

AMATH 582 Homework 2

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Abstract

In this assignment, we will analyze a portion of two of the greatest rock and roll songs. Specifically, we will reproduce the music score for the guitar in the “Sweet Child O’ Mine” and the bass in the “Comfortably Numb”. In addition, we will isolate the bass and the guitar solo in “Comfortably Numb”.

1 Introduction and Overview

Sounds are everywhere in our daily life and songs are the art of sounds. We can enjoy a song in time domain, which is a sound combination of different instruments (and singers sometimes). However, a normal listener usually cannot distinguish different instruments accurately, not mention distinguishing the music scores for different instruments. Luckily, we can analyze the music from spectral domain which will make it much easier to distinguish different instruments as well as music scores. I believe this is one of the key functions included in many music edit software. In this assignment, we will analyze a portion of two of the greatest rock and roll songs by looking into the spectral domain. Specifically, we will reproduce the music score for the guitar in the “Sweet Child O’ Mine” and the bass in the “Comfortably Numb”. In addition, we will isolate the bass and the guitar solo in “Comfortably Numb”.

In the following of this report, we will first introduce the theoretical background used in this assignment (Section 2). Then, we show how to design and implement the analysis algorithm (Section 3). We show the computation results in Section 4 and conclude this report in Section 5.

2 Theoretical Background

The given songs are in time domain. In order to distinguish different instruments and reproduce the music scores, we need to transform them to spectral domain. When it comes to the transformation between time and spectral domains, Fourier Transform is the first and natural choice. The Fourier transform and its inverse are defined as

$$F(k) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-ikt} f(t) dt \quad (1)$$

$$f(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{ikt} F(k) dk \quad (2)$$

In MATLAB, we use the Fast Fourier transform (FFT) to perform the forward and backward Fourier transforms.

However, FFT will generate the spectral information for the whole data set but will not tell us when they occur. That is, we will lose all time domain information when we take FFT on the whole data set. For a song, different instruments and different notes are played at different times. Pure FFT can not find when a note is played. To remedy this problem, we can use Gabor transforms instead of FFT. The key idea of Gabor transforms is to transform local time-domain information to frequency domain and do such transforms around different time points. The Gabor transform is

$$\tilde{f}_g(t, k) = \int_{-\infty}^{\infty} f(\tau) \bar{g}(\tau - t) e^{-ik\tau} d\tau \quad (3)$$

where $g(\tau-t)$ is a new term introduced to the Fourier kernel e^{ikx} , aiming to localize both time and frequency. The bar denotes the complex conjugate of the function. t is the time point that we want to localize. There are many types of the function $g(\tau-t)$, e.g., Gaussian, Mexican Hat, and Step function. We will use Gaussian in this assignment.

There is a trade-off between the time and frequency information that we can extract using Gabor transform. When we apply filter around a specific time point, it eliminates some long waves, which means the frequency range we can extract decreases. The good thing is we have the time information in this way. The smaller the filter window is, the more precise time information we can get, but the more frequency information we will lose. We will explore this trade-off in Section 3.

In addition, in order to get a good clean music score, we will filter out overtones and other instrument frequencies in frequency domain. A Gaussian filter is used

$$\mathcal{F}(k) = e^{-d(k-k_0)^2} \quad (4)$$

where d is the bandwidth of the filter and k_0 is the center frequency.

3 Algorithm Development and Implementation

3.1 Read the audio data and setup

We first read in the audio data and calculate the time in seconds, which defines the time domain. The number of Fourier modes n is the size of the sampled audio data. Since FFT assumes 2π periodic signals, we should re-scale the wavenumbers by $\frac{2\pi}{L}$ where L is the time length calculated before. Due to the same reason (periodic assumptions of FFT), the first and last points should be the same, therefore, only the first n Fourier modes should be considered. In addition, we can shift the original wavenumbers (i.e., $k = (2\pi/L) * [0 : (n/2 - 1) - n/2 : -1]$) back to its mathematically correct positions.

3.2 Create the Gabor filter

We use a Gaussian filter as the Gabor kernel. We also set up the width of the Gaussian filter in this stage. To do so, we test different widths to find the best one with clear spectrogram features. In addition, the number of time discretization points are also specified.

3.3 Create the Gabor spectrogram and plot

We iterate over all time points that defined in the previous step. At each time point, we first apply the Gaussian filter defined in the previous step to the whole data, then take the FFT of the filtered data. Considering that the guitar in “Sweet Child O’ Mine” and the bass in “Comfortably Numb” are pretty identifiable, the magnitudes of guitar and bass should dominate the frequency domains. Therefore, to filter out the overtones, we find the frequency with maximum magnitude and apply a Gaussian filter around this center frequency. Finally, we store the filtered frequency data to the spectrogram. After the iteration, we plot the spectrogram by `pcolor`. Based on the music score map, we can identify the music scores for the corresponding dominant instrument. This process will be conducted for both ‘Sweet Child O’ Mine’ and ‘Comfortably Numb’ so we can find the music scores for both the guitar and bass.

3.4 Isolate the bass in Comfortably Numb

This is done simultaneously with the previous step, where we filter out the overtones using Gaussian filter. Note that several tests are conducted to find the best width of the Gaussian filter (i.e., the width by which the Gaussian filter can eliminate overtones and other instrument frequencies as well as maintain the bass frequencies).

3.5 Extract the guitar solo in Comfortably Numb

The guitar is not dominant in Comfortably Numb. We will first filter out the bass and its overtones, then filter out the drum and its overtones. Finally, we put another filter around the rest center frequencies to make them clear.

4 Computation results

4.1 Sweet Child O' Mine

First, we show the parameter tuning results in Figure 1 and Figure 2. In 1, wt represent the filter width on time domain, which is the Gabor kernel. Note that we do not apply frequency domain filter in this figure. Based on the results, we select wt as 100 since the music scores are pretty clear and concentrated.

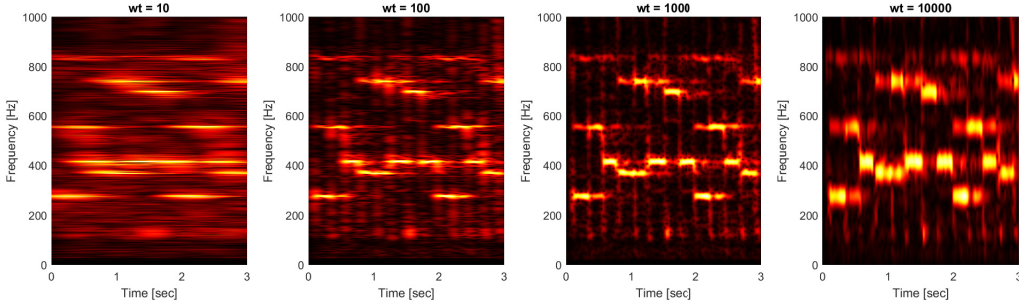


Figure 1: Parameter tuning: width of the filter in time domain

Figure 2 shows the parameter tuning for the width (noted as wq) of the filter in frequency domain, which is applied to the center frequency. Based on the results we select wq as 0.002, since the music scores are clear, concentrated and the details are reserved.

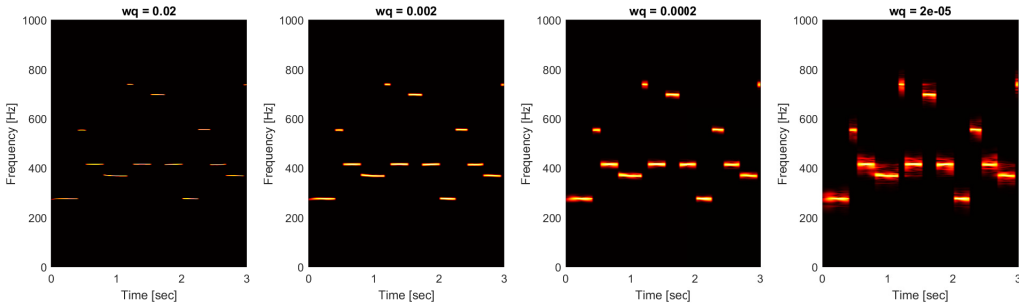


Figure 2: Parameter tuning: width of the filter in frequency domain

Using those parameters, we create the spectrogram of the whole data in Figure 3. Based on this figure and the map of music scores, we can extract the music scores for the guitar in Sweet Child O' Mine: middle C, high C, high A, middle F, high A, high, F, high A, middle C, high C, high G, high F, high A, ...

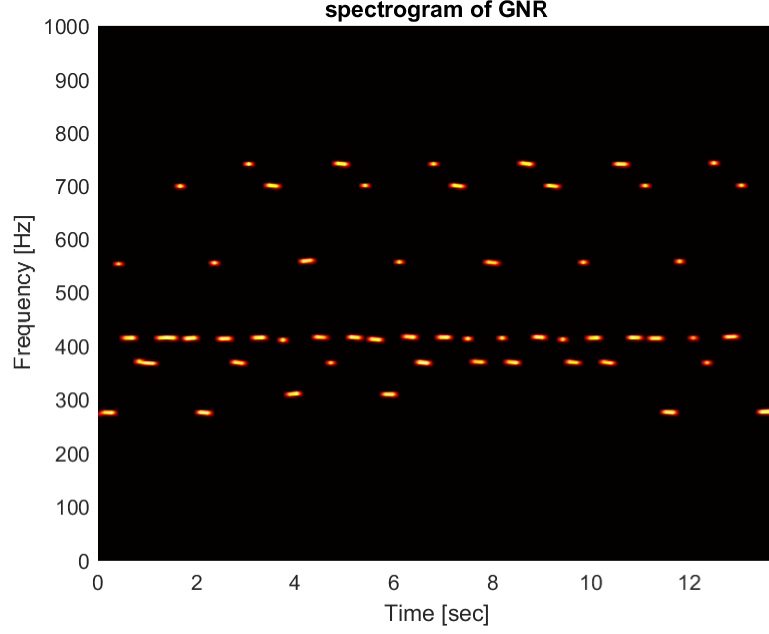


Figure 3: Spectrogram of the Sweet Child O' Mine

4.2 Comfortably Numb

Following the similar process as the previous section, we select the width for time domain (wt) as 100. Before filter in frequency domain, the spectrogram of the whole data is shown in Figure 4 (note that the whole data is clipped to 10 slices to prevent the MATLAB from running out of memory).

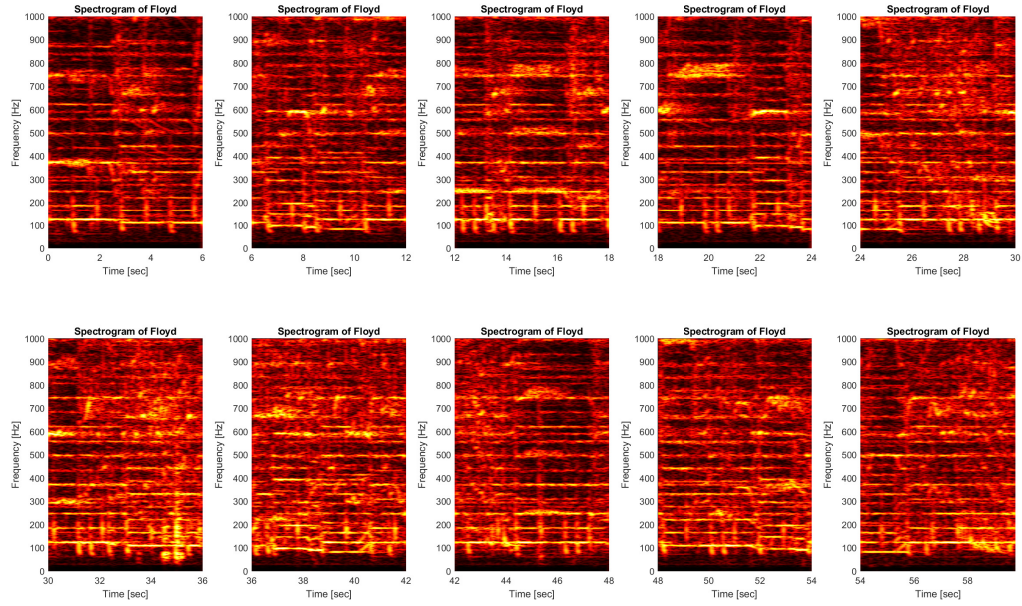


Figure 4: Spectrogram of Comfortably Numb before filter in frequency domain

It can be shown that there are lots of overtones. Considering that the base frequencies are always less than 150Hz, we find the maximum frequencies under 150Hz and filter around these center frequencies (using a Gaussian filter with 0.002 width) to filter out the overtones. The results are shown in Figure 5. The music scores can be extracted based on the music score map: low B, low A, ... Details are omitted here for brevity.

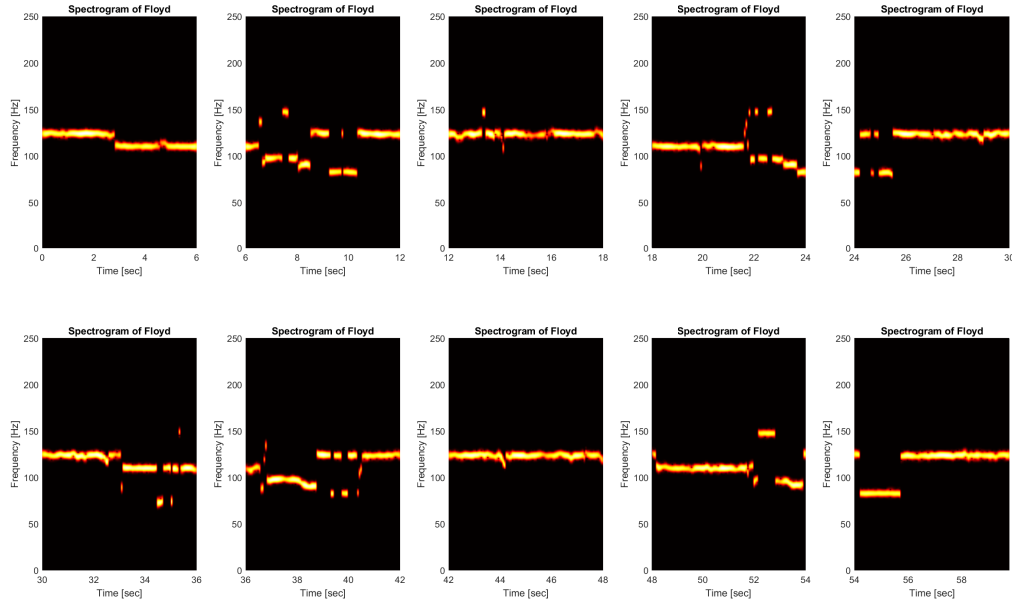


Figure 5: Spectrogram of Comfortably Numb after filter in frequency domain

4.3 Guitar solo in Comfortably Numb

Since bass dominates the Comfortably Numb, we need to filter out the bass in order to get the guitar solo. Considering there are lots of overtones (as shown in Figure 4), we use the base frequency shown in Figure 5 and create multiple filters at the frequencies which are multiple of the base frequency. For example, if the base frequency is 100Hz, we will create other 9 filters centered at [200, 300, 400, 500, 600, 700, 800, 900, 1000] and add them up to make a new filter. This integrated filter can be used to filter out the overtones. Based on our observation, there are still low-frequency peaks after such processing. We think those might be the drum frequencies since the drum is more obvious than guitar when we listen to the music. A quick search shows that the drum frequency is usually lower than 250Hz. Therefore, we apply the same filter process to filter out base (under 250Hz) drum frequencies and the related overtones. In addition, we put another filter around the center frequencies to make the rest center frequencies clear. After these steps, the spectrogram is shown in Figure 6. It is shown that there are lots of noises, but the music scores are relatively clear. The details of mapping Figure 6 to music scores are omitted here for brevity.

5 Summary and Conclusions

In this assignment, we designed algorithms to explore the two of the greatest rock and roll songs from frequency domain. We used Fourier transform to transform the time domain data to frequency domain. In order to reserve time information, e.g., what the specific guitar note is at a specific time point, we used Gabor transform to analyze the data. In addition, to eliminate the overtones, we detected the center frequencies in spectral domain and filtered out all related overtones. For Sweet Child O' Mine, we clearly identified the guitar scores. For Comfortably Numb, we successfully identified the bass scores and have tried to isolate the

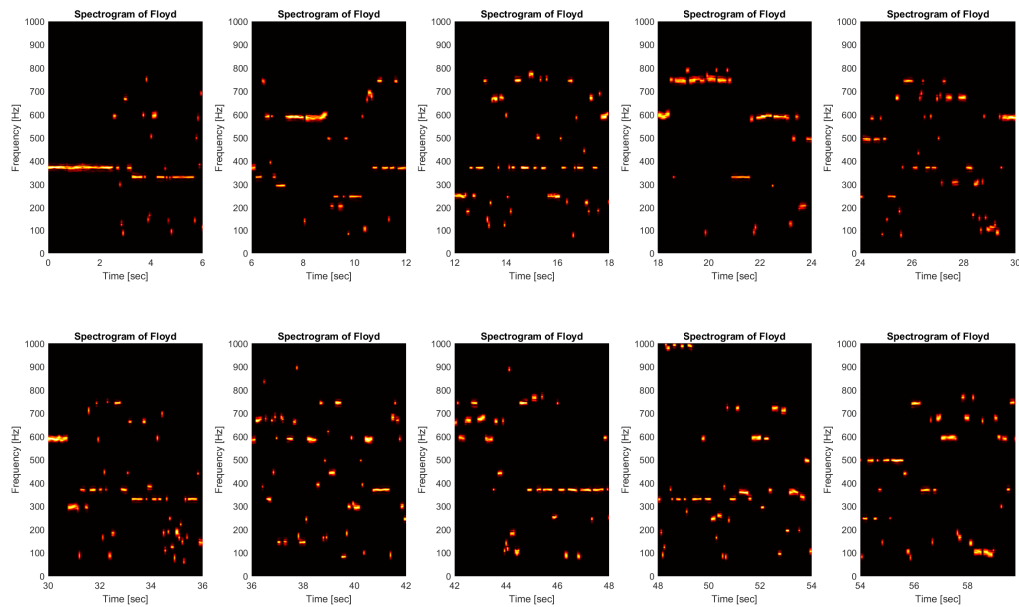


Figure 6: Spectrogram of Comfortably Numb: find the guitar

guitar solo. During this assignment, we have learned the power of Fourier transform and Gabor transform in time-frequency analysis.

Appendix A GitHub repository

<https://github.com/Guoqq17/UW-AMATH-582>

Appendix B Key MATLAB Functions

- `y = linspace(x1,x2,n)` returns a row vector of `n` evenly spaced points between `x1` and `x2`.
- `[y,Fs] = audioread(filename,samples)` reads the selected range of audio samples in the file, where `samples` is a vector of the form `[start,finish]`.
- `Y = fft(X)` computes the discrete Fourier transform (DFT) of `X` using a fast Fourier transform (FFT) algorithm.
- `[row,col] = ind2sub(sz,ind)` returns the arrays `row` and `col` containing the equivalent row and column subscripts corresponding to the linear indices `ind` for a matrix of size `sz`. Here `sz` is a vector with two elements, where `sz(1)` specifies the number of rows and `sz(2)` specifies the number of columns.

Appendix C MATLAB Code

```
1 %% understand the data
2 figure(1)
3 [y, Fs] = audioread('Floyd.m4a');
4 tr_gnr = length(y)/Fs; % record time in seconds
```

```

5 plot((1:length(y))/Fs,y);
6 xlabel('Time [sec]'); ylabel('Amplitude');
7 title('Sweet Child O Mine');
8 p8 = audioplayer(y,Fs); playblocking(p8);
9
10 %% GNR
11 [y, Fs] = audioread('GNR.m4a', [1, 3*Fs]); % read first 3 seconds
12 tr_gnr = length(y)/Fs; % record time in seconds
13 L = tr_gnr; % time domin
14 n = length(y); % Fourier modes
15 t1 = linspace(0, L, n + 1);
16 t = t1(1:n);
17 k = (2*pi/L)*[0:n/2-1, -n/2:-1];
18 ks = fftshift(k);
19
20 % create Gabor filter
21 width_t_all = [10, 100, 1000, 10000]; % width of the filter
22 width_q_all = [0.02, 0.002, 0.0002, 0.00002]; % width of the filter in frequency
    domain
23 num_gabor = 100; % number of the time points to take
24 t_gabor = linspace(0, t(end), num_gabor); % discretize the time
25 s_gabor = zeros(length(t_gabor), n); % matrix to store the Gabor transforms
26
27 % tune wt
28 figure(2)
29 for w_t = 1:length(width_t_all)
30     for i=1:length(t_gabor)
31         gabor = exp(-width_t_all(w_t)*(t - t_gabor(i)).^2);
32         gyt = fft(gabor.*y.);
33         gyts = abs(fftshift(gyt));
34         s_gabor(i,:) = gyts;
35     end
36
37     % plot the spectrogram
38     subplot(1, length(width_t_all), w_t)
39     pcolor(t_gabor, ks/(2*pi), log(s_gabor.' + 1)), shading interp
40     colormap('hot'), xlabel('Time [sec]'), ylabel('Frequency [Hz]')
41     axis([0, tr_gnr, 0, 1000])
42     title(['wt = ', num2str(width_t_all(w_t))])
43 end
44
45 % tune wq
46 figure(3)
47 for w_q = 1:length(width_q_all)
48     for i=1:length(t_gabor)
49         gabor = exp(-100*(t - t_gabor(i)).^2);
50         gyt = fft(gabor.*y.);
51         gyts = abs(fftshift(gyt));
52         [val, ind] = max(gyts(n/2:end));
53         [a,b] = ind2sub(size(gyts),ind+n/2-1);
54         s_filter = exp(-width_q_all(w_q) * ((ks - ks(b)).^2));
55         gytf = fftshift(gyt).*s_filter;
56         s_gabor(i,:) = abs(gytf);
57     end
58
59     % plot the spectrogram
60     subplot(1, length(width_q_all), w_q)
61     pcolor(t_gabor, ks/(2*pi), log(s_gabor.' + 1)), shading interp
62     colormap('hot'), xlabel('Time [sec]'), ylabel('Frequency [Hz]')
63     axis([0, tr_gnr, 0, 1000])
64     title(['wq = ', num2str(width_q_all(w_q))])
65 end
66
67 % whole data
68 [y, Fs] = audioread('GNR.m4a'); % read whole audio data
69 tr_gnr = length(y)/Fs; % record time in seconds
70 L = tr_gnr; % time domin
71 n = length(y); % Fourier modes

```

```

72 t1 = linspace(0, L, n + 1);
73 t = t1(1:n);
74 k = (2*pi/L)*[0:n/2-1, -n/2:-1];
75 ks = fftshift(k);
76
77 % create Gabor filter
78 num_gabor = 100; % number of the time points to take
79 t_gabor = linspace(0, t(end), num_gabor); % discretize the time
80 s_gabor = zeros(length(t_gabor), n); % matrix to store the Gabor transforms
81 score = zeros(1, length(t_gabor));
82
83 for i=1:length(t_gabor)
84     gabor = exp(-100*(t - t_gabor(i)).^2);
85     gyt = fft(gabor.*y.');
86     gyts = abs(fftshift(gyt));
87     [val, ind] = max(gyts(n/2:end));
88     [a,b] = ind2sub(size(gyts),ind+n/2-1);
89     score(i) = ks(b);
90     s_filter = exp(-0.002 * ((ks - ks(b)).^2));
91     gyt_f = fftshift(gyt).*s_filter;
92     s_gabor(i,:) = abs(gyt_f);
93 end
94
95 % plot the spectrogram
96 figure(4)
97 pcolor(t_gabor, ks/(2*pi), log(s_gabor.' + 1)), shading interp
98 colormap('hot'), xlabel('Time [sec]'), ylabel('Frequency [Hz]')
99 axis([0, tr_gnr, 0, 1000])
100 title('spectrogram of GNR')
101
102 %% Floyd
103 clear; clc;
104 close all
105 [y, Fs] = audioread('Floyd.m4a');
106 [y, Fs] = audioread('Floyd.m4a', [1, 10*Fs]); % read first 3 seconds
107 tr_floyd = length(y)/Fs; % record time in seconds
108 L = tr_floyd; % time domain
109 n = length(y); % Fourier modes
110 t1 = linspace(0, L, n + 1);
111 t = t1(1:n);
112 k = (2*pi/L)*[0:n/2-1, -n/2:-1];
113 ks = fftshift(k);
114
115 % create Gabor filter
116 width_t_all = [10, 100, 1000, 10000]; % width of the filter
117 width_q_all = [0.02, 0.002, 0.0002, 0.00002]; % width of the filter in frequency
118 domain
119 num_gabor = 100; % number of the time points to take
120 t_gabor = linspace(0, t(end), num_gabor); % discretize the time
121 s_gabor = zeros(length(t_gabor), n); % matrix to store the Gabor transforms
122
123 %% tune wt
124 figure(4)
125 for w_t = 1:length(width_t_all)
126     for i=1:length(t_gabor)
127         gabor = exp(-width_t_all(w_t)*(t - t_gabor(i)).^2);
128         gyt = fft(gabor.*y.');
129         gyts = abs(fftshift(gyt));
130         s_gabor(i,:) = gyts;
131     end
132
133 % plot the spectrogram
134 subplot(1, length(width_t_all), w_t)
135 pcolor(t_gabor, ks/(2*pi), log(s_gabor.' + 1)), shading interp
136 colormap('hot'), xlabel('Time [sec]'), ylabel('Frequency [Hz]')
137 axis([0, tr_floyd, 0, 1000])
138 title(['wt = ', num2str(width_t_all(w_t))])
139 end

```



```

139
140 %% all data before wq
141 [y_all, Fs] = audioread('Floyd.m4a');
142 step = 6; % time step to cut the whole audio to slices
143 num_gabor = 100; % number of the time points to take at each slice
144
145 figure(5)
146 for s_i=1:length(y_all)/(Fs*step)+1
147     if s_i*step*Fs < length(y_all)
148         [y, Fs] = audioread('Floyd.m4a', [(s_i-1)*step*Fs+1, s_i*step*Fs]);
149     else
150         [y, Fs] = audioread('Floyd.m4a', [(s_i-1)*step*Fs+1, length(y_all)-1]);
151     end
152
153     tr_floyd = length(y)/Fs; % record time in seconds
154     L = tr_floyd; % time domin
155     n = length(y); % Fourier modes
156     t1 = linspace(0, L, n + 1);
157     t = t1(1:n);
158     k = (2*pi/L)*[0:n/2-1, -n/2:-1];
159     ks = fftshift(k);
160
161     % create Gabor filter
162     width = 100; % width of the filter
163     t_gabor = linspace(0, t(end), num_gabor); % discretize the time
164     s_gabor = zeros(length(t_gabor), n);
165
166     % create the spectrogram
167     for i=1:length(t_gabor)
168         gabor = exp(-width*(t - t_gabor(i)).^2);
169         gyt = fft(gabor.*y.);
170         gyts = abs(fftshift(gyt));
171         s_gabor(i,:) = gyts;
172     end
173
174     subplot(2,5,s_i)
175     pcolor(t_gabor + step*(s_i-1), ks/(2*pi), log(s_gabor.' + 1)), shading interp
176     colormap('hot'), xlabel('Time [sec]'), ylabel('Frequency [Hz]')
177     axis([step*(s_i-1), step*(s_i-1) + tr_floyd, 0, 1000])
178     title('Spectrogram of Floyd')
179     drawnow
180 end
181
182 %% all data after apply frequency domain filter (under 150Hz)
183 [y_all, Fs] = audioread('Floyd.m4a');
184 step = 6; % time step to cut the whole audio to slices
185 num_gabor = 100; % number of the time points to take at each slice
186
187 figure(5)
188 for s_i=1:length(y_all)/(Fs*step)+1
189     if s_i*step*Fs < length(y_all)
190         [y, Fs] = audioread('Floyd.m4a', [(s_i-1)*step*Fs+1, s_i*step*Fs]);
191     else
192         [y, Fs] = audioread('Floyd.m4a', [(s_i-1)*step*Fs+1, length(y_all)-1]);
193     end
194
195     tr_floyd = length(y)/Fs; % record time in seconds
196     L = tr_floyd; % time domin
197     n = length(y); % Fourier modes
198     t1 = linspace(0, L, n + 1);
199     t = t1(1:n);
200     k = (2*pi/L)*[0:n/2-1, -n/2:-1];
201     ks = fftshift(k);
202
203     % create Gabor filter
204     width = 100; % width of the filter
205     t_gabor = linspace(0, t(end), num_gabor); % discretize the time
206     s_gabor = zeros(length(t_gabor), n);

```

```

207
208 % create the spectrogram
209 for i=1:length(t_gabor)
210     gabor = exp(-width*(t - t_gabor(i)).^2);
211     gyt = fft(gabor.*y.');
212     gyts = abs(fftshift(gyt));
213     [val, ind] = max(gyts(n/2:n/2 + 150 * 2*pi));
214     [a,b] = ind2sub(size(gyts),ind+n/2-1);
215     s_filter = exp(-0.002 * ((ks - ks(b)).^2));
216     gytf = fftshift(gyt).*s_filter;
217     s_gabor(i,:) = abs(gytf);
218 end
219
220 subplot(2,5,s_i)
221 pcolor(t_gabor + step*(s_i-1), ks/(2*pi), log(s_gabor.' + 1)), shading interp
222 colormap('hot'), xlabel('Time [sec]'), ylabel('Frequency [Hz]')
223 axis([step*(s_i-1), step*(s_i-1) + tr_floyd, 0, 250])
224 title('Spectrogram of Floyd')
225 drawnow
226 end
227 %% all data to find guitar
228 [y_all, Fs] = audioread('Floyd.m4a');
229 step = 6; % time step to cut the whole audio to slices
230 num_gabor = 100; % number of the time points to take at each slice
231
232 figure(5)
233 for s_i=1:length(y_all)/(Fs*step)+1
234     if s_i*step*Fs < length(y_all)
235         [y, Fs] = audioread('Floyd.m4a', [(s_i-1)*step*Fs+1, s_i*step*Fs]);
236     else
237         [y, Fs] = audioread('Floyd.m4a', [(s_i-1)*step*Fs+1, length(y_all)-1]);
238     end
239
240     tr_floyd = length(y)/Fs; % record time in seconds
241     L = tr_floyd; % time domin
242     n = length(y); % Fourier modes
243     t1 = linspace(0, L, n + 1);
244     t = t1(1:n);
245     k = (2*pi/L)*[0:n/2-1, -n/2:-1];
246     ks = fftshift(k);
247
248     % create Gabor filter
249     width = 100; % width of the filter
250     t_gabor = linspace(0, t(end), num_gabor); % discretize the time
251     s_gabor = zeros(length(t_gabor), n);
252
253     % create the spectrogram
254     for i=1:length(t_gabor)
255         gabor = exp(-width*(t - t_gabor(i)).^2);
256         gyt = fft(gabor.*y.');
257
258         % filter out the bass and overtones
259         gyts = abs(fftshift(gyt));
260         [val, ind] = max(gyts(n/2:n/2 + 150 * 2*pi));
261         [a,b] = ind2sub(size(gyts),ind+n/2-1);
262         s_filter = zeros(1, length(ks));
263         j = 1;
264         c_q = ks(b) * j;
265         while c_q <= 1000*2*pi
266             s_filter = s_filter + exp(-0.0002 * ((ks - c_q).^2));
267             j = j + 1;
268             c_q = ks(b) * j;
269         end
270
271         % filter out the drum and overtones
272         gyts = abs(fftshift(gyt).*(1-s_filter));
273         [val, ind] = max(gyts(n/2:n/2 + 250 * 2*pi));
274         [a,b] = ind2sub(size(gyts),ind+n/2-1);

```

```

275     j = 1;
276     c_q = ks(b) * j;
277     while c_q <= 1000*2*pi
278         s_filter = s_filter + exp(-0.0002 * ((ks - c_q).^2));
279         j = j + 1;
280         c_q = ks(b) * j;
281     end
282     s_filter = 1-s_filter;
283     gyts = fftshift(gyt).*s_filter;
284
285     % identify the guitar
286     [val, ind] = max(gyts(n/2:n/2 + 1000 * 2*pi));
287     [a,b] = ind2sub(size(gyts),ind+n/2-1);
288     s_filter = exp(-0.0002 * ((ks - ks(b)).^2));
289     gytf = gyts.*s_filter;
290
291     s_gabor(i,:) = abs(gytf);
292 end
293
294 subplot(2,5,s_i)
295 pcolor(t_gabor + step*(s_i-1), ks/(2*pi), log(s_gabor.' + 1)), shading interp
296 colormap('hot'), xlabel('Time [sec]'), ylabel('Frequency [Hz]')
297 axis([step*(s_i-1), step*(s_i-1) + tr_floyd, 0, 1000])
298 title('Spectrogram of Floyd')
299 drawnow
300 end

```