

In-Cabin Human-State Estimation Using Mental and Physical Stress Classification Based on Synchronized HRV and Endocrine Biomarkers

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Improving safety and comfort in vehicle cabins requires noninvasive, continuous monitoring of occupants' internal states. Current Driver Monitoring Systems (DMS) rely mainly on external cues such as gaze and facial expressions; therefore, DMS alone is limited in detecting discomfort before it becomes apparent and in identifying the type of stress. In this study, we developed a method that estimates changes in salivary alpha-amylase (sAA), an overall-stress indicator, and chromogranin A (CgA), a mental-stress indicator, from HRV^{*1}, which reflects autonomic nervous activity, and classifies stress into four states. Fig. 1 presents the framework comprising HRV acquisition, temporal synchronization, CNN^{*2} regression, and four-state stress classification using ROC^{*3}-derived thresholds.

We collected ECG (electrocardiogram), sAA, CgA, and subjective ratings from 13 participants in a driving-stress task experiment and 26 participants in comfort/discomfort task experiments, and calculated nine HRV features from RR intervals^{*4}. To account for the delayed endocrine response, HRV data from 0 to 400 s before saliva collection were synchronized at 20-s increments. For both biomarkers, the strongest correspondence was observed with HRV 180 s earlier. CNN regression using time-series HRV as input achieved $R^2 = 0.5253$ and $r = 0.7335$ for sAA estimation and $R^2 = 0.5860$ and $r = 0.7823$ for CgA estimation, outperforming linear regression (sAA: $R^2 = 0.4871$, $r = 0.7298$; CgA: $R^2 = 0.4630$, $r = 0.7266$). Using thresholds determined by ROC analysis, overall-stress detection achieved ROC-AUC^{*5} = 0.9016 and an accuracy of 0.8095, while mental-stress detection achieved ROC-AUC = 0.9903, an accuracy of 0.9756, and a recall of 1.0000. Combining the two decisions enabled classification into four states: comfort, physical stress, mental stress, and overall stress. These results demonstrate that salivary biomarkers are needed only as supervisory labels during training, whereas in actual operation, occupants' states can be continuously estimated from HRV obtained solely by wearable ECG/PPG^{*6}.

Future work will examine implementation on an in-vehicle ECU and integration with HVAC and HMI control to enable personalized comfort-enhancement systems that intervene before discomfort becomes apparent.

*1 HRV: Heart Rate Variability; *2 CNN: Convolutional Neural Network; *3 ROC: Receiver Operating Characteristic; *4 RR interval: time between successive R waves in an ECG waveform.

*5 ROC-AUC: Area Under the Receiver Operating Characteristic Curve; *6 PPG: Photoplethysmography.

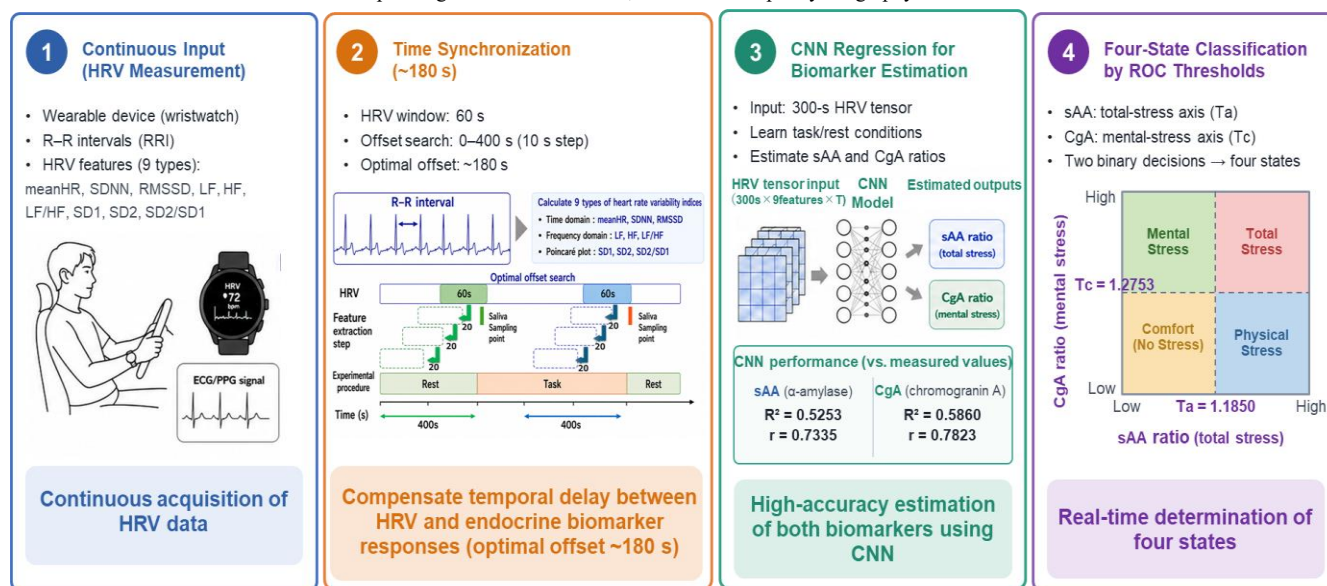


Fig. 1 Overall framework of HRV-endocrine synchronization for real-time human-state estimation