THE ANDREW & ERNA VITERBI
FACULTY OF ELECTRICAL ENGINEERING

Work in Progress

SIPL
Signal and Image Processing Lab

TECHNION
Israel Institute of Technology

Compression for Continuous Long-Term Electrocardiography Recordings

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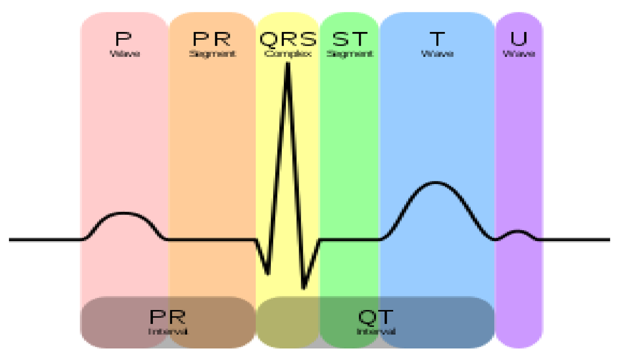
Introduction

The Problem

- An electrocardiogram (ECG) records the electrical signal from the heart.
- A long-term ECG provides insight into the behavior of the heart in the everyday life of the patient, for long periods of time.
- Such recordings have very large memory requirements and require compression for storing and transmitting.
- When lossy compression is applied to biomedical signals such as ECG, avoiding loss of important diagnostic data elements is critical.



Our Goal

- ECG compression with the following attributes

EFFICIENT COMPRESSION RATIO

DIAGNOSTIC EQUIVALENCY

Methods

Database

- Annotated ECG signals sampled at a frequency of 200[Hz].
- From 2,891 patients.
- Each record lasts approximately 24 hours.
- The data contains 3 heart abnormalities.
- Appropriate to assess whether the compression affected the diagnostic information.

Pre-Processing

- The data was resampled to 360Hz.
- Passed through a band pass filter.
- Scaled to be in the range $[0,1]$.

Evaluation Criteria

root means squared $RMS = \sqrt{\sum_{i=0}^{D-1} \frac{\left(S_o(i) - S_r(i)\right)^2}{D}}$

PRD normalized $PRDN(\%) = 100 * \sqrt{\frac{\sum_{i=0}^{D-1}\left(S_o(i) - S_r(i)\right)^2}{\sum_{i=0}^{D-1}(S_o(i) - S_m)^2}}$

$S_m = mean(S_0)$

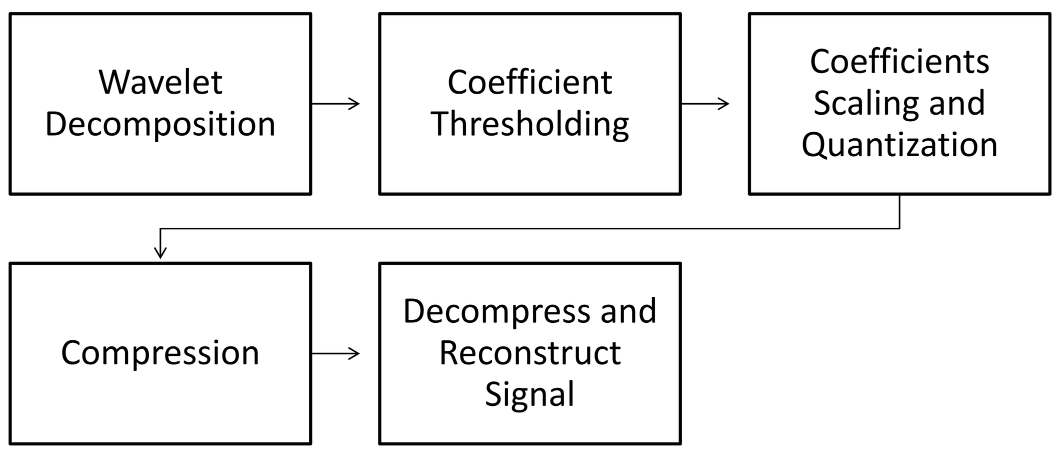
percentage RMS difference $PRD(\%) = 100 * \sqrt{\frac{\sum_{i=0}^{D-1}\left(S_o(i) - S_r(i)\right)^2}{\sum_{i=0}^{D-1}\left(S_o(i)\right)^2}}$

signal to noise ratio $SNR = 10 * \log\left(\frac{\sum_{i=0}^{D-1}(S_o(i) - S_m)^2}{\sum_{i=0}^{D-1}\left(S_o(i) - S_r(i)\right)^2}\right)$

quality-score $QS = \frac{CR}{PRD}$

Wavelet Baseline

- Lossy compression Based on (Elgendi et al, 2017 [1]).
- Uses a wavelet of type Bior4.4.



Deep baseline

- A deep network structure of an encoder and decoder totaling in 27 layers, based on (Yildirim et al, 2018 [2]).
- The training was preformed using the Adam Optimizer with initial learning rate of 0.001, weight decay of 1e-5 and batch size of 32.

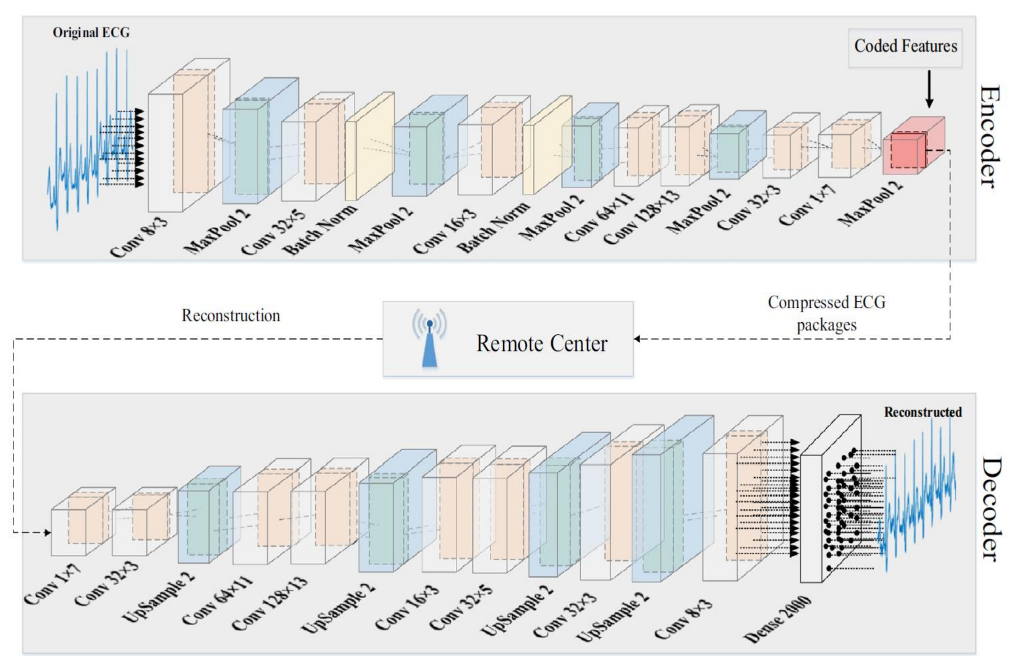


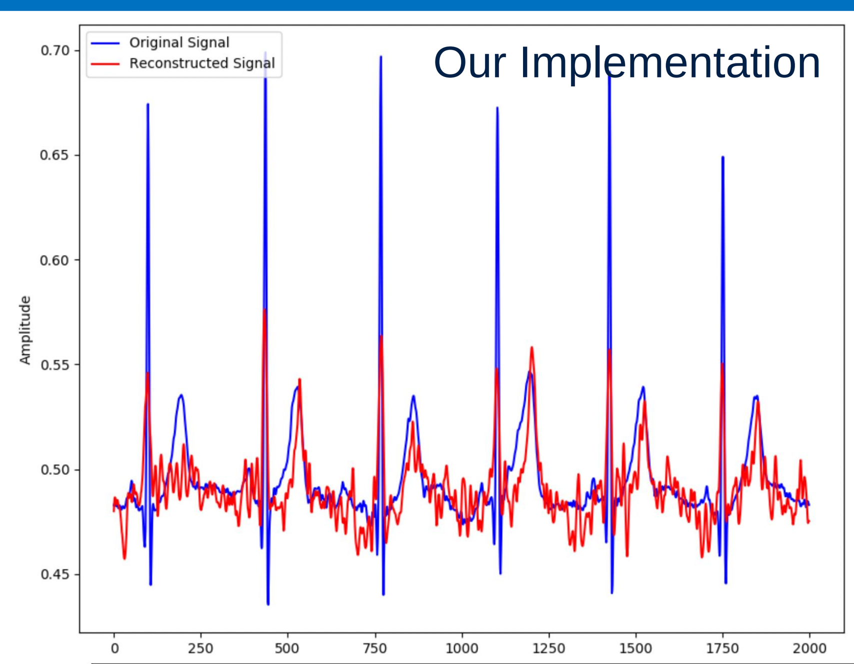
Fig. 3. The block representation of the proposed CAE model for ECG compression.

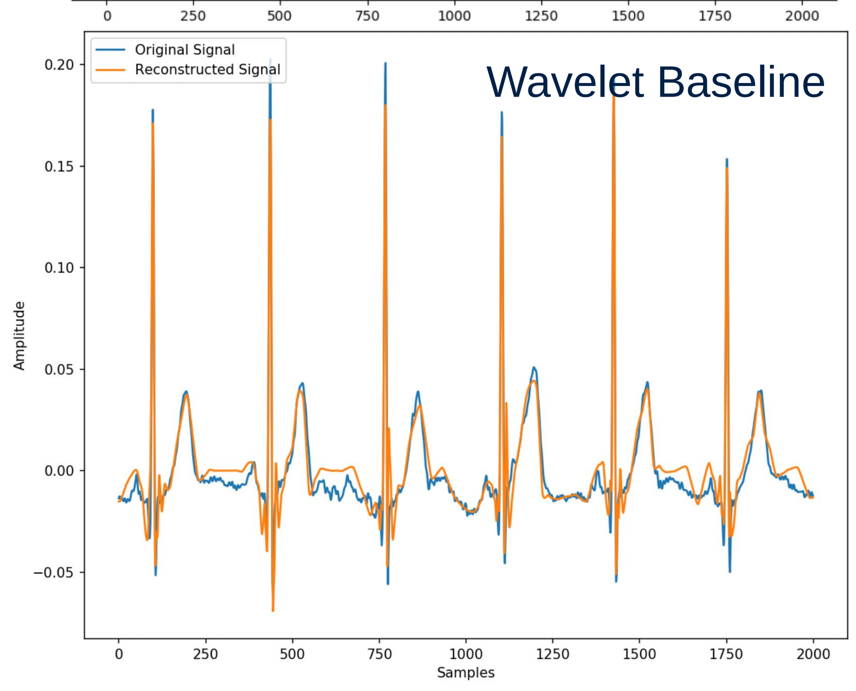
1. Mohamed Elgendi, et al. "Efficient ECG Compression and QRS Detection for E-Health Applications." Sci. Rep., vol. 7, no. 1, pp. 1–16, Dec. 2017, doi: 10.1038/s41598-017-00540-x.
2. Ozal Yildirim, et al. "An efficient compression of ECG signals using deep convolutional autoencoders." Cogn. Syst. Res., vol. 52, pp. 198–211, Dec. 2018, doi: 10.1016/j.cogsys.2018.07.004.

Results

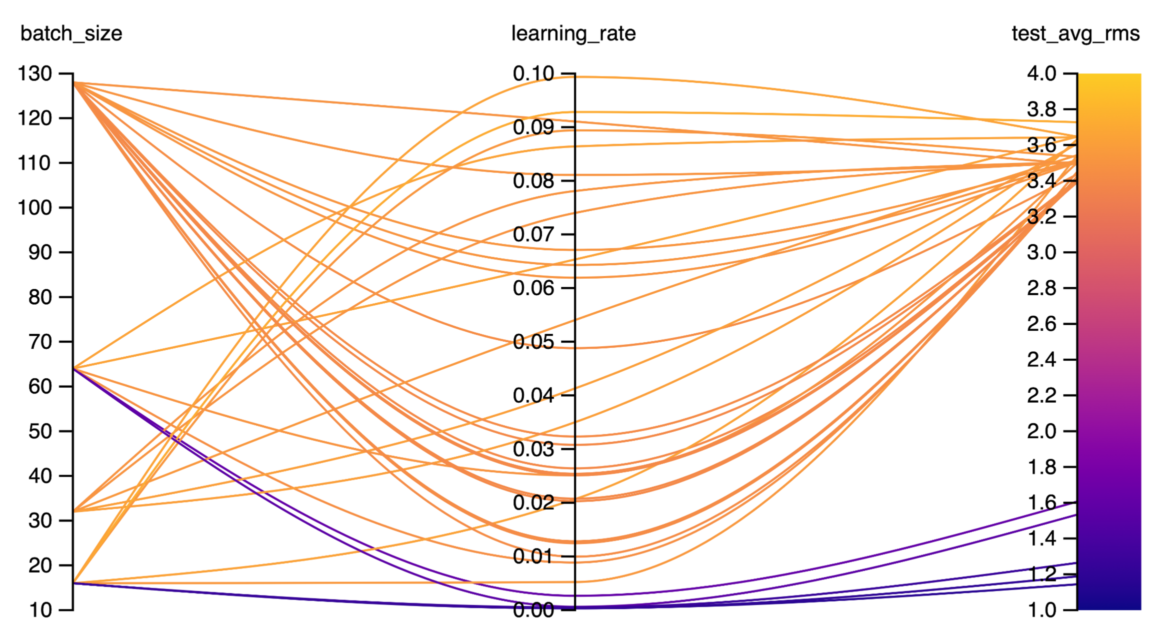
- Implementation was created using pyTorch. The training was preformed using the Adam Optimizer with initial learning rate of 0.001, weight decay of 1e-5 and batch size of 32.
- We compare the results of our implementation with the results of the original paper[1], both results were obtained by training with 48 healthy patients (20% used for validation), and the results of our wavelet baseline based on (Yildirim et al, 2018 [2]).
- The results on our data are not satisfying and so we continued to search for better parameters.

Criteria	Original Paper[2]	Our Implementation	Wavelet Baseline
RMS	0.013	1.314	0.011
PRD	2.73%	5.364%	30.985%
PRDN	31.17%	97.982%	30.985%
SNR	23.96 dB	2.9918dB	23.588dB
QS	13.38	11.381	0.343
CR	32.25	32.25	10.5





Graphic comparison of original and reconstructed ECG signal



- We computed a bayesian search on the hyper-parameters batch size and learning rate in order to find the best values. As seen in the figure the best values are batch size of 16 and learning rate of 0.0004.
- The results on the tests set were still not satisfying as seen in the table.

Criteria	Value
RMS	1.975
PRD	8.42%
PRDN	276.81%
SNR	-7.867dB
QS	6.907
CR	32.25

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