RELEVANCE OF MUSICAL FEATURES FOR CADENCE DETECTION

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ABSTRACT

Cadences, as breaths in music, are felt by the listener or studied by the theorist by combining harmony, melody, texture and possibly other musical aspects. We formalize and discuss the significance of 44 *cadential features*, correlated with the occurrence of cadences in scores. These features describe properties at the arrival beat of a cadence and its surroundings, but also at other onsets heuristically identified to pinpoint chords preparing the cadence. The representation of each beat of the score as a vector of cadential features makes it possible to reformulate cadence detection as a classification task. An SVM classifier was run on two corpora from Bach and Haydn totaling 162 perfect authentic cadences and 70 half cadences. In these corpora, the classifier correctly identified more than 75% of perfect authentic cadences and 50% of half cadences, with low false positive rates. The experiment results are consistent with common knowledge that classification is more complex for half cadences than for authentic cadences.

1. INTRODUCTION

1.1 Cadences

Music, like all languages, is organized into structural units. In Western tonal music, these units often end with strong harmonic formulas called *cadences*, from the Latin *cadere*, "to fall." Despite their structural function, cadences are hard to define. Based on a review of dozens of music theory papers, Blombach defined the cadence as *"any musical element or combination of musical elements, including silence, that indicates relative relaxation or relative conclusion in music"* [3]. This definition highlights the way a listener (whether musically trained or not) can *hear* the presence of a cadence by feeling that the music "breaths". A cadence is generally characterized by *local* musical elements, such as a specific harmonic progression and a falling melody. However, these elements do not necessarily imply a cadence. A global or high-level structure such as the sonata form may also induce the impression of a cadence [10].

Cadences are usually classified by harmonic progression. The *authentic* cadence is characterized by a *dominant* harmony (notated V) followed by a *tonic* harmony (notated I). In the American terminology, when both chords are in root position and the melody ends on the tonic, the authentic cadence is said to be *perfect* (PAC), otherwise it is *imperfect* (IAC). If the IAC is in root position (but the melody does not end on the tonic), it is said to be a *rooted IAC* (rIAC). The *half* cadence (HC) ends with a dominant harmony, generally in root position. The *deceptive* cadence (DC) is an authentic cadence where the expected final tonic is replaced by another harmony (often VI). Some authors theorize the *evaded* cadence as a particular IAC, while others see it as a DC-like progression but including a melodic break, for instance while repeating a phrase [19]. Some scholars do not consider the *plagal* progression IV/I as a cadence but rather as a post-cadential prolongation [4].

Each cadence type provide a different feeling of closure. The strongest cadence is the PAC, followed in turn by the rIAC, IAC, HC, and the DC and related cadences [20]. Some traditions consider the rIAC to be very conclusive. For instance, French music teachers refer to both PAC and rIAC as *cadence parfaite*. Using a preparation chord before the dominant chord, generally a *subdominant harmony* (SD, that is II, IV, or V/V), strengthens the salience of a PAC/rIAC. In contrast, DC and related cadences renew tension, extending the musical phrase and delaying closure until a more conclusive cadence is used.

1.2 Cadences, Musicology and MIR

Modeling cadences is a current challenge in musicology [15]. Although cadence definitions found in music education textbooks are often quite short, music theorists agree on the difficulty to define cadences because of the variety of their realizations observed in the repertoire [4].

Cadences are therefore usually studied within the frame of one specific corpus – see for example Martin and Pedneault-Deslauriers's study of HC in Mozart's piano sonatas [14]. However, more systematic analyses of large corpora would help to understand the evolution of compositional choices over time. Rohrmeier and Neuwirth suggested a first characterization using grammars, based on the degrees and the bass line [18].

Detecting cadences throughout the score requires a specific training to find clues pointing out to the breaths in music. Can we algorithmically detect cadences from a score encoded in symbolic notation? Some works in MIR have

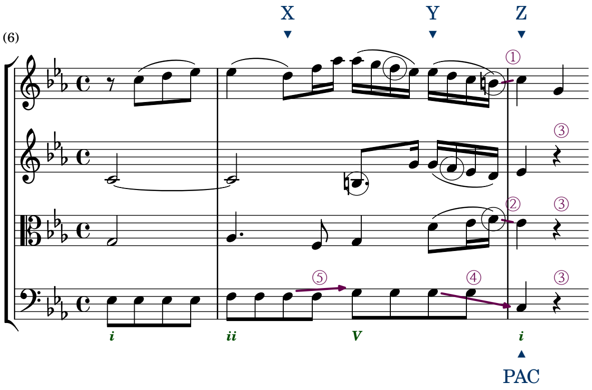

Figure 1. Haydn, op. 17/4, iv, PAC at measure 8 (offset Z). Compare to Figure 1 of [21]. Features describe here the constitution of the Z chord (*Z-in-perfect-triad*, *Z-in-perfect-triad-or-sus4*, *Z-highest-is-1*), voice leading to Z (*Z-1-comes-from-7* ①, *Z-3-comes-from-4* ②), rests after Z (*R-after-Z-rest-lowest*, *-middle* ③) and the metric structure (*R-Z-strong-beat*). Features also describe relations with chord Y (*Y-Z-bass-moves-compatible-V-I* ④, *Y-Z-bass-same-voice*), and cadence preparation (*X-Y-bass-moves-2nd-Maj* ⑤).
Note that the heuristic choice of a single offset Y implies here that the features *Y-in-V7-3* and *Y-has-7* are not true, even if the dominant chord actually contain several pitches $\underline{3}$ and $\underline{7}$ (circled notes). Nevertheless, these pitches are caught by the tonality features (*Z-bass-compatible-with-I*, *Z-bass-compatible-with-I-scale*) and some of them are considered by the voice leading features (①, ②).

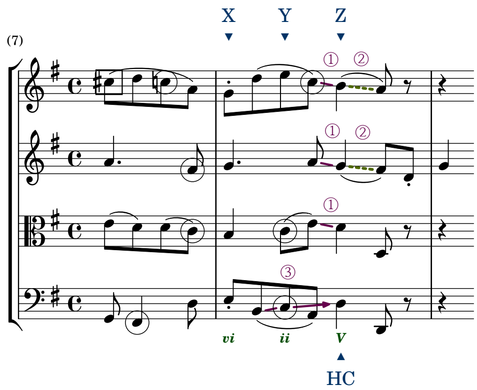

Figure 2. Haydn, op. 17/5, i, HC at measure 8. Features notably describe here a voice leading (*Z-6-comes-from-7*, *Z-4-comes-from-5*, *Z-1-comes-from-2* ①) continued by a 6/4 suspension (*Z-6-moves-to-5*, *Z-4-moves-to-3* ②). Other features also describe the tonality compatibility of an HC (*bass-Z-compatible-with-V*, circled notes, but both *Z-bass-compatible-with-I* and *Z-bass-compatible-with-I-scale* are also true due to the squared *c#*) as well as bass movements (*Y'-Y-bass-moves-chromatic*, *Y-Z-bass-moves-2nd-Maj* ③) and the metric structure (*R-Z-strong-beat*).

focused on melodic cadences [25] and a few studies have tackled the problem of the identification of harmonic progressions [16] or their representation as musical trajectories [1]. The authors of [7] took Rohrmeier's works further, extending it into a system deriving harmonic relations between chords, where grammars rules were inferred for jazz harmony. Currently, only a few algorithms recognize simple cadences [12]. We previously suggested a rule-based detection of PAC/rIAC in fugues [9] and used it in a study on the sonata form [2]. Recently, Sears and colleagues [22] used the software IDyOM [17] on a corpus of Haydn string quartets to show that music predictability increases at cadential points and decreases on the following note.

1.3 Contents

Our goal is to identify *binary*, *musical*, and *local* features that coincide with cadences and that can be used to train a model that detects new cadences, either PAC/rIAC or HC. Rather than agnostically discovering cadential features on the musical surface, we intend here to confirm and study traditional music theory knowledge regarding cadences. The proposed strategy avoids chord segmentation, which is itself a difficult MIR problem. Section 2 details the selected features and Section 3 describes the learning process. Finally, Sections 4 and 5 discuss the application of the method on Bach and Haydn corpora.

2. MUSICAL FEATURES AT THREE ONSETS

Each beat Z of the score is considered as the potential arrival point of a cadence. A set of 44 binary features is computed at each beat. These features are then used to train a classifier whose aims to predict whether a beat corresponds to the arrival point of a cadence or not. The features aim at detecting cadences at a *local* level, i.e. the surroundings of the cadential beat including its immediate past, presumably corresponding to the *preparation* of the cadence. The idea is to try and detect SD-V-I progressions for a PAC/rIAC, and progressions ending with V for an HC.

What we propose here is a simple heuristic focusing on three specific onsets: Z, $Y(Z)$ and $X(Z)$, or for short Z, Y, and X. Most of the features describe sets of notes sounding at these onsets (even when they begin before), namely *chord(Z)*, *chord(Y)*, and *chord(X)*. We therefore do not start from a complete harmony analysis nor a chord segmentation, that can be error-prone. Even when the methods finding $Y(Z)$ and $X(Z)$ return approximate onsets, the computed features may be relevant.

2.1 Features on the Arrival Point Z or around it

The arrival chord of a cadence is usually a perfect triad, possibly with some suspensions. A first set of features describes this chord and its immediate neighborhood:

- *Z-in-perfect-major-triad* (respectively *Z-in-perfect-triad*): *chord(Z)* is included in $\{\underline{1}, \underline{3M}, \underline{5}\}$ [1] (resp. $\{\underline{1}, \underline{3m}, \underline{3M}, \underline{5}\}$)

[1] Pitches in underlined figures (i.e. $\underline{1}$, $\underline{3}$, etc.) are here computed by the interval modulo octave relative to the bass. As some chords are not in root

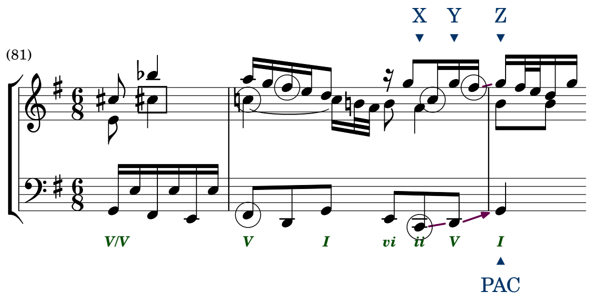

Figure 3. Bach, fugue #15 in G major BWV860, PAC at measure 83. Voice leading and highlighted notes as in the Figures 1 and 2. To cope with the faster harmonic rhythm, every eighth before Z is considered as a potential Y.

- *Z-in-perfect-triad-or-sus4*: *chord(Z)* is included in $\{\underline{1}, \underline{3}, \underline{4}, \underline{5}\}$
- *Z-is-sus4*: *chord(Z)* is exactly $\{\underline{1}, \underline{4}, \underline{5}\}$
- *Z-highest-is-1* (resp. *Z-highest-is-3*): The highest note of *chord(Z)* is the tonic $\underline{1}$ (resp. the major or minor third $\underline{3}$), as expected for a PAC (rIAC)

Another set of features describes *voice leadings* from preceding notes (see list on Table 2). *Z-β-comes-from-α* means that the note $\underline{\beta}$ in *chord(Z)* is an "immediate resolution" of a note $\underline{\alpha}$ (the interval being still relative to the bass of Z) that is *exactly before* $\underline{\beta}$ (even if this note is not at the onset Y that will be defined later). For example, *Z-3-comes-from-4* means that there is a $\underline{3}$ in *chord(Z)* that is an immediate resolution of a $\underline{4}$ (dominant seventh in the case of a PAC, see ② on Figure 1).

There can also be a suspension at the arrival point, as on the HC on Figure 2. We thus add symmetrical features *Z-α-moves-to-β* (see list on Table 2). For example, *Z-4-moves-to-3* means that there is a suspended fourth $\underline{4}$ in *chord(Z)* that is immediately resolved to the third $\underline{3}$.

Finally, features try to grasp the tonality in the neighborhood of Z. We do not perform tonality estimation [13,23] because of the usual difficulty of algorithms to disambiguate adjacent tonalities in the circle of fifths.

- *Z-bass-compatible-with-I* (resp. *Z-bass-compatible-with-V*): Both notes $\underline{4}$ and $\underline{7}$ of the tonality that would be implied if the bass of Z is I (resp. V) are present in the four beats before Z
- *Z-bass-compatible-with-I-scale*: The 8 previous beats exhibits the whole scale of the same implied tonality – Temperley suggesting that such PACs with SD before V-I feel more conclusive [24].

For example, on the PAC of Figure 1, *Z-bass-compatible-with-I* and *-with-I-scale* are true (and not *-with-V*), and on the HC of Figure 2, *Z-bass-compatible-with-V* is true. However, these features may be triggered by other events close on the circle of fifths: Both *Z-bass-compatible-with-I* and *-with-I-scale* may be triggered by a previous V/V (as on Figure 2) or, in minor, when Z is actually a III in root position.

2.2 Rhythmic Features around the Arrival Point Z

These textural features intend to detect either breaks or continuation in music.

- *R-Z-strong-beat*: Z is a strong beat (beat 1 and 3 for 4/4, and beat 1 for other time signatures)
- *R-Z-same-rhythm-1* (resp. *R-Z-same-rhythm-2*): There is exactly the same sequence of durations in the one (resp. the two) beat(s) preceding Z than on the one (resp. the two) beat(s) at onset Z
- *R-Z-sustained-note*: At least one note sounding at Z started before Z
- *R-after-Z-rest-highest*, *R-after-Z-rest-lowest*, *R-after-Z-rest-middle*: There is a rest in some voice right after the note at onset Z (see Figure 1)
- *R-after-Z-one-voice-ends*: Z is the last onset in at least one voice (end of the piece)

2.3 Features on the Point Y or around it

For each arrival beat Z, we identify a point Y prior to Z supposed to pinpoint the chord "preceding" Z. For example, identifying *chord(Y)* as a dominant chord is a sign indicating a potential PAC at Z. Although V chords generally span over more than one beat, associating Y with a single beat eases the computation of features.

We thus propose to identify the point Y as the latest beat preceding Z for which the bass voice includes a sounding note, limited to one measure in the past. If the bass includes a rest just before Z, we look just before. The usual time span corresponding to the preparation of a cadence depends on the *harmonic rhythm* and varies among musical styles. The beat resolution to search the Y point should therefore depend on the corpus.

- *Y-Z-offsets-at-most-1*: Y is at most one quarter note before Z

Some features are concerned with *chord(Y)* :

- *Y-has-7* (resp. *Y-has-9*): *chord(Y)* contains $\underline{7}$ (resp. $\underline{9}$), that is the leading tone (resp. the dominant seventh or the dominant ninth) in the case of a candidate PAC
- *Y-in-V7* : *chord(Y)* is included within a dominant seventh chord
- *Y-in-V7-3* : *chord(Y)* is included within a dominant seventh chord and contains a third

Other features focus on bass moves:

- *Y'-Y-bass-moves-8ve*: The bass note preceding Y is at the same pitch but with an octave jump (expected on some V or V64 chords)

position, these pitches may differ from the actual function. For example, the top voice d on offset X on Figure 1 is the sixth $\underline{6}$ of the chord II6 but is actually the tonic of the II chord.

		pieces	voices	beats	PAC (final)	rIAC	HC
`haydn-quartets`	Haydn string quartets [22]	42 expositions	4	7173	99 (21)	(8)	70
`bach-wtc-i`	Bach fugues [9]	24 fugues	2 to 5	4739	63 (23)	24	(5)

Table 1. Corpora with manual annotations of cadences. Cadences are labeled at about 2% of the beats. We narrow to sets with significant number of cadences (PAC and HC for the Haydn corpus, PAC and PAC+rIAC for the Bach corpus).

- *Y'-Y-bass-moves-chromatic*: The bass note preceding Y is at a distance of one semitone (HC)
- *Y-Z-bass-moves-2nd-min* (resp. *Y-Z-bass-moves-2nd-Maj*)
- *Y-Z-bass-same-voice*: Bass notes of both chords are on the same voice
- *Y-Z-bass-moves-compatible-V-I* (resp. *Y-Z-bass-moves-compatible-I-V*): The bass moves by an ascending fourth or descending fifth (PAC) (resp. ascending fifth or descending fourth, HC I-V)

2.4 Features on the Cadence Preparation (Point X)

We identify the onset X as the latest beat before Y whose lowest sounding note has a different pitch (modulo octave) than the lowest note of Y. Features focus on this bass move:

- *X-Y-bass-moves-2nd-min* (V/V-V-I)
- *X-Y-bass-moves-2nd-Maj* (IV-V-I or II6-V-I)
- *X-Y-bass-moves-4th* (expected in II-V-I)

3. CLASSIFICATION PROCESS

A model is built in order to reflect the correlation between the features listed in Section 2 and the occurrences of cadences in corpora. These corpora bear manual annotations indicating the position of PAC, rIAC and HC. Assuming that the arrival points of cadences do not fall between beats, each beat (quarter note, or three eights depending on the time signature) of each piece is described by:

- a *vector of boolean values* corresponding to the set of features and computed from the musical score,
- a boolean *class* specifying whether the beat is annotated in the reference as a PAC/rIAC/HC or not.

This way of representing data enables us to reformulate cadence detection as a *classification task*. To avoid overfitting, each dataset is randomly divided into two subsets: a *training set* used to train a classifier and a *test set* left to evaluate the classifier performance at the end. The classifier and the value of its hyper-parameters have been selected by performing *Leave-One-Piece-Out cross-validation* over the training set. This is done by evaluating the classification on each piece of the training set by a classifier trained on the remaining pieces of the training set. Indeed, the traditional *Leave-One-Out (LOO)* cross-validation approach that would consist in leaving only *one beat* of one piece out of the training set would result here in overfitting due to intra-piece musical repetitions.

4. EXPERIMENTS AND DISCUSSION

4.1 Corpora and Implementations

Table 1 shows the corpora which was used in this study. The corpus `bach-wtc-i` includes the 24 fugues of the first book of the Well-Tempered-Clavier by J.-S. Bach. Cadence annotations were taken from our previous work [9]. The corpus `haydn-quartets` includes 42 expositions from movements of Haydn string quartets in sonata form, annotated with cadences by Sears and colleagues [22]. Even if these annotated corpora model cadences in the light of a global analysis of the form, we have used them as a benchmark on our local feature-based detection. Only a minority of annotated PAC are *final* in the sense that they are included in the last four measures of the piece (or of the exposition).

Pieces were downloaded as voice-separated `.krn` files from `kern.ccarh.org` [11]. Note that the features proposed here could also apply to non-separated files, except for *after-Z-rest-** and *Y-Z-bass-same-voice*. In this case, features on voice leading would only check that the coming note or the suspended note is found at the right place in the polyphonic texture.

For each beat Z (and their related onsets X, Y), the features described in Section 2 are extracted using code based on the Python framework `music21` [6]. Points Y and X are searched at a beat resolution of a quarter note (Haydn) or eight note (Bach, see Figure 3). Classifiers were computed thanks to the `scikit-learn` framework [8].

4.2 Discussion on Feature Statistics

Table 2 shows tallies of features, their correlation with cadences as well as an estimation of their significance. Many features are significant in both corpora, despite differences in musical style. Unsurprisingly, features *R-Z-strong-beat*, *Y-Z-bass-moves-compatible-V-I*, *Z-perfect-triad-or-sus4* and *Z-highest-note-is-1* are activated nearly for every PAC. Note that PAC lacking the fifth leap are the ones where the bass passes by another note before tonic resolution. Rhythmic and break features are also quite significant. Some features differ between corpora. For example, *R-Z-sustained-note* is absent in nearly all PACs in the Haydn corpus, whereas it can be found in some PACs in Bach fugues due to the contrapuntal writing.

We were expecting to find more *suspensions* for both PAC and HC as a way to retain tension before the ultimate resolution but they do not appear significantly in these corpora. We also notably lack strong significant features for HC. Indeed, the Y-Z bass move in a HC is variable (it is typically similar to X-Y moves in PAC).

		bach-wtc-i			haydn-quartets		
	Features	beats	PAC	rIAC	beats	PAC	HC
Rythmic features R	*R-Z-strong-beat*	1920	**60*** / 25	**24*** / 9	3126	**98*** / 43	**70*** / 30
	R-Z-same-rhythm-1	394	1 / 5	· / 1	1254	_2*_ / 17	_2*_ / 12
	R-Z-same-rhythm-2	176	· / 2	· / 0	448	_0_ / 6	1 / 4
	R-Z-sustained-note	2341	_14*_ / 31	_5_ / 11	2521	_1*_ / 34	_8*_ / 24
	R-after-Z-rest-highest	166	**14*** / 2	1 / 0	501	**56*** / 6	10 / 4
	R-after-Z-rest-middle	477	**22*** / 6	**9*** / 2	1227	**72*** / 16	**35*** / 11
	R-after-Z-rest-lowest	194	**15*** / 2	**13*** / 0	1130	**59*** / 15	**34*** / 11
	R-after-Z-one-voice-ends	180	**19*** / 2	2 / 0	·	· / 0	· / 0
Arrival point Z	*Z-in-perfect-major-triad*	1167	**43*** / 15	12 / 5	2760	**94*** / 38	**53*** / 26
	Z-in-perfect-triad	1819	**56*** / 24	**19*** / 9	3256	**97*** / 44	**53*** / 31
	Z-in-perfect-triad-or-sus4	2078	**62*** / 27	**20*** / 10	3434	**97*** / 47	**55*** / 33
	Z-is-sus4	680	**20*** / 9	1 / 3	1308	14 / 18	_4_ / 12
	Z-highest-is-1	592	**55*** / 7	1 / 2	1765	**96*** / 24	19 / 17
	Z-highest-is-3	1488	_1*_ / 19	**21*** / 7	1596	_1*_ / 22	**28*** / 15
	Z-bass-compatible-with-I	1724	**63*** / 22	**23*** / 8	2279	**98*** / 31	**56*** / 22
	Z-bass-compatible-with-V	1265	_8_ / 16	4 / 6	1616	_3*_ / 22	**44*** / 15
	Z-bass-compatible-with-I-scale	1902	**63*** / 25	**22*** / 9	2104	**91*** / 29	**46*** / 20
	Z-1-comes-from-7	663	**52*** / 8	**15*** / 3	1016	**89*** / 14	**30*** / 9
	Z-1-comes-from-1	180	**13*** / 2	1 / 0	828	9 / 11	_0*_ / 8
	Z-1-comes-from-2	523	**23*** / 6	7 / 2	893	**65*** / 12	**27*** / 8
	Z-3-comes-from-4	1078	25 / 14	**16*** / 5	1488	**72*** / 20	**45*** / 14
	Z-4-comes-from-5	197	4 / 2	· / 0	291	· / 4	9 / 2
	Z-5-comes-from-5	153	**9*** / 2	· / 0	769	_2_ / 10	13 / 7
	Z-5-comes-from-6	510	1 / 6	2 / 2	495	_0_ / 6	9 / 4
	Z-6-comes-from-7	200	· / 2	· / 1	130	· / 1	· / 1
	Z-2-moves-to-1	57	· / 0	· / 0	90	2 / 1	1 / 0
	Z-4-moves-to-3	160	2 / 2	1 / 0	340	2 / 4	**11*** / 3
	Z-6-moves-to-5	138	1 / 1	· / 0	180	· / 2	**8*** / 1
	Z-7-moves-to-1	7	· / 0	· / 0	105	2 / 1	1 / 1
Point Y	*Y-in-V7*	1267	**52*** / 16	**17*** / 6	3290	**81*** / 45	_15*_ / 32
	Y-in-V7-3	721	**44*** / 9	**14*** / 3	2413	**69*** / 33	14 / 23
	Y-has-7	554	**22*** / 7	7 / 2	767	**66*** / 10	8 / 7
	Y-has-9	607	_1_ / 8	4 / 3	486	2 / 6	5 / 4
	Y-Z-offsets-at-most-1	4525	63 / 60	24 / 22	5668	90 / 78	**66*** / 55
	Y-Z-bass-same-voice	4270	63 / 56	24 / 21	5297	**98*** / 73	**70*** / 51
	Y-Z-bass-moves-2nd-min	1313	_0*_ / 17	_0*_ / 6	1328	_1*_ / 18	**35*** / 12
	Y-Z-bass-moves-2nd-Maj	880	_0*_ / 11	· / 4	559	_0*_ / 7	**28*** / 5
	Y-Z-bass-moves-compatible-I-V	125	1 / 1	· / 0	448	2 / 6	6 / 4
	Y-Z-bass-moves-compatible-V-I	512	**62*** / 6	**23*** / 2	578	**95*** / 7	6 / 5
	Y'-Y-bass-moves-chromatic	1139	_6_ / 15	2 / 5	2050	_10*_ / 28	33 / 20
	Y'-Y-bass-moves-8ve	193	**29*** / 2	**7*** / 0	522	**22*** / 7	6 / 5
Point X	*X-Y-bass-moves-2nd-min*	433	2 / 5	1 / 2	1060	10 / 14	10 / 10
	X-Y-bass-moves-2nd-Maj	568	**25*** / 7	**12*** / 2	803	**65*** / 11	5 / 7
	X-Y-bass-moves-4th	670	11 / 8	4 / 3	1626	_4*_ / 22	9 / 15
	Total	4739	63	24	7173	99	70

Table 2. Feature tallies for PAC (both corpora), rIAC (Bach corpus) and HC (Haydn corpus). The table shows, for each feature, the number of beats where this feature occurs (*all* beats, cadential points or not), followed by its number of occurrences on beats labeled as cadences in the reference annotation, as well as, in small, its expected number should the feature be random and uniformly distributed across the beats. (· means 0, and not significant). For example, there are 70 HC out of 7173 beats in the Haydn quartets corpus. There are 35 beats corresponding to a HC with the feature *Y-Z-bass-2nd-min*, out of 1328 beats with this feature, and compared to only 12 beats should this feature be random.

For each feature and each cadence type, p-values are estimated by an exact Fisher test computed by the Python `scipy` package. Fisher tests are computed independently. To account for the large number of tests, only features with p-values under .001 (**bold,** *) can be considered as significant, either by their absence (*italic*) or their presence. For example, the feature *Y-Z-bass-2nd-min* is significantly absent in PACs of both corpora ($p < 10^{-7}$) and significantly present in HCs of the Haydn corpus ($p < 10^{-8}$).

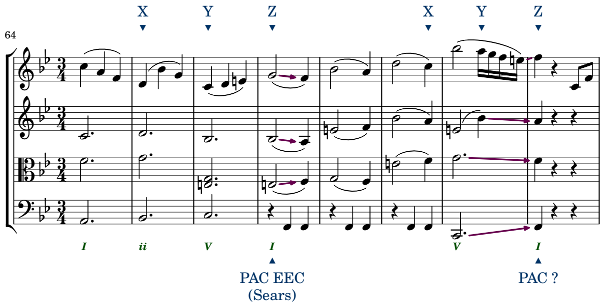

Figure 4. Haydn, op. 55/3, i, potential PACs at m67 and m71. The PAC at m67 is hard to detect with the silence at the bass. In their global analysis of the form, Sears et. al see the end of the secondary theme (called the EEC, for *Essential Expositional Closure* by [10]) at m67 and discard any further PAC in the following concluding section [22]: The PAC candidate at m71, found by the proposed strategy, is thus counted here as a FP. It could be debated whether the EEC is indeed at m67 (first cadential I, but weakened by the bass rest) or rather at m71 (cadential feeling augmented by the following rests and bass note on upbeat, m67 considered as an evaded cadence).

4.3 Learning Process

A linear Support Vector Machine (SVM) classifier was trained on each training set as explained in Section 3, splitting the feature space with a hyperplane [5]. As datasets are *unbalanced* (about 98% of the beats are "non-cadential"), we assigned stronger weights to data belonging to the under-represented class, here the cadential beats. Other classifying algorithms such as k-nearest-neighbor or decision trees were tested and turned out to provide comparable or inferior results.

4.4 Discussion on Detection Results

Table 3 shows the comparison between the predictions of each classifier on the test set of each corpus and the reference annotations. The detection of PAC is good, with more than 75% PAC detected and a low false positive rate ($< 1\%$). Note that we previously reported 82% of PAC detection in fugues [9] but with manual hard-coded rules that may have resulted in overfitting.

False positives (FP) beats may still have many cadential features. An inspection of the 28 PAC reported as FP in the Haydn corpus shows that at least 5 FP can be seen as actual cadences, for example measure 71 in Haydn op. 55/3, i, shown on Figure 4. Other notable sources of FP are tonic chords following actual HC cadences activating significant features for PAC. The same Figure 4 shows an example of FN, where a silence in the bass makes the computation of many features fail.

Adding rIAC (Bach corpus) lowers the results, but there may be too few such cadences to efficiently build the model. The detection of HC is difficult (Haydn corpus), as there is not a single feature applicable to every case. Half of them are detected, with about 2% FP.

		beats	ref	TP	FP	FN	F_1
`haydn-quartets`	PAC	3583	51	42	28	9	0.69
(21 quatuors)	HC	3583	32	18	73	14	0.29
`bach-wtc-i`	PAC	2357	36	26	3	10	0.80
(12 fugues)	PAC+rIAC	2357	46	30	12	16	0.68

Table 3. Detection of cadences on the test sets of both corpora using all features: Number of beats annotated in the reference annotation (ref), true positives (TP), false positives (FP), false negatives (FN), and F_1 measure (harmonic mean of the recall and the precision).

	`haydn-quartets`		`bach-wtc-i`	
	PAC	HC	PAC	PAC+rIAC
All features XYZR	0.69	0.29	0.80	0.68
Features YZR	0.69	0.27	0.71	0.68
Features ZR	0.59	0.24	0.52	0.34
Features XYZ	0.72	0.25	0.74	0.54

Table 4. F_1 measure while detecting cadences on the test sets of both corpora with different sets of features.

Table 4 further studies these results while varying the set of considered features. Some features in Z already consider the past. Nevertheless, the features around Y are essential to improve the overall detection. Features on X bring a small but significant gain for PAC. Rhythmic features (R) bring an improvement especially for HC, in particular with *R-Z-strong-beat* that correctly filters out more than half of the beats.

5. CONCLUSION

Different musical clues give the cadential impression of a "breath in music". We evaluated cadential features on and around three onsets at the arrival and in the preparation of cadences. Without performing any chord segmentation, these features describe the underlying harmony, the voice leading as well as structural aspects of the music.

These features reflect common knowledge of music: we have shown that some of them are specific to cadential points. They make it possible to learn how to predict cadences – PAC/rIAC, and, to a lesser extent, HC – in corpora with reference annotations. Such features may also be used in other systematic musicology approaches.

Perspectives include the extension of our set of features to cadential and non-cadential positions. Some features could be not necessarily theory driven and could possibly have metric values. Coupled with automatic selection, this could lead to the discovery of significant but unexpected features. More generally, the method used to identify points X and Y could be compared to other heuristics. Cadence preparations could for example be described by features regarding contiguous "spans" of onsets rather than single onsets X and Y, in order to improve the harmony relevance of the model. Research along these lines could significantly improve HC detection.

Acknowledgements. The authors are grateful to Robin Alais, Mikaela Keller, Marie Perrier, and the Algomus team for fruitful discussions and proofreading of the manuscript. We also thank the anonymous reviewers for their insightful comments. This work is partially funded by French CPER MAuVE (ERDF, Région Hauts-de-France) and by a grant from the French Research Agency (ANR-11-EQPX-0023 IRDIVE).

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