

Proposal of a Driver and Passenger State-Change Detection Method Aimed at Appropriate Intervention

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As automated driving technology advances, the demand for non-contact, real-time monitoring of driver and passenger states is paradoxically increasing to enable system interventions. Before full automation, safe authority transfer requires real-time monitoring of drivers. Once full automation is achieved, the objective expands to enhancing occupant comfort, mitigating motion sickness, and providing customized services. However, indicators vary greatly between individuals, and merely estimating states is insufficient for system design. To provide useful support, an in-vehicle system must decide "who," "when," and "how" to intervene. This paper summarizes the critical architectural requirements for such an intervention system and presents a preliminary verification using experimental driving data.

Realizing a practical intervention system involves two core challenges: low-burden measurement and adaptive intervention timing. Potential metrics include biological responses, behavioral indices, and subjective scales, each capturing different states at different timings. For vehicular deployment, low-burden measurement techniques (such as contactless camera-based image processing) are essential to minimize driver distractions. Furthermore, appropriate intervention timing depends entirely on the purpose and method of intervention (e.g., forced emergency stopping versus subtle arousal maintenance stimuli). Since user acceptance of these stimuli varies greatly, the system must adaptively select methods by considering past interaction history and user traits.

We propose a robust conceptual framework that constructs a clean baseline (BL) distribution using multivariate features and tracks subtle state changes through distance metrics (Fig. 1). Individualized BL data are accumulated during a stable period, and multivariate outliers are removed using a two-stage absolute median deviation process combined with a skewness-based loop brake to prevent over-pruning. To account for correlations among metrics, the Mahalanobis distance is utilized to define a unified state space with the BL median as its origin. For real-time monitoring, incoming windows are mapped into this space. A temporal majority vote filter, denoted as the M-of-N rule, triggers a state-change flag if N out of the last M windows are judged as outliers, filtering out sporadic artifacts.

The proposed framework was applied to experimental driving data collected from four participants across three days. The algorithm utilized three non-contact blink parameters in a 60-second moving window with 10-second steps ($M=3$, $N=2$). In the illustrated trial (Fig. 2), the system detected state changes immediately prior to or concurrent with subjective changes, demonstrating a relatively good capability. However, subjective ratings often deviate significantly from the experimenter's observations, proving insufficient as a definitive ground truth. Optimizing the parameters and evaluating the validity of detection timings remain crucial tasks for future work.

This paper conceptualizes driver and passenger monitoring as a tool for intervention, organizing architectural requirements for timing and method determination. By using low-computation static distance metrics for online tracking, this framework minimizes computational overhead to facilitate edge processing on in-vehicle hardware. Since empirical verification has just begun, optimizing methods and parameters under ambiguous ground truths requires vital feedback from occupants. Beyond traditional surveys, a mechanism to elicit acceptance and efficacy evaluations during natural post-intervention or post-trip dialogues is highly desired. Utilizing an AI-powered conversational in-vehicle partner is a promising direction, not only for real-time rating and intervention but also for harvesting this crucial user feedback.

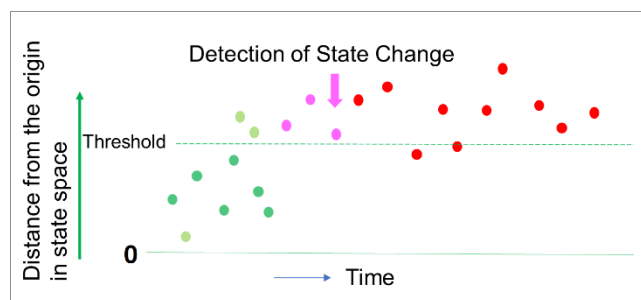


Fig. 1. Conceptual diagram of proposed multivariate state-change detection framework

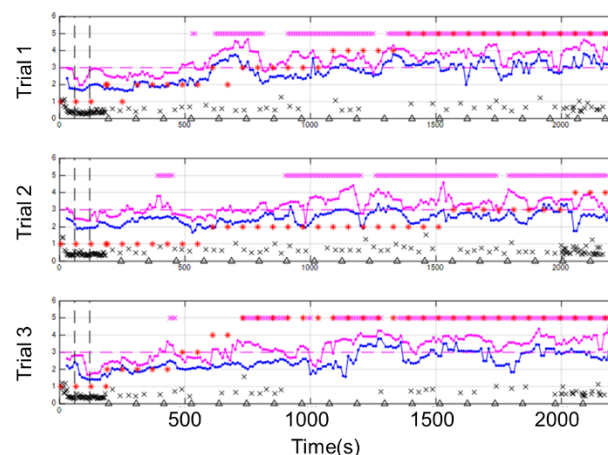


Fig. 2 Examples of state-change detection using the Mahalanobis distance shown with temporal profiles (Q75, median, subjective scales, reaction times) across three trials