An Open Case-based Reasoning Framework for Personalized On-board Driving Assistance in Risk Scenarios

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Abstract—Driver reaction is of vital importance in risk scenarios. Drivers can take correct evasive maneuver at proper cushion time to avoid the potential traffic crashes, but this reaction process is highly experience-dependent and requires various levels of driving skills. To improve driving safety and avoid the traffic accidents, it is necessary to provide all road drivers with on-board driving assistance. This study explores the plausibility of case-based reasoning (CBR) as the inference paradigm underlying the choice of personalized crash evasive maneuvers and the cushion time, by leveraging the wealth of human driving experience from the steady stream of traffic cases, which have been rarely explored in previous studies. To this end, in this paper, we propose an open evolving framework for generating personalized on-board driving assistance. In particular, we present the FFMTE model with high performance to model the traffic events and build the case database; A tailored CBR-based method is then proposed to retrieve, reuse and revise the existing cases to generate the assistance. We take the 100-Car Naturalistic Driving Study dataset as an example to build and test our framework; the experiments show reasonable results, providing the drivers with valuable evasive information to avoid the potential crashes in different scenarios.

Index Terms—Driving Assistance, Driving Maneuver Recommendation, Naturalistic Driving Study, Traffic Event Modeling, Case-based Reasoning, Intelligent Vehicles

I. INTRODUCTION

Reducing traffic risks is one of the most important public safety concerns across the world. The global statistics by World Health Organization show that more than 1.35 million humans lost their lives every year due to the road traffic accidents [1]. Contrary to other calamities, it is well acknowledged that the traffic crashes are not chance events [2] and hence the majority of traffic crashes can be mitigated (avoided) via appropriate driving maneuvers\(^1\) at proper operation time [3], [4]. As shown in Figure 1, the subject vehicle (SV) changes lane and triggers the risk of potential conflict with an adjacent vehicle; if the SV steers to the right side at a proper short cushion time after detecting this risk scenario, the risk could be avoided. For this proactive crash mitigation purpose, some advanced driving assistance systems (DASs) that offer safety recommendations have been proposed in this driver-vehicle co-driving situation, and showed significant safety improvement [2], [5], [6].

DASs have been greatly boosted by recent developments in sensing and computing technologies, and dynamic mobile communication between vehicles (V2V), vehicles and road infrastructures (V2I) [7], [8]. These systems assist drivers in plenty of aspects to perceive the contexts and make proper decisions thereby minimizing the driving risks and saving human lives, money and time [6], [7]. In fact, completely avoiding the traffic risk is still unrealistic at this point [5]. Several studies in the US show that driver error is the critical reasons for approximate 94\% of crashes, with 33\% attributing to human decision error [7], [9]. Therefore, determining what evasive maneuver should be performed to hinder the crash occurrence or at least minimize the crash severity, and also what is the optimal cushion time to take the corresponding maneuver, are of great importance in these inevitable risk scenarios. This is also the research questions that we want to solve in this paper.

Driving is a highly experience-dependent activity that requires various levels of driving skills, physical and cognitive characteristics of human drivers [10], [11]. The experience can be mutually imparted among human drivers and has been verified to effectively improve the on-road driving safety after learning [11]. When facing a new traffic scenario, human

\(^1\) A maneuver is denoted as a driver’s reaction in response to the precipitating event in a risk scenario. Braking, decelerating, accelerating and steering are common reactions.
drivers tend to rely on their experience to understand and perform similar operations to make reactions, especially in the short-term, sudden risk scenarios [10], [12]. Hence for the inexperienced drivers, the on-board driving assistance in these risk scenarios appears to be particularly important. Actually, many researches have reported that novice drivers between the age of 15-29 have the highest numbers of crash events [1], [13], and inexperienced drivers have a higher crash risk than their counterparts [14]. Moreover, professional drivers may occasionally make mistakes while attempting to prevent a crash [7]. Given the severe loss of human lives and money, the better leverage of human driving experience to provide driving assistance to all road drivers is promising to lower the crash rate considerably in these risk scenarios.

Meanwhile, recent technological developments in intelligent vehicles and transportation offer new wealthy sources of data about the drivers, the vehicles and the context information, making the building of a holistic view of natural driving roadway events (under the risk scenarios) both technologically possible and economically feasible. These large numbers of event cases contain valuable driving experience from numerous drivers on their operations to hinder the crash occurrence or reduce crash severity, which can be potentially used as human experience to instruct the drivers in the on-board DASs. However, these cases have rarely been used in existing researches to infer the optimal evasive maneuver and the cushion time in the risk scenarios.

This paper presents an open CBR-based framework for on-board driving assistance in risk scenarios, with the aim of inferring the optimal crash avoidance maneuver and cushion time to hinder the crash occurrence. We assume that the risk scenarios have already been detected using the LiDAR sensing or computer vision techniques [3], [13]. We take the “100-Car Naturalistic Driving Study (NDS)” dataset as an example to build our framework, which consists of three steps: the traffic event modeling, the case database building, the CBR-based on-board driving assistance. We present a field-aware factorization machine (FFM) [15] based approach, namely FFMTE, to model the traffic events considering the event information, driver-vehicle interaction, road condition and the driving context, and build the overall case database. Personal driving records are also stored into a personal driving and mitigate the crashes, a step further the risk situation being concerned with improving automobile safety features such as seat belts, airbags, and body structures to mitigate the severity in the inevitable crashes. Active methods proactively detect and evaluate the driving risks [3], [13], [17], recommend or take actions to control the vehicles to avoid and mitigate crashes [5], [10]. Among them, driving risk prediction and analysis is the hottest topic and initial step in this direction because only the risk scenarios are detected can the further actions be taken to avoid the potential risks. Wang et al. [3] proposed a deep learning model to handle both spatial and temporal dependence in driving risk evaluation incorporating the driving patterns of the target vehicle, the driving patterns of surrounding vehicles, and the interactions between the target and surrounding vehicles to improve driving safety. Chen et al. [13] presented a deep autoencoder based method for driving safety risk prediction and showed good prediction performance on the driving risk.

After detecting the potential risks, various action-taking methods are proposed to avoid and mitigate the crashes. Wang et al. [5] designed a motion planner for generating an emergency path to mitigate the inevitable crash as much as possible. Morales et al. [18] proposed a model for velocity control by abstracting the maneuvers from expert driving data to avoid the potential crashes in the blind interactions. Kaplan and Prato [19] applied the regret minimization as behavioral paradigm to choose the crash avoidance maneuvers.

This paper focuses on the action-taking method to avoid and mitigate the crashes, a step further the risk situation being detected. Different from the existing studies, we propose an open evolving framework for crash avoidance by leveraging the wealthy of human driving experience from the steady stream of traffic cases, which is the first work in this direction to use the overall human knowledge for crash avoidance.
The 100-Car NDS dataset provides a total of 57 variables to comprehensively describe an driving event. In this paper, we select parts of the significant variables that both satisfy our aim of inferring the proper evasive maneuver and the cushion time of the final evasive maneuver.

III. DATA DESCRIPTION AND EVENT CASE ABSTRACTION

This paper takes the 100-Car NDS dataset as an example to build our evolving framework.

A. Dataset

The 100-Car NDS [20] is the first large-scale instrumented vehicle study conducted in the Northern Virginia/Washington, D.C. area over a 2 year period with the primary purpose of collecting large-scale, naturalistic driving data. Naturalistic driving data depicting drivers’ daily driving in urban regions were unobtrusively collected from vehicles devised with a suite of sensors. The dataset includes approximately 2,000,000 vehicle miles, almost 43,000 hours of data, 102 primary drivers, 12 to 13 months of data collection for each vehicle.

From the data, an event database was created with three types of safety-related events identified: crashes, near-crashes, and other safety-critical incidents [20]. A crash is defined as “any collision between the subject vehicle and another item.” A near-crash is “a conflict scenario that necessitates a quick, severe evasive maneuver to prevent a crash.” The quick, evasive maneuver includes actions using steering, braking, accelerating, or any combination of control inputs [13]. A safety-critical incident is an accident of lesser magnitude than a near crash. The naturalistic approach makes it possible to record all kinds of these events.

In this paper, we use the crashes and near-crashes data to explore the potential for crash mitigation and avoidance. All the 68 crashes and 760 near-crashes in the 100-Car NDS dataset are used in our framework. Most drivers did not have the crash events, 26% drivers had one time of crash, and only one driver have 5 times of crash. In contract, most of the drivers had numerous near-crash events ranging from 1 to 16, with 52 the maximum. The collected event videos allow direct viewing of all of the pre-event and during-event parameters, based on which a event summary is created for each event including the pre-event maneuver, precipitating factor, event type, contributing factors, associative factors and avoidance maneuver, etc [21]. The detailed information on crashes and near-crashes demonstrates drivers’ unsuccessfully/successfully performing an evasive maneuver or decision making to choose the incorrect/correct evasive maneuver, providing insight into developing and refining crash avoidance countermeasures for these risk scenarios [21].

B. Abstraction of Driving Event Cases

The original dataset provides a total of 57 variables to comprehensively describe an driving event. In this paper, we select parts of the significant variables that both satisfy our aim of inferring the proper evasive maneuver and the cushion time.
for crash mitigation and avoidance, and also have been verified to contribute to the driving events in previous researches [3], [8], [17].

A novel data-transcription protocol that takes into account a broad range of significant variables that contribute to the driving events, is proposed in Table I. It is divided into four primary categories: the event information (event severity, event nature, precipitating event), driver-vehicle interaction (pre-incident maneuver, driver reaction, driving cushion time), static road condition (surface condition, traffic flow, etc.), and dynamic driving context (visual obstructions, traffic density, etc.). This protocol offers the capability for studying and explaining the relationship between driving events, driver/vehicle information, and static and dynamic surroundings.

As shown in Table I, each of these variables contains several possible values, for example, the “event nature” contains eight values coding from 0 to 7. For the driving cushion time, it is defined as the time period from the beginning of the precipitating event to the completion of the final evasive maneuver, which indicates the constrained time required for the drivers to take the quick evasive maneuver to avoid a potential risk. It is calculated as $t_{cushion} = (f_{end} - f_{start})/r$, where $f_{start}$ and $f_{end}$ are the starting and ending points in the collected driving video when the sequences defining the occurrence of the event begins or ends. The $r$ is the frame rate of the video (i.e., 7.5 frames per second). For most of the events, drivers took the evasive maneuver at 1~9 seconds. We abstract the driving cushion time into several intervals based on its distribution. Four intervals are obtained from the data: 0~7s, 7~14s, 14~20s, and more than 20s.

To improve the model interpretability and reduce the further computing complexity for overall variables, we use k-modes [22] to cluster the static road condition and dynamic driving context to further abstract the driving data, with $k$ the number of cluster centroids. We choose $k = 6$ for the road condition and $k = 7$ for the driving context with an elbow method for the optimal clusters.

Finally, each driving event is represented by eight variables in the four categories: event severity ($e_s$, 2), event nature ($e_n$, 8), precipitating event ($p_e$, 10), pre-incident maneuver ($p_m$, 10), driver reaction ($d_r$, 7), driving cushion time ($d_c$, 4), static road condition ($r_c$, 6), dynamic driving context ($d_c$, 7). The expressions and numbers in the brackets are the abbreviations and the total kinds of potential values of the corresponding variables. Note that the variable “driver reaction” shows the evasive maneuver the driver taken to avoid a crash.

**Definition 1 (Event Case Abstraction):** A event case is represented as $c = \{e_s, p_e, p_m, d_r, c_t, r_c, d_c\}$ with the $e_s$ as a label to indicate the case severity.

As all the eight variables are transformed into category ones, we use Cramer’s $V$ correlation to calculate the coefficient matrix, as shown in Figure 3. The event severity is correlated with all the other variables to different degrees, and these variables are also correlated with each other. For example, the precipitating events are highly correlated with the event nature, and also the road condition (icy, snowy) can also influence the driving context (traffic density). To better model the traffic events, such interactions among different variables must be considered.

**IV. OUR PROPOSED FRAMEWORK**

Figure 2 shows the overall framework for the on-board personalized driving assistance in risk scenarios. This framework mainly includes three steps: the traffic event modeling, the case database building, the CBR-based on-board personalized driving assistance, combining which we show how to leverage the wealthy sources of human driving experience from the steady stream of traffic cases to assist drivers to mitigate and avoid the potential crashes in the risk scenarios.
Algorithm 1 The proposed CBR-based framework for on-board driving assistance

Input: All drivers’ driving event data $X$, the personal driving event data $X_i$ for a driver in the risk scenarios, a new risk case $p_i$ for the driver.

Output: The overall case base $CB$, the personal driving case base $CB_i$ for the driver, the evasive maneuver $d_{r_i}$ and the optimal maneuvering time $e_{t_i}$ for the risk case $p_i$.

1: Traffic Event Modeling:
   1. train the model $FFMTE \leftarrow X$;
   2. label and abstract the event data $X$;
   3. case base building:
      4. generate all the possible cases $X'$ using SMOTE method: $X' \leftarrow \text{SMOTE}(X)$;
      5. obtain all the near crash cases using the trained model $(X_{\text{near-crash}}) \leftarrow FFMTE(X')$ and store them into the case base $CB$;
      6. store the personal data $X_i$ into the personal case base $CB_i$;
   7. CBR for on-board personalized driving assistance:
      8. $(d_{r_i}, e_{t_i}) \leftarrow \text{CBR}(p_i, CB, CB_i)$;
      9. update the framework:
         10. store the confirmed (crash/near-crash) new case $(p_i, d_{r_i}, e_{t_i})$ to $X, CB$ and $CB_i$;
         11. retrain the $FFMTE$ model for more accurate traffic event modeling;
         12. repeat the above process to evolve the framework constantly;
      13. return $(d_{r_i}, e_{t_i}, CB, CB_i)$.

For modeling the traffic event, we propose a the $FFMTE$ model to model the severity (crash or near-crash) of each event. For the case database building, our idea is that the near-crash cases involves the valuable information about the evasive maneuvers and the cushion time that can be used to instruct future driving in the risk scenarios, hence we generate all the possible cases and use the trained $FFMTE$ model to obtain all the near-crash cases to build the overall case database. Moreover, the personal driving event cases are also stored into the personal database. For the on-board personalized driving assistance, we propose a CBR-based method to retrieve and reuse the existing cases from the case database, and then use the personal driving history and the driving context to revise the reused cases to adapt to the individual situation and generate the personalized driving assistance. We claim this framework is an open one as it can evolve with increasingly driving event cases accumulated into the databases, and the naturalistic daily driving provides the steady stream of countless traffic cases thus making the framework more and more precise, a novelty of this work compared with all the existing studies. For reference, the algorithm for the proposed framework is shown in Alg. 1.

A. $FFMTE$ Model for Traffic Event Modeling

Formulation of Traffic Event Modeling: Given an event dataset of pairs of $(c, e_{s})$, we want to find a function $f$ that can best model the relationship between the vector of variable predictors, $c$, and the severity of the driving event, $e_{s}$ as: $f : c \rightarrow e_{s}$.

This section introduces the $FFMTE$ model for the traffic event modeling. As the event variables are correlated with each other, we build our model by considering both the variables and their interactions. The architecture of the $FFMTE$ is shown in Figure 4. The core of the model is a factorization machine (FM) [23]. Following [15], $FFMTE$ learns both low- and high-order feature interactions. Considering the latent interaction effect of different values for different variables may be different, such as the same evasive maneuvers on icy road or in extremely dense traffic context, we group all the values for a specific variable into a specific field. For each potential value $x_i$ for a specific variable in a specific field $F(i)$, a scalar $w_i$ is employed to weigh its first-order relevance. Moreover, each value $x_i$ has several dense embedding vectors $V_i \in \mathbb{R}^d$. Depending on the field of other features, one of them $V_i,F(j)$ is used to model the second order feature interactions. All parameters, including $w_i$ and $V_i$, are trained jointly for the combined prediction model:

$$f(x) = w_0 + \sum_{i=1}^{d} w_i x_i + \sum_{j=1}^{i-1} \sum_{j=1}^{K} V_{i,F(j)} V_{j,F(i)} x_i x_j$$ (1)

where $d$ is the number of variables, and $x_i$ is the value of a specific variable in event case $c$. We optimize the $FFMTE$ model using the log-loss function as follows:

$$\mathcal{L} = \frac{1}{2} ||V||_2^2 + \sum_{i=1}^{K} \log(1 + \exp(-y_i f(x)))$$ (2)

where $K$ is number of samples, the $\lambda$ is used to perform $L2$ regularization.

For the NDS, the near-crashes are generally several times more than the crash cases (crashes are comparatively rare) [13]. To improve the performance of traffic event modeling on these imbalanced datasets, we use the synthetic minority oversampling technique (SMOTE) [24] to augment the dataset to make it balanced between two categories of data. Training on this augmented dataset using Eq. 2, each traffic event is predicted as crash or near-crash.

$FFMTE$ shows several benefits for this task: first, it generates the latent embedding vectors $V_i$ for the variables in the model, which can be further used in the deductive reasoning process of case retrieval. These vectors facilitate the similarity calculation (e.g., cosine similarity) for ranking the relevant cases in the database (see Section IV-C). Second, it models
CBR. Considering the significant value of near-crash event cases to provide the instruction information for future driving, we store all such cases into the overall case base. Ideally, the case base should include all kinds of possibilities of near-crashes in the risk scenarios. However, for the existing collected naturalistic driving data, not all the required cases are presented in the public dataset.

To overcome this issue, we generate all the possible cases by combining the different potential values for all the variables (i.e., generate all the potential risk scenarios), and use the trained FFMTE model to classify these events. Benefiting from the merit of FFMTE model that learns the embedding vectors for all the variables across multiple records, it can be well applied to the never or rarely appeared cases in the training data. Hence we can obtain the set of the classified near-crash cases from all the generated cases, and use them to build the overall case base. Moreover, we store the personal driving history data into a personal case base, based on which the further personalized assistance is provided.

C. CBR for On-board Personalized Driving Assistance

CBR is the process of addressing new problems based on prior solutions to similar problems. For the task in this paper, we rewrite the case representation as $c = \{p, s\}$, where $p = \{e_n, p_c, p_m, r_c, d_c\}$ is the premise of a case and $s = \{d_r, c_e\}$ is the solution of the case.

When a new risk case is encountered, CBR will (1) retrieve the similar existing cases in the case base, and rank the retrieved cases as: $c_1 >^+ c_2 >^+ \ldots >^+ c_k$, where the partial order $c_i >^+ c_j$ suggests that the case $c_i$ is more similar to the current case than $c_j$ based on the similarity calculation $\text{sim}(p_i, p_j) > \text{sim}(p_i, p_j)$; (2) reuse the solutions $s_i >^+ s_j >^+ \ldots >^+ s_k$ by mapping it to the current case; (3) revise the proper solution by adapting it to address the current case; (4) retain the adopted solution $\{p, s\}$ to case base if the adaptation to the current case is successful. An example of the CBR process for generating personalized driving assistance is shown in Figure 5.

Case retrieval: we define the similarity of two cases by using cosine distance on the dense embedding vectors of the corresponding variables in the premise parts of two cases, as follows:

$$\text{sim}(p_i, p_j) = \frac{1}{N} \sum_{k=1}^{N} \cos(V_{i,k}, V_{j,k})$$

where the $V_{i,k} \in \mathbb{R}^d$ is the embedding vector of the $k_{th}$ variable in $p_i$, and $N$ is the total numbers of variables in the premise part. Based on this similarity, the cases in the case base are ranked, and the toppest ranked case shows the most similarity with the current situation. As shown in Figure 5, the new case (conflict with a forward decelerating vehicle) have several similar cases (steering right, steering left, etc.) after retrieving from the case base.

Case reuse: this step adapts the solutions in the retrieved cases and constructs a set of candidate solutions $\{\{p, s_1, \text{score}_{e_1}\}, \ldots, \{p, s_j, \text{score}_{e_j}\}\}$ that could be applicable to the current situation, each paired with a confidence level (similarity score).

Case revise: the candidate solutions are revised according to three empirical criterions:

- the final adopted solution has the highest confidence level;
- the solution appears in the personal driving history database;
- the solution does not conflict with the driving context.

The first criterion ensures the adoptability of the solution for the current situation. The second one is for the individualized adaption, it provides the personalized solution that is best fit to the individual driver. Drivers have different preferences and familiarity with different evasive maneuvers, they tend to select the most proficient one in the risk scenarios. Hence we generate the personalized driving assistance by referring their own driving histories, and selecting the most frequent solutions in the candidate sets. The third one is to consider the driving context in the current situation, for example, a driver prefers to steer left in the situation as in Figure 5, if the left adjacent lane has another vehicle, the select maneuver of steering left may lead to a crash, hence the final solution should also consider the driving context and do not conflict with the current context.

The personalized driving assistance is then generated for a specific driver. After validating its effectiveness in the realistic scenario, the confirmed case is then retained into the case base for future usage.

V. EXPERIMENTS

To validate the efficiency of the framework, we conduct experiments on the 100-Car NDS dataset. Our experiments aim to answer the following questions: (1) how does the FFMTE model perform on event case classification? (2) how well is the CBR results for generating the personalized driving assistance? A. Experimental Setup

The original imbalanced dataset is augmented with three methods and formed three balanced datasets: the SMOTE
dataset, the CTGAN dataset \(^3\), the random oversampling dataset, each with the same number (760) of crash and near-crash event data. CTGAN uses the generative adversarial networks (GAN) based data synthesizer to learn the data distribution and generate the minority samples [25]. We trained the FFMTE model for traffic event modeling using five-fold cross validation on the augmented dataset. Grid-search over heuristic choices of hyper-parameters is performed, after obtaining the validation on the augmented dataset. We trained the networks (GAN) based data synthesizer to learn the data distribution and generate the minority samples \(^2\). We trained all the models on the enhanced dataset, and test in predicting the event severity on the 100-Car NDS dataset.

**B. Performance on Event Case Classification**

The different models were evaluated by their performances in predicting the event severity on the 100-Car NDS dataset. We trained all the models on the enhanced dataset, and test their performance on the original dataset. As show in Table II, the proposed FFMTE model achieves the best performance on all the three criteria, with AUC score of 0.981579 and F1 score of 0.981747. The RF obtains the second best, with AUC score of 0.952051 but F1 0.851351. The LR gets the worst on this task, with F1 score only at 0.225, which is probably because the traffic event modeling is not a linear problem, as shown in Figure 3, the valuables are correlated with each other but a linear model does not consider such correlations. The high performance of the FFMTE model on this task may attributes to its unique characteristic to conduct efficient factorization on the sparse dataset and model the interaction between variables.

We also compared the different data augmentation techniques on the model performance. Table III shows the performance of the FFMTE model trained on different augmented datasets. The SMOTE method best fits our task, and shows about 11% improvement compared with the original data. Although the CTGAN method proves some improvement on the sparse dataset and model the interaction between variables, it shows little improvement.

**C. CBR Results for Personalized Driving Assistance**

Based on the 100-Car NDS dataset, we generated 1,034,880 possible cases by combining the different potential values for all the variables, and obtained 858,775 near-crash cases after being classified by the high-performance FFMTE model. We used all the 760 near-crash cases in the original dataset to build the personal case database, with an average number of 7.25 event cases collected for a specific driver.

To test the effectiveness of the CBR process for personalized driving assistance on the built case bases, we conducted three case studies using three query cases, as illustrated in Figure 6. The three query cases were occurring in different risk scenarios. The three query cases are shown in the first column, the adopted personalized solutions are in the second column, the third and fourth columns are the top-ranked general solutions.

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\(^3\) CTGAN for tabular data synthesis: https://sdv.dev/SDV/user_guides/single_table/ctgan.html

\(^2\) xLearn for FFM task: https://xlearn-doc-cn.readthedocs.io/en/latest/

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**Table II**

| Model | AUC  | ACC  | F1   |
|-------|------|------|------|
| DT    | 0.93666 | 0.973430 | 0.847222 |
| RF    | 0.952051 | 0.973430 | 0.851351 |
| SVM   | 0.908707 | 0.955314 | 0.758170 |
| LR    | 0.902545 | 0.925121 | 0.225000 |
| FFMTE | 0.981579 | 0.981579 | 0.981747 |

**Table III**

| Dataset                      | AUC     | ACC     | F1     |
|------------------------------|---------|---------|--------|
| Original dataset             | 0.896401 | 0.981884 | 0.870049 |
| SMOTE dataset                | 0.981579 | 0.981579 | 0.981747 |
| CTGAN dataset                | 0.890687 | 0.890707 | 0.891629 |
| Random oversampling dataset  | 0.893270 | 0.893325 | 0.894907 |

**Table IV**

| Query Case | # of General Solutions (thresholded) | # of Personalized Solutions |
|------------|-------------------------------------|----------------------------|
| Case (a)   | 42                                   | 2                          |
| Case (b)   | 56                                   | 3                          |
| Case (c)   | 28                                   | 2                          |
scenarios: conflict with the leading vehicle (a), conflict with the vehicle in adjacent lane (b), and single vehicle conflict (c). The numbers of thresholded general solutions and the personalized solutions are shown in Table IV. It shows reasonable retrieved results, the general solutions in the case base provide the feasible driving assistance based on the data from all the drivers, while the personalized solutions retrieved from the personal case database greatly reduce the number of recommended solutions by fitting the preference of individual drivers.

Based on the generated personalized solutions, drivers are alerted in proper cushion time to take the proper evasive maneuvers, thus greatly avoiding the potential crashes in different risk scenarios.

VI. CONCLUSION

This paper presented an open CBR-based framework for personalized on-board driving assistance in the risk scenarios by leveraging the wealth of human driving experience from the steady stream of traffic cases (especially the near-crash cases). This framework infers the optimal crash evasive maneuver and the cushion time to hinder the crash occurrence. To model the traffic events, we proposed the FFMETE model with high performance to classify these events into crash and near-crash cases; we then built the case base using all the near-crash cases as they provide valuable instruction to avoid the different potential risks. A tailored CBR-based method was proposed to retrieve, reuse and revise the similar cases to generate the personalized on-board driving assistance. With increasingly driving event cases accumulated into the databases, this open framework will be evolving and increasingly precise. We took the 100-Car NDS dataset as an example to build and test our framework. The results showed that the proposed FFMETE model achieves the best performance for the event modeling compared with the other baseline models; moreover, the personalized driving assistance in the CBR experiments also showed reasonable retrieval results, providing the drivers with valuable evasive information to avoid the potential crashes.

For future work, the driving event information, together with the time-series data collected during these events, will be utilized to conduct more holistic traffic event modeling, and to provide more individualized feedback to help drivers avoid potential risks on the road. Ultimately, we expect that the suggested framework will prove effective in real driving to promote safe driving and mitigate future traffic accidents.

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