Cello Ensemble PCA

This notebook reproduces the results related to ensemble PCA.

In [1]:
```
%matplotlib inline
%load_ext autoreload
%autoreload 2
from pathlib import Path

# Enter the locations of the sample directories
CELLO_PATH  = Path("/home/lukas/BA/philharmonia-samples/cello")
GUITAR_PATH = Path("/home/lukas/BA/philharmonia-samples/guitar")

# Output directories for figures and wavfiles
GFX_PATH    = Path("/home/lukas/BA/report/gfx/")
WAVS_PATH   = Path("/home/lukas/BA/report/wavs/")
```

In [2]:
```
# Initialization
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
import librosa
import pya
import random

import principal_harmonics as ph

for path in [GFX_PATH, WAVS_PATH]:
    if path.exists() and not path.is_dir():
        raise NotADirectoryError(path)
    if not path.exists():
        path.mkdir()
```

Let's open the dataset. As discussed in the report, we will ignore samples with an (R^2) score less than 0.5.

In [4]:
```
cello_df = ph.dataset.open_dataset(CELLO_PATH)
cello_df = cello_df[cello_df.harmonic_r2 > 0.5]
cello_df = ph.dataset.expand_ndarrays(cello_df, ['freqs', 'coefs'])
```

We use the sample pipeline as before:

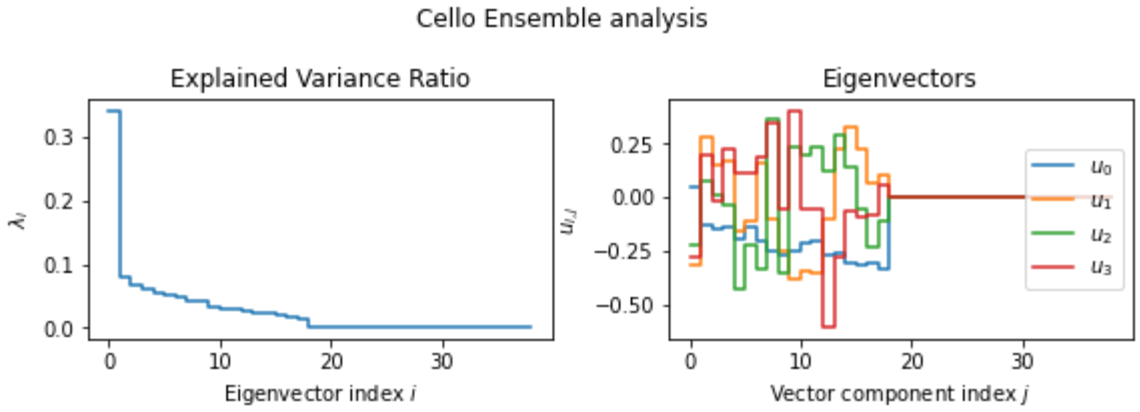
In [5]:
```
from sklearn.pipeline import make_pipeline
from principal_harmonics.models import *

cello_pipeline = make_pipeline(
    DropDCTransformer(),
    DBTransformer(),
    HoleImputer(hole_size_limit=10),
    FilterIncompleteTimbresTransformer(),
    PCA()
)
```

In [6]:
```
ampls = np.abs(cello_df.loc[:, "coefs-0":"coefs-39"].to_numpy())
trans = cello_pipeline.fit_transform(ampls)
```

The next plot shows the explained variance and the eigenvectors of the analysis

In [7]:
```
def plot_ensemble_pca(pca, instrument_name):
    fig, (var_ax, vec_ax) = plt.subplots(1, 2, figsize=(8.2, 3))

    fig.suptitle(f"{instrument_name} Ensemble analysis")

    var_ax.plot(pca.explained_variance_ratio_, ds='steps-post')
    var_ax.set_title("Explained Variance Ratio")
    var_ax.set_xlabel("Eigenvector index $i$")
    var_ax.set_ylabel("$\lambda_i$")

    vec_ax.set_title("Eigenvectors")
    vec_ax.set_xlabel("Vector component index $j$")
    vec_ax.set_ylabel("$u_{i,j}$")
    for i, vec in enumerate(pca.components_[:4]):
        vec_ax.plot(vec, label=f'$u_{i}$', ds='steps-post')
    vec_ax.legend(loc='right')

    fig.tight_layout()

pca = cello_pipeline[-1]
plot_ensemble_pca(pca, "Cello")
plt.savefig(GFX_PATH / "4-cello-ensemble.eps")
```

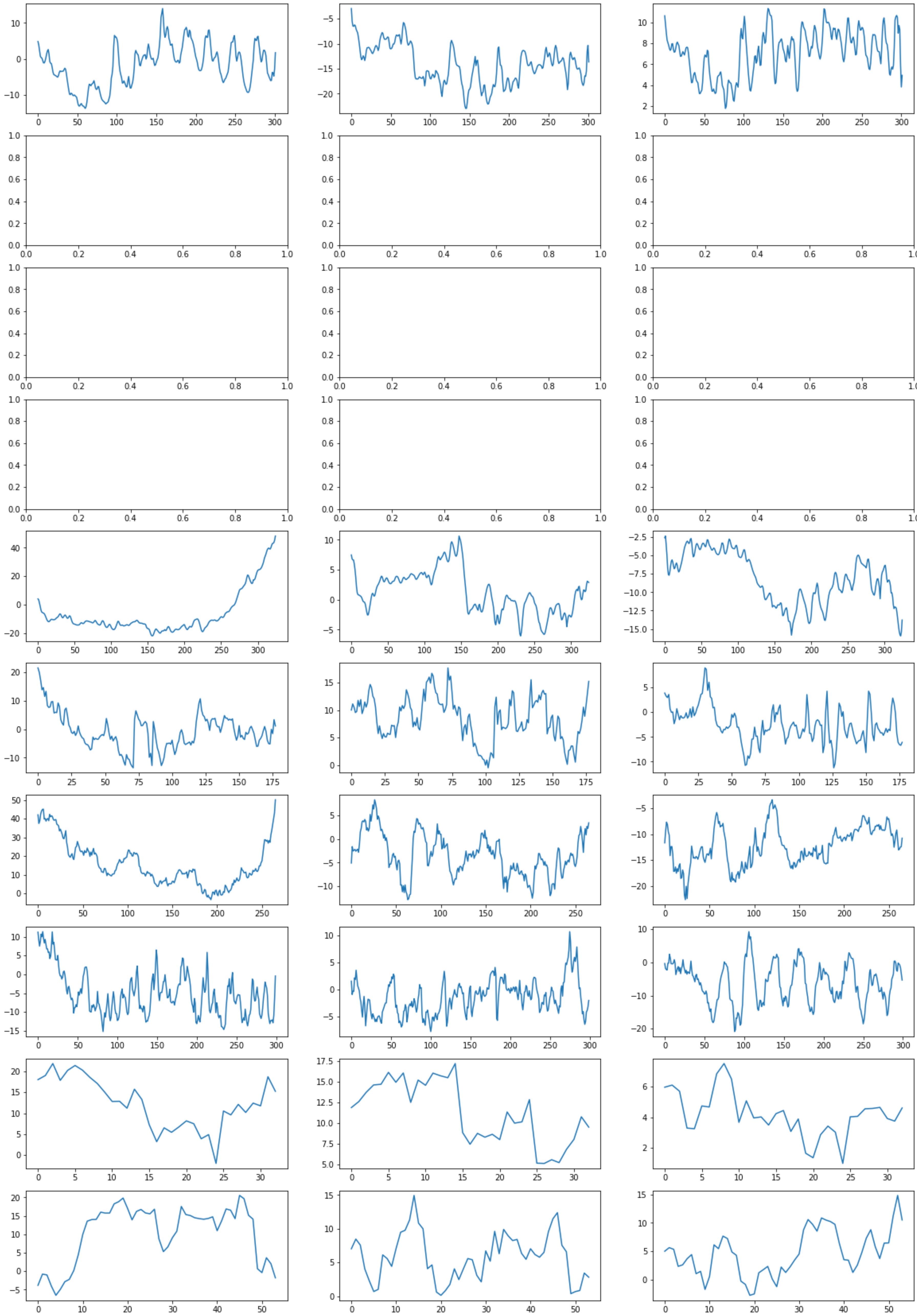
```
The PostScript backend does not support transparency; partially transparent artists will be rendered opaque.
```



Let's look at the trajectories of some randomly chosen samples. X axes denote the analysis frame index, Y axis the control parameter value. We show the trajectories of the 3 most significant control parameters for 10 samples.

Empty plots mean that the analysis failed in preprocessing: When performing timbre filtering, we discard timbre vectors that have at least one hole in the *reliable* partials. If an audio sample contains no values at all for a partial that was deemed reliable, all timbre vectors are discarded and the PCA analysis will fail.

In [8]:
```
fig, axs = plt.subplots(10, 3, figsize=(20, 30))
for sample_ix, filename in enumerate(cello_df.index.unique('filename').to_series().sample(10, random_state=42)):
    sample_df = cello_df.loc[filename]
    try:
        sample_trans = cello_pipeline.transform(np.abs(sample_df.loc[:, "coefs-0":"coefs-39"].to_numpy()))
    except NoCompleteTimbreError:
        continue
    for j, ax in enumerate(axs[sample_ix]):
        ax.plot(sample_trans[:, j])
```



Let's see what each eigenvector does to the timbre: (We'll look at the four most significant eigenvectors)

In [9]:
```
def make_axis_asig_oscillating(mean, ui, scale, note, f=0.5) -> pya.Asig:
    ts = np.linspace(0, 4, 4*int(44100 // 256))
    dbs = mean.reshape(1, -1) + ui.reshape(1, -1) * scale * np.sin(2*np.pi * ts * f).reshape(-1, 1)
    ampls = pya.dbamp(dbs)
    ampls = ampls / ampls.sum(axis=1).reshape(-1, 1) * 0.1
    return ph.pvoc.additive_resynth(librosa.note_to_hz(note), ampls)

cello_axis_asigs = []
for i in range(4):
    scale = np.std(trans[:, i])
    ui = pca.components_[i]
    mean = pca.mean_
    asig = make_axis_asig_oscillating(mean, ui, 2*scale, 'G3')
    asig.save_wavfile(str(WAVS_PATH / f'ch4_cello-ensemble-pca-u{i}.wav'))
    cello_axis_asigs.append(asig)
```

```
(1, 1) (1, 1) (688, 39)
(1, 1) (1, 1) (688, 39)
(1, 1) (1, 1) (688, 39)
(1, 1) (1, 1) (688, 39)
```

In [10]:
```
# Uncomment for playback
# u0
# cello_axis_asig[0].play()
# u1
# cello_axis_asig[1].play()
# u2
# cello_axis_asig[2].play()
# u3
# cello_axis_asig[3].play()
```

Let's see if we can find some corellations between control parameters and sample labels. Since the sample labels do not change the course of the sample, we compute corellation between the *mean* of the control parameters and the labels.

We will add some more features:

- `dynamic_int` is just a mapping from the dynamic (i.e. the loudness the instrument was played) to an integer, so that we can use it in corellation analysis.
- `minimum_fret` : A note on the guitar can be played on different strings, resulting in different timbres. For this dataset, we might expect that each note was played on the string that allowed to use the lowest fret possible, resulting in the richest timbre. Assuming this is true, we can calculate `minimum_fret` to perform corellation analysis between the timbre and the fret index.

In [11]:
```
# lets load the dataset without expanding ndarrays. This way, the
# this analysis is more convenient.
cello_sample_df = ph.dataset.open_dataset(CELLO_PATH)

# First, let's add some more inferred fields:

# Integer representation of dynamic
dynamics_ints = {
    'pianissimo':  0,
    'piano':       1,
    'mezzo-piano': 2,
    'mezzo-forte': 3,
    'forte':       4,
    'fortissimo':  5
}
cello_sample_df['dynamic_int'] = cello_sample_df.dynamic.apply(lambda d: dynamics_ints[d])

# Guess the fret index that the note was played on
cello_empty_string_midis = librosa.note_to_midi(['C2', 'G2', 'D3', 'A3'])
possible_frets = cello_sample_df.midi.to_numpy().reshape(-1, 1) - cello_empty_string_midis.reshape(1, -1)
possible_frets[possible_frets < 0] = np.inf
minimum_fret = np.amin(possible_frets, axis=1)
cello_sample_df['minimum_fret'] = minimum_fret

# Compute mean control parameters
for fname, row in cello_sample_df.iterrows():
    ampls = np.abs(row.coefs)
    try:
        sample_trans = cello_pipeline.transform(ampls)
    except NoCompleteTimbreError:
        continue
    means = np.mean(sample_trans, axis=0)
    cello_sample_df.loc[fname, ["mean-alpha0", "mean-alpha1", "mean-alpha2", "mean-alpha3"]] = means[:4]
```

In [12]:
```
cello_sample_df.loc[:, ['midi', 'dynamic_int', 'minimum_fret', 'harmonic_r2', 'mean-alpha0',
                        'mean-alpha1', 'mean-alpha2', 'mean-alpha3']].corr()
```

Out[12]:

	midi	dynamic_int	minimum_fret	harmonic_r2	mean-alpha0	mean-alpha1	mean-alpha2	mean-alpha3
midi	1.000000	0.051510	0.885666	0.375403	0.454891	-0.018490	-0.083263	-0.198994
dynamic_int	0.051510	1.000000	0.039716	0.028761	-0.434111	-0.081852	0.052683	-0.219672
minimum_fret	0.885666	0.039716	1.000000	0.204056	0.386444	0.261909	-0.071388	-0.248922
harmonic_r2	0.375403	0.028761	0.204056	1.000000	-0.134295	-0.073507	-0.125083	-0.104903
mean-alpha0	0.454891	-0.434111	0.386444	-0.134295	1.000000	0.043800	-0.039556	-0.088681
mean-alpha1	-0.018490	-0.081852	0.261909	-0.073507	0.043800	1.000000	0.012992	-0.030416
mean-alpha2	-0.083263	0.052683	-0.071388	-0.125083	-0.039556	0.012992	1.000000	-0.012045
mean-alpha3	-0.198994	-0.219672	-0.248922	-0.104903	-0.088681	-0.030416	-0.012045	1.000000

Guitar Ensemble PCA

Moving on to the guitar, we'll perform the same steps as above. The only difference is that we have to take the preprocessing steps for each sample separately.

In [13]:

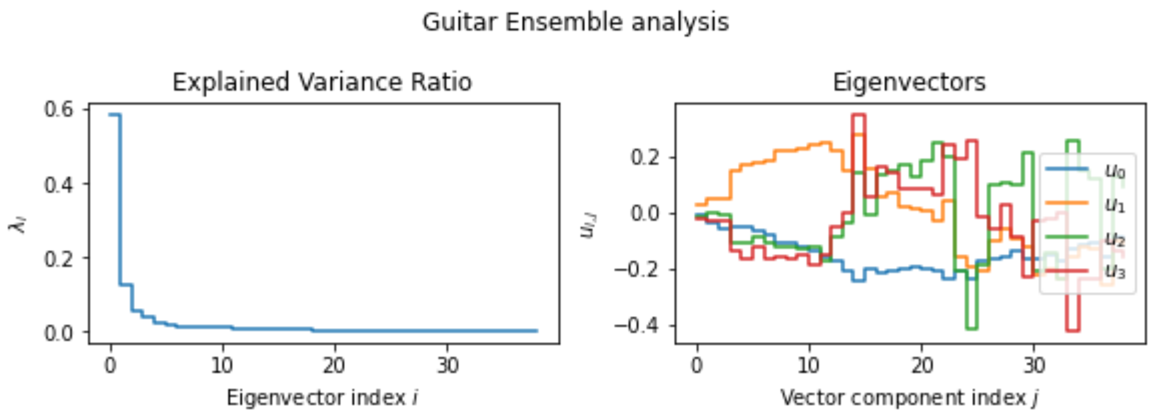
```
guitar_df = ph.dataset.open_dataset(GUITAR_PATH)
guitar_pipeline = make_pipeline(
    DropDCTransformer(),
    DBTransformer(),
    HoleImputer(hole_size_limit=10),
    RidgeSubNoiseImputer(constant_value=-240),
    PCA()
)
preprocessed = []
for filename, row in guitar_df.iterrows():
    prep = guitar_pipeline[:-1].fit_transform(np.abs(row.coefs))
    preprocessed.append(prep)
trans = guitar_pipeline[-1].fit_transform(np.vstack(preprocessed))

guitar_df = ph.dataset.expand_ndarrays(guitar_df, ['freqs', 'coefs'])
```

Explained variance and eigenvector plots:

In [14]:

```
pca = guitar_pipeline[-1]
plot_ensemble_pca(pca, "Guitar")
plt.savefig(GFX_PATH / "4-guitar-ensemble.eps")
```

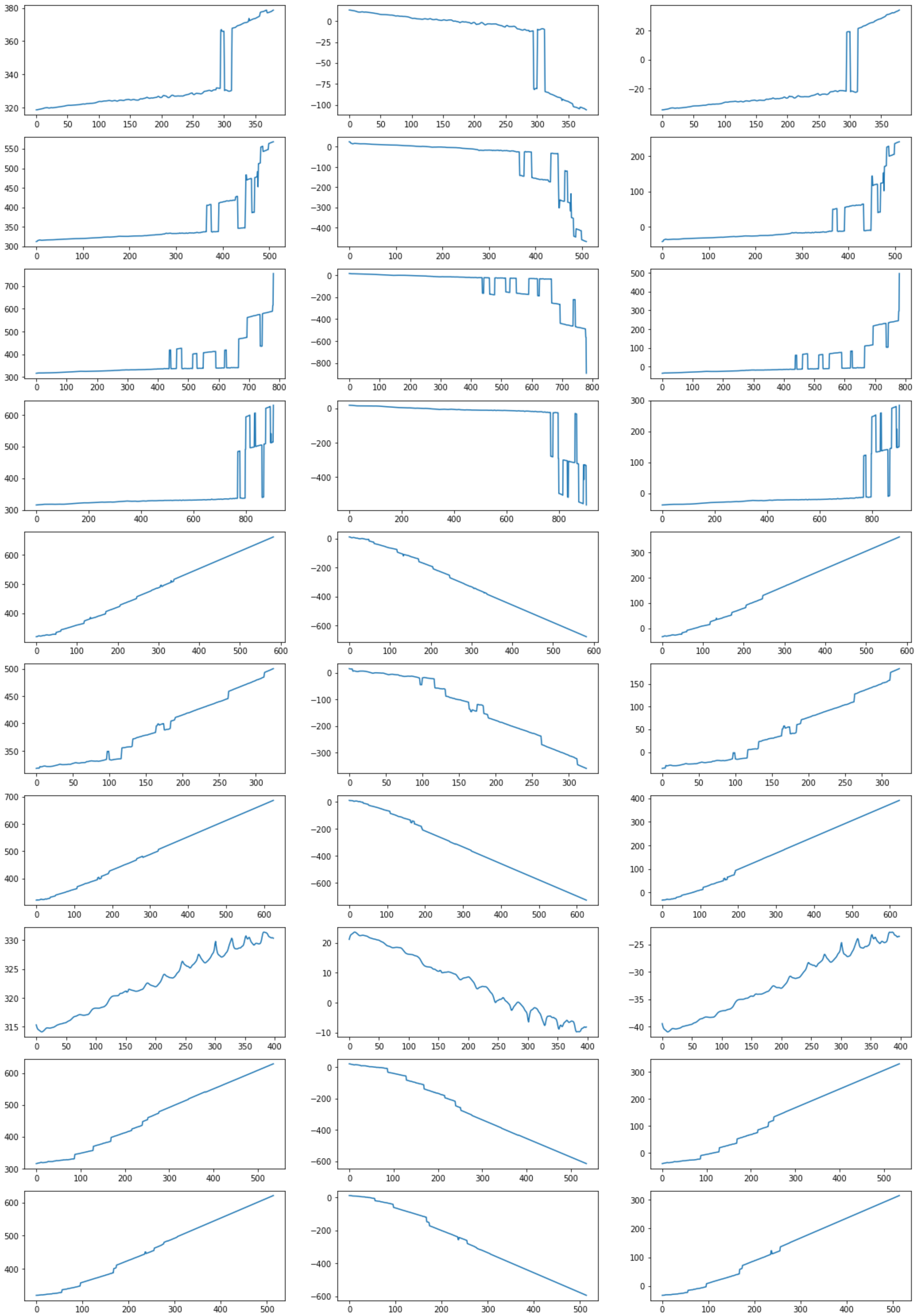
```
The PostScript backend does not support transparency; partially transparent artists will be rendered opaque.
```



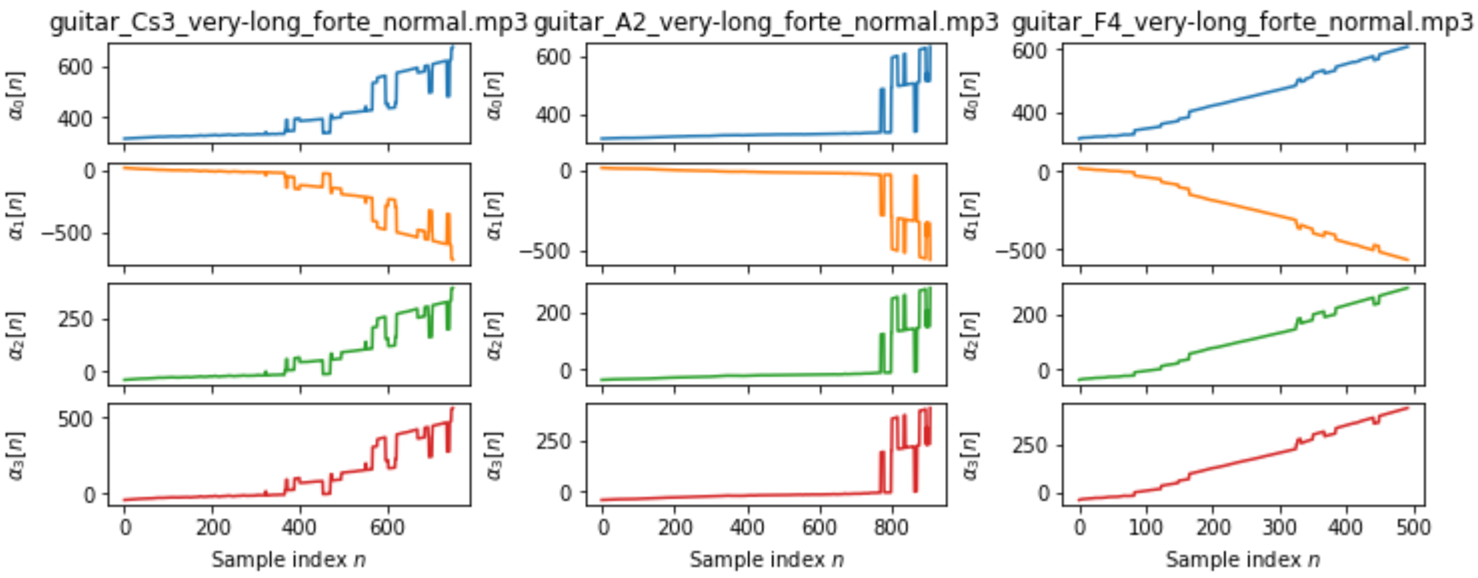
Again, plotting the trajectories of the first three control parameters for 10 random samples:

In [15]:

```
fig, axs = plt.subplots(10, 3, figsize=(20, 30))
for sample_ix, filename in enumerate(guitar_df.index.unique('filename').to_series().sample(10, random_state=1337)):
    sample_df = guitar_df.loc[filename]
    sample_trans = guitar_pipeline.transform(np.abs(sample_df.loc[:, "coefs-0":"coefs-39"].to_numpy()))
    for j, ax in enumerate(axs[sample_ix]):
        ax.plot(sample_trans[:, j])
```



In [16]:
```
colors = ['tab:blue', 'tab:orange', 'tab:green', 'tab:red']
fig, axs = plt.subplots(4, 3, figsize=(10, 4), constrained_layout=True, sharex='col')
for sample_ix, filename in enumerate(guitar_df.index.unique('filename').to_series().sample(3, random_state=42)):
    axs[0, sample_ix].set_title(filename)
    sample_df = guitar_df.loc[filename]
    sample_trans = guitar_pipeline.transform(np.abs(sample_df.loc[:, "coefs-0":"coefs-39"].to_numpy()))
    for j, (ax, color) in enumerate(zip(axs[:, sample_ix], colors)):
        ax.plot(sample_trans[:, j], color=color)
        ax.set_ylabel(f"$\\alpha_{j}[n]$")
for ax in axs[-1]:
    ax.set_xlabel("Sample index $n$")
fig.align_ylabels()
plt.savefig(GFX_PATH / '4-guitar-ensemble-control-parameters.eps')
```



In [17]:
```
guitar_axis_asigs = []
for i in range(4):
    scale = np.std(trans[:, i])
    ui = pca.components_[i]
    mean = pca.mean_
    asig = make_axis_asig_oscillating(mean, ui, 2*scale, 'A4')
    asig.save_wavfile(str(WAVS_PATH / f'ch4_guitar-ensemble-pca-u{i}.wav'))
    guitar_axis_asigs.append(asig)
```

```
(1, 1) (1, 1) (688, 39)
(1, 1) (1, 1) (688, 39)
(1, 1) (1, 1) (688, 39)
(1, 1) (1, 1) (688, 39)
```

In [18]:
```
# Uncomment for playback
# u0
# cello_axis_asig[0].play()
# u1
# cello_axis_asig[1].play()
# u2
# cello_axis_asig[2].play()
# u3
# cello_axis_asig[3].play()
```

In [19]:
```
# lets load the dataset without expanding ndarrays. This way, the
# this analysis is more convenient.
guitar_sample_df = ph.dataset.open_dataset(GUITAR_PATH)

# First, let's add some more inferred fields:

# Integer representation of dynamic
dynamics_ints = {
    'piano': 0,
    'forte': 1,
}
guitar_sample_df['dynamic_int'] = guitar_sample_df.dynamic.apply(lambda d: dynamics_ints[d])

# Guess the fret index that the note was played on
guitar_empty_string_midis = librosa.note_to_midi(['E2', 'A2', 'D3', 'G3', 'B3', 'E4'])
possible_frets = guitar_sample_df.midi.to_numpy().reshape(-1, 1) - guitar_empty_string_midis.reshape(1, -1)
possible_frets[possible_frets < 0] = np.inf
minimum_fret = np.amin(possible_frets, axis=1)
guitar_sample_df['minimum_fret'] = minimum_fret

# Compute mean control parameters
for fname, row in guitar_sample_df.iterrows():
    ampls = np.abs(row.coefs)
    sample_trans = guitar_pipeline.transform(ampls)
    means = np.mean(sample_trans, axis=0)
    guitar_sample_df.loc[fname, ["mean-alpha0", "mean-alpha1", "mean-alpha2", "mean-alpha3"]] = means[:4]
```

In [20]:
```
guitar_sample_df.loc[:, ['midi', 'dynamic_int', 'minimum_fret', 'harmonic_r2', 'mean-alpha0',
                         'mean-alpha1', 'mean-alpha2', 'mean-alpha3']].corr()
```

Out[20]:

	midi	dynamic_int	minimum_fret	harmonic_r2	mean-alpha0	mean-alpha1	mean-alpha2	mean-alpha3
midi	1.000000	0.026958	0.718109	-0.147222	0.472524	-0.473341	0.473970	0.476116
dynamic_int	0.026958	1.000000	0.010100	0.518304	-0.102497	0.099994	-0.097764	-0.100630
minimum_fret	0.718109	0.010100	1.000000	-0.294816	0.024170	-0.027748	0.030559	0.031780
harmonic_r2	-0.147222	0.518304	-0.294816	1.000000	-0.049477	0.049055	-0.047590	-0.049926
mean-alpha0	0.472524	-0.102497	0.024170	-0.049477	1.000000	-0.999520	0.998722	0.999119
mean-alpha1	-0.473341	0.099994	-0.027748	0.049055	-0.999520	1.000000	-0.999765	-0.999872
mean-alpha2	0.473970	-0.097764	0.030559	-0.047590	0.998722	-0.999765	1.000000	0.999867
mean-alpha3	0.476116	-0.100630	0.031780	-0.049926	0.999119	-0.999872	0.999867	1.000000

In [21]:

```
guitar_sample_df.loc[:, ['mean-alpha0', 'mean-alpha1', 'mean-alpha2', 'mean-alpha3']]
```

Out[21]:

	mean-alpha0	mean-alpha1	mean-alpha2	mean-alpha3
filename				
guitar_A2_very-long_forte_normal.mp3	352.686488	-50.638363	0.921082	14.607563
guitar_A2_very-long_piano_normal.mp3	352.654770	-48.061947	-1.532717	12.133728
guitar_A3_very-long_forte_normal.mp3	442.622773	-233.967155	108.087241	166.507185
guitar_A3_very-long_piano_normal.mp3	442.076904	-233.090403	107.333268	166.323256
guitar_A4_very-long_forte_normal.mp3	463.915644	-276.738789	131.049455	201.448053
...	...	...	...	...
guitar_Gs3_very-long_forte_normal.mp3	346.580745	-40.275697	-3.809051	6.943206
guitar_Gs3_very-long_piano_normal.mp3	390.671918	-130.780321	48.214163	82.179157
guitar_Gs4_very-long_forte_normal.mp3	470.976603	-291.935479	140.293271	214.795348
guitar_Gs4_very-long_piano_normal.mp3	445.643865	-240.463458	110.584798	172.257796
guitar_Gs5_very-long_forte_normal.mp3	396.709920	-142.535462	54.771870	91.745823

71 rows × 4 columns