Landon Buell

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Audio Classification of Musical Instruments with a Multimodal Neural Network

1. Abstract
2. Introduction

Signal classification is a broad area of digital signal processing that seeks to group waveform-like objects into categories based on properties within the signal. From musical

Consider a library of synthetically generated signals that represent digital audio waveforms that we would like t associate with a real-world musical instruments. If there were only a few dozen or hundreds of samples, it’s feasible to have a human manually open each file as an audio track, listen to it, and then determine what instrument it most sounds like. However, this process is intensive and very subjective when it comes to producing a label. Listeners that grew up in different regions of the world, exposed to different musical styles, played across multiple instruments may produce wildly inconsistent conclusions when analyzing the same audio sample. This, combined with a library of waveforms that may number in the thousands or millions makes it impossible for even a group of humans to complete in a reasonable amount of time with reasonable accuracy of category assignment.

Because of the constraints that humans add, it makes sense to attempt to automate this process with the aid of a computer, but audio classification from a waveform is not a task that classical computer algorithms are known to excel at [citation needed]. To succeed, we need to combine the computational efficiency, with the intelligence of a human brain. For this, we look no further than a *neural network.*

A neural network is a mathematic function that accepts a collection of numerical inputs that encode a particular sample to produce a set of outputs that encode the probability of that sample belonging to each of the possible output. In the cause of digital audio classification, inputs called *features* are qualitative characteristics of each signal sample, and the outputs called *classes*

1. Feature Selections

Neural networks are mathematical functions that use a collection of inputs called *features* to produce outputs called *predictions* [citation needed]. Features are compact-low dimensional representations of a given input which must effectively capture the key characteristics of their parent sample. Features with a category or class should behave similarly and features between classes should behave differently. For example, if characterizing cats against dogs, we might use weight since dogs in general are heavier than cats, whereas using the number of legs would not be very useful as cats and dogs typically have four legs.

1. Spectrogram Features

A spectrogram is a 2D representation of a waveform that characterizes a signals spectral evolution over time. A spectrogram is built by first dividing up a waveform into a collection of overlapping slices of time called *analysis frames* and then applying a Discrete Fourier Transform to each frame, and then aggregating the frames back together. The result is a 2D matrix S with entry *S*[*i,j]* encoding the energy of the waveform at time frame *i* and frequency bin *j*, which also allows us to represent a 2D image as opposed to a 1D signal.

1. Time-Domain Features

Features drawn from the time-domain parse the waveform in its amplitude vs. time representation. Note that for this set of features, the actual waveform itself is never presented to the neural network, it is only used to build up the collection of features with are then presented to the neural network.

1. Time Domain Envelope
2. Zero Crossing Rate
3. Temporal Center of Mass
4. Auto Correlation Coefficients
5. Frequency-Domain Features

Features drawn from the frequency domain parse the waveform in its energy vs. frequency representation. Note that for this set features, the actual frequency spectrum

1. Mel Frequency Cepstrum Coefficients
2. Frequency Center of Mass
3. Multimodal Architecture

We have chosen a collection of features derived from both the time and frequency domain of a digital signal. Each of those features is a single scaler value that represents a physical, quantitative property of the sample. Moreover, each feature can stand by itself because it does not directly rely on any other feature. For this reason, we simply take each feature from the time and frequency domains and simply concatenate them into a single *feature vector.* This is a (1 x p) array that neatly summarizes the characteristics of the sample in a sort of list-of-describing-qualities format.

We have also chosen a spectrogram to represent our waveform in an image-like format. Unlike the previous describe feature vector, the elements of the spectrogram matrix cannot stand on their own. Entry S[i,j] has meaning within the context of the spectrogram, but taken alone has little meaning. We could arrange the elements of the matrix into similar feature vector, but then we lose information on how any entry in the matrix relates to any other entry in the matrix. By leaving the matrix as an image format

The problem then arises that these are to different *modalities* of the same sample. Both the (1 x p) feature vector and then (m x n) spectrogram encode information derived from the same source, but in incompatible formats. This can be though of like a driver’s license where one side will contain a list of qualities such as height, weight, hair color, and eye color, and is paired with an image that was taken on the day it was issued. Both ideas describe the driver, but in two different ways. To take full advantage of both modalities, we must build a *multimodal neural network* which can accept both formats, learn a set of weights that allow for classification, and then use the combined inputs to generate a single prediction label.

1. Performance Evaluation Techniques
2. Performance of models