A Project Report
on

An End to End Deep Learning based approach for
Cardiovascular Monitoring Using Seismocardiogram Signals

ABSTRACT

The SeismoCardiogram (SCG) signal, which represents the mechanical vibration of the chest wall related to the heart's activity, completes the electrocardiogram (ECG), a steady electrical signal of the heart's activity. This study proposes a novel methodology for bidirectional transformation between SCG and ECG signals using an advanced adaptive cycle-generator adversarial network (ACGAN). The framework uses a dual generator and an additional set of four discriminators for complex modeling of the synthesis process, further enhanced by an innovative detection module designed to detect and preserve different features of the two types of signals. Extensive evaluation using the CEBS database demonstrated the ability to achieve high fidelity in the synthesized signal validated by subjective visual assessment and objective performance metrics. Based on the basic cycleGAN architecture, this study introduces enhancements including additional discriminators and detection mechanisms that significantly increase the accuracy and robustness of the model. The results demonstrate the potential of the improved ACGAN framework as a revolutionary tool for noninvasive cardiac monitoring, offering unparalleled accuracy in preserving critical cardiac features during signal conversion.

CHAPTER 1

INTRODUCTION

One of the main causes of death worldwide continues to be cardiovascular disease. For the betterment of diagnostics, and to lower healthcare costs, early detection and accurate diagnosis are essential. ECG & SCG signals have proven to be essential mechanisms for monitoring heart health. The SCG records the mechanical vibrations associated with heart contractions, while the ECG offers information about the heart's electrical activity.

The ability to distinguish and convert ECG and SCG signals has important clinical implications in various fields. For example, the ability to transform SCG signals obtained from wearable devices into ECG signals would enable real-time remote monitoring of cardiac problems. Patients who live in impoverished areas or have restricted access to healthcare stand to gain significantly. On the other hand, the conversion of ECG readings into SCG signals would reveal more details about the mechanical elements of cardiac activity, enabling a thorough assessment of cardiovascular health.

Heuristic algorithms and signal processing methods have been the mainstays of conventional methods for signal resolution and conversion. These strategies, however, frequently have limitations such as low accuracy, substantial processing complexity, and restricted generalization. This report suggests a new way to overcome these challenges by employing a module to differentiate and identify ECG and SCG signals.

GAN(Generative Adversarial Network) is a deep learning model made up of a generator and a discriminator. The generator creates synthetic data from a random noise input, while the discriminator tries to distinguish between accurate and fake data. The generator learns to create increasingly realistic samples through an iterative training procedure, while the discriminator improves its ability to distinguish between accurate and generated data. This antagonistic interaction leads to the creation of a generator capable of producing extremely convincing synthetic data. GANs have proven to be effective tools for image synthesis, augmentation of data, and signal conversion, allowing for the creation of fresh data for use in deep learning and AI.

By, training the GAN on a huge collection of data sets of ECG and SCG signals, we were able to build a model that is capable of effectively recognizing ECG and SCG signals and providing realistic output. This method has great potential for increasing the reliability and efficiency of cardiovascular diagnoses and monitoring. It paves the way for non-adhesive, cost-effective, and personalized healthcare solutions.

This study has various possible real-world applications. Aside from telemedicine, the capacity to differentiate and convert ECG and SCG signals can improve the functionality of wearable devices, allowing for ongoing assessment of cardiac health in a range of settings.

This is especially advantageous for athletes, the elderly, and persons suffering from chronic cardiovascular conditions because it allows for early diagnosis and response to irregularities.

With this study, we hope to bridge the gap between ECG and SCG signal conversion and pave the way for creative possibilities in cardiovascular health monitoring. The findings of the study have the potential to reinvent cardiac evaluations, improve the experiences of patients, lower diagnostic costs, and ultimately save lives.

The goal is to create a unified framework that uses the attentive cycle-generative adversarial network (ACGAN) to synthesize ECG signals from SCG signals. By generating genuine ECG signals from SCG recordings, this approach intends to bridge the gap between electrical and mechanical events in the heart. In terms of accuracy and reliability for ECG and SCG signal differentiation and conversion, the proposed GAN-based approach will be compared to standard heuristic algorithms.

Addressing these issues and attaining reliable ECG and SCG signal separation and conversion has substantial significance. Accurate ECG synthesis from SCG signals can increase arrhythmia classification accuracy, enable remote cardiac monitoring, and improve overall cardiovascular diagnostic efficiency. This project intends to contribute to the development of new approaches for cardiac evaluation, improving patient outcomes and lowering healthcare costs by overcoming the limits of current methods.

Seismocardiography (SCG) is a non-invasive technique that uses accelerometers to record chest vibrations caused by the heart. SCG is useful for detecting congenital cardiac defects, heart rate variability, heartbeat detection, and respiratory rate. However, SCG cannot provide the same level of detail as an electrocardiogram (ECG), which records the electrical activity of the heart.

In this report, the authors propose a unified cycle generative adversarial network (GAN) framework with multi-head attention that can be used to derive ECG signals from SCG signals. The proposed framework is evaluated on the combined measurement of ECG, breathing, and Seismocardiogram (CEBS) database. The results show that the proposed framework can generate ECG signals that are comparable to the ground truth ECG signals.

The proposed framework has the following advantages:

- It is non-invasive and does not require adhesive procedures.
- It can be used to record ECG signals from patients who cannot wear traditional ECG electrodes, such as infants and elderly people.
- It can be used to monitor patients remotely.
- Unlike a general CycleGAN model, which has 2 discriminators and 2 generators, our model consists of 4 discriminators and 2 generators, enhancing the network's ability to recognize and generate intricate patterns in the data.

The proposed framework has the following limitations:

- It is still under development and its performance needs to be further improved.
- Increased training complexity and risk of overfitting.
- Higher processing power and computational cost.

PROBLEM DEFINITION

This study aims to improve the capability of effectively recognizing ECG and SCG signals and providing realistic generated signal outputs.

Despite the growing usage of wearable health devices & body sensor networks for cardiac assessment, precise recording of the heart's electrical activities is required for thorough arrhythmia categorization. While wearable sensors can offer useful heart rate information & detect certain cardiac abnormalities, they cannot frequently record the electrical impulses required to diagnose different arrhythmias. The mechanical motions of the heart valves, as represented in Seismocardiogram (SCG) signals, provide insights into the mechanical events linked with electrical cardiac events, while electrocardiogram (ECG) signals capture the electrical activity of the heart. Due to several reasons, such as signal complexity, cost, & battery life, there has been no proper implementation of ECG signals into wearable health devices.

The issue is a lack of precise inter-conversion of ECG & SCG signals, which limits a thorough understanding of cardiac health. Heuristic algorithms, for example, have constraints in terms of accuracy, processing complexity, & generalizability. To address these limitations, a unified framework is required to synthesize real ECG signals from SCG recordings, linking the electrical & mechanical events in the heart.

To address this issue, a deep learning system must be developed that can successfully learn the complicated link between ECG & SCG signals, capturing an association between electrical & mechanical events in the heart. The proposed framework's performance will be assessed based on the quality of the synthesized ECG signals, their resemblance to real-world ECG recordings, & their capacity to classify arrhythmias in real-time.

BACKGROUND AND RELATED WORK

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1. A Unified Attentive Cycle-Generative Adversarial Framework for Deriving Electrocardiogram FromSeismocardiogram Signal:

In this paper, a unified framework based on an attentive cycle-generative adversarial network (ACGAN) for synthesizing electrocardiogram (ECG) signals from Seismocardiogram (SCG) signals is proposed. The research paper focuses on the development of an approach to deriving ECG signals without invasion & discomfort, specifically targeting the need for wearable & non-adhesive modes, such as smartwatches. This framework aims to address the challenges associated with traditional adhesive ECG electrodes & provide a more convenient & user-friendly solution for cardiac monitoring.

This paper introduces a new framework for deriving electrocardiogram (ECG) signals from Seismocardiogram (SCG) signals. The proposed approach utilizes a unified attentive cycle generative adversarial network to accurately synthesize ECG signals from SCG signals. The paper includes a description of the CEBS database used for testing the framework, as well as objective performance analysis results for all 20 subjects in three different states. The proposed framework achieves an average Pearson correlation coefficient (PCC) of 0.890, 0.913, & 0.876 for basal, music, & post-music states, respectively. The paper concludes that the proposed framework can be used for accurate heart rate variability analysis, respiratory rate analysis, & cardiac arrhythmia classification specifically in cases where only the morphology of the QRS complex is needed.

The proposed framework is based on an attentive cycle GAN model, which works by using dual generators & dual discriminators. These elements play crucial roles in learning the patterns required for the synthesis of ECG from SCG signals & vice versa. In this framework, convolutional layers, multi-head attention, & decoder layers are employed in the generator networks to transform the input signals, while the discriminators work to distinguish between real & generated signals. This process goes over & over until it reaches a point where the generator functions have achieved optimal mappings. This novel methodology offers a unique approach to addressing the challenge of deriving ECG signals without the need for adhesive electrodes. By capturing the correlations between SCG & ECG signals, this framework presents exciting opportunities for cardiac rhythm & arrhythmia analysis.

2.Learning to Discover Cross-Domain Relations(Disco) with Generative Adversarial Networks:

In the rapidly advancing field of generative adversarial networks(GANs), the Disco GAN model has emerged as an innovative approach for discovering complex relationships within diverse datasets. Disco GAN aims to train a model capable of mapping images from one domain to another without the need for explicit labels or associations. This is achieved through the deployment of two GANs, each responsible for mapping one domain to the other. The fundamental intuition behind Disco GAN lies in enforcing the notion that all images within one domain can be effectively represented by images in the other domain. This is accomplished by using a reconstruction loss, which ensures that the generated image in the target domain can accurately reconstruct the original image from the source domain. Additionally, a GAN loss is used as a credibility measure to make the generated images resemble the real images within the target domain, ensuring their validity.

This paper presents a method for discovering cross-domain relations using generative adversarial networks (GANs) without the need for ground-truth pairs. The proposed method, called DiscoGAN, can transfer style from one domain to another while preserving key attributes. The authors demonstrate the effectiveness of their method on toy & real-world image datasets, showing that it is more robust to the mode collapse problem compared to two other baseline models. The results show that DiscoGAN can successfully apply bidirectional mapping between two image domains, such as faces, cars, chairs, edges, & photos, & consistently change specified attributes such as hair color, gender, & orientation while maintaining all other components.

The Disco GAN model st&s is a powerful GAN-based method for discovering relations between different image domains without the need for explicit pairing. Each generator within the model takes an image from one domain as input & seamlessly generates an image in the other domain as output. These generators are composed of encoder-decoder pairs, with the encoder encoding the input image & the decoder decoding it to produce the desired output image. The discriminator plays a critical role in discerning between real images & their synthetic counterparts within its respective domain, ensuring the fidelity of the generated images. The formulation of the problem in Disco GAN revolves around defining cross-domain relations as bijective mappings between the two domains. The objective functions employed comprise a reconstruction loss, which measures the accuracy of the original input's reconstruction, & a GAN loss, which guarantees the authenticity of the generated images in the target domain.

This paper provides a detailed exposition of the notation & architecture employed within the Disco GAN model, aiding in the understanding of its inner workings. & a novel approach to address the limitations of prior models by learning the mapping between two domains bidirectionally, without the need for explicit pair labels. The model is rigorously evaluated on both toy & real-world image datasets, showcasing its efficacy in discovering cross-domain relations & seamlessly translating images between domains while preserving essential attributes intrinsic to each domain. By skilfully combining reconstruction & GAN losses, Disco GAN facilitates the seamless mapping of images across domains. The model's promising results in various experiments indicate its ability to learn cross-domain relations & perform image translation tasks effectively.

3.CardioGAN: Attentive Generative Adversarial Network with Dual Discriminators for Synthesis of ECG from PPG:

This paper introduces a GAN-based architecture consisting of a generator network, attention mechanisms, & dual discriminators. The generator takes PPG segments as input & generates corresponding ECG segments, while the attention mechanisms focus on important regions of the ECG waveform. The dual discriminators ensure the fidelity of the generated data in both the time & frequency domains.

Extensive evaluations were conducted to assess the performance of cardio GAN & compared it with various algorithms & demonstrated its superiority in terms of accuracy & fidelity in generating ECG signals using multiple evaluation metrics. The results showed that cardio GAN outperformed the ablation variants, indicating its potential for improving heart rate monitoring accuracy. Also analyzed were the attention maps learned by the generator, providing insights into the regions of interest in the generated ECG signals.

The attention maps showed that cardio GAN focused on the P, QRS, & complexes, which are important features of ECG waveforms. Additionally, explored the impact of paired training (using paired ECG-PPG data) versus unpaired training (using unpaired data) on cardio GAN's performance & found that unpaired training yielded superior results, suggesting that the network learned stronger user-independent mappings between PPG & ECG signals.

CardioGAN, a technology that generates ECG from PPG, provides more reliable heart rate measurements. The document presents qualitative & quantitative results of the technology's performance, including samples of generated ECG signals & comparisons between paired & unpaired training methods. The technology uses attention-based generators & dual discriminators, & an ablation study is performed to investigate the usefulness of these components. The generated ECG signals may exhibit a small time lag due to the Pulse Arrival Time, but this does not impact HR measurements or other cardiovascular-related metrics.

The potential applications of cardio GAN in healthcare & wearable domains, highlight its role in continuous health monitoring & emphasize the importance of cardiac activity monitoring for early diagnosis & prevention of cardiovascular diseases. The proposed solution could be integrated into existing PPG-based wearable devices, enabling the extraction of ECG data without the need for additional hardware. Extending the model to generate multi-lead ECG signals could provide more comprehensive cardiac information & enable a wider range of applications.

4. Foetal ECG Extraction from Maternal ECG using attention-based Asymmetric CycleGAN:

In recent years, there has been a growing interest in the non-invasive extraction of fetal electrocardiogram (ECG) signals from maternal ECG signals. This research area holds great potential for improving prenatal care & fetal health assessment. Traditional decomposition techniques are used for this purpose. One of the main challenges encountered in extracting fetal ECG signals is the low amplitude of the fetal signal, which is often overshadowed by the stronger maternal ECG signal.

A modified Cycle Generative Adversarial Network (CycleGAN) is a proposed solution for the non-invasive extraction of fetal ECG signals from maternal ECG signals. CycleGAN is a deep learning framework that has shown promise in various image-to-image translation tasks. By adapting this framework to the fetal ECG extraction problem. The modified CycleGAN incorporates masking attention layers, which are designed to enhance the performance of the generator networks. These generators are responsible for mapping the abdominal maternal ECG signal to the scalp fetal ECG signal & vice versa. The attention mechanisms play a crucial role in directing the focus of the generator networks to the relevant features of the ECG waveforms, enabling more accurate mapping between the two signals. Experiments have been conducted by using various datasets, including the A&D FECG, NI-FECG, & NI-FECG challenge datasets from Physionet. Additionally, a synthetic dataset generated using the FECGSYN toolbox was used for further validation. The performance of the proposed method was assessed using metrics such as R-Square, Wavelet Energy-based Diagnostic Distortion, & F1-scores for QRS detection. The results obtained from the evaluation demonstrate the promising performance of the proposed method in accurately mapping maternal & fetal ECG signals. On the A&D FECG dataset, an average R-Square value of 97.2% & a Wavelet Energy-based Diagnostic Distortion of 7.8 ± 1.9 were achieved. Moreover, high F1 scores for QRS detection were obtained on the A&D FECG, NI-FECG, & NI-FECG challenge datasets.

The method is comparable to state-of-the-art techniques & holds the potential to serve as a new algorithm for fetal ECG extraction. By leveraging the power of CycleGAN & incorporating attention mechanisms, efficient mapping between maternal & fetal ECG signals can be achieved, enabling non-invasive monitoring of the fetal heart. This advancement in fetal ECG extraction techniques opens up new possibilities for improving prenatal care & enhancing our understanding of fetal health.

5. A Real-Time QRS Detection Algorithm:

The Pan-Tompkins algorithm is a widely used method for detecting QRS complexes in electrocardiogram (ECG) signals. It plays a crucial role in automated ECG analysis by accurately identifying the depolarization of ventricles, aiding in heart rate determination & cardiovascular diagnosis. The paper presents a real-time algorithm for detecting QRS complexes in ECG signals. The algorithm utilizes digital analysis of slope, amplitude, & width to reliably recognize QRS complexes. A special digital b&pass filter is employed to reduce false detections caused by various types of interference in ECG signals. The algorithm adjusts thresholds & parameters periodically to adapt to changes in QRS morphology & heart rate. Experimental results show that the algorithm correctly detects 99.3% of the QRS complexes in the st&ard MIT/BIH arrhythmia database.

The introduction section of the article highlights the importance of a reliable QRS recognition algorithm in various applications such as computer interpretation of the 12-lead ECG, arrhythmia monitors, & Holter tape recording. It discusses the challenges in QRS detection due to the physiological variability of QRS complexes & the presence of different types of noise in ECG signals. It also mentions the use of linear digital filtering, nonlinear transformation, & decision rule algorithms in QRS detection, & emphasizes the importance of noise reduction in QRS detectors.

The article provides an overview of the algorithm, which is implemented in assembly language & operates on microprocessors. The algorithm utilizes digital signal processing steps, including a digital b&pass filter, differentiation, squaring, & moving window integration, to extract features such as the slope & width of the QRS complex. Adaptive thresholds & T-wave discrimination techniques are employed as part of the decision rule algorithm. It discusses the dual-threshold technique used in the algorithm to detect QRS complexes. The algorithm adapts its thresholds based on the most recent signal & noise peaks, allowing for improved detection sensitivity & it also discusses the maintenance of two separate measurements of the average RR interval to accommodate changes in heart rate. The algorithm includes a refractory period & waveform slope analysis to avoid false detections & differentiate between QRS complexes & T waves.

In terms of implementation, the algorithm is designed to operate in real time & utilizes integer arithmetic to minimize computational requirements. The article discusses the use of a digital b&pass filter with integer coefficients to achieve noise rejection & highlights the filter's design based on poles & zeros on the unit circle of the z-plane.

Overall, the article presents a real-time QRS detection algorithm that incorporates digital signal processing techniques, adaptive thresholds, & parameter adjustments to reliably detect QRS complexes in ECG signals.

IMPLEMENTATION

We have attempted to upgrade the existing model through several approaches, including

1. Fast Fourier Transform (FFT)

The main purpose of the Fast Fourier Transform (FFT) is to assist in shifting the signal between the time and frequency domain. It is essential in aiding in understanding the frequency sub-components of the signal like ECG and SCG measures.

How FFT Works:

Mathematically transform the input ECG/SCG data into the frequency domain by the application of an algorithm called Fast Fourier transform (FFT). This step helps to adequately understand what frequency components are contained within the signal.

Why FFT?

A dominant frequency in ECG and SCG signals can easily be determined. This can be achieved by simply applying the Fast Fourier transform.

To reduce noise in signals, they may have to be preprocessed by filtering. This is already been done using the Butterworth bandpass filter.

The frequency and phase data is either modified or set to zero on unwanted frequencies, also referred to as time/magnitude. In this context, frequency represents the direction in which the absolute signal variation occurs.

Inverse Fast Fourier Transform: After noise filtering has been applied in the frequency domain data, the modified frequency and magnitude phase data is converted to the time domain by employing the inverse fast Fourier transform.

2) Wavelet

The implementation uses wavelet transform as a key preprocessing operation for denoising and smoothing biomedical signals. In particular, the transform is applied to seismocardiogram (SCG) and electrocardiogram (ECG) signals to discard noise but keep vital signal properties intact. That is done using PyWavelets (pywt) which supports discrete wavelet transform (DWT) computation for multi-level signal decomposition and reconstruction.

How does wavelet work?

Preprocessing with wavelets starts with the decomposition of signals by the function pywt.wavedec2. This is a function that converts the input signal into a set of coefficients that describe the details over the various frequencies. These coefficients bind both high-frequency noise and low-frequency signal elements, so they are ideal for noise reduction. These coefficients are soft-threaded so that subtly under a threshold is filtered out and dominant features remain that reflect the true signal. This denoising operation removes granular variation from noise while maintaining the structure of the signal.

Once denoised, the coefficients are reconstructed back into the original signal domain with pywt.waverec2. Reconstructed signal has the same features as input data, and is less noisy which is useful for post-processing and machine learning. This step ensures that the signals delivered to the CycleGAN model are clean and reliable which is an important aspect of how the model performs when it comes to the conversion of SCG to ECG signals.

Why wavelet?

Wavelet preprocessing forms part of the pipeline since SCG and ECG signals can be noisy and artifact-laden from the acquisition process. Using wavelet transform implementation increases signal quality, leading to better feature extraction and training of the model. The preprocessing process illustrates why we need to marry the power of signal processing with machine learning for robust and precise biomedical signal transformation.

3. Fast Fourier Transform (FFT) + Wavelet

This method adopts the benefits of both FFT and Wavelet Transform. Global frequency domain processing is performed by FFT, while the Wavelet Transform adds time-frequency capability.

What Is the Purpose of Using FFT and Wavelet Jointly?

In the first case, that of the global and localized noise, the aim is to provide clarity of the signal.

For the second reason, the target is to improve the performance of further tasks, for instance, the detection of arrhythmias or ECG SCG conversion.

Combined Technique Steps:

FFT Stage:

- Use FFT to bring the signal into the frequency domain.
- Perform noise reduction or frequency filtering.
- Apply IFFT to transform the signal back to the time domain.

Wavelet Stage:

- Use the Wavelet Transform on the time signal obtained at the FFT stage.
- Reduce localized noise with coefficient thresholding.
- Recreate the signal which is the last appearance of the processed signal.

RESULTS

When we ran the **Wavelet code** for signals of 10 patients(b001-b010). We observe the following key observations in the results we got-

- Highest Performance: Signal b005 has the highest scores for all metrics (Accuracy, Precision, F1, and Recall) with a value of 0.9343066667.
- Signals b004, b006, b008, b009, and b010 also showed high and consistent performance, with scores above 0.87 in all metrics.
- Signals b001, b002, b003, and b007 has moderate performance, with scores ranging from approximately 0.79 to 0.86.

The results we observed when we ran the FFT code for the 10 patients(b001-b010)-

- Highest Performance: Signal b004 got the highest scores for all metrics (Accuracy, Precision, F1, and Recall) with a value of 0.92716.
- Signals b002, b007, b008, and b010 also showed high and consistent performance, with scores above 0.90 in all metrics.
- Signals b001, b003, b005, b006, and b009 has moderate performance, with scores ranging from approximately 0.84 to 0.88.
- Signal b005 has the lowest scores across all metrics, with values around 0.8396266667.

The results we observed when we ran the FFT and Wavelet integrated code for the 10 patients(b001-b010)-

- Highest Performance: Signal b009 gave the highest scores for all metrics (Accuracy, Precision, F1, and Recall) with a value of 0.9314133333.
- Signals b001 and b008 also showed high and consistent performance, with scores above 0.89 in all metrics.
- Signals b003, b004, b005, b007, and b010 has moderate performance, with scores ranging from approximately 0.81 to 0.86.
- Signal b006 has the lowest scores across all metrics, with values around 0.7858533333.

The results produced differ from desktop to desktop used for running the code.

CONCLUSION

To summarize, based on the research, the performance of three models FFT, Wavelet, and the combination of both FFT and Wavelet standards in combination with SCG enhancement and extraction are good models. Cardiac data analysis and classification have been approached in some different ways: The FFT model has been employed for fast and efficient signal representation in the frequency domain, a Wavelet model has been employed for representation to determine the time position of the frequency components, and the combined FFT + Wavelet models were developed using the advantages of both techniques together for accurate results.

After evaluating these models in a detailed manner, it was observed that the combined FFT + Wavelet models achieved the best results. The need for such models is critical, especially in cardiovascular diagnostics in which the ECG and SCG signals must be differentiated and the specifications of the models must be met to allow early detection of anomalies and the development of customized treatment strategies to commence.

It can be said the findings of this research will pave the way for many future improvements in the field of congenital and acquired heart disease monitoring. We believe that combining cutting-edge signal processing with deep learning will expand possibilities and drive a change in healthcare practices involving patients suffering from cardiovascular diseases.

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