Instrument Classification

Data Exploration Technical Report

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Abstract

Introduction

The purpose of this project is to examine whether we can build a model that predicts the instrument being played from a sound recording. This project will utilize data from isolated sound recordings of different instruments being played, with predictors related to differences in the frequency wave patterns, the modulation of frequency or amplitude over time, or the prevalence of different overtones in the sound. The goal will be to predict which instrument is being played based on a sound recording.

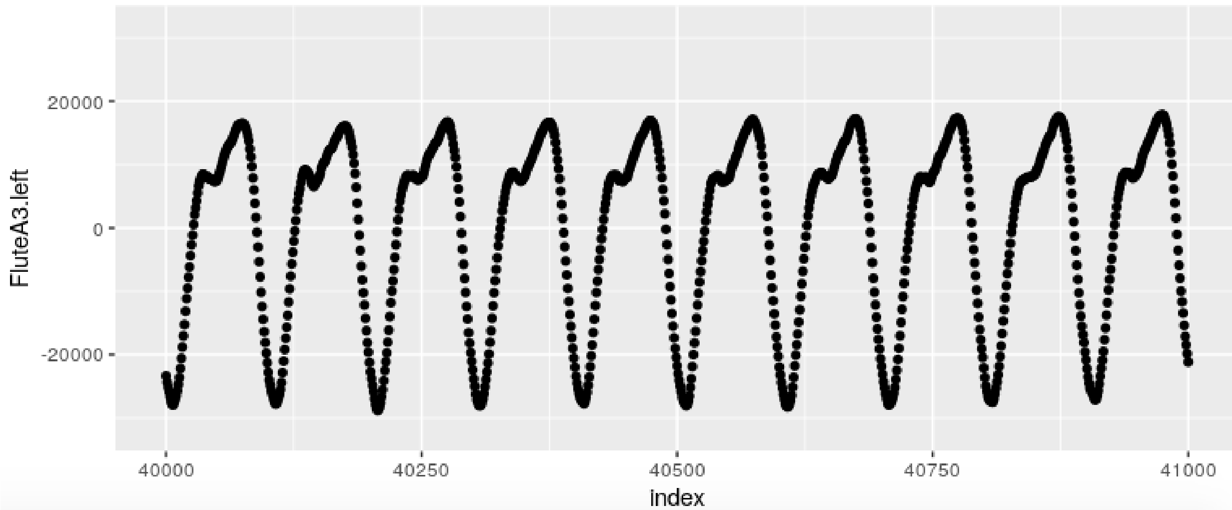
The Data

The data used to construct this classification model came from clips of audio recordings made in GarageBand. For 6 different instruments, we recorded 10 notes as MP3 files and then exported them to RStudio. The `tuneR` package provided convenient functions for reading these files as "Wave" objects which contains information about the audio file including the left and right channels, frequency, and amplitude. The six instruments from which we collected sound recordings are violin, flute, piano, guitar, mandolin, and ukulele. In total, we have 65 observations of data (10 for each instrument except piano, which has 15). We used around 5-10 predictors that relate to attack, decay, volume of different overtone frequencies, and the residuals from fitting a sine curve to the data.

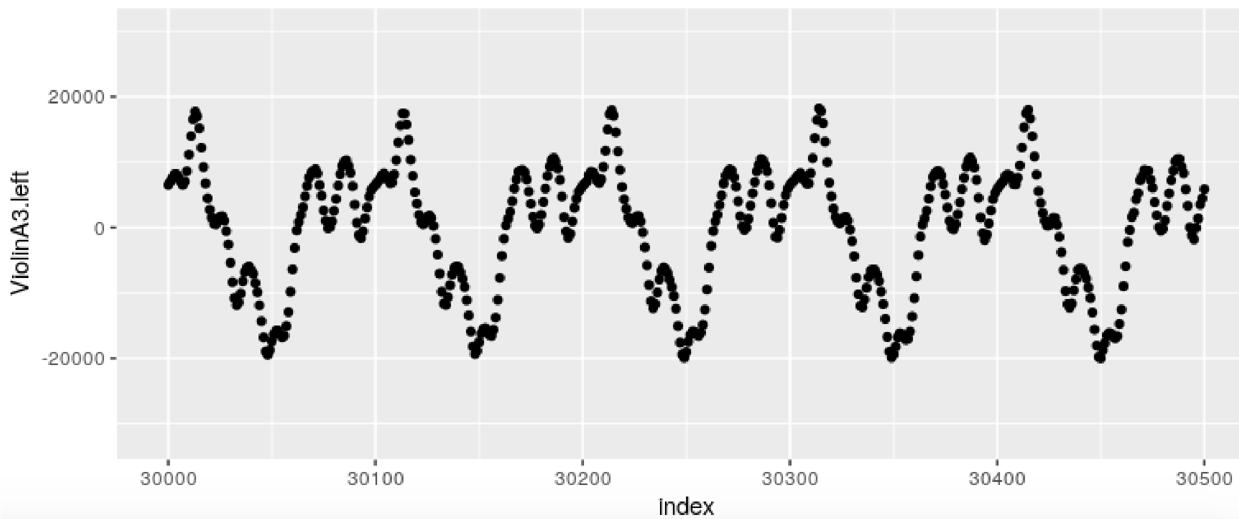
Exploratory Data Analysis

The features that we intend to extract from our observations are some measurement for the attack of the note, some measure of the decay, and some measure of the tonal qualities of the note.

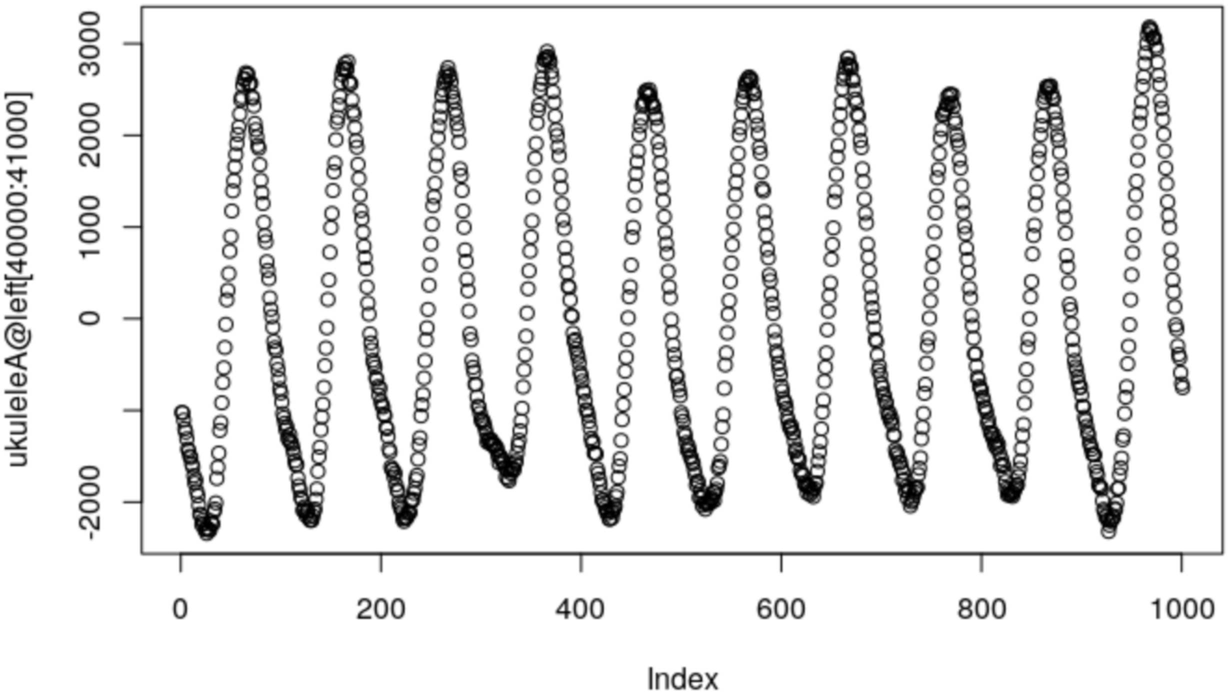
In theory, we should be able to tell instruments apart based on qualities of their waveforms. For example, the three images below show waveforms from recordings of flute, violin, and ukulele. Despite similarities, they seem distinct enough that a human observer could tell these instruments apart solely by looking at graphs like these.



FluteA3.left
20000
0
-20000
40000
40250
40500
40750
41000
index



ViolinA3.left
20000
0
-20000
30000
30100
30200
30300
30400
30500
index



In order to extract a value relating to the shape of the waveforms, we opted to fit a sine wave to each waveform and then record the MSE and RSS. This produced a reasonable value for how much each waveform resembled a sine wave. A lower value implied a more pure signal, while a higher value meant the waveform was more messy.

To extract more features of tonal quality, we wanted to identify which frequencies were loudest in each recording. By using the periodogram function, we were able to see a list of frequencies and their relative loudness, shown below.

From here, we made a function that filtered out all points that weren't a local maximum, and that were smaller than 0.01 of the maximum value in the set. The resulting data frame only includes points at the top of the peaks seen in the plot above. The function then rescaled the data so that the volume of the loudest frequency was equal to 1. Below is a plot of this resulting data frame.

For each instrument recording, we extracted the number of points, the median loudness, and the ratio between the lowest and second lowest frequencies, in an attempt to use what we thought would be the most identifiable traits of the data set as predictors.

To analyze the attack and decay of each note, we started with a data frame that held a measurement for volume over a long list of times. An illustration of this for a Ukulele note is shown below.

We then created a function that filtered out all values that weren't local maxima, and then filtered out all values that were smaller than a certain threshold. After this, the function rescaled the units of time to actually reflect time in seconds. It also rescaled the volume to have a maximum of one, allowing us to compare the decay of a note without worrying about its volume relative to other instruments. The resulting data frame is illustrated below.

Fitting a Sine Curve

One way to try to pick up on nuanced differences in the waveforms would be to fit a sine curve to the data, and perform analysis on the residuals. However, this proves to be a much more difficult task than one might expect. A general sine curve with constant wavelength and amplitude can be written as $A + B\sin(Cx - D)$, thus there

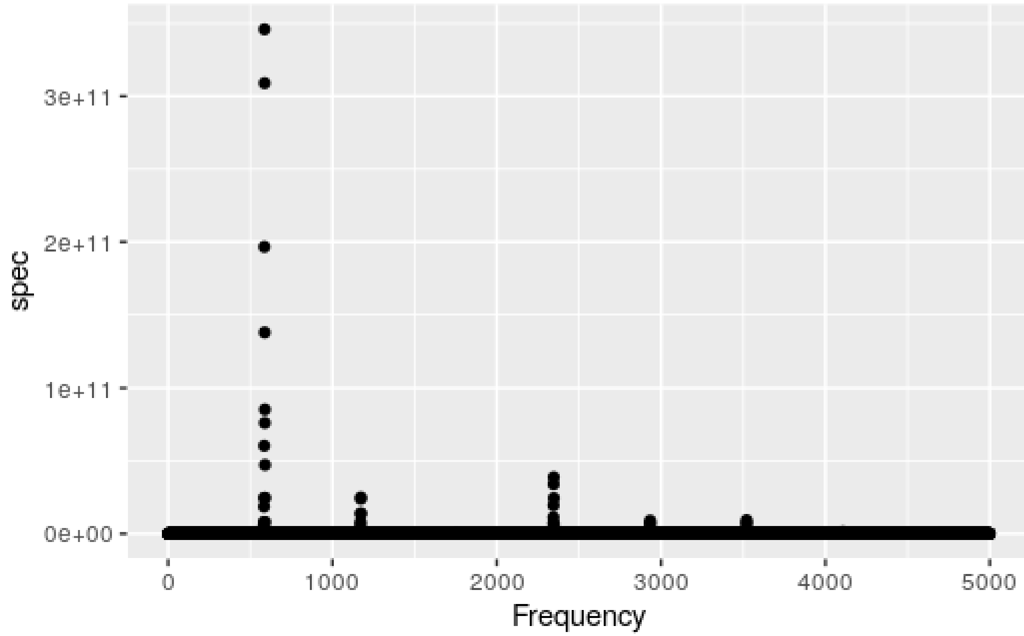


Figure 1:

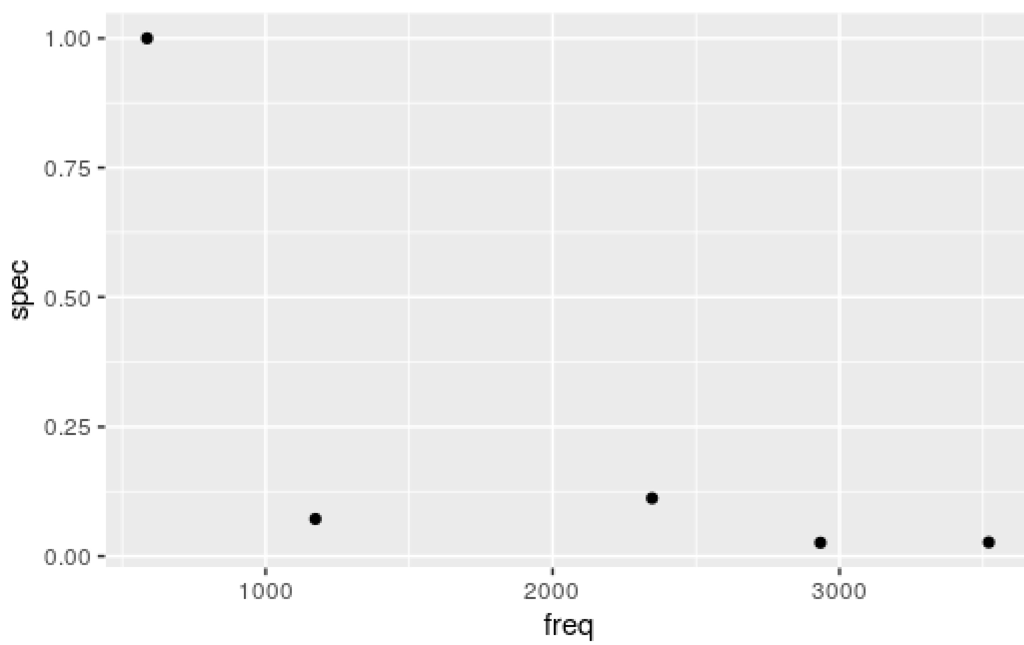


Figure 2:

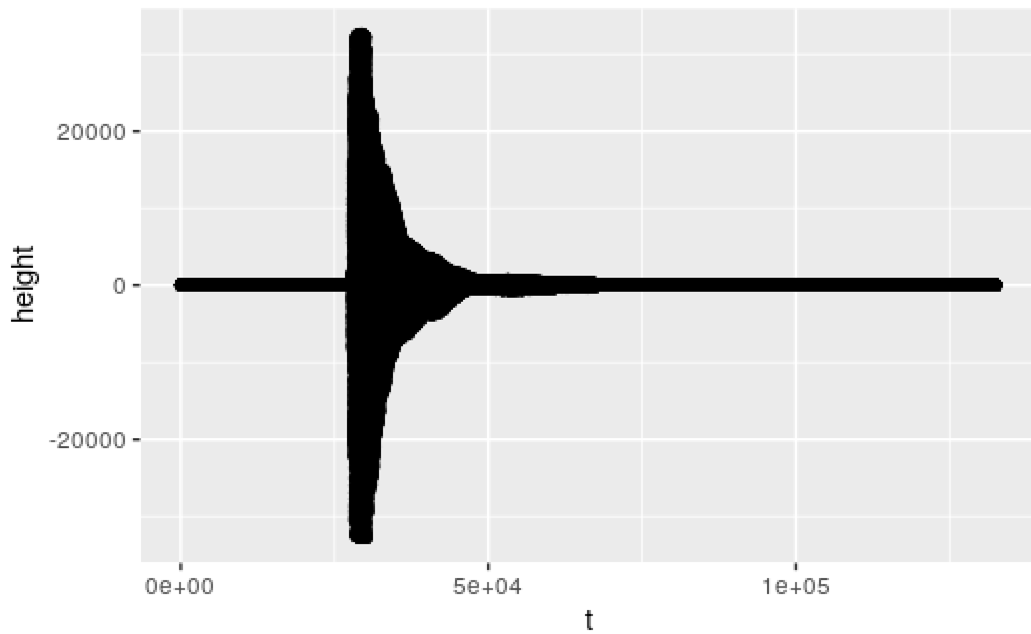


Figure 3:

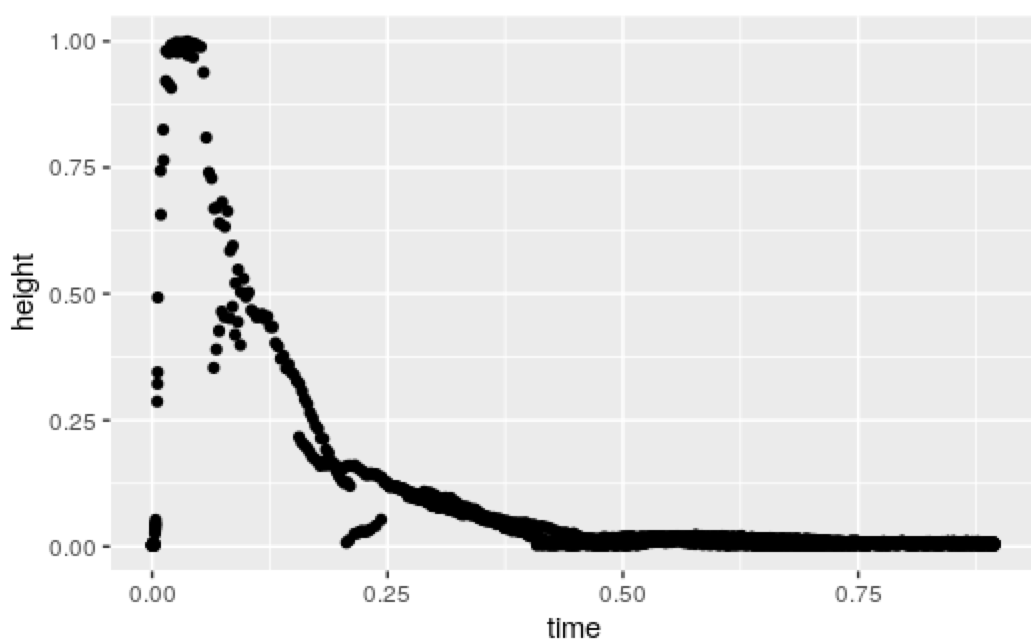
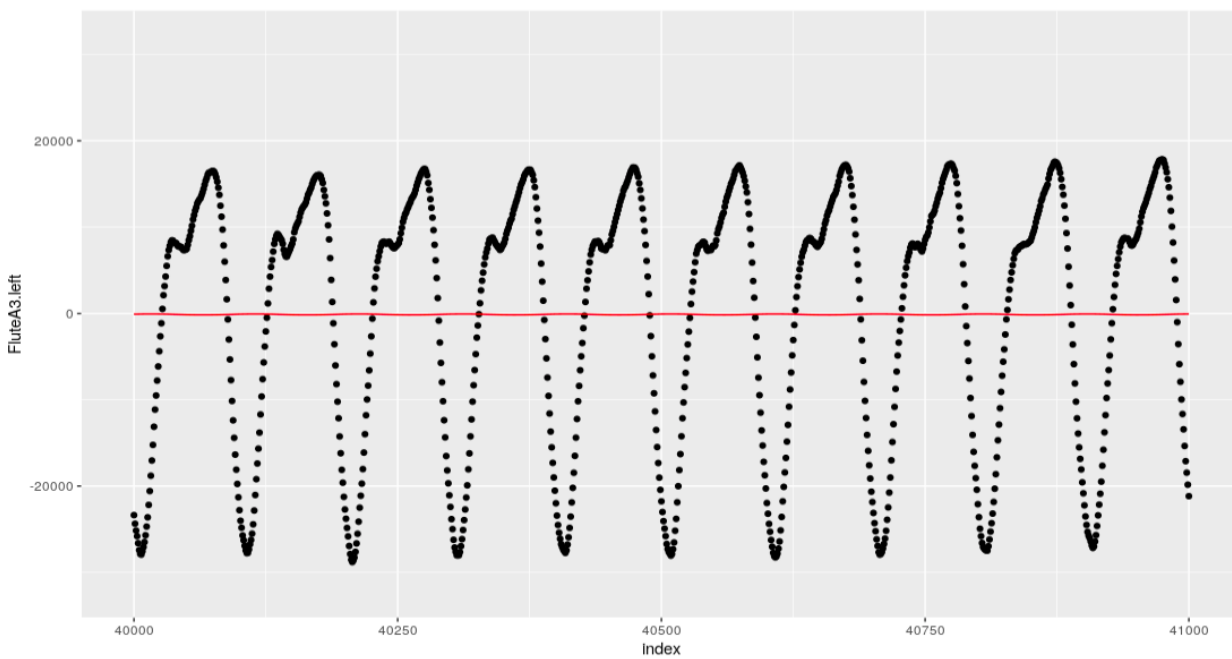
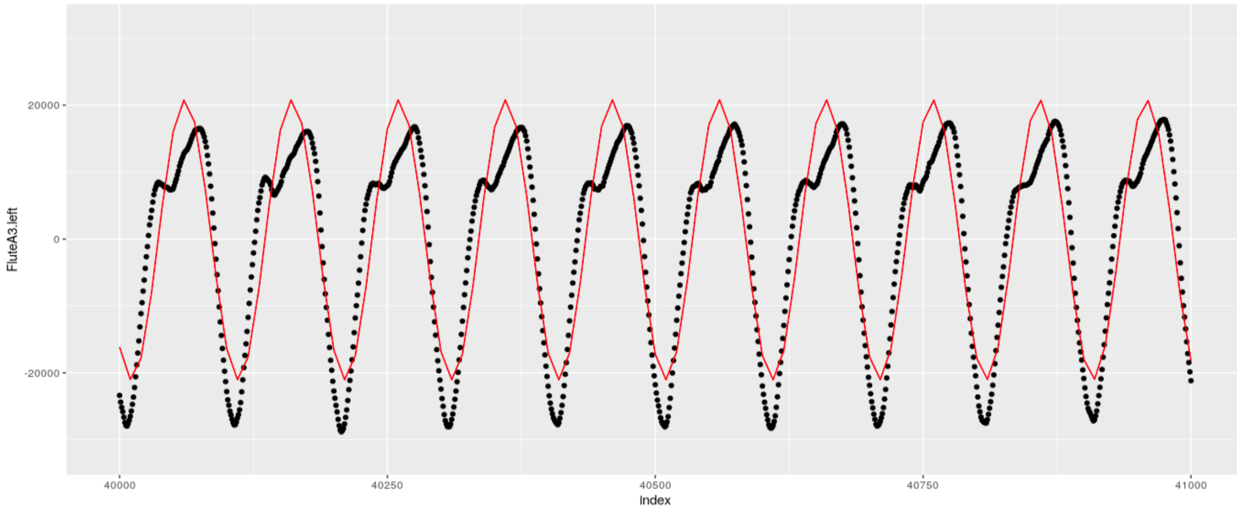


Figure 4:

are at least four parameters to estimate which can be thought of as the horizontal and vertical shift of the curve, as well as controls for wavelength and amplitude. Each of these parameters is necessary to obtain a good fit for an arbitrary curve. We attempt to do this by defining a loss function $\sum_{i=1}^{n}(y_i - (A + B\sin(Cx_i - D)))^2$ (where n is the number of samples in the part of the sound file we are analyzing) and finding a minimum using the optim function in r. From a given starting point, this function searches for a local minima using several possible established methods. While simple in theory, it turns out that it is nearly impossible for algorithmic search functions to find the true best sine fit over these four parameters without being given very good starting values for most of the parameters. Conceptually, this is because the loss function is very sensitive to each of the parameters, thus the global minima (the true best fit sine curve) is surrounded by very large values and thus hard for an algorithm to find based on gradients. For example, even if the amplitude, wavelength, and vertical shift parameters are very well tuned, a bad horizontal shift will produce massive residuals which can be reduced by decreasing amplitude towards zero. The main solution to this problem is to attempt to find a very good starting point for the minimization search function. We do this by estimating values for amplitude, vertical shift, and frequency. The fundamental frequency can be estimated by the periodogram, while the amplitude can be estimated as the half the difference between the min and max of the wave and the vertical shift can be estimated as the halfway point between the min and max. So far, we have mixed success with using this method. However, we hope to improve our method enough to be able to extract features from it, such as the mean squared residuals from the sinusoidal regression, and residual frequencies in the signal (indicating frequency patterns that the sine wave was not able to account for)



A poor fitting sine curve generated by the optim function. The amplitude is suppressed to a very small number to essentially draw a line through the center of the data. The vertical shift is close to zero, but not exactly zero. It appears to be above center because of the clustering of data at the peaks of the waves, at least in the case of this flute sample.



A better sine curve fit obtained by restricting most of the parameters to estimates and simply fitting the horizontal shift.

Measuring the Decay of a Note

One measurement that distinguishes between the sounds of air vibrating down a tube, strings being plucked, strings being strummed, or strings being hit by a hammer is the decay of a sound. Decay is the rate at which a sound dies off to silence. For example, we expect a plucked instrument to have an exponential decay to reflect the fast vibrations that occur just after being pulled back from equilibrium and released followed by the gradual decline in amplitude over time. On the other hand, a flute undergoes slower decay, since the instrument produces music by

Modeling

Discussion

References