Accident Analysis and Prevention 113 (2018) 1–11

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

The potential of clustering methods to define intersection test scenarios: Assessing real-life performance of AEB

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ARTICLE INFO

Keywords:
Straight crossing path
SCP
Left turn across path
LTAP/OD
Intersection
Junction
AEBS
AEB
Test scenarios
Clustering

ABSTRACT

Intersection accidents are frequent and harmful. The accident types 'straight crossing path' (SCP), 'left turn across path – oncoming direction' (LTAP/OD), and 'left-turn across path – lateral direction' (LTAP/LD) represent around 95% of all intersection accidents and one-third of all police-reported car-to-car accidents in Germany. The European New Car Assessment Program (Euro NCAP) have announced that intersection scenarios will be included in their rating from 2020; however, how these scenarios are to be tested has not been defined.

This study investigates whether clustering methods can be used to identify a small number of test scenarios sufficiently representative of the accident dataset to evaluate Intersection Automated Emergency Braking (AEB).

Data from the German In-Depth Accident Study (GIDAS) and the GIDAS-based Pre-Crash Matrix (PCM) from 1999 to 2016, containing 784 SCP and 453 LTAP/OD accidents, were analyzed with principal component methods to identify variables that account for the relevant total variances of the sample. Three different methods for data clustering were applied to each of the accident types, two similarity-based approaches, namely Hierarchical Clustering (HC) and Partitioning Around Medoids (PAM), and the probability-based Latent Class Clustering (LCC). The optimum number of clusters was derived for HC and PAM with the silhouette method. The PAM algorithm was both initiated with random start medoid selection and medoids from HC. For LCC, the Bayesian Information Criterion (BIC) was used to determine the optimal number of clusters.

Test scenarios were defined from optimal cluster medoids weighted by their real-life representation in GIDAS. The set of variables for clustering was further varied to investigate the influence of variable type and character. We quantified how accurately each cluster variation represents real-life AEB performance using pre-crash simulations with PCM data and a generic algorithm for AEB intervention.

The usage of different sets of clustering variables resulted in substantially different numbers of clusters. The stability of the resulting clusters increased with prioritization of categorical over continuous variables. For each different set of cluster variables, a strong in-cluster variance of avoided versus non-avoided accidents for the specified Intersection AEB was present. The medoids did not predict the most common Intersection AEB behavior in each cluster. Despite thorough analysis using various cluster methods and variable sets, it was impossible to reduce the diversity of intersection accidents into a set of test scenarios without compromising the ability to predict real-life performance of Intersection AEB. Although this does not imply that other methods cannot succeed, it was observed that small changes in the definition of a scenario resulted in a different avoidance outcome. Therefore, we suggest using limited physical testing to validate more extensive virtual simulations to evaluate vehicle safety.

1. Introduction

Detailed understanding of the real-life performance of active safety and Advanced Driver Assistance Systems requires the evaluation of all possible scenarios. This takes effort, and not all scenarios are equally important. The more common a scenario, the more influence it will have on the safety benefit. Hence, performance evaluation is commonly restricted to a set of frequent scenarios, depending on the required accuracy of the performance estimation and the effort needed and tolerable to add more scenarios.

Computer simulations have removed some of the need for physical testing. However, simulations with complex, accurate models still take time, and the models themselves need to be created and validated. Furthermore, it is still common for performance evaluation and

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https://doi.org/10.1016/j.aap.2018.01.010
Received 12 July 2017; Received in revised form 24 November 2017; Accepted 9 January 2018
0001-4575/

validation to be carried out by hardware testing, as the example of the European New Car Assessment Program (Euro NCAP, 2017) shows.

Euro NCAP provides consumers with safety ratings for selected new cars and thus has become an important driver for advances in vehicle safety. The consumer organization applies more stringent tests of safety performance compared to regulations and includes safety assessments in new areas not yet regulated (van Ratingen et al., 2016).

For one of these new assessments, the Automated Emergency Brake (AEB) assessment, test conditions and assessment criteria have been defined for car-to-car rear-end accidents (Schram et al., 2013) and car-to-pedestrian accidents (Schram et al., 2015). Tests are carried out with the car under assessment and hardware targets on a track. Recently, Euro NCAP has introduced a "grid approach" for active safety testing, requiring the vehicle manufacturer to provide performance information for a wide range of scenarios while only verifying some (Euro NCAP, 2017). Additional information is therefore collected at no extra cost to Euro NCAP, as the effort is shifted to the manufacturer. This may be a result of the expectation that, for a manufacturer, the additional effort of testing more scenarios is negligible as simulation methods are utilized.

However, it is unclear which scenarios need to be tested to give a reliable estimate of real-life performance. A common approach is to segment accident data into homogenous groups using expert knowledge and to define a limited number of tests for the most frequent groups. Decisions are often made on the basis of what can technically be tested and how much can economically be tested; in consequence, real life performance receives less attention. Some years after active safety systems have come to the market and accidents have been observed, real-life performance can be estimated and compared with test performances. Good correlation between real-life and test performances indicates that the tests are relevant and valid (Kullgren et al., 2010; Pastor, 2013; Strandroth et al., 2011). However, until sufficient accidents are observed, the test scenarios might lead to system designs that are irrelevant or even harmful to real-life safety. Therefore, the selection of test scenarios needs careful attention even at the introduction stage.

Intersection accidents are frequent and have severe consequences. Approximately fifty percent of all injury accidents in the US occur at intersections or are intersection-related; further, approximately thirty percent of fatal road traffic accidents occur at these locations (NHTSA, 2016). In Europe, about twenty-four percent of road traffic fatalities are caused by junction accidents (European Commission, 2015). The most frequent types of car-to-car intersection conflicts in Germany are: straight crossing path (SCP), left turn across path – oncoming direction (LTAP/OD), and left turn across path – lateral direction (LTAP/LD), illustrated in Fig. 1 (Sander, 2017).

Euro NCAP expects next-generation AEB to be able to address more complex accident scenarios, such as turning into oncoming traffic or crossing a junction. Consequently, Euro NCAP is planning to incorporate updated car-to-car AEB test and assessment procedures reflecting real-life scenarios and addressing, besides others, junction and intersection crossing accidents, by 2020 (Euro NCAP, 2015).

In this paper, we provide the much-needed answer to the question: Is it possible to reduce the diversity of intersection accidents into a set of test scenarios without compromising the ability to predict real-life performance of Intersection AEB? We do this in three steps. First, we apply three different clustering methods and choose medoids, the cluster centers, as cluster representatives. Second, we run virtual simulations of real-world intersection accidents with a generic Intersection AEB system and compare how well the cluster representatives predict the collision avoidance potential compared to the whole accident sample. Third, we investigate whether there is a demonstrable advantage in using predictions made by cluster representatives over those made through random sampling.

2. Background: clustering methods

This section provides the background to the clustering methods used in our analysis.

2.1. Distance- or similarity-based clustering

For many cluster analysis methods, the clustering is done by evaluating the distances or (dis-) similarities between observations, such as Euclidean or Manhattan distance for continuous variables, Jaccard similarity (coefficient) for categorical variables, and Gower's generalized coefficient of similarity for mixed-type data. The input is usually an object-by-attribute matrix, where the rows stand for the observations and the columns stand for attributes. Intermediate output can be a distance or dissimilarity matrix, which is a symmetric matrix where d (i,i') = d(i',i), measuring the distance and dissimilarity, respectively, between the observations i and i'.

Euclidean and Manhattan are true distances since they obey the triangle inequality with

$$\boldsymbol{d}_{\boldsymbol{ii'}} = \left(\sum_{j=1}^{J} |\boldsymbol{x}_{\boldsymbol{ij}} - \boldsymbol{x}_{\boldsymbol{i'j}}|\right)^{1/\boldsymbol{p}} \tag{1}$$

where d = distance, J = number of attributes, j = attribute index, i,i' = object indices, and p = 1 for Manhattan and p = 2 for Euclidean distance. In general, the input data is standardized and adjusted to the mean to give all attributes the same weight.

Jaccard index dissimilarity is used for dichotomous data; thus for polytomous data, zero-unity dummy variables have to be created which can only take the value '0' or '1'. The Jaccard index ignores the co-

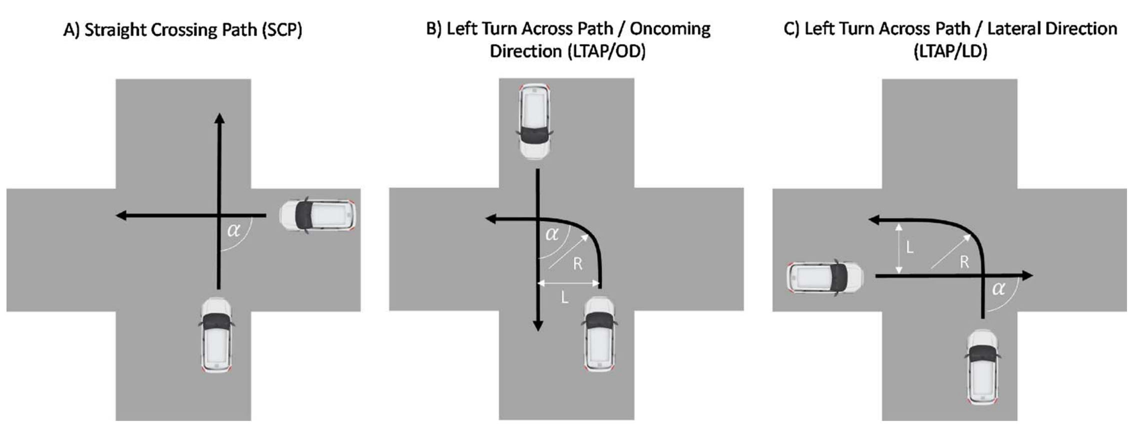

Fig. 1. Pictograms of most frequent car-to-car intersection accident scenarios in Germany: A) Straight Crossing Path, B) Left Turn Across Path / Oncoming Direction, and C) Left Turn Across Path / Lateral Direction; where α = collision angle, L = lateral offset, and R = turning radius.