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Automating the Classification of Disengagements using FoxGlove

Batchelor’s Thesis (9 ECTS)

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Abstract:

This thesis presents the Disengagement Classification Method (DCM) for analysing autonomous driving disengagements and its validation. The DCM aims to improve the current manual classification by leveraging expert knowledge and the functionality provided by the FoxGlove tool. This results in integrating a custom panel with FoxGlove Studio, which provides semi-automated disengagement categorisation and real-time data viewing. Compared to the manual method, this improves the efficiency of the analysis. Possible future developments involve improving the documentation for manual analysis and extending the classification of unplanned events to provide better automated analysis tools.

Keywords:

Autonomous Driving, Automated Disengagement Analysis, FoxGlove Custom Panel, Validation Study

CERCS: P170 Computer science, numerical analysis, systems, control

Ülevõtmiste klassifitseermise automatiseerimine kasutades FoxGlove

Lühikokkuvõte:

Selles lõputöös esitatakse ülevõtmise klassifitseerimise meetod (DCM) autonoomse sõidu ülevõtmiste analüüsimiseks ja selle valideerimiseks. DCM-i eesmärk on täiustada praegust manuaalset klassifikatsiooni, kasutades selleks ekspertteadmisi ja FoxGlove'i tööriista poolt pakutavaid funktsioone. Tulemuseks on integreeritud kohandatud paneel FoxGlove Studioga, mis pakub poolautomaatset ülevõtmiste kategoriseerimist ja andmete reaalajas jälgimist. Võrreldes manuaalse meetodiga parandab see analüüsi efektiivsust. Võimalikud tulevased edasiarendused hõlmavad käsitsi analüüsi dokumentatsiooni täiustamist ja planeerimata sündmuste klassifikatsiooni laiendamist, et pakkuda paremaid automatiseeritud analüüsitööriistu.

Võtmesõnad:

Autonoomne sõitmine, Automatiseeritud ülevõtmise analüüs, FoxGlove kohandaud paneel, Kinnitamisuuring

CERCS: P170 Arvutiteadus, arvutusmeetodid, süsteemid, juhtimine (automaatjuhtimisteooria)

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1 Introduction

Automated Driving Systems (ADS) are revolutionising transportation, but ensuring safety is challenging. Based on collected data from the test drives, one way to improve ADS safety is to analyse disengagements during test drives with the ADS. Disengagement is an event where the automatic driving is interrupted by the safety driver sitting in the ADS behind the steering wheel taking over control. Disengagements during test drives may have several reasons. For example, when the ADS leaves the assigned Operational Design Domain (ODD), automated driving becomes unsafe, and the safety driver must take over. However, disengagements may also be unplanned. Those are situations where the safety driver takes over because the ADS seems to be unsafe, or no undue risk shall be taken – although the ADS is still in its assigned ODD. The analysis of unplanned disengagements is helpful to improve the quality of the autonomy software stack.

Previously, disengagement analysis was done manually by visualising data from ROS1 files and using Excel to record timestamps and describe disengagement reasons. These disengagements were divided into planned and unplanned events. Furthermore, events were subcategorised according to the reason behind the disengagement. For example, during the drive, the safety driver takes over to ensure safety at an intersection with Give way road sign, this event would be categorised as a planned event with a sub-classification of Give way event. The proposed Disengagement Classification Method (DCM) uses FoxGlove[1] for data visualisation and previous semi-automatic classification, which reduces the need for manual inspection and classification for the analyst. Thus, disengagement pre-categorisation would be first done by the program in FoxGlove, resulting in less time by categorising for the analyst and focusing more on the unplanned events to analyse the reasoning behind them.

Events in the context of this thesis refer to disengagement periods during which the safety driver takes control of the vehicle. These events happen due to legal requirements and safety concerns. Even if the line between them is thin, events must be categorised as planned or unplanned events. Planned events are defined as disengagements where the safety driver takes action based on prior agreements. For example, when a human is waiting to cross a zebra, the safety driver will take over, resulting in a planned event. Unplanned events are defined as disengagements due to unsafe external factors, traffic, vehicle or code error.

[1] https://foxglove.dev/

The research conducted in this thesis project focuses on answering the question of whether it is possible to distinguish between planned and unplanned disengagements using only data from ROS1 files. These requirements eliminate the need to analyse video and photo data, as these are simpler for humans to look at and analyse but are too complex to analyse by code. This thesis aims to improve the efficiency of disengagement analysis in Autonomous Driving Labs (ADL) by developing a DCM custom panel in FoxGlove. This panel will categorise disengagements into planned and unplanned events. Additionally, planned events will be categorised as one of the five specifically defined planned events. The expected outcome of the DCM custom panel in FoxGlove is to semi-automate disengagement categorisation, thus simplifying the analysis process.

With the aim of keeping the number of misclassifications low for DCM, the categorisation hierarchy has been defined in a simple manner to eliminate false positives and false negatives. This hierarchy first focuses on separating the unplanned events from the others for an analyst to review, these would be marked as Manual inspection needed. The rest of the events would then be searched for planned event indicators and categorised accordingly. These pre-categorised planned events would not need to be looked over by an analyst. If an event fails both of these steps, it will be also marked as Manual inspection need, as it would need attention from an analyst.

The original idea was to simplify disengagement analysis for ADL. This progressed into a more optimised approach focused on categorisation and aimed to separate between planned and unplanned disengagements. However, the efficiency of this proposed method depends on identifying distinct combinations in the data to distinguish between planned and unplanned events, a problem that this thesis aims to solve.

The goals of the thesis are:

1. Propose a methodology for a semi-automatic classification of disengagements, the DCM
2. Validate the methodology with the ADL as a use case:
    a. Proof-of-concept for the proposed methodology
    b. Quality control by comparing the results with the previous manual method by ADL.

The following thesis will describe, discuss and document the process of achieving the defined goals.

2 Background

This section will address the basic concepts of Automated Driving Systems (ADS) and the work of the Autonomous Driving Lab (ADL), as well as how disengagements in autonomous driving are analysed. ADS vehicles can drive autonomously by using sensors and software. Usage of ADS promises safer roads by lowering human error, as researchers have emphasised [1]. The Society of Automotive Engineers (SAE) classifies the level of autonomy of ADS into six categories [2]. ADL, founded in 2019, aims to achieve high autonomy using AI and open-source software, testing their technologies on Lexus RX450h vehicle [3]. They are working towards Level 4 automation, in which the ADS decides primarily driving choices [4]. In order to accomplish this, they manually analyse disengagements, categorising them and determining why they occur.

2.1 Automated Driving System

Automated Driving System (ADS) vehicles are capable of driving themselves without the need for human intervention. It accomplishes this by utilising sensors to collect data from its surroundings, such as other vehicles and road signs. Then complex software programs analyse the data to determine where to steer, when to accelerate and brake, etc. These programmes can additionally use artificial intelligence[2] (AI) to advance even more in the future. This technology improves driving safety and convenience for everyone.

In "Autonomous Driving Changes the Future", authors Chai et al. [1] emphasise the significance of autonomous driving (AD) and its impact on safety, efficiency, convenience, and the future. According to a survey investigating the reasons for vehicle crashes, around 94% of critical reasoning was attributed to the driver [5]. ADS is aimed at reducing this percentage. This is because ADS software can react faster when an obstacle appears on the road, reducing the total braking distance and decreasing the likelihood of collisions. Additionally, accidents caused by driver distractions, such as phone usage or passengers, can be eliminated. Better efficiency could be achieved with the optimal driving style, fewer breaking and accelerations by the software, and additionally minimalising congestion by improving traffic flow with fewer crashes [6]. The authors Chai et al. [1] envisioned a comfortable future with AD where vehicle passengers can use their time on the road more productively or relax, while AD ensures safe transportation, even for children. This

[2] “Artificial intelligence, or AI, is technology that enables computers and machines to simulate human intelligence and problem-solving capabilities. [20]“

technology would also allow better accessibility for the elderly, visually impaired, disabled, etc.

Today, it is increasingly common to encounter ADS vehicles with driver support functions on the road and in dealerships. Tesla, the most well-known autonomous car, is an example of this. For a better understanding of the differences between the responsibility of the human and vehicle in ADS vehicles, the Society of Automotive Engineers (SAE) International has defined the most used levels of driving automation [2]:

- Level 0 – No Driving Automation
- Level 1 – Driver Assistance
- Level 2 – Partial Driving Automation
- Level 3 – Conditional Driving Automation
- Level 4 – High Driving Automation
- Level 5 – Full Driving Automation.

The following sums up SAE's levels of driving automation in Figure 1. Levels 0 to 2 are required for the driver to drive. The automation is more of an assistance for the driver, for example like automatic emergency braking, lane centring and adaptive cruise control. The third level requires the driver to drive when the feature requests, but from level 3 to level 5, the driver is not driving, when the automation is engaged then the program is in charge.

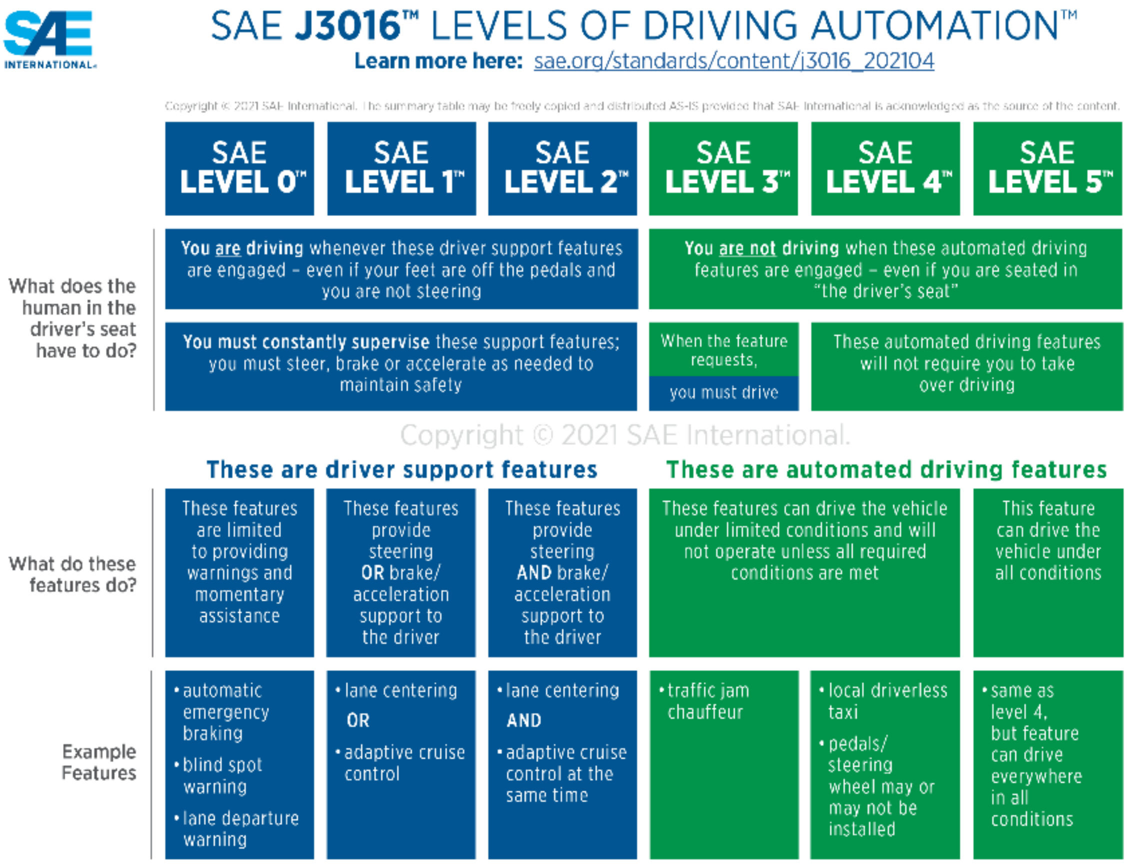

Figure 1 SAE Levels of Driving Automation (source: [7])

2.2 Autonomous Driving Lab

Autonomous Driving Lab[3] (ADL) was founded in 2019, and its overarching goals are in these fields: Technology, Research and Education [8]. Working principles aim for true autonomy using AI and machine learning, focus on data-driven methods, and use open-source software when possible. The ADL is using a Lexus RX450h, as seen in Figure 2, for test runs, this car is equipped with many sensors and runs on in-house software [3]. The ADL uses Autoware Mini software, which is a ROS1[4] (Robot Operating System) and Python-based autonomy open-source software. This project is aimed at teaching and research, and its key modules are Localization, Global planning, Obstacle detection, Traffic light detection, Local planning, and Follower [9]. Additionally, the ADL describes their simulation program [10], and for safety, they run untried code or tech in the Estonian National Museum parking lot [11]. The demo track is available publicly on their website [12].

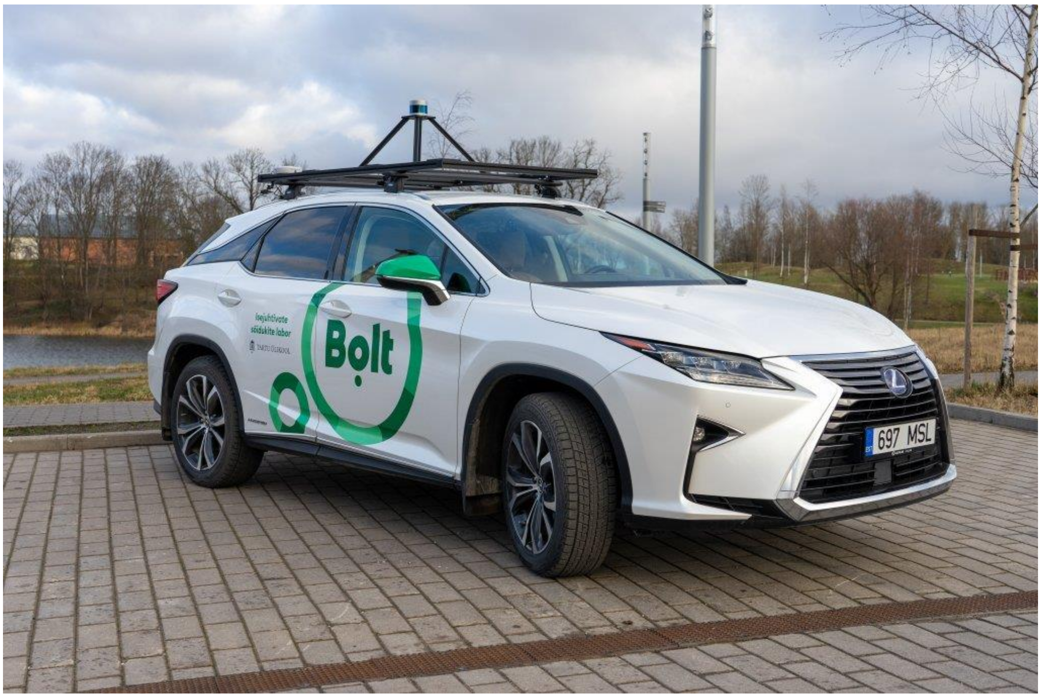

Figure 2 ADL Vehicle (source: [4])

ADL have declared reaching Level 2.5 as of now, but they have set an ambitious goal of advancing to Level 4 on the SAE levels of automation [4], as seen in Figure 1. The aim of this strategy means that the software made by ADL would no longer require driver assistance in difficult situations, instead the software would take priority in decision-making

[3] https://adl.cs.ut.ee/
[4] https://www.ros.org/

processes. In order to accomplish this goal, ADL is dedicated to further improving the accuracy of its algorithms and thoroughly testing them in difficult situations in the real world. During these test runs, a lot of data is gathered and compiled into a framework file – ROS1. This ROS1 file contains comprehensive data about each manoeuvre, braking action, traffic light responses, and more. This use of the ROS1 framework allows for thorough analysis and AI training.

In the context of this thesis, the ROS1 data file is critical because it serves as a primary source of information for identifying patterns that distinguish planned from unplanned disengagements. The result of such analysis would be displayed visually using FoxGlove, which provides information and simplifies analysis workflow. Analysts can view a wide range of critical data using the FoxGloves interface, which includes photos, GPS locations, braking behaviours, steering inputs, etc. By combining all important information into a single programme, ADL analysts may rapidly go through previously categorised events and gather enough data for a complete analysis, increasing productivity and efficiency in their work processes.

2.3 FoxGlove

FoxGlove[5] is a tool that supports the analysis of live and pre-recorded data [13]. This is done with the customisation of the panels, which can be moved around and split to accommodate more panels to the users liking. These panels fall into different categories: 3D, Data Source Info, Diagnostics – Detail (ROS), Diagnostics – Summary (ROS), Gauge, Image, Indicator, Log, Map, Parameters, Plot, Publish, Raw Messages, Service Call, State Transitions, Tab, Teleop, Topic Graph, Users Scripts, Variable Slider [14]. Depending on the type of analysis needed to be done, the user can put together a personalised view in FoxGlove to see, review, annotate and interact with the data.

Understanding how and why each panel is used helps to sort out important and needed information to analyse the disengagement. The following descriptions of the panels function are based on the FoxGlove application and FoxGlove documentation [14].

2.3.1 3D Panel

The 3D panel has seven different editable settings, which allow the user to change the background and labels to help locate and visualise the surroundings. The frame setting

[5] https://foxglove.dev/

configures what gets rendered and changes the viewport according to the following behaviour. Scene setting can render performance statistics. View setting configures the camera settings. Transforms setting helps visualise and manage spatial relationships between different coordinate frames. Topics settings allow the user to display every suitable message type individually. Custom layers setting adds visual elements such as a grid and a URDF. The final setting, Publish, is to configure click-to-publish behaviour for the 3D panel.

2.3.2 Map

The Map panel comes in handy when locating, and it is comfortable to get the timestamp at the same time. This panel can be shown in map or satellite view, and this works best with the Follow topic showing GPS data from the drive.

2.3.3 Image

The Image panel is vital to analyse disengagements as the human eye can recognise what went wrong or what happened from recorded videos and images. From the General setting, the preferred camera view is chosen for the corresponding calibration as well, which can be chosen to sync annotations. Scene, Transforms, Topics, and Custom layers are the same as 3D panel.

2.4 Disengagements

Analysing disengagements in autonomous driving is critical to assuring the safety of everybody involved, including the driver, passengers, pedestrians, etc. Analysts can get insights that can help prevent future accidents by thoroughly examining disengagement events. A disengagement occurs when the safety driver intervenes to take control of the autonomous vehicle for their own security or to reduce the risk to other road users. It is critical to understand the aspects behind disengagements in order to develop methods that improve overall safety in ADS.

It must be highlighted to provide a buffer time for the driver to respond appropriately in dangerous disengagement events [15]. This buffer time is critical, as the safety driver must have enough of time to take control of the vehicle and take the necessary manoeuvres to avoid or reduce accidents. Without enough buffer time, the safety driver might be unable to switch from autonomous to manual driving mode, thus risking the lives of the driver, passengers, pedestrians, etc.

Furthermore, analysing disengagements helps to improve autonomous driving algorithms and the software. Analytics with developers can improve the vehicle functions and outcomes by identifying frequent data values for disengagements. This constant process of analysis and improvement is critical to improving the reliability and safety of autonomous vehicles.

2.5 Manual Method for Analysing Disengagements

ADLs method of analysing disengagements is fully manual. This method requires the analyst to look through the whole ROS1 file and write it down into an Excel file when the disengagements start and end. Then, the analyst must view the video and image data for indicators of planned event categorisation and write the type of sub-category of the planned or unplanned event into the Excel file. The analyst might review some raw data for complicated cases of disengagements. If the disengagement is not categorised as a planned event, it is categorised as an unplanned event. Furthermore, the unplanned event must be analysed thoroughly to determine the possible cause of the error resulting in untypical ADS vehicle behaviour.

All of these disengagements would be categorised as planned or unplanned. Additionally, the events would receive one of the following categories: Obstacle, Safety, Pedestrian crossing, Give way, Turnback, Bad engage, Localization, SPEED or STOP. Furthermore, these events would be described by the situation as seen in Figure 3.

Event and Situation

See pivot table

Obstacle	67
Safety	49
Pedestrian crossing	26
Give way	17
Turnback	14
Bad engage	13
Localization	10
SPEED	2
STOP	1

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Vehicle approaching in opposite lane	52
Driving, no obstacles	31
Pedestrian crossing	28
Roadside parked car	19
T-intersection, main road, roundabout, etc	14
Turnback	14
Vehicle following	14
Traffic lights	8
Roadside pedestrian(s)	5
Roadside pole(s)	3
Traffic sign on safety island	3
Bus stop, exiting	2
Roadside trees or bushes	2
Bus stop, approaching	1
Ego vehicle doing lane change	1
Roadside house(s)	1
Stopped behind stopline	1

Figure 3 Event and Situation (source: [16])

3 Methodology

3.1 Steps taken to define the DCM

This chapter describes the process of developing the Disengagement Classification Method (DCM), explaining each step individually.

Step 1. Researching Foxglove custom panel development

An explorative review of FoxGlove's custom panel development capabilities is conducted to initiate the process. This involves downloading the FoxGlove Studio application and familiarising with it. Additionally, ROS1 data files are imported for the initial analysis of the available dataset provided by ADL. While documentation and tutorials [17] [18] provide some guidance, improvisation is often necessary due to limited academic resources on FoxGlove customisation.

Step 2. Identifying clear patterns in data

To further understand the analysis requirements, knowledge is gathered from various sources such as FoxGlove manuals, tutorials, and external sources. Three different levels of separation and categorisation are required: disengagement, planned or unplanned, and planned event categorisation. An effective and easy method has been found for the first one, using drivemode data value from the ROS1 file provided by the ADL. This value describes whether the car is autonomous or manual, with the drivemode value corresponding to 1 for autonomous and 0 for manual. To differentiate between unplanned and planned events, a function with many different data types is being written. For the last one, five planned events are selected and described. The ones selected are either one of the most common ones or events that can be easily identified by data values. For this thesis, the following planned events are selected: Pedestrian crossing, Temporary roadwork, Bus stop, Turnback, and Give way.

Step 3. Proposing a methodology

When proposing the methodology, two distinct approaches for event categorisation are developed: categorisation by definition and categorisation scheme with threshold values. With categorisation by definition, the aim is to set clear rules to separate unplanned events and define the five selected types of planned events based on their characteristics, including logical explanation. Meanwhile, a categorisation scheme with threshold values is developed for a data-centred approach. The goal is to determine suitable raw data and its threshold values through analysis, making it possible to categorise the events using data values received from the ROS1 file. This means that the first approach will be used for describing, and the second approach makes the development of a custom panel in Foxglove possible. These two approaches are utilised to develop a comprehensive methodology for as accurate event pre-categorisation in the DCM as possible.

Step 4. Expert interview and methodology improvement

An interview will be conducted with an expert to confirm the viability of the proposed approach. For this, Edgar Sepp from ADL will be contacted, whose position in ADL is Research Engineer, High-Definition Maps Team Lead. This interview will gather knowledge on how to modify the DCM. The goal will be to filter out events, which are "perfect" examples. This means that events that are combinations of many problems or events will not be categorised in the proposed approach for better precision. Based on the feedback, the definitions and threshold values will be discussed and tweaked to improve accuracy. Afterwards, reviews and suggestions will be received through several e-mail conversations. Additionally, many tables and short descriptions will be written for Edgar Sepp for compact review.

Step 5. Development of FoxGlove custom panel

A TypeScript[6] file using React[7] components is developed. Assistance for better comprehension of these components was sought from their respective websites, listed in the footnotes. The development of the custom panel within FoxGlove Studio becomes achievable after refining the approach. This involves implementing the categorisation criteria and analysis functions into practice and establishing the necessary framework for data analysis. The development of the panel can be divided into the following sections: data reception, disengagement detection, collection of necessary data in suitable buffers, analysis of data for indicators of unplanned events, analysis of data for indicators of five different planned events for categorisation and rendering the analysis suitable and visible to the analyst in the panel.

To receive the data, an interface is created for every data type, and the topic must be subscribed to receive messages from that data type. For convenience, every data variable is assigned a declared state variable to receive and set the values for that data type. The drivemode data variable from the VehicleStatus data type is utilised to detect when a

[6] https://www.typescriptlang.org/
[7] https://react.dev/

disengagement occurs. When the drivemode data value is 1, indicating autonomous mode, and when it is 0, indicating manual mode, the disengagement is identified. Additional boolean variables are declared and used accordingly to determine when an event has started, if the event is ongoing, and if it has been analysed after the event concludes.

In some scenarios, data from five seconds ago is necessary to analyse disengagements. To address this, a buffer variable is created, allowing the recall of data from up to five seconds ago. Initially, to differentiate unplanned events from others, several data variables are checked for anomalies. For instance, if there were insufficient satellites during the disengagement, indicating a poor connection and inaccurate localisation, it would be flagged as an unplanned event.

When there are more than two errors received for an event, meaning by error as an indicator of an unplanned event categorisation like a low number of satellites, it gets categorised as unplanned, and the panel categorises it as Manual inspection needed, errors: received errors. If the disengagement does not indicate an unplanned event, it is checked for the occurrence of the five described planned events. Every planned disengagement gets searched for indicators of the defined planned events. Thus, it is possible for an event to receive more than one planned event categorisation. In the case of an event that gets no categorisation and no errors, it will be categorised as Manual inspection needed. Around half of the analytics are continuously done during the disengagement, the rest get analysed after the event, and everything gets printed out to the panel. After the event has ended, the collected and analysed information is printed to the Events section: Event ID, Start time, End time and Categorisation with errors if there are any.

Step 6. Configuration of the FoxGlove panel

In this thesis, the development of the FoxGlove custom panel code is finalised to integrate seamlessly with the data obtained from the ROS1 file provided by ADL. This optimisation ensures efficient data flow and enables the analysis to handle various test runs using ROS1 files from ADL, thereby enhancing its utility for future applications. However, other users who want to use the DCM must verify the compatibility of their data types and use message converters or modify the code as necessary for it to work properly. For other users, a read.md file will be created to describe the integration process.

Combining these steps into one cohesive method involves managing the development of the DCM in an organised and methodical manner. This includes researching FoxGlove custom panel development capabilities, identifying clear patterns in the data, proposing a methodology, conducting expert interviews for methodology improvement, and finally, developing the FoxGlove custom panel. Integrating these steps coherently ensures a systematic approach to the DCM development process, leading to effective data analysis and panel functionality within FoxGlove Studio.

3.2 Steps taken to validate the DCM

A thorough case study will be presented to validate the Disengagement Classification Method (DCM) described in the previous chapter. This case study will be carried out step by step to ensure adequate validation. A case study was conducted to validate the DCM. The steps of the case study are as follows:

Step 1. Define the scope
Step 2. Retrieve the ADL files that were previously analysed manually
Step 3. Apply the DCM steps
Step 4. Compare the outcome of DCM with the outcome of the manual analysis
Step 5. Receive feedback from ADL.

The first step will clearly define the scope of the validation process. This will include outlining the goals, identifying the dataset being examined, and supporting the selection criteria. The reasoning for selecting the dataset will be explained, highlighting its extensive scope and previous analysis by ADL.

After defining the scope, the focus will shift to retrieving the ADL files that were previously examined by hand. This will require accessing the relevant files from the Tartu dataset in ROS1 files and ensuring that they comply with the validation study specifications. Once the dataset is received, the next step will involve the methodical implementation of each step described in the DCM. Using a custom panel developed with FoxGlove, this method will implement the DCM algorithms in the code and automatically analyse the ADL files. After the DCM is applied, a careful comparison will be made between the automated and manual analysis results that ADL had previously done. Every disengagement occurrence will be examined and categorised according to previously established requirements, and differences or similarities between the two approaches will be identified as part of this evaluation. Including feedback from ADL researchers will be important to the validation process. In this stage, ADL will be asked for their thoughts and opinions about the precision, effectiveness, and usability of the DCM results. All feedback will be carefully examined and considered for possible improvements or adjustments to the DCM process.

4 Results

In this section, we present the outcomes of our method, detailing the development and functionality of the custom panel within FoxGlove, along with the Disengagement Classification Method (DCM). The custom panel integrates live data streams, event tracking, and categorisation features for the analysis. Additionally, the DCM method describes the planned and unplanned disengagement events, using a systematic categorisation scheme with defined threshold values. We further discuss the comparison between the DCM and manual analysis methods, addressing efficiency gains and limitations encountered during implementation.

4.1 Custom Panel in FoxGlove

The developed custom panel source code can be found inside the “ADL2023.zip” in other files named “ADL2023.tsx” Additionally, there is a “read.md” file with instructions on how to use the panel. The developed custom panel in FoxGlove, as visualised in Figure 4, contains mainly of three sections: live data, events, current event. The live data section contains continuous data streams of the necessary data for analysts, which is the same data that has been used in the pre-categorisation. The data gets updated by the second or by the framerate of the current frame. The events section is scrollable to fit many events. Events will get updated after the disengagement has ended, as will the final analytics at the end of the event. This section contains the following information about each event: Event ID, Start time, End time and Categorisation with errors if there are any. Here, the analyst will receive the pre-categorised events, indicating which events need to be analysed more in-depth and which do not. The planned events can be categorised as the following: Pedestrian crossing, Temporary roadwork, Bus stop, Turnback, Give way. Unplanned events can be categorised as Manual inspection needed or Manual inspection needed, errors: list of received errors. The current event section has been added to see categorisations and errors as they occur and for the analyst to know that the code has detected a disengagement. This section is similar to the events section, but all of the values are 0, except the ID showing the analyst what the next event will be, indicating there is no current event happening now. It can also be determined whether an event is happening at the moment in the calculated data value “Is event happening ” in the first section. As all of these values from all of these sections are either from the ROS1 file or calculated, the analyst does not have to put much effort into finding data. As unplanned events are what need the most analysis, this function of calculated errors becomes very helpful and time-saving.

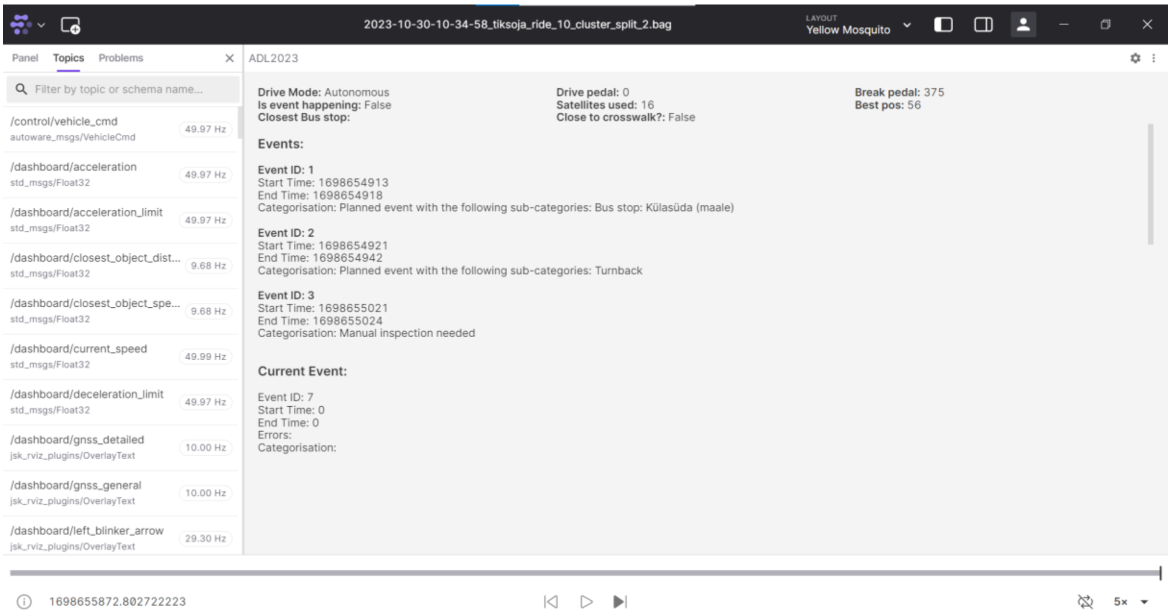

Figure 4 Custom panel in FoxGlove

4.2 The Disengagement Classification Method (DCM)

The Disengagement Categorisation Method is divided into two parts: categorisation by definition and categorisation scheme with threshold values. Additionally, the events were defined and the hierarchy of categorisation. The results of the DCM will be described in this chapter and as seen in Table 1.

Events: This thesis defines events as disengagement periods in which the safety driver is in charge of driving the vehicle. These events occur due to the law requirements and human safety reasons. Even if the line between them is thin, the events must be categorised into planned and unplanned events.

Planned – These events are described as disengagements where the safety driver takes over due to agreements made before the drive.

Unplanned – These events are described as disengagements where the safety driver takes over due to unsafe circumstances from the vehicle behaviour.

Hierarchy of categorisation:

1. Check if the event had more than two errors, meaning by error as an indicator of an unplanned event categorisation, then it will be categorised as an unplanned event.
2. If the event was not categorised as unplanned, check for requirements for planned events and categorise if suitable.
3. When the event does not fit into any category, it will be categorised as unplanned.

4.3 Categorisation Scheme with Threshold Values

Pedestrian crossing

1. Pedestrian crossing location in regards to disengagement time – Is there a pedestrian crossing within 17 m:
    - a. Yes – Continue
        - 1. Obstacle – During the disengagement, is there an obstacle detected in < 20 m and > 6 m with the velocity of < 9 m/s and > -9 m/s and the velocity is not 0:
            - a. Yes – Categorise the event as Pedestrian crossing
            - b. No – Categorise the event as Unplanned
    - b. No - Categorise the event as Unplanned

Temporary roadwork

1. Obstacle - During the disengagement, is there an obstacle detected >= 15 m and its velocity is < 5 m/s and > -5 m/s:
    - a. Yes – Continue
        - i. Start and end on the planned path – The disengagement starts and ends on the planned path, with the difference of the planned and actual path < 1m:
            - 1. Yes – Continue
                - a. Lots of steering – The difference of the planned and actual path < 1 m
                    - i. Yes – Categorise the event as Temporary roadwork
                    - ii. No – Categorise the event as Unplanned
                - b. No – Categorise the event as Unplanned
            - 2. No - Categorise the event as Unplanned
    - b. No – Categorise the event as Unplanned

Bus stop

1. Bus stop location - Coordinates of are in a bus stop location < 10 m during the disengagement:
    - a. Yes – Continue
        - i. Velocity – Velocity of the vehicle is <1m/s at the start of disengagement
            - 1. Yes - Categorise the event as Bus stop
            - 2. No - Categorise the event as Unplanned
    - b. No - Categorise the event as Unplanned

Turnback

1. Orientation – Start of disengagement orientation differs from end orientation > 110 and < 225 degrees:
    - a. Yes – Categorise the event as Turnaback
    - b. No - Categorise the event as Unplanned

Give Way

1. Turning signal – During the event, the turn signal is used, and the next steering state of that location is either 1 or 2 (right or left)**:**
    - a. Yes – Continue

        i. Sudden braking – At the start of the disengagement, the brakes are engaged noticeably >= 150
            1. Yes – Categorise the event as Give Way
            2. No - Categorise the event as Unplanned
    b. No - Categorise the event as Unplanned

Unplanned events

1. GNSS metrics during the disengagement:
    a. RTK Fixed best pose position type is not 56
        - Yes – Add to error messages "Bad BESTPOS"
    b. Not enough satellites < 15
        - Yes – Add to error messages "Not enough satellites"
    c. The standard deviation is bad > 0.2m
        - Yes – Add to error messages "Latitude or Longitude standard deviation is bad"
    d. INSPVA is not 3 (INS_SOLOUTION_GOOD)
        - Yes – Add to error messages "INSPVA is not 3"
2. At the beginning of the disengagement, the drive pedal is being pressed
    a. Yes – Add to error messages "Drive pedal is being pressed at the beginning of the disengagement"

If none of these pass, the error messages will be empty and get categorised as Manual inspection needed.

4.4 Categorisation by Definition

Table 1 Categorisation by Definition

Name	Planned or not	Description	Variables
Unplanned	Unplanned	Check first if the event could be unplanned. Check the GNSS metrics, if one of them is bad, then GNSS is bad. If the RTK Fixed position type is not 56. If there were less than 14 satellites. If the standard deviation was bigger than 0.2m. If the drive pedal is immediately pressed at the beginning of the disengagement. Disengagement gets categorised as unplanned if at least 3 of 4 are true.	• GNSS metrics are bad ○ RTK Fixed best pose position type = !56 ○ Satellites <15 ○ Standard deviation >0.2m • The drive pedal is pressed at the start of disengagement
Pedestrian crossing	Planned	When approaching a pedestrian crossing (zebra), it is agreed upon that when a human is waiting to cross or is crossing it, the safety driver takes over for pedestrian safety.	• Pedestrian crossing location +-17m • Obstacle in our path, ○ Closest object velocity <9 and >-9 and not 0 ○ Closest object distance <20 and >6
Temporary roadwork	Planned	As agreed upon, the safety driver takes over when temporary roadwork is ahead. During the disengagement, the vehicle path is disrupted due to temporary roadwork and must drive around it, but returns to the	• Obstacle in our path, ○ Closest object velocity <5 and >-5 and not 0 ○ Closest object distance >= 15

		planned path. During the disengagement, the planned path does not match the steering.	• Disengagement starts and ends on the planned path <1m • The difference of the planned and actual path <1m
Bus stop	Planned	As agreed upon, the safety driver takes over when stopping at the bus stop. This can be located with a set of bus stops. During the disengagement, the vehicle location is near (+-10m) of a bus stop location. Additionally, the vehicle's velocity is less than 1m/s as it has come to a full stop.	• Bus stop location <10m • Velocity < 1km/h at the start of disengagement
Turnback	Planned	As agreed upon, the safety driver takes over to do manual turnbacks. During the disengagement, the vehicle makes a 180-degree turn. As a result of this, the orientation differs 180 degrees (+-25 degrees).	• Start of disengagement orientation differs from the end orientation > 110 and < 225 degrees
Give way	Planned	As agreed upon, when coming up to a give-way intersection, the safety driver must ensure everyone's safety. During the disengagement, the vehicle is at an intersection location (+-10m). If the safety driver suddenly stops to see if it is safe to continue, then the disengagement results from a sudden brake pedal increase (>150).	• During the event, the turn signal is used, and the next steering state of that location is either 1 or 2 • At the start of disengagement, the brake pedal is noticeably pressed >150

4.5 The DCM versus Manual Method

There are four possible categorisation outcomes for the analyst when using the panel:

1. Unplanned without any errors
2. Unplanned with errors
3. Planned with one categorisation
4. Planned with many categorisations.

In the case of the first one, this event did not catch any established errors and must be analysed manually, but the analyst can eliminate the established errors as the code has already been checked for these. When the unplanned event shows errors, the analyst would not have to manually check those variables covered in established errors. Instead, the analyst can focus on categorising the unplanned event, as in the DCM, unplanned events were not sub-categorised. When a planned event gets categorised with only one categorisation, this event has all of the defined indicators of DCM for the categorisation result. It is up to the analyst to decide whether to check this manually or to focus on the unplanned events. However, when a planned event gets many categorisations, meaning that it was flagged in many indicators of the DCM planned events, this should be analysed as it could be an odd case with many events happening simultaneously. For example, when a turnback has been done near a bus stop.

The manual analysis method previously done by ADL can be divided into 6 steps:

1. Press play in the application to start rendering data from the ROS1 file
2. When the drivemode data variable value turns to 0, write down the start time in Excel
3. Analyse image and video data to understand the reasoning behind the disengagement
4. If needed, analyse other data, numbers, text, etc
5. Categorise the event
6. Write in Excel the end time of the disengagement.

As the video goes on, there would be more disengagements to analyse and repeat steps 2-6.

Understandably, using the developed panel to generate disengagement data, such as event ID, start time, end time, and categorisation with errors, is much more efficient. As there is no need for rigorous manual work, the analyst can focus on unplanned events.

As for the shortcomings of the developed panel, the timestamps could not be generated immediately due to the inability to preload the data at the beginning. Meaning that the analyst cannot "jump to" the next disengagement on the video progress bar. Additionally, as the data gets generated with current data, for the best result, the analyst should not skip time on the progress bar during the disengagement. This could cause the loss of some data and interrupt working functions in the code. It was found that there were data path differences in the 2022 and 2023 ROS1 files. The 2022 year file did not use the same mapping. Thus, the method realised for locating crosswalks and intersections did not work on the 2022 year files. As ADL no longer uses the system used in 2022, there was no use in developing a separate method to locate crosswalks and intersections for 2022 files. The panel in FoxGlove updates when it receives a new message from the data, which causes an error catching the last disengagement if the data stream ends during a disengagement. As the panel does not get updated after the data stream ends, it will not be updated with information that the disengagement has ended, and it cannot analyse the event. Luckily, this does not occur often at all.

As there are no records of the time spent analysing the disengagements manually by ADL, it can not be compared to the time spent analysing disengagements with the custom panel in FoxGlove with DCM. The time spent analysing with the custom panel in FoxGlove could not be calculated very accurately, and as a result, would always depend on different variables like length of the test-drive, number of disengagements and if they are planned or unplanned, comicality of the disengagements, etc.

4.6 Validating and Results

Four ROS1 files were selected for the testing, with many disengagements being defined as one of the five defined planned events categorisation in this thesis. These ROS1 files contain a total of 46 disengagements. These disengagements are divided into 14 planned events and 32 unplanned events. The 5 defined planned events are Pedestrian crossing, Temporary roadwork, Bus stop, Turnback and Give way. The unplanned events are OBS, Safety, Bad engage and Localization. The custom panel results in Manual inspection needed when an event gets categorised as unplanned. For this analysis, the manual method analysis of ADL results was taken as the base, and these were accepted as the absolute truth. To retrieve the results for comparison to the manual method, all of the ROS1 files were run using the custom panel in FoxGlove with applied DCM. The results are documented in Table 3[8]. The results will be interpreted by calculating precision (1), recall (2) and accuracy (3) and presented by ROS1 files in Table 2.

Here are the following formulas used (1)(2)(3), note that TP stands for True Positive, TN stands for True Negative, FP stands for False Positive and FN stands for False Negative.

$$Percision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$Accuracy = \frac{TP+TN}{P+N} \tag{3}$$

The results will be divided into three results categories: DCM Classification, DCM sub-classification, and DCM sub-classification in 5 defined planned events. Firstly, it must be noted that the custom panel caught every occurrence of disengagement. Additionally, it must be said that for this analysis, when an event got many categorisations if it did contain the correct one, it resulted in a positive result. This is because many things might happen simultaneously, but the manual method has just listed the most important one.

Table 2 Precision, Recall and Accuracy by ROS1 files of Comparison of Ground truth and DCM results

ROS1 file	Subject of analysis	Precision	Recall	Accuracy
Ride 7	DCM Classification	87.5%	100%	95%
Ride 7	DCM sub-classification	87.5%	100%	87.5%

[8] Table 3 is located in the Appendix

Ride 7	DCM sub-classification in 5 defined planned events	100%	100%	100%
Ride 12.1	DCM Classification	100%	100%	100%
Ride 12.1	DCM sub-classification	100%	100%	100%
Ride 12.1	DCM sub-classification in 5 defined planned events	33.3%	100%	33.3%
Ride 12.2	DCM Classification	50%	100%	81.8%
Ride 12.2	DCM sub-classification	50%	100%	50%
Ride 12.2	DCM sub-classification in 5 defined planned events	100%	100%	100%
Ride 10.2	DCM Classification	75%	100%	83.3%
Ride 10.2	DCM sub-classification	50%	100%	50%
Ride 10.2	DCM sub-classification in 5 defined planned events	66.7%	100%	66.7%
All ROS1 files	**DCM Classification**	**78.1%**	**100%**	**90%**
All ROS1 files	**DCM sub-classification**	**71.9%**	**100%**	**71.9%**
All ROS1 files	**DCM sub-classification in 5 defined planned events**	**75%**	**100%**	**75%**

Note: The used files are marked in the table: "2023-10-16-14-39-15_tiksoja_ride_07_sfa.bag" as Ride 7, "2023-10-30-14-28-38_tiksoja_ride_12_sfa_split_1.bag" as Ride 12.1 and "2023-10-30-14-43-40_tiksoja_ride_12_sfa_split_2.bag" as Ride 12.2, "2023-10-30-10-34-58_tiksoja_ride_10_cluster_split_2.bag" as Ride 10.2.

The first result looks at whether the custom panel categorised events into planned or unplanned correctly. Out of the 46 disengagements, 4 events were wrongly categorised, and unplanned events were categorised as planned events in all of these four cases, meaning that the remaining 42 events were correctly categorised accordingly as planned or unplanned. This results in the Planned and unplanned precision of 78%, recall of 100% and accuracy of 90%. Meaning that it did catch all of the planned events, but in 4 cases, it also categorised unplanned events as planned. This was sometimes due to a fantom object, meaning that the car received that an object was blocking the way and started to brake, but in reality, there was no object. Additionally, as the vehicle was at a pedestrian crossing, the DCM categorised this event as Pedestrian crossing.

The second result looks at just the results of the planned events provided by the custom panel. This means that if we do not know if the categorisation and sub-categorisation of the planned event were true, what would the result be? As there were a total of 19 planned event categorisations by the custom panel, 4 of these were wrongly categorised. This results in precision and accuracy of 72% and recall of 100%.

The final result, there were 15 planned events of these 5 defined planned event categories for this thesis: Pedestrian crossing, Temporary roadwork, Bus stop, Turnback and Give way. Here, we are looking at whether only these 5 events did receive the right categorisation. Only 3 of these 15 events were wrongly categorised, leaving us with 12 planned events with the right categorisation. This results in precision and accuracy of 75% and recall of 100%. For example, when two disengagements happened right after each other, both of these were categorised as Turnbacks, but when the DCM calculated the first disengagement orientation difference as around 0.17 degrees, it did not fit the criteria and was not categorised as Turnback. However, the second disengagement orientation difference was around 170 degrees and was categorised as Turnback correctly. Additionally, as this happened at a bus stop, the first event was wrongly categorised as a Bus stop.

In conclusion, while the custom panel accurately identified disengagements, there were occasional errors, particularly in categorising planned versus unplanned events and specifying subcategories within planned events.

4.7 Feedback from ADL

The following feedback was received from Edgar Sepp at ADL.

4.7.1 General impression

The opinion for the developed tool is based on a brief demo by the author. Unfortunately, we didn't manage to set up the tool on another computer for more thorough testing. Nonetheless, the tool's functionality and capabilities were clear enough to have this initial opinion.

The tool's primary function is to categorise disengagements in the autonomy into planned and unplanned events, with additional subcategories for planned disengagements. The planned disengagements are events that are currently outside of the current operational design domain (ODD) of our car (we don’t have the functionality or capability to handle these situations yet, and that is why in these situations, we always disengage the autonomy).

This aims to reduce the workload of human analysts who wouldn't have to go through all the disengagements and focus more on unplanned events (where something went wrong). The tool would be helpful only if it is able to accurately label the planned disengagements, so that it could be trusted.

Despite the student's limited timeframe, and lack of prior knowledge about rosbags, the data, and the domain in general, the initial results were very promising. The current rule-based classification with the selected indicators and their values showed quite a few errors with planned disengagements. With further refinement, incorporating additional indicators and methods such as machine learning algorithms, the tool could yield more accurate results, enhancing confidence and potentially bringing some automation into disengagement labelling.

4.7.2 Usability

Usage of the developed tool is simple once it is installed and configured. It can be loaded as a Foxglove panel, and when the rosbag is loaded, it scans through all of it and classifies the disengagements (events) as it reaches those. The rosbag files can be very big and long (40+ minutes of driving and more than 200Gb of data), and thus, the processing can take quite a long time (several minutes). With the current implementation, it is impossible to process the bags offline. The processing script is tied to Foxglove and runs when the bag file is loaded. Ideally, it would be nice if the processing could be done before and when loaded, the analyst can click through already categorised disengagements.

4.7.3 Functionality

There is not much functionality in how users can interact with the tool, and it does not need much. It needs to do well with the classification of disengagements. The main desired functionality would be a list of disengagements with classifications and an option to click on events for automatic placement on the timeline. From there on the Foxglove standard visualisation panels could be used. Currently, the analyst has to manually scroll through the timeline to find the exact locations for the disengagements.

Suggestions for future

- Focus on making the event list interactive for efficient navigation.
- Consider implementing offline processing to provide immediate access to the event list upon loading the rosbag.

- The custom panel currently display some data from the rosbags at that specific timestep and I find that not that useful (for example, lat lon standard deviations or drive and brake pedal values). For the analyst, much more interesting are the trends of what happened before, how this reacts after that etc… So I would suggest skipping these from custom panels and using already existing and quite flexible Foxglove panels for those.

5 Conclusions

This thesis focused on developing and validating the Disengagement Classification Method (DCM) for autonomous driving analysis. Using FoxGlove custom panel developing features, our aim was to simplify the process of identifying and categorising disengagement occurrences, eventually leading to improved safety and efficiency in autonomous vehicle research.

Summary of Findings

The main results of our analysis show the efficiency and usability of the customised panel integrated with the DCM. By following a methodical approach, we accomplished the following. Our approach included many stages in developing a detailed methodology, from researching the custom panel framework to proposing a categorisation scheme consisting of particular requirements and threshold values. The DCM was successfully implemented in the FoxGlove custom panel, demonstrating its ability to automatically evaluate disengagement, accurately categorise them, and straightforwardly provide the results. The DCM was validated through a procedure that involved comparing it with manual analysis and gathering feedback from experts in the field. This method demonstrated that the DCM is precise and successful at detecting disengagement instances. Using the customised panel and DCM results in notable enhancements in efficiency as compared to manual analysis method, enabling analysts to dedicate more attention to unplanned events and essential safety issues.

Limitations and Future Directions

Although our study accomplished important objectives, it is essential to point out limitations and propose future research and improvement opportunities. For technical challenges we encountered technical difficulties related to differences in data paths in ROS1 files. As a result, we had to focus only on the 2023 year data. As for the manual analysis comparison, ADL's manual analysis lacked specific descriptions of the events, causing problems and asking for clarification requests from Edgar Sepp. Future research might look into methods to improve the documentation of manual analysis techniques, offering more precise directions to analysts and accelerating the analysis process. For the improvements to the custom panel, we could use better timestamp generation and handle possible issues when data streams suddenly end. Classifying unplanned events in further detail is an important topic for future research. To further improve the accuracy and efficiency of the categorisation process, future researchers or students might expand upon our work by methodically reducing the remaining unplanned events.

Final Remarks

In conclusion, our research results in a notable advancement in the automation of disengagement classification for research on autonomous driving. Through the creation of the DCM and its integration into the FoxGlove custom panel, we have given researchers a helpful tool for improving overall safety in autonomous vehicle development by categorising disengagements. We thank all individuals and ADL who contributed to this research project, and we intend to continue advancing automated analytical tools for autonomous driving.

Validation Results

In addition to developing the Disengagement Classification Method (DCM) and thoroughly testing, it was evaluated for its effectiveness with ROS1 files from ADL. The custom panel, with applied DCM, showcased notable precision and accuracy throughout the analysis. The results of the testing revealed several key findings.

The custom panel efficiently evaluated disengagement occurrences, accurately categorising them according to previously defined criteria in the DCM. With methodological development, including research on the custom panel framework and the defining of categorisation schemes, the DCM was integrated into the FoxGlove custom panel. Validation procedures, which involved comparison with manual analysis and feedback from ADL expert, confirmed the precision and success of the DCM in detecting and categorising the disengagements.

References

[1] Z. Chai, T. Nie and J. Becker, “Autonomous Driving Technology Empowers Future Travel: Safe, Efficient, and Intelligent Mobility are Coming Soon,” in *Autonomous Driving Changes the Future,* Springer Singapore, 2020.

[2] American National Standards Institute, “Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles,” 30 April 2021. [Online]. [Accessed 24 March 2024].

[3] “The Lab: Vehicle,” [Online]. Available: https://adl.cs.ut.ee/lab/vehicle. [Accessed 24 March 2024].

[4] “Research: Applied Research on Development of Autonomous Driving Lab for Level 4 Autonomy,” [Online]. Available: https://adl.cs.ut.ee/research/projects/bolt1. [Accessed 1 April 2024].

[5] S. Singh, “Critical reasons for crashes investigated in,” NHTSA’s National Center for Statistics and Analysis, Washington, DC, 2015.

[6] Z. Wadud, D. MacKenzie and P. Leiby, “Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles,” *Transportation Research Part A: Policy and Practice,* vol. 86, pp. 1-18, 2016.

[7] “SAE Levels of Driving Automation™ Refined for Clarity and International Audience,” 3 March 2021. [Online]. Available: https://www.sae.org/blog/sae-j3016-update. [Accessed 27 March 2024].

[8] “About Us,” [Online]. Available: https://adl.cs.ut.ee/discover/about. [Accessed 24 March 2024].

[9] “The Lab: Software,” [Online]. Available: https://adl.cs.ut.ee/lab/software. [Accessed 24 March 2024].

[10] “The Lab: Simulation,” [Online]. Available: https://adl.cs.ut.ee/lab/simulation. [Accessed 24 March 2024].

[11] “The Lab: Parking lot,” [Online]. Available: https://adl.cs.ut.ee/lab/parking-lot. [Accessed 24 March 2024].

[12] “The Lab: Demo track,” [Online]. Available: https://adl.cs.ut.ee/lab/demo-track. [Accessed 24 March 2024].

[13] [Online]. Available: https://foxglove.dev/. [Accessed 19 February 2024].

[14] “Panels: Introduction,” [Online]. Available: https://docs.foxglove.dev/docs/introduction. [Accessed 20 February 2024].

[15] F. M. Favarò, S. O. Eurich and N. Nader, “Analysis of Disengagements in Autonomous Vehicle Technology,” in *2018 Annual Reliability and Maintainability Symposium (RAMS),* Reno, NV, USA, 2018.

[16] E. Sepp, “Tiksoja “on-demand transportation” 2023 Autoware.ai vs Autoware mini !#?,” Tartu, 2023.

[17] [Online]. Available: https://docs.foxglove.dev/docs/visualization/extensions/guides/create-custom-panel/#examplepaneltsx. [Accessed 24 March 2024].

[18] E. Weon, “Building a Custom React Panel with Foxglove Studio Extensions,” 1 September 2022. [Online]. Available: https://foxglove.dev/blog/building-a-custom-react-panel-with-foxglove-studio-extensions. [Accessed 3 March 2024].

[19] U. Stojanovic, S. Stefanovic, G. Ferenc and A. Rikalo, “Analysis of protocols used for visualization in automotive industry,” in *2023 Zooming Innovation in Consumer Technologies Conference (ZINC)*, Novi Sad, 2023.

[20] “What is AI?,” [Online]. Available: https://www.ibm.com/topics/artificial-intelligence. [Accessed 2 April 2024].

[21] “React,” Meta Open Source, [Online]. Available: https://react.dev/. [Accessed 5 May 2024].

Summary of Figures and Tables

Appendix 1. DCM validation raw data

Table 2 shows the raw data of the manual classification of four ROS1 files (ground truths – column: Manual method by ADL), the results of the DCM classification and sub-classification (columns: DCM Classification, DCM sub-classification), and the comparison between the Manual method by ADL and the results of the DCM. Additionally, the table shows the results of DCM Classification (column: Result in DCM Classification), DCM sub-classification (column: Result in DCM sub-classification) and DCM sub-classification in 5 defined planned events (column: Result in DCM sub-classification in 5 defined planned events).

Table 3 Comparison of Ground truth and DCM results

ROS 1 file	Event ID	Manual method by ADL	DCM Classification [Planned, Manual inspection needed]	DCM sub-classification	Result in DCM Classification	Result in DCM sub-classification	Result in DCM sub-classification in 5 defined planned events
Ride 7	**1**	**Give way**	Planned	Give way	True positive	True	True
Ride 7	2	Safety	Manual inspection needed		True negative		
Ride 7	**3**	**Pedestrian crossing**	Planned	Pedestrian crossing	True positive	True	True
Ride 7	**4**	**Give way**	Planned	Give way	True positive	True	True
Ride 7	5	OBS	Manual inspection needed		True negative		
Ride 7	6	Bad engage	Manual inspection needed		Ture negative		
Ride 7	7	OBS	Manual inspection needed		True negative		
Ride 7	8	Safety	Planned	Pedestrian crossing	False positive	False	
Ride 7	9	OBS	Manual inspection needed		True negative		
Ride 7	**10**	**Turnback**	Planned	Turnback, Give way	Ture positive	True	True
Ride 7	11	Safety	Manual inspection needed		True negative		
Ride 7	**12**	**Give way**	Planned	Give way	True positive	True	True
Ride 7	13	Safety	Manual		True negative		

			inspection needed				
Ride 7	14	Bad engage	Manual inspection needed		True negative		
Ride 7	15	Safety	Manual inspection needed		True negative		
Ride 7	16	Safety	Manual inspection needed		True negative		
Ride 7	17	Safety	Manual inspection needed		True negative		
Ride 7	**18**	**Pedestrian crossing**	Planned	Pedestrian crossing	True positive	True	True
Ride 7	19	Safety	Manual inspection needed		True negative		
Ride 7	**20**	**Pedestrian crossing**	Planned	Pedestrian crossing	True positive	True	True
Ride 12.1	**1**	**Give way**	Planned	Pedestrian crossing	True positive	True	False
Ride 12.1	**2**	**Pedestrian crossing**	Planned	Pedestrian crossing	True positive	True	True
Ride 12.1	3	Bad engage	Manual inspection needed		True negative		
Ride 12.1	4	Safety	Manual inspection needed		True negative		
Ride 12.1	5	Safety	Manual inspection needed		True negative		
Ride 12.1	**6**	**Give way**	Planned	Pedestrian crossing	True positive	True	False
Ride 12.1	7	OBS	Manual inspection needed		True negative		
Ride 12.1	8	Localization	Manual inspection needed		True negative		
Ride 12.1	9	OBS	Manual inspection needed		True negative		
Ride 12.2	**1**	**Turnback**	Planned	Turnback, Give way	True positive	True	True
Ride 12.2	2	Safety	Manual inspection needed		True negative		
Ride 12.2	3	Safety	Planned	Give way	False positive	False	
Ride 12.2	4	OBS	Manual inspection needed		True negative		

Ride 12.2	5	Safety	Manual inspection needed		True negative		
Ride 12.2	6	OBS	Manual inspection needed		True negative		
Ride 12.2	7	Safety	Planned event	Give way	False positive	False	
Ride 12.2	**8**	**Pedestrian crossing**	Planned event	Pedestrian crossing	True positive	True	True
Ride 12.2	9	OBS	Manual inspection needed		True negative		
Ride 12.2	10	OBS	Manual inspection needed		True negative		
Ride 12.2	11	Safety	Manual inspection needed		True negative		
Ride 10.2	**1**	**Turnback**	Planned event	Bus stop	True positive	True	False
Ride 10.2	**2**	**Turnback**	Planned event	Turnback	True positive	True	True
Ride 10.2	3	OBS	Manual inspection needed		True negative		
Ride 10.2	4	OBS	Manual inspection needed		True negative		
Ride 10.2	5	OBS	Planned event	Pedestrian crossing	False positive	False	
Ride 10.2	**6**	**Pedestrian crossing**	Planned event	Pedestrian crossing, Give way	True positive	True	True

Note: The used files are marked in the table: “2023-10-16-14-39-15_tiksoja_ride_07_sfa.bag” as Ride 7, “2023-10-30-14-28-38_tiksoja_ride_12_sfa_split_1.bag” as Ride 12.1 and “2023-10-30-14-43-40_tiksoja_ride_12_sfa_split_2.bag” as Ride 12.2, “2023-10-30-10-34-58_tiksoja_ride_10_cluster_split_2.bag” as Ride 10.2.

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