University of Peradeniya

Towards Synergistic Noise Reduction in Fetal Phonocardiograms Through Entropy-Guided Preprocessing and Sparse Autoencoders

K.L. Kotuwage[1]
Supervised by: H.R.O.E. Dayaratna[1], D.A. Gunawardane[2]
[1]Department of Statistics and Computer Science, Faculty of Science, University of Peradeniya. [2] Department of Community Medicine, Faculty of Medicine, University of Peradeniya.

Abstract- This study proposes a novel approach to enhance phonocardiogram(PCG) fidelity by employing sparse autoencoders(SAE) for noise reduction in realistic noise scenarios. Results show a significant noise reduction, indicating promising potential towards enhancing fetal PCG signal quality.

Introduction- Fetal phonocardiograms (fPCGs) are a non-invasive and cost-effective method for assessing fetal heart sounds, but they often suffer from noise interference. Current literature lacks realistic noise scenarios in fPCGs. This study aims to enhance phonocardiogram fidelity by using sparse autoencoders for noise reduction as a potential step towards enhancing the fidelity of fPCGs and realistic noise modelling.

Methodology- A dataset with clean heart sound signals was selected for the study. Realistic noise was introduced by compiling a separate dataset focusing on five noise categories likely to appear as unwanted noise in PCG signals: burping and eructation, chewing and mastication, sneezing and respiratory sounds, coughing, and finger snapping. The noisy PCG dataset was formed by iteratively adding noise audio signals to clean heart sounds. Two sparse autoencoders were subsequently trained on this dataset: one model directly on the noisy signals and another incorporating an entropy-guided preprocessing technique. The de-noising performance of these models was evaluated using the metrics summarized in Table 1.

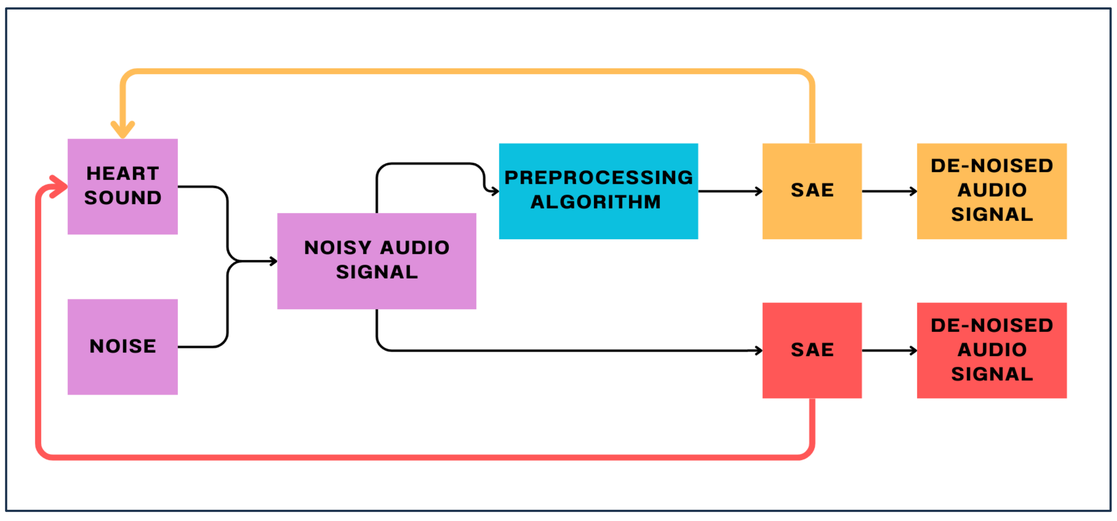

Figure 1: Process flow of the methodology

$$N(t) = \left\{x\left(t - \frac{W}{2}\right), x\left(t - \frac{W}{2} + 1\right), \ldots, x\left(t + \frac{W}{2}\right)\right\}$$

N(t) = Neighborhood centered at time t
x(t) = noisy time series signal
W = window size

$$H(N(t)) = -\sum_{i=1}^{m} P(x_i) \times log_2\,(P(x_i))$$

H(N(t)) = Shannon entropy of the neighborhood N(t)
m = number of unique values within the neighborhood N(t)
x_i= unique values within the neighborhood N(t)
$P(x_i)$ = probability of the value xi

noise reduced estimate value at time t $\hat{x}(t) = \frac{1}{W}\sum_{i=t-\frac{W}{2}}^{t+\frac{W}{2}} x(i)$

Figure 2: Entropy-guided preprocessing algorithm

Results and Discussion- Visual examination of the acquired results demonstrated that high-frequency, low-amplitude noise could not be efficiently reduced by sparse autoencoder alone. On the other hand, high-frequency, low-amplitude noise could be substantially reduced by the sparse autoencoder trained using the preprocessing technique.

Table 1: Quantitative evaluation of de-noising with and without the preprocessing algorithm

Evaluation metric	Without preprocessing	With preprocessing
Pearson Correlation Coefficient	0.832	0.877
average Dynamic Time Warping distance	823	788
Spectral Coherence	0.106	0.100

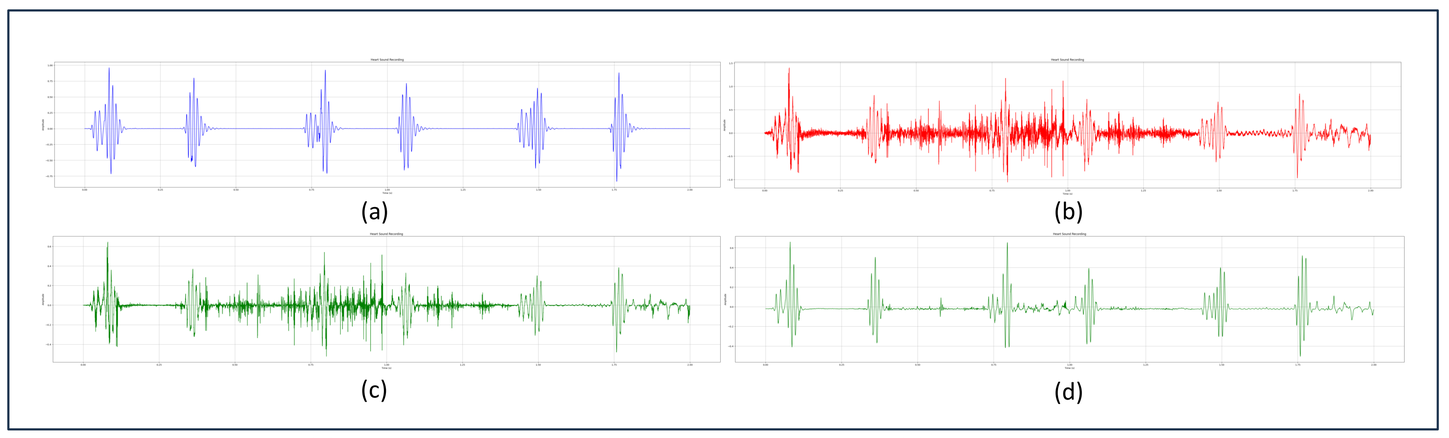

Figure 3: De-noising results (a) Original noiseless signal, (b) Noise introduced signal, (c) De-noised signal without the preprocessing algorithm, (d) De-noised signal with the proposed preprocessing algorithm

Conclusion- The study introduced an entropy-guided preprocessing technique for the enhancement of PCG de-noising performance of sparse autoencoders. The results demonstrated that, this approach could attain better time domain similarity and waveform alignment between the de-noised and ground truth signals.

Contact details
Name : Dr. Erunika O. Dayartna
Tel. No.: +94 76 049 5054
Email : erunika.dayaratna@sci.pdn.ac.lk

Multidisciplinary AI Research Centre (MARC)
University Research Council
University of Peradeniya
Peradeniya, 20400, Sri Lanka