SCG Signal Denoising Using Deep Learning

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Seismocardiography (SCG) refers to vibrations detectable on the chest wall surface originating from cardiac valve, muscle, and turbulent blood flow. SCG analysis appears to be useful in the diagnosis and monitoring of various cardiac pathologies. Removing noise artifacts from SCG is essential for proper extraction of the signal features that may have a diagnostic value. SCG signals contain both low-frequency cardiac vibrations (<20 Hz) and heart valve sounds (>20Hz) [1]. It would not be effective to apply simple band-pass filtering when the noise spectrum is within SCG frequency band. Deep learning (DL) has shown promising results in removing noise artifacts from electroencephalogram (EEG) and other signals [2][3][4][6][7]. Increasing SCG signal to noise ratio (SNR) would help determine signal features more accurately which can increase the SCG diagnostic utility.

In the current study, a supervised DL approach is utilized to study denoising SCG signals by the removal of building noise. SCG was recorded from 4th intercoastal space using a uniaxial accelerometer while a second accelerometer detected building noise during the same recording session. Two different models were implemented. First, a recurrent neural network (RNN) using long short-term memory (LSTM) network (called Model-1 in the current study) that can denoise signals. The second model (called Model-2)



Figure 1. Flowchart showing preprocessing, noise addition, segmentation and dataset creation

first converts 1D time series into 2D data using short term Fourier transform (STFT) then use a RNN involving LSTM network to remove noise then converts the 2D data back to a denoised time series signal. Both DL models showed promising results in removing actual building noise from SCG where SNR improvement was achieved. When supervised learning methods are employed, clean SCG signals are needed as a "ground truth" reference signal. The data was collected for 3 minutes from two male subjects who sat still on a chair. Bandpass filtering (0.1-50 Hz) was applied and the resulting signal was used as the ground truth SCG. SCG signal is known to have most of its energy in this frequency band [5][8]. The second accelerometer was attached to the chair to simultaneously collect the building noise signal. To generate the noisy SCG signal, the building noise was added to the clean SCG signal at different signal to noise ratios (SNR) from 1 to 3 in 0.1 increments (resulting in 21 different SNR levels), which was chosen based on expected noise levels. The clean and the 21 noisy signals were then segmented using the R-peaks of the ECG signals which yielded 186 heart beats at each SNR level resulting in 3906 (=186x21) pairs of noisy SCG and clean SCG signals. All signals were normalized by (maximum - minimum values to have the same range). Figure 1. shows the detailed dataset creation method.

The deep learning model takes the noisy SCG as input, denoted by x_c in equation (1), trains itself to learn a nonlinear function 'f' which maps the noisy SCG into denoised SCG, defined as y in the equation (1). The mean square error (MSE) between the denoised output, y and the ground truth x_g are used to calculate a loss function (equation (2)). Here, the model compares each SCG beat and tries to minimize the loss function for all beats used for model training. After the training, all data in the test dataset are used to evaluate the models. The training and testing took about 24 hours on a system having Intel®Xeon® processor and NVDIA RTX 2080.

$$y = f(x_c)$$

$$Loss_{MSE} = \frac{1}{N} \sum_{i=1}^{N} (y_i - x_{gi})^2; N \text{ is the length of a beat}$$

$$(1)$$

Learning rate = 0.05, β₁ = 0.9, β₂ = 0.999, Epsilon = 1e-8. Epoch 400.

Figure 2. Flowchart of RNN model-1.

The performance of the models is evaluated based on the three matrices given by equations (3), (4) and (5). The first two are the relative root mean squared error (RRMSE) for both the temporal and spectral domains

(equation 3 and 4, respectively). The third matric is the correlation coefficient (CC). Each matric provides a different measure of signal distortion.



Optimizer = Adam. Hyperparameters: Same as RNN model-1

Figure 3. Flowchart of RNN model-2. The conversion of time series data using STFT, and conversion of the denoised 2D output back to 1D data.

The temporal and spectral representation of a typical SCG beat, where the ground truth (i.e., original), contaminated, and denoised signal (using RNN Model-2) are provided in Figure 4.



Figure 4. Denoised SCG from RNN model-2, contaminated SCG and the original SCG beat in the (a) time domain. (b) frequency domain



Figure 5. Denoised SCG from lowpass filter, contaminated SCG and the original SCG beat in the (a) time domain. (b) frequency domain

The performance metrics against SNR values of the test dataset is shown in the Figure 6. and Figure 7. By comparing the temporal and spectral metrics for the low-pass and the DL filtering methods, it can be seen that the two DL models showed similar results.



Figure 6. Peromance matrics of first recording against the SNR values, (a) Average RRMSE (Temporal), (b) Average RRMSE (Spectral), (c) CC (Temporal)

These results also indicated that both RNN models performed better than low-pass filtering since they reduced the root mean square difference (RRMSE) between filtered and clean SCG beat and achieved higher correlation coefficient. For example, as can be seen in Figure 6., the lowpass filter resulted RRMSE of 0.39-0.66 (for the SCG waveform) while denoising with DL resulted in RRMSE of 0.23-0.33. In addition, the lowpass filter resulted RRMSE of 0.26-0.44 (for the SCG Spectrum) while denoising with DL resulted in RRMSE of 0.14-0.21. Figure 7. Showed similar trends. In addition, at the lowest SNR (SNR=1), the RNN Model-2 slightly outperformed Model-1 in the frequency domain while Model-1 performed slightly better in the time domain.



Figure 7. Peromance matrics of second recording against the SNR values, (a) Average RRMSE (Temporal), (b) Average RRMSE (Spectral), (c) CC (Temporal)

The current pilot study suggests the technical feasibility of the proposed DL models for filtering building noise from SCG signals. Limitations of the study include considering a small number of subjects and studying only one type of noise. Larger number of subjects will be included in future studies as SCG in different individuals are expected to vary [9][10]. A leave-one-subject-out approach can be used to help test the generality of the trained models. The current study is an initial step towards denoising SCG in real life environments. Building noise was considered first since it was the most consistent and uncontrollable noise in the current study. Future studies will investigate other kinds of noise (e.g., movement artifacts, speech, coughing, which are usually intermittent) that are encountered in clinical settings.

ACKNOWLEDGMENTS

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- Two different supervised DL models were implemented. All the models uses LSTM networks, only difference is first model takes 1D timeseries data while the second model deals with 2D data using short term Fourier transform (STFT).



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- All the performance metrics against SNR values of the test dataset is shown in the Figure 6. and Figure 7. By comparing the temporal and spectral metrics for the low-pass and the DL filtering methods, it can be seen that the two DL models showed similar results.
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Conclusion

- The current pilot study suggests the technical feasibility of the proposed DL models for filtering building noise from SCG signals.
- Limitations of the study include considering a small number of subjects and only one type of noise.
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Preprocessing



- Data collected from one subject. •
- Uniaxial accelerometer used for . SCG and noise recording.
- Sampling frequency 10kHz. .
- Duration 3 minutes. •

Figure 1. Flowchart showing preprocessing, noise addition, segmentation and dataset creation

Noise Addition

Segmentation

- Noise added to clean SCG
- SNR range 1 to 3 in 0.1 . increments.
- Total 21 sets of noisy SCG signals created.
- The noisy and clean signals are segmen ٠
- R-peaks of ECG signal is used as refere •
- There are 186 segments for each noisy ٠
- Clean SCG signal is also segmented, using the ٠ same reference.

Dataset creation

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signal.	

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Each noisy segment is paired with its clean counterpart to create a single dataset.

The whole dataset is split into training (80%), validation (10%) and testing (10%) dataset.

Noisy SCG



Number of time steps = LNumber of features =1

Figure 2. Flowchart of RNN model-1.

Flowchart of The Models



- The input and output data size of the model = $(L \times 1)$.
- The first and second LSTM layers have 80 and 100 hidden units, respectively.
- Loss function is the MSE between denoised SCG and the ground truth. . Optimizer = Adam. .
- Learning rate = 0.05, $\beta_1 = 0.9$, $\beta_2 = 0.999$, Epsilon = 1e-8. Epoch 400. .

Number of time steps = L Number of features =1





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- •

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$$\begin{aligned} x_{c} \\ y_{c} &= \frac{1}{N} \sum_{i=1}^{N} \left(y_{i} - x_{gi} \right)^{2}; N \text{ is the length of} \\ y_{temporal} &= \frac{RMS(y - x_{g})}{RMS(x_{g})} \\ y_{spectral} &= \frac{RMS(FFT(y) - FFT(x_{g}))}{RMS(FFT(x_{g}))} \\ y_{cov}(y, x_{g}) \end{aligned}$$

$$Var(y)Var(x_g)$$

.....(1)(2) f a beat(3)(4)(5)

Sample Denoised Output

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