive approaches that integrate diverse data sources and adapt to varying conditions [9].

This paper purposes to provide a systematic overview of recent advances in drowsiness detection for road vehicles, focusing on literature published over the last five years. Existing methods are categorized into physiological-signal–based, computer-vision–based, vehicle-behavior–based, and multimodal fusion approaches. The paper also discusses the main challenges faced by current systems, emerging trends such as lightweight edge computing and personalized models, and future directions for research and practical deployment. By consolidating state-of-the-art techniques. Finally, a supervision system is presented in the form of an incremental hierarchical fuzzy inference system. In the first level of the system, camera-based drowsiness level estimation is carried out using simple independent variables: blinking per minute, respiratory level, and the position of the head. Drowsiness is determined on a scale of 0…5. At the second level, the supervision is managed. Based on the drowsiness level and the relative distance, the required action of the system is defined using intervention into the braking system. The introduced system can be a potential basis to create a simultaneously operating supervision system for highly automated vehicles to improve driver state monitoring and road safety.

2 Categorization of drowsiness detection methods

Detecting driver drowsiness has been approached through multiple methodologies that leverage diverse types of data and sensing technologies. Broadly, these methods can be classified into four main categories: physiological-signal–based, computer-vision–based, vehicle-behavior–based, and hybrid or multimodal systems. Each category captures different aspects of driver fatigue and alertness, offering unique advantages and challenges.

2.1 Physiological-Signal–Based Methods

Physiological-signal–based methods rely on direct measurement of the biological signals of the driver that reflect their cognitive and alertness state. Commonly used signals include electroencephalography (EEG), electrooculography (EOG), electrocardiography (ECG), photoplethysmography (PPG), and electromyography (EMG). EEG signals, for example, capture brainwave activity and are highly indicative of drowsiness levels, often analyzed using deep learning models such as CNNs and LSTMs for classification [13-15]. EOG measures eye movements and blink patterns, which correlate with sleepiness onset. ECG and PPG monitor heart rate variability, providing indirect markers of fatigue and stress. Although physiological methods can offer high accuracy, they often require wearable or contact sensors that may affect driver comfort and long-term usability [16].

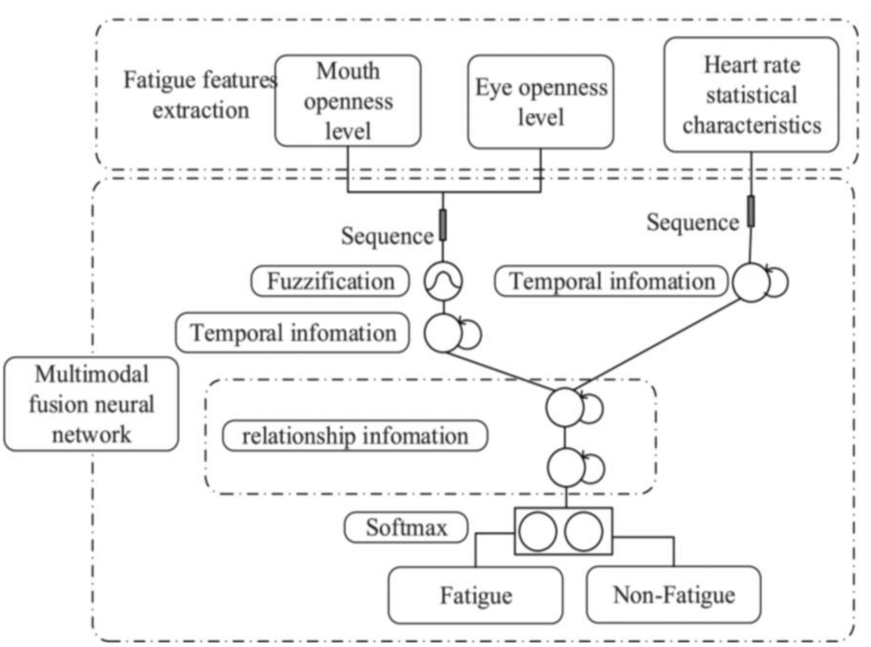


Figure 1

Fatigue detection methods [13]

In this proposed framework for fatigue detection, there were two primary data sources integrated: physiological signals (specifically, heart rate) and facial features (eye openness level and mouth openness level). To effectively process and fuse these heterogeneous modalities.

2.2 Computer-Vision–Based Methods

The computer vision module is designed for the real-time analysis of facial features and behaviors, which are critical for detecting signs of drowsiness. This module utilizes advanced face detection and tracking algorithms to robustly and accurately localize the face of the driver, even under challenging conditions such as varying lighting and head poses. For instance, our system achieves a face detection accuracy of 98.5% under normal lighting conditions[3]. Once the face is detected, the module performs detailed eye closure state analysis using convolutional neural networks (CNNs)[7]. The CNNs are trained to identify and quantify key indicators of drowsiness, including:

- **Blink frequency:** The number of blinks per minute, which tends to decrease as drowsiness increases.
- **Blink duration:** The length of time each blink lasts, with prolonged blinks indicating higher drowsiness risk.
- **Prolonged eye closure:** Episodes where the eyes remain closed for extended periods, a strong marker of microsleep or severe fatigue.

By continuously monitoring these facial cues in real time, the computer vision module provides a reliable and non-intrusive means of assessing driver alertness, forming a crucial component of the overall drowsiness detection system[17].

2.3 Vehicle-Behavior–Based Methods

Vehicle-behavior–based detection leverages data from the control systems or sensors of the vehicle itself, analyzing patterns in steering wheel movements, lane position deviations, speed fluctuations, and pedal usage to infer driver state. For instance, increased steering entropy or erratic lane departures can be indicative of reduced alertness [18]. This category has the advantage of using existing vehicle telemetry without requiring direct monitoring of the driver, making it less intrusive. However, this method faces several inherent challenges that can limit reliability and effectiveness.

Susceptibility to external factors, such as strong winds, uneven road surfaces, or adverse weather conditions, can affect vehicle dynamics, leading to an increased number of false positives. These factors may cause erratic vehicle behavior that is unrelated to the human alertness level.

Behavioral compensation concerns that some drivers can compensate for their drowsiness by consciously maintaining lane position and driving performance. As a result, the system may register “normal” vehicle behavior even when the driver is experiencing significant fatigue, resulting in false negatives and missed detections.

Indirect measurements are applied since vehicle-based systems primarily reflect the behavior of the car rather than directly measuring the physiological or behavioral state of the driver. This makes it difficult to distinguish between drowsiness and other causes of impaired driving, such as distraction, emotional stress, or intoxication.

Delayed detection appears because vehicle-based indicators often manifest after the onset of drowsiness; detection may be delayed, reducing the ability of the system to provide timely warnings and prevent accidents.

2.4 Hybrid/Multimodal Methods

Hybrid or multimodal approaches combine two or more of the above sensing modalities to leverage complementary information and improve detection accuracy and robustness. Fusion techniques may integrate physiological signals with visual features and vehicle dynamics, often employing attention mechanisms or deep networks to weigh input sources adaptively [19][20]. Despite their advantages, multimodal systems also present several notable challenges:

- **Computational Complexity:** Processing and analyzing diverse data streams in real time requires significant computational resources, which can be a barrier for deployment on embedded automotive platforms or edge devices.
- **Risk of Overfitting:** The increased complexity of multimodal models, especially those based on deep learning, raises the risk of overfitting, particularly when training data is limited or when modalities introduce noise and artifacts.
- **Data Quality and Consistency:** Different modalities may vary in quality, availability, and reliability under real-world driving conditions. For instance, physiological sensors may lose contact, or camera-based features may be affected by occlusion or poor lighting, leading to inconsistent data fusion.
- **Robustness in Real-World Scenarios:** Ensuring that the system remains reliable and accurate across diverse drivers, environments, and vehicle types remains a significant challenge.

Addressing these challenges is critical for the successful translation of multimodal drowsiness detection systems from research prototypes to robust, real-world automotive safety solutions.

Figure 2, shows a summary of the Principal methods of Driver Drowsiness measurement. This approach exemplifies the latest trend in drowsiness detection: leveraging deep learning and attention mechanisms to intelligently integrate multimodal data for more accurate, timely and practical driver monitoring systems [6].

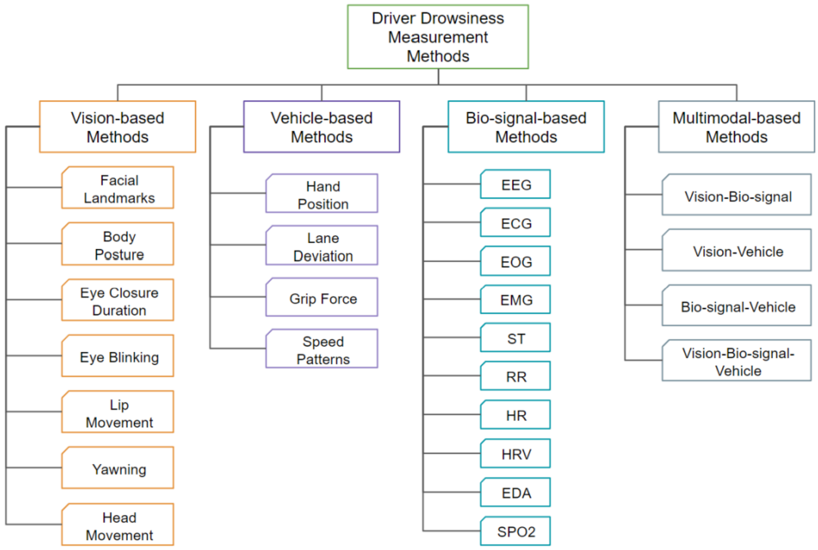


Figure 2
Main methods of driver drowsiness measurement [6].

2.5 Limitations and challenges

The above-mentioned techniques and methods are strongly limited by the circumstances and the performance of the system. The possibilities of the testing procedure do not exactly match real-world conditions. Models trained in controlled or simulated environments may not generalize well to real-world driving due to the vast range of possible scenarios and individual differences. Moreover, image-based systems struggle with occlusion (e.g., sunglasses, facial hair), lighting variability, and head movement. Real-time video analysis and multimodal data fusion require significant computational resources, posing challenges for deployment on embedded automotive platforms [27]. Physiological sensors can be uncomfortable and are sensitive to movement artifacts, reducing signal quality [26]. There is a need for rigorous, subject-independent validation and explainable AI to ensure system reliability and user trust, especially for physiological-signal–based systems.

The challenges in driver drowsiness detection systems include inter-subject variability, which makes it difficult to develop models that generalize well across different drivers; sensor intrusiveness, as some physiological monitoring devices can be uncomfortable or impractical for everyday use; environmental factors, such as poor lighting conditions and occlusions in computer-vision–based methods; and computational constraints, especially when deploying complex algorithms on embedded or edge devices with limited resources [34]. Additionally, privacy concerns and data security pose challenges, particularly when handling sensitive physiological or behavioral data [35].

This paper focuses on the monitoring of the state of the driver, extended with a supervision system. For that purpose, a serial-type hierarchical fuzzy system was generated as follows: firstly, the *drowsiness level* was determined using camera-based simple independent parameters. At this step, the *blinking* per minute, the *respiratory rate*, and the *position of the head* were applied to estimate the current state of the driver. On the second level, the type of *action* required was determined, using the *drowsiness level* and the *relative distance* to the object in front of the vehicle. The introduced model can be a potential basis to create a continuously operating supervision system for highly automated vehicles

3 Materials and Methods

Fuzzy logic was introduced by L. A. Zadeh [32]. The main idea was to provide a potential solution to handle imprecision, uncertainty, and vagueness. In real-life problems, the mathematical definitions of parameters or the boundaries of sets are not exact. As a result, the concept of Zadeh can be a useful tool.

The Mamdani-type fuzzy inference system [33] includes four modules: the fuzzification module helps to define fuzzy sets with the help of the membership function. At this step, the partition of the variables is determined. The rule base contains the available knowledge: the connections between independent and output variables are registered. The inference engine is the main part, where the firing strength is defined for the activated rules. The output of the engine is a fuzzy set. The last module, the defuzzification, helps to convert this result into a crisp value.

In the case of many independent variables, the complexity of the system is enhanced, which also results in an increased computation capacity. To avoid this issue, subsystems can be introduced and combined in hierarchical structures [34]. This solution provides the possibility to handle independent parameters only at those steps that are influenced by them.

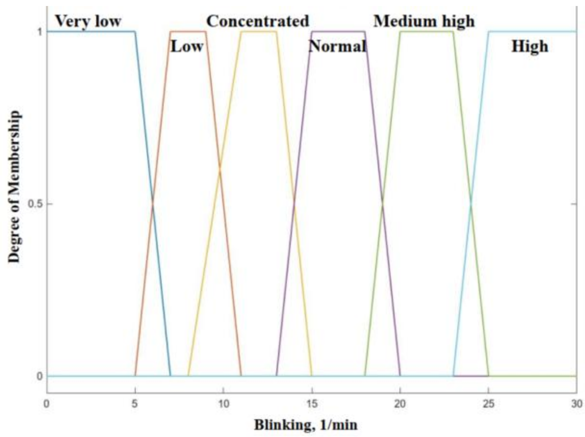
3.1 Independent Variables

The main idea of the project was to create a potential monitoring system with continuous operation for highly automated vehicles, for the special cases when several important functions are turned off. In this case, since the safety of the journey strongly relies on the human driver, it is a crucial issue to monitor the driver.

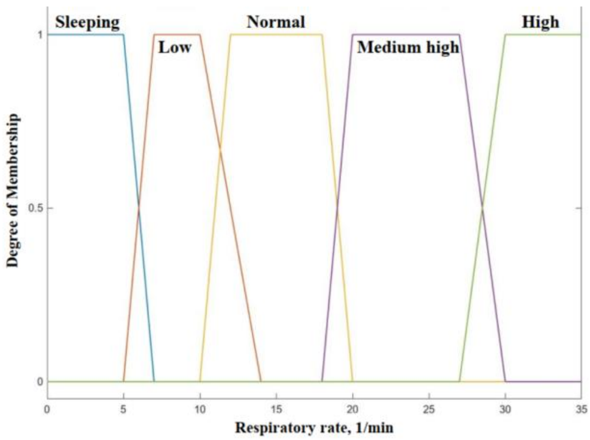
In modern transportation, especially in the highly automated sector, computer vision is widely used [35]. In addition, Shvets et al. [36] revealed that camera-based fatigue recognition systems can be useful in proper driver monitoring, mostly optical parameters were chosen as independent variables. Based on the literature, the number of *blinks* per minute [37], the *respiratory rate* [38], and the *position of the head* [36]. were chosen as input variables.

Their partitions are shown in Figure 3. In the case of *blinking*, six levels were determined (see Figure 3/a): very low, low, concentrated, normal, medium high, and high. To describe *respiratory rate* (Figure 3/b), five linguistic levels were used: sleeping, low, normal, medium high, and high. Finally, the *position of the head* (Figure 3/c) had three levels: downward, forward, and upward looking.

a.



b.



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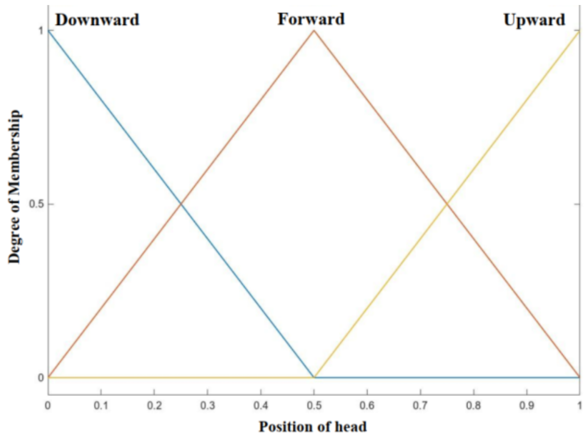


Figure 3
Partition of the independent input variables at the first level

At the second level of the structure, a further independent variable is introduced. The *relative distance* is used to describe how far the object is in front of the vehicle: the ratio between the necessary and the available distance to stop the car safely with a normal decelerating braking procedure. The value of 1 means that the distance is exactly the necessary length. The partition is shown in Figure 4; five levels were defined: very low, low, normal, long, and very long.

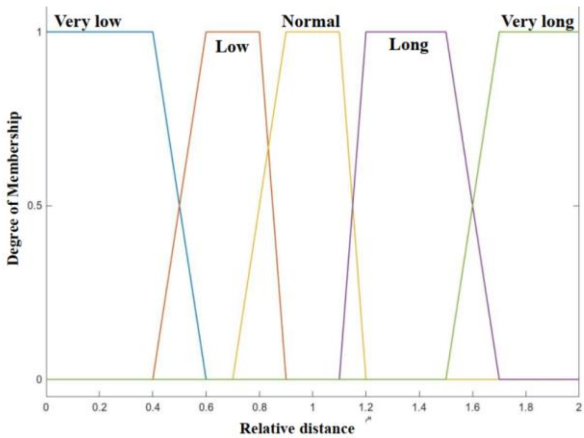


Figure 4
Partition of *relative distance*

3.2 Output Variables

In the system, two output variables were defined. The output at the first level was the *drowsiness level* of the driver. The partition is shown in Figure 5.

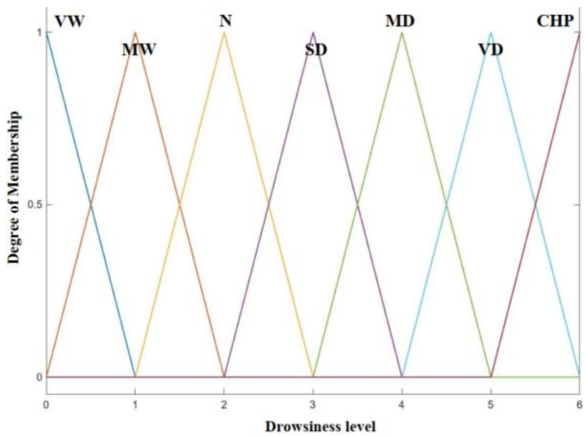


Figure 5
Partition of *drowsiness level*

Based on [39], seven levels were defined: very wake (VW), medium wake (MW), normal (N), slightly drowsy (SD), medium drowsy (MD), very drowsy (WD), and critical health problems (CHP).

Finally, the output of the system was the potential action required to be handled by the vehicle itself, even in the case of having safety functions turned off. Figure 6 shows the different levels from a simple monitoring system having no intervention (-), through a signaling system (light, light-sound combined signals) to a real acting system with several strengths of the actions: deceleration braking, emergency braking, or even stopping the car.

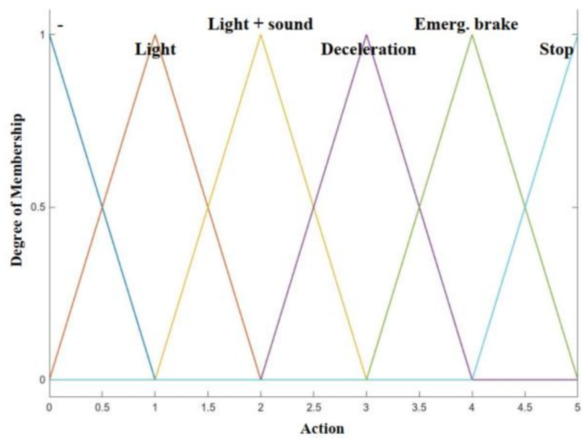


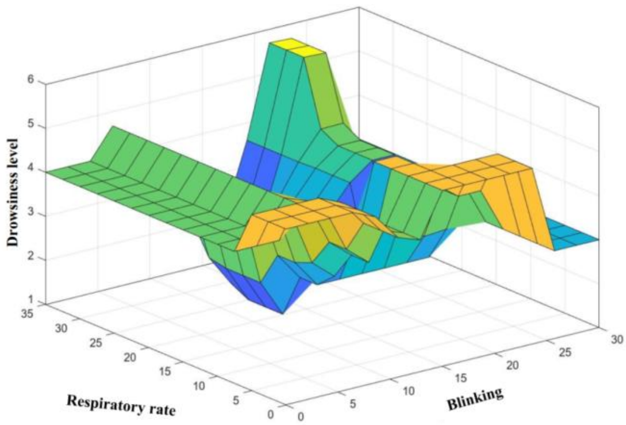
Figure 6
Partition of *relative distance*

At both levels, rules covered all the possible combinations of the levels of the independent variables. At the first level, 75, and at the second level, 35 rules were determined.

4 Results

In the evaluation procedure, firstly, the *drowsiness level* was investigated. Having an output value as a function of three independent variables, the 3D graphical analysis cannot be used. However, since the *position of the head* is a qualitative-like factor with only three levels, this parameter can be fixed to examine the effect of *blinking* and *respiratory rate*. The three parts (a,b,c) of Figure 7 show the three levels of the *position of the head*. At both plots, the lower levels are marked with dark blue, and the higher levels are yellow.

a.



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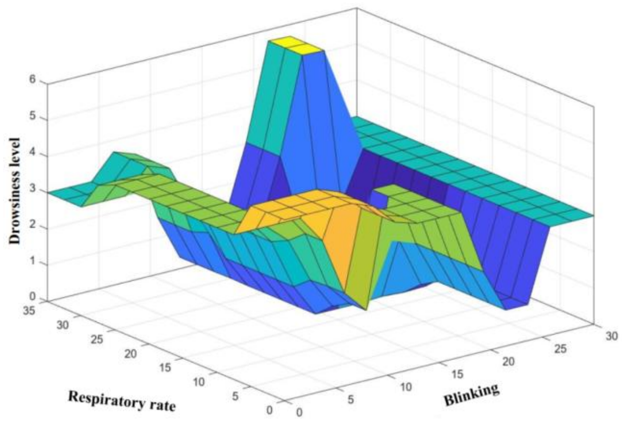

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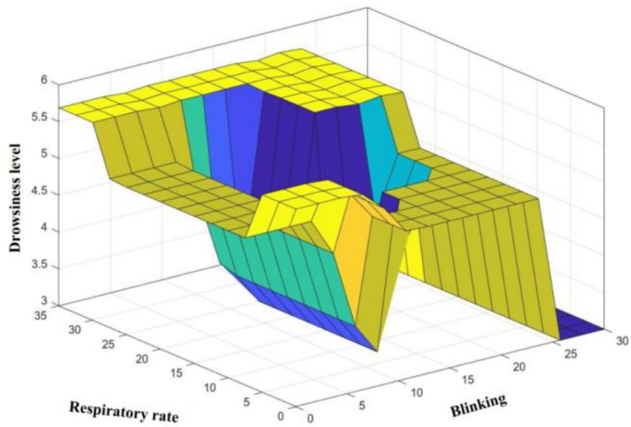

Figure 7
Drowsiness level estimations

In the case of the downward head position (Figure 7/a), the *blinking* and the *respiratory rate* show similarities: too low and too high values also refer to a higher level of drowsiness. The optimal area is small.

Regarding the forward-looking position, which is a normal driving state (Figure 7/b), it can be said that the optimal area is more extended. What is more, the average level of drowsiness is reduced compared to the downward position.

The upward head position (Figure 7/c) is not a general driving position; it is linked to a higher drowsiness level and risk. The average drowsiness level is high, the area of the elevated driver fatigue is extended, and the lowest value in this position is 3 (referred to slightly drowsy).

In total, it can be said that the head position will have a significant impact on the drowsiness level; the preferred position is the forward-looking position.

On the second level, the system output will be provided: the required action. Figure 8, shows the surface plot as a function of the *drowsiness level* and the *relative distance*.

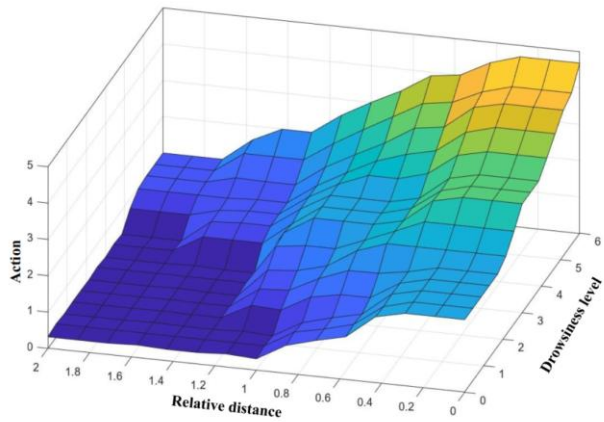

Figure 8
Surface plot of the required *action*

It can be said that the increase in the drowsiness level requires a higher action. On the other hand, in the case of having a relative distance long enough, monitoring is acceptable for safe driving.

5 Conclusions

In this paper, a driver state monitoring system was introduced and extended with a supervision system. For that purpose, a serial-type hierarchical fuzzy system was generated as follows: In the first level of the system, camera-based drowsiness level estimation was carried out using simple independent variables: *blinking* per minute, *respiratory level*, and the *position of the head*. Drowsiness is determined on a scale of 0…5. On the second level, the type of *action* required was determined, using the *drowsiness level* and the *relative distance* to the object in front of the vehicle.

The conclusions are as follows:

- It was shown that the first-level independent variables have a different impact on the drowsiness level: in the case of *blinking* and *respiratory level*, it can be said that the middle area is optimal, too low and too high values, also increase the drowsiness level. Regarding the *position of the head*, the worst and most critical position is the downward-looking position.
- It was demonstrated that a hierarchical structure can help in reducing system complexity.

- It was found that the introduced system can operate at several levels, depending on the circumstances, a monitoring system, a signaling system, and there is also a possibility to carry out real intervention.

In total, it can be said that the introduced model can be a potential basis to create a continuously operating supervision system for highly automated vehicles, to support driver monitoring and, based on real-time states, manage life-saving interventions.

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