Cameron Embree
Math448, S2014

Final Project – Exploring Rudimentary Sound Identification

1. INTRODUCION

Sound identification and classification are increasingly integrated into recent technologies as a move towards a hands-free user interface is developed. Our phones can now accurately provide us with information from verbal queries we provide. When requesting something of a device, it records our voice, parses our voice into words, and determines our question from these words. I am interested in learning more about how sound identification works including what measurements can be used from an audio recording that characterize that recording in a way that it can be used to classify other similar sounding audio. For example, after measuring a person saying "one" multiple times, by using some measurement of the audio recordings, we can identify later utterances of the word "one."

Mathematica offers some tools for audio importing and manipulation. Although not as robust as other audio analysis frameworks, Mathematica allows for taking Fourier Transforms of an imported audio clip. I want to test how effective using a Fourier Transform to classify an audio segment might be. To make a conclusion about the ability for just a Fourier Transform to classify an audio segment, I tested it's ability to classify a word set of six words. The results of these tests can help determine if using a Fourier Transform of previously sampled audio can help make future audio classifications.

2. BACKGROUND

The Fourier Transform is a transformation that takes a signal from the time/spatial domain to the frequency domain. Essentially, A Fourier Transform of an audio sample will provide the frequencies that exist in that sample. Therefore, we can use this transform to see the different frequencies that exists in pronunciations of various words. Different words have differing amount of various frequencies that could be used to recognize a new recording as being very similar to, as thus classified as, a previously analyzed recording.

3. METHODOLOGY

A word bank of 6 "simple" words with multiple recordings is used for this testing. The word bank is the six numbers in English from zero to five.

0	1	2	3	4	5	6
zero	one	two	three	four	five	six

Each of these words was recorded 6 times so that testing could be handled in a NxN matrix in Mathematica, where N=number of words in the word bank. Further, multiple recordings of a single word could then have each respective Fourier Transform averaged to have an approximate average of the Fourier Transform for a given word in the word bank. To only collect information that measures the Fourier Transforms that humans can hear, a high pass filter was applied at 10000Htz. This filter was applied under the assumption that the only data that should characterize our audio sample is frequencies that can actually be heard.

After an average Fourier Transforms were generated for each of the words in the bank, each of the originally sample of words was compared to the averages based on the differences in Fourier Transforms. Differences are measured by generating functions that best-fit the Fourier data and then integrating to find the difference between that average fit and this current audio's Fourier best-fit. The average Fourier best-fit which is least different than the new sample (lowest absolute value integration difference), is what the new sample is classified as. In other words, an audio sample should have a similar best-fit polynomial to it's Fourier Transform as the average best-fit of the Fourier Transforms from which it is borrowed.

4. RESULTS

Using just the average Fourier Transform of the word bank, accuracy of just over 86% was achieved.

4.1 Classification Results

The second element of each position in the following matrix is what word that particular piece of audio was classified as being. The first element of each position represents the time in seconds it took to perform the classification operation.

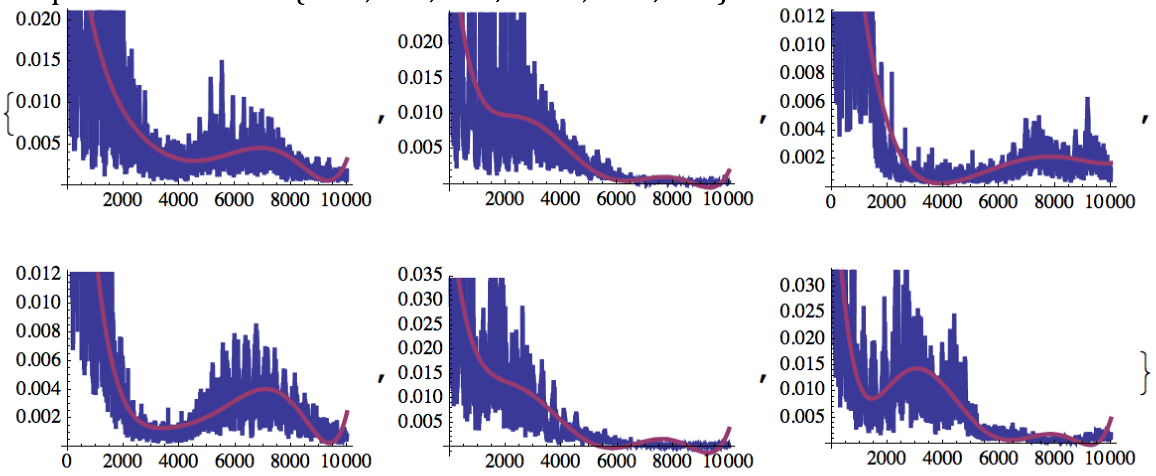
$$\begin{pmatrix}
\begin{pmatrix}0.000055\\0\end{pmatrix} & \begin{pmatrix}0.000032\\0\end{pmatrix} & \begin{pmatrix}0.000030\\0\end{pmatrix} & \begin{pmatrix}0.000028\\0\end{pmatrix} & \begin{pmatrix}0.000029\\2\end{pmatrix} & \begin{pmatrix}0.000028\\1\end{pmatrix} \\
\begin{pmatrix}0.000029\\1\end{pmatrix} & \begin{pmatrix}0.000028\\1\end{pmatrix} & \begin{pmatrix}0.000028\\1\end{pmatrix} & \begin{pmatrix}0.000027\\1\end{pmatrix} & \begin{pmatrix}0.000028\\1\end{pmatrix} & \begin{pmatrix}0.000027\\1\end{pmatrix} \\
\begin{pmatrix}0.000026\\2\end{pmatrix} & \begin{pmatrix}0.000027\\3\end{pmatrix} & \begin{pmatrix}0.000028\\2\end{pmatrix} & \begin{pmatrix}0.000028\\2\end{pmatrix} & \begin{pmatrix}0.000028\\2\end{pmatrix} & \begin{pmatrix}0.000028\\2\end{pmatrix} \\
\begin{pmatrix}0.000028\\3\end{pmatrix} & \begin{pmatrix}0.000027\\3\end{pmatrix} & \begin{pmatrix}0.000028\\3\end{pmatrix} & \begin{pmatrix}0.000029\\3\end{pmatrix} & \begin{pmatrix}0.000028\\3\end{pmatrix} & \begin{pmatrix}0.000027\\3\end{pmatrix} \\
\begin{pmatrix}0.000028\\4\end{pmatrix} & \begin{pmatrix}0.000028\\4\end{pmatrix} & \begin{pmatrix}0.000028\\4\end{pmatrix} & \begin{pmatrix}0.000028\\1\end{pmatrix} & \begin{pmatrix}0.000032\\4\end{pmatrix} & \begin{pmatrix}0.000032\\4\end{pmatrix} \\
\begin{pmatrix}0.000029\\1\end{pmatrix} & \begin{pmatrix}0.000028\\5\end{pmatrix} & \begin{pmatrix}0.000027\\5\end{pmatrix} & \begin{pmatrix}0.000027\\5\end{pmatrix} & \begin{pmatrix}0.000028\\5\end{pmatrix} & \begin{pmatrix}0.000028\\5\end{pmatrix}
\end{pmatrix}$$

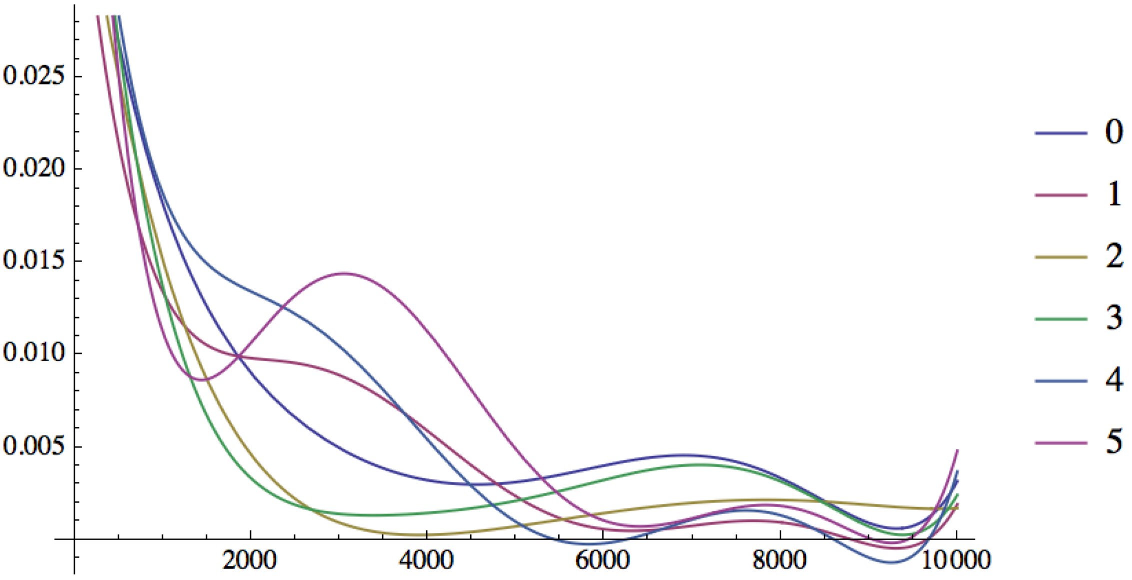
A 100% accuracy would have been a matrix of the approximate form

$$\begin{pmatrix}
0 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 1 & 1 & 1 & 1 \\
2 & 2 & 2 & 2 & 2 & 2 \\
3 & 3 & 3 & 3 & 3 & 3 \\
4 & 4 & 4 & 4 & 4 & 4 \\
5 & 5 & 5 & 5 & 5 & 5
\end{pmatrix}$$

4.2 Average Best-fit Functions for Fourier Transforms

The following are the overlay of each best-fit to average Fourier Transform for each word as well as the average Fourier transform with each best fit function overlaid. Output is in the form {zero, one, two, three, four, five}.



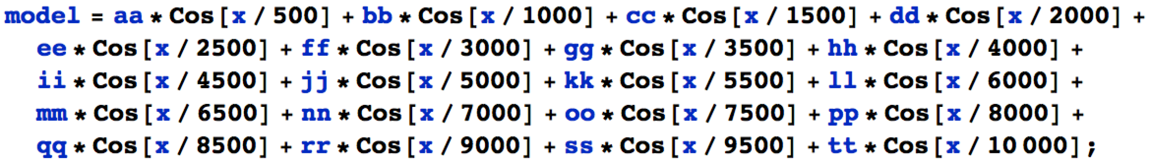


REFLECTION

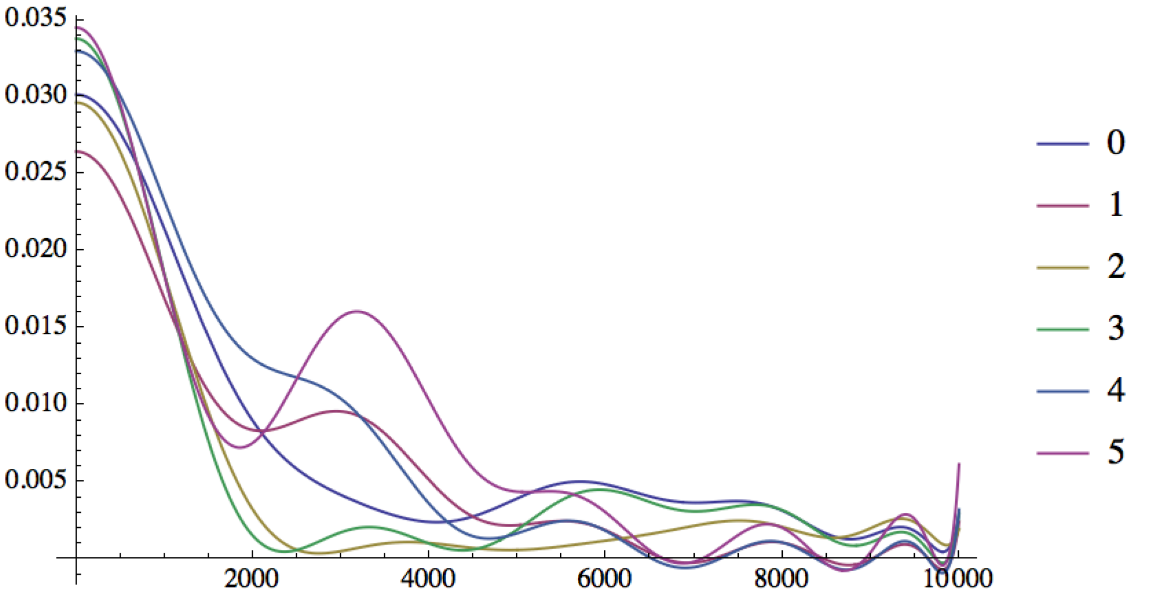
The best fit polynomial performed most optimally when using the function a*x^1+b*x^2+c*x^3+d*x^4+e*x^5+f*x^6, where a,…,f are real numbers. Attempts to use various scalar combinations of periodic functions was also tried to attempt and provide a more accurate fit to the Fourier data. Unfortunately, various attempts to make an improved fit were not successful and results of one such best-fit attempt can be seen in the references section. Using multiple measurements to classify audio and then finding the most similar across all measurements, not just the Fourier Transform, may achieve better results on classification.

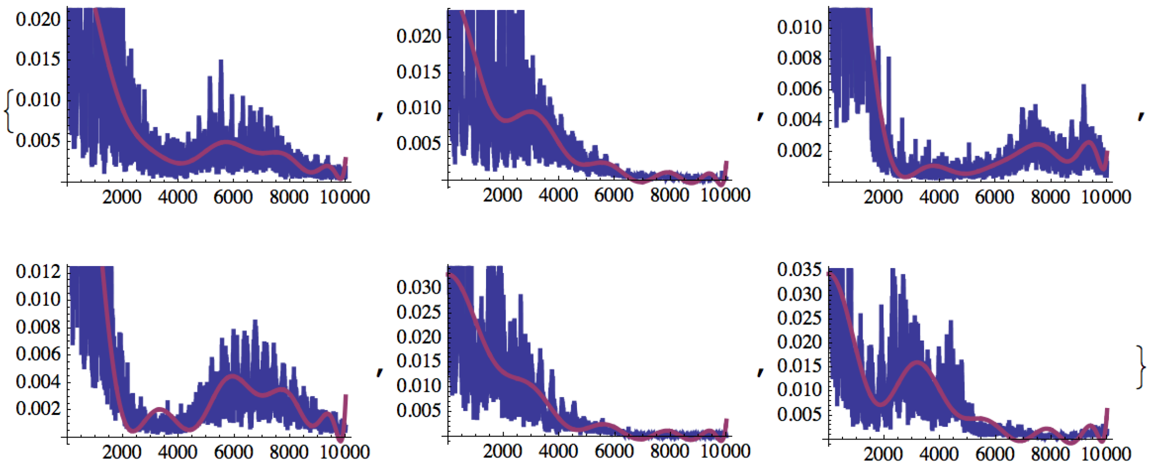
Cameron Embree
Math448, S2014

REFERENCES
The following are the results of best-fit operations using the following periodic model with scalar multiples {aa,bb,…,tt}.



```
model = aa * Cos[x / 500] + bb * Cos[x / 1000] + cc * Cos[x / 1500] + dd * Cos[x / 2000] +
   ee * Cos[x / 2500] + ff * Cos[x / 3000] + gg * Cos[x / 3500] + hh * Cos[x / 4000] +
   ii * Cos[x / 4500] + jj * Cos[x / 5000] + kk * Cos[x / 5500] + ll * Cos[x / 6000] +
   mm * Cos[x / 6500] + nn * Cos[x / 7000] + oo * Cos[x / 7500] + pp * Cos[x / 8000] +
   qq * Cos[x / 8500] + rr * Cos[x / 9000] + ss * Cos[x / 9500] + tt * Cos[x / 10 000];
```


0.035
0.030
0.025
0.020
0.015
0.010
0.005
2000
4000
6000
8000
10000
0
1
2
3
4
5


{
0.020
0.015
0.010
0.005
2000 4000 6000 8000 10000
,
0.020
0.015
0.010
0.005
2000 4000 6000 8000 10000
,
0.010
0.008
0.006
0.004
0.002
2000 4000 6000 8000 10000
,
0.012
0.010
0.008
0.006
0.004
0.002
2000 4000 6000 8000 10000
,
0.030
0.025
0.020
0.015
0.010
0.005
2000 4000 6000 8000 10000
,
0.035
0.030
0.025
0.020
0.015
0.010
0.005
2000 4000 6000 8000 10000
}