Generalizable ECG-based Driver Cognitive Load Estimation: Adversarial Invariant and Plausible Uncertainty Learning

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Abstract:

[Objectives]The cognitive load of drivers is a critical factor influencing driving safety, drawing considerable attention from researchers aiming to objectively assess this load using physiological measures. Electrocardiography (ECG) data, collected non-invasively through wearables like smartwatches or steering wheel-integrated sensors, provides a promising avenue for such assessments. Unlike other physiological indicators that can only be collected invasively, such as electroencephalography (EEG) or galvanic skin response (GSR), ECG can be collected less intrusively and thus it is more appropriate for real-time driver cognitive state monitoring. However, on one hand, despite the potential advantages of ECG signals for cognitive load estimation, the direct use of raw ECG data in this context remains underexplored. Traditional approaches often depend on manual extraction of ECG indicators, which is time-consuming and not suitable for real-time analysis. Thus, direct utilization of ECG signals without manually extracting the hand-crafted features could streamline the process, making the driver state monitoring (DSM) systems more efficient and accurate. On the other hand, the performance of DMS can also be impaired by the generalizability issue. Models trained on laboratory data often fail to adapt to the complexity of real-life driving conditions, where variations in environment, driver behavior, and physiological responses are more pronounced. Moreover, the issue of domain shift, where training and testing data come from different distributions, compounds this difficulty. While transfer learning has been posited as a solution, its application generally addresses either cross-subject or cross-task generalization, not both simultaneously. Furthermore, traditional domain adaptation methods pre-suppose the availability of target domain data, a premise unworkable in many practical situations.

[Methods] In response to these challenges, we introduce a novel plug-in framework, CogDG-ECG, designed to enhance the generalization of cognitive load estimation using ECG raw data across diverse domains. The core idea of our framework is the extraction of domain-invariant features (i.e., the stable correlations between physiological signals and cognitive load levels, unaffected by domain-specific variations). We employ adversarial learning to mitigate the effects of domain variability on feature extraction. Simultaneously, we embrace uncertainty to account for domain attribute-related features, synthesizing statistically plausible variations to improve the resilience of out-of-distribution (OOD) samples of the network. Then, the CogDG-ECG is developed for multi-source domain generalization (MSDG), where it is trained on multiple datasets to minimize the discrepancy in feature distributions across domains, thereby achieving more accurate cross-domain cognitive load estimation. In summary, our network is trained using a composite loss function that includes domain-invariant feature regularization, uncertainty introduction, and classification accuracy, making it well-suited to multi-dataset training environments.

[Results]

[Conclusions] The primary contributions of this work are threefold: Firstly, we introduce CogDG-ECG, an innovative end-to-end method that addresses domain shift issues in large-scale ECG-based cognitive load estimation, marking the first instance of MSDG application in this field. Secondly, we integrate adversarial and contrastive loss to align domain-invariant features and generate unseen instance-level variations, thereby enhancing the generalizability of the models to handle OOD instances. Lastly, we establish a benchmark for cognitive load estimation using ECG under the MSDG protocol,

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demonstrating the superior performance of our approach. The end-to-end training capability and the plug-in nature of our method are particularly advantageous for large-scale industrial applications. Moreover, our proposed protocol and benchmark set a new precedent, stimulating further research in this vital area of intelligent transportation systems.

Keywords: Cognitive load estimation, ECG, multi-source domain generalization, deep learning

Short Abstract
(filling in the submission system Abstract column ,the length should be within 400 words) ↓

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Abstract: Cognitive load estimation using physiological measures is critical for driving safety. While ECG can be acquired through non-invasive wearables and offers a promising method for monitoring cognitive states, the direct use of raw ECG data for cognitive load estimation is still underutilized. Current methods rely on manual extraction of ECG-based features, which is unsuitable for real-time applications. Moreover, the generalizability of existing models is limited due to domain shift—the discrepancy between controlled laboratory data and the unpredictable nature of on-road driving. In this work, we present CogDG-ECG, a novel framework that leverages multi-source domain generalization (MSDG) to train on varied datasets, which can enhance the ability of the model to predict cognitive load across different driving conditions. The framework extracts domain-invariant features through adversarial learning, ensuring the relevance of physiological signals to cognitive load levels despite domain-specific differences. To further improve robustness to out-of-distribution (OOD) samples, we introduce uncertainty into domain attribute-related features. The CogDG-ECG is optimized with a composite loss function that includes domain-invariant feature regularization, uncertainty introduction, and classification accuracy, making it adept for multi-dataset environments. Our contributions are threefold: (1) We propose CogDG-ECG, a unique end-to-end method for ECG-based cognitive load estimation that overcomes domain shift challenges, and it is the first to apply MSDG in this context. (2) We employ adversarial and contrastive loss to enhance the generalizability of the model to handle OOD instances by aligning domain-invariant features and simulating unseen instance-level variations. (3) We establish a benchmark for cognitive load estimation using ECG under the MSDG protocol, demonstrating the effectiveness of our approach. Our work signifies a substantial advancement in intelligent transportation, offering a scalable solution for in-vehicle cognitive load assessment that can adapt to the complexities of real-world driving. The introduction of CogDG-ECG and its benchmark provides a foundation for future research, driving progress in the field of driver safety and intelligent transportation systems.

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