Toward Wearables of the Future: Affordable Acquisition of Continuous ECG with Deep Learning

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Introduction

Electrocardiogram (ECG) is the electrical measurement of cardiac activity, whereas **Photoplethysmogram (PPG)** is the optical measurement of volumetric changes in blood circulation. While both signals are used for heart rate monitoring, from a medical perspective, ECG is more useful as it carries additional cardiac information. However, there are no reliable solutions for continuous ECG monitoring in wrist-based wearable, feasible for everyday and pervasive use.

Problem Statement: Our goal is to enable the use of **ECG** in wrist-based wearable devices such as smart watches, for continuous cardiac monitoring.

Broader Impact: Cardiovascular diseases cause approximately 31% of global deaths. We believe continuous wearable-based ECG could enable early diagnosis of cardiovascular diseases, and in turn, early preventative measures can be taken to overcome severe cardiac problems.

Method

We propose a novel framework called **CardioGAN** (see Fig. 1) for generating ECG signals from PPG inputs. We utilize attention-based generators and dual time and frequency domain discriminators along with a CycleGAN backbone to obtain realistic ECG signals.

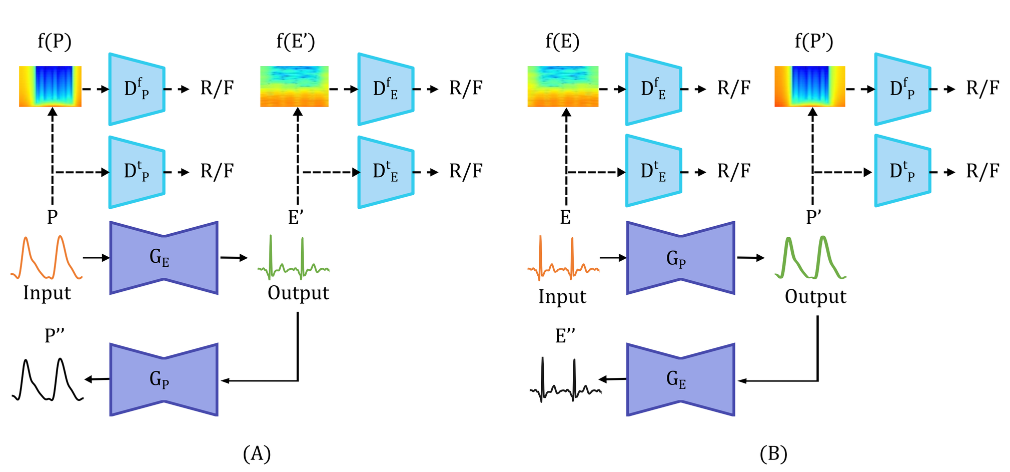

Fig. 1: The architecture of the proposed CardioGAN is presented.

Our final objective function is a combination of adversarial loss and cyclic consistency loss as presented below.

Adversarial Losses are applied in both forward and inverse mappings. For the mapping function $G_E : P \rightarrow E$, and discriminators D^t_E and D^f_E, the adversarial losses are defined as $\mathcal{L}_{adv}(G_E, D^t_E)$ and $\mathcal{L}_{adv}(G_E, D^f_E)$ respectively. Similarly, for the inverse mapping function $G_P : E \rightarrow P$, and discriminators D^t_P and D^f_P, the adversarial losses are defined as $\mathcal{L}_{adv}(G_P, D^t_P)$ and $\mathcal{L}_{adv}(G_P, D^f_P)$ respectively.

Cyclic Consistency Loss is introduced to ensure that forward mappings and inverse mappings are consistent, i.e., $p \rightarrow G_E(p) \rightarrow G_P(G_E(p)) \approx p$, as well as $e \rightarrow G_P(e) \rightarrow G_E(G_P(e)) \approx e$, we minimize the cycle consistency loss denoted as $\mathcal{L}_{cyclic}(G_E, G_P)$.

Final Loss function of CardioGAN is computed as:

$$\mathcal{L}_{CardioGAN} = \alpha\mathcal{L}_{adv}(G_E, D^t_E) + \alpha\mathcal{L}_{adv}(G_P, D^t_P) + \beta\mathcal{L}_{adv}(G_E, D^f_E) + \beta\mathcal{L}_{adv}(G_P, D^f_P) + \lambda\mathcal{L}_{cyclic}(G_E, G_P)$$

where α and β are adversarial loss coefficients corresponding to D^t and D^f respectively, and λ is the cyclic consistency loss coefficient.

Experiments

Datasets: We combine 4 very popular ECG-PPG datasets, namely **BIDMC**, **CAPNO**, **DALIA**, and **WESAD** to enable a multi-corpus approach leveraging large and diverse distributions of data.

Data Preparation: As a first step we **re-sampled** both the ECG and PPG signals with a sampling rate of 128 Hz. Next, **person-specific z-score normalization** is performed on both ECG and PPG. Then, the normalized ECG and PPG signals are **segmented** into 4-second windows. Finally, we perform **min-max** $[-1, 1]$ normalization on both ECG and PPG segments to ensure all the input data are in a specific range.

Architecture:

- **Attention U-Net** is used as our **generator** (G_E and G_P), where self-gated soft-attention units are used to filter the features passing through the skip connections.
- **Dual discriminators** are used to classify real and fake data in time and frequency domains. D^t_E and D^t_P take time-series signals, whereas, spectrograms are given as inputs to D^f_E and D^f_P.

Training:

- 80% of the users from each dataset (a total of 101 participants, equivalent to 58K segments) for training, and the remaining 20% of users from each dataset (a total of 24 participants, equivalent to 15K segments) for testing.
- To enable CardioGAN to be trained in an *unpaired* fashion, we shuffle the ECG and PPG segments from each dataset separately eliminating the couplings between ECG and PPG followed by a shuffling of the order of datasets themselves for ECG and PPG separately.
- We use a batch size of 128, to train our model for 15 epochs, where the learning rate ($1e^{-4}$) is kept constant for the initial 10 epochs and then linearly decayed to 0.

Results

Qualitative Results: We present a number of samples (see Fig. 2) of ECG signals generated by CardioGAN, clearly showing that our proposed network is able to learn to reconstruct the shape of the original ECG signals from corresponding PPG inputs.

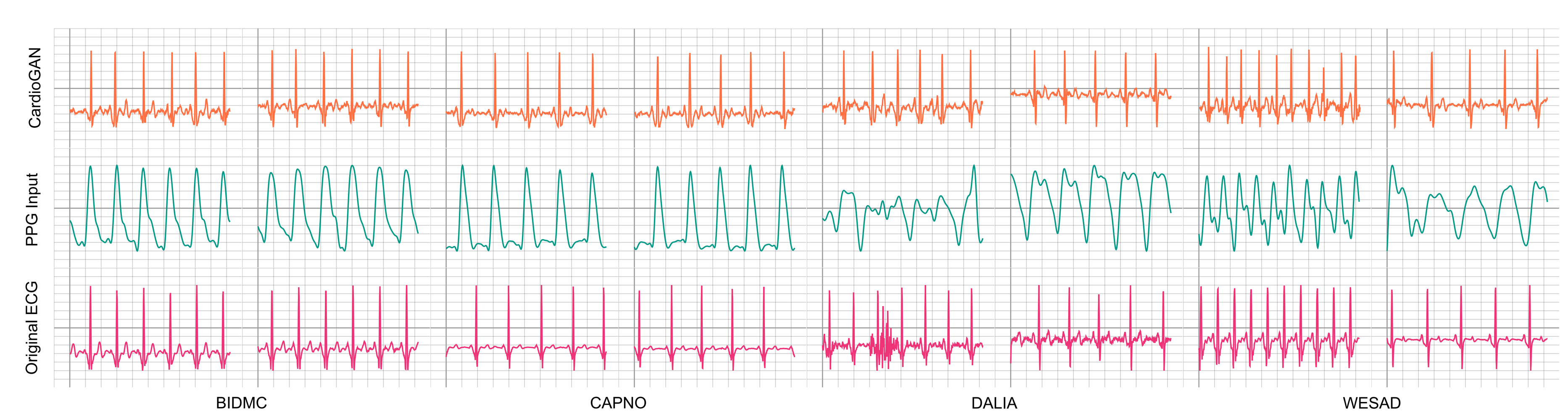

Fig. 2: We present ECG samples generated by our proposed CardioGAN.

Quantitative Results: To evaluate the impact of our solution, we measure mean absolute error for the HR estimation (in BPM) obtained from generated ECG and PPG signal with respect to a ground-truth HR obtained from original ECG. Our result shows significant improvement in minimizing error while using CardioGAN, the HR estimation error from synthetic ECG is 2.89 beats compared to original PPG, 9.74 beats. Please note, lower error rate is better.

Live Demonstration

We present a live demonstration showing how our model can be used in real-time using a wrist-based wearable device to feed it with PPG data and generate continuous ECG signals. Please check our project page here: https://pritamqu.github.io/ppg2ecg-cardiogan/.

Analysis

Attention Map: We visualize the attention maps (see Fig. 3) applied to the very last skip connection of the generator (G_E). This shows that our model learns to generally focus on the PQRST complexes, which in turn helps the generator to learn the shapes of ECG waveform better as evident from qualitative and quantitative results presented earlier.

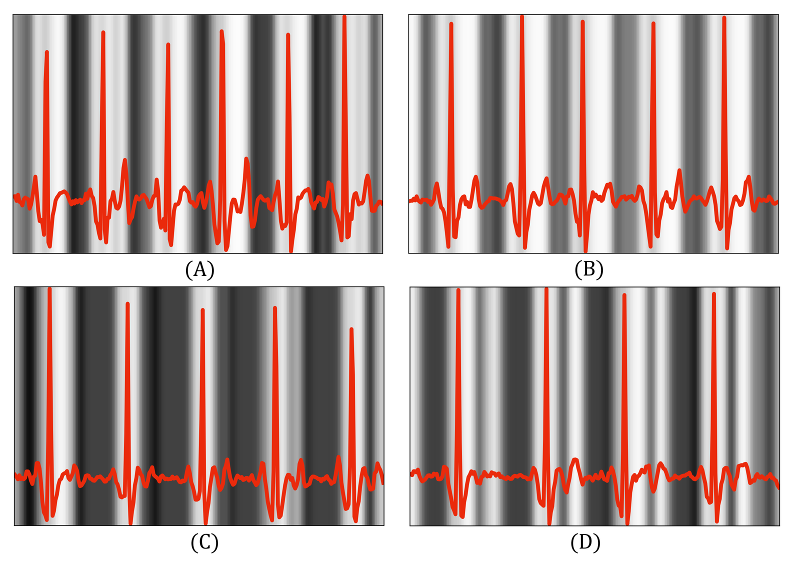

Fig. 3: Visualization of attention maps are presented where the brighter parts indicate regions to which the generator pays more attention compared to the darker regions.

Failed Cases: We notice there are instances (see Fig. 4) where CardioGan fails to generate ECG samples that resemble the original ECG data very closely. Such cases arise only when the PPG input signals are of very poor quality.

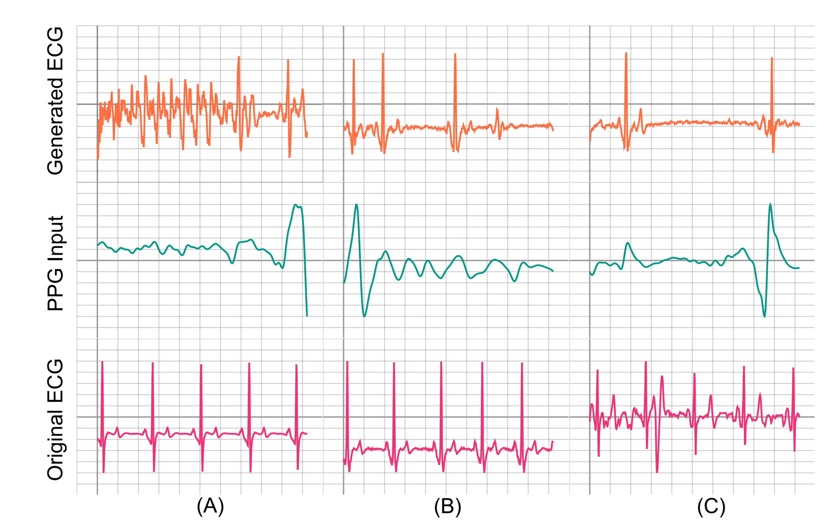

Fig. 4: Few failed ECG examples generated by CardioGAN are presented.

Summary

- We propose a novel framework called CardioGAN for generating ECG signals from PPG inputs.
- More accurate and reliable HR from generated ECG by CardioGAN vs. original PPG.
- We present a novel and innovative solution towards cheap, and continuous ECG monitoring, using off-the-shelf PPG-based wearables.
- This is the first study, attempted towards generating ECG from PPG (or in fact any cross-modality signal-to-signal translation in the biosignal domain) using GANs or other deep learning techniques.

Question?

You may direct any questions or additional queries at: pritam.sarkar@queensu.ca. To find more about my research, please visit my homepage: pritamsarkar.com.