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Enhancing Driver Monitoring and Decision-Making in Autonomous Vehicles

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Abstract — **This paper examines the integration of advanced Human-Machine Interfaces (HMI) and driver monitoring systems in level-3 autonomous vehicles, where a car can be self-driven, but requires intervention in severe conditions. It highlights key research advancements in cognitive workload and driver interaction studies, emphasizing the importance of real-time assessment of driver state using multi-modal data. The study explores innovative decision-making approaches using fuzzy logic and machine learning to manage control transitions in semi-autonomous driving scenarios. The goal is to enhance safety and efficiency in autonomous vehicles by providing a nuanced understanding and prediction of driver behavior, contributing to the development of intelligent, human-centered automotive technology.**

Keywords - autonomous vehicles; driver monitoring; human-machine interface; cognitive workload; machine learning; fuzzy logic; situational awareness; decision-making in autonomous driving

I. INTRODUCTION

Driving is a complex and routine task where attention lapses can lead to serious consequences. Despite technological advancements in the automotive industry, driving still demands high cognitive engagement from drivers. They must perform various mental tasks, including perception, expectation, judgment, planning, and execution, to drive effectively. According to the World Health Organization, road traffic accidents claim approximately 1.2 million lives annually, with nearly half of these accidents attributed to driver inattention[1].

In the evolving landscape of automotive technology, the integration of SAE level-3 and higher autonomous systems[2] (outlined by the Society for Automotive Engineers in 2014) into vehicles brings a new emphasis on the importance of driver monitoring systems for ensuring road safety. This need is particularly highlighted by incidents like the 2016 road fatality[3], where a distracted driver of a level-2 autonomous vehicle failed to take control in time. Such incidents underscore the risks associated with semi-autonomous systems, exemplified by Tesla's recent recall of over 2 million vehicles in the U.S. due to potential safety risks with its Autosteer feature[4]. The National Highway Traffic Safety Administration's investigation, which included a review of nearly 1,000 crashes where autopilot was initially alleged to have been used, highlighted the need for this recall.

In SAE level-3, also known as conditional automation, human drivers are allowed to hand over the primary driving task to the Automated Driving System (ADS) and engage in non-driving related tasks. However, they must be prepared to resume control in emergency situations. In such cases, the system issues a Take Over Request (TOR) to transition back to manual driving.

Intelligent vehicles are becoming a focal point of interest in both academic and industrial circles [1]. This field is multidisciplinary, encompassing aspects of transportation systems, psychology and medicine, automotive engineering, information technology, energy, security, and others. While intelligent vehicles have advanced towards highly or fully automated driving, challenges persist due to the uncertainties in driving conditions, driving situations, experiences of traffic participants, and the complexities of driver-vehicle interactions [2]. To facilitate a smooth transition to complete autonomy in driving, a deeper understanding and integration of driver behavior is essential for improving vehicle performance and traffic efficiency.

The increase in in-vehicle human-machine interfaces (HMI) has also led to more distractions, raising the importance of research in attention and driving safety. As future vehicles may allow drivers the freedom to disengage their hands from the wheel and their eyes from the road, monitoring systems must evolve to adopt new parameters for determining the driver's readiness during transitions of vehicle control. These adaptations are vital for maintaining safety in the era of advanced autonomous vehicles.

1 https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries
2 https://www.sae.org/blog/sae-j3016-update
3 https://www.freep.com/story/news/local/michigan/2017/01/23/michigan-traffic-fatalities-increase-2016/96239084/

4 https://www.reuters.com/business/autos-transportation/tesla-update-software-autopilot-control-issue-2-mln-vehicles-nhtsa-2023-12-13/
5 https://aware2all.eu
6 https://linkedin.com/company/aware2all

The European Union has stringent regulations for introducing autonomous vehicles into the traffic system [3]. Many studies are focused on improving driving conditions and integrating autonomous vehicles into daily life. The AWARE2ALL[5, 6] project aims to facilitate the deployment of Highly Automated Vehicles (HAVs) by developing innovative safety and Human-Machine Interface (HMI) systems, leveraging insights from prior research and addressing new safety challenges in mixed traffic environments. The project prioritizes occupant safety through in-vehicle monitoring and adaptive response systems, and the safety of Human Road Users (HRUs) via advanced perception and external communication systems. Crucially, AWARE2ALL integrates social sciences to consider cultural and psychological factors, promoting the inclusiveness and acceptance of these technologies among diverse and underrepresented user groups.

In this paper, the recent, promising research papers on level-3 automation, specifically concentrating on driver monitoring are presented. The review does not encompass the entire field but selectively highlights notable advancements. Additionally, a specific problem the authors are addressing as part of the AWARE2ALL project has been discussed, along with a proposed design for solutions to the challenges that are currently dealt with.

II. Focused Insights: Key Advances in Cognitive Workload and Driver Interaction Studies

Cognitive or mental workload refers to the degree of cognitive resources engaged and utilized while performing a task [17]. This factor is a critical determinant of human performance, as an increased workload often results in diminished performance. Several studies have been conducted to understand the cognitive behavior and mental workload of drivers during in-vehicle interactions while driving.

The study in [4] investigates the effectiveness of average heart rate as an indicator of driver mental workload, a shift from traditional methods like steering behavior and ocular monitoring. It involved participants from three age groups (21-34, 35-53, 54-70 years) and examined how mental workload (induced by voice interactions with the infotainment system) and age affect heart rate, using a portable monitor. Results showed an increase in heart rate with more complex tasks, particularly among younger drivers.

Participants were familiarized with a vehicle and a 2.7-mile route. The experiment required them to perform six voice-activated tasks during a 20-minute drive. Heart rate responses varied with task type and showed differences across age groups but not significantly by gender or session. The highest heart rate was in the OSPAN condition (average 76.53 bpm), with younger participants showing a greater increase in demanding tasks compared to older groups. This study suggests age-specific variations in heart rate response to task difficulty, informing the design of adaptive driver monitoring systems.

The research in [5] examines the use of eye gaze (specifically pupil diameter) and EEG measurements to evaluate human workload in a multi-modal driving simulation with four workload levels. The study compares the effectiveness of five machine learning models—□-Nearest Neighbor, Naive Bayes, Random Forest, Support-Vector Machines, and a Neural Network-based model—on pupil diameter, EEG data, and their combination.

In the experimental setup, participants engaged in driving, dialogues, and a tactile task to increase cognitive load. The data processing utilized Deep Neural Networks, specifically EEGNet for EEG data and Multi-layer Perceptron for other data, with a focus on stability and overfitting prevention. Pupil diameter data proved more effective than EEG in predicting cognitive workload in driving simulations. Although multi-modality learning was explored, it did not significantly enhance prediction accuracy beyond single-modality methods. This finding emphasizes pupil diameter as a more reliable indicator for cognitive workload assessment in such contexts.

The study [7] developed a support vector regression (SVR) model to analyze the relationship between driver workload and various inputs. It used a Nonlinear Finite Impulse Response (NFIR) model with 136 candidate terms, analyzing data from 10 participants. Key findings showed that while parameters like heart rate and GPS had minimal impact on workload prediction, ECG and vehicle speed were highly correlated.

The study used Error Reduction Ratio Coefficient (ERRC) values to identify seven significant measures for estimating workload, excluding temporal lag due to limited impact. SVR models trained with selected indicators, including ECG and skin conductance, effectively predicted workload. It was observed that vehicle state measurements outperformed physiological signals in workload estimation, but combining human body features with GPS data provided the most comprehensive workload estimations.

In paper [8] mental workload (MWL) in driving is estimated using performance, subjective, and psychophysiological measures. Distinguishing between MWL and perceptual load (PL), which affects task awareness, is important for safety. Advances in automotive Human-Machine Interface (HMI) aim to minimize these loads through user-centric designs and real-time adaptation.

In this study the auto-sklearn Python library is used for classification and it applies Bayesian optimization to select optimal machine learning models and hyperparameters, focusing on 15 classifiers and various preprocessing methods. An ensemble approach, combining top models for improved accuracy, is employed.

Vehicle automation increases the need for enhanced driver situation awareness (SA) to foster trust and acceptance in automated vehicles (AVs). Study [9] explores this by introducing an SA level-based explanation framework using explainable AI. An experiment with 340 participants showed that tailored explanations improve drivers' SA, situational trust, cognitive workload, and satisfaction in AVs.

In the [10] study, a Bayesian inference model was employed to merge four different machine learning models, each targeting a specific eye-related feature: SVMs for pupil size change, HMM for gaze trajectory, SVMs for fixation feature, and GMMs for fixation trajectory in order to detect workload level. Participants wore Tobii Pro Glasses 2 to measure pupil sizes and gaze points in real-time. The study involved a two-part experimental procedure where participants first underwent a training session with driving and surveillance tasks, followed by a formal experiment. The Bayesian inference model effectively utilized the strengths of different machine learning models for various features, represented by a probabilistic graphical model. The model's performance was evaluated using cross-participants and within-participants methods, demonstrating significant improvements over single models in workload estimation. This approach was validated through various tests, showing its robustness and reliability in predicting workload based on eye-related features.

Video-based drowsiness detection faces challenges such as varying lighting, head position changes, and time dependencies. The study in [11] introduces a Long-term Multi-granularity Deep Framework using frontal facial videos. It combines a Multi-granularity Convolutional Neural Network (MCNN) and a deep Long Short Term Memory (LSTM) network. The MCNN uses parallel CNN extractors on aligned facial patches, capturing detailed features for the LSTM to analyze across frames. Facial alignment technology helps create these patches, enabling the CNN to integrate appearance information and facial dynamics. The LSTM learns long-term data dependencies, enhancing detection accuracy. The method achieved a 90.05% accuracy and 37 fps using the NTHU-DDD dataset, making it a leading approach in drowsiness detection. Additionally, it also focuses on recent methods like electroencephalography (EEG) and eye gaze analysis for assessing human cognitive workload.

Understanding how the environment impacts drivers' stress and workload is key to improving driver-vehicle interactions and safety. Since stress and workload are psychological and not directly measurable, they're inferred from psychophysiological measurements like gaze, heart rate, EEG signals, and others. In semi-automated vehicles, monitoring driver attentiveness for control takeover is critical [12].

In the [13] study, a stress detection system is developed using skin potential response (SPR) and ECG data in a car simulator. By analyzing these signals with SVM and ANN classifiers is achieved up to 79.94% Balanced Accuracy in detecting stress during simulated driving.

Another paper presents a review of driver distraction detection methods, highlighting their importance in the era of increasing vehicle automation [14]. It emphasizes the need for advanced systems as drivers move to supervisory roles in automated vehicles. The review covers various distraction detection methods, including vision-based, driving style, and physiological signals, and discusses the challenges of detecting inattentive drivers amidst advancing automation.

While many studies focus on workload and stress in driving, few examine them together, which is essential for a complete understanding of driver behavior. A study [15] uses entropy measures, Stationary Gaze Entropy (SGE) and Gaze Transition Entropy (GTE), to analyze driver behavior. SGE assesses workload by measuring gaze dispersion, while GTE predicts eye movement sequences. Additionally, facial action units are analyzed for workload detection, with latent variable modeling interpreting these measures. This model, which considers errors in sensor data and the coexistence of psychological constructs, better captures the dynamic interplay of individual stress and workload factors.

The research favors a model with two interacting latent variables for its accuracy and comprehensive data interpretation. This approach reveals a complex, bidirectional relationship between stress and workload, varying with individual differences and external conditions. The findings underscore the importance of personalized monitoring of driver states, acknowledging the temporal influence of past states on current driver behavior.

The paper [16] investigates the effectiveness of a shared control algorithm in a driving simulator for critical lateral maneuvers. It focuses on how this technology assists in avoiding collisions, specifically when a motorcycle enters the vehicle's lane unexpectedly. The study tests different levels of assistance (gentle, intermediate, aggressive) under varying driver conditions (focused and distracted) to evaluate performance, safety, and user acceptance. The findings are crucial for developing shared control algorithms in automated vehicles, aiming to enhance road safety and efficiency.

III. ADVANCED DECISION-MAKING STRATEGIES AND SYSTEM INTEGRATION IN THE AWARE2ALL PROJECT

The occupant monitoring system is designed to evaluate situational awareness on two levels: a general awareness and a more detailed understanding of specific traffic and automation conditions. The authors proposed a multi-sourcing physiological data fusion approach to determine cognitive workload in real-time. This approach relied on AI algorithms for the data fusion part. These algorithms were trained using the following dataset: "WAUC: A Multi-modal Database for Mental Workload). The study resulted in a model capable of evaluating in real time cognitive workload from two physiological measures: Blood flow variation using the EMPATICA E4 watch, Electroencephalogram using the EMOTIV INSIGHT helmet. The challenges such as lighting variations, occlusions, posture differences, and individual characteristics have been addressed by employing a hybrid, multi-sensor approach in order to evaluate the condition of the driver.

The research in this paper is aimed at identifying the optimal state for drivers and occupants in various scenarios. The system is central to this goal, as it monitors and reports on the state and behavior of the occupants consistently to the HMI and the integral safety subsystem. A key aspect of this task is the development of a system-wide state machine, which includes detailed mapping of trigger events and state transitions.

To practically test these concepts, a hybrid (virtual and physical) demonstrator has been constructed based on a Peugeot Traveller cockpit installed in the IRT SystemX, France driving simulator with environment visualization, displayed immersive 180° screen, based on SCANeR Studio environment (Fig. 1). The goal is to evaluate multimodal HMI configurations at different SAE automation levels. The cockpit is equipped with screens (cluster, central display, head up displays, steering wheel and mirrors), LEDs (side windows, windshield and steering wheel), speakers (cockpit + headrest) and driver's seat haptic actuators. Haptic feedback in the steering wheel can also be controlled using a Sensodrive motor.

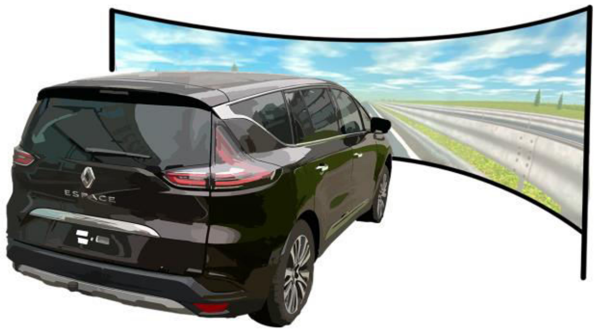

Figure 1. Hemispheric screen for driving simulation

At the heart of the vehicle's HMI concept is the idea of cognitive augmentation, adaptively and contextually designed to boost occupant awareness, intentions, and behavior. HMI and interior designs are being developed that respond dynamically to the state of the occupants, focusing on safety and role-appropriateness. This involves incorporating multimodal elements—displays, sounds, vibrations, lighting, and traditional interaction channels, including haptic feedback via controls like the steering wheel and pedals. Synchronizing these diverse elements is a critical part of the proposed design process.

To bring these ideas to life, the authors are leveraging the Android Automotive platform, which runs on a digital cockpit domain controller. This platform will facilitate various user experience modes that adapt to the driving context. Currently, an Android Automotive simulator has been developed that responds to voice commands like "start" or "stop." The next step is to integrate this functionality within the vehicle, enabling the car to react seamlessly to these commands. This integration represents a significant stride in the AWARE2ALL project, aligning with the overall goal of enhancing safety, awareness, and responsiveness in vehicle interactions.

A. Decision-Making module

The Decision-Making module in our autonomous vehicle system plays a crucial role in determining the appropriate control transition between the vehicle and the driver. Since not all inputs are equal, and different situations may require different actions, the authors follow a dynamic approach to assess the contributions of each input and decide the control transfer accordingly.

The module evaluates the percentage contribution of each input based on its severity level and relevance to the situation. Inputs are categorized as high, mid, or low priority, depending on their significance for decision making.

- **High Priority Inputs:** These inputs represent critical situations, such as emergencies or imminent safety risks. The module primarily focuses on the driver's health status (e.g., impairment) to determine if the driver must or can handle the situation. If the driver is impaired, the vehicle takes immediate control, ensuring the safety of all occupants. Other factors like drowsiness are considered but given lower priority.
- **Mid Priority Inputs:** These inputs pertain to moderately important scenarios, like highway exits or complex driving maneuvers. Here, the module assesses the driver's health, including factors like drowsiness and cognitive load, to determine if the driver is capable of taking over safely. This evaluation ensures a seamless and timely transfer of control between the vehicle and the driver when needed.
- **Low Priority Inputs**: In less critical situations, the vehicle considers all relevant inputs, such as cognitive load, distraction, and gaze region, to make decisions. Control transitions are made thoughtfully, considering the overall driving environment and the driver's capacity to intervene effectively if required.

Also, different transition control scenarios have been investigated. Vehicle to Driver (V2D) scenarios:

- **High Priority Scenario:** If the vehicle identifies a high-priority situation, it relinquishes control to the driver only if the driver is in a fit state to handle it. The main concern here is the driver's health, and the vehicle takes immediate actions if necessary, such as emergency stop as quickly and safely as possible if the driver is impaired.
- **Mid Priority Scenario:** In moderately important situations, the module evaluates the driver's health, drowsiness, and cognitive load. If the driver is deemed capable of taking over safely, the vehicle initiates a smooth transfer of control to the driver.
- **Low Priority Scenario:** For less critical situations, the vehicle considers various factors, including cognitive load, distraction, and gaze region. The

module ensures a balanced approach in deciding whether to maintain control or involve the driver.

In mid and low-priority scenarios, iHMI may be employed to notify the driver of the current situation and the vehicle's intentions, fostering a shared understanding between the vehicle and the driver.

Driver to Vehicle (D2V) scenario is in manual mode, if the vehicle detects the need to take control, it does so efficiently and safely. The system continuously monitors the driving environment and driver inputs to ensure a seamless transition from manual to autonomous mode, whenever necessary. This will be expanded further.

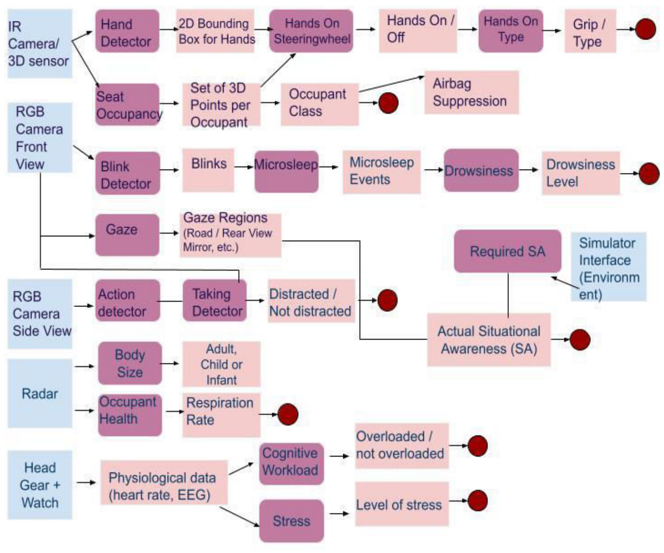

Figure 2. Diagram for Decision Making Module

The accompanying diagram (Fig. 2) illustrates the Decision-Making module under consideration. Contrary to the selective focus of previous research, the methodology proposed in this paper adopts a comprehensive approach, encompassing a broad spectrum of inputs. These include health parameters such as heart rate, respiration rate, and EEG data; cognitive factors like workload; physiological states such as drowsiness and distraction; as well as situational awareness and activity. Leveraging these diverse inputs, the objective of the proposed system is to accurately predict the driver's capacity to assume control and estimate the required time for an appropriate reaction response. This holistic approach aims to enhance the reliability and effectiveness of the decision-making process in dynamic driving environments. In this research, the authors are investigating two distinct approaches for enhancing decision-making processes: a fuzzy logic solution and a machine learning solution.

B. Fuzzy logic approach

The fuzzy logic approach involves developing algorithms based on fuzzy set theory, where decision parameters are not limited to binary true or false values, but can represent degrees of truth. This methodology is particularly suited for handling uncertain or imprecise information, making it ideal for complex scenarios where inputs may not always be clear-cut or fully quantifiable.

In addressing the challenge of assessing a driver's readiness during transitions from autonomous to manual vehicle control, the approach used in this paper involves the utilization of a cascade fuzzy logic system. To enhance flexibility and adaptability, the authors propose a multi-tiered cascade system designed to dynamically adjust to varying inputs and evolving scenarios.

The proposed cascade system begins with a smaller fuzzy logic system, initially integrating two pivotal parameters—driver awareness and cognitive load—to infer the driver's cognitive state. This primary system generates an output crucial for subsequent stages. Building on this, the cascade architecture incorporates successive smaller fuzzy logic systems. Each system uses the output from the previous stage along with the next input parameter to calculate the subsequent output. This iterative process continues until the final stage, where a comprehensive decision about the driver's readiness to take control from the autonomous system is reached.

As relationships between inputs and output in this paper's case are complex and involve multiple conditions or scenarios, a cascade of rules can help break down the problem into more manageable steps. Additionally, the cascade approach allows for a more fine-tuned control system, where different aspects of the input space are considered in separate steps. This can be beneficial if certain input combinations have a significant impact on the output.

Moreover, this multi-tiered cascade system offers a significant advantage in rule management and modification. Each smaller system has a more concise set of rules, making it easier to manage and update. Furthermore, as new scenarios or data patterns emerge, it becomes simpler to enhance the system's capacity to handle diverse driving conditions.

Code example:

```
rule1 = ctrl.Rule(health['good’] & awareness['average'] & cognitive_load['high'] & criticality['low'], readiness['high'])
```

New:

```
rule0 = ctrl.Rule((health['good'] & awareness['average']), driver_internal['high'])

rule1 = ctrl.Rule((health['good'] & cognitive_overload['average'] ), driver_internal['mid'])
```

From this get driver_readiness is extracted. Combining that with criticality a final decision has been reached:

```
rule0 = ctrl.Rule((critical['low'] & driver_readiness['not']), readiness['not'])
```

This code example demonstrates breaking one rule in a cascade of rules where an initial rule infers the driver's internal state based on health and awareness. Subsequent rules combine this internal state with other parameters like cognitive load and criticality to reach a final decision on driver readiness. The cascade approach is favored for its ability to handle complex relationships between inputs and outputs, providing a fine-tuned control system adaptable to various driving conditions.

C. Future work: Machine learning approach

The research the authors deal with critically evaluates the application of fuzzy logic and machine learning models, particularly Deep Neural Networks (DNN) and Reinforcement Learning, in predicting driver reactions. The fuzzy logic approach offers rapid processing capabilities, yet it falls short in accurately estimating the time required for drivers to react and assume control. Consequently, the focus of the authors has shifted towards exploiting machine learning models to predict occupant actions.

Long Short-Term Memory (LSTM) networks have demonstrated significant efficacy, especially when processing data like heart rate and EEG, to predict driver drowsiness or cognitive overload. However, current research appears to overlook the integration of these diverse measures in predicting reaction time. Addressing this gap, the authors are currently analyzing data collected from an experiment designed to investigate this very aspect. The data, still in its raw form, comprises approximately 70 CSV files, each representing a participant and containing columns with various metrics gathered during the experiment.

The immediate task involves extracting driver response times from these files. Alongside this, the application of transformer networks to this dataset is being explored. Transformer networks have shown remarkable success in natural language processing, handling large sequential datasets effectively. Given the sequential nature of the used data, their application appears promising. However, transformer networks often grapple with overfitting issues, particularly with datasets that are not sufficiently large. Another challenge that needs to be addressed is reducing noise in the dataset, a crucial step to ensure the effectiveness of any machine learning model that should be employed. This process of noise reduction is integral to enhancing the reliability and accuracy of the predictive models in assessing driver reaction times.

IV. Conclusion

The AWARE2ALL project represents a significant stride in enhancing the safety and efficiency of autonomous vehicles. By focusing on advanced driver monitoring and decision-making systems, the project addresses key challenges in level-3 automation and beyond. The review of recent research the authors have evaluated underscores the importance of cognitive workload and driver interactions in semi-autonomous scenarios. The integration of diverse sensor data, combined with innovative approaches like fuzzy logic and machine learning, enables a more nuanced understanding and prediction of driver behavior and readiness. This research contributes to the development of intelligent vehicles that are not only technologically advanced but also attuned to the nuances of human behavior, ensuring safer and more efficient roadways. While continuously refining these systems, the goal remains to seamlessly integrate human and machine capabilities, fostering a future where autonomous vehicles are an integral, trusted part of our daily lives.

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