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THE COOPER UNION
ALBERT NERKEN SCHOOL OF ENGINEERING

A Deep Partitioned Autoencoder
for De-Noising Live Audio

by
Ethan Lusterman

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Engineering

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Professor Sam Keene, Advisor

054 THE COOPER UNION FOR THE
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056 ADVANCEMENT OF SCIENCE AND ART
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Acknowledgements

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Abstract

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1 Introduction

Advances in smartphone technology have led to smaller devices with more powerful audio hardware, allowing for common consumers to make higher quality recordings. However, recorded speech and music are subject to noisy conditions, often hampering intelligibility and listenability. The goal of denoising audio recordings is to improve intelligibility and perceived quality. A variety of applications of audio denoising exist, including listening to a recording of a band or an artist’s live performance in a noisy crowd, or listening to a recorded conversation or speech under noisy conditions.

A common technique for denoising involves the use of deep neural networks (DNN). [PARIS] Advances in parallel graphics processing units (GPU) and in machine learning algorithms have allowed for training deeper networks faster, utilizing more hidden layers with more neurons.

Prior work in denoising audio has involved access to noise-free training data. Since common consumers do not often have access to clean audio, we seek to denoise without the use of clean audio.

In this thesis, we compare several neural network architectures and problem scenarios, ranging from data input types, level of noise, depth of network, training objectives, and more. In Chapter 2, we present background information on machine learning and neural networks as well as prior work in audio denoising. In Chapter 3, we detail all considered network architectures. In Chapter 4, we compare results from different data inputs, levels of noise, network architectures, and training objectives and discuss methods of evaluation. Finally, we make conclusions and recommendations for future work in Chapter 5.

2 Background

2.1 Machine Learning

Machine learning involves the use of computer algorithms to make decisions based on training data. Generally, this falls into categorizing input data (classification) or determining a mathematical function to determine a continuous output given an input (regression). Popular classification examples include recognizing handwritten digits (MNIST) as well as determining whether an image contains a cat or a dog. (REF) An example of a regression problem is determining the temperature given a set of input features (humidity, latitude, longitude, date, etc.).

Problems where training data contain input data vectors as well as the correct output vectors (targets) are known as supervised learning problems. Training a model to denoise audio where noise was introduced to the clean audio would be a supervised learning problem. On the other hand, training a model to denoise audio where the underlying clean signal is not known is an unsupervised learning problem. Different loss functions and neural network architectures can be exploited to accomplish denoising without the clean data.

For the purposes of this thesis, we use machine learning to determine an underlying nonlinear function that removes noise from time slices of audio (i.e. regression). These slices can then be pieced back together through overlap-add resynthesis.

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2.1.1 Regression

2.1.2 Overfitting and Curse of Dimensionality

2.1.3 Loss functions and Regularization

2.1.4 Gradient Stuff?

2.2 Neural Networks

2.2.1 Dense Layer

2.2.2 Convolutional Layer

2.2.3 Nonlinearity Choice

2.3 Signals and Systems

Domain knowledge of discrete audio signals and systems better informs our decisions for an audio denoising system, so some background information on signals and systems as it pertains to this thesis is detailed below.

2.3.1 Signals

We deal exclusively with discrete-time audio signals in this thesis. A discrete-time audio signal $x[n]$ is represented as a sequence of numbers (samples), where each integer-valued slot n in the sequence corresponds to a unit of time based on the sampling frequency f_s . This comes from sampling the continuous-time audio signal $x_c(t)$:

$$x[n] = x_c(nT) \tag{1}$$

where $T = 1/f_s$. For example, a 1-second speech signal sampled at 8kHz has 8000 samples. Furthermore, digital signals also have discrete valued sample amplitudes. For the purposes of this thesis, the bit depths of computers we

use for analysis are high enough to allow for perfect reconstruction between continuous-time signals and digital signals.

We also assume signals collected have been properly sampled according to the Nyquist-Shannon sampling theorem, which states that a discrete-time signal must be sampled at at least twice the highest frequency present in the signal to prevent aliasing of different frequencies. For example, speech signals generally have information up to 8kHz, so many speech signals are sampled at 16kHz. Music is more complex in that signals often span up to about 20kHz, so CD quality recordings are often sampled at 44.1kHz or higher. For this thesis, we use recordings sampled at 44.1kHz or lower.

2.3.2 Convolution

The discrete-time convolution operation takes two sequences $x[n]$ and $h[n]$ and outputs a third sequence $y[n] = x[n] * h[n]$:

$$y[n] = \sum_{k=-\infty}^{\infty} x[k]h[n-k] \quad (2)$$

A linear, time-invariant (LTI) system is characterized by its impulse response $h[n]$, which allows us to determine samples $y[n]$ when $x[n]$ is subject to $h[n]$. For the purposes of this thesis, our underlying clean signal $x[n]$ might be subject to the conditions of an acoustic environment $h[n]$ and crowd noise $N[n]$:

$$y[n] = h[n] * x[n] + N[n] \quad (3)$$

In this scenario, our system would attempt to recover $h[n] * x[n]$ and possibly $x[n]$ if the acoustic environment were deemed “noisy enough.”

594 One of our proposed systems also incorporates convolutional neural networks
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596 (CNN), which use convolutions between samples instead of simple linear com-
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598 binations (discussed later).
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601 **2.3.3 Frequency Transforms**

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603 **2.3.4 Windowing and Perfect Reconstruction**

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3 System Description

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4 Results

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5 Conclusion