Digital Health and Informatics Innovations for Sustainable Health Care Systems
J. Mantas et al. (Eds.)

doi:10.3233/SHTI240576

Robust In-Vehicle Signal Quality Assessment Using Multimodal Signal Fusion

Laushya SENTHILKUMAR[a], Joana M. WARNECKE[b,1], Julian BOLLMANN[b] and Thomas M. DESERNO[b]
[a] *Indian Institute of Technology Madras, India*
[b] *Peter L. Reichertz Institute for Medical Informatics of TU Braunschweig and Hannover Medical School, Germany*

Abstract. Continuous monitoring of physiological signals such as electrocardiogram (ECG) in driving environments has the potential to reduce the need for frequent health check-ups by providing real-time information on cardiovascular health. However, capturing ECG from sensors mounted on steering wheels creates difficulties due to motion artifacts, noise, and dropouts. To address this, we propose a novel method for reliable and accurate detection of heartbeats using sensor fusion with a bidirectional long short-term memory (BiLSTM) model. Our dataset contains reference ECG, steering wheel ECG, photoplethysmogram (PPG), and imaging PPG (iPPG) signals, which are more feasible to capture in driving scenarios. We combine these signals for R-wave detection. We conduct experiments with individual signals and signal fusion techniques to evaluate the performance of detected heartbeat positions. The BiLSTMs model achieves a performance of 62.69% in the driving scenario city. The model can be integrated into the system to detect heartbeat positions for further analysis.

Keywords. Sensor fusion, Machine learning, Personal mobility, BiLSTM, Heartbeat detection.

1. Introduction

According to the World Health Organization, cardiovascular diseases are a leading cause of global mortality, responsible for approximately 17.9 million deaths annually and accounting for 32% of all deaths globally [1]. Continuous monitoring of heartbeats enables early disease detection, improves therapeutic outcomes, and ultimately reduces mortality rates [2]. Several studies have explored heartbeat detection during driving, highlighting the potential for integrating health monitoring into vehicles [3]. Sensor fusion techniques are crucial for integrating data from multiple sensors to enhance the reliability of peak detection in physiological signals. By combining signals from different sensors, we can overcome the limitations of individual sensors and improve the overall quality of the data. In this paper, we use bidirectional long short-term memory (BiLSTMs) models, which are well suited for analyzing sequential data, such as time series from physiological signals [4].

[1] Corresponding Author: Joana M. Warnecke; E-mail: joana.warnecke@plri.de.

BiLSTM models can capture long-term dependencies in the data, making them more suitable for analyzing ECG signals over time. Overall, this paper aims to answer the research question “Does the BiLSTM model outperform the existing signal fusion model for in-vehicle heartbeat monitoring?”. To demonstrate the importance of continuous monitoring in driving spaces and the potential of sensor fusion techniques with the BiLSTMs model in improving the reliability and accuracy of heartbeat detection in physiological signals.

2. Methods

2.1. Data Set

In previous work, we published study data with 19 subjects while driving [5]. The data comprises reference ECG, steering wheel ECG, and PPG signals in a comma-separated value (CSV) format, as well as red, green, and blue (RGB) channels for the segmented cheeks in MatLab (MAT) format. The iPPG data was pre-processed using the SeetaFace face engine to ensure the anonymity of participants [5]. Additionally, data includes subject information such as subject ID, age, height, weight, gender, and known diseases. For 15 min each, the dataset encompasses recordings from healthy young subjects in city, highway, and rural settings, both at rest and in motion. Only the city data was utilized for experimentation.

2.2. Data-Preprocessing

2.2.1. Ground Truth

We obtain ground truth from a reference ECG sensor, which records the ECG with three adhesive electrodes placed on the chest's standard positions. We detect the R-peaks position using the simultaneous truth and performance level estimation (STAPLE) algorithm of Kashif et al. [6]. STAPLE integrates nine state-of-the-art algorithms and determines R-wave positions through a weighted majority vote.

2.2.2. Input Data and Pre-Processing

The input data for the signal fusion algorithm are ECG, PPG, iPPG, and the ECG reference as ground truth. The pre-processing has three different steps: 1. Median filtering is applied, 2. Normalization of the amplitude for the interval [−1, 1], 3. Calculation of the signal-to-noise ratio (SNR) for individual windows using an optimal threshold to eliminate noisy segments. Segments removed from the steering wheel ECG are subsequently removed from the PPG and iPPG signals. The 15-minute recording with a sampling rate of 500 Hz is divided into snippets of 501 samples. The overlap is 490 for training data snippets and 500 for testing snippets, which is based on Chandra et al. [7].

2.3. Signal Fusion using BiLSTMs

The BiLSTM network architecture for peak detection in ECG signals consists of three bidirectional LSTM layers, each followed by batch normalization to enhance training stability [4].

The first bidirectional LSTM layer comprises eight units, while the subsequent layers consist of four and two units. This design allows the model to capture temporal dependencies in both forward and backward directions, aiding in the identification of ECG peaks (Fig. 1). To mitigate overfitting, we apply a dropout with a rate of 0.2 to each LSTM layer, while we utilize L2 regularization with a strength of 0.01 in the final dense layer to further enhance generalization.

We define the input shape of the model as (length of signal, 500, 3), indicating sequences of 500-time steps with a fusion of three signals. The output layer is a dense layer with a sigmoid activation function, suitable for binary classification tasks. We train the model using the hinge loss function, commonly used in support vector machine (SVM)-like models for binary classification and use the Adam optimizer with a learning rate of 0.001.

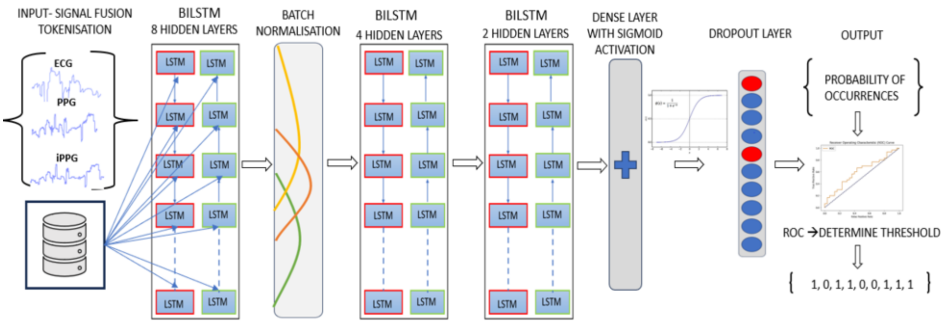

Figure 1. BiLSTM model architecture.

2.4. Attention Mechanism

The attention layer built initializes a trainable weight matrix that represents the attention weights. These weights are learned during the training process and determine the importance of each element in the input sequence.

The call method applies these attention weights to the input sequence, scaling each element by its corresponding attention weight. This scaling process allows the model to prioritize important signals that contribute to decision-making and suppress irrelevant ones, effectively focusing its attention on the most informative parts of the input sequence.

2.5. Performance Metrics

Class 0 for a snippet means no heartbeat and class 1 includes a heartbeat. The results for each snippet are compared to the ground truth to evaluate the performance.

We determine the optimal threshold for classification using the area under the receiver operating characteristic (ROC) curve (Fig. 2). The receiver operating characteristic (ROC) curve illustrates the trade-off between the true positive rate (and the false positive rate.

The threshold is a value used to convert the continuous output of the model (predicted probabilities) into binary predictions (0 or 1).

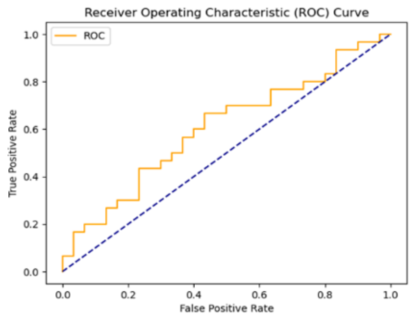

Figure 2. ROC curve for the BiLSTM.

The evaluation of the BiLSTM model involves several key metrics to assess its performance in peak detection within ECG signals. We train and test the model by leaving-one-out cross-validation (LOOCV). The evaluation includes metrics such as positive predictive value (PPV), sensitivity (S), and performance (P), which is $P = (PPV + S)/2$. The loss-epoch curve is used to monitor the training and validation performance of a machine learning model over the course of training epochs.

3. Results

For the driving scenario city, the BiLSTM approach with the fusion of all signals outperforms the BiLSTM approach with just one signal by 62.69% (Table 1). The iPPG signal has the lowest performance with 53.50%. These results show that the fusion of all sensors outperforms the usage of a single sensor.

Table 1. Performance of the BiLSTM for ECG, PPG, and iPPG during the driving scenario city.

Approach	Sensitivity in %	PPV in %	Score in %
ECG	49.51	58.85	54.18
PPG	58.42	53.54	57.34
iPPG	49.13	57.86	53.50
ECG+PPG+iPPG	68.97	56.37	62.69

4. Discussion

Several publications are focusing on heart rate detection during driving with one sensor [8,9]. Walter et al. implemented capacitive ECG (cECG) into the backrest of the seat to derive the heart rate and remained stable after approx. 250 seconds [8]. Gomez-Clapers et al. integrated ECG electrodes into a plastic steering wheel and analyzed the performance of a 60 s recording with twelve subjects in a lab environment [9]. Warnecke et al. analyzed the utilizable recording time with signal fusion based on a convolutional neural network (CNN) structure [5]. Because of the same data set, the performance results are directly comparable.

For the driving scenario city, the new BiLSTMs model achieved a performance of 62.69%, outperforming the existing CNN fusion approach from Warnecke et al., which had a performance of 47.90% [5].

This improvement demonstrates the effectiveness of the proposed method in enhancing the accuracy of heartbeat detection in driving environments. However, the analysis has not considered the entire signal including all the driving scenarios such as in [5]. The signal fusion with BiLSTM has a runtime of less than 5 minutes. In terms of memory and speed, BiLSTM models are more efficient in handling sequential data. CNNs require more memory and computation due to their kernel operations and pooling layers. BiLSTMs sequential processing captures long-term dependencies in the data more effectively, better performing in tasks such as peak detection. For the driving scenarios of highways and countryside, we still need to calculate the score with the BiLSTM approach. There are several suggestions for improving upon the BiLSTM model. Transformer architectures, known for their parallel processing capabilities, can also be explored for further improving memory and speed efficiency [10]. Additionally, meta-learning models combined with high-performance processors offer enhanced learning capabilities and faster processing speeds, leading to improved overall performance.

5. Conclusions

We developed a model for multi-modal signal fusion that works effectively and fast. Performing a larger number of experiments with multiple combinations of networks improves the performance of heartbeat detection. This is a primary step towards explaining the black-box nature of deep learning models.

6. References

[1] Cardiovascular diseases [Internet]. Genève: World Health Organization [cited 2024 Apr 2]; [about screen Available from: https://www.euro.who.int/en/health-topics/noncommunicable-diseases/cardiovascular-diseases/cardiovascular-diseases2

[2] Steinhubl SR, Waalen J, et al. Effect of a home-based wearable continuous ECG monitoring patch on detection of undiagnosed atrial fibrillation: the mSToPS randomized clinical trial. JAMA. 2018;320(2):146-55.

[3] Leonhardt S, Leicht L, Teichmann D. Unobtrusive vital sign monitoring in automotive environments: a review. Sensors (Basel). 2018 Sep 13;18(9):3080.

[4] Zhao Y, Yang R, Chevalier G, Xu X, Zhang Z. Deep residual bidir-LSTM for human activity recognition using wearable sensors. Math Problem Eng. 2018 Dec 30;2018:1-3.

[5] Warnecke JM, Lasenby J, Deserno TM. Robust in-vehicle heartbeat detection using multimodal signal fusion. Sci Rep. 2023;13:20864.

[6] Kashif M, Jonas SM, Deserno TM. Deterioration of R-wave detection in pathology and noise: a comprehensive analysis using simultaneous truth and performance level estimation. IEEE Trans Biomed Eng. 2016;64(9):2163-75.

[7] Chandra BS, Sastry CS, Jana S. Robust heartbeat detection from multimodal data via CNN-based generalizable information fusion. IEEE Trans Biomed Eng. 2018;66(3):710-7.

[8] Walter M, Eilebrecht B, Wartzek T, Leonhardt, S. The smart car seat: personalized monitoring of vital signs in automotive applications. J Pers Ubiquit Comput.2011;15(7):707–15.

[9] Gomez-Clapers J, Casanella, R. A fast and easy-to-use ECG acquisition and heart rate monitoring system using a wireless steering wheel. IEEE Sensors.2012;12(3):610–6.

[10] Zhou F, Wang J. Heartbeat classification method combining multi-branch convolutional neural networks and transformer. iScience. 2024 Feb 23;27(3):109307.