Deep Network for Capacitive ECG Denoising

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0. Overview

- Introduction to Capacitive Electrocardiogram
- Need for denoising
- Dataset Description
- Proposed Network
  - Architecture
  - Training method
- Experiments & Results
- Conclusion

1. Introduction to Capacitive Electrocardiogram

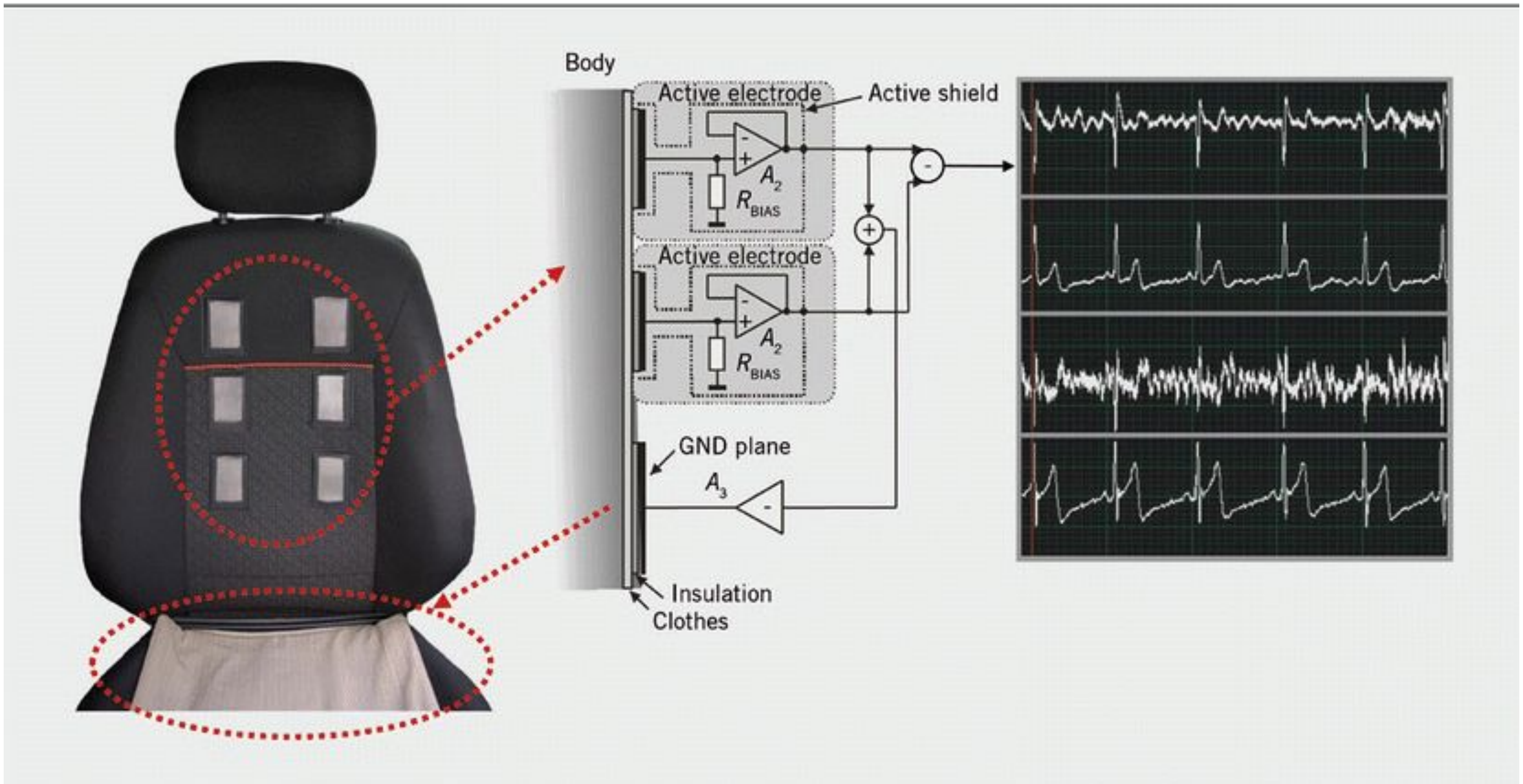
- Capacitive Electrocardiogram (cECG) is a method for ECG monitoring without requiring skin contact

- Allows for comfortable and long term monitoring of ECG without risk of skin irritation or introducing disturbance to a patient's daily life

- Capacitive ECG which is measured using capacitively coupled electrodes measures the changes in electric field associated with cardiac activity

- Can be integrated to be used in clothing, furniture and car seats

2. Introduction to Capacitive Electrocardiogram



Capacitive ECG measurement in a seat [1]

3. Need for denoising

- cECG is highly vulnerable to motion artifacts by design
- Motion artifacts is particularly significant while user is active like while on an automobile seat or on a chair which results in variance in coupling capacitance
- Noise in the signal significantly impacts the ability of traditional algorithms for tasks like QRS detection
- Algorithms proposed to derive useful information from noisy cECG has been limited to QRS detection rather than denoising the signal [2].
- Ability to denoise cECG can allow for morphological and rhythmic analysis of ECG in everyday conditions.

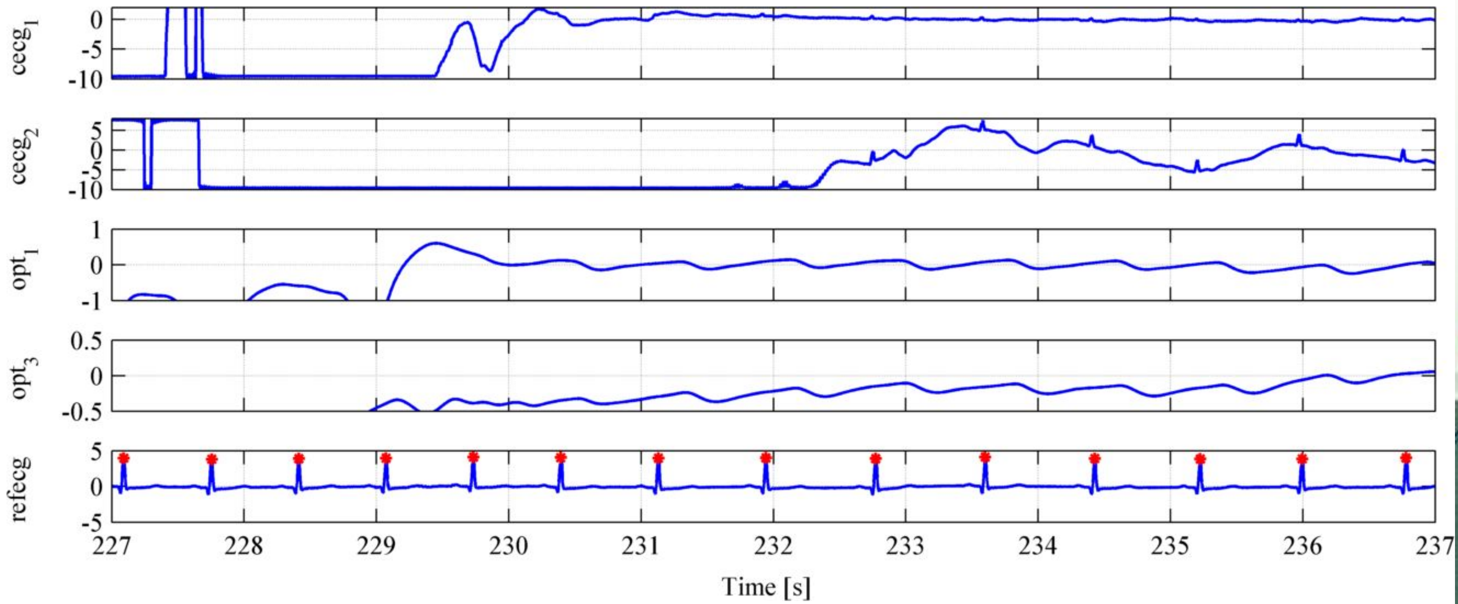
4. Dataset Description

- UnoViS database contains several hours of unobtrusive medical monitoring Photoplethysmogram (PPG) and capacitive ECG in free living conditions along with reference ECG. [3]

- Comprised of 13.4hr worth of recording under active driving in 31 sessions

- Three bipolar capacitive ECG leads were obtained similar to the Einthoven's triangle. Simultaneous reference LEAD I ECG was obtained from a clinical grade ICU monitor along with its QRS annotations

5. Dataset Description

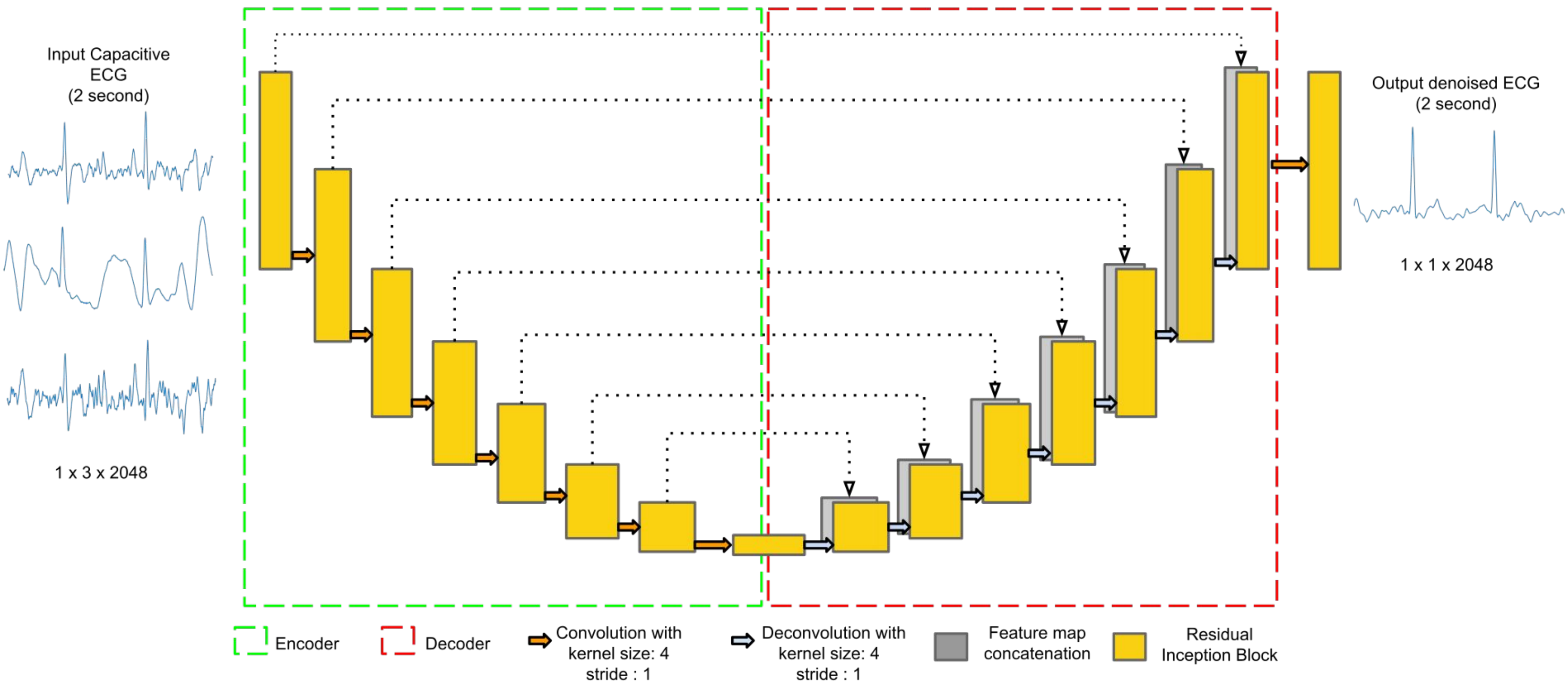


Courtesy: Helmholtz-Institute for Biomedical Engineering, UnoVis (https://www.medit.hia.rwth-aachen.de/publikationen/unovis/) [3]

6. Proposed Network

- The task of denoising in images has increasingly been carried out by deep learning networks (autoencoders)
- U-Net is one specific deep learning architecture which has shown excellent results for medical image denoising
- The task of denoising cECG is similar image denoising where we would like to obtain an approximate reconstruction of the reference ECG rhythm
- The proposed network would take 2 second windows of multichannel (3 ch) cECG as input and LEAD I ECG as reference

7. Proposed Network - Architecture



Architecture of the proposed network

8. Proposed Network - Training Method

- The proposed network was inspired by the IncResU-Net network which is used for 2D medical image segmentation application [4]

- We apply multi-domain loss:
  - Time domain: L1 Loss
  - Frequency domain: L1 Loss between FFT's of prediction and ground truth

- Training was carried out for 2500 epochs for a batch size of 256 with a learning rate of 0.01 using a Stochastic Gradient Descent optimizer

- The model was developed and implemented in PyTorch

9. Experiments and Results

- Two different models are proposed for the task of capacitive ECG denoising, the first model was exclusively trained on the signal domain L1 loss while the second model was trained on both signal domain and frequency domain L1 loss.

- The evaluation of the proposed models are carried out by two methods:
  - Comparison of RR interval and HRV parameters for model prediction and reference ECG
  - Comparison of similitude and signal reconstruction error against a reference LEAD I ECG.

10. Experiments and Results

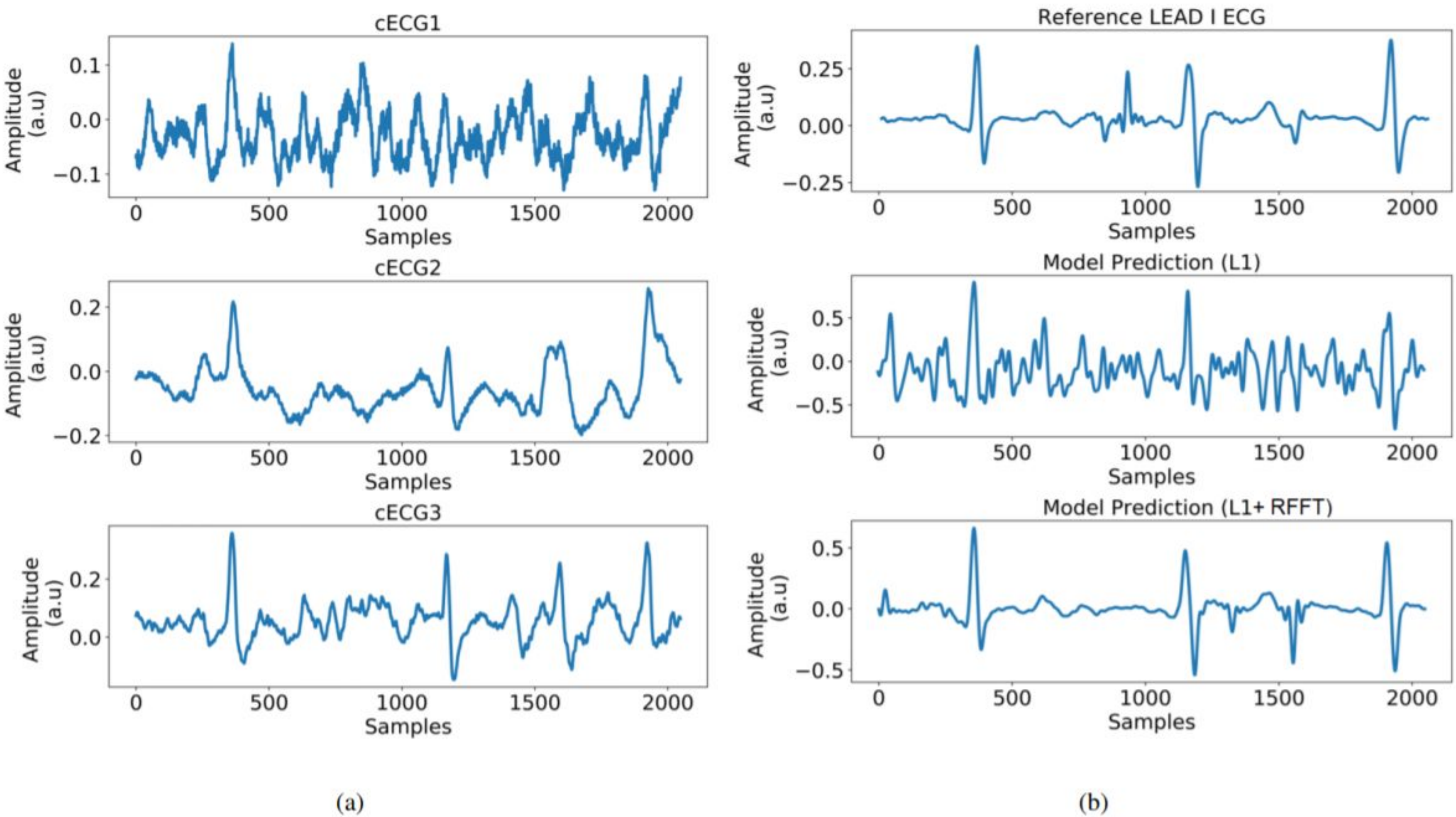
TABLE I : HRV analysis of proposed models and ground truth ECG

File Number	Ground Truth ECG HRV metrics				Model predictions (L1) HRV metrics					Model predictions (L1+RFFT) HRV metrics				
	Mean RR intervals (s)	**RMSSD (s)**	**pNN50 (%)**	**LF/HF**	**Mean RR intervals (s)**	**RMSSD (s)**	**pNN50 (%)**	**LF/HF**	**Cross Correlation**	**Mean RR intervals (s)**	**RMSSD (s)**	**pNN50 (%)**	**LF/HF**	**Cross Correlation**
1	0.742	0.077	40.10%	0.563	0.785	0.089	47.20%	1.221	0.248	0.821	0.084	44.70%	1.343	0.458
2	0.782	0.027	6.42%	5.271	0.765	0.039	13.41%	0.347	0.347	0.779	0.0369	9.24%	5.828	0.384
3	0.785	0.0258	3.85%	5.326	0.695	0.082	17.26%	1.73	0.272	0.716	0.063	13.27%	2.791	0.463
4	0.787	0.0253	3.92%	5.267	0.712	0.097	36.13%	2.617	0.316	0.726	0.067	24.63%	3.182	0.374
5	0.815	0.034	4.37%	5.326	0.697	0.082	37.32%	0.831	0.461	0.728	0.054	7.36%	8.857	0.464
6	0.772	0.025	4.58%	7.31	0.726	0.073	28.18%	3.184	0.273	0.755	0.033	8.95%	5.456	0.347
7	0.769	0.0287	8.41%	3.718	0.734	0.027	7.40%	3.878	0.449	0.754	0.031	9.39%	3.611	0.464

TABLE II : Comparison for LEAD I ECG reconsturction

Model	**MSE**	**Cross Correlation**	**Lag**
L1	0.235	0.241	0.989
L1 + RFFT	**0.167**	**0.476**	**0.998**

11. Experiments and Results



(a) Sample input multi-channel capacitive ECG signal
(b) Reference Lead I ECG, Model predictions (L1, L1+RFFT)

12. Conclusion

- The present work describes a novel approach to denoise capacitive ECG signals using a learning based model.
- The model trained on joint loss provides lower error when compared to the model trained exclusively on the signal domain loss.
- Extensive validation is crucial to determine the capability of the proposed predictions for providing morphological information
- Training has to be carried out on a wide range of cardiac anomalies and the corresponding performance study needs to conducted

References

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Thanks