Conceptualizing a Safety Tolerance Zone: A Machine Learning Framework for Vehicle-Driver-Environment Interaction

Eva Michelaraki[1*], Thodoris Garefalakis[1], Tom Brijs[2], George Yannis[1]

[1] *National Technical University of Athens, Department of Transportation Planning and Engineering, 5 Heroon Polytechniou str., 15773, Athens, Greece*
[2] *UHasselt, School for Transportation Sciences, Transportation Research Institute (IMOB), Agoralaan, 3590 - Diepenbeek, Belgium*

* Corresponding author: evamich@mail.ntua.gr

Abstract

Background

The Safety Tolerance Zone (STZ) refers to the real-world phenomenon of (technology assisted) drivers self-regulating control over transportation vehicles in the context of crash avoidance. The concept of the STZ attempted to describe the point at which self-regulated control is considered safe. It is the zone where the demands of the driving task are balanced with the ability of the driver to cope with them.

The STZ comprises three phases: normal driving, danger and avoidable accident phase. The normal driving refers to the phase where conditions at that point in time suggest that a crash is unlikely to occur and therefore the crash risk is low and the driver is successfully adjusting their behaviour to meet task demands. The danger phase is characterised by changes to the normal driving that suggest a crash may occur and therefore, there is an increased crash risk. At this stage a crash is not inevitable but becomes more likely. The STZ switches to the danger phase whenever instantaneous measurements detect changes that imply an increased crash risk. Lastly, the switch to avoidable accident phase occurs when a collision scenario is developing but there is still time for the driver to intervene in order to avoid the crash. In this phase, the need for action is more urgent as if there are no changes or corrections in the road or rail traffic system or an evasive manoeuvre is performed by the driver, a crash is very likely to occur.

One of the most novel contributions of this research is the introduction of the STZ concept. This innovative framework offers a new way of understanding and managing road safety by considering how drivers perceive and respond to their driving environment. The STZ theory integrates insights into driver behaviour and risk factors, providing a more comprehensive understanding of road safety dynamics. This holistic perspective is unique and significantly enhances the ability to predict and prevent unsafe (e.g. danger and avoidable accident) driving conditions.

Methods

The aim of this study was to assess road, vehicle and behavioural risk indicators for the identification of Safety Tolerance Zone (STZ). Towards that end, a simulator driving experiment was carried out involving 55 drivers and a database consisting of 165 trips was created. Participants were asked to complete a driving behaviour questionnaire to collect detailed information on various aspects of driving, socio-demographics, safety attitude and psychological factors. True STZ categories are identified using a variable time-headway

threshold, adjusted by task complexity and coping capacity, with fixed boundaries: >2 sec (normal), 1.4-2 sec (danger), and <1.4 sec (avoidable accident).

A feature importance algorithm was used to evaluate the significance of variables on forecasting STZ. Additionally, a Neural Network model was implemented for real-time data prediction. Furthermore, a comprehensive assessment of the performance of three machine learning classifiers (i.e. Decision Trees, Random Forests and k-Nearest Neighbors) was implemented. These classification models were selected due to their strong performance and widespread use in the literature for identifying unsafe driving patterns and real-time risk prediction. The results were evaluated based on several metrics, such as accuracy, precision, recall, false alarm rate and F1-score.

Results

According to the feature importance analysis, time-to-collision, average speed, driving duration, hands-on event and fatigue found to be the most influential factors among all examined indicators. Conversely, parameters such as lane departure warning or forward collision warning had a negligible impact on STZ headway.

A dataset of 745,251 rows was used and a feed-forward multilayer perceptron NN model was implemented. Based on the feature importance and the significance of the relevant indicators, the results were incorporated into the integrated NN model for predicting STZ headway. The multi-layer NN model applied consisted of five neurons in the input layer (i.e. TTC, average speed, duration, hands-on event and LDW) and three neurons in the output layer (i.e. STZ1, STZ2, STZ3). It should be noted that STZ1 headway refers to normal phase, STZ2 headway refers to danger phase, while STZ3 headway refers to avoidable accident phase. Results demonstrated that the level of STZ can be predicted with an accuracy of up to 89.8%. Simulator experiments showed exceptional performance, especially in predicting STZ headway, with strong precision and recall, indicating the model's effectiveness in identifying positive samples and safety-critical classes.

The examination of machine learning results revealed a commendable performance by the classification models. All models applied (i.e. DT, RF and kNN) exhibited a high level of accuracy, indicating the overall correctness of its predictions. In particular, it was found that RF model outperformed the other classifiers, achieving the highest overall accuracy at 90.1%. Furthermore, DT showed moderate performance with an accuracy of 87.1%, while kNN demonstrated the lowest performance, with an accuracy of 85.0%. Among the different methods applied, RF stranded out with the highest accuracy, indicating its ability to accurately classify driving behaviours in a controlled environment.

Figure 1 presents the comparison of classifier metrics of the three machine learning techniques for headway.

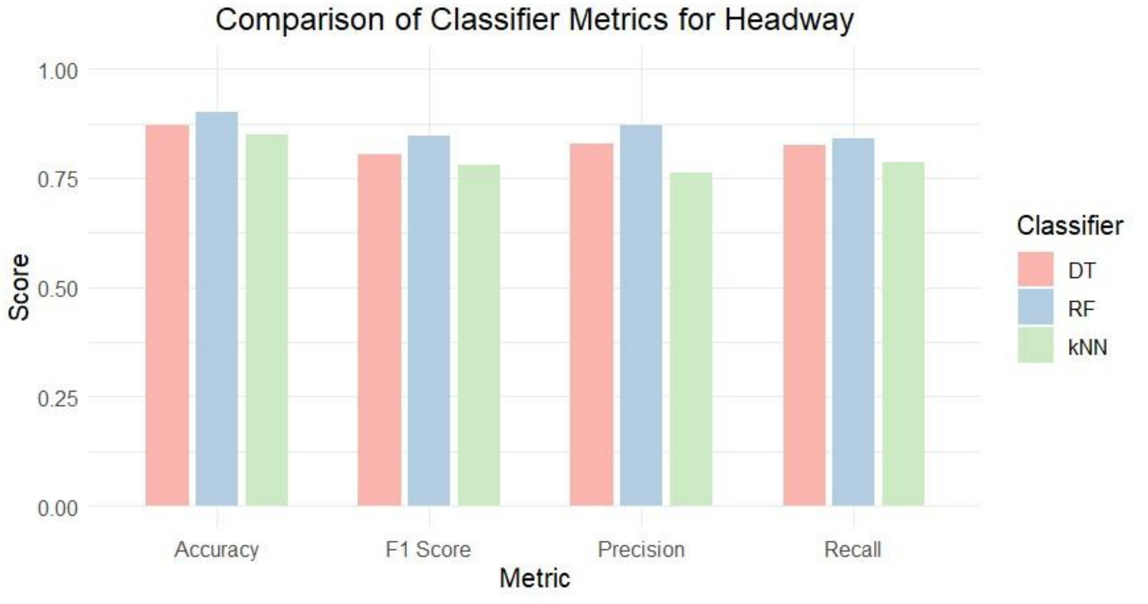

Figure 1: Comparison of classifier metrics of machine learning techniques for headway

Discussion and Conclusion

Findings from the current research highlighted the models' reliability and effectiveness in classifying instances of headway. The models performed best in normal driving phases, likely because these conditions were more consistent and made up the majority of the training data. Additionally, normal driving features were more distinct and less ambiguous compared to hazardous conditions, reducing misclassification risks. These results not only showcased their potential for real-world applications but also emphasised their significance in the realm of road safety and traffic management.

The outcomes of this study hold significant implications for road safety interventions. Utilising machine learning algorithms and data-driven insights can facilitate the identification of safe driving behaviour, enable prompt feedback to drivers, and foster a safer driving environment. The insights derived from this study can play a pivotal role in refining the capabilities of the STZ by providing a deeper understanding of driving behaviour dynamics and improving the prediction of risky driving scenarios.

The results can be used in practice to provide real-time feedback to drivers, support adaptive driver assistance systems, and inform road safety interventions. Further research avenues should concentrate on evaluating the long-term effects of interventions, assessing real-time systems, and considering human factors and driver engagement. Additionally, investigating the generalisability and scalability of the developed models and interventions across diverse populations, geographic regions and vehicle types is vital to ensuring their widespread impact on enhancing road safety.

Selected references

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