Assignment3

November 13, 2022

1 Imports

[1]:
```
import numpy as np
import pandas as pd
from scipy import signal
import cv2
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report, accuracy_score
from sklearn.svm import SVC
```

2 Data Collection, Preprocessing and Cleansing

2.1 Reading in data

2.1.1 Climbing down

[2]:
```
path = "Climbing_down_stairs/CL"
Climbing_down = []
for i in range(1, 51):
    df = pd.read_csv(path +f"{i}" + "/Accelerometer.csv" )
    df = df.rename(columns={ df.columns[2]: "ACCELEROMETER Z (m/s²)" ,df.
 ↪columns[3]: "ACCELEROMETER Y (m/s²)",
                            df.columns[4]: "ACCELEROMETER X (m/s²)"   })
    df = df[['seconds_elapsed', 'ACCELEROMETER X (m/s²)',
   'ACCELEROMETER Y (m/s²)', 'ACCELEROMETER Z (m/s²)']]
    df1 = pd.read_csv(path +f"{i}" + "/Gyroscope.csv" )
    df1 = df1.rename(columns={ df1.columns[2]: "GYROSCOPE Z (rad/s)" ,df1.
 ↪columns[3]: "GYROSCOPE Y (rad/s)",
                            df1.columns[4]: "GYROSCOPE X (rad/s)"   })
    df1 = df1[['time', 'seconds_elapsed', 'GYROSCOPE X (rad/s)',
   'GYROSCOPE Y (rad/s)', 'GYROSCOPE Z (rad/s)']]
    df1.drop(['time', 'seconds_elapsed'], axis=1, inplace=True)
    Climbing = pd.concat([df, df1], axis = 1).values.tolist()
```

```
    Climbing_down.append(Climbing)
```

2.1.2 Standing up

[3]:
```
path = "standing_up/Stand"
Standing = []
for i in range(1, 51):
    df = pd.read_csv(path +f"{i}" + "/Accelerometer.csv" )
    df = df.rename(columns={ df.columns[2]: "ACCELEROMETER Z (m/s²)" ,df.
 ↪columns[3]: "ACCELEROMETER Y (m/s²)",
                            df.columns[4]: "ACCELEROMETER X (m/s²)"   })
    df = df[['seconds_elapsed', 'ACCELEROMETER X (m/s²)',
   'ACCELEROMETER Y (m/s²)', 'ACCELEROMETER Z (m/s²)']]
    df1 = pd.read_csv(path +f"{i}" + "/Gyroscope.csv" )
    df1 = df1.rename(columns={ df1.columns[2]: "GYROSCOPE Z (rad/s)" ,df1.
 ↪columns[3]: "GYROSCOPE Y (rad/s)",
                            df1.columns[4]: "GYROSCOPE X (rad/s)"   })
    df1 = df1[['time', 'seconds_elapsed', 'GYROSCOPE X (rad/s)',
   'GYROSCOPE Y (rad/s)', 'GYROSCOPE Z (rad/s)']]

    df1.drop(['time', 'seconds_elapsed'], axis=1, inplace=True)

    Stand = pd.concat([df, df1], axis = 1 , join='inner').values.tolist()
    Standing.append(Stand)
```

2.1.3 Walking

[4]:
```
path = "data/walking/walking_"
walking = []
for i in range(20):
    df = pd.read_csv(path +f"{i}.csv",header=1,sep=";")
    df = df[['Time since start in ms ', 'ACCELEROMETER X (m/s²)',
      'ACCELEROMETER Y (m/s²)', 'ACCELEROMETER Z (m/s²)', 'GYROSCOPE X (rad/s)',
    'GYROSCOPE Y (rad/s)', 'GYROSCOPE Z (rad/s)']]
    df['Time since start in ms ']/= 1000
    df = df.rename(columns={ df.columns[0]: "seconds_elapsed"}).values.tolist()
    walking.append(df)
```

2.1.4 Rowing

[5]:
```
rowing = pd.read_csv("RowingMachine_20221102_210235_AndroSensor.
 ↪csv",header=1,sep=";")
rowing = rowing[['Time since start in ms ', 'ACCELEROMETER X (m/s²)',
      'ACCELEROMETER Y (m/s²)', 'ACCELEROMETER Z (m/s²)', 'GYROSCOPE X (rad/s)',
    'GYROSCOPE Y (rad/s)', 'GYROSCOPE Z (rad/s)']]
rowing['Time since start in ms ']/= 1000
```

```
rowing = [rowing.rename(columns={ rowing.columns[0]: "seconds_elapsed"}).values.
↪tolist()]
```

2.1.5 Climbing up

[6]:
```
climbing_up = pd.read_csv("climbing_Up_stairs.csv",header=1,sep=";")
climbing_up = climbing_up[['Time since start in ms ', 'ACCELEROMETER X (m/s²)',
      'ACCELEROMETER Y (m/s²)', 'ACCELEROMETER Z (m/s²)', 'GYROSCOPE X (rad/s)',
    'GYROSCOPE Y (rad/s)', 'GYROSCOPE Z (rad/s)']]
climbing_up['Time since start in ms ']/= 1000
climbing_up = [climbing_up.rename(columns={ climbing_up.columns[0]:␣
↪"seconds_elapsed"}).values.tolist()]
```

2.1.6 Create data list

The data is sorted by it class, with the order: walking, rowing, climbing down, climbing up and standing

[7]:
```
#All data [walking,rowing,climbing_down,climbing_up,standing]
data = [walking, rowing, Climbing_down, climbing_up, Standing]
```

2.2 Removing start and end period

Some activities are more prown to wrong values at the beginning and end, because you have to move the phone to start/stop the recording. Therefore are the first five and last five seconds ignored for these activities

[8]:
```
for i in [0, 1, 3]:
    for j in range(len(data[i])):
        data[i][j] = data[i][j][10:-10]
```

2.3 Windowing

For activities that are not instance based, the data has to be windowed. For walking a window size of 2 minutes is chosen and for rowing and climbing up a window size of 1 minute, because they have less data overall. A overlap of 80% is chosen (seemed to work best after testing different overlaps)

[9]:
```
window_length = {0: 240, 1: 120, 3: 120}  # In indexes, one index is equal to 0.
↪5 seconds
overlap = 0.8

for i in [0, 1, 3]:
    windows = []
    for j in range(len(data[i])):
        end_index = window_length[i]
        window_number = 1
        while end_index - 1 < len(data[i][j]):
            window = data[i][j][end_index - window_length[i]:end_index]
```

```
            windows.append(window)
            window_number += 1
            end_index += int((1 - overlap) * window_length[i])
    data[i] = windows
```

2.4 Spectrogram

To extract the frequency information over time from the data, spectograms are created

[10]:
```
fs_values = {0: 2, 1: 2, 2: 100, 3: 2, 4: 200}
FFT_SIZE=1024
data_spectrograms = [[] for _ in range(len(data))]
for cls_number in range(len(data)):
    for i in range(len(data[cls_number])):
        features_spectograms = []
        for j in range(1, 7):
            data_points = np.asarray([x[j] for x in data[cls_number][i]])
            nperseg = FFT_SIZE if len(data_points) > FFT_SIZE else␣
 ↪len(data_points)
            f,t,pxx = signal.spectrogram(data_points, nperseg=nperseg,␣
 ↪fs=fs_values[cls_number] , noverlap=nperseg/2)
            features_spectograms.append([f, t, pxx])
        data_spectrograms[cls_number].append(features_spectograms)
```

2.5 Binning

To keep as much information of the spectrograms as possible, but without having to much features, a semi high bin number is chosen. Testing and comparing different numbers of bins and its results showed that 45 in each axis seems to be a good mix between these two requirements

[11]:
```
num_freq_bins = 45
num_time_bins = 45
data_spectrograms_binned = [[] for _ in range(len(data))]
for cls_number in range(len(data_spectrograms)):
    for i in range(len(data_spectrograms[cls_number])):
        features_spectograms = []
        for j in range(6):
            resized_pxx = cv2.
 ↪resize(data_spectrograms[cls_number][i][j][2],(num_time_bins,num_freq_bins))
            features_spectograms.
 ↪append([data_spectrograms[cls_number][i][j][0],␣
 ↪data_spectrograms[cls_number][i][j][1], resized_pxx])
        data_spectrograms_binned[cls_number].append(features_spectograms)
```

2.6 Feature selection

As features only the binned spectrograms for all values (acceleration x, acceleration y, acceleration z, gyroscope x, gyroscope y and gyroscope z) are chosen. This is enough to achieve a sufficient accuracy with a Random Forest and SVM model

[12]:
```
data_features = [[] for _ in range(len(data))]

for cls_number in range(len(data_spectrograms_binned)):
    for i in range(len(data_spectrograms_binned[cls_number])):
        features = []
        for j in range(6):
            features.extend(data_spectrograms_binned[cls_number][i][j][2].
 ↪reshape((-1,)).tolist())
        data_features[cls_number].append(np.asarray(features))
```

2.7 Creating labels

[13]:
```
data_list = []
labels_list = []

for cls_number in range(len(data_features)):
    for i in range(len(data_features[cls_number])):
        data_list.append(data_features[cls_number][i])
        labels_list.append(cls_number)
```

2.8 Normalization

Sligthly improves testing accuracy of SVM by 0.5 % and has no effect on testing accuracy of the Random Forest model

[14]:
```
scaler = StandardScaler()
data_list = scaler.fit_transform(data_list)
```

2.9 Create training and test data

A 70/30 split is chosen, which means that 70% of the data is used for training and 30% for testing

[15]:
```
xtrain, xtest, ytrain, ytest = train_test_split(data_list, labels_list,␣
 ↪test_size=0.30, random_state=42)
```

3 ML models

3.1 Random forest

[16]:
```
clf = RandomForestClassifier()
clf.fit(xtrain, ytrain)
cv_scores = cross_val_score(clf, xtrain, ytrain, cv=10)
print('Average Cross Validation Score from Training:', cv_scores.mean(),␣
 ↪sep='\n', end='\n\n\n')

ypred = clf.predict(xtest)
```

```
cm = confusion_matrix(ytest, ypred)
cr = classification_report(ytest, ypred)

print('Confusion Matrix:', cm, sep='\n', end='\n\n\n')
print('Test Statistics:', cr, sep='\n', end='\n\n\n')

print('Testing Accuracy:', accuracy_score(ytest, ypred))
```

```
Average Cross Validation Score from Training:
1.0


Confusion Matrix:
[[135   0   0   0   0]
 [  0  33   0   0   0]
 [  0   0  13   0   0]
 [  0   0   0  24   0]
 [  0   0   0   0  13]]


Test Statistics:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       135
           1       1.00      1.00      1.00        33
           2       1.00      1.00      1.00        13
           3       1.00      1.00      1.00        24
           4       1.00      1.00      1.00        13

    accuracy                           1.00       218
   macro avg       1.00      1.00      1.00       218
weighted avg       1.00      1.00      1.00       218



Testing Accuracy: 1.0
```

3.2 SVM

[17]:
```
clf = SVC(kernel="linear")
clf.fit(xtrain, ytrain)
cv_scores = cross_val_score(clf, xtrain, ytrain, cv=10)
print('Average Cross Validation Score from Training:', cv_scores.mean(),
 ↪sep='\n', end='\n\n\n')

ypred = clf.predict(xtest)
cm = confusion_matrix(ytest, ypred)
```

```
cr = classification_report(ytest, ypred)

print('Confusion Matrix:', cm, sep='\n', end='\n\n\n')
print('Test Statistics:', cr, sep='\n', end='\n\n\n')

print('Testing Accuracy:', accuracy_score(ytest, ypred))
```

```
Average Cross Validation Score from Training:
0.9980392156862745


Confusion Matrix:
[[135   0   0   0   0]
 [  0  33   0   0   0]
 [  0   0  13   0   0]
 [  0   0   0  24   0]
 [  0   0   0   0  13]]


Test Statistics:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       135
           1       1.00      1.00      1.00        33
           2       1.00      1.00      1.00        13
           3       1.00      1.00      1.00        24
           4       1.00      1.00      1.00        13

    accuracy                           1.00       218
   macro avg       1.00      1.00      1.00       218
weighted avg       1.00      1.00      1.00       218



Testing Accuracy: 1.0
```

4 Results

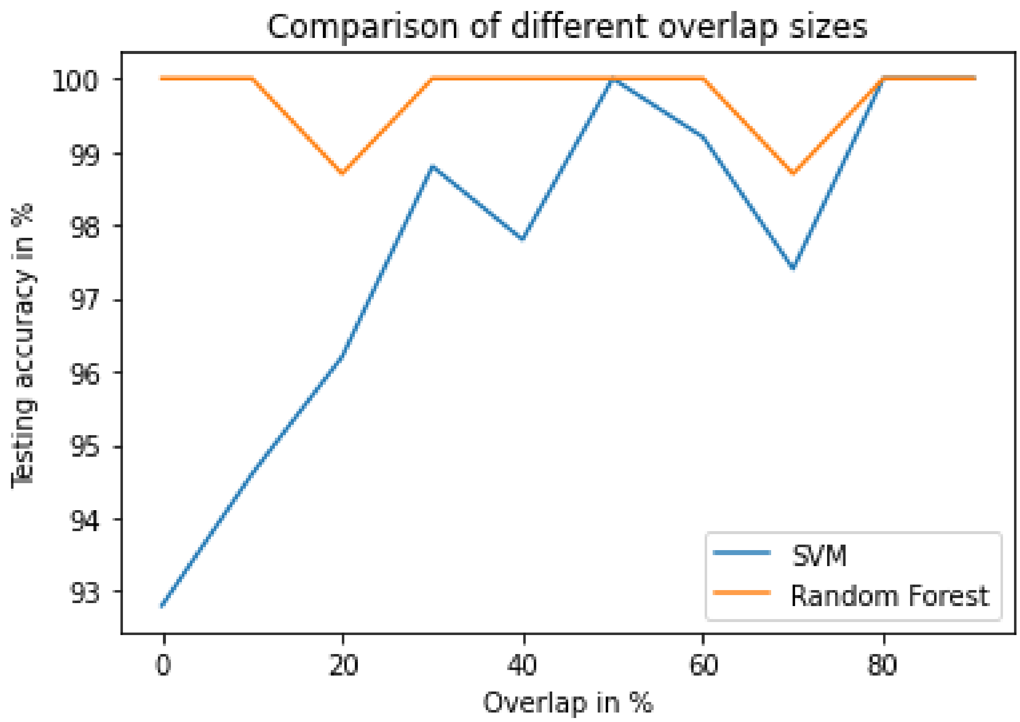
4.1 Choosing overlap for windowing

An overlap of 80% is chosen, because it has the best training (k-cross validation) accuracy of the ones with a 100% testing accuracy for both models

[18]:
```
import matplotlib.pyplot as plt

overlaps = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90]
results_rf = [100, 100, 98.7, 100, 100, 100, 100, 98.7, 100, 100]
results_svm = [92.8, 94.6, 96.2, 98.8, 97.8, 100, 99.2, 97.4, 100, 100]
```

```
plt.plot(overlaps, results_svm, label='SVM')
plt.plot(overlaps, results_rf, label='Random Forest')
plt.xlabel("Overlap in %")
plt.ylabel("Testing accuracy in %")
plt.title("Comparison of different overlap sizes")
plt.legend()
plt.show()
```



4.2 Choosing binning size

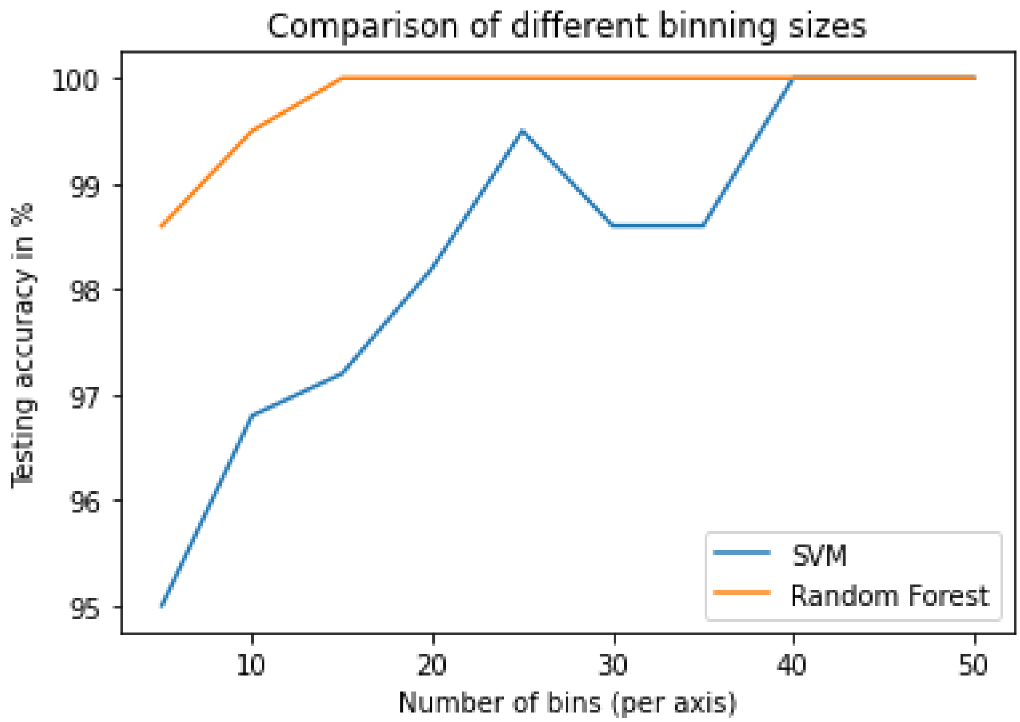
45 bins per axis are chosen, because it has the best training (k-cross validation) accuracy of the ones with a 100% testing accuracy for both models

[19]:
```
import matplotlib.pyplot as plt

binning_size = [5, 10, 15, 20, 25, 30, 35, 40, 45, 50]
results_rf = [98.6, 99.5, 100, 100, 100, 100, 100, 100, 100, 100]
results_svm = [95.0, 96.8, 97.2, 98.2, 99.5, 98.6, 98.6, 100, 100, 100]

plt.plot(binning_size, results_svm, label='SVM')
plt.plot(binning_size, results_rf, label='Random Forest')
plt.xlabel("Number of bins (per axis)")
```

```
plt.ylabel("Testing accuracy in %")
plt.title("Comparison of different binning sizes")
plt.legend()
plt.show()
```



5 Data visualization (binned spectrograms)

[20]:
```
import numpy as np
import matplotlib.pyplot as plt

%matplotlib inline
cmap=plt.cm.bone
cmap.set_under(color='k', alpha=None)
```

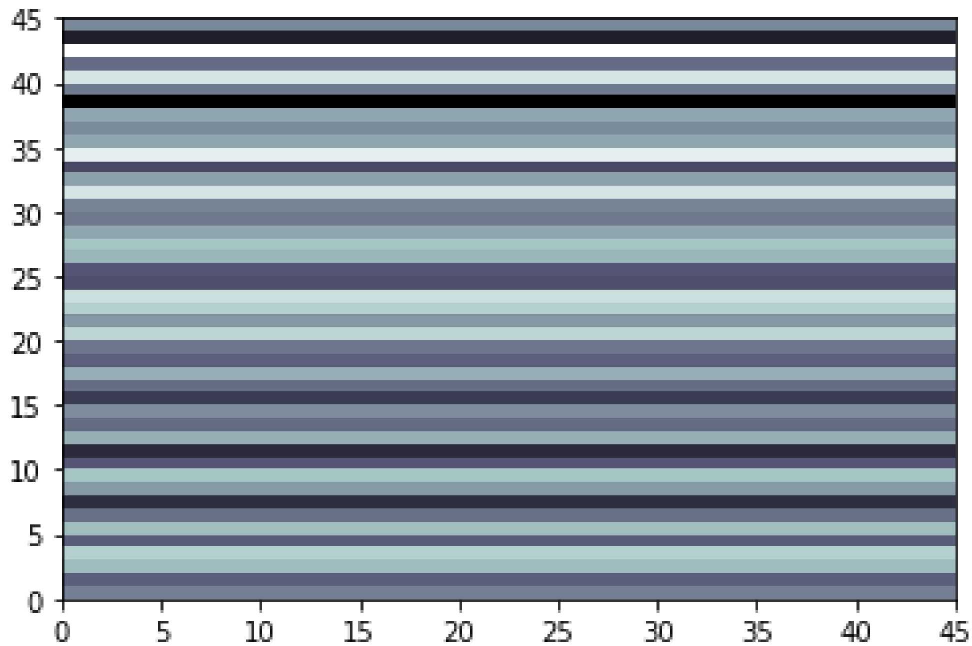
```
C:\Users\Timmy\AppData\Local\Temp\ipykernel_15620\3670946234.py:6:
MatplotlibDeprecationWarning: You are modifying the state of a globally
registered colormap. This has been deprecated since 3.3 and in 3.6, you will not
be able to modify a registered colormap in-place. To remove this warning, you
can make a copy of the colormap first. cmap = mpl.cm.get_cmap("bone").copy()
  cmap.set_under(color='k', alpha=None)
```

5.1 Walking

5.1.1 Accelerometer x

[21]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[0][0][0][2]),cmap=cmap)
```

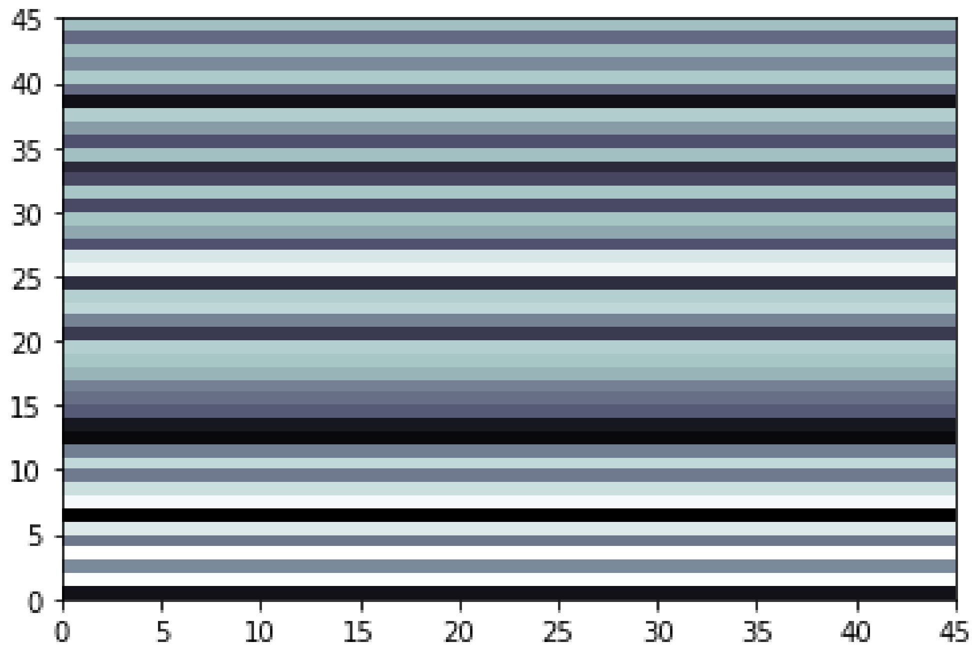
[21]: <matplotlib.collections.QuadMesh at 0x1b064f8ce20>



5.1.2 Accelerometer y

[22]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[0][0][1][2]),cmap=cmap)
```

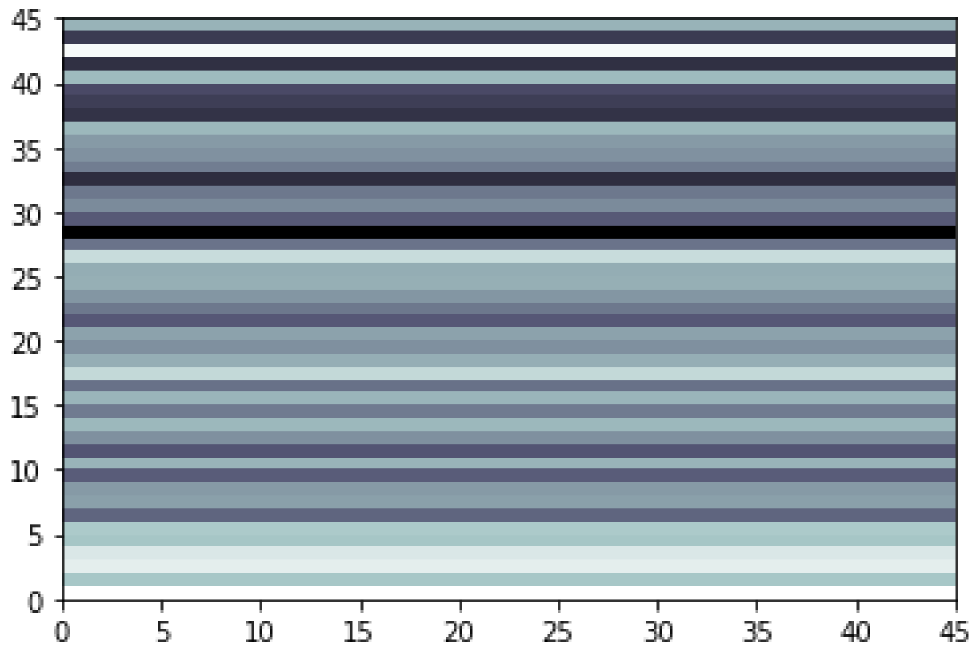
[22]: <matplotlib.collections.QuadMesh at 0x1b04ab0ebe0>



5.1.3 Accelerometer z

[23]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[0][0][2][2]),cmap=cmap)
```

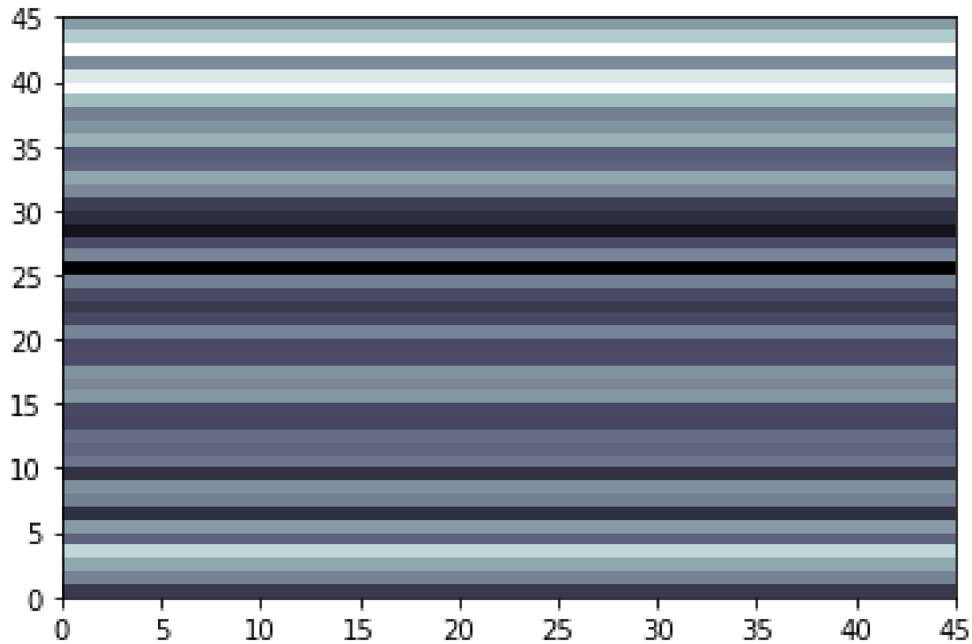
[23]: <matplotlib.collections.QuadMesh at 0x1b04ab80a30>



5.1.4 Gyroscope x

[24]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[0][0][3][2]),cmap=cmap)
```

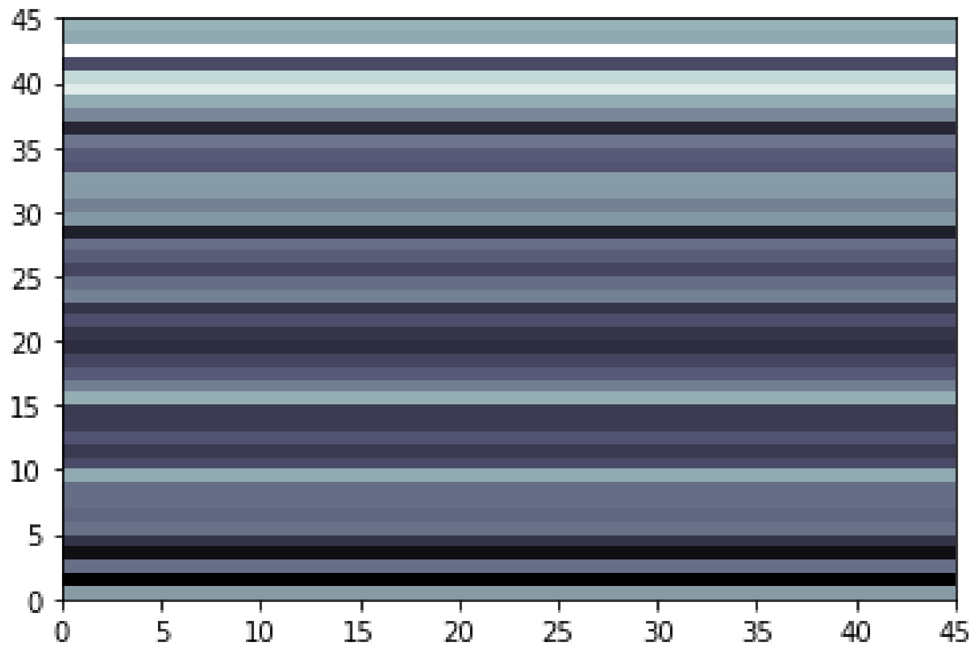
[24]: <matplotlib.collections.QuadMesh at 0x1b04abf68e0>



5.1.5 Gyroscope y

[25]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[0][0][4][2]),cmap=cmap)
```

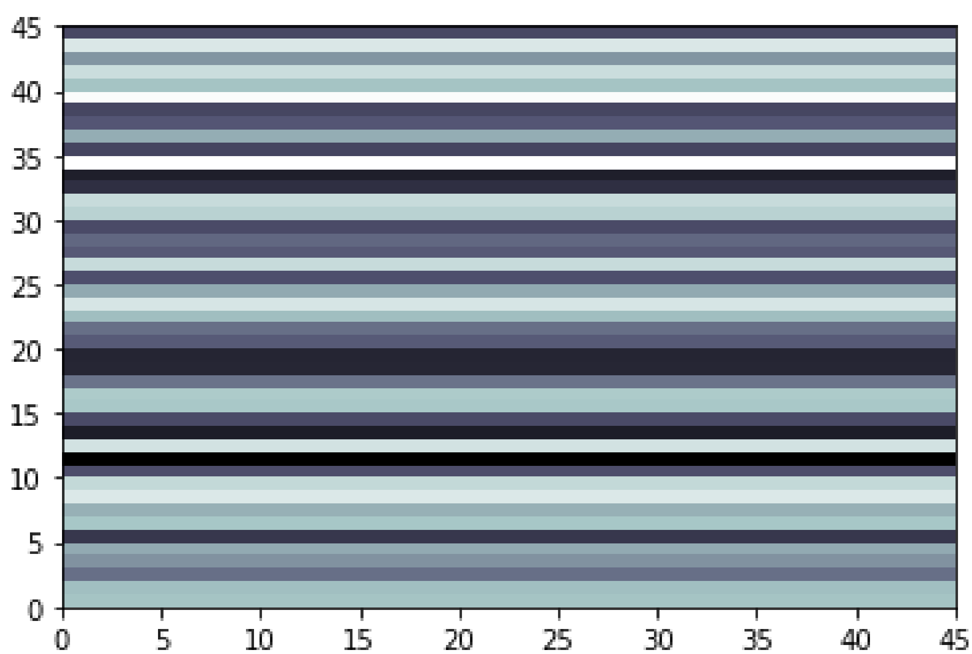
[25]: <matplotlib.collections.QuadMesh at 0x1b04ac6b820>



5.1.6 Gyroscope z

[26]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[0][0][5][2]),cmap=cmap)
```

[26]: <matplotlib.collections.QuadMesh at 0x1b04ace1490>

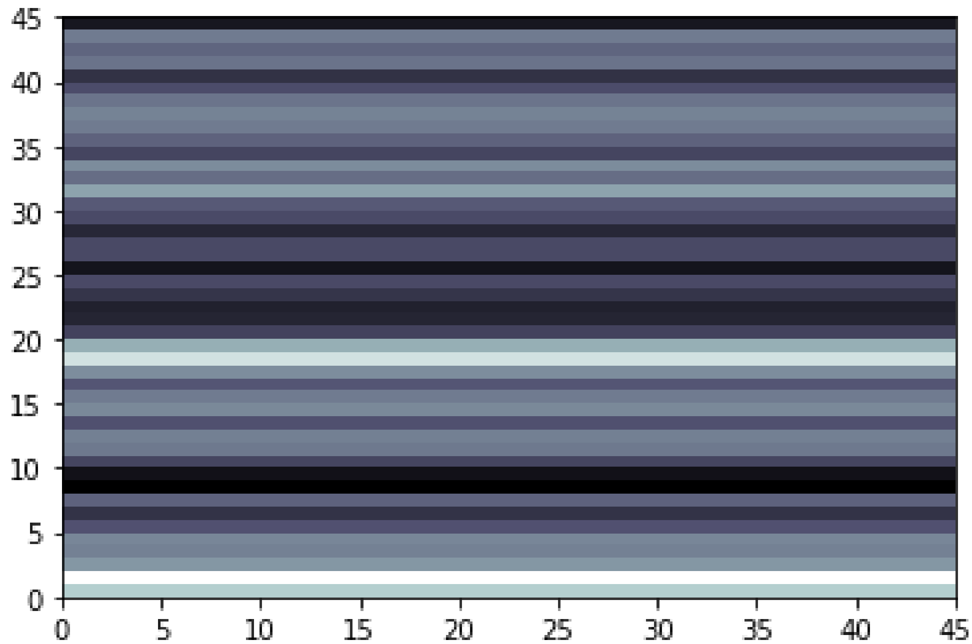


5.2 Rowing

5.2.1 Accelerometer x

[27]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[1][0][0][2]),cmap=cmap)
```

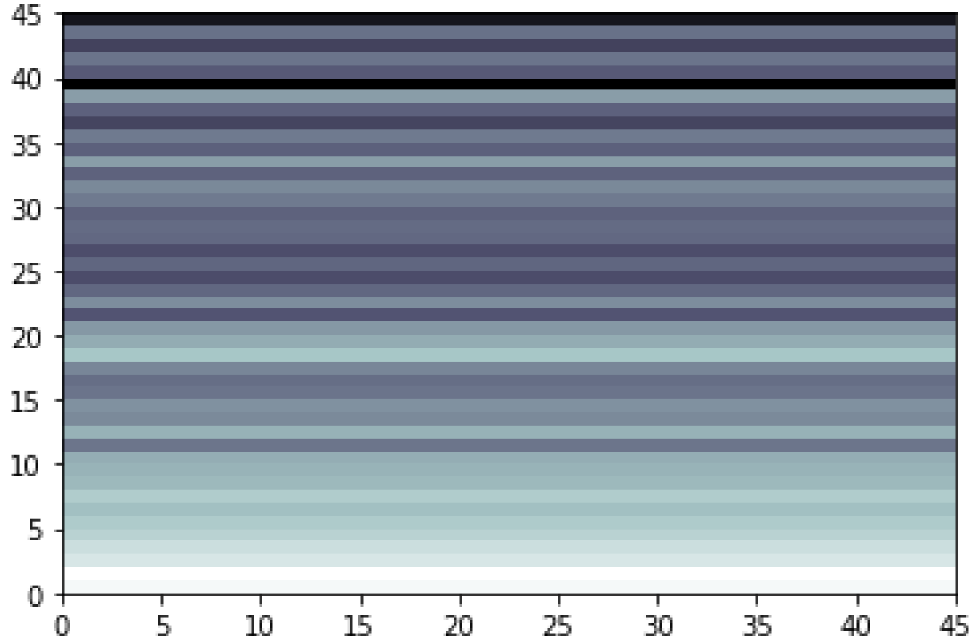
[27]: <matplotlib.collections.QuadMesh at 0x1b064f455e0>



5.2.2 Accelerometer y

[28]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[1][0][1][2]),cmap=cmap)
```

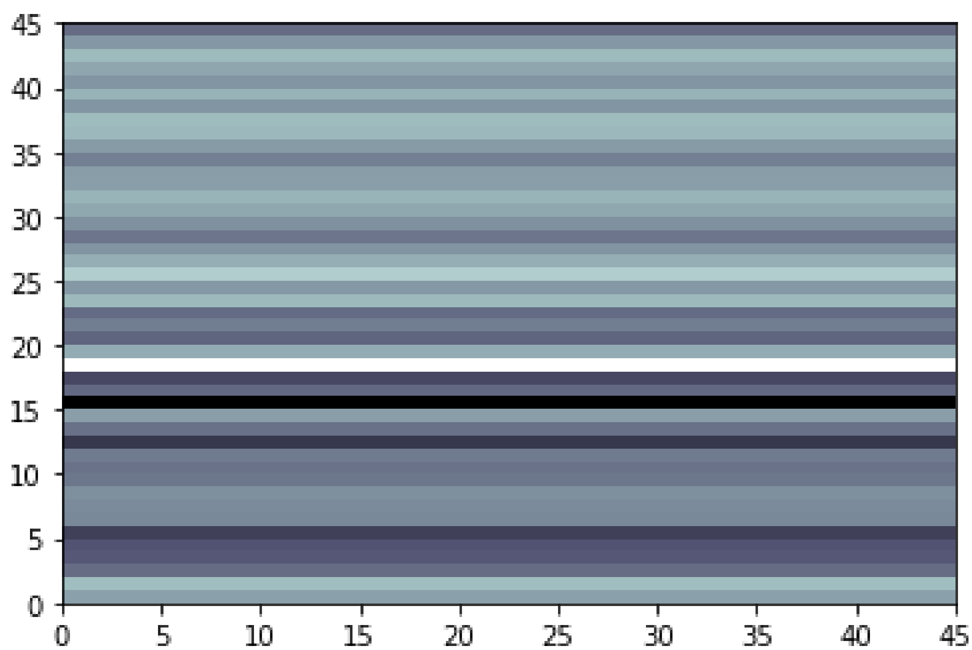
[28]: <matplotlib.collections.QuadMesh at 0x1b064f452e0>



5.2.3 Accelerometer z

[29]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[1][0][2][2]),cmap=cmap)
```

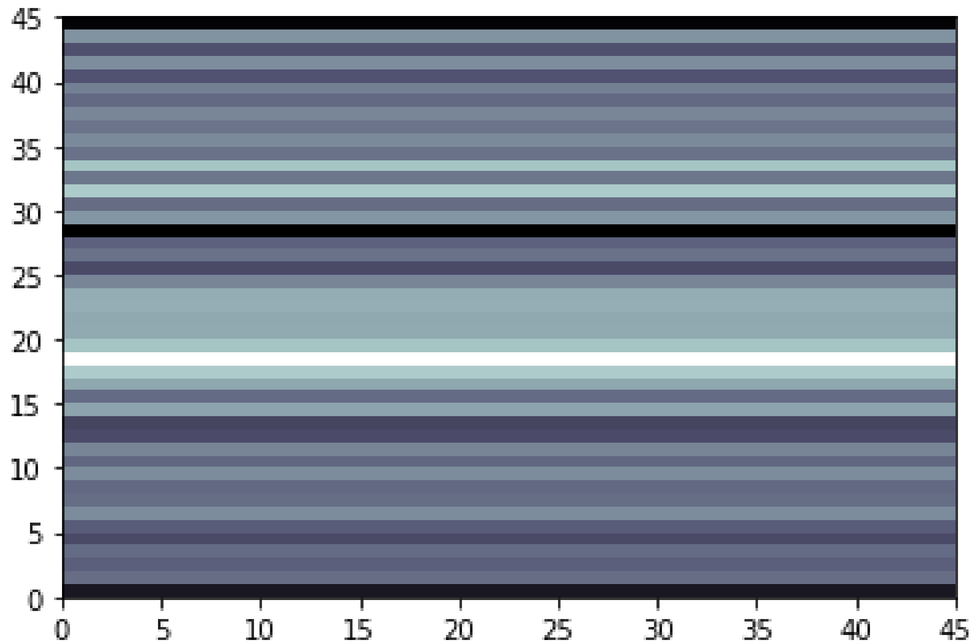
[29]: <matplotlib.collections.QuadMesh at 0x1b0664af190>



5.2.4 Gyroscope x

[30]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[1][0][3][2]),cmap=cmap)
```

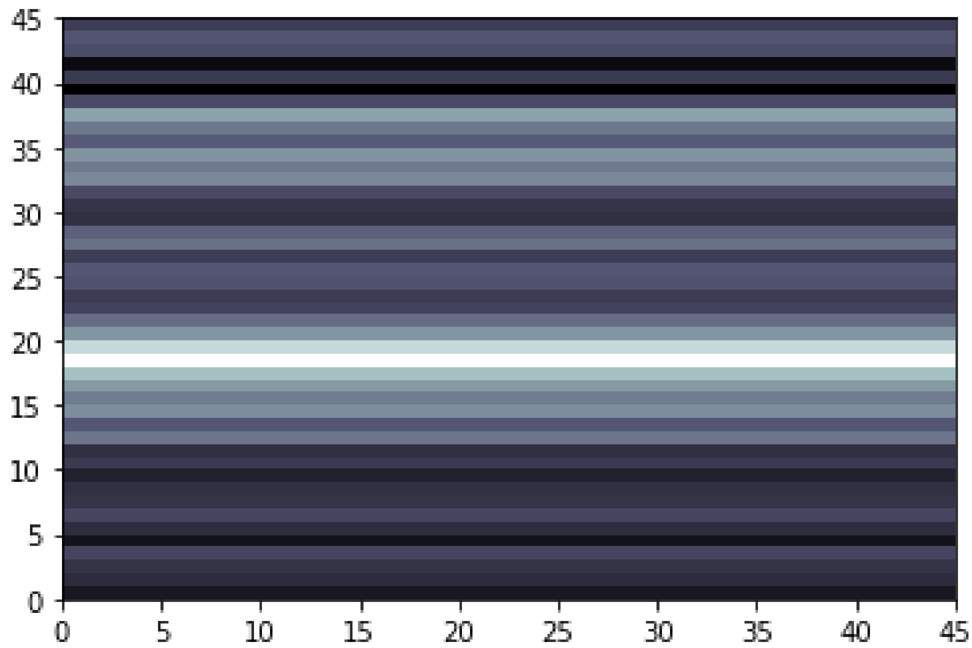
[30]: <matplotlib.collections.QuadMesh at 0x1b066523160>



5.2.5 Gyroscope y

[31]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[1][0][4][2]),cmap=cmap)
```

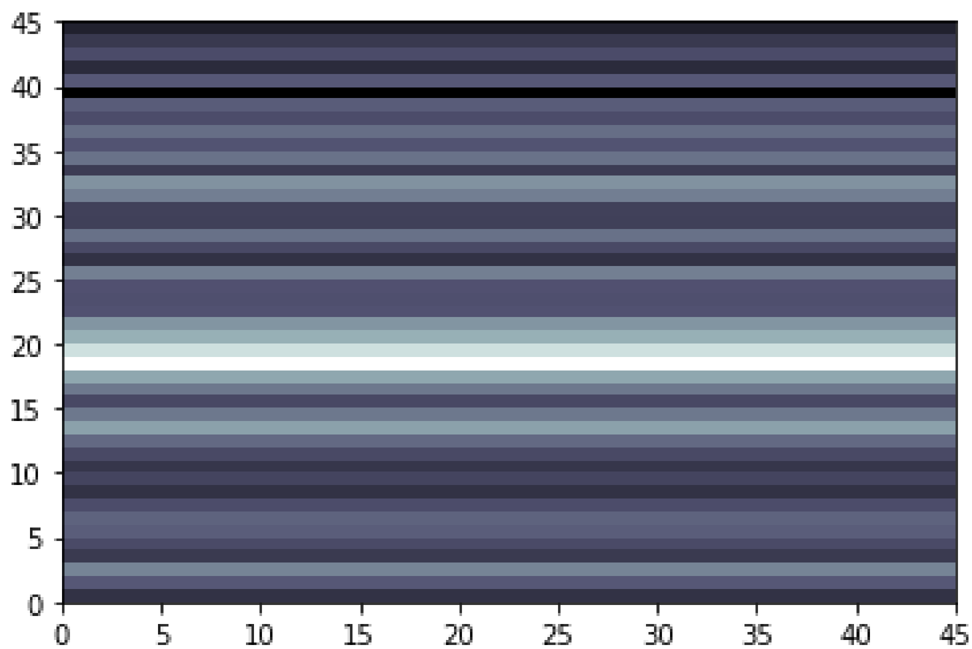
[31]: <matplotlib.collections.QuadMesh at 0x1b06658cb20>



5.2.6 Gyroscope z

[32]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[1][0][5][2]),cmap=cmap)
```

[32]: <matplotlib.collections.QuadMesh at 0x1b0665feb20>

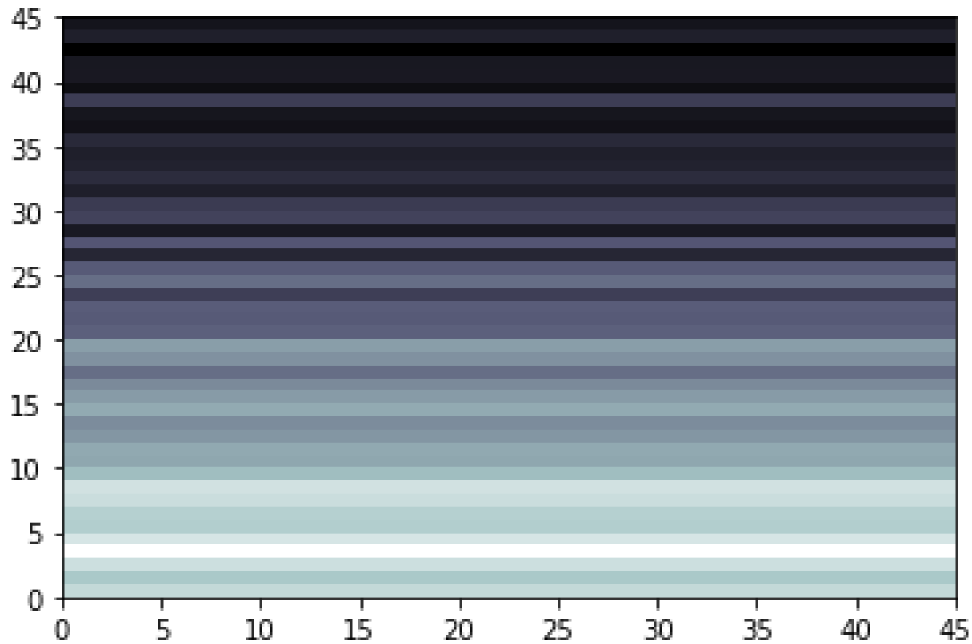


5.3 Climbing down

5.3.1 Accelerometer x

[33]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[2][0][0][2]),cmap=cmap)
```

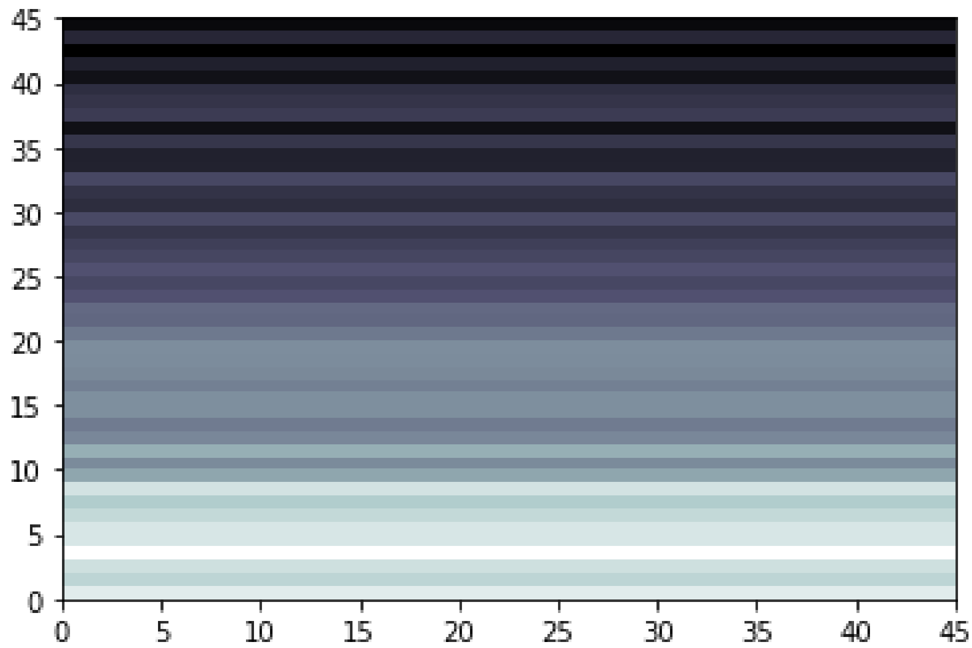
[33]: <matplotlib.collections.QuadMesh at 0x1b0666726a0>



5.3.2 Accelerometer y

[34]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[2][0][1][2]),cmap=cmap)
```

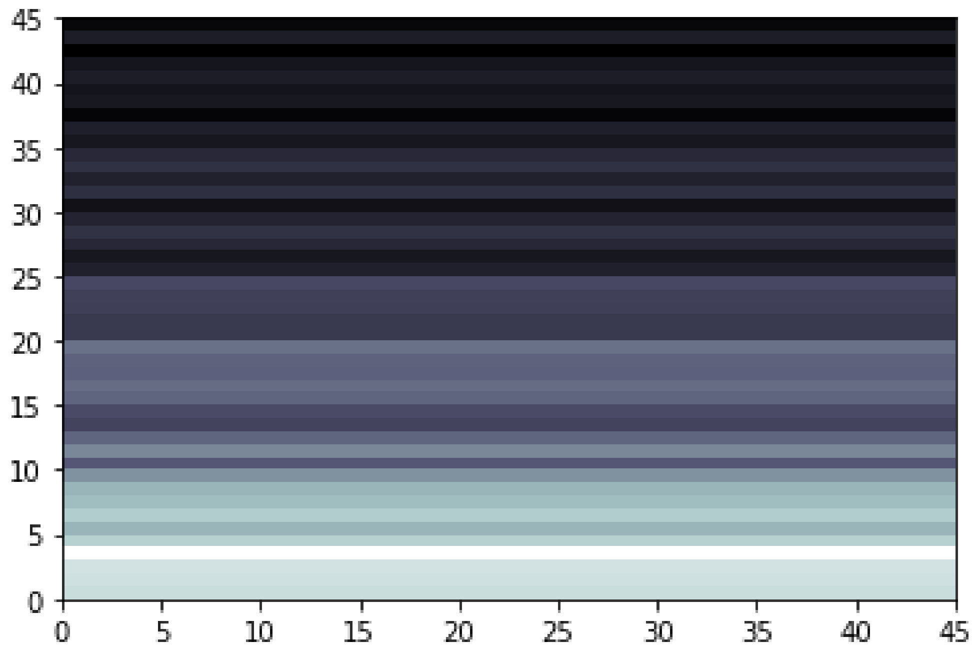
[34]: <matplotlib.collections.QuadMesh at 0x1b0666e6520>



5.3.3 Accelerometer z

[35]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[2][0][2][2]),cmap=cmap)
```

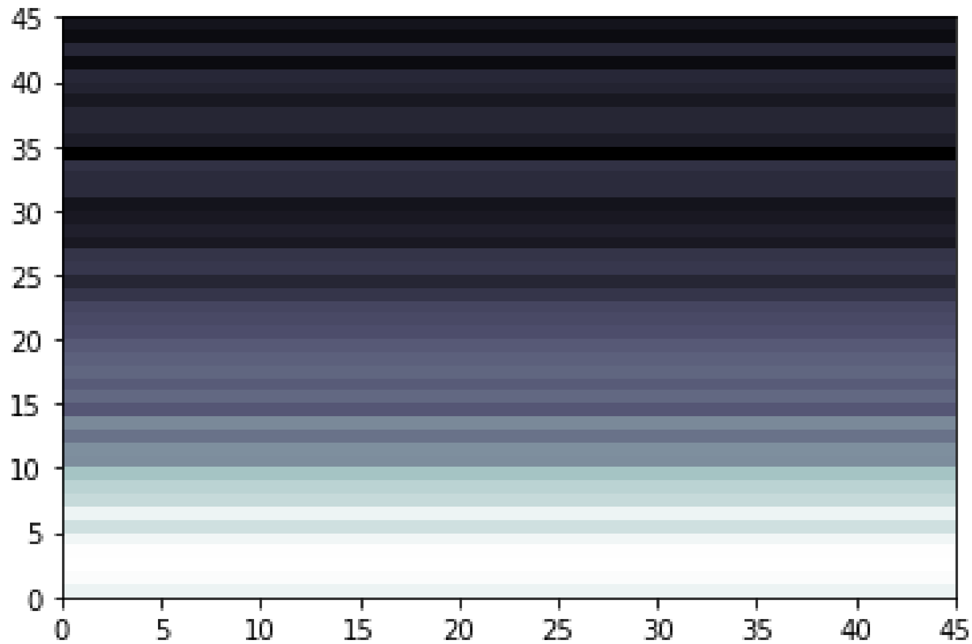
[35]: `<matplotlib.collections.QuadMesh at 0x1b0666fe580>`



5.3.4 Gyroscope x

[36]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[2][0][3][2]),cmap=cmap)
```

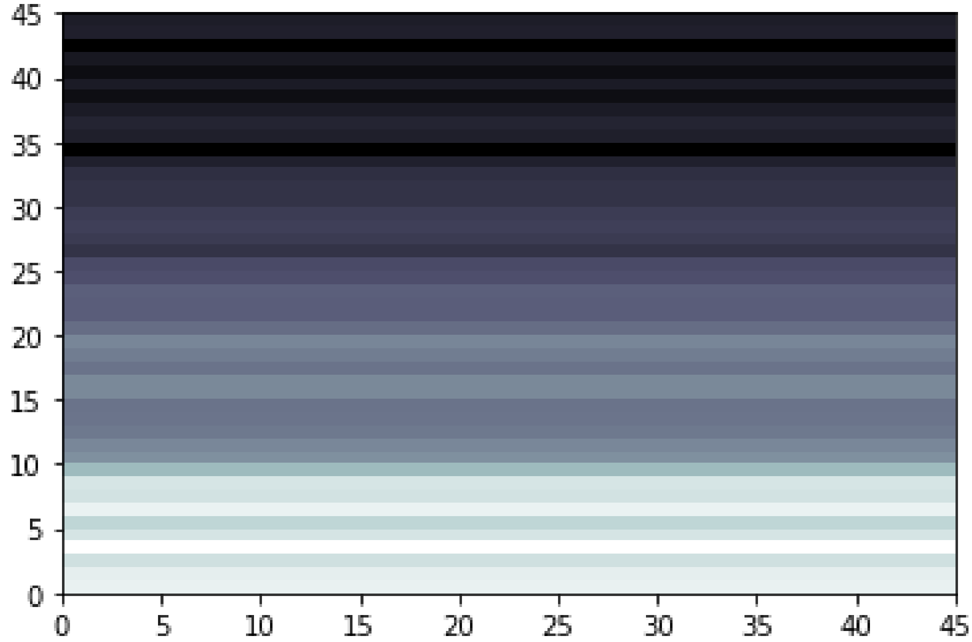
[36]: <matplotlib.collections.QuadMesh at 0x1b0667c5e20>



5.3.5 Gyroscope y

[37]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[2][0][4][2]),cmap=cmap)
```

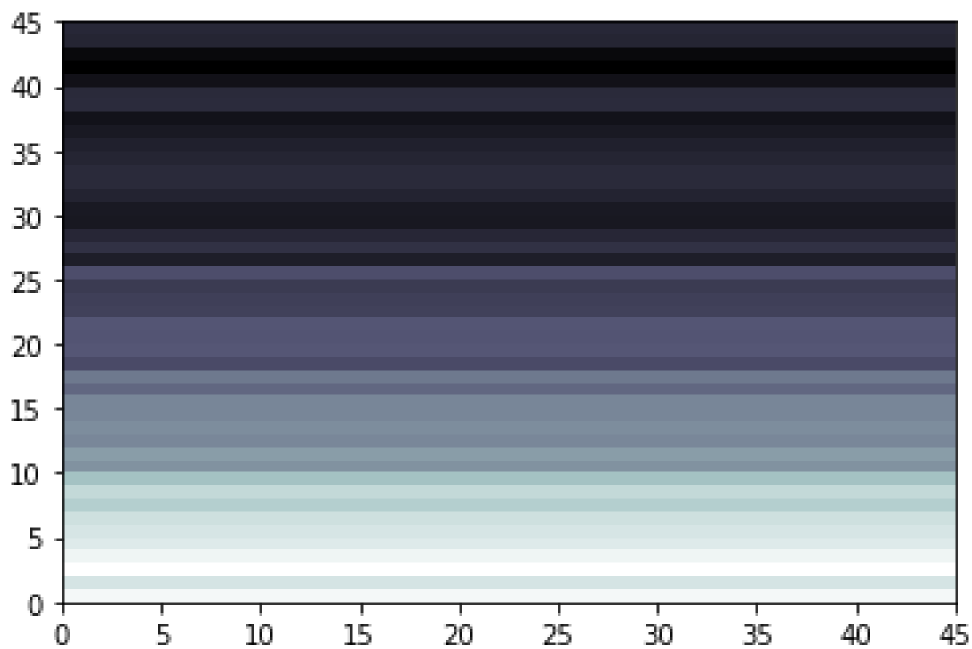
[37]: <matplotlib.collections.QuadMesh at 0x1b066838c40>



5.3.6 Gyroscope z

[38]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[2][0][5][2]),cmap=cmap)
```

[38]: <matplotlib.collections.QuadMesh at 0x1b0666360a0>

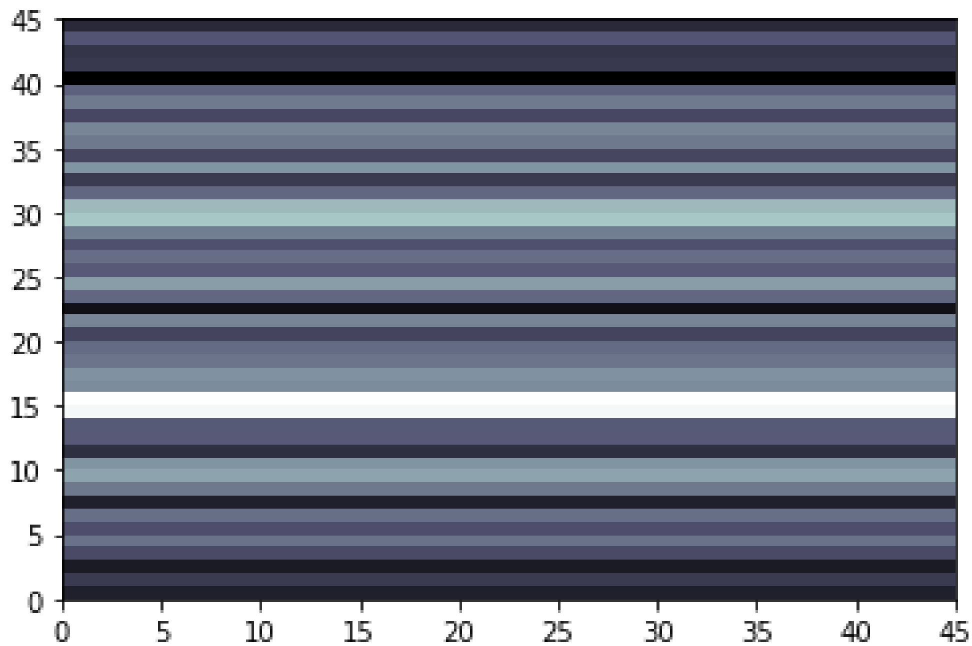


5.4 Climbing up

5.4.1 Accelerometer x

[39]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[3][0][0][2]),cmap=cmap)
```

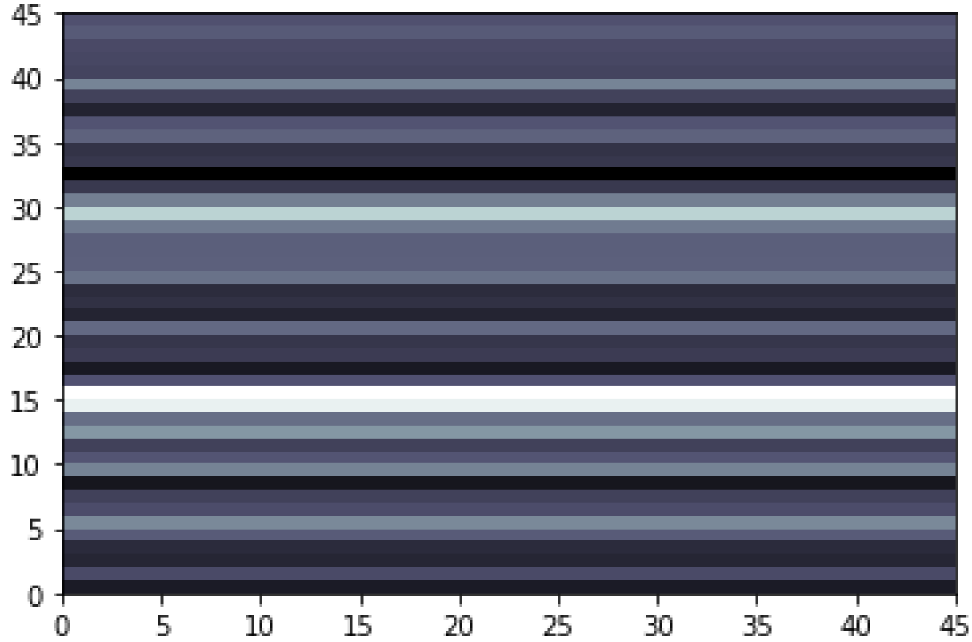
[39]: <matplotlib.collections.QuadMesh at 0x1b066921af0>



5.4.2 Accelerometer y

[40]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[3][0][1][2]),cmap=cmap)
```

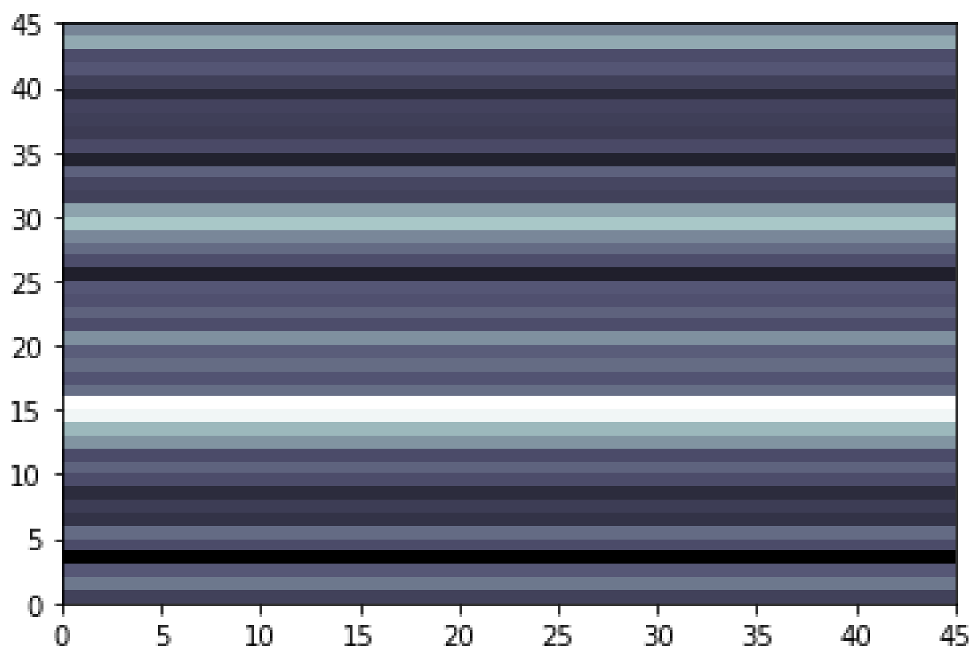
[40]: <matplotlib.collections.QuadMesh at 0x1b0669945b0>



5.4.3 Accelerometer z

[41]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[3][0][2][2]),cmap=cmap)
```

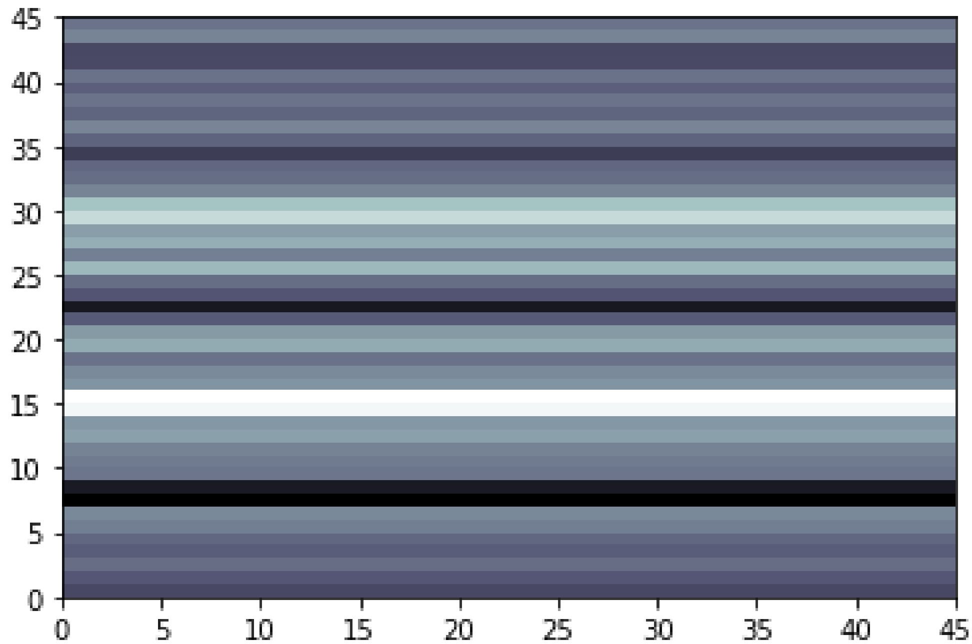
[41]: <matplotlib.collections.QuadMesh at 0x1b066a09130>



5.4.4 Gyroscope x

[42]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[3][0][3][2]),cmap=cmap)
```

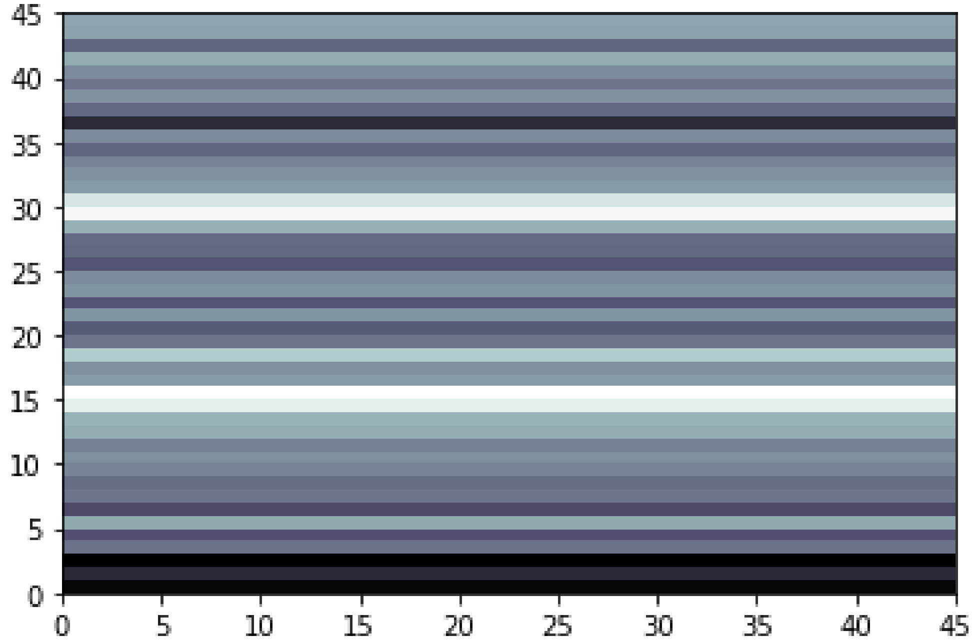
[42]: <matplotlib.collections.QuadMesh at 0x1b066a71e50>



5.4.5 Gyroscope y

[43]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[3][0][4][2]),cmap=cmap)
```

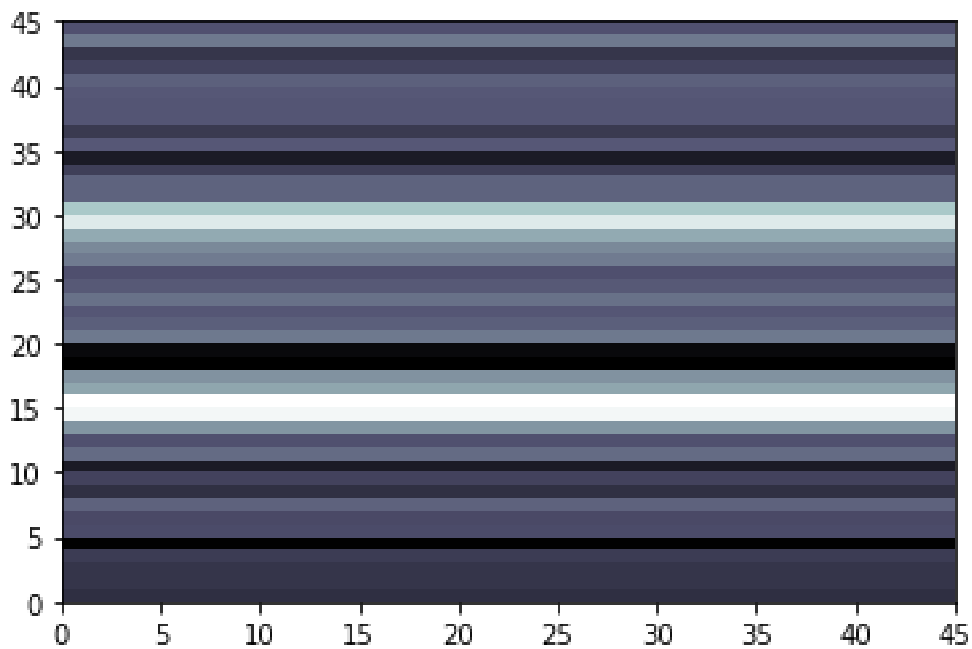
[43]: <matplotlib.collections.QuadMesh at 0x1b066ae5a00>



5.4.6 Gyroscope z

[44]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[3][0][5][2]),cmap=cmap)
```

[44]: <matplotlib.collections.QuadMesh at 0x1b066b5a7f0>

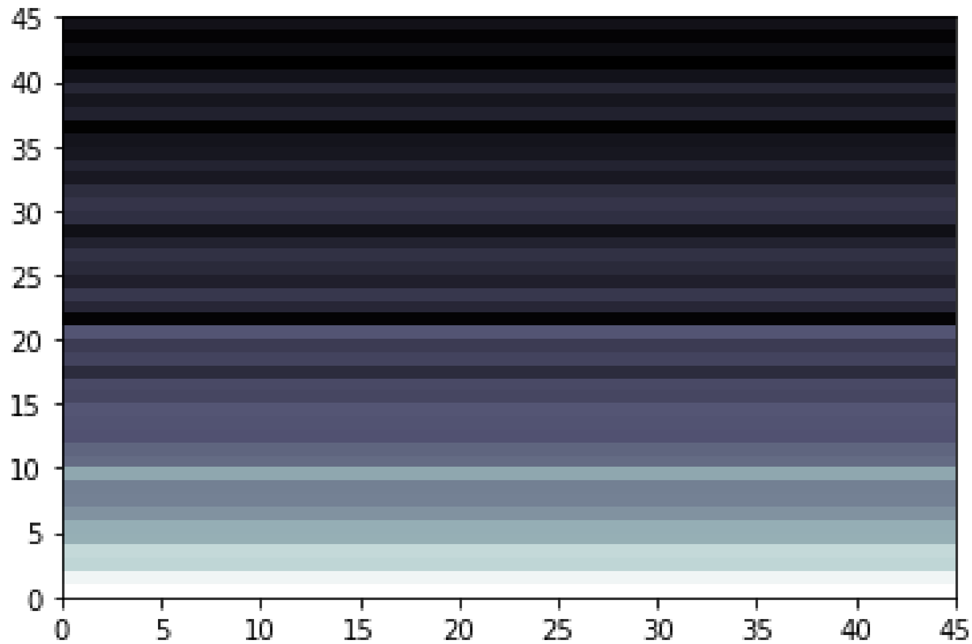


5.5 Standing

5.5.1 Accelerometer x

[45]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[4][0][0][2]),cmap=cmap)
```

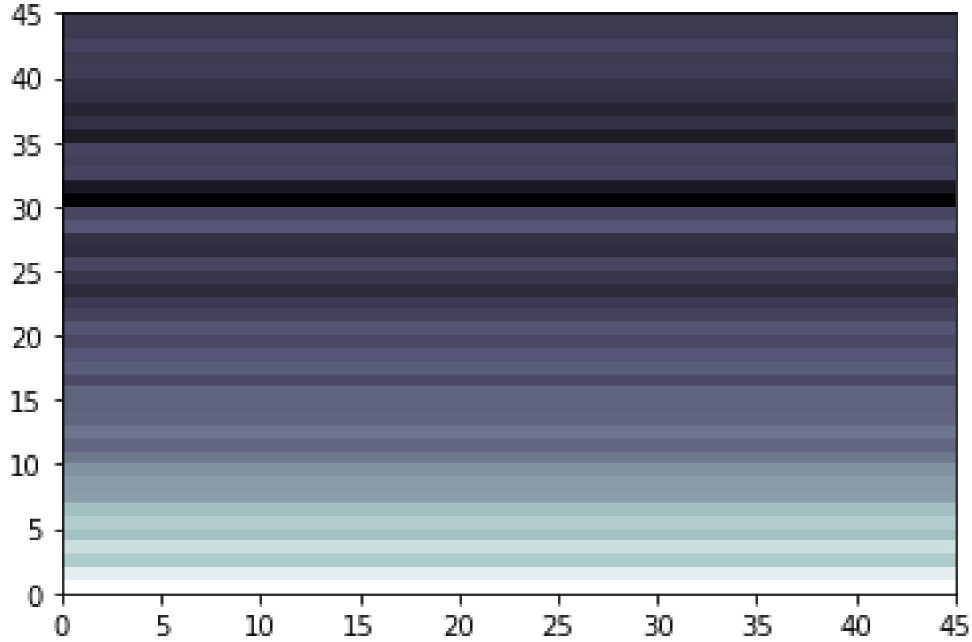
[45]: <matplotlib.collections.QuadMesh at 0x1b066ac3a00>



5.5.2 Accelerometer y

[46]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[4][0][1][2]),cmap=cmap)
```

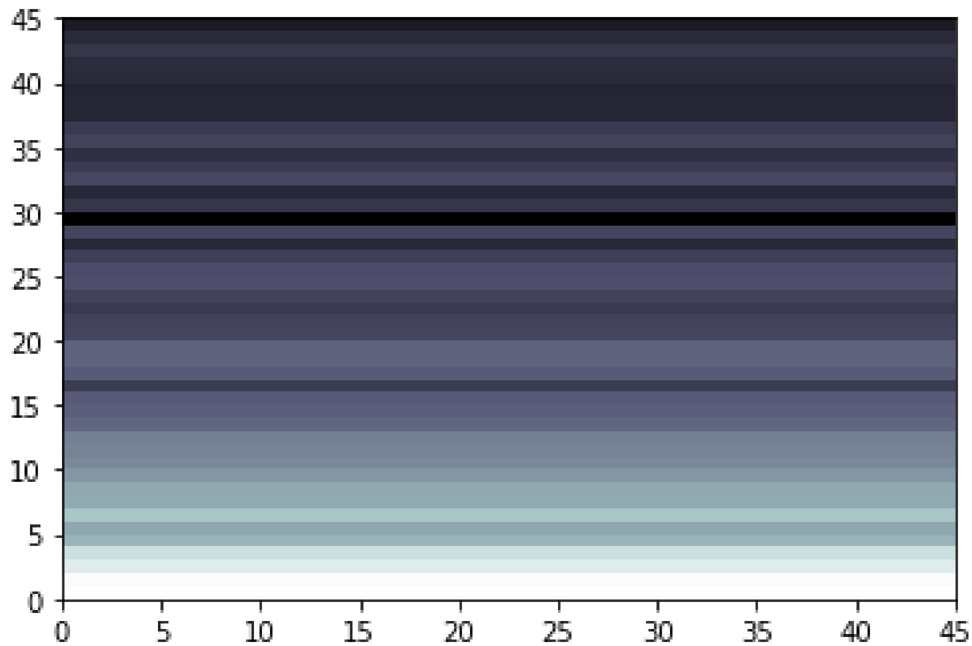
[46]: <matplotlib.collections.QuadMesh at 0x1b066c371f0>



5.5.3 Accelerometer z

[47]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[4][0][2][2]),cmap=cmap)
```

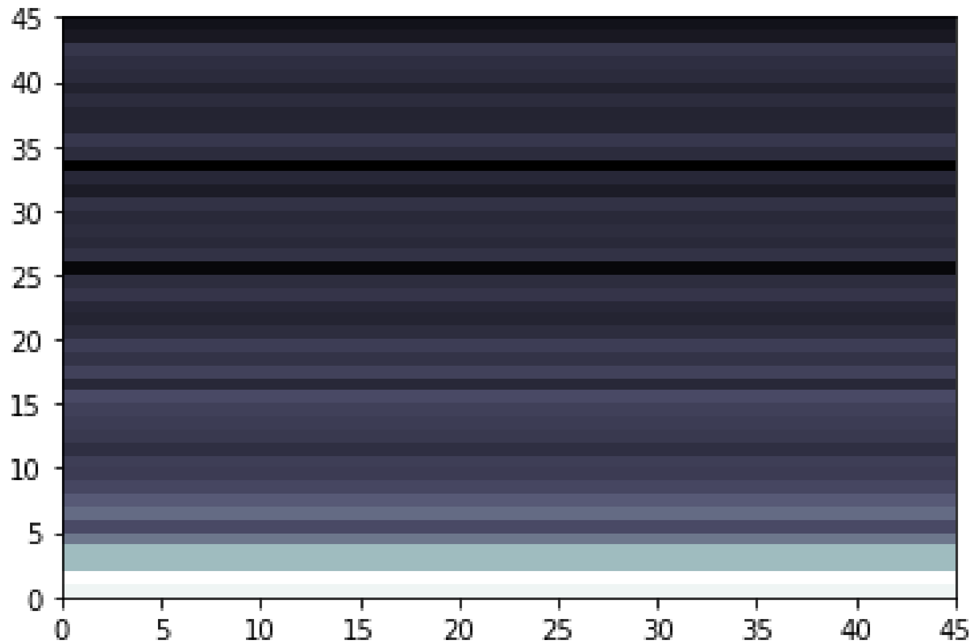
[47]: <matplotlib.collections.QuadMesh at 0x1b066ca7e80>



5.5.4 Gyroscope x

[48]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[4][0][3][2]),cmap=cmap)
```

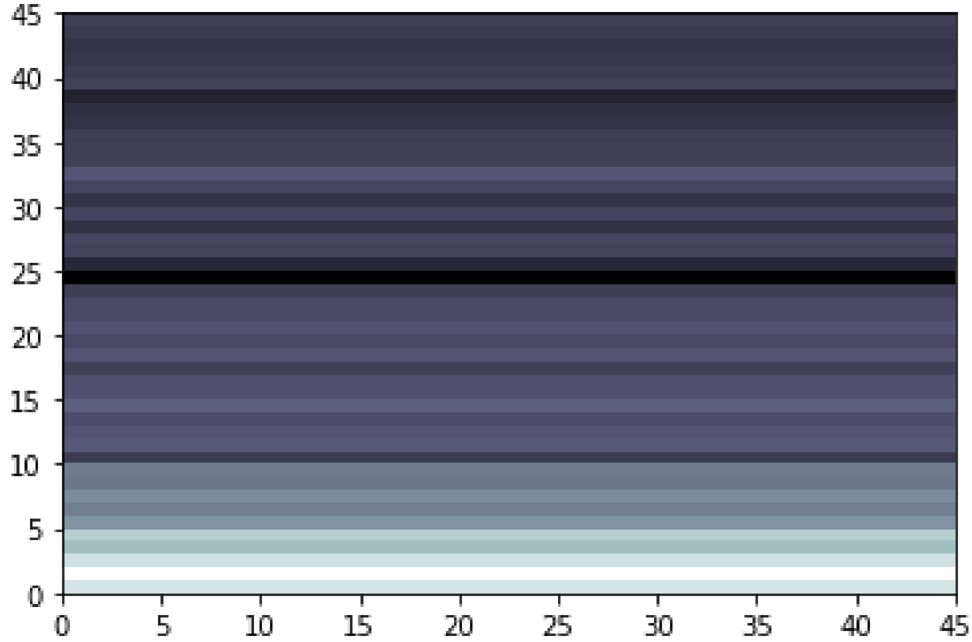
[48]: <matplotlib.collections.QuadMesh at 0x1b066d1ad90>



5.5.5 Gyroscope y

[49]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[4][0][4][2]),cmap=cmap)
```

[49]: <matplotlib.collections.QuadMesh at 0x1b066d8cb20>



5.5.6 Gyroscope z

[50]:
```
plt.pcolormesh(np.log10(data_spectrograms_binned[4][0][5][2]),cmap=cmap)
```

[50]: <matplotlib.collections.QuadMesh at 0x1b066df77f0>