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STUDIO DEGLI INDICI DI DISTRAZIONE E SPERIMENTAZIONE PRELIMINARE SUL SIMULATORE DI GUIDA DI UN INNOVATIVO DRIVER MONITORING SYSTEM

STUDY OF DISTRACTION INDICES AND PRELIMINARY EXPERIMENTATION ON THE DRIVING SIMULATOR OF AN INNOVATIVE DRIVER MONITORING SYSTEM

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Sommario (Italian abstract)

Il lavoro descritto in questa tesi è incentrato su un obiettivo specifico all'interno del più ampio progetto nazionale Epignosis. Il progetto coinvolge l'Università Politecnica delle Marche (Univpm) e varie aziende per creare un prototipo di veicolo all'avanguardia che anticipi i progressi nel settore automobilistico dei prossimi anni. In particolare, lo scopo della tesi è di dare un contributo alle fasi iniziali dello sviluppo di un innovativo sistema di monitoraggio del conducente (Driver Monitoring System, DMS), specificatamente trovando indicatori appropriati in grado di rilevare le variazioni dello stato di attenzione del conducente. Per raggiungere questo obiettivo, è stato inizialmente condotto un lavoro di ricerca per definire lo stato dell'arte di questi sistemi e raccogliere gli indici utilizzati negli studi correlati, che possano essere adatti all'implementazione nel DMS in fase di sviluppo. L'esigenza di questi sistemi è evidenziata anche dal Report Globale sullo Stato della Sicurezza Stradale del 2023, che definisce gli incidenti stradali come un problema globale di salute e sviluppo, sottolineando la necessità di una valutazione globale della sicurezza su strada. Nonostante i progressi, un'azione urgente è necessaria per raggiungere l'obiettivo di ridurre almeno del 50% morti e feriti da incidenti stradali entro il 2030, a livello mondiale. Le principali cause di incidenti stradali includono errori umani e cattive condizioni stradali. In Europa, l'errore umano è coinvolto in circa il 95% degli incidenti stradali, evidenziando l'importanza di sistemi di supporto alla guida. Di conseguenza, l'Unione Europea ha stabilito normative per rendere obbligatori sistemi come il DMS con l'obiettivo di rendere le strade più sicure, sia per le persone a bordo del veicolo sia per gli utenti della strada in generale.

In particolare, la distrazione e la sonnolenza sono fattori interconnessi che possono avere un impatto significativo sulla sicurezza stradale, portando a compiere errori e contribuendo quindi agli incidenti.

La distrazione, nel contesto della sicurezza stradale, è definita come la deviazione dell'attenzione da attività critiche per la guida sicura verso un'attività concorrente, come l'uso dello smartphone, l'aggiustamento dei sistemi di intrattenimento in auto, mangiare, impegnarsi in conversazioni ed in generale tutte quelle attività che possono portare a un'attenzione insufficiente o assente alle attività cruciali della guida. La sonnolenza è definita invece come lo stato di affaticamento, che può portare a un livello ridotto di allerta e a funzioni cognitive e motorie compromesse durante la guida. Quando un conducente è sonnolento, il suo livello di allerta e la capacità di reagire a eventi imprevisti sono pregiudicati, rendendo i conducenti più suscettibili a diventare distratti al volante. Questi stati hanno quindi effetti simili sul comportamento di guida e spesso sovrapponibili. Per questo motivo la loro rilevazione condivide alcune somiglianze, in particolare nell'uso di soluzioni tecnologiche, dato che entrambi possono manifestarsi come tempi di reazione rallentati e stili di guida erratici.

Dalla fase di ricerca sullo stato dell'arte sono stati quindi individuati i parametri ritenuti più adatti alla rilevazione di questi comportamenti. In particolare sono stati scelti cinque indici riferiti alla dinamica del veicolo: deviazione standard della posizione in corsia (Standard Deviation of Lane Position, SDLP), tempo per l'attraversamento della linea di corsia (Time to line Crossing, TLC), deviazione standard della velocità (Standard deviation of Speed, SDS), movimenti rapidi del volante (Steering Wheel Rapid Movements, RSWM) e le inversioni del volante (Steering Wheel Reversal Rate, SWRR). A questi indici sono stati poi affiancati altri parametri di natura diversa, andando ad indagare lo stato d'attenzione del conducente anche attraverso sistemi di computer vision, già precedentemente sviluppati dall'Università, che analizzano le emozioni in tempo reale attraverso le sei emozioni universali di Ekman e la posizione della testa del soggetto alla guida.

Per verificare l'andamento di tutti questi parametri è stata quindi eseguita una fase sperimentale di raccolta dati in un simulatore di guida stazionario, opportunamente attrezzato, presente nella sede di una delle aziende che collaborano al progetto (RE-Lab), in cui 19 soggetti hanno eseguito prove di guida nelle quali sono stati inseriti eventi per indurre distrazione durante la conduzione del veicolo.

I dati ottenuti dai log del simulatore e dai software per la determinazione della posizione della testa ed il rilevamento delle emozioni sono stati poi processati per porli in una struttura adatta alla successiva fase di analisi.

In particolare sono stati raccolti in file CSV, organizzati per soggetto e scenario, utilizzando il linguaggio di programmazione Python nell'editor Visual Studio Code. Per farlo sono state utilizzate le due librerie principali per l’analisi dei dati Numpy e Pandas. Sono stati poi sviluppati gli algoritmi per l’analisi dei dati e la loro visualizzazione grafica tramite la libreria Matplotlib in modo da poter svolgere un’analisi qualitativa dei risultati ottenuti.

L’analisi dei risultati del software di rilevamento delle emozioni evidenzia come in alcuni dei soggetti esaminati, il software sia stato in grado di rilevare cambiamenti significativi nelle emozioni, in termini di engagement e di valence, durante le fasi di distrazione.

In alcuni soggetti si è visto come, in particolare durante le ultime tre attività di distrazione, il software abbia rilevato picchi al di fuori della tendenza registrata precedentemente alla distrazione. Ciò porta alla conclusione che, in quei momenti, il soggetto ha provato emozioni ben definite e con particolare trasporto. La risposta emotiva alle distrazioni si dimostra molto soggettiva, con differenze tra una persona e l’altra. In alcuni casi il soggetto esprime un repentino cambiamento nel tipo di emozione provata rispetto a quella precedente all’evento. Alcuni soggetti mostrano bassi valori di valence ed alto engagement facendo presupporre un’emozione di preoccupazione, probabilmente attribuibile allo sforzo cognitivo richiesto per svolgere un compito secondario e alla consapevolezza di impegnarsi in attività di distrazione che quindi lo distolgono dal concentrarsi sulla guida. In altri soggetti, si è potuto anche osservare che i picchi nei valori di engagement, indicanti cioè un alto coinvolgimento emotivo, si verificano poco prima che l'azione di distrazione si verifichi effettivamente. Ciò fa intendere che questi soggetti abbiano avuto una risposta emotiva già al comando vocale che descrive l'azione da eseguire, evidenziando come il comando stesso possa essere una fonte di distrazione. Va considerato però che, per la maggior parte degli altri utenti, non è stato possibile identificare tendenze specifiche. Ciò potrebbe essere attribuito al fatto che le misurazioni non siano state prese con precisione.

In particolare, per quanto riguarda gli indici basati su telecamere, la tendenza osservata per tutta la durata del test differisce da quanto ci si potrebbe aspettare. Durante la guida, ad eccezione dei momenti in cui è imposta la distrazione, l’andamento del segnale dovrebbe essere molto più lineare. I fattori che potrebbero aver compromesso i dati raccolti possono essere una illuminazione inadeguata, che può causare problemi nella rilevazione facciale per i sistemi di visione artificiale e problemi di posizionamento della telecamera, come angoli errati rispetto al viso del soggetto. Per un'analisi più approfondita dei dati raccolti e del loro effettivo significato emotivo, consultare un esperto nel campo come uno psicologo fornirebbe inoltre una comprensione più completa degli stati emotivi dei conducenti durante le attività.

Passando all'analisi dei dati raccolti dal software per determinare l'attenzione del conducente in base all'orientamento della testa, si osserva che deviazioni più pronunciate in yaw portano a una perdita di attenzione come ci si aspettava, dato che la rotazione in yaw rappresenta la rotazione attorno all'asse verticale. Pertanto, valori elevati di questa misurazione, indicano che il soggetto, in quel momento, ha la testa girata in una direzione diversa da quella frontale. Durante i test condotti, la maggior parte delle attività di distrazione richiedeva all'utente di girarsi a destra. Come previsto, le maggiori variazioni sono state registrate sia durante queste attività che durante le fasi iniziali o finali del test, dove è consueto vedere il conducente guardarsi attorno.

Analizzando i dati relativi alla dinamica del veicolo, ci sono varie considerazioni da fare. Esaminando la tendenza degli indici, è evidente come essi subiscano fluttuazioni durante le fasi di distrazione, raggiungendo i valori soglia raccolti nella fase di ricerca in letteratura. L’analisi della velocità dell’auto mostra come per diversi soggetti, in corrispondenza degli scenari di distrazione, si può osservare una deviazione nella tendenza del segnale rispetto al periodo precedente all'evento di distrazione. Come evidenziato in precedenti studi, durante la distrazione o nei momenti che la precedono, il soggetto tende a ridurre la velocità del veicolo: questa riduzione è attribuita ad un comportamento comune in cui il conducente, consapevole che sta per impegnarsi in un compito secondario che distrae la sua attenzione dalla guida per un certo periodo, abbassa istintivamente la velocità come misura di protezione, spesso estendendola per tutta la durata del compito.

L'analisi dei dati relativi a SDLP e TLC con una soglia di 6,4 secondi come indicato dalla letteratura, rivela una correlazione tra questi indici, indicando che variazioni in uno corrispondono a variazioni nell'altro. Esaminando l'andamento di diversi soggetti si è visto come, anche se durante il test il conducente sia riuscito a mantenere quasi sempre la traiettoria all'interno della corsia, durante l'attività di distrazione più impegnativa, i conducenti spesso sperimentino un'uscita di corsia, rilevabile dal picco di SDLP ed allo stesso tempo, da una concentrazione di valori di TLC al di sotto della soglia, anche nulli o molto bassi, che suggeriscono prossimità alla linea limite di corsia o il suo attraversamento.

È importante sottolineare come la conformazione del tracciato stesso può influenzare significativamente i valori registrati per queste metriche legate alla dinamica del veicolo ed associate al comportamento del conducente.

L'ultimo insieme di dati sulla dinamica del veicolo da analizzare riguarda l'uso del volante. Esaminando questo tipo di dati emerge immediatamente quanto la configurazione del tracciato sia ancora più rilevante nell'interpretare questi indici, poiché mostrano una sensibilità significativa ad essa. Tra tutti i soggetti, vengono rilevati numerosi segnali correlati ai movimenti rapidi del volante (SWRM) mentre i segnali relativi alle inversioni del Volante (SWRR) sono probabilmente distorti dalle curve del tracciato. Tuttavia, approfondendo l'analisi dei dati specifici di un singolo soggetto, è evidente che, in alcuni casi, vi è effettivamente una concentrazione di valori di SWRM coincidenti con gli eventi di distrazione. Questo identifica un uso anomalo del volante, che però viene anche registrato in altre fasi del test. Una soluzione potenziale per affrontare questo problema potrebbe prevedere che il soggetto percorra un tracciato predeterminato dove gli eventi di distrazione si verifichino solo su tratti rettilinei. Questo approccio mira ad escludere l'uso del volante per percorrere le curve durante gli eventi di distrazione così da non alterare i risultati.

Infine, occorre fare alcuni considerazioni per quanto riguarda i valori soglia degli indici di dinamica del veicolo identificati durante la fase iniziale del progetto, ed approfondire il loro significato.

Sebbene questi valori forniscano un quadro fondamentale per condurre le analisi, è essenziale approfondirli ulteriormente ed ottimizzarli per migliorare l'accuratezza e l'efficacia delle analisi. La messa a punto di questi valori soglia in base alle scoperte empiriche e ad applicazioni in contesti reali di guida in strada può portare ad un miglioramento dei risultati. Quelli ottenuti da questo studio mettono in luce aspetti significativi legati al monitoraggio del conducente e all'analisi della distrazione.

In particolare, l'approccio adottato in questo studio ha fornito nuovi spunti sulla comprensione del comportamento del conducente e sulla valutazione degli indici di distrazione. L'uso di diversi parametri ha permesso di esplorare il comportamento del conducente da varie prospettive durante i diversi test. Analizzando i dati sulla dinamica del veicolo e sull'uso del volante, è stata valutata la capacità del conducente di mantenere la traiettoria all'interno della corsia ed identificato le correzioni necessarie per prevenire le deviazioni. Questi risultati forniscono una comprensione completa del comportamento dell'auto sulla strada e dell'interazione del conducente con essa attraverso l'uso del volante. Rilevare variazioni in questi indici durante le fasi simulate di distrazione nella sperimentazione, fornisce una base per sviluppare l'architettura successiva del software integrato nel DMS, che nelle fasi di sviluppo future potrebbe essere in grado di segnalare gli eventi di distrazione dalla sola interpretazione dei dati.

Oltre ai dati telemetrici, sono stati esaminati anche i dati relativi al volto. L'analisi del software relativo all'attenzione basato sulla posizione della testa rivela prove che indicano una perdita di attenzione durante la guida quando la testa del conducente non è rivolta in avanti, come previsto da studi precedenti e dall'esperienza reale. Riguardo alle emozioni, si osserva come queste siano altamente soggettive.

Come in ogni ricerca, è essenziale riconoscere determinate limitazioni e sfide incontrate durante lo studio. I test ed il set-up del simulatore utilizzati, sebbene efficaci, presentavano vincoli intrinseci che hanno influenzato i risultati. Queste considerazioni sono necessarie per interpretare l'affidabilità e la generalizzabilità dei risultati.

L'uso di un simulatore statico all'interno di una stanza, sebbene fornisca una simulazione realistica e fedele delle condizioni di guida reali, potrebbe far sentire il soggetto in una situazione leggermente diversa rispetto alla guida nel mondo reale, potenzialmente portando a effetti diversi sui livelli di attenzione alla guida. Per migliorare la generalizzabilità, aumentare il numero di partecipanti nell'esperimento può essere utile, data la soggettività intrinseca legata allo stile di guida di ciascun individuo. Inoltre, analizzando i dati, è stato possibile valutare che le azioni imposte ai conducenti per indurre la distrazione erano effettivamente poche e brevi rispetto a quanto potrebbe essere stato necessario per una rilevazione più completa delle tendenze nei parametri selezionati per lo studio.

La selezione di indicatori dalla letteratura adatti per rilevare la distrazione e compatibili con i dati disponibili, unitamente all'analisi preliminare condotta, fornisce una base da cui sviluppare ulteriormente il DMS. Questo è essenziale per raggiungere l'obiettivo di progettare un innovativo sistema di analisi in tempo reale del conducente come previsto dal Progetto Epignosis, riservando quindi un potenziale pratico per future implementazioni in scenari del mondo reale. Inoltre, lo studio suggerisce percorsi per la ricerca e l'esplorazione di perfezionamenti al DMS, considerando l'indagine di ulteriori fattori che influenzino la distrazione del conducente. In particolare, una parte significativa della letteratura attuale è concentrata sulla rilevazione della stanchezza e sulla sua correlazione con il livello di attenzione del conducente, su come possa influenzarlo e su come ciò, a sua volta, influenzi il comportamento del conducente. Le dinamiche derivanti dalla perdita di attenzione dovuta alla stanchezza, sebbene sovrapponibili in larga misura a quelle dell'attenzione comune, possono presentare differenze. Pertanto, continuare ad indagare su altre potenziali cause di distrazione, come quelle derivanti da compiti secondari o da fattori ambientali, potrebbe essere un catalizzatore per lo sviluppo di questi sistemi. Questo consente una prova più ampia dell'efficacia degli indici identificati, confermando o confutando l'utilità di ciascuno e apportando le necessarie correzioni per garantirne l'adattabilità a tutti gli scenari di distrazione.

Inoltre, lo step successivo potrà essere quello di effettuare la fusione tra questi dati di diversa natura. In questo modo, come anche evidenziato nella letteratura, l'uso combinato di dati provenienti da diverse fonti consente una maggiore precisione e una più rapida rilevazione di potenziali casi di distrazione del conducente.

I risultati di questo lavoro confermano e sottolineano l'importanza di integrare tali tecnologie innovative nel contesto più ampio dei Sistemi Avanzati di Assistenza al Conducente (Advanced Driver Assistance System, ADAS), offrendo spunti per il progresso di queste tecnologie e mirando a fungere da base per lo sviluppo del DMS che sarà installato sul veicolo prototipo previsto dal progetto Epignosis.

Chapter 1

Introduction

This thesis is focused on a specific goal within the broader framework of a national project named Epignosis. The project involves collaborative efforts between the Polytechnic University of Marche (Univpm) and various companies to create a prototype vehicle that anticipates the advancements in the automotive sector. In particular, the functionalities included in the prototype vehicle will encompass:

1. Assisted driving systems and active safety
2. Integration of predictive functions related to Advanced Driver Assistant Systems (ADAS) and Powertrain domains
3. Integrated Driver Monitoring System (DMS) for continuous monitoring of the driver's attention level
4. Adaptive Human-Machine Interface (HMI) based on artificial intelligence algorithms considering human factors (behavior, emotions, eye and head orientation) recognized by non-invasive multimedia sensors
5. "Augmented audio" system for pedestrian safety on the road, especially for electric vehicles, and to achieve an immersive driving experience

The work described in this thesis regards in particular the third point of the project, with the purpose to give a contribution on the early stages of the development of an innovative Driver Monitoring System (DMS). The specific goal here is to find appropriate indicators that are able to detect the changes on the attention state of the driver. To achieve this, a research effort was initially conducted to define the state-of-the-art of these systems and gather the indicators used in related studies that could be suitable for implementation in the developing DMS.

Moreover, an experimental phase was carried out using a driving simulator provided by one of the project's collaborating companies (RE-Lab). Additionally, the presence of cameras in the simulator allowed the detection of the driver's state, particularly enabling the application of pre-existing machine learning software developed by the university. Through these software applications, it was possible to detect the driver's head position and categorize their emotions using Ekman's emotion methodology. This information was utilized to determine the driver's attention state and the relationship between a non-neutral emotional state and the variation in attention level. After a data preprocessing phase, a comparison was made between the trends of the literature-selected indices, video detection, and the software-generated outputs. In this way we've been able to determine the actual behaviour of these indices during an alteration of the driver's attention state. The results obtained from conducted analyses highlight how emotion detection software detected significant emotional changes in some subjects during distraction phases. Some subjects exhibited peaks in engagement and valence values during specific distraction activities, showing emotional responses to distractions and to vocal commands. However, for most users, specific trends couldn't be identified, potentially due to inaccurate measurements, particularly with cameras. Further analysis involved examining data on driver attention based on head orientation, which showed that pronounced yaw deviations led to attention loss, as expected, especially during distraction phases. The vehicle dynamics data analysis revealed correlations between Standard Deviation of Lane Position (SDLP) and Time to Line Crossings (TLC), indicating variations in one corresponding to variations in the other. Subjects often exhibited increased SDLP values, indicating deviations from their usual lane-keeping behavior during distraction events. This deviation was particularly notable during demanding distraction tasks, where subjects displayed significant lane position variability, accompanied by low TLC values. Steering wheel usage analysis in terms of Steering Wheel Rapid Movements (SWRM) and Steering Wheel Reversal Rate (SWRR) highlighted significant sensitivity to track layout. While the initial threshold values found in the literature provide a foundational framework for the vehicle dynamics indices, deeper exploration and optimization are essential to enhance analysis accuracy and efficacy.

Fine-tuning these thresholds based on empirical findings and real-world scenarios can improve results and analytical robustness.

In the remainder of this paragraph, a brief overview of the thesis structure and the content of the various chapters is provided. The thesis is structured as follows: the first chapter begins with an introduction about the context, followed by a description of Advanced Driver Assistance Systems (ADAS) and Driver Monitoring Systems (DMS). The technology commonly applied in these systems is also discussed. The second chapter presents the state-of-the-art of DMS, focusing on studies related to indices that have contributed to the development of this work. The third chapter provides an overview of all the steps undertaken to achieve the thesis objective, with an emphasis on the indices found in the literature. The fourth chapter describes the entire experimental phase and data collection conducted at the driving simulator, the set-up, the test methodology, how the software for head position detection and emotion recognition work and the dataset obtained. In the fifth chapter, the data analysis phase is presented, with a focus on the selection of the indices and the description of the algorithms used to calculate them. The sixth chapter contains the qualitative analysis of the results. Finally, in the seventh chapter, a discussion of these results and the potential for further research is presented.

1.1 Context

The Global Status Report on Road Safety 2023 defines road traffic injuries as a global health and development problem, emphasizing the need for a global assessment of road safety. The political and social contexts of global road safety have evolved as a global public health issue, with efforts to re-evaluate the role and strategy for improving road safety (World Health Organization, 2023). The key findings of the report are as follows:

- Reduction in Road Traffic Deaths: The report indicates that the number of annual road traffic deaths has slightly decreased to 1.19 million, reflecting a 5% reduction between 2010 and 2021.
- Impact of Road Safety Efforts: Efforts to improve road safety are shown to have an impact, with significant reductions in road traffic deaths achievable through the application of proven measures.
- Vulnerable Road Users: More than half of the fatalities occur among pedestrians, cyclists, and motorcyclists, particularly those in low and middle-income countries. Road traffic injuries remain the leading cause of death for children and young people aged 5-29 years.
- Urgent Action Needed: Despite the progress, the report emphasizes that the price paid for mobility remains too high, and urgent action is needed to achieve the global goal of at least halving road traffic deaths and injuries by 2030.

These findings underscore the importance of continued efforts and interventions to address road safety and reduce the significant impact of road traffic injuries worldwide. The main causes of road traffic deaths, as highlighted in the report, include:

- Human Error: The highest percentage of world's fatalities on the roads are caused by human errors such as over-speeding, distracted driving, drunk driving, and reckless driving. More than half of all road traffic deaths are among vulnerable road users.

- Poor Road Conditions: Traffic accidents are also attributed to poor maintenance of the road network and inefficient road design.

These factors underscore the need for comprehensive strategies and interventions to address road safety and reduce the significant impact of road traffic deaths worldwide. European countries face several challenges in reducing road traffic injuries. The progress in reducing serious road traffic injuries has been considerably less than the reduction in road fatalities. Between 2010 and 2020, the EU27 collectively reduced the number of road deaths by 37%, while serious injuries showed only a smaller reduction estimated at around 14%. In addition, The COVID-19 pandemic and associated lockdowns and travel restrictions across Europe in 2020 have distorted the data, leading to a considerable reduction in both road deaths and serious injuries. This makes it challenging to assess the true impact of ongoing road safety measures. Thus, while road fatalities in the EU have more than halved in the last two decades, the latest figures show that the decline in the fatality rate is stagnating, indicating a need for additional measures to continue the downward trend (European Commission, 2021).

In Europe human error is involved in about 95% of all road traffic accidents, highlighting the persistent challenge of addressing and mitigating human factors in road safety. Moreover, the technological developments produced new causes of distraction for drivers, especially the use of electronic devices while driving. In this scenario, it is clear that the introduction of systems that can support the driver during his activity it is of extremely importance. In the last decades, this kind of systems have been studied and developed and several car's manufacturers have begun to install them in their newest vehicles with promising results in terms of safety. Due to this, the European Union has set a timeline to mandate the inclusion of these systems in new cars, aiming to continually enhance road safety in Europe. Regulatory bodies and advisory groups such as Society of Automotive Engineers (SAE) , International Organization for Standardization (ISO), National Highway Traffic Safety Administration (NHTSA), and New Car Assessment Program (NCAP) continuously update their recommendations on designing experiences that prioritize the safety of drivers, passengers, and others nearby.

They emphasize the importance of creating user-friendly experiences that are as simple as tuning a radio station on a traditional radio head unit. The European Union's General Safety Regulation (GSR) has established a plan to make Driver Monitoring Systems (DMS) mandatory for the registration of every new car. The regulation mandates the compulsory integration of Driver Drowsiness and Attention Warning (DDAW) systems, a component of DMS. These systems evaluate the driver's alertness by only analyzing vehicle dynamics. Starting from 2022, new type approvals must include these systems, and from 2024 onward, all newly manufactured vehicles must be equipped with them. Additionally, Advanced Driver Distraction Warning (ADDW) systems, that asses the driver attentional state by analyzing the driver’s eyes and face movements will be mandatory for new type approvals from 2024 and all new vehicles from 2026, but these dates can be reviewed. Thus, from 2022 onwards, new vehicle types must be approved only if they are equipped with Driver Drowsiness and Attention Warning (DDAW) systems. However, the requirement for these systems on all new vehicles will come into effect starting from 2024 while ADDW systems are going to be mandatory for new vehicle types from 2024 and all new vehicles from 2026. This initiative aims to reduce accidents and fatalities, bringing the EU closer to its goal of halving the number of fatal and serious injuries from traffic accidents.

Relying on state-of-the-art sensors and technologies, these systems are constantly evolving, seeking to achieve increasingly higher standards of accuracy while reducing their size and possibly their costs.

1.2 Drowsiness and distraction

Drowsiness and distraction are interconnected factors that can significantly impact road safety and contribute to injuries (Fredriksson et al., 2021).

Drowsiness is defined as the state of being sleepy or fatigued, which can lead to a decreased level of alertness and impaired cognitive and motor functions while driving, similar to the effects of alcohol and drugs.

Distraction, in the context of road safety, is defined as the diversion of attention away from activities critical for safe driving toward a competing activity, such as smartphone use, adjusting in-car entertainment systems, eating or engaging in conversations which may result in insufficient or no attention to the crucial driving activities.

When a driver is drowsy, their level of alertness and ability to react to unexpected events are compromised, leading to impaired driving performance. This state of drowsiness makes drivers more susceptible to becoming distracted while driving, increasing the risk of accidents.

As described above, both drowsiness and distraction are associated with a high percentage of road injuries and fatalities. Their effects are not mutually exclusive, and they often overlap. Fatigue-induced impairment mirrors the cognitive decline seen with distractions, for this reason their detection shares some similarities, particularly in the use of technological solutions.
Both of them can manifest as:

- Impaired Reaction Time: Both can lead to delayed reaction times. Fatigue slows down cognitive processes, while distracted drivers may take longer to respond to unexpected situations.
- Inconsistent Driving Patterns: Drivers experiencing drowsiness or distraction may exhibit inconsistent or erratic driving behaviors. This can include weaving within lanes, abrupt speed changes, or difficulty maintaining a constant speed.
- Wandering Attention: Both drowsy and distracted drivers may display wandering attention, where their focus shifts away from the road. This can result in missed traffic signals, failure to notice road signs, or delayed responses to changing road conditions.
- Poor Concentration: Drowsy and distracted drivers often struggle with maintaining concentration on the task of driving. This can lead to a lack of awareness of their surroundings and an increased likelihood of making errors.

Both conditions significantly increase the risk of accidents. Drowsy drivers may experience microsleeps, brief episodes of unintentional sleep, while distracted drivers may fail to perceive critical information, increasing the probability of collisions.

This detection often involves the use of technological systems that can monitor various indicators, such as face position, eye movements and vehicle dynamic data to provide real-time assessments of the driver's state and driving performance.

1.3 ADAS and DMS systems

Advanced Driver Assistance Systems (ADAS) are electronic systems in vehicles that use advanced technologies to assist drivers and increase the safety of driving. These systems are designed to prevent accidents and reduce the impact of those that cannot be avoided, as the majority of vehicle accidents are caused by human error. ADAS use sensors such as radar and cameras to perceive the vehicle's surroundings and can provide information to the driver or take automatic actions based on the detected situations (Antony et al, 2021).

They can include various active safety features, such as adaptive cruise control, lane centering, automatic emergency braking, and parking assistance.

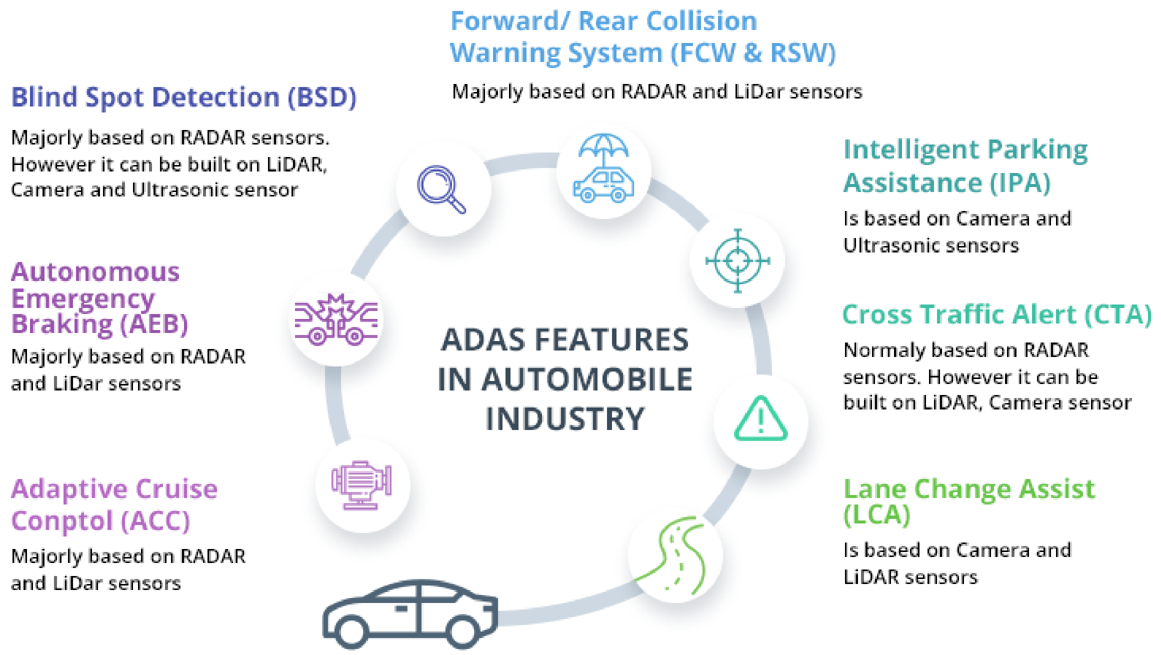

Figure 1: ADAS functionalities. Source: https://shorturl.at/TUZ17

ADAS can also enable various levels of autonomous driving and are categorized into different levels based on the amount of automation, as defined by the Society of Automotive Engineers (SAE).

The components commonly used in ADAS systems include windshield cameras, radar sensors, ultrasonic sensors, and controllers. These components work together to support the driver while informing them of potential hazards and ensuring the correct and safe movement of the vehicle. Some of the more advanced ADAS features can even manage steering and propulsion without the need for hands, such as in highway driving or stop-and-go traffic, representing some of the most advanced functionality currently available on the market.

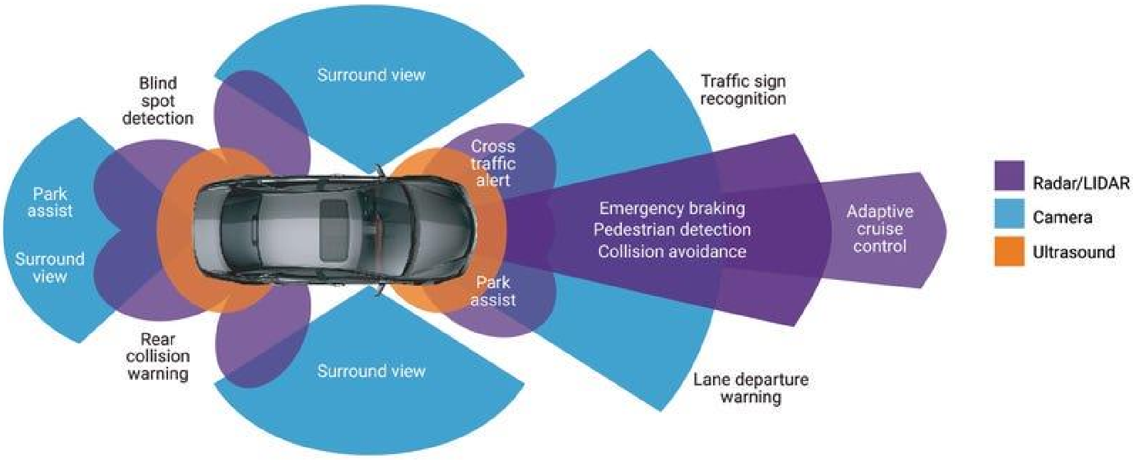

Figure 2: ADAS sensors. Source: https://shorturl.at/TUZ17

As mentioned above, some examples of Advanced Driver Assistance Systems (ADAS) technologies include:

- Adaptive cruise control: Automatically adjusts the vehicle's speed to maintain a safe following distance from the vehicle ahead.
- Lane departure warning/assistance: Alerts the driver when the vehicle is drifting out of its lane and, in some cases, can also steer the vehicle back into the lane.
- Automatic emergency braking: System that can detect an imminent crash and automatically apply the brakes if the driver does not respond in time.
- Blind spot detection: Warns the driver of vehicles in adjacent lanes that may not be visible in the side mirrors.
- Traffic sign recognition: Identifies and notifies the driver of traffic signs, such as speed limits and stop signs.
- Forward collision warning: Alerts the driver of an imminent collision with a vehicle or object in the vehicle's path.
- High beam assist: Automatically switches between high and low beams based on oncoming traffic and ambient light conditions.

ADAS improve the driving experience for both drivers and passengers in several ways. These systems are designed to enhance safety and driving comfort through the use of various components, sensors, and controllers. By providing real-time information and assistance, ADAS technologies contribute to a safer and more convenient driving experience. Some of the ways ADAS improves the driving experience include:

- Increased Safety: ADAS components help prevent accidents and mitigate their severity, thus enhancing the safety of both drivers and passengers.
- Improved Driving Comfort: By assisting with tasks such as parking, traffic sign recognition, and driver fatigue detection, ADAS technologies contribute to a more comfortable driving experience.
- Enhanced Awareness: ADAS systems provide drivers with real-time information about their surroundings, potential hazards, and traffic conditions, thereby increasing their situational awareness and contributing to a more informed and confident driving experience.

ADAS, in most of the cases, works together with the DMS (Driver Monitoring System) to enhance safety in vehicles, particularly in commercial and autonomous driving contexts. The integration of these technologies allows for comprehensive monitoring of both the driver and the surrounding environment, resulting in improved safety for all road users. The data collected by ADAS sensors are then processed by sophisticated algorithms and software to identify potential hazards, while DMS utilizes a combination of state-of-the-art sensors, high-resolution cameras, and artificial intelligence algorithms to assess whether the driver is alert, attentive, and capable of safely operating the vehicle. DMS can detect signs of fatigue, drowsiness, distraction, and other abnormal driver behavior.

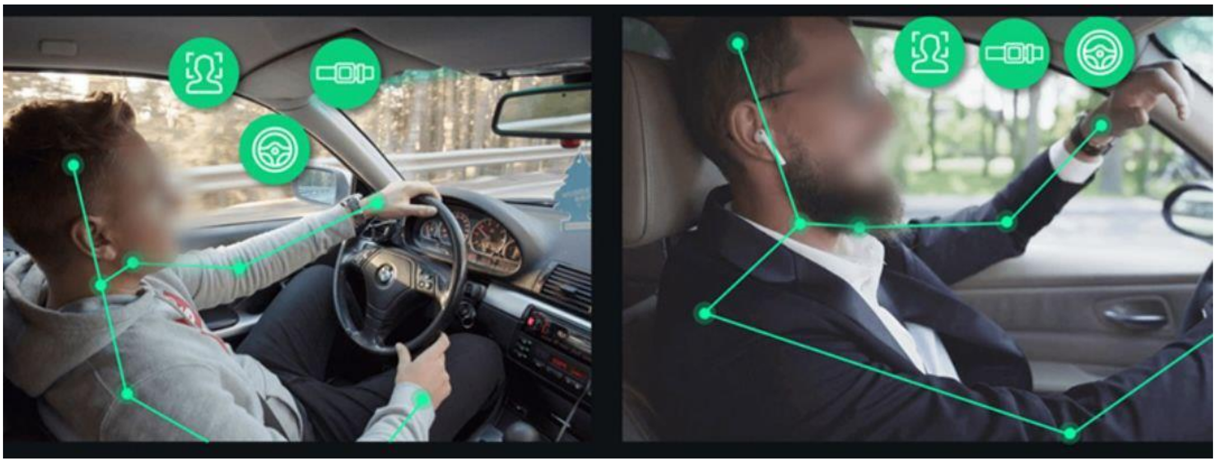

Figure 3: DMS representation. Source: https://shorturl.at/aeBT9

When integrated with ADAS, the DMS system can alert the driver and warn them to take corrective action in the event that the ADAS system detects a potential collision or other hazards.

By combining the capabilities of ADAS and DMS, the system can provide a more comprehensive approach to safety, addressing both external environmental factors and the internal state of the driver. This integration is particularly valuable in commercial vehicles and autonomous driving scenarios, where the safety of the driver, passengers, and other road users is of paramount importance. DMS are systems that can use in-vehicle infrared camera sensors to detect driver fatigue, eye gaze, facial gestures, and other visual cues that indicate risky driver behavior. The primary purpose of DMS is to enhance vehicle safety by alerting the driver and, in some cases, initiating safety measures in response to detected risky behavior.

For example, a DMS can detect when a driver looks down at a smartphone, prompting an alert to the digital display. DMS has become an essential safety feature for detecting driver distraction and drowsiness, and it is being recognized and implemented by legislators and influential organizations worldwide. For instance, the US, the EU, and China are in different stages of implementing regulations that require the use of DMS in all new passenger vehicles.

As anticipated in the previous subchapter, Euro NCAP, a prominent car safety performance assessment program, is also expected to make Driver Monitoring practically a requirement for any new car model launched in Europe. These systems are also evolving to include broader Occupant Monitoring System (OMS) applications, enabling automakers to provide a transformative driving experience for all passengers. OMS can detect and monitor events such as safety seatbelt status, seat occupancy, child seats, passenger identification, age, and gender.

DMS available in the automotive industry can be of different types, each designed to enhance safety and improve the driving experience. These types of DMS include:

- Driver Alertness/Distraction Monitoring: This type of DMS is designed to detect signs of driver distraction or inattention, such as looking away from the road or engaging in activities that divert attention from driving.
- Driver Fatigue Monitoring: These systems are specifically aimed at detecting signs of driver fatigue, such as drowsiness and eyelid movements, and issuing warnings to the driver to prevent potential accidents.
- Drunk Driving Monitoring: Some DMS are equipped to detect signs of impaired driving, such as erratic steering or unusual driving patterns, and can alert the driver or take preventive measures.
- Identity Recognition: This type of DMS is used for identity verification and can be employed for various purposes, such as personalization of vehicle settings and security.

The features equipped in DMS to assess and address driver behavior include:

- Infrared Camera Monitoring: DMS uses infrared cameras to monitor the driver's face, particularly the eyes, mouth, and head movements, to detect signs of fatigue, distraction, or drowsiness.
- Real-time Detection: The system continuously analyzes the driver's behavior in real time, such as eye closure, yawning, rapid blinking, head nodding, and other indicators of drowsiness or distraction.
- Warning and Intervention: Upon detecting risky behavior, the system issues warnings to the driver through visual and auditory alerts. In some cases, it can also initiate

interventions, such as applying the brakes or making the driving environment less conducive to distraction.

- Specific Activity Detection: Advanced DMS systems can detect specific activities like phone use, smoking, or other behaviors that contribute to driver distraction.

DMS features are designed to comply with regulations mandating the detection of inattention, drowsiness, and other forms of driver impairment, as seen in the EU's General Safety Regulation. These features collectively aim to improve road safety by alerting and assisting the driver in mitigating the risks associated with drowsiness and distraction. The combination of ADAS and DMS systems in literature (Izquierdo et al., 2018) can be find under the name of Advanced Driving Monitoring and Assistance Systems (ADMAS) that can be seen as a more comprehensive system that includes a DMS as one of its components. The subtle difference between the two can be realized as the monitoring systems understand the driving situation, and assistance systems assist the drivers to handle the situation. Alternatively, the monitoring systems are more focused on safety while assistance systems have more to do with the drivers' comfort (Mukhtar et al, 2015).

1.4 Concepts of computer vision, machine learning, deep learning and data fusion applied in the automotive industry

Artificial intelligence (AI) refers to the intelligence exhibited by machines or software, as opposed to the natural intelligence displayed by humans and other animals. It is a field of study in computer science that develops and studies intelligent machines, enabling them to mimic human problem-solving and decision-making capabilities. AI encompasses various sub-fields, including machine learning and deep learning, and is widely used in applications such as expert systems, natural language processing, speech recognition, and computer vision.

AI makes it possible for machines to learn from experience, adjust to new inputs, and perform tasks that typically require human intelligence. This technology has numerous benefits, such as automating repetitive tasks, processing information quickly, and performing tasks that may be too dangerous for humans. The integration of AI has also a huge impact in the automotive industry. This technological advancement has not only opened a new era but has also significantly altered the landscape of automotive engineering. In recent years, AI has become one of the leading factors in shaping the way vehicles are designed, manufactured, and operated. One of the primary areas where AI has made a profound impact is in the development of ADAS, DMS and autonomous vehicles. The capabilities of AI algorithms have enhanced vehicle safety by enabling features almost impossible to achieve before. As shown in the previous section, these intelligent systems utilize sensors and data processing algorithms to interpret the surrounding environment and the driver's state, making split-second decisions to enhance overall driving safety. Moreover, AI has revolutionized the manufacturing processes within the automotive sector.

Machine learning algorithms are employed in quality control, predictive maintenance, and optimization of production workflows. This not only ensures higher precision and efficiency in manufacturing but also contributes to the overall reliability and durability of vehicles. In the automotive design phase, AI plays a crucial role in computational simulations, aiding engineers in optimizing vehicle performance, fuel efficiency, and aerodynamics. The ability of AI to process vast amounts of data and identify patterns empowers engineers to create vehicles that are not only safer but also more energy efficient.

Additionally, AI has permeated the in-car experience, enhancing user interfaces and infotainment systems. Some of the key applications of AI in cars onboard systems include:

- Generative AI for Talking Cars: Companies like Google Cloud and Continental are integrating generative AI in cars to create "talking cars," allowing drivers to interact with their vehicles through natural language conversations.
- Onboard AI Computer for Driving Decisions: Bosch is utilizing onboard AI computers to enable cars to access and learn from millions of driving situations, allowing them to make decisions and react appropriately.

- Data Processing and Real-time Information: AI systems in cars process vast amounts of data from sensors and external sources, such as GPS and real-time traffic information, to determine the best routes, provide accurate trip information, and help drivers navigate around traffic and obstacles.
- Safety Features: AI powers safety features like ADAS and DMS.

1.4.1 Computer vision

Onboard systems typically rely on the use of high-resolution cameras or infrared cameras to detect the driver's state, in which computer vision technology is applied. Computer vision is a field of AI that enables computers to interpret and understand the visual world, primarily through digital images and videos. It involves the automatic extraction, analysis, and comprehension of useful information from visual data. Computer vision tasks include image recognition, object detection, and 3D scene modelling. The field has seen significant progress due to advances in deep learning and has found applications in various industries.

The different techniques used in computer vision include:

- Image Classification: This technique involves categorizing an image into a specific class or label, such as identifying whether an image contains a human or an animal.
- Feature Extraction: Features are specific patterns or characteristics within an image that are crucial for analysis. Feature extraction involves identifying and extracting relevant information, which could be edges, corners, textures, or other patterns.
- Object Recognition: One of the fundamental tasks in computer vision is recognizing and identifying objects within images. Object recognition involves training models to classify and detect objects in images.
- Object Detection: Object detection is the process of identifying and locating objects within an image or video. It involves drawing a bounding box around the detected objects and assigning them a label.

- Semantic Segmentation: Semantic segmentation aims to understand the role of each pixel in an image by labelling and classifying them. It is used to differentiate and segment the various objects and areas within an image.
- Instance Segmentation: This technique is an extension of object detection and semantic segmentation, where the goal is to detect each instance of a specific object within an image and assign it a unique label.
- Object Tracking: Object tracking involves locating and following a specific object or multiple objects over a sequence of frames in a video.
- 3D Computer Vision: Some computer vision applications deal with three-dimensional data, reconstructing and analyzing the 3D structure of objects from multiple 2D images or using depth sensors.

These techniques are applied in the automotive industry for various purposes. Focusing on ADAS and DMS they enable vehicles to perceive and understand their surroundings, leading to the detection of potential hazards and the implementation of preventive measures. DMS, for example, utilize the image classification technique to monitor the driver behavior and attentiveness by detecting the driver's facial features, signs of distraction, distress or fatigue, and take appropriate actions.

1.4.2 Machine learning and deep learning

Machine learning and deep learning are two subsets of artificial intelligence that differ in their approach to learning from data. Machine learning focuses on the development of algorithms and statistical models that enable computers to perform tasks without explicit programming. It involves the creation of models that can learn from data and make predictions or decisions based on that learning. The 3 main types of machine learning are supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the model is trained on labeled data, where the input data and corresponding desired output are provided.

Unsupervised learning involves finding patterns or relationships in data without explicit labels, while reinforcement learning involves training a model through a system of rewards and punishments.

Common algorithms used in machine learning include linear regression, decision trees, support vector machines, and neural networks. Neural networks, especially deep learning models, have gained significant popularity for their ability to handle complex tasks, such as image and speech recognition. Data plays a crucial role in machine learning, and the quality and quantity of data can significantly impact model performance. Preprocessing techniques, such as normalization and feature engineering, are often applied to improve data quality and enhance model training. Machine learning applications are widespread, ranging from image and speech recognition to natural language processing and recommendation systems. Deep learning is a subfield of machine learning that involves training neural networks (inspired by the structure and function of the human brain) with multiple layers, named deep neural networks.

Convolutional Neural Networks (CNNs) are particularly effective for image recognition, while Recurrent Neural Networks (RNNs) are suitable for sequence data, such as language processing. The key differences between machine and deep learning involve the use of algorithms to analyze data, learn from it, and make decisions based on the learning. ML can learn from relatively small datasets and requires less data compared to DL and typically requires more human intervention to correct and learn from mistakes. It utilizes traditional algorithms to solve problems based on explicit programming. DL, on the other hand, utilizes artificial neural networks to learn from large amounts of data. For this reason, it requires big data sets that might include diverse and unstructured data. It learns on its own from the environment and past mistakes, requiring minimal human intervention and can solve problems based on the layers of neural networks, drawing conclusions similar to humans. DMS make use of both machine learning and deep learning techniques for various functions such as (Hanafi et al., 2021):

- Facial Recognition with Deep Learning: CNNs are employed for facial recognition, these models can identify facial features and expressions with high accuracy, allowing to detect the driver's face, track facial landmarks, and analyze expressions.
- Eye Tracking and Gaze Detection: Machine learning algorithms, often based on deep learning architectures, analyze eye movements and gaze patterns to determine if the driver is looking away from the road for an extended period or if their gaze suggests drowsiness. ML models can learn normal eye movement patterns and identify deviations that may indicate distraction or fatigue.
- Head Pose Estimation: CNNs or pose estimation networks, are used to estimate the driver's head pose. DMS analyze the head orientation to ensure the driver is facing forward. Unusual head positions or erratic movements can be indicative of inattention or impairment.
- Behavioral Analysis: Both traditional machine learning and deep learning techniques are applied to analyze broader driver behavior so the systems can learn and recognize patterns related to distracted driving behaviors.
- Integration with Sensor Data: Machine learning algorithms are often integrated with data from various sensors for a comprehensive analysis of the driving environment. For example, ML models can correlate steering patterns with eye movements to assess driver engagement.
- Real-time Decision Making: Deep learning models are deployed for real-time inference to make quick decisions based on the analysis of driver behavior to generate immediate responses, such as generating warnings, alerts, or even triggering semi-autonomous driving features.

1.4.3 Data fusion

Data fusion is a process that involves combining information from multiple sources to generate a more comprehensive and accurate representation of the underlying data. This integration of diverse data sets aims to enhance the overall understanding and reliability of the information. In other words, data fusion seeks to leverage the strengths of individual data sources while compensating for their respective weaknesses. The sources of data can vary, encompassing a range of modalities such as sensors, databases, and even human input. By fusing these disparate data sets, analysts and systems can obtain a more holistic view of the subject under investigation. Data fusion can occur at different levels, including sensor, feature, decision, and information fusion. Sensor fusion involves merging data from various sensors to create a unified and more accurate representation of the environment. Feature fusion combines relevant characteristics or attributes from multiple data sources to enhance the overall understanding of a specific aspect. Decision fusion focuses on integrating diverse decisions or outputs to reach a more informed and robust conclusion.

Information fusion involves the process of merging data at various levels to generate a comprehensive and coherent understanding of the overall scenario. In the context of DMS, data fusion involves integrating and analyzing data from multiple sources (D.Liu et al., 2020):

- Sensor Fusion:
    - Camera Data: Cameras capture visual information about the driver.
    - Infrared Sensors: These sensors can be used to monitor the driver even in low-light conditions or when the driver is wearing sunglasses.
    - Steering and Pedal Sensors: Information about steering wheel movements and pedal activities provides insights into the driver's control of the vehicle.
- Feature Fusion:
    - Behavioral Analysis: Combining data from different sensors allows for a more detailed analysis of the driver's behavior. For example, correlating gaze direction with steering wheel movements can provide a better understanding of the driver's focus on the road.
    - Emotion Recognition: Integrating facial expression data with other behavioral cues can help in recognizing the driver's emotional state.
- Decision Fusion:
    - Alert Generation: Combining information from various sensors enables the system to make more informed decisions about when to generate alerts.

  - Context Awareness: By fusing data from GPS and environmental sensors, the system can better understand the driving context, adapting its analysis based on factors like traffic conditions, weather, and time of day.
- Information Fusion:
  - Comprehensive Driver State Model: Integrating all the information gathered from different sources allows for the creation of a comprehensive driver state model. This model can include parameters such as attention level, fatigue, and emotional state.
  - Situational Awareness: By combining data from internal vehicle sensors (speed, acceleration) with external environmental data, the DMS can enhance its situational awareness, providing a more nuanced understanding of the driving environment.
- Adaptive Systems:
  - Real-time Calibration: Fusion of real-time data allows for continuous calibration of the DMS, ensuring that it remains accurate and reliable even in dynamically changing driving conditions.

By integrating data from different sources, these systems can provide high resolution, flexibility, and accurate analysis of driver behavior enhancing performance evaluation and safety.

Chapter 2

State of the art

The most recent ADAS technologies are transforming the automotive industry by harnessing the power of advanced sensors and the capabilities of artificial intelligence. Ongoing research, standardization efforts, and technological advancements continue to drive progress in the field, with a growing consensus that the presence of an in-vehicle DMS is required for any ADAS platform to function efficiently. The integration of ADAS and DMS technologies is also a crucial step towards achieving fully autonomous driving. In the literature, several articles explore various methodologies for the development of ADAS and DMS, along with their associated technologies. In particular, to achieve the aim of this thesis, a targeted investigation was conducted to identify the various indices used in previous studies to detect signs of driver distraction and fatigue, which, as discussed earlier, are often overlapping.

The paper that most inspired this work is (Daza et al., 2014). The authors present a non-intrusive approach for monitoring driver drowsiness using a fusion of several optimized indicators based on driver physical and driving performance measures. The study was conducted in simulated conditions using ADAS and focused on real-time drowsiness detection technology. The indicators used in the study were primarily based on driver physical and driving performance skills. These indicators included PERCLOS (Percentage of Eye Closure), MSE he (Mean Squared Error of Heading Error), STD he (Standard Deviation of Heading Error), TLC avg (Average Time to Line Crossing), MSE lp (Mean Squared Error of Lateral Position), and RSWM (Rapid Steering wheel Movements). These indicators were evaluated using a neural network and a stochastic optimization method to obtain the best combination.

The study was designed such that each driver would carry out some sessions under two different conditions: without sleep deprivation, and with sleep deprivation. The performance of single indicators and the best combinations of them were evaluated. The results obtained for all the users taking the parameters of the indicators specified in the literature, with and without optimization, were considered. The experimental part of the study involved an evaluation of indicators derived from trials over a simulator with several test subjects during different driving sessions. The dataset consists of several sequences collected in a driving simulator.

A total of nine professional drivers participated in the experiments. The results showed that the performance, measured using the objective function, ranged from 0.37 to 0.75 for the indicators based on driving behaviour signals, whereas a score of 0.86 was obtained from the PERCLOS. The driver behaviour indicator, PERCLOS, obtained the best results. The generation of the ground truth was based on a supervised Karolinska Sleepiness Scale (KSS). The binary output of the KSS was fed back by three experts, previously trained in driver drowsiness detection. Each expert classified each interval as alert or drowsy based on the binary KSS level assigned by the driver, the indicators obtained from the vision-based driver monitoring system, and the driving indicators obtained from the vehicle sensors. The study, by the way, has several limitations: Firstly, the sample size is relatively small, involving a total of 9 drivers, all classified as professionals, which may limit the generalizability of the study. Additionally, the study was conducted in a simulated environment.

While there is existing literature supporting the effectiveness of fatigue tests using simulation methodologies, it is equally important to acknowledge that these tests may not fully replicate real fatigue conditions in an actual driving situation. Furthermore, the simulated scenarios were consistently limited to a highway with the same distance, width, and speed limits. This limitation prevents the generalization of findings to other driving contexts, such as different weather conditions or urban driving scenarios.

It is essential also to note that the fatigue measurement method KSS has inherent limitations due to its subjective nature, relying on the driver's self-reporting of their fatigue level and their actual ability to express their state of fatigue accurately. Lastly, it is crucial to consider that the drivers subjected to sleep deprivation still slept for 4 hours, which may not necessarily lead to detectable symptoms of fatigue in every driver. These limitations should be considered when interpreting the findings of the study and when applying them to real-world driving scenarios, but for our purpose we can rely on them to have a base for the choice of the indices that could be appropriate to reach our objective. This is true also because this study is actually inspired from a previous one, where the authors tested even more indices, to verify their capabilities to detect drowsiness symptoms and how they affect the attentional state of the driver. The article in question is (Sandberg et al., 2011) where the authors considered three classes of indicators: indicators from the literature, optimized indicators, and generalized indicators, totalling 35 different indicators. The authors used stochastic optimization algorithm for optimizing detection systems. The evaluation of a solution candidate proceeds by a search for the threshold value that gives the best performance. The indicators are based on various driving behavior signals, such as standard deviation and mean square error of the lateral position, fraction of lane exits, steering-wheel reversal rate, and rapid steering wheel movement. The paper also discusses the Sleep/Wake Predictor (SWP) model, which captures the effects of time of day and prior sleep on sleepiness level. The results are evaluated using an objective function that considers sensitivity and specificity. The experimental part of the paper involves the optimization of the parameters of the indicators. The results of the study are presented in terms of the performance of the optimized indicators and detection systems in detecting driver sleepiness. The evaluation is based on an objective function that considers sensitivity and specificity, with the values ranging between 0 and 1. The study had similar limitations to the previous one, having only 12 subjects actually utilized for the creation of the data set and the use of the subjective KSS. Moreover, some intervals had to be removed from the data due to simulator problems or test subject discomfort, which could have impacted the overall analysis and results. The analysis conducted on both articles has provided an initial foundation from which to extract the indices necessary to identify behaviors associated with fatigue and lower attention levels in vehicle dynamics that could be suitable for our case.

In particular, from this evaluation, three indices deemed suitable for our requirements were selected: the Standard Deviation of Lateral Position (SDLP), Steering Wheel Rapid Movements (SWRM), and Time to Line Crossing (TLC), as more thoroughly explained in the chapter on data analysis.

(Bergasa et al., 2006) has been another useful paper where the authors present a nonintrusive prototype computer vision system for monitoring a driver's vigilance in real time. The system in this case is based on a hardware system for the real-time acquisition of a driver's images using an active IR illuminator and the software implementation for monitoring some visual behaviours that characterize a driver's level of vigilance. The paper describes the system's architecture, the visual parameters used for monitoring driver vigilance, and the experimental results obtained. The system calculates six parameters: Percent eye closure (PERCLOS), eye closure duration, blink frequency, nodding frequency, face position, and fixed gaze. These parameters are combined using a fuzzy classifier to infer the level of inattentiveness of the driver. The system has been tested with different sequences recorded in night and day in real driving conditions in a motorway and with different users. The system is based on the analysis of visual behaviours, it calculates the ocular measures to characterize eyelid movements while the face pose determination is related to the computation of the face orientation and position, and the detection of head movements. Frequent head tilts indicate the onset of fatigue. The authors used fuzzy decision trees (FDT) with the pruned method (FDT+P) to generate rules. The induced rules with FDT+P were integrated into the expert knowledge base, resulting in a rule base consisting of 94 rules, eight expert rules, and 86 induced ones. The fundamental properties of the rule base, such as consistency, lack of redundancy, and interpretability, were guaranteed through a consistency analysis and a simplification process.

The experimental results obtained are very similar for different drivers in various circumstances. The system's performance was measured by comparing it to results obtained by manually analysing the recorded sequences. This article has proven useful as a reference in the application of indicators related to head position in a real-world driving context. These indicators are one of the type of data we can collect from the simulator available to us during the preliminary experimentation phase. The simulator is equipped with cameras and software designed for head position detection, particularly described in terms of rotation along the three reference axes (yaw, pitch, and roll) that allow to determine the head orientation of the driver. The limitations of this study are attributed to the fact that only visual parameters were analyzed. Focusing on the infrared (IR) system used to analyze the ocular dynamics, it provided highly reliable outcomes in nighttime and low-light conditions but demonstrated inaccuracies with daylight, when external artificial lights illuminated the cabin or when the driver wore sunglasses. This could also be attributed to the fact that the study was conducted in 2006, with a level of technology consistent with that time. A more recent article than the previous ones, (Zhang et al.,2016), allowed for a further assessment of the correlation between parameters related to vehicle dynamics, already present in the literature, and the driver's level of fatigue. The authors present a detailed analysis of the sensitivity of lane position and steering measurements to driver fatigue. The study involved a field test with 36 male professional taxi drivers, where lane position, steering wheel angle data, and self-reported fatigue level from KSS scale were recorded. The main objective was to evaluate the most sensitive parameter value of the lane position and steering measurements for monitoring driver fatigue. The experimental design involved the use of a laptop computer to acquire real-time data of lane position and steering angle. The participants were surveyed every 5 minutes and required to self-report their fatigue level. The results indicated that individual differences may affect the accuracy of the correlation coefficient with fatigue level, and significant differences were found among individual participants when SDLP have been considered.

The study also established a linear regression model between fatigue level and driving performance for Steering Wheel Reversal Rate (SWRR) and SDLP, showing a strong correlation between these parameters and fatigue level, but the sensitivity analysis of SWRR demonstrated that SWRR was more reliable than SDLP for monitoring fatigue level. This study further confirms that fatigue diminishes driving abilities and impairs the attention level. The article highlights the effectiveness of the Steering Wheel Reversal Rate parameter in detecting variations in the driver's behavior. Specifically, in this particular case, it proves to be even more effective than SDLP, a parameter generally considered suitable for this purpose according to the literature. For this reason, it has been chosen to include this parameter in our study, as we have access to simulator data related to the steering wheel angle. Also in this case there are some limitations involving the sample subjects, which are all male professional taxi-drivers so the findings cannot be generalized to the entire community of drivers. Another recent and useful article in the selection of indices to adopt for the development of the new DMS is (Bassani et al., 2023), where the authors present a simulation study to evaluate the impact of an auditory driver distraction warning (A-DDW) device on driving performance. The study used a driving simulator to assess the effects of distraction and the A-DDW device on driving behaviour. The experimental design included distraction level and traffic density as factors, and the dependent variables investigated were average speed (S), standard deviation of speed (SDS), average lateral position (LP), and standard deviation of lateral position (SDLP). The study was conducted using a fixed-base driving simulator and the road scenario consisted of a rural motorway with varying traffic density conditions. The participants were instructed to drive as they would in a real motorway setting, while respecting traffic regulations. The distraction phase involved a written message on the central windscreen, inviting participants to perform simple mathematical operations using a tablet positioned to the right of the steering wheel. The A-DDW device was used to detect and alert drivers in real-time when distracted. The study involved 42 participants, and their characteristics, such as age and driving experience, were recorded.

The study used linear mixed-effects models (LMM) and generalized linear models (GLM) to analyze the data. The LMM and GLM included the experimental factors (distraction level and level of service) and gender as categorical variables, while age and driving experience were included as covariates. The results showed that the A-DDW device did not significantly affect average speed (S) or lateral position (LP). However, it was found that distracted drivers reduced speed variation more than non-distracted drivers did. The study also revealed that distracted males supported by the A-DDW device drove at significantly higher speeds than male drivers without the device. Additionally, it was observed that distracted females drove at lower speeds than distracted males when supported by the A-DDW device. Analyzing this paper, another parameter has been added to those already chosen for the purpose of our work. The selected parameter is the standard deviation of the vehicle speed (SDS) which, as described in the study, varies depending on the driver's level of distraction. Some distraction activities have also been selected from this work to execute during the experimental phase, as described in the next chapter. Also the correlation between a driver's emotional state and their attention level has been the subject of several studies. Research has shown that emotions can have specific effects on the attention mechanism of driving behavior. Furthermore, the level of arousal and the valence of emotional states have been shown to determine how cognition is influenced, indicating a direct relationship between emotional states and driving behavior. While a neutral and relaxed emotional state may show no significant impact on attention level, negative emotional states such as depression can lead to reduced attention to safety-related areas while driving. Similarly, happy drivers may exhibit a greater number of errors and perceived workload, while also being more likely to be distracted from certain driving events. Emotions like happiness and anger can alter the effects of attentional demands on driving behavior, exerting indirect effects on driving. There are existing evidence pointing to a direct relationship between a driver's state of anger and aggressive driving, highlighting the influence of specific emotions on driving behavior.

For these reasons, the detection in real-time of the emotional state of the driver it is another subject deeply developed in the DMS field. For example, The paper (Wu et al., 2018) proposes a DMS, which aims to prevent potential driving risks by recognizing and easing the driver's negative emotions. The system utilizes a deep convolutional neural network for facial emotion recognition and an audio on demand mechanism to collect and play audio resources for preventing driving risks from negative emotions. The experiment results demonstrate that the system provides accuracy and reliability in terms of facial emotion recognition. The paper also presents the proposed system's architecture, including a facial emotion recognition module and an audio on demand module, along with the experimental evaluation results comparing the system with other CNN-based methods. Thus, we also opted to incorporate an emotion detection system to examine the relationship between the emotional state and the driver's distraction level, specifically focusing on valence and engagement. This integration was allowed through the utilization of the software described in (Ceccacci et al., 2021). The paper proposes an emotion-aware in-car architecture to adapt driver's emotions to vehicle dynamics, investigating the correlations between negative emotional states and driving performances. The research aims to provide a model and implement an in-car emotion-aware architecture through a human-computer interface. The proposed system consists of a driving style detection module, an emotion recognition module based on a Convolutional Neural Network, and a smart car interface to manage the adjustment of dashboard lights and radio music playlists based on the detected driver's emotional state. The CNN has been trained using a merged dataset with both "in the wild" and "in lab" properties, and it is capable of recognizing six main Ekman's Emotions. An experimental case study is presented, which investigates the relationship between driving performance parameters and detected emotions within a driving simulation environment. The study aims to understand the impact of altered emotional states on driving performance and discusses the importance of equipping vehicles with intelligent driver assistant systems to prevent road traffic accidents. The description of the software is deepened in chapter 4, regarding the experimental phase of the thesis project.

Chapter 3

Methodology

The methodology employed in this study follows a systematic approach that includes several key stages:

1. Research: The research phase involved an in-depth exploration to find the parameters used in similar projects. This encompassed a thorough review of existing literature and studies related to driver distraction, video analysis, and signal correlation during distracted driving.

2. Data Collection: A significant component of the research involved the collection of relevant data. This was achieved through experimental trials using a driving simulator. Participants engaged in driving scenarios while their actions were recorded. The data collected included video footage, video data elaborated from software EMOJ and vehicle dynamics data.

3. Parameter Selection: The next step involved the selection of parameters essential for assessing distracted driving. These parameters were chosen based on the literature review and the specific goals of the study, considering the most adequate to the dataset built from the trials.

4. Manual Video Analysis: To extract meaningful information, a manual analysis of the video footage was conducted. This step involved observing and annotating the behavior of drivers during periods of distraction. Facial expressions, gaze direction, and other relevant visual cues were examined to provide qualitative insights.

5. Data Preprocessing: Raw data obtained from the experimental phase underwent preprocessing. This step involved cleaning, filtering, and organizing the data to ensure its suitability for subsequent analysis.

6. Algorithmic Parameter Calculation: To quantitatively evaluate distracted driving, algorithms were employed to calculate specific parameters chosen in the earlier stages. This automated approach aimed to extract numerical values from the data, allowing for a more objective and consistent analysis.

With this methodology, the study aimed to provide a better understanding of the correlation between the various signals selected in the first steps and their reliability for future development of the DMS.

The following lists all the parameters collected during the research conducted on the state of the art. As evident, for the most accurate and precise detection of the driver's attention state, a wide variety of parameters have been experimented with and evaluated over the years. One key insight gained from this research is the necessity of considering these parameters always in combination with others, as none of them, taken individually, can be deemed accurate enough to comprehensively define such a complex state as distraction. For this reason, in all studies, an increasing number of parameters are analyzed to assess the driver's state, which may belong to the same category or not. The categories are defined by the nature of the parameters themselves, particularly physiological, video, vehicle dynamics, or ocular dynamics. Almost all studies focus on using these parameters to detect states of distraction and/or fatigue (which, as often observed, overlap), hence the table indicates whether they are suitable for detecting one, the other, or both.

CATEGORY	VARIABLE	DROWSINESS	DISTRACTION	REFERENCE
Physiological	Electroencephalogram measures (EEG)	Yes	Yes	(Kircher et al., 2002)
Physiological	Heart rate variability (HRV)	Yes	Yes	(Kircher et al., 2002) (Hansen et al., 2017)
Physiological	Heart rate (HR)	Yes	Yes	(Kircher et al., 2002) (Hansen et al., 2017)
Physiological	Electrodermal activity (EDA)	Yes	Yes	(Milardo et al., 2022) (Esteves et al., 2021)
Physiological	Respiration	Yes	No	(Doudou et al., 2020)
Physiological	Skin Temperature	Yes	Yes	(Milardo et al., 2022)

CATEGORY	VARIABLE	DROWSINESS	DISTRACTION	REFERENCE
Video based	Observation of body motions	Yes	No	(Kircher et al., 2002)
Video based	Nodding frequency	Yes	No	(Bergasa et al., 2006)
Video based	Face position	Yes	Yes	(Bergasa et al., 2006) (Doudou et al., 2020)
Video based	Drivers' interaction with car interior	No	Yes	(Milardo et al., 2022)
Video based	Emotions detection	No	Yes	(Ceccacci et al., 2021) (Generosi et al., 2022)
Video based	Expression recognition	Yes	Yes	(Junaedi et al.,2018) (Ceccacci et al., 2020)

CATEGORY	VARIABLE	DROWSINESS	DISTRACTION	REFERENCE
Vehicle behaviour	Steering wheel rapid movements (SWRM)	Yes	Yes	(Kircher et al., 2002) (Daza et al., 2014)
Vehicle behaviour	Steering wheel reversal rate (SWRR)	Yes	Yes	(Ceccacci et al., 2021) (Zhang et al., 2016)
Vehicle behaviour	Standard deviation of lane position (SDLP)	Yes	Yes	(Kircher et al., 2002) (Ceccacci et al., 2021)
Vehicle behaviour	Standard deviation of steering wheel movements (STDSW)	Yes	Yes	(Kircher et al., 2002) (Ceccacci et al., 2021)
Vehicle behaviour	Mean square of the lane deviation	Yes	Yes	(Kircher et al., 2002)
Vehicle behaviour	Microcorrection steerings	Yes	No	(Kircher et al., 2002)
Vehicle behaviour	Time to line crossing (TLC)	Yes	Yes	(Kircher et al., 2002) (Daza et al., 2014)
Vehicle behaviour	Lane keeping offset	Yes	Yes	(Aksjonov et al., 2019) (Doudou et al., 2020)
Vehicle behaviour	Standard deviation of speed (SDS)	Yes	Yes	(Bassani et al., 2023) (Ceccacci et al., 2021) (Doudou et al., 2020)
Vehicle behaviour	Standard deviation of pressure (SDP) of the gas pedal	Yes	Yes	(Ceccacci et al., 2021)
Vehicle behaviour	Brake pedal angular position	No	Yes	(Milardo et al., 2022)
Vehicle behaviour	Gas pedal angular position	No	Yes	(Milardo et al., 2022)
Vehicle behaviour	Heading Error	Yes	Yes	(Daza et al., 2014)

CATEGORY	VARIABLE	DROWSINESS	DISTRACTION	REFERENCE
Ocular dynamics	Blink duration	Yes	No	(Kircher et al., 2002)
Ocular dynamics	Blink frequency	Yes	No	(Kircher et al., 2002) (Bergasa et al., 2006)
Ocular dynamics	Partial eye closures during fixation	Yes	No	(Kircher et al., 2002)
Ocular dynamics	Eye closures	Yes	No	(Kircher et al., 2002)
Ocular dynamics	Eye closure duration	Yes	No	(Bergasa et al., 2006)
Ocular dynamics	Saccade frequency	Yes	No	(Catalbas et al., 2017) (Biswas et al., 2018)
Ocular dynamics	Percent eyelid closure (PERCLOS)	Yes	No	(Kircher et al., 2002) (Bergasa et al., 2006)
Ocular dynamics	Fixation	Yes	Yes	(Bergasa et al., 2006) (Çetinkaya et al., 2023)
Ocular dynamics	Eye glance position	No	Yes	(Çetinkaya et al, 2023) (Hansen et al., 2017)
Ocular dynamics	Pupil diameter	Yes	Yes	(Bergasa et al., 2006)

Detecting distraction and drowsiness in drivers can relies on a set of physiological parameters that provide insights into their cognitive and physical states. These indicators include variations in heart rate, which can escalate during periods of distraction or diminish when drowsiness sets in. Skin conductance, gauges changes in the electrical conductance of the skin, reflecting alterations in the autonomic nervous system that occur during both distraction and drowsiness.

Furthermore, monitoring electroencephalography (EEG) signals provides valuable information about brain activity. An increase in theta waves, for instance, may signify drowsiness, while sudden shifts in beta waves can suggest distraction. Respiratory rate is also monitored, as irregularities may indicate a lack of alertness or focus. In addition, changes in skin temperature can be indicative of alterations in the autonomic nervous system, revealing the physiological responses to distraction or drowsiness. The temperature tends to fluctuate based on blood flow and sympathetic nervous system activity. In detail, increased distraction might result in heightened sympathetic nervous system activity and vasoconstriction, causing a drop in skin temperature. Conversely, drowsiness may lead to decreased sympathetic activity, allowing for vasodilation and an increase in skin temperature.

Video-based parameters involve the analysis of various visual cues within the captured video feed. One critical aspect is facial expressions, as an evaluation in facial features changes to identify signs of distraction, such as excessive yawning or facial grimaces. Additionally, head movements are scrutinized, with a focus on the head orientation that may indicate a lack of attentiveness. This parameter is evaluated by the definition of 3 angular measures referred to the rotations around the 3 principal axes of the relative frame of reference, defined as yaw, pitch and roll. As already seen in the previous chapter the detection of the emotional state is also relevant to establish the potential lack of attention of the driver. Also the posture is another parameter usually monitored, assessing any unusual slouching or body movements that deviate from the norm. Hand movements on the steering wheel can signal potential distraction when correlated to sudden or erratic adjustments. The analysis extends to the overall spatial awareness of the driver, examining their responsiveness to the surrounding environment.

Vehicle dynamics parameters encompass a set of factors that collectively contribute to understanding the state of the vehicle and, by extension, the attentiveness of the driver. Variables such as steering wheel movement, erratic accelerations and decelerations, and lateral movements provide valuable insights into the driver's engagement with the driving task.

Examining the steering behavior involves analyzing the frequency, amplitude, and smoothness of steering inputs. Abrupt or erratic steering changes can be indicative of distraction or drowsiness. Acceleration and deceleration patterns are also critical, as sudden or inconsistent changes in speed may suggest a lack of focus. Lateral movements, such as lane deviations or drifting, offer additional clues about the driver's state. Moreover, the analysis of vehicle dynamics extends to parameters like yaw rate, which measures the rotation of the vehicle around its vertical axis that can lead to lane exits measured as heading error. Unusual yaw behavior, such as excessive swaying or instability, can be linked to impaired driving attention. Additionally, the study of brake usage, gas pedal, and other control inputs contributes to a comprehensive assessment of driver vigilance.

Finally, ocular dynamics parameters can give a more comprehensive understanding of the driver's alertness and focus. One crucial factor is the frequency and duration of eye closures, as prolonged or frequent closures may indicate drowsiness. Additionally, the measurement of blink rate and amplitude provides valuable insights into cognitive workload and attention levels. Tracking the gaze direction is another essential parameter, as shifts in focus away from the road suggest distraction. The analysis of saccades, rapid eye movements between fixations, helps assess the ability to shift attention efficiently. Reduced saccadic velocity may indicate drowsiness, affecting the driver's responsiveness. Pupil diameter is also a sensitive indicator, with dilation often associated with increased cognitive load. Variations in pupil size can reveal fluctuations in alertness, helping identify moments of distraction or drowsiness. Moreover, the assessment of eye movement patterns, such as smooth pursuit, helps gauge the driver's ability to track moving objects. Jerky or irregular movements may indicate impaired concentration. PERCLOS, or Percentage of Eye Closure, measures the percentage of time that a person's eyes are closed over a specific duration, usually expressed as a percentage. In the context of DMS, PERCLOS is commonly employed to assess the level of drowsiness a driver may be experiencing.

As a driver becomes drowsy, the frequency and duration of eye closures tend to increase. By continuously analyzing PERCLOS, DMS can provide real-time feedback on the driver's level of alertness. In the course of this investigation, we have chosen to adopt a set of parameters derived from the existing state.

These parameters encompass Standard Deviation of Lane Position (SDLP), Steering Wheel Rapid Movements (SWRM), Time to Line Crossing (TLC), Standard Deviation of Speed (SDS), Steering Wheel Reversal Rate (SWRR), Valence and Engagement derived from emotional analysis, and head orientation measures, specifically focusing on yaw and pitch. The rationale behind this selection was grounded in the identification of the most influential parameters in the existing literature, which effectively signify both the driver's level of distraction and drowsiness.

Chapter 4

Experimental Phase

4.1 Description of RE-Lab simulator and instrumentation

The experimental phase took place in Reggio Emilia, at RE-Lab facility, where the driving simulator is settled. The simulator is based on SCANeR Studio 1.7 platform, including features for sensors simulation and automated driving functionalities. It's a platform designed to simulate real-world driving scenarios, allowing to perform our tests in a controlled environment and includes features for sensors simulation, and automated driving functionalities.

The static driving simulator has a simulation engine and is equipped with real car commands (e.g., driving seat, pedals, indicators, gearbox) and SensoDrive steering wheel including haptic force feedback. SCANeR Studio offers a suite of tools and models essential for constructing a realistic virtual world. This encompasses various elements such as the road environment, vehicle dynamics, traffic dynamics, sensors, headlights, diverse weather conditions, and the ability to script complex scenarios. This versatility allows for the creation of highly realistic scenarios but also facilitates a wide range of setups to address diverse simulation needs. The simulator also includes a video projector (to display the scenarios) and a 15.6" display placed behind the steering wheel to display a full digital Human-Machine Interface. The system is synchronized using the simulator machine timestamp. This feature allows obtaining the distributed system feature for the architecture which is the requirement needed to test and validate all the AI algorithms involved in the system.

The software used for the driving simulation is AVSimulation SCANeR. Using this tool two different environmental scenarios have been created.

The driver, to interact with the vehicle during simulated driving sessions, has at their disposal a tablet conveniently positioned on the dashboard of the simulator. Through this device, they have the ability to monitor various parameters of the vehicle and, simultaneously, issue commands to it.

The tablet serves as a multifunctional interface, allowing the driver to manage different aspects of the vehicle in an intuitive and immediate manner. In addition to its control function, the tablet screen has also been utilized as a tool to introduce distraction events. This approach aims to replicate realistic scenarios in which the driver may need to handle external factors that impact their attention while driving. The use of the tablet as a source of distraction contributes to making the simulation more lifelike, enabling a thorough assessment of the driver's response to distracting stimuli.

HD cameras have been strategically deployed to analyze the driver from various angles, ensuring a comprehensive view of their behaviors and movements. Specifically, one camera is positioned directly in front of the driver, where the EMOJ software is applied. Another camera is placed at the level of the interior rearview mirror, providing an additional perspective within the cabin. The third camera is situated in the passenger-side rearview mirror, all directed towards the driver. This camera setup allows for thorough observation and analysis of the driver's expressions, head movements, and overall engagement from different vantage points.

Figure 4: Simulator Set-up

Sensors and modules installed to capture and analyze the data required for the continuation of our work are:

- HD Cameras: Hikvision Digital Technology DS-2CE16H0T-ITF
- Tablet: Samsung Galaxy Tab A8 1920x1200
- Emotion Detection Module Component EMOJ: The EMOJ module plays a crucial role in the system, actively monitoring the driver's satisfaction and emotional state throughout their experience. This is achieved through the utilization of an RGB camera strategically positioned atop the steering wheel. One of the distinctive features of the emotional module is its capacity to aggregate data over a predefined time window, with the current setting at 1 second. Within this timeframe, the module discerns and categorizes the driver's emotions, offering insights into states such as neutrality, joy, surprise, sadness, anger, disgust, and fear. This comprehensive emotional spectrum ensures a nuanced understanding of the driver's affective responses.
- Head Position Module: The module has the ability to deliver reliable results for both face and head orientation detection, even in the presence of challenging lighting conditions and other environmental complexities, in terms of yaw, pitch, and roll. This analysis provides valuable information about the driver's engagement and attentiveness during different stages of the driving experience.
- Onboard dedicated processing modules: These specialized modules are seamlessly integrated into the static driving simulator, leveraging the advanced AVSimulation SCANeR software. The static driving simulator boasts authentic car controls and a responsive steering wheel, featuring haptic force feedback for a lifelike driving experience. As already mentioned, the simulator is equipped with a video projector, enhancing the visualization of various scenarios. Furthermore, the simulator houses dedicated onboard modules and sensors designed specifically for monitoring and analyzing vehicle dynamics.

4.2 Description of software for head rotation and emotion analysis

The software used for analyzing the driver's state through video data has been previously developed by the university and employed in other studies, as described in (Ceccacci et al., 2021).

The system is based on a Convolution Neural Network, and it utilizes computer vision techniques to detect and interpret a person's emotions based on their facial expressions, as well as their head position and orientation. By analyzing facial features and movements, the system can accurately identify various emotional states, providing a comprehensive understanding of the individual's emotional response while driving, allowing real time analysis. In the case study of the cited paper, the software, that includes an emotion-aware in-car architecture that adapts driver's emotions to vehicle dynamics, investigates the correlations between negative emotional states and driving performances, and regulates the driver's engagement through an innovative user experience in the car cabin.

Thus, the Emotion Detection Classifier software module evaluates the driver's emotional state through video processing algorithms. To enable emotion detection, it implements an emotion recognition algorithm able to recognize Ekman's universal emotions (happiness, sadness, anger, fear, disgust, surprise) by analysing the driver's facial expressions from a video stream. Additionally, the module analyses the head orientation of the driver and provides feedback in terms of yaw, pitch and roll of the head with respect to the camera position.

The module takes as input the stream of an RGB camera and sends output in a JSON format to the downstream modules. It works with a varying framerate from 14 to 22 FPS depending on the performance of the hardware and produces the following output:

- for each frame an estimation of the driver head orientation is provided with this JSON structure:


```
{
"person0" :
        {
        "pitch": "-5.53973",
        "yaw": "29.1441",
        "roll": "-1.68987”
        }
}
```


Figure 5: Head position data structure

- It aggregates emotional data for a specified time interval (by default 1 second) and then provides an emotional evaluation in this form:


```
{
"person0" :
        {
        "predominant" : "0",
        "neutral":" 0.643123",
        "happiness": "0.0495257",
        "surprise":"0.0401397",
        "sadness": "0.00242789",
        "anger": "0.241407",
        "disgust": "0.00315792",
        "fear": "0.0202183",
        "engagement": "35.6877",
        "valence": "-0.0877294“
        }
}
```


Figure 6: Emotions detection data structure

All the data is published on the broker which is set up for communication between the modules. The emotion detection software is also able to determine valence and engagement based on facial expression recognition and physiological measures. In particular, engagement refers to the emotional involvement or interest of a person in response to a stimulus, activity, or situation while valence refers to the positivity or negativity of an emotion or emotional experience. The module leverages the PAD model (Pleasure, Arousal, Dominance) to assess valence (pleasure) and engagement (arousal) through facial expression analysis.

It uses a Facial Expression Recognition (FER) tool based on a CNN to recognize Ekman's six universal emotions from facial images.

The final layer of CNN is specifically crafted to forecast both valence and engagement, derived from the percentages of predicted emotions. Valence reflects the overall positivity or negativity on a scale from -100 to 100, while engagement gauges the deviation of facial expressiveness from neutrality, ranging from 0 to 100. Furthermore, the system integrates an attention recognition tool utilizing facial landmarks and head orientation to assess attentiveness. It identifies yaw, pitch, and roll values of head orientation, determining lack of attention based on empirically set thresholds. Additionally, the system computes the eye aspect ratio (EAR) to detect frontal head tilting, with a noticeable reduction in the ratio when users look downwards. The EAR is a facial feature particularly employed in the context of detecting eye blinks and monitoring eye movements. It is calculated based on the ratios of the distances between various facial landmarks around the eye region. Specifically, it involves the ratio of the horizontal distance between the outer and inner corners of the eye to the vertical distance between the upper and lower eyelids. To prevent false positives, the EAR feature is combined with Pitch evaluation, and the user is considered distracted if both the EAR and Pitch are under certain thresholds.

4.3 Description of scenarios and tests methodology

The software used for the driving simulation is AVSimulation SCANeR. Using this tool 2 environments have been created: highway and urban. In the highway scenario, the behaviour of the traffic vehicle is randomized with some vehicles that have the possibility to overtake the others in order to add randomness to the simulation and make it more realistic. The urban scenario comprises a lot of semaphores, roads and zebra crossing. Several kinds of elements are present in this scenario: cars, motorbikes, bikes and pedestrians.

In both environments, different traffic conditions can be encountered, ranging from minimal to severe, as well as various weather conditions such as sunny or rainy. The visual setting for the driving tests encompasses a city road with varying levels of traffic density, designed to prompt the driver to adapt their driving style to external conditions. Additionally, each test included an explanation to the participant regarding the context they were placed in at that moment.

Figure 7: Example of urban scenario

Three contexts have been created: the first simulated the experience of a parent running late to pick up his son from school, aiming to induce a sense of urgency in the driver. The second, prompted the participant to envision embarking on a long-awaited trip, with the intention of inducing feelings of carefreeness and happiness. The third one tells the driver that it is their day off, but they have received a work call requesting them to attend the office for a long and important meeting. This situation aims to provoke feelings of frustration and anger in the individual. In each of these tests, secondary tasks were introduced during the session to prompt the driver to perform actions, aiming to induce distraction.

These tasks involved activities such as:

- Using or reaching for objects within the vehicle

- Executing actions like turning around
- Interacting with the Human-Machine Interface (HMI)

To extend attention diversion and induce mental distraction over a longer period, interactions with the car's dashboard, in this case the tablet, were implemented. These interactions involved completing various tasks to simulate potential distraction activities in real-world scenarios, including:

- Answering the phone
- Sending messages on the phone
- Talking on the phone while holding it to the ear
- Drinking

The test included 19 participants, comprising 10 males and 9 females, aged between 21 and 53 years old. Each participant underwent three separate sessions, each lasting approximately 10 minutes, during which one of three different contexts was introduced. In all sessions, participants were instructed to perform the actions mentioned above to induce distraction.

4.4 Description of the obtained dataset

The log file generated by the driving simulator captures a snapshot of the simulated vehicle's dynamics.

The log is a data structure in JSON format that includes various parameters and measurements related to the vehicle's state and surroundings at a specific point in time. The key components of the JSON created are:

- Timestamp: Date and time
- Topic: Vehicle Dynamics

- Position and Orientation:
    - Center of gravity (COG) position (x, y, z)
    - Vehicle's orientation (heading, pitch, roll)
    - Current speed and acceleration details.
- Control Inputs:
    - Gearbox mode, accelerator, brake, clutch status.
    - Engine speed, engine status, and engaged gear.
- Steering:
    - Steering torque, steering wheel angle, and speed.
- Road and Radar Information:
    - Road information like lane and intersection details.
    - Radar information such as angle, distance to collision, and speed.
- Scanner Timestamp:
    - Scanner timestamp for specific sensor readings.
- Wheel States:
    - Detailed information for each wheel, including position, rotation, speed, grip, and other relevant parameters.

The log essentially provides a comprehensive snapshot of the vehicle's state, control inputs, and environment perception.

```
{
"VehicleDynamics": {
      "COGPos": {
         "x": 754.2067073700205,
         "y": 328.4710596038787,
         "z": 102.27193652990292
      },
      "GearBoxMode": 10,
      "accelerator": 0.4144689738750458,
      "brake": 0,
      "clutch": 0,
      "engineSpeed": 78.15003967285156,
      "engineStatus": 1,
      "gearEngaged": 1,
      "position": {
         "heading": 2.8396023326381004,
         "pitch": -0.04091459480631755,
         "roll": -0.9299057003103055,
         "x": 755.7537411823656,
         "y": 328.4161398095118,
         "z": 101.9064427109016
      },
      "roadInfo": {
         "intersectionId": -1,
         "laneGap": 221.87997436523438,
         "laneId": 0,
         "roadAbscissa": 201.37770080566406,
         "roadAngle": 1.573729395866394,
         "roadGap”": 226.83998107910156,
         "roadId": 12
      },
      "speed": {
         "heading": -0.30176129937171936,
         "pitch": -3.347975254058838,
         "roll": -4.515239715576172,
         "x": -0.6887339353561401,
         "y": -1.6413218975067139,
         "z": -3.8638110160827637
      },
   "wheelState": {
      "0,1,2,3": {
         "angle": 5263.85498046875,
         "grip": 1,
         "laneType": -1,
         "posx": 2.8001773357391357,
         "posy": 0.7370080351829529,
         "posz": 0.23862798511981964,
         "rotx": -0.044390443712472916,
         "roty": -0.09579485654830933,
         "rotz": 0.1462181657552719,
         "speed": -9.78660512004903e-14,
         "vhlDelta": -1.3726208209991455,
         "vhlSx": 1
      },
}
```


Figure 8: Vehicle dynamics data structure

The logs obtained from the simulator and the software for head position determination and emotion detection were pre-processed to obtain structured data suitable for subsequent analysis. These data were collected in CSV files, organized by subject and test scenario, using the Python programming language in the Visual Studio Code editor. In particular, 3 main libraries have been used: Numpy, Pandas and Matploltlib. NumPy is a fundamental library for scientific computing in Python, providing high-performance data structures by implementing multidimensional arrays and functions for mathematical operations on them. It introduces the concept of arrays, that represent a grid of values, all of the same data type, indexed by a tuple of non-negative integers, which allow efficient representation of data, particularly numerical data. NumPy facilitates vectorized operations, enabling operations to be performed on entire arrays, thus avoiding explicit iterations, and making the code more concise and efficient. NumPy arrays provide a powerful way to store and manipulate numerical data in Python and are used as a foundation for many other scientific and data analysis libraries.

In fact, Pandas is designed to simplify data manipulation and analysis in Python, building upon NumPy. It offers data structures and functions for handling tabular data and time series data. Its primary data structure is the DataFrame, a tabular data structure with labeled rows and columns, similar to a spreadsheet. It provides powerful indexing options and tools for aggregation, grouping, and transformation of data. Additionally, it includes features for handling missing data efficiently, allowing users to fill or drop missing values.

COGPos_x	COGPos_y	COGPos_z	GearBoxMode	acceleration_headi	acceleration_pitch	acceleration_roll	acceleration_x	acceleration_y	acceleration_z
-357.0328404	-71.74934773	11.81442911	0	-7.07E-05	-0.005375284	-0.000234949	-0.396601051	-0.020052819	0.012361447
-357.0328404	-71.74934773	11.81442911	0	-7.07E-05	-0.005375284	-0.000234949	-0.396601051	-0.020052819	0.012361447
-357.0328404	-71.74934773	11.81442911	0	-7.07E-05	-0.005375284	-0.000234949	-0.396601051	-0.020052819	0.012361447
-353.5800218	-70.89225373	11.71902934	0	-8.67E-05	1.30E-05	-0.000285305	-0.395137697	-0.019462325	0.012570874
-353.5800218	-70.89225373	11.71902934	0	-8.67E-05	1.30E-05	-0.000285305	-0.395137697	-0.019462325	0.012570874
-353.5800218	-70.89225373	11.71902934	0	-8.67E-05	1.30E-05	-0.000285305	-0.395137697	-0.019462325	0.012570874
-353.5800218	-70.89225373	11.71902934	0	-8.67E-05	1.30E-05	-0.000285305	-0.395137697	-0.019462325	0.012570874
-353.5800218	-70.89225373	11.71902934	0	-8.67E-05	1.30E-05	-0.000285305	-0.395137697	-0.019462325	0.012570874
-350.0466595	-70.0182895	11.62375885	0	0.000235133	0.011481497	0.000246158	-0.372183561	-0.018838128	0.012682556
-350.0466595	-70.0182895	11.62375885	0	0.000235133	0.011481497	0.000246158	-0.372183561	-0.018838128	0.012682556
-350.0466595	-70.0182895	11.62375885	0	0.000235133	0.011481497	0.000246158	-0.372183561	-0.018838128	0.012682556
-346.8814213	-69.23806292	11.54055355	0	0.00010072	-0.008007775	-8.86E-05	-0.393169224	-0.018349778	0.014902053
-346.8814213	-69.23806292	11.54055355	0	0.00010072	-0.008007775	-8.86E-05	-0.393169224	-0.018349778	0.014902053
-346.8814213	-69.23806292	11.54055355	0	0.00010072	-0.008007775	-8.86E-05	-0.393169224	-0.018349778	0.014902053
-346.8814213	-69.23806292	11.54055355	0	0.00010072	-0.008007775	-8.86E-05	-0.393169224	-0.018349778	0.014902053
-343.5984758	-68.43150657	11.45654896	0	9.55E-05	-0.00064396	7.04E-05	-0.39163655	-0.01780591	0.014702705
-343.5984758	-68.43150657	11.45654896	0	9.55E-05	-0.00064396	7.04E-05	-0.39163655	-0.01780591	0.014702705
-341.0025501	-67.79567721	11.39189447	0	1.53E-05	-0.001269038	3.08E-05	-0.391530991	-0.017307809	0.014590534
-341.0025501	-67.79567721	11.39189447	0	1.53E-05	-0.001269038	3.08E-05	-0.391530991	-0.017307809	0.014590534
-339.4994306	-67.428297	11.35520146	0	3.39E-05	-0.000971349	-0.00041724	-0.390954256	-0.017005492	0.015959583
-339.4994306	-67.428297	11.35520146	0	3.39E-05	-0.000971349	-0.00041724	-0.390954256	-0.017005492	0.015959583
-338.078582	-67.08155399	11.32103464	0	0.000260653	0.000208022	6.41E-06	-0.390440762	-0.016673883	0.015406292
-336.4232598	-66.67823949	11.28188103	0	0.000273209	-0.000412342	0.000307386	-0.390695572	-0.016634388	0.015092809
-336.4232598	-66.67823949	11.28188103	0	0.000273209	-0.000412342	0.000307386	-0.390695572	-0.016634388	0.015092809
-334.7461343	-66.27032582	11.24295829	0	-8.75E-05	0.006020496	0.000282811	-0.363868624	-0.016082918	0.015809326
-334.7461343	-66.27032582	11.24295829	0	-8.75E-05	0.006020496	0.000282811	-0.363868624	-0.016082918	0.015809326

pitch	yaw	roll	timestampID
0.481257	5.75962	-15.9086	1.69599E+12
-0.342985	1.30378	-13.7968	1.69599E+12
-1.4172	0.468387	-13.1089	1.69599E+12
0.256535	1.70465	-13.3065	1.69599E+12
1.14071	0.631006	-12.6977	1.69599E+12
-0.236528	0.270364	-12.5377	1.69599E+12
-0.0534098	0.241691	-12.1787	1.69599E+12
0.261702	0.75939	-12.1741	1.69599E+12
-1.18689	0.700676	-12.3895	1.69599E+12
-0.642354	0.291255	-11.5239	1.69599E+12
-1.85653	0.110408	-11.4977	1.69599E+12
-1.50267	0.240108	-11.0503	1.69599E+12
0.0295231	-0.913474	-11.0229	1.69599E+12
-0.79406	-0.90198	-10.6837	1.69599E+12
-1.19281	-0.275659	-9.32828	1.69599E+12
-2.15077	-2.63857	-4.75973	1.69599E+12
-3.22853	-8.04866	-2.00427	1.69599E+12
2.87791	-9.16126	0.426203	1.69599E+12
-0.555951	-8.38706	2.13129	1.69599E+12
-0.800535	-8.05109	1.78799	1.69599E+12
-0.647024	-8.05053	1.32902	1.69599E+12
-0.988456	-9.39988	1.61616	1.69599E+12
-1.85132	-8.9501	3.12798	1.69599E+12
-1.5859	-7.26783	2.95244	1.69599E+12
-1.25957	-8.45071	2.22407	1.69599E+12

engagement	valence	timestampID
45.0598	-0.256687	1.69599E+12
62.4871	-0.288718	1.69599E+12
49.9201	-0.227429	1.69599E+12
25.4796	-0.0851581	1.69599E+12
47.527	-0.159256	1.69599E+12
48.3399	-0.181762	1.69599E+12
67.1646	-0.310996	1.69599E+12
29.1259	-0.0311922	1.69599E+12
31.0633	-0.168011	1.69599E+12
55.5978	-0.32683	1.69599E+12
55.1215	-0.378635	1.69599E+12
30.7019	-0.104142	1.69599E+12
22.3437	0.0522756	1.69599E+12
31.1514	0.0145178	1.69599E+12
24.1505	-0.0419769	1.69599E+12
50.3774	-0.187322	1.69599E+12
40.3745	-0.0400041	1.69599E+12
35.4387	-0.094034	1.69599E+12
55.106	-0.198622	1.69599E+12
63.2505	-0.35133	1.69599E+12
68.6825	-0.38959	1.69599E+12
54.6073	-0.235691	1.69599E+12
40.3821	-0.129313	1.69599E+12
40.5038	-0.144071	1.69599E+12
61.3878	-0.338259	1.69599E+12

Figure 9: Example of csv generated after data pre-processing

Matplotlib is a data visualization library, enabling the creation of high-quality graphs and visualizations.

It supports various types of plots and their customization such as colors, styles, labels, and more. For the representation of the data obtained in this project the line plot type was chosen. Together, these three libraries form a powerful stack for data analysis and visualization in Python, allowing to manipulate, analyze, and present data effectively.

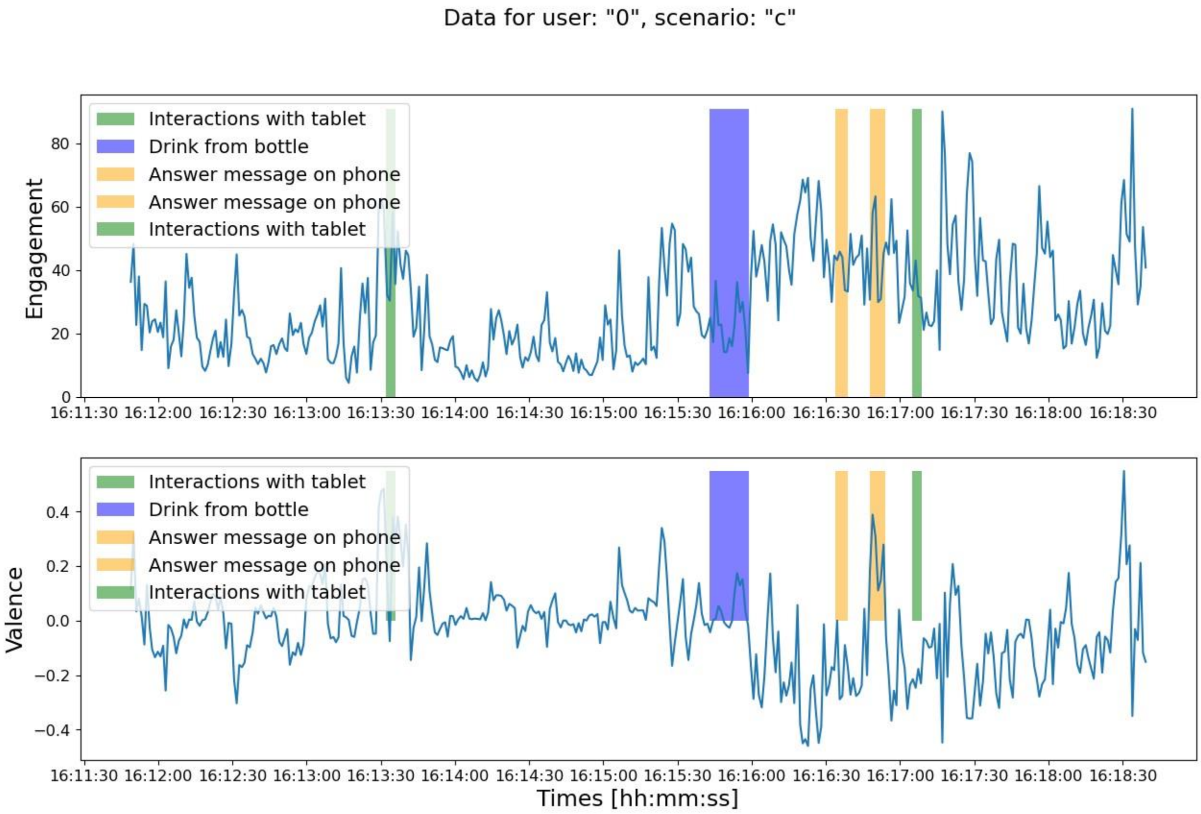

Figure 10: Example of plots generated for the results analysis

Finally, the ground truth has been generated from the video recordings. In the context of data analysis, "ground truth" refers to the data or information considered as absolute truth or accurate reference point to evaluate or validate the results obtained from an analysis. In this case the reference data have been collected from the video footage captured by cameras. An extensive manual analysis of the recorded videos was conducted for each subject's test to pinpoint the moments when the user engaged in distracting actions.

This process provided a temporal reference frame to evaluate any deviations, during these moments, in all the indices considered, compared to their trends during the remaining distraction-free periods. In this way we obtained a known truth to evaluate the accuracy of results obtained from the analysis.

PERSON	SCENARIO	START TIME OF THE DISTRACTION (AUDIO)	END TIME OF THE DISTRACTION (AUDIO)	START TIME OF THE DISTRACTION (VIDEO LATERAL)	END TIME OF THE DISTRACTION (VIDEO LATERAL)
18	a	00:02:26		00:02:09	00:02:11
		00:03:30	00:04:24		
		00:04:30	00:04:41	00:04:11	00:04:24
		00:04:54	00:04:56	00:04:36	00:04:38
		00:05:07	00:05:09	00:04:49	00:04:51
		00:05:20		00:05:00	00:05:03
		00:05:34		00:05:13	00:05:16
		00:05:50		00:05:37	00:05:41
	b	00:02:19			
		00:03:27	00:04:20		
		00:04:27	00:04:38	00:04:08	00:04:21
		00:04:50	00:04:52	00:04:33	00:04:35
		00:05:04	00:05:06	00:04:48	00:04:50
		00:05:18		00:05:00	00:05:02
		00:05:31			
		00:05:48		00:05:29	00:05:35
	c	00:02:20		00:02:07	00:02:10
		00:03:28	00:04:19		
		00:04:25	00:04:36	00:04:08	00:04:22
		00:04:49	00:04:51	00:04:32	00:04:34
		00:05:03	00:05:05	00:04:46	00:04:48
		00:05:17		00:04:58	00:05:01
		00:05:30		00:05:10	00:05:12

Figure 11: Example of the ground truth generated

Chapter 5

Data analysis

5.1 Selected parameters for driver state evaluation

As outlined in the chapter about the state-of-the-art, the parameters selected for the development of the DMS in our project have been inspired by previous works documented in the literature. The chosen parameters regarding the vehicle dynamics and driving behavior are:

- SDLP (Standard Deviation of Lateral Position): It is a metric that measures the variability or dispersion of a vehicle's lateral (sideways) position within its lane over a period of time. It is used to evaluate the stability and consistency of a driver's lane-keeping behavior. In practical terms, SDLP is calculated based on the lateral position of a vehicle relative to the center of the lane. The lateral position is typically measured in meters. A higher SDLP value indicates greater variability in lateral position, suggesting less stable or consistent lane-keeping behavior.
  It is used to assess the impact of various factors on driving performance, such as road design, vehicle characteristics, driver fatigue, distraction, and impairment.
  Focusing on distraction and drowsiness, a strong correlation exists between them and this parameter. Distraction, stemming from various sources such as mobile phone use, in-car entertainment systems, or conversations, has been consistently associated with an increased SDLP. Drivers who engage in distracting activities tend to exhibit greater variability in their lateral position within a lane.

This positive correlation underscores the detrimental effects of distraction on a driver's ability to maintain a stable and consistent trajectory. Similarly, drowsiness, fatigue, or sleepiness can significantly influence driving performance and is also linked to elevated SDLP values. As drivers become drowsy, their reaction times may slow, attention levels may diminish, and the ability to consistently stay within a lane can be compromised. The positive correlation between drowsiness and SDLP underscores the impact of driver fatigue on lateral vehicle movements.

- SWRM (Steering Wheel Rapid Movements): SWRM involves monitoring the steering wheel movements to identify rapid and erratic changes, which could indicate that the driver is distracted, fatigued, or drowsy. In the context of distraction, SRWM systems monitor the driver's steering behavior to identify deviations from typical driving patterns. Distraction can manifest as sudden and unplanned movements, such as overcorrections or frequent changes in direction. When a driver is engaged in secondary tasks, like texting or adjusting in-car entertainment, the steering wheel may exhibit irregular movements. By detecting these deviations, the system contributes to preventing potential accidents caused by distracted driving. The correlation with drowsiness is rooted in the observation that fatigue often leads to lapses in attention and slower reaction times. SRWM track the smoothness and consistency of steering input. As drowsiness sets in, a driver may experience microsleep episodes, resulting in momentary lapses of control reflected in erratic steering movements. By monitoring these subtle cues. Values for drowsy drivers are higher than alert ones.

- SWRR (Steering Wheel Reversal Rate): SWRR can reflect a driver’s ability to maintain stable control of the steering wheel. It can be used as a metric to detect driver fatigue and attentional state of the driver as it is proven that it changes as the cognitive workload changes. It detects all the reversals in the steering wheel angle above a determined threshold. This metric is intended for the assessment of the effects of secondary tasks, visual and cognitive load, and fatigue level on driving.

- TLC (Time to Line Crossing): TLC is used to detect driver distraction and drowsiness by analyzing the driver's behavior in relation to the time it takes for the vehicle to cross a lane marking.
  It can be used as an indicator of driver attentiveness, and it's a measure often integrated into real-time driver monitoring systems, allowing for the simultaneous tracking of drowsiness and distraction.
  Although TLC can be accurately calculated using trigonometry, approximations are commonly employed due to the complexity of these operations and the problem of obtaining the required variables. In this work, the lateral speed is applied.

- SDS (Standard Deviation of Speed): Studies conducted using driving simulations reveal that the speed of a driver tends to decrease when engaged in cell phone usage, while the standard deviation of speed shows an upward trend with an increase in the complexity of secondary tasks. In response to potential hazardous events that may necessitate evasive manoeuvres like steering and/or braking, countermeasures often involve a reduction in speed and/or an increase in the distance between the driver and the vehicle ahead. It is important to acknowledge that distracted drivers don't consistently exhibit degraded performance levels. In instances of self-inflicted distractions, drivers may deliberately opt for lower speeds as a compensatory measure for the perceived risks they are taking.

VEHICLE BASED PARAMETERS			
MEASURE	FORMULA	SOURCE	SYM VARIABLES
SDLP	$STD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}}$	(Daza et al., 2014)	laneGap
TLC APPROXIMATED (Without trigonometry)	$TLC\_5s = \sum_{i=1}^{n-1} f(TLC_i)$ $f(TLC_i) = \begin{cases} 1 & if \quad TLC_i < a \\ 0 & otherwise \end{cases}$ $TLC = \begin{cases} d_R/\dot{x} & \text{if} \quad \dot{x} < 0 \\ d_L/\dot{x} & \text{if} \quad \dot{x} > 0 \end{cases}$	(Daza et al., 2014)	speed_y laneGap
SRR	$\lvert\theta_i - \theta_{i-1}\rvert \geq 6°$	(Zhang et al., 2016)	Steeringwheel angle
SWRM	$RSWM = \frac{1}{n-1}\sum_{i=2}^{n} h(\dot{s}_i)$ $h(\dot{s}_i) = \begin{cases} 1 & \text{if} \quad \lvert\dot{s}_i\rvert > d \\ 0 & otherwise \end{cases}$	(Daza et al., 2014)	Steeringwheel speed
SDS	$STD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}}$	(Bassani et al., 2023)	Speed_x

Figure 12: Vehicle dynamics indices chosen from the literature

The selection of these indices is grounded in various factors. Firstly, literature findings consistently indicate their reliability in detecting variations in driver behavior due to signs of fatigue or distraction across different case studies. Furthermore, these parameters align with the data available in our dataset and its structure, allowing us to conduct their analysis effectively. Therefore, by relying on these parameters, we have access to information about different aspects of vehicle dynamics. SDLP and TLC offer perspectives on the lateral movement of the vehicle, viewed from two different logics, a critical aspect to monitor as it can lead to lane departure or off-road incidents.

SRWM, on the other hand, provides an analysis of steering wheel usage, another aspect sensitive to changes in the driver's state and SWRR similarly, has been pointed in the literature as one of the most useful parameters to detect driver fatigue and distraction.

Finally, SDS evaluates the vehicle's dynamics in terms of longitudinal direction. With these five parameters, we obtain a comprehensive view of the dynamic behavior of the vehicle and the driver's driving style from different perspectives. In addition to the vehicle dynamics parameters, by having access to video analysis software related to head position and driver emotion detection, we also have the opportunity to utilize these indices to analyze the driver. Specifically, the head orientation will be described through the angular rotations of yaw, pitch, and roll, while the impact of emotions on the driver's attention state will be assessed through the obtained values of valence and engagement.

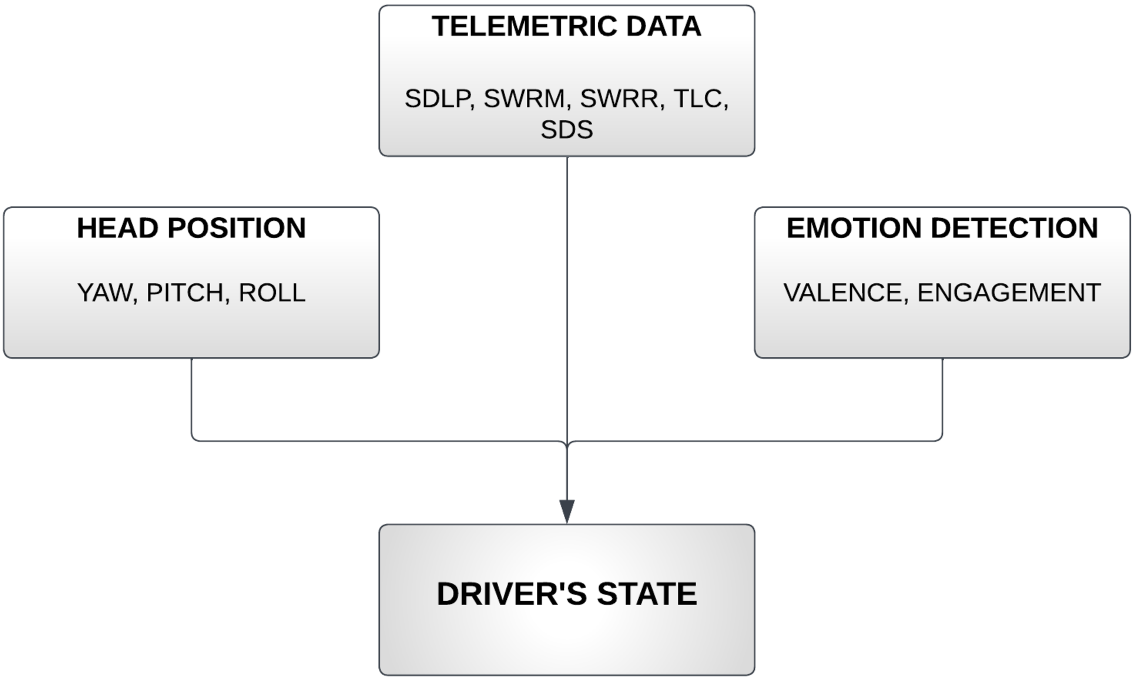

Figure 13: Resume of the indices involved in the detection of the driver's attentional state

5.2 Calculation of identified parameters trough algorithm

In the following of this chapter the algorithms used to calculate the selected parameters are presented. The code has been developed using Python programming language in the Visual Studio Code editor. The indices related to the vehicle dynamics were calculated according to the following logics:

SDLP (Standard Deviation of Lane Position):

1. Output: List of SDLP values calculated within a predefined time window, which is advanced by a given timestep to process the lane gap data obtained from a subject throughout the entire duration of the test.
2. Input: Lane Gap, time window, time step.
3. Lane Gap = The lateral distance of the vehicle regarding to the middle of the lane reported in (m).
4. Time window = 5 (s).
5. Time step = 1 (s).
6. Sum all lane gap values of the subject in the defined time window.
7. Divide the obtained sum by the total number of elements in the sample to calculate the arithmetic mean.
8. Find the difference between each i-th value and the mean.
9. Square each of these differences.
10. Sum all squared differences and divide by the total number of elements -1.
11. Calculate the square root of the obtained value to achieve the standard deviation of the lane position and append this value in a list.
12. Iterate the process by advancing the time window with a timestep of 1 (s) throughout the entire duration of the test.

SDS (Standard Deviation of Speed):

1. Output: List of SDS values calculated within a predefined time window, which is advanced by a given timestep to process the lane gap data obtained from a subject throughout the entire duration of the test.
2. Input: speed x, time window, time step.
3. speed x = The x-component of the vehicle's speed in its reference frame, where x aligns with the longitudinal direction, in (m/s)
4. Time window = 5 (s).
5. Time step = 1 (s).
6. Sum all x speed values of the subject in the defined time window.
7. Divide the obtained sum by the total number of elements in the sample to calculate the arithmetic mean.
8. Find the difference between each i-th value and the mean.
9. Square each of these differences.
10. Sum all squared differences and divide by the total number of elements -1.
11. Calculate the square root of the obtained value to achieve the standard deviation of the longitudinal speed and append this value in a list.
12. Iterate the process by advancing the time window with a timestep of 1 (s) throughout the entire duration of the test.

SWRM (Steering Wheel Rapid Movements):

1. Output: List of values reporting steering wheel speed as 1 if greater than or equal to the threshold value, and 0 if less.
2. Input: Steering wheel speed, threshold
3. Steering wheel speed = Steering wheel angular speed in (rad/s)
4. Set a threshold value d = 13 (°/s).
5. If the absolute value of the i-th steering wheel speed is > d, set it to 1, otherwise, 0 and append this value in a list.

SWRR (Steering Wheel Reversal Rate):

1. Output: List of values reporting the SWRR
2. Input: steering wheel angle, threshold
3. Steering wheel angle = Angular position of the steering wheel (rad)
4. Threshold = 6°
5. Find the differences in the steering wheel angle greater than or equal to the threshold where the steering wheel has returned to the central position, defined as a steering wheel angle smaller or equal to 2°
6. If these conditions are true append this value as SWRR to a list, otherwise assign 0 to it.

TLC (Time to Line Crossing):

1. Output: List of values reporting TLC as 1 if greater than or equal to the threshold value, and 0 if less.
2. Input: speed y, lane gap, right distance, left distance, lane width, car width, threshold.
3. Speed y = The y-component of the vehicle's speed in its reference frame, where y aligns with the lateral direction, in (m/s).
4. Lane Gap = The lateral distance of the vehicle regarding to the middle of the lane reported in (m).
5. Right distance = distance between the right side of the vehicle and the right line of the lane in (m).
6. Left distance = distance between the left side of the vehicle and the left line of the lane in (m).
7. Lane width = distance between the right line and the left line of the lane in (m)
8. Car width = distance between the left side and the right side of the vehicle in (m)
9. Threshold = 6.4 (s)
10. Knowing that a positive speed describes a leftward movement and vice versa, if v > 0 and the left distance > 0, then the car is moving left, so calculate TLC = left distance / speed.

11. Otherwise, if v < 0 and the right distance > 0, then the car is moving right, so TLC = -right distance / speed.
12. Additionally, there should be a TLC max in the case of speed = 0.
13. If TLC < threshold, then TLC = 1, otherwise, TLC = 0.

The head position software has the ability to determine the attentional state of the driver based on empirical threshold.

Finally, the CNN used for the emotion detection software has the ability to recognize the six universal Ekman's emotions from images of faces as input and giving as output a percentage of probability for each emotion.

Chapter 6

Results

6.1 Qualitative Analysis

In this chapter, the obtained results from the conducted analyses are presented. Graphical representations will show how the selected indices behave during the various tests executed by the subjects. A comparison will be made among these indices and the recorded signals. An exploration of the behavior of the parameters will be carried out through a qualitative analysis, evaluating the trends, especially during distraction events.

Starting the analysis of the results from the emotion detection software, it is evident that in some of the examined subjects, the software was able to detect significant changes in emotions, particularly in the values of engagement and valence, during distraction phases. Specifically, in subject 16, it is notable that although during the initial distractions, the subject remained in average engagement values associated with undefined emotions, during the last 3 distraction activities (answering to 2 messages received on the phone and using the tablet) the software detected peaks outside the previous trend in both engagement and valence. This leads to the conclusion that, during those moments, the subject experienced emotions of joy with particular enthusiasm. Referring to another subject, analyzing subject 6, it is noticeable that this subject also exhibits an emotional response to distraction actions.

Although subjective and different from the previously considered case, it allows the detection of a variation in the engagement values compared to moments when distraction is not imposed.

In this case, the subject consistently appears with relatively high engagement values. Moreover, looking to the valence plot, it is evident that when the distraction phases begin, the subject reaches very low values, describing a negative state of concern, likely attributed to the cognitive effort required to perform a secondary task and awareness of engaging in distracting activities. In another subject, when the person becomes distracted by the "drink from bottle" activity, there is a decrease in engagement, and generally, the valence lowers. This can be attributed to the fact that even though there might have been an initial emotional response, the task requiring greater cognitive effort applied to a secondary activity other than driving leads to a more neutral state, deviating from the emotional trend observed previously. In some subjects, it can also be observed that peaks in engagement values, indicating high emotional involvement, occur shortly before the distraction action actually takes place. This could be due to the fact that these subjects had a heightened emotional response to the vocal command describing the action to be performed, highlighting how the command itself can be a source of distraction. It should be considered that, for the majority of other users, it was not possible to identify specific trends. This could be attributed to the measurements not being taken accurately, particularly those involving cameras. In particular, concerning camera-based indices, the observed trend throughout the entire duration of the test differs from what one would expect. During driving, except for moments when distraction is imposed, the signal's trend should be much more linear and therefore devoid of the peaks and valleys that instead compose all the data gathered. Various factors may have compromised the collected data, usually stemming from the environment. For example, inadequate lighting can cause issues in facial detection for computer vision systems. Similarly, camera positioning problems, such as incorrect angles relative to the subject's face, can challenge the software. Finally, for a more in-depth analysis of the collected data and their actual emotional significance, consulting with an expert in the field, such as a psychologist, would provide a more comprehensive understanding of the drivers' emotional states during the activities.

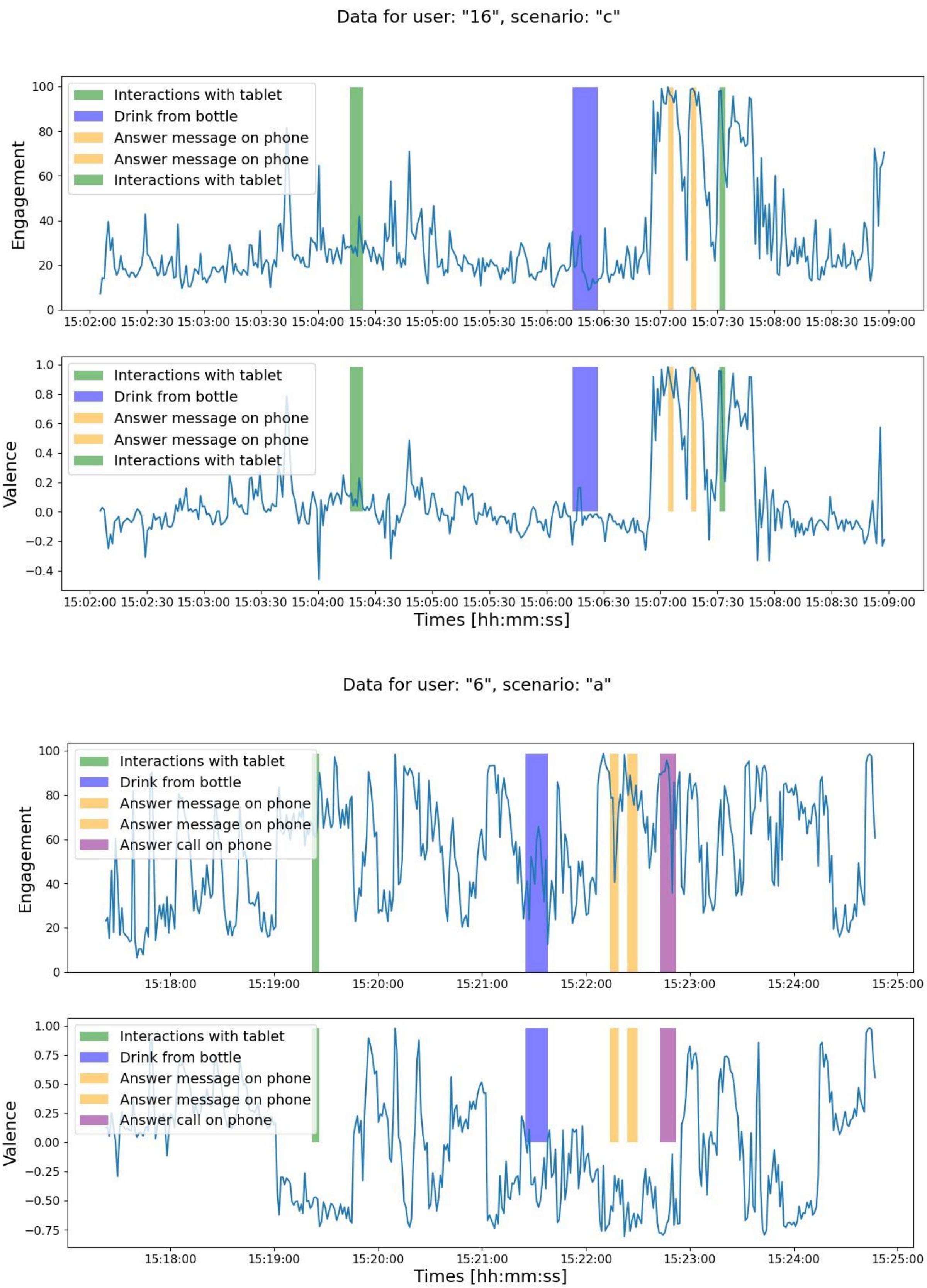

Figure 14: Emotion detection plots

From the analysis of the data collected by the software to determine driver attention based on head orientation, it is observed that more pronounced yaw deviations lead to a loss of attention, as expected, given that yaw rotation represents rotation around the vertical axis. Therefore, high values of this measurement indicate that the subject, at that moment, has the head turned in a direction other than the frontal one. In particular, during the conducted tests, most distraction activities required the user to turn to the right. As expected, the greatest variations were recorded either during these activities or during the beginning or end phases of the test, where it is customary to see the driver looking around.

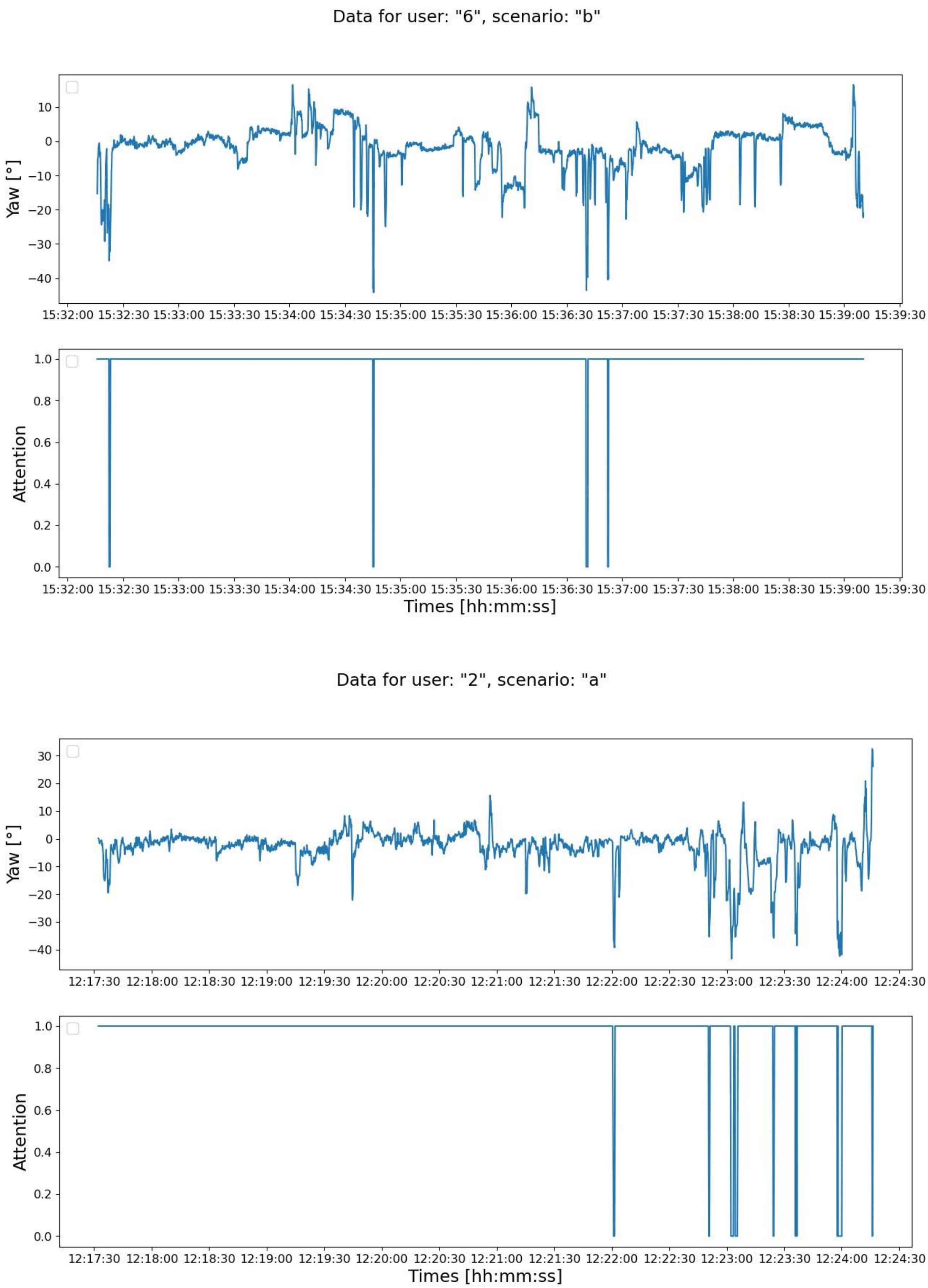

Figure 15: Attention level based on head position

Analysing the data related to the vehicle dynamics, there are various considerations to be made. Examining the trend of the indices, it's evident that they experience fluctuations during the distraction phases, reaching the threshold values collected in the initial phase of this project's development. Starting with the analysis of the car's speed, referring to the subject 2, it is noted that in correspondence with the distraction scenarios, particularly the one where the subject is instructed to drink from a bottle, a deviation in the signal trend can be observed compared to the period preceding the distraction event. As highlighted in the literature, during distraction or in the moments leading up to it, the subject tends to decrease the vehicle's speed, as evident from the reduction in speed along the x-axis, as well as the deceleration and the peak in relative standard deviation, indicating a sudden change in speed values. This reduction is attributed to a common behavior where the driver, aware that they are about to engage in a secondary task that will divert their attention from driving for a certain period, instinctively lowers the speed as a protective measure, extending throughout the duration of the task. Also in subject 4 there is a relevant change in the trend, having an inversion compared to the behavior before the distraction event.

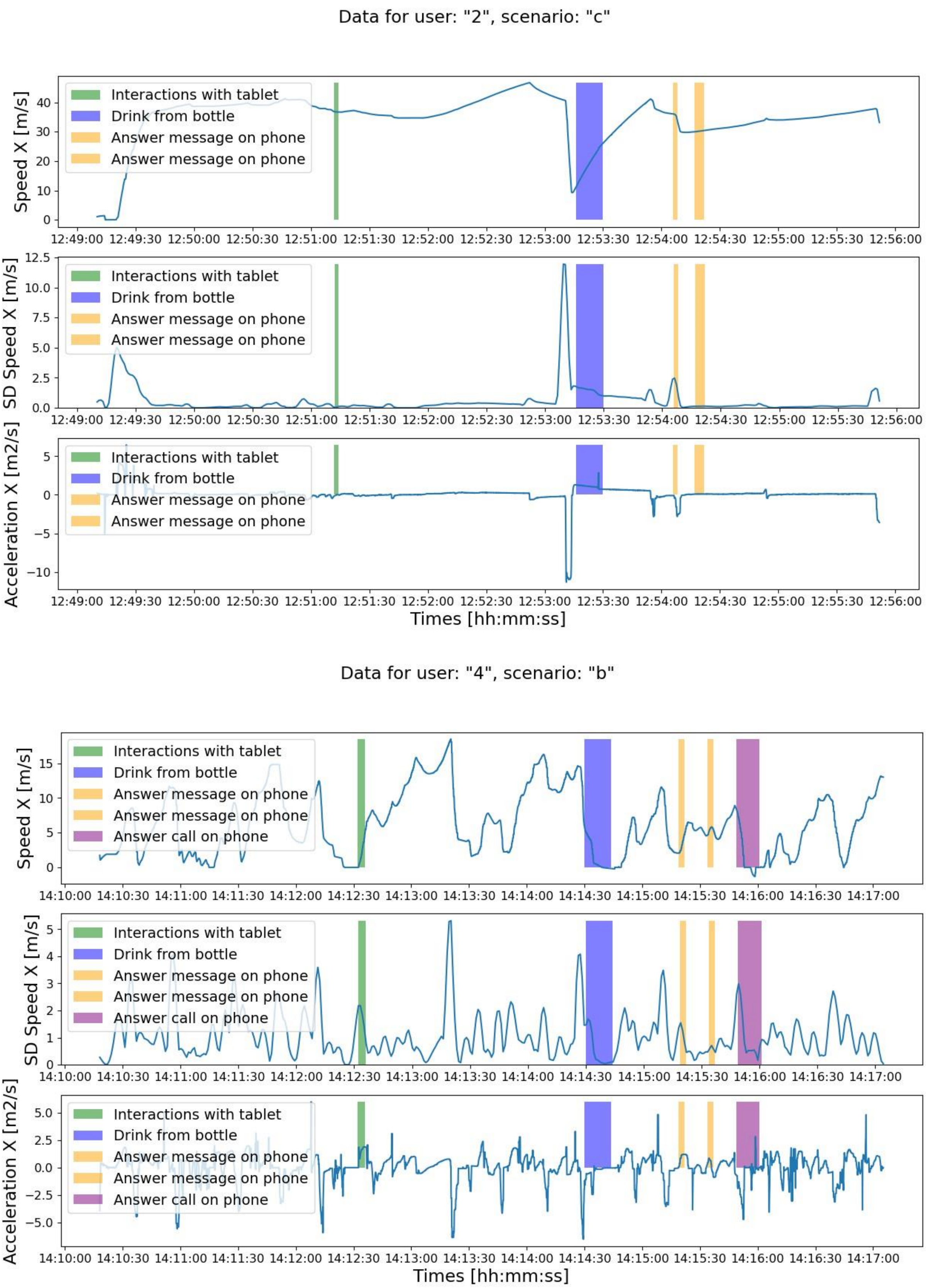

Figure 16: SDS plots

The analysis of the data related to SDLP and TLC with a threshold of 6.4 seconds as indicated from the literature, reveals a notable correlation between these indices, indicating that variations in one correspond to variations in the other. Taking a closer look at subject 9's analysis, it becomes apparent that the subject effectively maintained position within the lane for the majority of the test duration. This assessment considers the lane's width of 3.5 meters and the car's width of 1.65 meters, allowing for approximately 0.93 meters on each side if the car is centred. A deviation of this magnitude would signal a departure from the lane. During the distracting "drink from the bottle" activity, known for inducing cognitive fatigue, the driver experiences the sole lane departure, aligning with the highest peak in the overall trend of SDLP. Simultaneously, in the TLC graph, there is a concentration of values under the threshold, null or very low, during this distraction event compared to the rest of the trend. These low TLC values suggest instances of crossing or nearing the lane's limit. Another interesting trend, common to several subjects, is evident in the plot of subject 5, where the driver maintains effective control of the vehicle within the lane for most of the track. However, during distraction moments, notable peaks in SDLP are observed, consistently associated with clusters of low TLC values. It's important to highlight that the layout of the track itself can significantly influence the recorded values for these metrics related to vehicle dynamics and, more broadly, those associated with the driver's behavior.

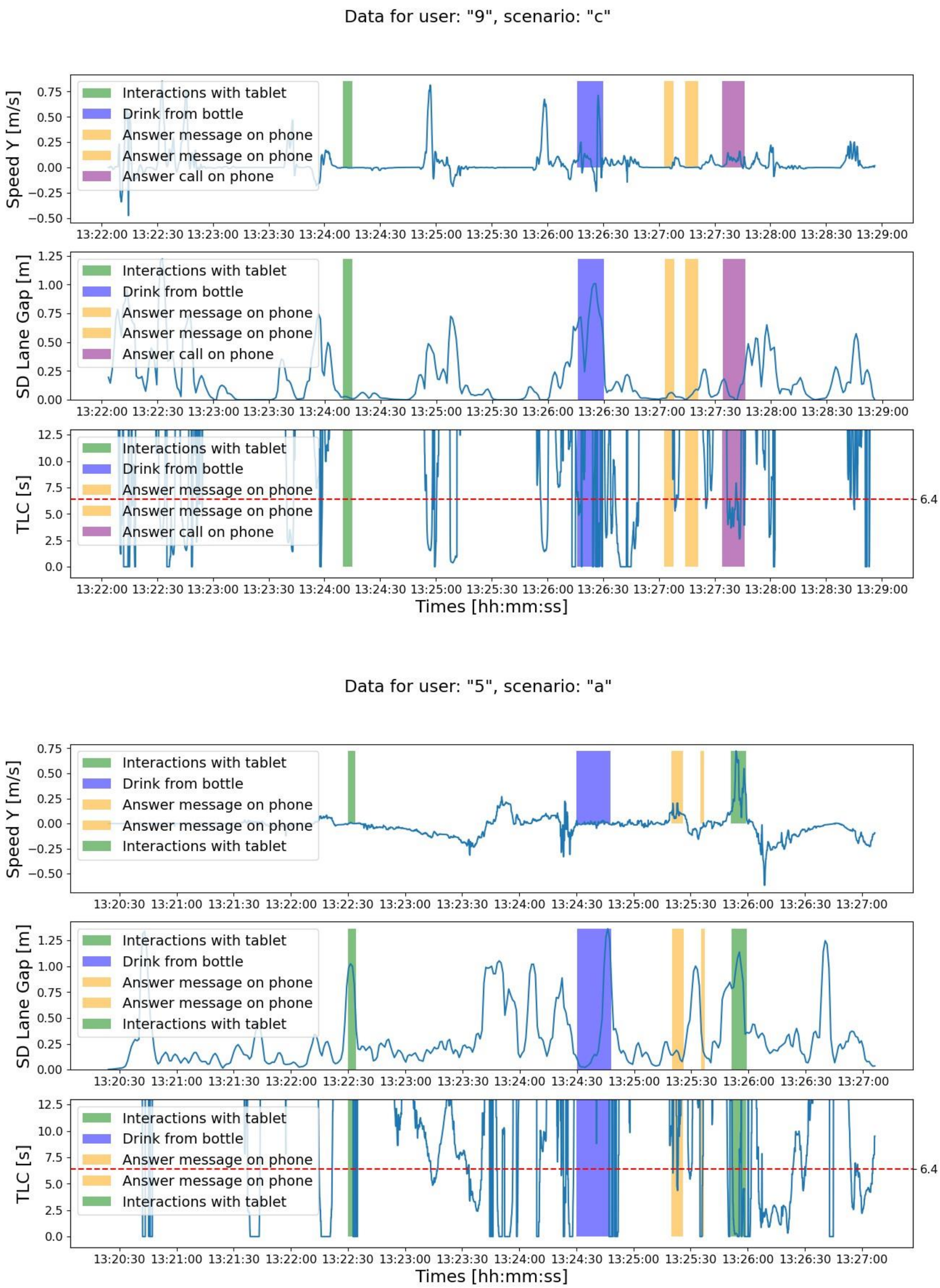

Figure 17: SDLP and TLC plots

The last set of vehicle dynamics data to analyze pertains to steering wheel usage. Examining this type of data immediately reveals how the track layout is even more relevant in interpreting these indices, as they exhibit a significant sensitivity to it. Across all subjects, numerous signals related to Steering Wheel Reversal Movements (SWRM) are detected, while signals related to Steering Wheel Reversal Rate (SWRR) are likely distorted by track curves. However, delving into the analysis of data specific to an individual subject, it is noticeable that, in some cases, there is indeed a concentration of SWRM values coinciding with distraction events. This identifies an abnormal use of the steering wheel, but it is also recorded in many other phases of the test. A potential solution to address this issue could involve having the subject navigate a predetermined track where distraction events occur only on straight sections. This approach aims to exclude steering wheel usage for turning during distraction events. Lastly, regarding the threshold values of vehicle dynamics indices identified during the initial phase of the project, it is worth delving into their significance. While these thresholds provide a foundational framework for conducting analyses, it is essential to further deepen and optimize them to enhance the accuracy and efficacy of the analyses. Fine-tuning these thresholds based on empirical findings and real-world application scenarios can lead to improved results and a more robust analytical approach.

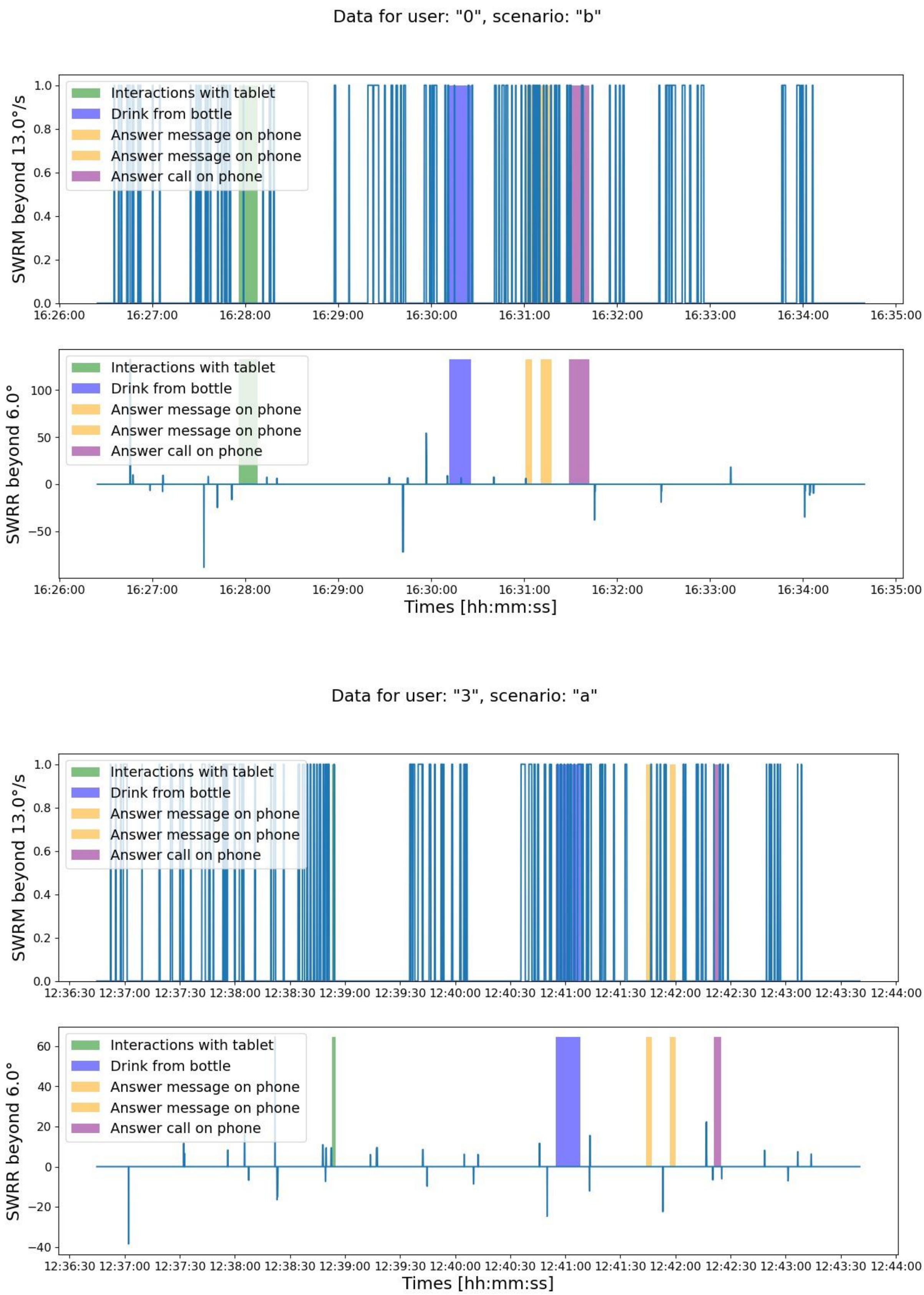

Figure 18: SWRM and SWRR plots

Chapter 7

Conclusions and future work

The attained results shed light on significant aspects related to driver monitoring and distraction analysis. In particular, the research has made valuable contributions to the existing knowledge in the field of Driver Monitoring Systems (DMS). The approach adopted in this study has provided new insights into the understanding of driver behavior and the effective assessment of distraction indices. The use of diverse parameters has allowed us to explore the driver's behavior from various perspectives during different tests. By analyzing data on vehicle dynamics and steering wheel usage, we assessed the driver's ability to maintain trajectory within the lane and identified necessary corrections to prevent deviation. These findings provide a comprehensive understanding of the car's behavior on the road and the driver's interaction with it, in particular with the steering wheel usage. Detecting variations in these indices during simulated distraction phases in the experimental trial provides a foundation for developing the subsequent architecture of the software integrated into the DMS, that in the next phases of the development could be capable of signaling distraction events by interpreting the data.

In addition to telemetric data, we also examined facial-related data, focusing on head position in terms of yaw, pitch, and roll, along with valence and engagement values provided by the emotion recognition software based on Ekman's six universal emotions. Analysis of attention-related software based on the head position reveals evidence indicating a loss of attention while driving when the driver's head is not facing forward, as expected by previous studies and real life experience. Concerning emotions, particularly valence and engagement values, it is observed that these are highly subjective and vary from individual to individual.

Some subjects exhibit high engagement values, signifying emotional involvement during the driving test and in the distraction actions, but at different levels of valence, indicating that at the moment we cannot say which type of emotion is more correlated to the lack of attention.

As with any research endeavour, it is essential to acknowledge certain limitations and challenges encountered throughout the study. The experimental trials and the simulator setup utilized, while effective, had inherent constraints that influenced the scope of the findings. A transparent acknowledgment of these limitations is crucial for interpreting the reliability and generalizability of the results. In particular, the use of a static simulator within a room, while providing a realistic and faithful simulation of real driving conditions, may lead the subject to feel in a somewhat different situation compared to driving in the real world, potentially resulting in different effects on levels of driving attention. To enhance generalizability, increasing the number of participants in the experimentation can be beneficial, given the inherent subjectivity related to each individual's driving style. Furthermore, upon analyzing the data, we were able to assess that the actions imposed on the drivers to induce distraction were indeed few and brief compared to what might have been necessary for a more comprehensive detection of the trends in the selected parameters for the study.

The practical implications of this research extend beyond the academic field, with possible applications in enhancing driver safety. The selection of indicators from the literature suitable for detecting distraction and compatible with the available data, coupled with the preliminary analysis conducted, provides a guiding foundation from which to further develop the required DMS. This is essential for achieving the goal of developing an innovative real-time driver analysis system as mandated by the Epignosis Project, thereby reserving practical potential for future implementation in real-world scenarios.

Furthermore, the study suggests avenues for future research and development in this dynamic field. Recommendations include exploring refinements to the DMS, considering alternative data analysis approaches, and investigating additional factors influencing driver distraction.

In particular, a significant portion of the current literature is focused on fatigue detection and its correlation with the driver's attention level, how it can affect it and how this, in turn, affects the driver's behavior. The dynamics resulting from attention loss due to fatigue, while broadly overlapping with those of common inattention, may exhibit differences. Therefore, continuing to investigate other potential causes of distraction, such as those arising from secondary tasks or environmental factors, could be a catalyst for advancing the development of these systems. It allows for a broader testing of the efficacy of identified indices, confirming or refuting the utility of each and making necessary adjustments to ensure adaptability to all distraction scenarios. Moreover, the next step to undertake, now that these indices are at our disposal, it is to perform their fusion through data fusion techniques. In this way, as also highlighted in the literature, the combined use of data from different sources allows for greater accuracy and quicker detection of potential instances of driver distraction. These suggestions aim to guide future researchers to build upon the foundations laid by this study. The findings of this work confirm and underscore the importance of integrating such innovative technologies into the broader context of Advanced Driver Assistance Systems (ADAS). In essence, this study offers tangible insights for the advancement of technologies designed to enhance road safety and aims to serve as a foundation for developing the innovative DMS that will be installed on the prototype vehicle envisioned within the Epignosis project.

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