APPLICATION OF GENERATIVE ADVERSARIAL NETWORK TO MUSCLE NOISE REMOVAL IN ECG TEMPLATES

Olena Shevchenko, Ivan Franko National University of Lviv, olenashevch@gmail.com

Mykola Maksymenko, SoftServe Inc., m.maksymenko@gmail.com

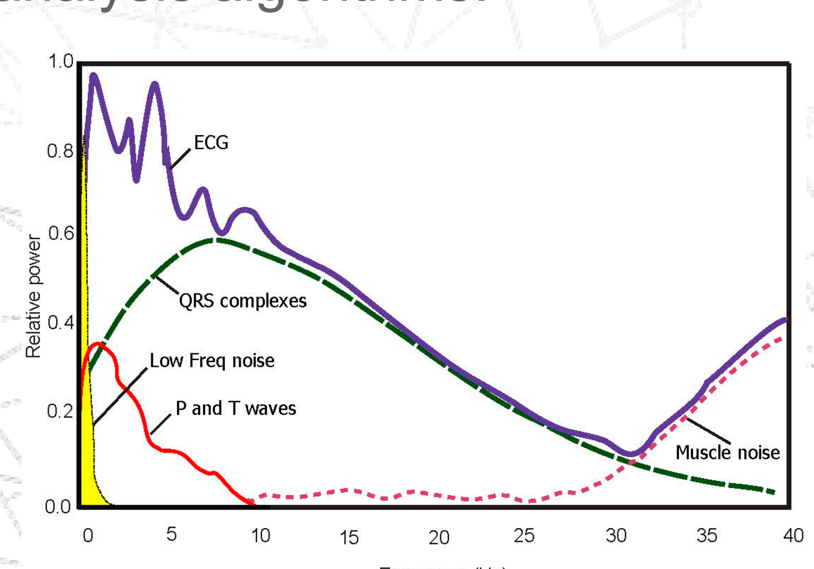
Volodymyr Budzan, Ukrainian Catholic University, budzan.v@gmail.com

Introduction

In this research, we propose a practical approach to denoising of Electrocardiogram signal templates using Generative adversarial networks (GAN) trained in an unsupervised manner on MIT-BIH Normal Sinus Rhythm Database[1] mixed with real muscle noise extracted from CapgMyo database[2]. To show how this approach can improve person authentication based on ECG, we tested our denoising technique on PhysioNet ECG-ID Database[3].

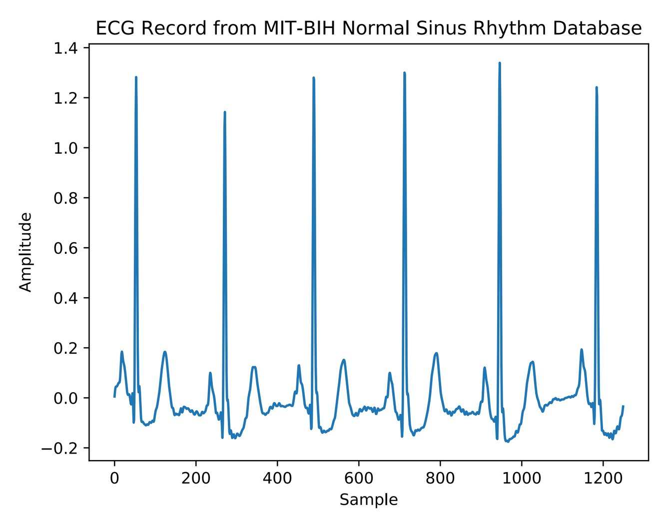
Problem

In real-life scenarios, the ECG signal is often corrupted by various noise sources. While the former types of noise could be effectively removed by the application of standard signal filtering techniques, the muscle noise strongly overlaps with the ECG Fourier spectrum, and its removal may change the shape of the original signal and affect the performance of further analysis algorithms.

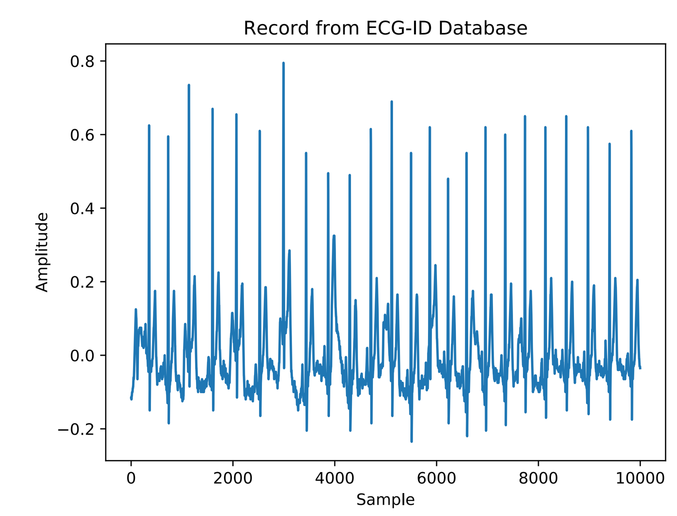


Datasets

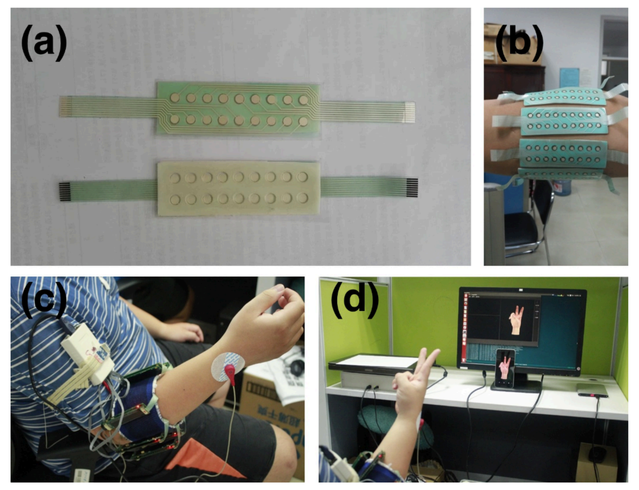
A MIT-BIH Normal Sinus Rhythm



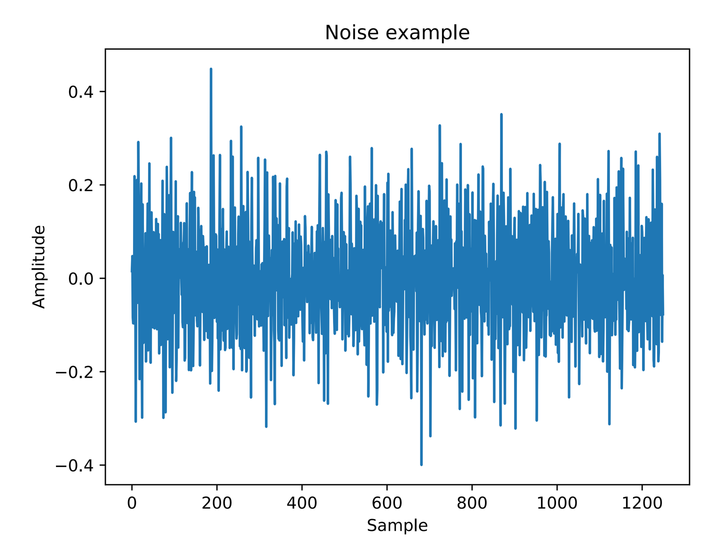
B ECG-ID Database



C CapgMyo: A High Density Surface Electromyography Database for Gesture Recognition



The acquisition setting-up: (a) The HD-sEMG electrode array; (b) 8 HD-sEMG electrode arrays on the right forearm; (c) The HD-sEMG acquisition device ready for capture; (d) The software subsystem to present the guided hand gesture and record HD-sEMG data simultaneously.



Use cases

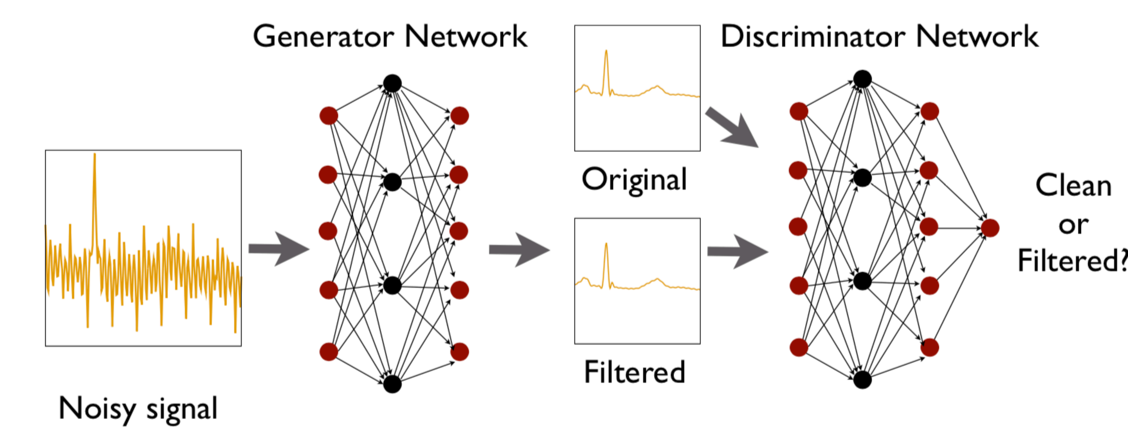
The problem gets particularly severe in multiple real-world applications where the high-quality ECG signal is expected to be recorded from subject hands and strong impact of muscle noise in unavoidable.

1 *ECG from wristband*

2 *Biometric security*

Architecture

A recent research proved that Autoencoders (AE) outperform traditional filtering techniques for ECG signals[6]. We propose using a Generative adversarial network for templates denoising. One of the main advantages of this architecture is that comparing to AE, we don't need a clean pair for every training example. GAN is expecting to perform better than AE as it learns to mimic data distribution.



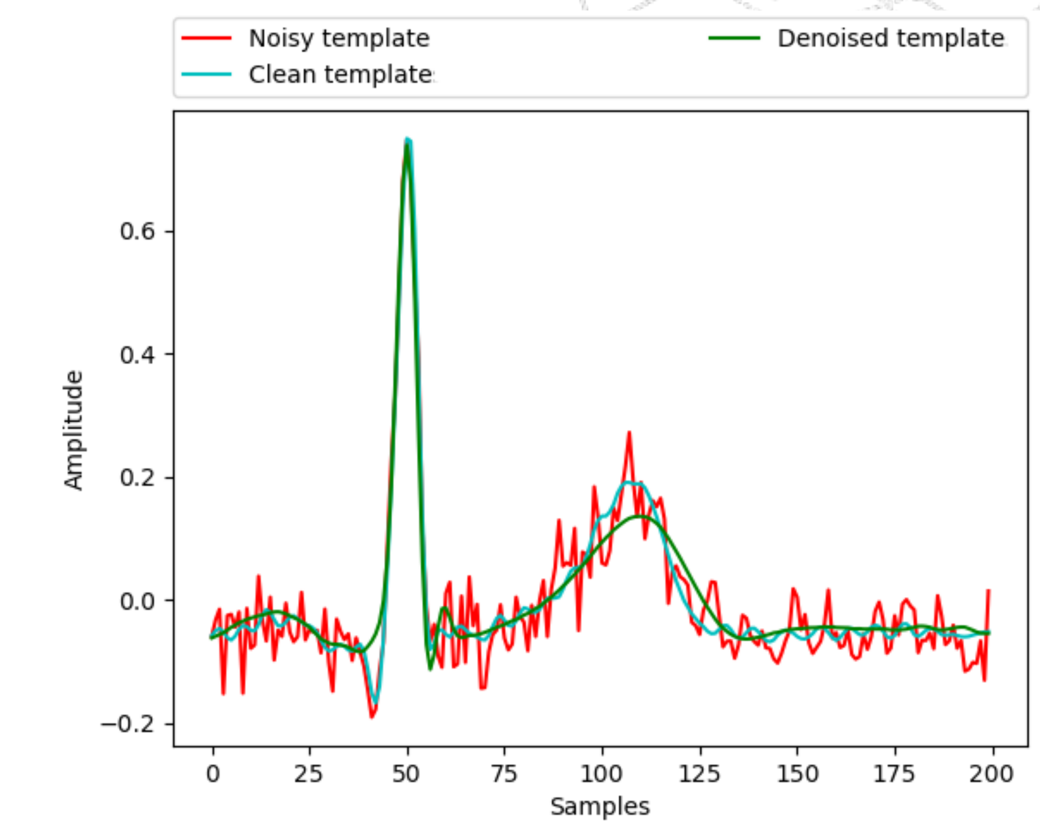
Metrics

The core metrics for person authentication is accuracy. As a metrics of denoising, we use Signal-to-noise ratio. SNR is a measure that compares a level of the desired signal with a level of background noise. Where x - is original, x_m - is noisy.

$$SNR = 10\log\frac{\sum_{n=0}^{N-1} x(n)^2}{\sum_{n=0}^{N-1} (x_m(n) - x(n))^2}$$

Results

GAN achieves better results comparing to AE in cases of strong muscle noise. On average it is 1% more accurate. The additional advantage of GAN architecture is possibility to train it on an extended dataset of real-life ECG collected from the device. System trained on reconstructed signal chunks achieves on average 2% lower accuracy of recognition then clean signal. For detailed results, see the table.



References

1. https://www.physionet.org/physiobank/database/nsrdb/
2. http://zju-capg.org/myo/data/
3. https://www.physionet.org/physiobank/database/ecgiddb/
4. https://demo.softserveinc.com/biolock/
5. https://mawi.band/
6. https://doi.org/10.1016/j.engappai.2016.02.015

Identity Recognition accuracy of SVM classifier and 1 vs 100 users setup

User	Clean signal from chest	Noisy signal from hands	GAN filtered signal	AE filtered signal	SNR noisy signal (dB)	SNR filtered with GAN (dB)
2	96,67%	69,46%	92,04%	94,30%	5,06	20,26
34	98,28%	91,29%	99,03%	98,60%	0,77	20,33
35	99,57%	90,75%	98,71%	96,67%	3,81	20,01
52	99,14%	71,18%	97,31%	96,67%	0,80	18,71
72	97,31%	70,54%	95,38%	94,30%	4,50	20,70
Average	***98,53***%	86,38%	***97,24***%	96,82%	3,99	21,41