Traffic Data Evaluation for Automated Driving Handover Scenarios

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Abstract: At the current stage of automated vehicle development, the control handover from the system to a human driver (and back) is inevitable. It is essential to distinguish between situations in which the handover is possible and in which it could be dangerous and is therefore highly undesirable. We evaluated traffic situations based on two modalities: own vehicle state and traffic objects. To assess the former, supervised machine learning was applied, reaching an accuracy of 80.3% and specificity of 77.8% with Multilayer perceptron Classification. Traffic objects data were subject to different clustering techniques. The final grouping was done according to manually elaborated rules, resulting in a range of situation complexity scores. Improving the discriminative power of vehicle state classification, including driver's state and weather information, and predicting situation complexity are to be addressed in future research.

1 INTRODUCTION

The future of mobility is automated. Researchers all over the world are working towards fully automated vehicles. Connected and cooperative automated mobility (CCAM) is one important keystone to accomplishing that goal. Vehicles by themselves can only have a limited view as today the driver of a vehicle. To enhance the safety and efficiency of road traffic, cooperation and information exchange are vital to see around the corner and to help traffic run smoothly. The research goal of fully automated condition-independent driving (SAE Level 5 (SAE International, 2018)) is not yet on the horizon for market introduction. Levels 3 and 4 serve as transition steps from lower-level driver-support features. At the current moment, Level 3 automated vehicles (AV) just start being publicly available (Honda, 2020). Level 3 implies occasional handover from autonomous to human control, which is one of its challenges. In this paper, we particularly focus on the control handover from automated to manual driving. There are many possible reasons for this handover. Automated driving could only be allowed on some roads or road classes, the driver could indicate the willingness to drive because she wants the pleasure to drive or feels more comfortable driving in a certain situation. The handover, however, should not be a surprise for the driver and therefore requires the driver's awareness and sufficient transition time (Trimble et al., 2014). It can be planned, and the transition can be done smoothly in situations, where the traffic allows a switch of responsibility. There are, however, more demanding and challenging situations. What if an automated vehicle is not able to steer through a certain situation because of technical limitations or the fact that not enough sensor information is available (e.g., due to weather conditions or malfunction)? In some situations, especially in urban environments, the handover is not possible. For example, at a confusing construction site or an intersection with many pedestrians, a human driver needs time to adapt to the situation and gain an overview.

In this paper, situations that could hinder a handover process from the automated driving to the driver are investigated. The focus is on determining which situations in an urban environment are critical and should not be used for handover scenarios.

The paper is structured as follows: first, the related work is presented. Then, the methods of how we handled the data are described in Section 3. In Section 4, the results of the data modalities are

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analyzed. The conclusion in Section 5 features the significance of the results that were obtained and highlights open research questions.

2 RELATED WORK

Most research related to the transition from automated driving to manual driving is related to the human factor of reaction to the takeover request (TOR) (Eriksson and Stanton, 2017; Clark et al., 2020). The awareness of the drive may be increased by augmented reality (Schroeter and Steinberger, 2016). Some research sees the decision between the two options: drivers are allowed to do other tasks or drivers have to monitor the system at all times (Borojeni et al., 2017). The traffic situation has an important impact on the reaction time and the probability of accidents (Radlmayr et al., 2014; Gold et al., 2016).

To assess the possibility of a takeover, the time necessary for the driver to react is the decisive factor (Ayoub et al., 2022). Some research estimates the readiness of the driver to take over the driving task based on the complexity of the traffic situation, the secondary task, and the gazes at the road (Braunagel et al., 2017). For this estimation, only vehicle sensors are used. To our knowledge, no research was conducted using the combination of infrastructure and vehicle sensor information to estimate factors for takeover. More information can help to lower the stress factor during and shortly after the handover (Kerautret, 2023)

3 MATERIALS AND METHODS

3.1 Data Collection

Traffic situation information consisted of data gathered from the following sources:

- Own vehicle state, consisting of sensor data from the vehicle Controller Area Network (CAN) bus (ISO, 2015) system.
- Information from message exchange between other road users and infrastructure via Vehicle-To-Everything (V2X) communication, such as:
  - Detected road users in the immediate vicinity by optical sensors (e.g., traffic cameras) at intersections; distribution of this information by Collective Perception Messages (CPM) (ETSI, 2019a) of Intelligent Transportation System (ITS) Roadside Stations (IRS);
  - Other V2X communication like warnings of dangerous events via Cooperative Awareness Messages (CAM) (ETSI, 2019c) and Decentralized Environmental Notification Messages (DENM) (ETSI, 2019d) from ITS Vehicle Stations (IVS's) and IRS's (e.g., broken down vehicle warning, pedestrian collision warning, etc.).
- Topology information of intersections: MAP (ETSI, 2019b) information at traffic intersections.
- Weather conditions: weather information provider in the backend.

Since all the data were collected under similar weather and lighting conditions (daylight, warm temperature, zero precipitation), the weather data were not included in the further analysis as a discriminative factor.

To control the condition of the driver, driver-monitoring functionality and corresponding equipment must be included in an (automated) vehicle. However, in the current research, data on the driver's condition are not available yet, so the evaluation is based only on non-driver data.

Description of traffic situations included 1) data recording, 2) aggregation and fusion of information from several sources, and 3) storage in the database. Data collection and pre-processing are described in (Otte et al., 2021). Several test drives were performed to generate the (training) data in the city of Saarbrücken. It must be noted that our test vehicle was not automated so the control handover was explored hypothetically.

A traffic situation is a certain point in time represented by the vehicle state and the detected objects at the corresponding traffic intersection. A test drive represents a chain of several successive traffic situations. The time interval between two situations is one second. Since situations are snapshots, they were assessed individually, or independently from the previous and following states. During the execution of several test drives, a total of 7,854 traffic situations were recorded and stored in the fusion database.

The goal of the evaluation is to determine the degree of suitability of traffic situations for the handover, in other words – the degree of situation complexity. To keep the decision-making process transparent and explainable, a cumulative multimodal approach to situation evaluation was chosen. One modality was sensor data of the test vehicle, and the other modality was the information on detected traffic objects. The final decision depended on the outcomes of each modality evaluation.

3.2 Vehicle Data Modality

Own state of the vehicle has a direct straightforward influence on the control handover. “Handover possible” and “handover not possible” are binary labels that could be assigned to situations by human raters and are further used for supervised machine learning (classification algorithms and logistic regression) (Awad & Khana, 2015).

An evaluation basis was required for labeling the handover as possible or not possible. For this purpose, videos were recorded from the interior of the test vehicle during the test drives, capturing the driver's point of view. The videos were time-stamped so that they could be matched to the data in the fusion database. With the help of the self-generated MAP messages and the GNNS (global navigation satellite system) position information from the test vehicle, it was possible to perform lane matching with the corresponding traffic light phases. This provided an information gain to the overall traffic situation.

Recorded traffic situations were assessed empirically according to the four-eyes principle. First, transition points, where the handover status changed from possible to not possible and vice versa, were determined. All time points in between counted as having the same handover status. The time interval between two situations was set to one second to keep a certain degree of differentiation of adjacent situations as well as to avoid generating too much data. “Handover possible“ (1) and “handover not possible” (0) labels were stored in the situation database, which was linked to the vehicle database and traffic objects database through equivalent situation identification numbers.

It was assumed that the movement state of the vehicle was the most decisive for the evaluation, whether it was moving, stationary, accelerating, or braking. Based on the mentioned features, a decision was made on whether the vehicle state was suitable for the handover to the driver in the current situation (see Table 1).

Table 1: Presumed handover decision matrix.

Handover possible	**Handover not possible**
Vehicle is stationary (even at red traffic light)	Traffic light turns green, vehicle starts moving
Vehicle moves at a constant speed	Vehicle accelerates or brakes
Vehicle is driving straight ahead	Vehicle is in a curve (or at an intersection)

This information was provided directly by the vehicle sensors from the CAN bus interface. Vehicle data dimensionality was reduced by filtering out the features, whose values did not change during the test drive. The remaining features are listed in Table 2.

Table 2: Vehicle data set.

Brake actuation	Direction of driving	Current gear	Clutch switch actuation
Door position	Hazard warning	Lateral acceleration	Longitudinal acceleration
Pedal force	Speed	Steering wheel angle	Steering wheel angle velocity
Turn signal level	Wiper front system	Yaw rate	

The classification process consisted of applying different classification algorithms to the vehicle data set and comparing the accuracy score. To achieve a better understanding of how the model would perform in practice, 10-fold cross-validation (70/30 split) was applied, after which the mean accuracy score of each algorithm was calculated. All utilized algorithms and methods came from the free software machine learning library scikit-learn (Pedregosa et al., 2011).

For selected algorithms, an attempt to increase the accuracy was made by applying “GridSearchCV” (CV = Cross Validation), which performed an exhaustive search on parameter values for the best estimator. Optimized models were evaluated not only based on the accuracy but on the specificity of the model (True Negatives / (True Negatives + False Positives)), which was considered a more important metric for the investigated scenarios (False positives would be more dangerous errors than False Negatives).

3.3 Traffic Objects Modality

Situation complexity/criticality level was considered depending on the level of danger of each traffic object present in the current situation so that the primary goal was to find a way of assessing the danger level of individual traffic objects.

Traffic objects data consisted of entries for 18,030 objects of two types: 13,384 (passenger) cars and 4,646 pedestrians. These objects corresponded to 1,868 situations. The number of objects in a situation ranged from 1 to 33, mean (M) = 9.7, and standard deviation (SD) = 6.9. Each data entry contained the following features:

- situation id;

- object information: type of object; distance to the test vehicle; speed; heading; longitude; latitude; time to intersection (tti);
- test vehicle information in the corresponding situation: heading; longitude; latitude; time to intersection (tti_v).

Time-to-intersection calculations are explained in (Jiménez et al., 2013). When the intersection point did not lie ahead on the course of the object/test vehicle, the time-to-intersection was set to -1 (e.g., when the object and the test vehicle moved parallel). Including a negative value, however, disrupted the continuity of the feature: -1 was not less than non-negative values. Since maximum positive values of time-to-intersection features were great enough (ttimax= 83,542.98 s; tti_vmax = 43,955.02 s) to be seen as irrelevant at the current time point, all the -1 values were converted into the maximum positive value of the corresponding feature.

To make the data points more comparable and easier to visualize, they were brought into the same 2D-coordinate system where the test vehicle would be at the origin (0,0) moving towards the geographical North (compass bearing = 0°, which corresponds to π/2 (90°) in the polar coordinate system). With this we consider the world view in this paper to be flat, because here the curvature of the earth is negligible. First, the differences between the longitude (long) and latitude (lat) of the object and the longitude and the latitude of the vehicle, respectively, were calculated. Then these differences were expressed in meters:

$$x = \frac{2\pi \cdot radius_{Earth}}{360° \cdot cos(\frac{lat\_object + lat\_vehicle}{2}) \cdot difference_{long}}; \quad (1)$$

$$y = \frac{2\pi \cdot radius_{Earth}}{360° \cdot difference_{lat}}; \quad (2)$$

$$where\ radius_{Earth} = 6371000.8\ m.$$

Relative X and Relative Y were calculated, using trigonometric formulae for an axis rotation (Becker et al., 1999, p. 48) for clockwise rotation through an angle of the test vehicle's heading. Longitude and latitude were mapped onto the abscissa and the ordinate, ignoring the z-axis because the objects were relatively close to each other (the maximum distance from the test vehicle was 100 m).

The next step was to calculate the relative bearing of the objects (IVAO, 2020). For still objects, the true bearing was calculated first, using the coordinates of an object and the test vehicle (Ellis, 2020). Then, the relative bearing was calculated by subtracting the vehicle's heading (true heading) from the object's true bearing. For moving objects, their heading was used as the true bearing. The values were normalized to the [0, 360°) range.

These and the following calculations were performed in JupyterLab environment, using various Python libraries (Pedregosa et al., 2011; Van Rossum, 2020; Harris et al., 2020; Virtanen et al., 2020; Gillies et al., 2007), unless otherwise specified. Data visualizations were carried out in matplotlib (Hunter, 2007). Illustrations of traffic objects in the coordinate system were obtained with the help of TeachingDemos package (Snow, 2020) in R (R Core Team, 2020).

3.4 Clustering

Situation complexity is multifaceted. First, the number of participants and their type varied. On the other hand, each object was described with several features. The situation's complexity itself was difficult to define in terms of the limited number of labels. It seemed more reasonable to explore the data and find the tendencies to group the objects, which were addressed via unsupervised machine learning, or clustering (Awad & Khana, 2015).

Several clustering options were explored to group the objects. The evaluation of clusters was empirical. Thus, a sample (<=80 samples) of observations from each cluster was visualized and analyzed, whether most of the objects in one cluster could be described as having the same danger level. The algorithms were first applied to the subset of data for pedestrians because it was smaller and required less computational space and time. When the approach was not considered suitable for the data (i.e., the results of clustering were not interpretable in terms of intuitive understanding of the danger level), it was not further applied to the subset of data for cars.

3.4.1 Position and Speed Features

Position features included relative X and Y coordinates and relative bearing. To be treated as a circular variable in centroid-based clustering, the relative bearing was transformed into two features: sine and cosine of the angular value. Since both sine and cosine functions take values from -1 to 1, the other features were scaled by their maximum absolute value. An attempt to treat relative bearing linearly proved to be inappropriate for circular variables.

Two centroid-based clustering algorithms were applied to five features (scaled speed, scaled relative X, scaled relative Y, sine of relative bearing, and cosine of relative bearing), namely, Mean shift and K-Means. For Mean shift clustering, bandwidth was estimated with a given quantile = 0.05. For K-Means clustering, the Elbow Method was used to select the optimal number of clusters.

Hierarchical agglomerative clustering was performed in R (Murtagh & Legendre, 2014). For the dissimilarity matrix with a circular variable, two options were explored: one implemented in dist.ktab function (Pavoine et al., 2009) of the ade4 package (Dray & Dufour, 2007), and the other – implementation of Gower's dissimilarity (Maechler et al., 2019) proposed by Will (2016). Will discusses both methods applied to The Cape Blanco dataset, which contains hourly measured temperature, wind speed, and wind direction. The optimal number of clusters (tree cuts in R terminology) was estimated visually from the corresponding dendrograms.

3.4.2 Time-to-Intersection Features

Time-to-intersection (tti) features had exceptionally wide ranges of values. For both subsets of data, the median was equal to the maximum, which means that the data was highly skewed. Classical feature-clipping to a fixed maximum value did not solve this problem. However, since situations were snapshots, large time-to-intersection values seemed to be out of interest then. Therefore, an intuitive border of 20 s was established, so that all the samples of data with tti > 20 s or tti_v > 20 s were excluded from further analysis. The total number of objects with "suitable" time-to-intersection features was 755: 139 pedestrians and 616 cars. Since reduced times to intersection had the same range of values for both pedestrians and cars subsets, the analysis was carried out in three variations: for each of the subsets and the whole dataset.

Mean shift and K-Means were also applied to time-to-intersection features, both on reduced pedestrians and cars subsets separately and all the reduced data. For Mean shift clustering, the bandwidths were estimated with quantiles 0.15, 0.1, and 0.07 for the pedestrians' subset, cars' subset, and all the data, respectively. For K-Means clustering, the Elbow Method was used to select the optimal number of clusters.

Hierarchical agglomerative clustering with Ward's linkage was performed. First, a dendrogram of hierarchical clustering was plotted, from which the optimal number of clusters was estimated. Then, the clustering with the selected number of clusters was performed using AgglomerativeClustering.

3.4.3 Manual Evaluation

Based on both the insights from machine learning clustering and the empiric account of time-to-intersection features, a manually elaborated scheme for grouping the data points was proposed. Generally, it was considered critical if the time-to-intersection of the object and the test vehicle had similar values. Besides, lower values of time-to-intersection features were more dangerous than the higher ones. The evaluation scheme is presented in Figure 1.

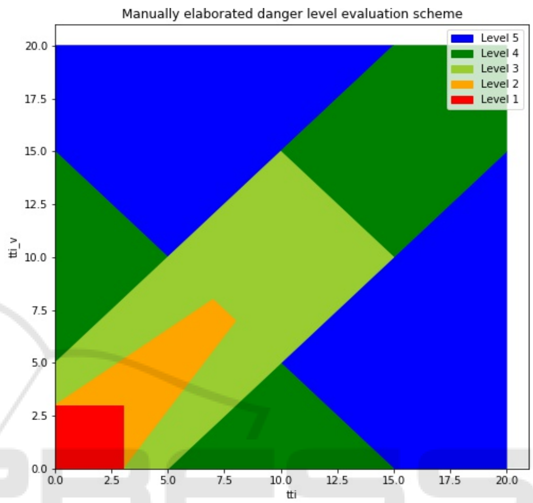

Figure 1: Manually elaborated scheme for grouping the data points according to the values of time to intersection features: Level 1 – the most critical (dangerous), Level 5 – the least dangerous.

Since the objects were treated as points while they had certain widths and lengths, and possible imprecisions by data acquisition, it was decided to add one more manually evaluated group of dangerous objects. This group consisted of all objects located in the 90° range zone in front of the test vehicle (45° to the right and the left from the vehicle trajectory, or octants 2 and 3 in the 2D coordinate system, in which the test vehicle is at the origin and is moving towards the geographical North) at the distance closer than 7.5 m.

3.4.4 Situation Evaluation

Eventually, the objects were divided into six groups according to their danger level. Each object then received a score from zero to five: zero – irrelevant in the current situation, and five – representing a critical level of danger in the current situation. To increase the importance of critical objects, the situation score was calculated as the sum of the squared scores of all the objects.

4 RESULTS

4.1 Vehicle Data Modality

The results of classification with 10-fold cross-validation are shown in Figure 2.

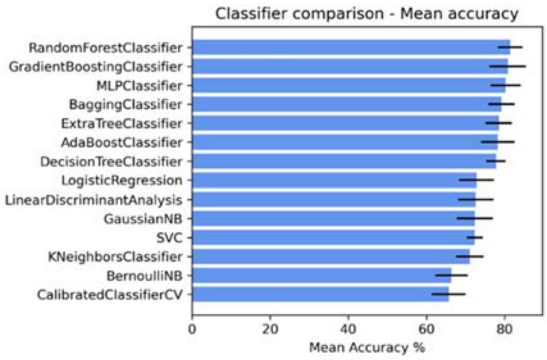

Figure 2: Classifier comparison - Mean accuracy.

4.1.1 Random Forest Classifier

Random Forest Classifier performed with the highest accuracy. Implementation of GridSearchCV algorithm achieved an accuracy score of 81.83%. However, the specificity of this model (66.95%, True Negatives = 640, False Positives = 316) was considered unacceptably low to predict a safety-critical handover.

Nevertheless, Random Forest Classifier provided useful insights into the impurity-based feature importance, or how much a single feature of the vehicle data set affected the result (see Figure 3). The presumed handover decision matrix (Table 1) could be confirmed with the obtained feature ranking: the values influencing the motion state of the vehicle were the most decisive for the accuracy of prediction.

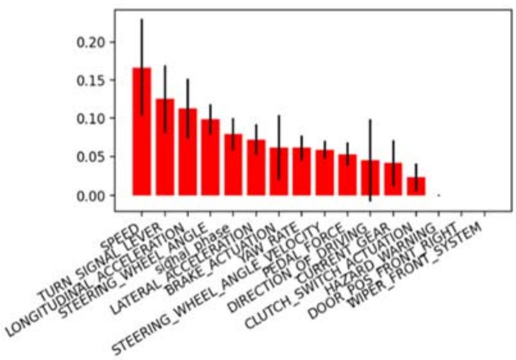

Figure 3: Feature importance revealed by Random Forest Classifier.

From the bar chart in Figure 3, one can see that the feature importance values varied strongly. Furthermore, it is noticeable that the value direction_of_driving had an unusually high variance compared to the other features. Such variance resulted from the fact that the direction_of_driving feature in 1,609 cases was assigned as unknown, which made those values incorrect. The position of the three last-placed values can be explained by the fact that during the test drives not enough data were collected where these values were activated.

4.1.2 Multilayer Perceptron (MLP) Classifier

Since the specificity of the Random Forest Classifier was regarded as insufficient, it was necessary to consider another classification algorithm. MLP Classifier had a lower mean accuracy score than Gradient Boost Classifier in the overall ranking, but a lower standard deviation signaled higher robustness of the former. After applying GridSearchCV method for two different combinations of parameter grids and increasing the accuracy by 0.25% compared to the usage of the standard parameters, a final accuracy value of 80.31% was achieved. The specificity of this model reached 77.82% (see Figure 4), which was 14.64%, greater than that obtained with Random Forest Classifier (see Figure 2).

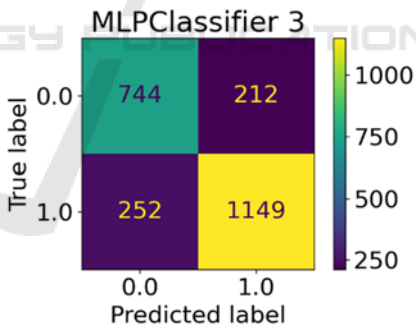

Figure 4: MLP Classifier confusion matrix.

4.2 Traffic Objects Data Modality

4.2.1 Position and Speed Features

As mentioned above, the relative bearing is a circular variable and should not be treated linearly. Such attempts lead to losing the meaning of the values. Objects from the same cluster corresponded to a wide range of relative bearing values and could not be meaningfully interpreted.

Sample visualizations of clusters obtained from Mean shift (nine clusters), K-Means (five clusters), and hierarchical clustering with a circular variable (six clusters with both methods) applied on speed and position features suggested that the clusters could be described as having similar relative bearing features but not as having certain tendencies in terms of danger level so that the approach was not applied further.

4.2.2 Time-to-Intersection Features

According to visual analysis of dendrograms, the optimal number of clusters would be two. Such gross division, however, did not seem reasonable, considering the nature of the data. Thus, the number of clusters was selected as where the dendrogram was "cut" before going into finer clusters (the same principle was applied to hierarchical clustering with a circular variable).

Visualization of the clustering results can be seen in Figure 5. Cluster evaluation from the empirical point of view suggested that the proposed clusters might lack the necessary granularity and symmetry. Machine learning algorithms provided, however, useful insights on how the data tended to be grouped naturally.

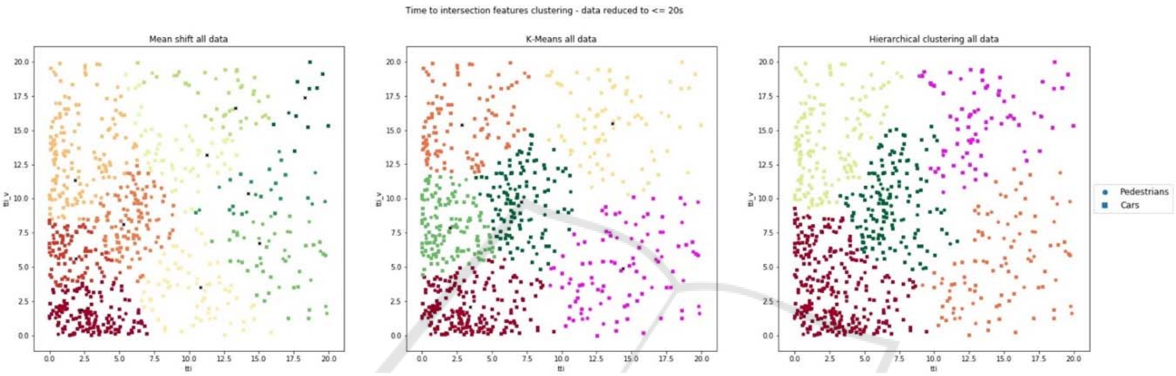

Figure 5: Mean shift, K-Means, and hierarchical clustering applied on time to intersection features (data reduced to <= 20 s).

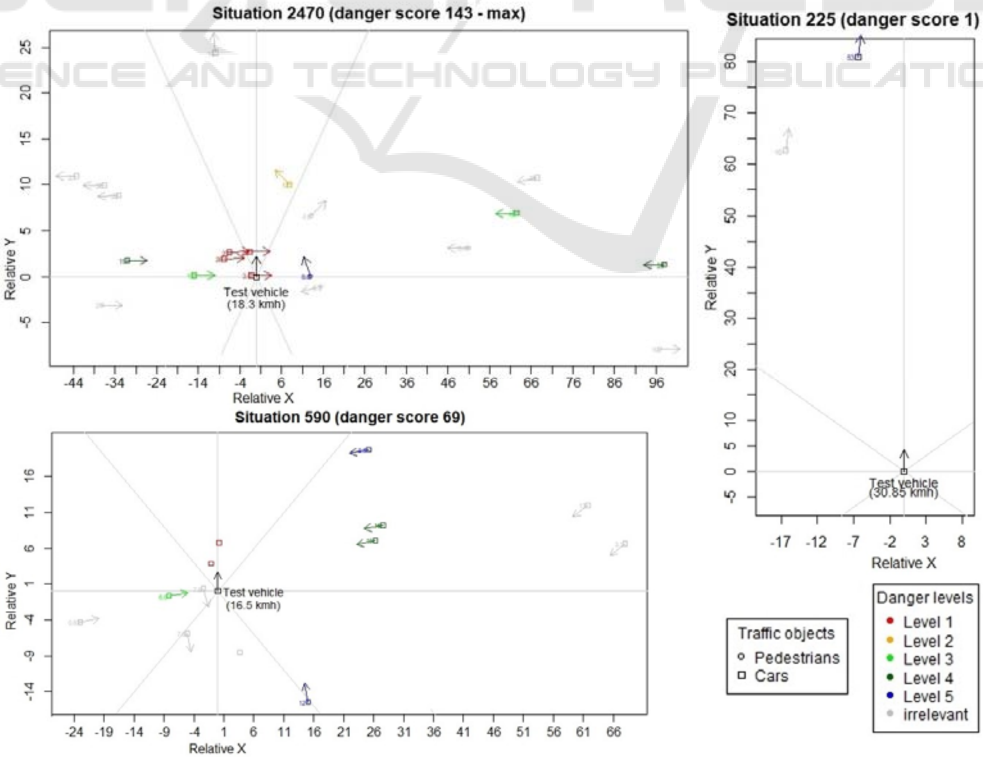

Figure 6: Examples of situations with different danger scores/complexity.

4.2.3 Manual Evaluation and Final Situation Evaluation

Objects in the dangerous proximity zone were selected first. There were 319 such objects: 27 pedestrians and 292 cars. Of 755 that were to undergo dangerous level analysis based on time to intersection features, 62 were excluded because they were already in the dangerous proximity zone (Danger Level 1). In total, 1,012 objects were considered relevant in terms of danger. These objects corresponded to 552 situations. The number of participants per situation ranged from 1 to 10, M = 1.83, SD = 1.52. Excluding situations with zero danger, situation scores ranged from 1 to 143, M = 23.13, SD = 18.76. In 1,316 situations (70.4% of all the obtained data) there were only objects with a danger Level of 0. Symbolic representations of situations with different danger scores/complexity can be seen in Figure 6.

5 CONCLUSIONS

We addressed the problem of a handover from automated to human control through the multimodal description and analysis of traffic situations. We have focused on two modalities, namely own vehicle state and detected traffic objects.

Own vehicle state can be directly mapped on one of the two labels, “handover possible” or “handover not possible”. These binary labels assigned by a human rater have been used as ground truth for training a range of classification models. The mean accuracy of algorithms ranges from 65.7% to 81.4%, the highest accuracy obtained with Random Forest Classifier. Optimization of the algorithm allows to improve the accuracy to 81.8%, However, False negatives (algorithm attributes the handover as “not possible” while in truth it is possible) do not seem to have the same impact as False positives so the trade-off should be made towards higher specificity. The specificity of the Random Forest Classifier model is 67%, which is unacceptably low. With a slightly lower overall accuracy of 80.3%, MLP Classifier provides a significantly higher specificity of 77.8%, which is nevertheless still unacceptable for robust prediction of the handover. Balancing the dataset in terms of outcome labels and feature weighting is seen as the way to improve the performance of machine learning models.

Traffic objects can be described in terms of their danger level, which cumulatively corresponds to the traffic situation complexity/danger score. Different combinations of features have been explored with the help of centroid-based and hierarchical clustering. When features include a circular variable (relative bearing), this feature seems to become dominant, while the others are not interpreted by algorithms in a way that could be explained in real life. Clustering on time-to-intersection features with machine learning algorithms does not result in desired granularity and cluster symmetry, therefore a manual approach was selected for grouping the data points. Almost 30% of the investigated situations have been evaluated as having a complexity/danger score higher than 0, with maximum complexity of 143.

The possibility of the control handover is determined via a cascade approach. First, own state of the vehicle is assessed. In the current work, vehicle data are available at any time, whereas the data of detected objects (traffic situation data) are only available at certain intersections. When the own state of the vehicle allows the handover, the complexity of the situation based on traffic objects is evaluated. The higher the complexity, the more critical the requirement of sufficient transition time, making an immediate control handover not possible. Predicting situation complexity in time, setting thresholds for handover, and issuing corresponding warnings are the topics for further research.

Limitations of the current study include the absence of information on the driver’s state and attention, and uniformity of weather conditions, as well as the lack of perceptive capability of the onboard vehicle sensors for obstacles on the road. Adding these modalities and exploring the decision-making with fusion at different levels (e.g., feature fusion and modality fusion) are planned as the following steps. Bringing data analysis into real-time, while the vehicle is performing test routes, and exploring delays in data processing and the ways of minimizing them are also seen as one of the future research directions.

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