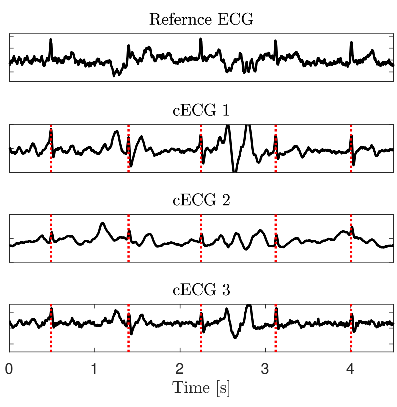
Signal-Level Fusion with Convolutional Neural Networks for Capacitively Coupled ECG in the Car

Erik Breuer, Marian Walter, Steffen Leonhardt, Christoph Hoog Antink

Philips Chair for Medical Information Technology,
RWTH Aachen University, Aachen, Germany

Unobtrusive measurement technologies for vital signs, such as capacitively coupled electrocardiography (cECG), allow for health monitoring outside the clinical domain. With the advent of autonomous vehicle technologies, monitoring the driver's state has seen increased attention and has become a major research challenge. While cECG has the potential to deliver accurate information about the driver's heart, the signal quality is very volatile compared to standard ECG and can be corrupted easily by motion artifacts. This renders the problem of identifying individual heartbeats challenging. To increase accuracy and robustness, the fusion of multiple channels and / or modalities has proven to be a potent tool. Fusion on the signal level is particularly powerful, as the maximum amount of information is available.



In this work, we present a fusion algorithm based on a convolutional neural network (CNN) to locate individual heartbeats in three-channel cECG signals. To design and optimize the CNN's structure, standard ECG data from the PhysioNet / CinC challenge "Robust Detection of Heart Beats in Multimodal Data" was used as an independent source. The developed architecture consisted of four convolutional layers per cECG channel, which we integrated with a fully connected layer. To train and test the algorithm, we used data from six subjects and three different driving scenarios (highway, city, and proving ground) that is freely available as part of our UnoViS-database. Data consisted of 31 recordings with a total duration of 13.4 hours. Leave-one-recording-out cross validation was performed to assess the algorithm. During training, between 105,000 and 140,000 snippets of the signal were used. For evaluation, we applied the CNN to the left-out recording in a sliding window approach combined with basic peak detection on its output. Using cross validation, we achieved a sensitivity of 83.7% and a positive predictive value of 95.2% compared to the reference ECG.