Music Classification

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Abstract

Using Spectrograms, Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA) we build a classifier to differentiate between several music pieces. We compare how well our classifier works when using it with three artists from separate genres (test 1), three artists from the same genre (test 2), and multiple artists from three different genres (test 3). We take a variety of 5 second training clips for each test and then test our classifier with songs that are not used as part of the training data. Our purpose is to analyse how well our classifier holds up under these three tests.

Sec. I. Introduction and Overview

When listening to music, humans are able to hear clear distinctions between different songs, and instantly recognize artists or genres. However, this process is so natural that it can be difficult to discern exactly how or why we know when a song is from a certain artist or genre. By building a music classifier, we allow a computer to have the ability to recognize various songs and classify them for us. Since this ability is not an innate quality of a computer, we must build this classifier using certain properties of the songs.

We first use the Gábor Transform to take the spectrogram of each song clip and gather the frequencies within each piece. Then, we do PCA by taking the Singular Value Decomposition (SVD) of the transformed data and projecting each song onto its principal components. Next, we find the variance between and within each group of songs for a given artist/genre. Finally, we do LDA to determine the two significant eigenvectors of the two variances and then project our songs onto each of them. This projection is plotted in two dimensions in order to show the location of each song clip relative to the others. We are able to use these spatial orientations to determine which set of songs our test data is closest to and therefore "classify" that song as within that group.

Sec. II. Theoretical Background

A couple of important aspects of this paper are the Gábor Transform and the SVD. However, since both of these are mentioned in detail in previous papers, we will not cover their theoretical background in this paper. Instead, in this paper, we will cover the LDA and the variances that are found and used for this part of the analysis. The first important equation to note is the equation for the variances between groups, S_b , as shown in equation 1.

$$S_b = \sum_{j=1}^{n} (\bar{\mu}_j - \bar{\mu})(\bar{\mu}_j - \bar{\mu})^T \tag{1}$$

In equation 1, n gives the number of groups, j specifies the current group, $\bar{\mu}_j$ gives the row-wise mean of the j^{th} group, and $\bar{\mu}$ gives the row-wise mean across all groups. In order to create the most spread between all groups and effectively classify new test songs we want to maximize this S_b value.

Another important equation is given by S_w , or the variance within groups, as shown in equation 2.

$$S_w = \sum_{j=1}^n \sum_{\bar{x}} (\bar{x} - \bar{\mu}_j) (\bar{x} - \bar{\mu}_j)^T$$
 (2)

In equation 2, n gives the number of groups, j specifies the current group, \bar{x} gives the corresponding generalized eigenvector of each song, and $\bar{\mu}_j$ gives the row-wise mean of the j^{th} group. Unlike S_b , we want to minimize S_w because this will cause each group to occupy a more compact area on the plot and therefore allow for clearer distinctions to be made between each group.

Equations 1 and 2 are then used in the LDA in order to find the projection onto which our groups have the largest variance between each other and the smallest variances within themselves. This is given by equation 3, defined as a generalized eigenvalue problem.

$$S_b \bar{w} = \lambda S_w \bar{w} \tag{3}$$

In equation 3, λ gives the eigenvalues and \bar{w} gives the eigenvectors. We solve this equation for the eigenvector that corresponds to the largest eigenvalue. This ensures that we are maximizing the distance between classes, minimizing the distance within classes, and therefore finding the projection onto which we will have the best chance of accurately classifying songs.

Sec. III. Algorithm Implementation and Development

In this section there will often be references to the MATLAB code which is located in Appendix B. The specific line of the code that is being referenced will be stated at the end of the sentence. All references refer to the main code. Although we built three separate classifiers in our code, they were all created in the same way, so we will explain the algorithm implementation for all of these classifiers in general.

In order to create a classifier, we began by gathering a large number of 5 second clips for each artist. Each test included three groups, and 18 clips were gathered for each groups, summing to a total of 54 clips per test. After loading all of these clips into MATLAB, we began by setting a feature number to 10 (line 28). This feature number represented the number of details we wanted to gather from each song clip in order to differentiate them from each other. It was chosen through methods of trial and error in order to find the best-fitting value. Before using these clips to perform any calculations, we first resampled them, taking

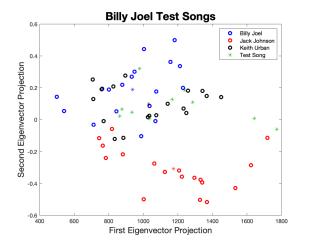
out only every other point, in order to reduce the amount of time needed to run the code. This resampling caused the maximum possible frequency observed to decrease by a factor of two. However, this did not affect our results because none of the clips were at high enough frequencies for this to matter. We then found the spectrogram of all song clips using the function get_spec(), which converted our data into frequency values over time (line 38). The return data from the spectrogram was reshaped into a column and all 54 clips were set as individual columns in the matrix spec songs() (line 39).

Next, we put this transformed data into a function called $song_trainer()$ which found the two significant eigenvectors corresponding to the components that maximized S_b and minimized S_w (line 43). This was found by first taking the SVD of the all song clips and then multiplying S * V in order to get the projection of the songs onto their principal components. Equations 1 and 2, S_w and S_b , were then calculated for the number of specified features and the generalized eigenvalue problem (equation 3) was solved. The solution to this equation provided us with the eigenvectors in V that we projected our data onto, which correspond to the two largest eigenvalues in D.

After projecting onto these eigenvectors, we were ready to test our classifier with new clips that were not involved in the training data. 30 new clips were loaded into MATLAB for tests 1 and 2, and 27 clips were used for trial 3. All of the same steps that were followed for the training data were applied to the testing data as well. We first took the spectrogram of the test data, then multiplied it by U from the SVD, and finally found the projection of this data onto the two significant eigenvectors (lines 74-78). In order to determine which group the test data belonged to, we took the taxicab distances between the location of the center of each group and the test song on the two dimensional scale given by the eigenvector projections. The value corresponding the the first eigenvector was much larger than that given by the second eigenvector so we divided the first distance by 1000 in order to ensure the two values carried a similar weight (lines 79-81). Whichever distance ended up being the smallest was the group that the test song was classified under. All classifications were compared against the correct classification in order to give an accuracy rating for each test.

Sec. IV. Computational Results

For all figures in this section, the red, blue, and black asterisks represent the center of each corresponding group of songs. Test one involved three artists from different genres. These three artists were Billy Joel (rock), Jack Johnson (folk), and Keith Urban (country). For this test, 56.67% of the 30 test songs were correctly classified. Of these, 4 were Billy Joel's, 4 were Jack Johnson's, and 9 were Keith Urban's. Looking at figures 1-3 we see the distribution of the three artists training data as the blue, red, and black open points. All of the test songs are plotted as green asterisks. The test data for Billy Joel is in figure 1, Jack Johnson is in figure 2, and Keith Urban is in figure 3. When looking at these three figures one might guess that Jack Johnson's songs would be best classified since the red points are the most separated from the blue and black ones. However, this was not the case. As can be seen by the green asterisks in each of the figures, many of Jack Johnson's test songs ended up being closer to the blue and black asterisks than to the red one.



| O.6 | O.6

Figure 1: Test 1 - Band Classification. All test songs for Billy Joel. Groups centers are denoted by correspondingly colored asterisks.

Figure 2: Test 1 - Band Classification. All test songs for Jack Johnson. Groups centers are denoted by correspondingly colored asterisks.

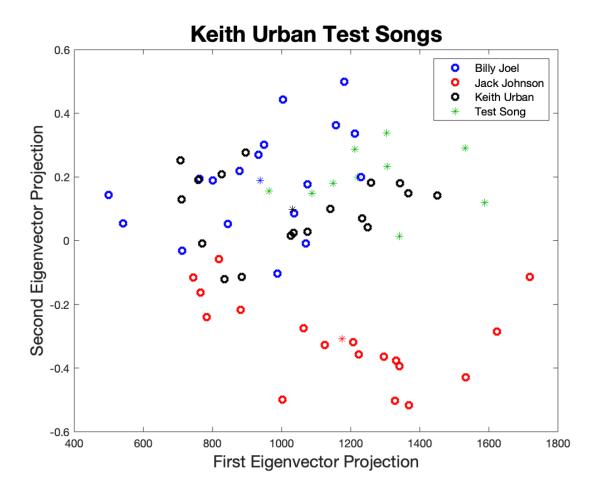
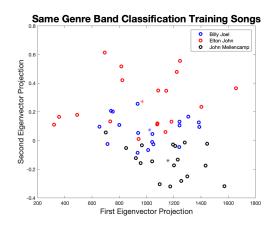
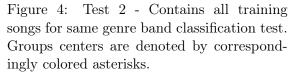


Figure 3: Test 1 - Band Classification. All test songs for Keith Urban. Groups centers are denoted by correspondingly colored asterisks.





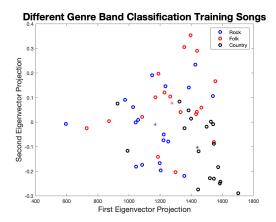


Figure 5: Test 3 - Contains all training songs for genre classification test. Groups centers are denoted by correspondingly colored asterisks.

This is most likely due to not having enough songs in the training data. The qualities of training songs used were not able to fully encapsulate all of Jack Johnson's songs, therefore causing many of the test songs to be incorrectly classified. In contrast, figure 3 shows how a majority of Keith Urban's songs are correctly classified, with only one song being mistaken as Billy Joel's.

Test two involved three artists from the same genres. These three artists were Billy Joel, Elton John, and John Mellencamp. For this test, 53.33% of the 30 test songs were correctly classified. Of these, 8 were Billy Joel's, 3 were Elton John's, and 5 were John Mellencamp's. In comparison to test one, the accuracy for this test is slightly lower. Figure 4 shows all of the songs used in the training data for this test. Again, the fact that there is so much overlap in each of these groups is likely due to an insufficient amount of training data. It is interesting to note that the best classified artist, Billy Joel, was actually in the center of all the artists. The data points associated with Billy Joel tend to have less variance within their group when compared to Elton John and John Mellencamp. This suggests that Billy Joel's songs may, in general, tend to be more similar to each other, therefore allowing them to be classified better.

Test three involved multiple artists from different genres. For this test, three different artists were chosen from the genres of rock, folk, and country. For rock, these artists were Billy Joel, Elton John, and John Mellencamp. For folk, these artists were Jack Johnson, Jason Mraz, and John Mayer. For country, these artists were Keith Urban, Blake Shelton, and Tim McGraw. For this test, 40.74% of the 27 test songs were correctly classified. Of these, 4 were rock, 2 were folk, and 5 were country. Figure 5 shows how there is a large amount of overlap between each group, so it's no surprise that this classification test does not perform was well as the previous two. In this case, it is hard to tell which group has the smallest S_w since all of groups seem to span a similar region. In order to improve this classification test, a much larger number of training songs should be used.

Sec. V. Summary and Conclusions

By using spectrograms, the SVD, and LDA we were able to extract the most important features of songs from various artists and genres. In doing so, we were then able to build a classifier that attempted to correctly classify each song into one of the three training groups. Although none of our tests had a very high success rate, the success could be improved by training the algorithm with more songs before performing the testing. From our analysis of three different groups of training and testing data, we can also conclude that it is more difficult to classify songs when they belong to the same genre or when multiple artists are used to train each genre. In these cases, it's especially important to have a large training set.

Appendix A. MATLAB Functions

Listed below are the important MATLAB functions used in this paper, along with a brief explanation of how they are implemented.

- [Y, FS] = audioread(FILENAME) : reads an audiofile and return the sampled data in Y and the sample rate in FS.
- [V, D] = eig(A): produces a diagonal matrix D of eigenvalues and a matrix V with corresponding eigenvectors.
- [U,S,V] = svd(X, 'econ'): finds the "economy size" singular value decomposition of X. If x is m-by-n, where m < n, only the first m columns of V are computed and S is m-by-m.
- diag(X): returns the main diagonal values of X as a vector.
- reshape(X,NxM,1): converts the NxM matrix X into a column vector with NxM values.

Appendix B. MATLAB Code

Main Code

```
1 % Test 1 Traning - Band Classification
  clc; clear all; close all
   test = 1; % specify test number for plotting at bottom
  % Contains all training songs for test 1
   song titles = {
        'vienna1.wav', 'vienna2.wav', 'vienna3.wav', ...
        'piano_man1.wav', 'piano_man2.wav', 'piano_man3.wav', ...
        'uptown1.wav', 'uptown2.wav', 'uptown3.wav', ...
10
        'my_life1.wav', 'my_life2.wav', 'my_life3.wav', ...
11
        'still_rock1.wav', 'still_rock2.wav', 'still_rock3.wav', ...
12
        'good_die1.wav', 'good_die2.wav', 'good_die3.wav', ...
13
        'better1.wav', 'better2.wav', 'better3.wav', ...
14
        'mind_sale1.wav', 'mind_sale2.wav', 'mind_sale3.wav', ...
15
        'upside1.wav', 'upside2.wav', 'upside3.wav', ...
16
        'banana1.wav', 'banana2.wav', 'banana3.wav', ...
17
        'sunsets1.wav', 'sunsets2.wav', 'sunsets3.wav', ...
18
        'remember1.wav', 'remember2.wav', 'remember3.wav', ...
'we_were1.wav', 'we_were2.wav', 'we_were3.wav', ...
'cop_car1.wav', 'cop_car2.wav', 'cop_car3.wav', ...
'fighter1.wav', 'fighter2.wav', 'fighter2.wav', ...
19
        'cop_car1.wav', 'cop_car2.wav', 'cop_car3.wav', ...
'fighter1.wav', 'fighter2.wav', 'fighter3.wav', ...
21
22
        'blue1.wav', 'blue2.wav', 'blue3.wav', ...
23
        'parallel1.wav', 'parallel2.wav', 'parallel3.wav', ...
        'female1.wav', 'female2.wav', 'female3.wav'
25
        };
26
27
   feature = 10; % set feature number
   num songs = length (song titles); % number of training songs
29
   spec songs = zeros(5622750, num songs); \% initialize spectrogram
      data
31
  % Get all transformed data for each song clip and set each clip as
       a column
  % in the spec songs matrix
   for ii = 1:num songs
34
        [y,Fs] = audioread(song titles{ii});
35
       Fs = Fs/2;
36
       y = y(1:2:length(y));
        [spec] = get spec(y, Fs);
38
       \operatorname{spec} \operatorname{songs}(:, ii) = \operatorname{reshape}(\operatorname{spec}, 5622750, 1);
```

```
end
41
  % Take the SVD of all transformed song clips
  [U, w, w2, mid1, mid2, mid3, v, v 2] = song trainer(spec songs, feature);
43
45
  \%\ Test 1 Testing − Band Classification
46
47
  % Contains all testing songs for test 1
  test songs = {
49
       'billy_woman.wav', 'billy_longest.wav', 'billy_innocent.wav',
50
       'billy shot.wav', 'billy dreams.wav', 'billy lullabye.wav',
51
       'billy_right.wav', 'billy_york.wav', 'billy_alexa.wav', ...
52
       'billy extremes.wav', ...
53
       'jack_constellations.wav', 'jack_flake.wav', 'jack_angel.wav',
54
       'jack_tape.wav', 'jack_belle.wav', 'jack_fade.wav', ...
55
       'jack_staple.wav', 'jack_believe.wav', 'jack_radiate.wav', ...
56
       'jack_ones.wav', ...
57
       'keith_john.wav', 'keith_texas.wav', 'keith_thunder.wav', ...
58
       'keith_habit.wav', 'keith_worry.wav', 'keith_shame.wav', ...
59
       'keith camaro.wav', 'keith everything.wav', 'keith georgia.wav
          , . . . .
       'keith winning.wav'
       };
62
63
  test num = length(test songs); % total tested songs
64
  num correct = zeros(1, test num); % stores if song was correctly
      classified
66
  % Tests each song clip to determine which category it should be
     placed in
  % based on training data. Saves whether or not the correct value
     is given
  % for each clip.
  for ii = 1:test num
70
       [y, Fs] = audioread(test songs{ii});
71
       Fs = Fs/2;
72
       y = y(1:2:length(y));
73
       |\operatorname{spec}| = \operatorname{get} \operatorname{spec}(y, \operatorname{Fs});
74
       test\_spec(:,1) = reshape(spec,5622750,1);
       TestMat = U'*test spec;
76
       x pos = w' * TestMat;
77
```

```
y pos = w2'*TestMat;
78
       dist1 = sqrt((abs(mid1(1)-x_pos)/1000) + abs(mid1(2)-y_pos));
79
       dist2 = sqrt((abs(mid2(1)-x pos)/1000) + abs(mid2(2)-y pos));
80
       dist3 = sqrt((abs(mid3(1)-x pos)/1000) + abs(mid3(2)-y pos));
81
       dist = [dist1 \ dist2 \ dist3];
       if find (dist = min(dist)) = 1 && ii <= 10
83
            num correct(ii) = 1;
       elseif find (dist = min(dist)) = 2 && ii > 10 && ii <= 20
85
            num correct(ii) = 1;
86
       elseif find (dist = min(dist)) = 3 && ii > 20 && ii < 30
87
            num correct(ii) = 1;
       end
89
   end
90
91
   % Gives percentage of correctly classified songs
92
   percent correct = sum(num correct)/length(num correct);
93
94
   % Test 2 Training - Same Genre
95
   clc; clear all; close all
96
   test = 2; % specify test number for plotting at bottom
98
   % Contains all training songs for test 2
100
   song titles = \{
        'vienna1.wav', 'vienna2.wav', 'vienna3.wav', ...
102
        'piano_man1.wav', 'piano_man2.wav', 'piano_man3.wav', ...
103
       'uptown1.wav', 'uptown2.wav', 'uptown3.wav', ...
104
       'my_life1.wav', 'my_life2.wav', 'my_life3.wav', ...
105
       'still_rock1.wav', 'still_rock2.wav', 'still_rock3.wav', ...
106
        'good_die1.wav', 'good_die2.wav', 'good_die3.wav', ...
107
       'tiny_dancer1.wav', 'tiny_dancer2.wav', 'tiny_dancer3.wav',
108
          . . .
       'rocket1.wav', 'rocket2.wav', 'rocket3.wav', ...
'bennie1.wav', 'bennie2.wav', 'bennie3.wav', ...
109
110
       'your_song1.wav', 'your_song2.wav', 'your_song3.wav', ...
111
       'standing1.wav', 'standing2.wav', 'standing3.wav', ...
112
       'daniel1.wav', 'daniel2.wav', 'daniel3.wav', ...
113
       'jack_diane1.wav', 'jack_diane2.wav', 'jack_diane3.wav', ...
114
                           'small_town2.wav', 'small_town3.wav', ...
       'small_town1.wav',
       'aint_done1.wav', 'aint_done2.wav', 'aint_done3.wav', ...
116
       'hurts_good1.wav', 'hurts_good2.wav', 'hurts_good3.wav', ...
117
       'cherry1.wav', 'cherry2.wav', 'cherry3.wav', ...
118
       'life_now1.wav', 'life_now2.wav', 'life_now3.wav'
119
       };
120
121
```

```
feature = 10; % set feature number
   num songs = length(song titles); % number of training songs
   spec songs = zeros(5622750, num songs); \% initialize spectrogram
      data
125
   % Get all transformed data for each song clip and set each clip as
       a column
   % in the spec_songs matrix
   for ii = 1:num songs
       [y,Fs] = audioread(song titles{ii});
129
       Fs = Fs/2;
130
       y = y (1:2: length(y));
131
       [spec] = get spec(y, Fs);
132
       \operatorname{spec} \operatorname{songs}(:, ii) = \operatorname{reshape}(\operatorname{spec}, 5622750, 1);
133
   end
134
135
   % Take the SVD of all transformed song clips
136
   [U,w,w2,mid1,mid2,mid3,v,v_2] = song_trainer(spec songs, feature);
137
138
   % Test 2 Testing - Same Genre
139
140
   % Contains all testing songs for test 2
141
   test songs = {
142
        'billy woman.wav', 'billy longest.wav', 'billy innocent.wav',
143
        'billy shot.wav', 'billy dreams.wav', 'billy lullabye.wav',
144
        'billy_right.wav', 'billy_york.wav', 'billy alexa.wav', ...
145
        'billy_extremes.wav', ...
146
        'elton_candle.wav', 'elton_blues.wav', 'elton crocodile.wav',
147
        'elton sacrifice.wav', 'elton sorry.wav', 'elton lucy.wav',
148
        'elton breaking.wav', 'elton honky.wav', 'elton train.wav',
149
        'elton wcn.wav', ...
150
        'john crumbling.wav', 'john not running.wav', 'john paper fire
151
           . wav ', ...
        'john wild night.wav', 'john rumbleseat.wav', 'john dance.wav'
152
        'john_minutes.wav', 'john_china.wav', 'john_brass.wav', ...
153
        'john troubled.wav'
154
        };
155
156
   test num = length(test songs); % total tested songs
```

```
num correct = zeros(1, test num); % stores if song was correctly
       classified
159
   % Tests each song clip to determine which category it should be
160
       placed in
  % based on training data. Saves whether or not the correct value
       is given
   % for each clip.
   for ii = 1:test num
        [y, Fs] = audioread(test songs{ii});
164
        Fs = Fs/2;
165
        y = y (1:2: length(y));
166
        [\operatorname{spec}] = \operatorname{get} \operatorname{spec}(y, \operatorname{Fs});
167
        test\_spec(:,1) = reshape(spec,5622750,1);
168
        TestMat = U'*test spec;
169
        x pos = w' * TestMat;
170
        y pos = w2'*TestMat;
171
        dist1 = sqrt((abs(mid1(1)-x pos)/1000) + abs(mid1(2)-y pos));
172
        dist2 = sqrt((abs(mid2(1)-x pos)/1000) + abs(mid2(2)-y pos));
173
        dist3 = sqrt((abs(mid3(1)-x pos)/1000) + abs(mid3(2)-y pos));
174
        dist = [dist1 \ dist2 \ dist3];
175
        \inf \ \operatorname{find} (\operatorname{dist} = \min (\operatorname{dist})) = 1 \&\& \ \operatorname{ii} <= 10
176
             num correct(ii) = 1;
177
        elseif find (dist = min(dist)) = 2 && ii > 10 && ii <= 20
178
             num correct(ii) = 1;
179
        elseif find (dist = min(dist)) = 3 && ii > 20 && ii < 30
180
             num correct(ii) = 1;
181
        end
182
   end
183
   % Gives percentage of correctly classified songs
185
   percent correct = sum(num correct)/length(num correct);
186
187
   77 Test 3 Training - Genre Classification
188
   clc; clear all; close all
189
190
   test = 3; % specify test number for plotting at bottom
191
192
   % Contains all training songs for test 3
   song\_titles = \{
194
        'vienna2.wav', 'piano_man2.wav', 'uptown2.wav', ...
195
        'my_life2.wav', 'still_rock2.wav', 'good_die2.wav', ...
196
        'tiny_dancer2.wav', 'rocket2.wav', 'bennie2.wav'...
'your_song2.wav', 'standing2.wav', 'daniel2.wav', ...
197
198
        'jack diane2.wav', 'small town2.wav', 'aint done2.wav', ...
199
```

```
'hurts_good2.wav', 'cherry2.wav', 'life_now2.wav', ...
200
       'better2.wav', 'mind_sale2.wav', 'upside2.wav', ...
201
        'banana2.wav', 'sunsets2.wav', 'remember2.wav', ...
202
       'new_light.wav', 'wonderland.wav', 'burning_room.wav', ...
203
       'gravity.wav', 'carry_me.wav', 'daughters.wav', ...
'give_up.wav', 'have_it.wav', 'yours.wav', ...
204
205
       'unlonely.wav', 'million_miles.wav', 'lucky.wav', ...
206
       'we_were2.wav', 'cop_car2.wav', 'fighter2.wav', ...
207
       'blue2.wav', 'parallel2.wav', 'female2.wav', ...
208
       'god_country.wav', 'sangria.wav', 'guy_girl.wav', ...
209
       'hell_right.wav', 'name_dogs.wav', 'honey_bee.wav', ...
210
       'neon_church.wav', 'thought.wav', 'humble.wav', ...
211
       'like_dying.wav', 'something_like_that.wav', 'smile.wav'
212
       };
213
214
   feature = 10; % set feature number
   num_songs = length(song_titles); % number of training songs
   spec songs = zeros(5622750, num songs); % initialize spectrogram
      data
  % Get all transformed data for each song clip and set each clip as
219
       a column
   \% in the spec songs matrix
220
   for ii = 1:num songs
221
       [y,Fs] = audioread(song_titles{ii});
222
       Fs = Fs/2;
223
       y = y (1:2: length(y));
224
       [spec] = get spec(y, Fs);
225
       spec songs(:, ii) = reshape(spec, 5622750, 1);
226
   end
227
228
   \% Take the SVD of all transformed song clips
   [U, w, w2, mid1, mid2, mid3, v, v 2] = song trainer(spec songs, feature);
230
231
   M Test 3 Testing - Genre Classification
232
233
   % Contains all testing songs for test 3
234
   test songs = {
235
        'billy_woman.wav', 'billy_longest.wav', 'billy_innocent.wav',
236
        'elton candle.wav', 'elton blues.wav', 'elton crocodile.wav',
237
        'john_crumbling.wav', 'john_not_running.wav', 'john_paper_fire
238
           .wav ', ...
        'jack constellations.wav', 'jack flake.wav', 'jack angel.wav',
239
```

```
'john_who_says.wav', 'john_georgia.wav', 'john_wildfire.wav',
240
        \label{eq:constraint} \verb|'jason_night.wav', | \verb|'jason_dance.wav', | \verb|'jason_remedy.wav', | \ldots | \\
241
        'keith_john.wav', 'keith_texas.wav', 'keith_thunder.wav', ...
'blake_cool.wav', 'blake_beach.wav', 'blake_fool.wav', ...
242
243
        'like love.wav', 'tim speak.wav', 'tim southern.wav'
244
245
246
   test num = length(test songs); % total tested songs
247
   num correct = zeros(1, test num); % stores if song was correctly
248
       classified
249
   % Tests each song clip to determine which category it should be
       placed in
   % based on training data. Saves whether or not the correct value
       is given
   % for each clip.
   for ii = 1:test num
253
        [y, Fs] = audioread(test songs{ii});
        Fs = Fs/2;
255
        y = y(1:2:length(y));
256
        |\operatorname{spec}| = \operatorname{get} \operatorname{spec}(y, \operatorname{Fs});
257
        test spec (:,1) = \text{reshape}(\text{spec}, 5622750, 1);
258
        TestMat = U'*test spec;
259
        x pos = w' * TestMat;
260
        y pos = w2'*TestMat;
261
        dist1 = sqrt((abs(mid1(1)-x_pos)/1000) + abs(mid1(2)-y_pos));
262
        dist2 = sqrt((abs(mid2(1)-x pos)/1000) + abs(mid2(2)-y pos));
263
        dist3 = sqrt((abs(mid3(1)-x pos)/1000) + abs(mid3(2)-y pos));
264
        dist = [dist1 \ dist2 \ dist3];
265
        if find (dist = min(dist)) = 1 && ii <= 9
266
             num correct(ii) = 1;
267
        elseif find (dist = min(dist)) = 2 && ii > 9 && ii < 18
268
             num correct(ii) = 1;
269
        elseif find (dist = min(dist)) = 3 && ii > 18 && ii <= 27
270
             num correct(ii) = 1;
271
        end
272
   end
274
   % Gives percentage of correctly classified songs
275
   percent correct = sum(num correct)/length(num correct);
276
277
   % Plot Single Song
   close all; % close figure
```

```
% Get data for test song
281
   [y, Fs] = audioread('john crumbling.wav'); % specify song to test
   Fs = Fs/2;
283
   y = y(1:2: length(y));
   [\operatorname{spec}] = \operatorname{get} \operatorname{spec}(y, \operatorname{Fs});
285
   test spec (:,1) = \text{reshape}(\text{spec}, 5622750, 1);
286
287
   % Calculate position of test song
288
   TestMat = U'* test spec;
289
   x pos = w' * TestMat;
290
   y pos = w2'*TestMat;
291
292
   % Calculate distances between test song and center of each traning
293
       set
   dist1 = sqrt((abs(mid1(1)-x pos)/1000) + abs(mid1(2)-y pos));
294
   dist2 = sqrt((abs(mid2(1)-x_pos)/1000) + abs(mid2(2)-y_pos));
295
   dist3 = sqrt((abs(mid3(1)-x pos)/1000) + abs(mid3(2)-y pos));
296
   dist = [dist1 \ dist2 \ dist3];
297
   % Blue: Test 1 − Billy Joel, Test 2 − Billy Joel, Test 3 − Rock
299
   p1 = plot(v(1,:), v 2(1,:), 'ob', 'Linewidth', 2);
   hold on
301
302
   \% Red: Test 1 - Jack Johnson, Test 2 - Elton John, Test 3 - Folk
303
   p2 = plot(v(2,:), v 2(2,:), 'or', 'Linewidth', 2);
304
305
   % Black: Test 1 - Keith Urban, Test 2 - John Mellencamp, Test 3 -
306
      Country
   p3 = plot(v(3,:), v_2(3,:), 'ok', 'Linewidth', 2);
307
308
   p4 = plot(mid1(1), mid1(2), '*b'); \% plots center of blue points
   p5 = plot(mid2(1), mid2(2), **r'); % plots center of red points
310
   p6 = plot(mid3(1), mid3(2), '*k'); % plots center of black points
311
   p7 = plot(x pos, y pos, '*c'); \% plots test song in cyan
312
313
   xlabel('First Eigenvector Projection');
314
   ylabel('Second Eigenvector Projection');
315
   % Creates legend and title depending on test number
317
   if test == 1
318
       legend ([p1 p2 p3 p7], 'Billy Joel', 'Jack Johnson', 'Keith
319
           Urban', 'Test Song');
        title ('Projection of Song Clips onto Eigenvectors Test 1');
320
   elseif test == 2
321
```

Spectrogram Code

20

```
1 % This function takes in values for the sampled data and sampling
      rate for
2 % a given song clip. It returns the transformed data of this clip
      by
3 % finding the frequencies associated with the spectrogram.
4 function [spec] = get_spec(y, Fs)
v = y.;
_{6} L = 5;
n = Fs*L;
  t2 = linspace(0,L,n+1); t = t2(1:n);
  a = 1;
   t \, s \, l \, i \, d \, e = 0 : 0 . 1 : L;
   spec = zeros(length(tslide),n);
11
   for j=1:length(tslide)
13
       g=\exp(-a*(t-tslide(j)).^2);
14
        vg=g.*v;
15
        vgt = fft(vg);
16
       \operatorname{spec}(j,:) = \operatorname{fftshift}(\operatorname{abs}(\operatorname{vgt}));
17
  end
18
19
  end
```

Song Trainer Code

```
1 % This function takes in values for the transformed data of all
      training
2 % song clips and the number of features. It returns the U matrix
      from the
3 % SVD of this data along with its two largest eigenvectors (w, w2)
      , the
4 % location of each song clip in two dimensional space (mid1, mid2,
      mid3).
_{5} % and the projection of each song onto the two largest
      eigenvectors (v,
6 \% v_2).
7 function [U, w, w2, mid1, mid2, mid3, v, v 2] = song trainer (spec songs,
      feature)
      % Separate out songs
9
       song1 0 = spec songs(:,1:18);
10
       song2 \ 0 = spec \ songs(:,19:36);
11
       song3 \ 0 = spec \ songs(:, 37:54);
12
13
      % length of Songs
14
       n1 = size(song1 \ 0.2); n2 = size(song2 \ 0.2); n3 = size(song3 \ 0.2)
15
          ,2);
16
       [U, S, V] = \text{svd}([\text{song1} \ 0 \ \text{song2} \ 0 \ \text{song3} \ 0], \text{'econ'}); \% \text{SVD}
17
       songs = S*V'; % projection onto principal components
18
19
       % Extracts data corresponding to specified feature number
20
       U = U(:, 1:feature);
21
       song1 = songs(1:feature, 1:n1);
22
       song2 = songs(1:feature, n1+1:2*n1);
23
       song3 = songs(1:feature, 2*n1+1:3*n1);
25
      % Finds mean value for each song
26
      m = mean(songs(1:feature), 2);
27
       m1 = mean(song1, 2);
28
       m2 = mean(song2, 2);
29
       m3 = mean(song3, 2);
30
31
       % Calculates within class variance
32
       Sw = 0;
33
       for k=1:n1
34
           Sw = Sw + (song1(:,k)-m1)*(song1(:,k)-m1)';
35
       end
36
```

```
for k=1:n2
            Sw = Sw + (song2(:,k)-m2)*(song2(:,k)-m2)';
38
       end
39
       for k=1:n3
40
            Sw = Sw + (song3(:,k)-m3)*(song3(:,k)-m3)';
       end
42
43
       % Calculates between class variance
44
       Sb = (m1-m)*(m1-m)' + (m2-m)*(m2-m)' + (m3-m)*(m3-m)';
45
46
       % Linear discriminant analysis
47
       [V2,D] = eig(Sb,Sw);
48
49
       % Finds two largest eigenvectors and projects data onto each
50
           of them
       [ \tilde{\ }, ind ] = max(abs(diag(D)));
51
       w = V2(:, ind); w = w/norm(w, 2);
52
       D(ind, ind) = 0; % remove largest singular value
53
       [ \tilde{\ }, ind ] = max(abs(diag(D)));
54
       w2 = V2(:, ind); w = w/norm(w, 2);
55
56
       % Projects songs onto two largest eigenvectors
57
       v1 = w' * song1;
58
       v2 = w' * song2;
       v3 = w' * song3;
60
       v = [v1; v2; v3];
61
       v1 2 = w2 * song1;
62
       v2 \ 2 = w2' * song2;
63
       v3 \ 2 = w2 * song3;
64
       v 2 = [v1_2; v2_2; v3_2];
65
66
       % Finds approximate two dimensional position of each song
67
       mid1 = [mean(v1), mean(v1 2)];
68
       \operatorname{mid} 2 = |\operatorname{mean}(v2), \operatorname{mean}(v2 2)|;
69
       mid3 = [mean(v3), mean(v3 2)];
70
  end
71
```