Synthetic Seismocardiography Signal Generation by a Generative Adversarial Network

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Abstract

***Aims**: Seismocardiography (SCG) signals provide valuable information about the heart's performance. The technique subsists in a noisy environment where deep learning is often needed to extract important information, requiring large amounts of training data which can be expensive to obtain. In this work, we aim to create synthetic SCG heartbeats that are realistic and diverse to affordably augment current SCG datasets. **Methods**: We trained a Generative Adversarial Network (GAN) on real SCG heartbeats to produce synthetic SCG data. The architecture consisted of a deep convolutional GAN that was conditioned on an embedded identifier label for each subject to enable the generation of subject-specific heartbeats. **Results**: Our results demonstrated that the GAN could generate SCG heartbeats that closely resembled real SCG morphology. Generated heartbeats had an average root-mean-squared-error of 0.1831 when compared to the ensemble average of their real counterparts. **Conclusion**: The study presented a novel approach of using GANs to generate artificial SCG heartbeats. The use of GAN-generated SCG heartbeats has the potential to overcome the limitations of real SCG data availability, allowing for enhanced research and clinical applications of this valuable cardiac diagnostic technique.*

1. Introduction

Seismocardiography (SCG) is a growing cardiovascular monitoring technique. The wearable method measures the vibrations of the chest wall generated by the heart's mechanical activity. SCG's portability and non-invasive nature make it an appealing tool for remote patient monitoring, enabling continuous assessment of heart function in environments outside of the clinic [1]. By capturing key vibrations corresponding to valvular movements, SCG has been shown to produce metrics such as heart rate [2], pre-ejection period [3], left-ventricular ejection time [4], and respiratory information [5]. More recently, as the technology evolves, subtleties in the SCG-derived cardiac mechanics have been combined with machine learning techniques to indicate various conditions such as heart failure [6], valvular disorders [7], stroke volume [8], and blood pressure [9].

The accuracy of these models requires large amounts of SCG datasets to train machine learning models. As an upcoming technology, there are very few established online datasets [10]. Collecting relevant data can be challenging due to time, costs, and expertise constraints, limiting its use in research and clinical potential.

Synthetic data generation offers a compelling solution to the challenges posed by SCG data collection. This synthetic data can closely approximate the complexities of actual cardiac mechanics, allowing researchers and practitioners to train and validate machine learning models without the prohibitive costs associated with large-scale data collection efforts.

In this work, we propose a generative adversarial network (GAN) to synthetically generate SCG data. GANs can learn the underlying distribution of real SCG signals and generate synthetic SCG data that closely resembles the characteristics of actual cardiac vibrations. We then analyzed the model to assess the realism and diversity of synthetic heartbeats on an inter- and intra-subject level.

2. Methods

2.1. Data

The study was conducted at McGill University and approved by the McGill Review Ethics Board (no: 6-0619). The dataset consisted of 62 subjects (27 female) with (mean ± standard deviation) age: 24.6 ± 4.5 years, height: 172 ± 10.4 cm, and weight: 70.2 ± 16.3 kgs. All subjects were supine and motionless during the study. An inertial measurement unit (Invensense, MPU9250) was secured to the xiphoid process using a piece of double-sided tape. The inertial measurement unit was controlled by a Raspberry Pi Zero W using I2C protocol and sampled at approximately 600 Hz. SCG data was then lowpass filtered at 90Hz and down sampled to 200 Hz. Reference electrocardiogram (ECG) was concurrently recorded using

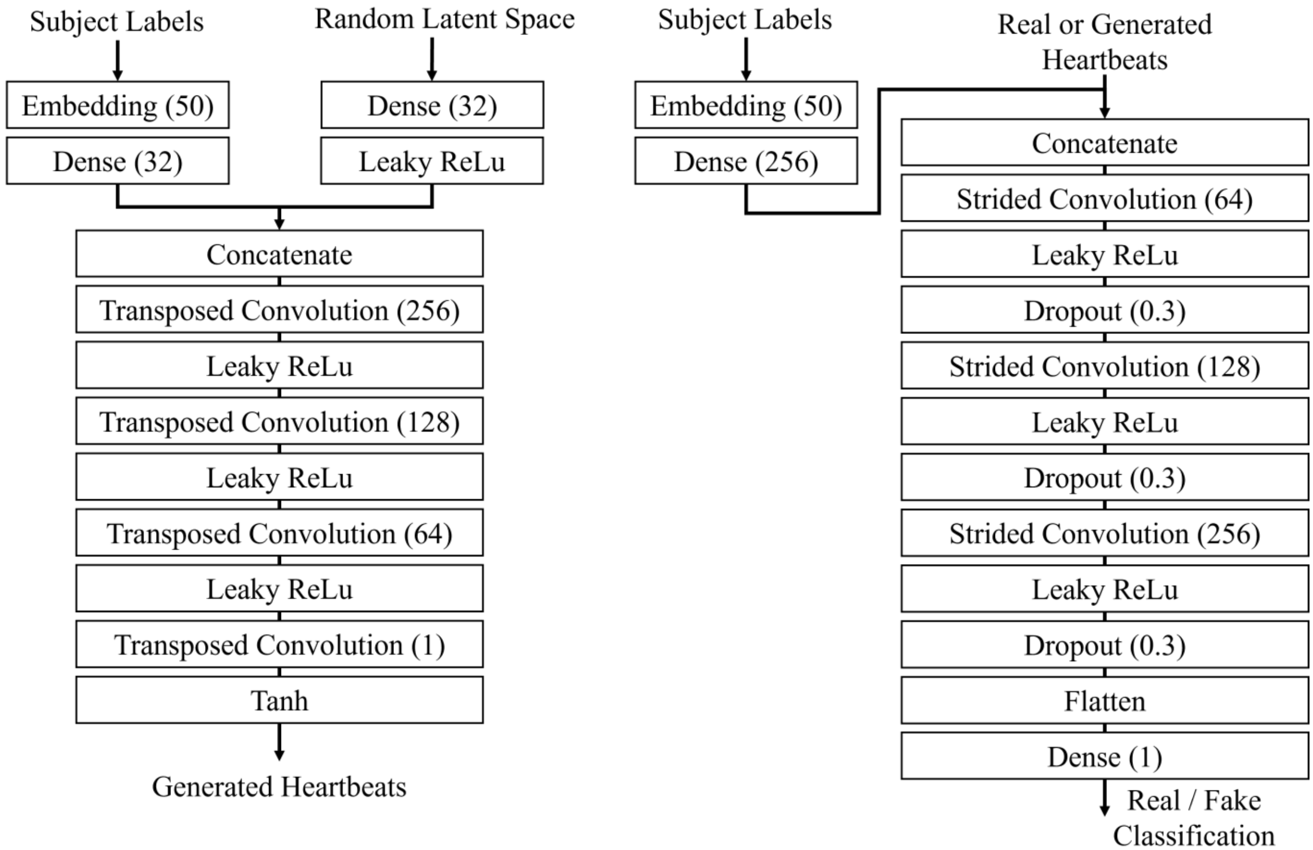

Figure 1. Architecture of the proposed GAN. The generator (left) receives inputs from subject labels and a random latent space and outputs a generated heartbeat pattern. On the other hand, the discriminator (right) takes inputs from subject labels and either real or generated heartbeats and subsequently performs a classification task to discern the authenticity of the heartbeat data.

the BIOPAC system. The raspberry pi and BIOPAC were synchronized with an externally wired clock from the BIOPAC to the Raspberry Pi. ECG R-peaks were used to segment the SCG into cardiac cycles, with 0.1 seconds prior to the R-peak defined as the start of each cycle. Each heartbeat was mean padded to standardize the length to 256 samples, corresponding to 1.28 seconds. Each heartbeat was normalized by its maximum absolute value.

2.2. Model

We employed a conditional GAN (cGAN) to generate synthetic SCG heartbeats. A traditional GAN is a network that simultaneously trains two models, a generator and a discriminator, against each other. The generator is tasked with generating fake heartbeats from a random latent space to fool the discriminator, whereas the discriminator is tasked with classifying if a heartbeat is real or fake. In a cGAN, the model is given some additional information such as class, subject, or features, and must produce a beat that is within that condition.

Our cGAN model was built with a deep convolutional framework and conditioned on a unique identifier for each subject. The model architecture can be seen in Figure 1.

For the generator, two inputs were supplied, the subject labels and the random latent space. The subject labels consisted of an integer between 0 and 61. They were then fed into an embedding layer with 50 XX, and a fully connected layer with 32 nodes. The latent space was a randomly generated vector with 100 samples. It was fed to a fully connected layer with 32 nodes, then a leaky ReLu activation was applied. Both inputs were then concatenated. The main structure consisted of four one-dimensional transposed convolutional layers with 256, 128, 64, and 1 filters, respectively. Each layer had a kernel size of 4, stride of 2, and same padding. The layers were followed by a leaky ReLu activation layer, except for the final layer which used a tanh activation.

The discriminator model also had two inputs: the subject labels, and the heartbeats (either real or fake heartbeats). The subject labels were embedded with the same method as the generator. The input heartbeats were taken directly and concatenated with the subject identifiers. The main structure had three one-dimensional strided convolutional layers, with 64, 128, and 256 filters. Each had a kernel size of 4, stride of 2, same padding, and leaky ReLu activation. A dropout layer of 0.3 was added between each convolutional block. Finally, there was a flatten layer, and a fully connected layer with a single node. The model used an Adam optimizer with a learning rate of 0.0002, and beta1 of 0.5. The model was trained on a binary cross-entropy loss function.

2.3. Training and Evaluation

The model was trained for 100 epochs with a batch size of 256, and the following steps were performed on each epoch. First, a half-batch of random real SCG samples were used to train the discriminator. Then a half batch of fake samples were generated using the generator and were used to train the discriminator. Finally, we trained the entire GAN with the discriminator layers frozen to train the generator using the error from the discriminator.

The resulting heartbeats were evaluated by visual inspection to confirm the resemblance to real SCG heartbeats. They were judged on similarity to each other within the subject, and difference between subjects.

We quantified the error using root-mean-squared-error (RMSE). First, we randomly selected 50 real and 50 generated heartbeats from each subject. Then, using the real SCG data, we calculated an ensemble average. The RMSE was calculated from each fake heartbeat to the ensemble average of the real heartbeats. Since there is naturally a lot of variances in SCG beats, we also calculated the RMSE from the real heartbeats to their respective ensemble average to give a baseline of expected error. Finally, we compared the RMSE from the generated heartbeats to the ensemble averages of other subjects to confirm subject-specific similarity.

3. Results

The model was trained on to minimize error on the entire dataset. We randomly selected 50 real and 50 generated heartbeats to evaluate the model. A random selection of heartbeats from 5 subjects can be seen in Figure 2. Each column corresponds to the same subject where four heartbeats were randomly generated for that subject. It can be observed that within each subject, there is visually more similarity than between subjects. Additionally, we can visually see variability in both inter- and intra-subject heartbeats.

RMSE was calculated on the subset of heartbeats. We observed a (mean ± standard deviation) RMSE of 0.1757 ± 0.0584 when comparing real SCG heartbeats to their respective ensemble average. For the generated heartbeats, we observed a 0.1831 ± 0.0386 when comparing the fake SCG heartbeats to the respective real ensemble averages. We also observed a RMSE of 0.2357 ± 0.0503 when comparing generated heartbeats to the real ensemble averages from the other subjects. This shows that generated heartbeats have an error on the same scale as their real counterparts. Additionally, it shows that on average, each beat is more similar to their own ensemble average, than to the ensemble averaged from other subjects.

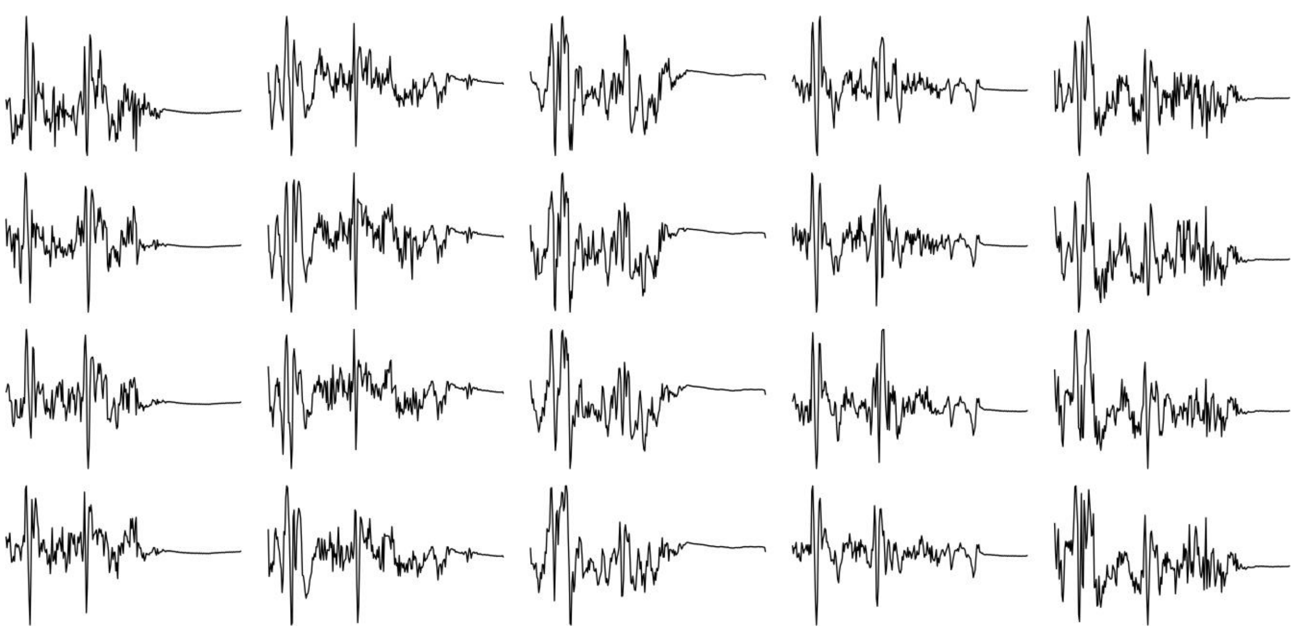

Figure 2. Randomly generated heartbeats from five subjects across four random samples. Each column shows heartbeats from the same subject.

4. Discussion

The results of the study showed that the generated beats closely resembled SCG-like patterns, with RMSE levels that were comparable to actual beats. Furthermore, the observed increase in error between different subjects suggest that the model had successfully captured subject specific SCG features, validating its ability to generate diverse SCG heartbeats. This validation highlights the potential of the model to enhance deep learning SCG research by contributing to dataset augmentation, template generation, and increasing dataset diversity. However, its important to note some limitations. The analysis for diversity within each subject is relatively limited, and it remains challenging to ascertain whether the generated beats truly represent useful cardiac information without further validation in diverse situations. Additionally, the study is constrained to healthy subjects, and the normalization process limits variability in the Aortic Opening (AO), which is the most extensively analyzed feature. Future work should address these limitations to examine morphological features and their variation to broaden the validation of the model.

5. Conclusion

This study investigated the use of a GAN to synthetically generate SCG heartbeats. The results demonstrate that generated heartbeats closely resembled their actual counterparts. This indicates that the synthetic SCG heartbeats produced by the GAN possess the potential to serve as a valuable resource for the training and validation of SCG analysis algorithms while reducing the dependence on authentic patient data exclusively. This contribution has the potential to surmount the cost-associated obstacles that often hinder SCG research, thereby simplifying access to SCG data for the development of novel solutions. Consequently, this accelerated development holds promise for advancing the technology and its diverse applications.

Acknowledgments

This work was supported by the National Sciences and Engineering Research Council (NSERC) of Canada and McGill University.

References

[1] A. Taebi, B. E. Solar, A. J. Bomar, R. H. Sandler, and H. A. Mansy, "Recent advances in seismocardiography," *Vibration,* vol. 2, no. 1, pp. 64-86, 2019.

[2] Y. D'Mello, J. Skoric, S. Xu, P. J. Roche, M. Lortie, S. Gagnon, and D. V. Plant, "Real-time cardiac beat detection and heart rate monitoring from combined seismocardiography and gyrocardiography," *Sensors,* vol. 19, no. 16, p. 3472, 2019.

[3] M. M. H. Shandhi, B. Semiz, S. Hersek, N. Goller, F. Ayazi, and O. T. Inan, "Performance analysis of gyroscope and accelerometer sensors for seismocardiography-based wearable pre-ejection period estimation," *IEEE journal of biomedical and health informatics,* vol. 23, no. 6, pp. 2365-2374, 2019.

[4] M. Di Rienzo *et al.*, "Wearable seismocardiography: Towards a beat-by-beat assessment of cardiac mechanics in ambulant subjects," *Autonomic Neuroscience,* vol. 178, no. 1-2, pp. 50-59, 2013.

[5] J. Skoric, Y. D'Mello, E. Aboulezz, S. Hakim, N. Clairmonte, M. A. Lortie, and D. V. Plant, "Respiratory modulation of sternal motion in the context of seismocardiography," *IEEE Sensors Journal,* vol. 22, no. 13, pp. 13055-13066, 2022.

[6] O. T. Inan *et al.*, "Novel wearable seismocardiography and machine learning algorithms can assess clinical status of heart failure patients," *Circulation: Heart Failure,* vol. 11, no. 1, p. e004313, 2018.

[7] C. Yang, N. D. Aranoff, P. Green, and N. Tavassolian, "Classification of aortic stenosis using time–frequency features from chest cardio-mechanical signals," *IEEE Transactions on Biomedical Engineering,* vol. 67, no. 6, pp. 1672-1683, 2019.

[8] V. G. Ganti *et al.*, "Wearable Seismocardiography-Based Assessment of Stroke Volume in Congenital Heart Disease," *Journal of the American Heart Association,* vol. 11, no. 18, p. e026067, 2022.

[9] J. Skoric *et al.*, "Cuff-less Estimation of Blood Pressure from Vibrational Cardiography Using a Convolutional Neural Network," in *2022 Computing in Cardiology (CinC)*, 2022, vol. 498: IEEE, pp. 1-4.

[10] S. Siecinski, E. J. Tkacz, and M. Grzegorzek, "Publicly available signal databases containing seismocardiographic signals — the state in early 2023," presented at the Engineering in Medicine and Biology (EMBC) 2023, Sydney, Australia, 2023.

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