Constructing an Experimental and Multifaceted Dataset of Driver Active Responses under Safety-critical Scenarios

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I. INTRODUCTION

The active response of drivers to imminent collisions includes their risk perception, trajectory prediction, and evasive manoeuvre. Such responses exhibit high individual variability and significantly influence subsequent collision occurrence and injury severity. Effective responses during pre-crash can mitigate or avoid collision risks, thereby impacting the efficacy of safety interventions [1]. To understand driver dynamic behaviours comprehensively, it is imperative to acquire multifaceted driver data encompassing behavioural, physiological and environmental information. However, conventional data-collection methods frequently fail to capture the entirety of such crucial data, especially under time-sensitive traffic conditions. Our study introduces a driver-in-the-loop (DIL) simulation approach to construct a comprehensive dataset that captures drivers' active responses under safety-critical scenarios.

II. METHODS

Hazard-Triggering Algorithm through Driving Simulator-based Investigation

We employed a six-degree-of-freedom driving simulator to replicate rear-end collision scenarios and lane-changing conflicts, which NHTSA identifies as the most prevalent car-to-car pre-crash scenarios [2]. We developed a hazard-triggering algorithm to dynamically generate a spectrum of safety-critical scenarios, prompting participants to execute evasive manoeuvres. This algorithm assesses potential interactions and collision risks between the participant-controlled vehicle and its surrounding traffic. The algorithm considers the kinematic state of all vehicles denoted as x. It proceeds to estimate the risk, $R(x)$, for each environmental vehicle based on the probability distributions (Q_{env}) of their future behaviours (Eq. 1). Then, the algorithm identifies the most aggressive vehicle (t^*), which is programmed to execute manoeuvres likely to lead to pre-crash scenarios (Eq. 2):

$$R(x) = \sum\nolimits_{u_i \in U} Q_{\text{env}}(u_i|x) \cdot P_{\text{coll}}(x, u_i) \tag{1}$$

$$t^* = \text{argmax}_{t\epsilon\{1,2,\ldots,T\}} R_t(x), \qquad if \sum\nolimits_{t=1}^{T} R_t(x) > R_{\text{thr}} \tag{2}$$

where u_i represents a specific action taken by an environmental vehicle. The collection of all feasible actions within the executable domain (not interfering with other environmental vehicles and obeying basic traffic rules) is denoted by U, such as changes in speed, steering adjustments, braking, etc. $Q_{\text{env}}(u_i|x)$ is the likelihood of an environmental vehicle executing action u_i given the current state x. $P_{\text{coll}}(x, u_i)$ denotes the probability of a collision between the participant-controlled vehicle and an environment vehicle given the state x and the action u_i. $R_t(x)$ measures the risk with the t-th environmental vehicle, and R_{thr} specifies the triggering threshold value.

The algorithm maintains baseline behaviour patterns for non-aggressive vehicles. Each hazard-triggering instance is followed by a minimum 30 s interval, enabling drivers to return to their inherent driving styles. This hazard-triggering algorithm is designed to elevate the frequency of safety-critical scenarios by inducing heightened aggressiveness among environmental vehicles.

Data Collection

An automated data-collection system was designed to capture a range of driver behavioural and physiological responses. The system recorded drivers' active responses across multiple dimensions (Fig. 1a): risk perception through eye fixation tracking; threat evaluation via electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) signals; the initiation of collision avoidance behaviours captured from a depth camera; along with vehicle kinematics and dynamics data from the simulator. All data were time-synchronised using the simulator's clock as the master time source to ensure alignment across different data streams.

We recruited 12 participants, aged between 22 and 43 years (mean = 30 years; seven males), with an average annual driving distance of 8,791 km. Participants underwent four 30-minute simulation sessions with 10-minute rest intervals. One participant withdrew due to motion sickness. Participants were instructed to drive through a simulated urban area featuring complex multi-lane roads and intersections, freely choosing their routes and performing evasive manoeuvres when needed.

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III. INITIAL FINDINGS

We recorded, identified and analysed 1,689 safety-critical events from 22.5 hours of continuous driving data. These events are captured within a time window from 3 s before to 3 s after the onset of a hazardous situation. The onset of hazard-triggering (OHT) was determined by either a deviation of the risk vehicle from the lane centreline by 0.7 m or by activating its brake lights. These safety-critical events were composed of cut-in events (59.4%), rear-end conflicts (22.4%) and merging incidents (18.2%). The urgency and nature of these generated scenarios were evaluated using critical metrics at OHT. The average time headway was observed at 0.88±0.64 s. Furthermore, the average relative distance and velocity between vehicles were measured at 17.20±12.47 m and 6.38±5.39 m/s, respectively.

In our initial exploration of the multifaceted dataset, we analysed driver manoeuvres and employed Early Response Time (ERT) as a metric to assess individual variability during pre-crash. First, a significant variation in driver manoeuvres to imminent threats was observed. Most events involved a dual evasive approach of the combination of braking and steering (62.4%). Particularly in near-collision events requiring immediate action, the distance needed for a lane change was often less than that required for a complete stop. This strategic combination of braking and steering effectively prevented collisions and minimised the need for heavy braking [3]. Subsequently, ERT was measured from the OHT to initiate braking or steering manoeuvres. The average ERT was 0.63±0.09 s. We employed Kernel Density Estimation (KDE) with a Gaussian kernel to understand the distribution of ERTs among drivers (Fig. 1b). The Interquartile Range (IQR) of ERTs from the 25th percentile (Q1) to the 75th percentile (Q3), along with its overlapping region, shows the variability in drivers' risk perception and ability to avoid collisions. This variability can highly influence both the occurrence of collisions and the boundaries within which they are likely to happen.

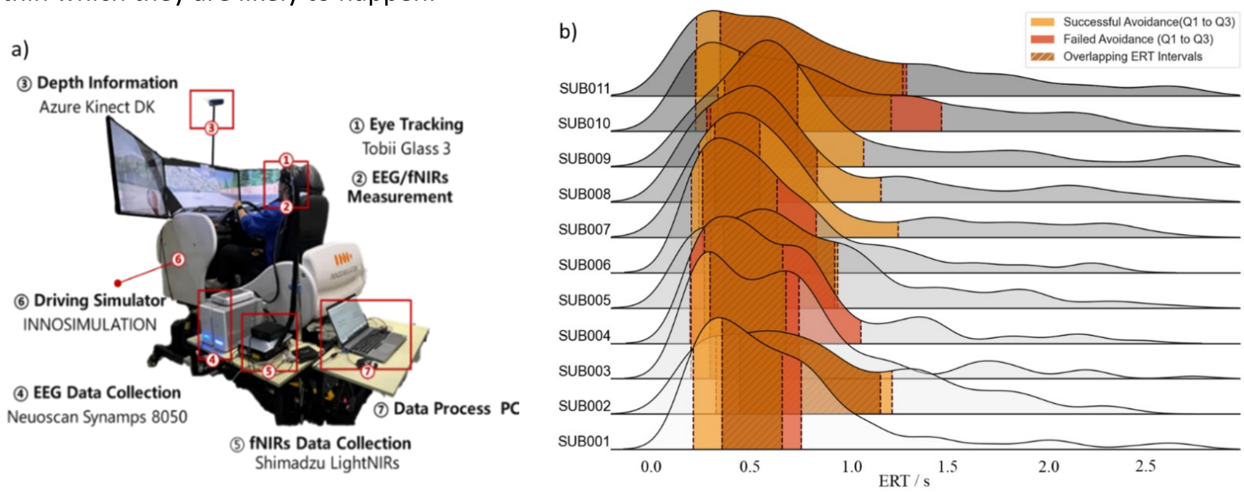

Fig. 1. a) Experimental setup for collecting multifaceted data. b) KDE distribution of the participants' ERTs.

IV. DISCUSSION

The study has established a methodological framework for effectively collecting multifaceted data on drivers' active responses across various safety-critical scenarios. ERTs observed in our study fall within a reasonable range compared to other research on road traffic and simulators [4-5]. Our results indicate the complex nature of drivers' behavioural responses under high-pressure traffic conditions. Consistent with existing research, we note that human reaction times predominantly follow a Gaussian distribution with extended tails [6]. Given the rapid advancement of highly automated vehicles, the significance of drivers' active responses during pre-crash has become even more critical in safety investigations. From this perspective, future research will prioritise combining collision occurrence and human injury outcomes with this dataset to provide a comprehensive understanding. We anticipate that such data can offer a precise depiction and serve as a valuable resource for exploring collision risks, developing personalised active human body models, and enhancing adaptive restraint design.

V. ACKNOWLEDGEMENTS

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VI. REFERENCES

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