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Expressive Concatenative Synthesis by Reusing Samples from Real Performance Recordings

The manipulation of sound properties such as timing, amplitude, timbre, and pitch by different performers and styles is an important fact not to be missed when approaching instrumental sound synthesis. Expressive music performance studies the manipulation of such sound properties in an attempt to understand expression, so that it can be applied to sound synthesis for obtaining expressive instrumental sound in the shape of a synthetic performance.

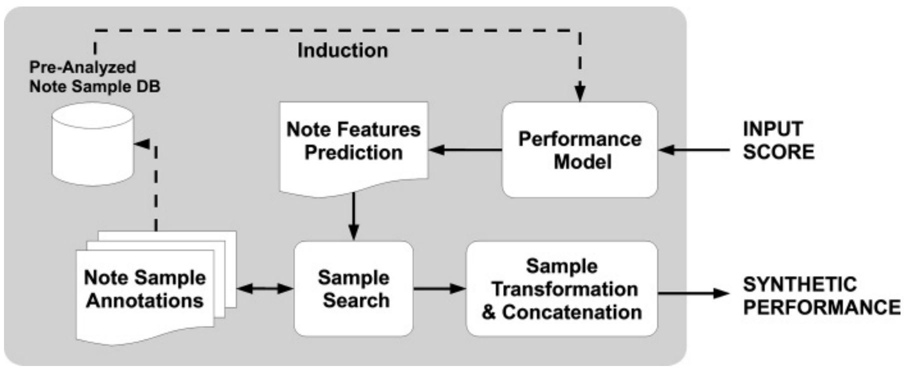
During the past few years, the availability of technology for high-fidelity sound synthesis based on samples has pushed the consolidation of sample-based concatenative synthesizers as the most popular and flexible mean of reconstructing the sound of traditional musical instruments (Schwarz 2006). Recent implementations (Bonada and Serra 2007; Lindemann 2007) have yielded high-quality sound synthesis and often offer a wide range of synthesis parameters, including some related to expression, normally concerning either a note or the transition between two successive notes. However, these parameters must in most of cases be tuned manually, which is extremely time consuming and requires considerable effort and knowledge from the user. Ideally, expression-related parameters should be tuned automatically by the synthesis system by applying some prior knowledge about the expressive transformations a particular musician introduces when performing a piece.

In the past, such knowledge has been traditionally obtained by empirically studying real expressive performance recordings (e.g., Repp 1992; Todd 1992; Friberg et al. 1998), and more recently, by applying machine-learning techniques (e.g., Widmer 2001; Lopez de Mantaras and Arcos 2002; Ramirez, Hazan, and Maestre 2006a, 2006b). Machine-learning approaches to expressive-performance modeling reside on top of a symbolic representation to which machine-learning techniques can be applied. This symbolic representation can be easier to obtain, as it is for the case of excitation-instantaneous musical instruments (e.g., piano), or more difficult to obtain, as is the case for excitation-continuous musical instruments (e.g., wind or bowed-string instruments). In excitation-continuous instruments, both excitation and control of the sound-production mechanisms are achieved by continuous modulations; thus, the extraction of symbolic-level information requires the analysis of the recorded audio stream instead of measuring note durations or dynamics from MIDI-like representations.

Here we describe an approach to the expressive synthesis of jazz saxophone melodies that reuses audio recordings and carefully concatenates note samples. The aim is to generate an expressive audio sequence from the analysis of an arbitrary input score using a previously induced performance model and an annotated saxophone note database extracted from real performances. We push the idea of using the same corpus for both inducing an expressive performance model and synthesizing sound by concatenating samples in the corpus. Therefore, a connection between the performers' instrument sound and performance characteristics is kept during the synthesis process.

The architecture of our system, depicted in Figure 1, can be briefly summarized as follows. First, given a set of expressive performance recordings, we obtain a description of the audio by carrying out segmentation and characterization at different temporal levels (note, intra-note, note-to-note transition) and build an annotated database of pre-analyzed note segments for later use in the synthesis stage. A performance model is trained using inductive logic-programming techniques by matching the score to the description of the performances obtained while constructing the database. For synthesizing expressive audio, the input score is first analyzed, and a set

Figure 1. Schematic view of the system architecture.



of descriptors is extracted. From such a description, the performance model obtains an enriched score including expression–related parameters. Finally, by considering the enriched score, the most suitable note samples from the database are retrieved, transformed, and concatenated. This article presents an extended description of an off-line audio analysis/synthesis application based on previous work (Maestre et al. 2006; Ramirez, Hazan, and Maestre 2006b; Ramirez et al. 2007).

The rest of the article is organized as follows. The next section describes related work, from sample-based concatenative synthesis to expressive performance modeling. The following sections present the audio analysis carried out to annotate our database of performance recordings, and the details of the database-construction process. Next, we reveal the insights of building the expressive performance model from the database annotations. Then, we present the audio synthesis methods, giving special emphasis to the sample search. Finally, we present some conclusions and state further work for future improvements.

Related Work

Sample-Based Concatenative Synthesis

Sample-based concatenative synthesis is an emerging approach to sound generation based on concatenating short audio excerpts (samples) from a database to achieve a desired sonic result given a target description (e.g., a score) or sound (Schwarz 2000). Although sampling cannot be strictly considered as a sound-synthesis technique, it provides, in terms of sound quality and realism, one of the most successful approaches for reproducing real-world musical sound (Bonada and Serra 2007). The main reason is that the naturalness of sounds is maintained, because the audio slices used for concatenation are actual samples collected from realistic contexts to which just some meaningful sound transformations need to be applied, both to smooth concatenations and to match the input specification given ad hoc distance metrics. Moreover, for greater database sizes, it is more probable that a closely matching sample will be found, so the need to apply transformations is reduced (Schwarz 2006). The samples can be non-uniform—i.e., they can comprise any duration from a sound snippet, through an entire instrumental note, up to a whole phrase. Even though it is customary to consider homogeneous sizes and types of samples, and sometimes a sample is just a short time window of the signal used in conjunction with some spectral analyses and overlap-add synthesis (Schwarz 2007), we approach the synthesis of melodies by concatenating note samples, each one corresponding to an entire performed note of arbitrary duration.

Apart from the transformations to be applied to the retrieved samples, which might end up resulting in a degradation of the sound quality when the target features and the retrieved sample are far apart given a particular distance metric, the way in which the most convenient sequence of samples is selected from the database is important when trying to maintain the feeling of sound continuity. This issue has been treated from an optimization perspective in general-purpose, concatenative-synthesis applications for music and speech, where not just the descriptions of the samples are considered, but also their context (Hunt and Black 1996; Aucouturier and Pachet 2006). In our work, we have similarly placed emphasis on respecting the sample's original context during the retrieval stage.

Concatenative sound synthesis (CSS) has been used and studied for some time, with its first applications found in the early text-to-speech (TTS) synthesis systems, which transform input text into speech sound signals (Klatt 1983; Prudon 2003). Although speech synthesis and music synthesis have different objectives (intelligibility and naturalness vs. expressivity and musical flexibility), similar principles can be found in speech synthesis and musical sound synthesis, and thus important parts of the methodology have traditionally been shared (Sagisaka 1988; Beller et al. 2005). Although used for strictly musical purposes in many different ways, only recently has sample-based CSS has been formally defined in a purely musical context.

According to Schwarz (2007), one of the main applications of corpus-based CSS is *high-level instrument synthesis*, where natural-sounding transitions can be synthesized by selecting samples from matching contexts. This is a particularly challenging issue for the case of excitation-continuous instruments (e.g., wind instruments). Some relevant implementations have appeared recently, from which we will briefly review those that resulted the most inspiring or closely related for the work presented in this article. For a comprehensive review of CSS, we refer the reader to Schwarz (2006).

One of the most important and broad contributions to the topic of CSS is Schwarz's PhD dissertation (2004). In addition to formally defining several important aspects involved and unifying concepts, this work introduces a general-purpose, corpus-based system based on data-driven unit selection. In his general framework, the target specification is obtained from either a symbolic score or audio analysis as a sequence of descriptor values. In our case, we introduce an expressivity component when constructing an enhanced symbolic score, generated as an enrichment of an input musical score, by means of performance knowledge induced from the database itself. In our system, selection of the best sample sequence is accomplished by distance functions and a path-search sample-selection algorithm, including some constraint-satisfaction techniques. One of the extensions that we introduce is that the knowledge of our expressive-performance modeling component has been induced from the synthesis database itself, and therefore there is a strong connection between the expressivity and synthesis modules of our system. Thus, we could make the "corpus-based" term also cover the induced expressive performance model.

Staying on the musical side but particularly closer to the speech, we find the singing-voice synthesizer developed by Bonada and Loscos (2003) and Bonada and Serra (2007). This system, developed over several years, has become the most successful singing voice commercial synthesizer: Yamaha's Vocaloid (www.vocaloid.com). The system, based on phase-vocoder techniques and spectral concatenation, searches the most convenient sequence of diphonemes (samples) of an annotated database of singing voice excerpts, recorded at different tempi and dynamics, to render a virtual performance out of the lyrics and an input score. Although based on complex articulation-oriented concatenation constraints, sample selection relies on a full search of sample candidates, examining the context of two score notes. Traits of the original voice and articulation characteristics are impressively retained after transformations, owing to a refined source-filter spectral model. However, the expressive possibilities are limited to manual editing of some pitch and dynamics curves, or adding pre-defined transformation templates for including expressive resources. In this article, we use explicit expressivity knowledge induced from the synthesis corpus, and we later automatically apply it when selecting and transforming samples.

The approach introduced by Lindemann (2007), referred to as reconstructive phrase synthesis (RPM), achieves musical expressivity through a blend of functional additive synthesis and phrase-oriented parametric concatenative synthesis that can be used both off-line from a score, and real-time from standard MIDI performance controls. This approach has resulted in a successful commercial application of concatenative sound synthesis: Synful (www.synful.com). Slow-varying harmonic components are directly predicted from the input score or controls via spectral nonlinear prediction based on neural networks. Then, an annotated database containing the rapidly varying components of a selection of the most representative phrases is searched to get the most appropriate sequence of samples taking into account local contexts spanning several notes. Those rapidly varying components are added to the low-frequency ones to form the harmonic part of the sound. Noisy elements, also stored in the database, are added on top of the concatenated harmonic sound. Although the results obtained for excitation-continuous instruments are impressive, especially in attacks and transitions, this system again lacks an explicit high-level expressive component representing the deviations or nuances that a particular performer introduces in particular contexts.

Expressive Performance Modeling

Understanding and formalizing expressive music performance is an extremely challenging problem that in the past has been studied from different perspectives (e.g., Seashore 1936; Gabrielsson 1999; Bresin 2002). The main approaches to empirically studying expressive performance have been based on statistical analysis (e.g., Repp 1992), mathematical modeling (e.g. Todd 1992), and analysis-by-synthesis (e.g., Friberg et al. 1998). In each of these approaches, a human is responsible for devising a theory or mathematical model that captures different aspects of expressive performance. The theory or model is later tested on real performance data to determine its accuracy. Recently, machine-learning-based approaches have been proposed. The most related work was undertaken by Arcos, de Mantaras, and Serra (1997), Lopez de Mantaras and Arcos (2002), Ramirez, Hazan, and Maestre (2006a, 2006b), and Ramirez et al. (2008).

Arcos, de Mantaras, and Serra (1997) and Lopez de Mantaras and Arcos (2002) report on SaxEx, a performance system capable of generating expressive solo performances in jazz. Their system is based on case-based reasoning, a type of analogical reasoning where problems are solved by reusing the solutions of similar, previously solved problems. To generate expressive solo performances, the case-based reasoning system retrieves, from a memory containing expressive interpretations, those notes that are similar to the input inexpressive notes. However, there is no analysis at the intra-note level, which means that the note's instantaneous amplitude and timbre is not considered.

Ramirez et al. (2008) explore and compare different machine-learning techniques for inducing both an interpretable expressive performance model (characterized by a set of rules) and a generative expressive performance model. Based on this, they describe a performance system capable of generating expressive monophonic jazz performances and providing "explanations" of the expressive transformations it performs. This work extends the work of Ramirez, Hazan, and Maestre (2006a, 2006b) by incorporating inter-note analysis of the expressive recordings in the machine-learning and synthesis components.

Traditionally, research in expressive performance using machine-learning techniques has focused on classical solo piano music (Widmer 2001) where the tempo of the performed pieces is not constant and melody alterations are not permitted. (In classical music, melody alterations are often considered performance errors.) Thus, in such works, the focus is on global tempo and energy (loudness) transformations. We are interested in note-level timing and energy transformations as well as in melody ornamentations that are a very important expressive resource in jazz. Moreover, we deal with the saxophone as an example of an excitation-continuous instrument.

Dealing with excitation-continuous musical instruments in particular, we find several relevant studies also very relevant to the work presented here. In Canazza et al. (2004), the authors present an approach to modify the expressive content of a performance in a gradual way among different moods. They use a linear model to carry out the alterations based on previous segmentation, and they modify the melodies at both the symbolic and audio-signal levels. Instead, we aim here to model the expressivity of particular performers by picking up notes from their own performance recordings and applying rules discovered from the same data.

Trumpet performance is studied in Dannenberg, Pellerin, and Derenyi (1998) by computing amplitude descriptors, and the statistical analysis techniques used for analyzing trumpet envelopes led the authors to find significant envelope groupings, an approach that is similar to the database annotation that we use. Afterward, they extended the work to a system that combined instrument and performance models (Danneberg and Derenyi 1998), although the authors did not take into account duration, onset deviation, or ornamentations. The authors followed a similar line in Dubnov and Rodet (1998), who perform analysis of sound behavior as it occurs in the course of an actual performance of several solo works to build a model capable of reproducing aspects of sound textures originating in the performer's expressive inflections. However, these models are devised after a preliminary statistical analysis rather than being induced from the training data, possibly because of the difficulties in parameterizing continuous data from real-world recordings.

Simon et al. (2005) introduce the use of concatenative synthesis for obtaining, given an input MIDI score, a new performance from a monophonic recording and its MIDI transcription. Their use of a recorded melody is interesting, as is their methodology for searching samples (single notes or pairs of notes), but the system lacks any expressive knowledge to be applied.

Preliminary results of the work we present in this article were introduced in Maestre et al. (2006), where the authors built a concatenative synthesizer for rendering jazz saxophone melodies from a database of recorded performances and an expressivity model induced from the same database that is used for synthesis. Although promising results were achieved, issues like context-aware expressivity knowledge induction and sample selection needed to be further improved. Here we extend the work with significant improvements in sample selection and by giving a more detailed description of each part of the whole system.

Audio Analysis

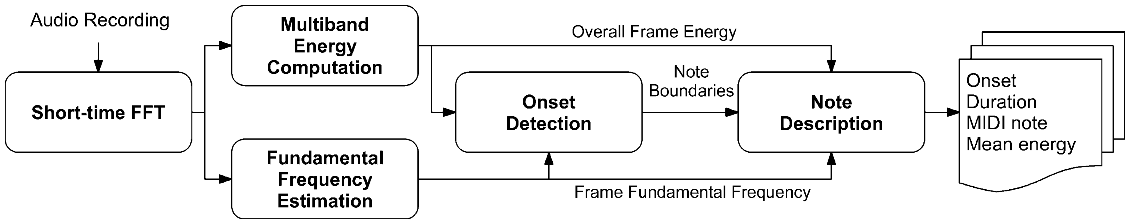
In this section, we give the details of the methods we used for the analysis of the recordings of expressive performances. First, a set of low-level descriptors is computed for each frame. Then, we perform note segmentation using low-level descriptor values and fundamental-frequency estimation. Using note boundaries and low-level descriptors, we perform energy-based intra-note segmentation, posterior intra-note-segment amplitude-envelope characterization, and a transition description. This information will be used for both modeling expressive performance and annotating the sample database used later in the synthesis stage. Audio analysis data obtained with these methods has already been used for expressive-performance rule induction (Ramirez, Hazan, and Maestre 2006a), intra-note feature prediction (Ramirez, Hazan, and Maestre 2005), and genetic programming-based expressive-performance modeling (Ramirez et al. 2008).

The contents of the section can be summarized as follows. First, we present the audio description scheme we followed. Then, the procedures for melodic description, musical analysis, and intra-note/inter-note segmentation and description are detailed.

Description Scheme

To define a structured set of audio descriptors able to provide information about the expressivity introduced in the performance, we define and extract descriptors related to different temporal scales. Some features are defined as instantaneous or related to an analysis frame, such as energy, fundamental frequency, spectral centroid, and spectral tilt. We also obtain intra-note/inter-note segment features, i.e., descriptors attached to a certain intra-note segment (attack, sustain and release segments, considering the classical ADSR model of, e.g., Bernstein and Cooper [1976], or transition segment). After observing the shape of the energy envelope of our recorded notes, we realized that most of the notes did not present a clear decay segment but rather a fairly constant-slope sustain segment. Thus, we decided not to consider decay and

Figure 2. Schematic view of the melodic-description process. Note onsets are extracted based on the study of energy and fundamental frequency.



sustain segments separately, but just a linear sustain segment with variable slope. Finally, Note features or descriptors attached to a certain note are also extracted. We considered that the proposed features set up a simple but concise scheme for representing the typical expressive nuances in which we are interested, adapted to our application context. For the complete list of descriptors, see Table 1 in the "Database Construction" section, subsequently.

Melodic Description

The first step once the low-level descriptors have been extracted for each frame is to get a melodic description of the audio phrases consisting of the exact onset and duration of notes, along with the corresponding MIDI equivalent pitch. We base our melody transcription on the extraction of two different onset streams, the first based on energy, and the second based on fundamental frequency. Energy onsets are first detected following a band-wise algorithm that uses psychoacoustic knowledge (Klapuri 1999). In a second step, fundamental-frequency transitions are also detected. Finally, both results are merged to find note boundaries (see Figure 2). We compute note descriptors using the note boundaries and the low-level descriptors values. The low-level descriptors associated with a particular note segment are computed by averaging the frame values within this note segment. Pitch histograms are used to compute the pitch note of each note segment. An extended explanation of the methods we use for melodic description can be found in Gomez et al. (2003).

Musical Analysis

It is widely recognized that expressive performance is a multilevel phenomenon and that humans perform music considering a number of abstract musical structures. After having computed the note descriptors, and as a first step toward providing an abstract structure for the recordings under study, we decided to use Narmour's (1990) theory of perception and cognition of melodies to analyze the performances.

The implication/realization model proposed by Narmour is a theory of perception and cognition of melodies. The theory states that a melodic musical line continuously causes listeners to generate expectations of how the melody should continue. The nature of these expectations in an individual are motivated by two types of sources: innate and learned. According to Narmour, on the one hand, we are all born with innate information that suggests to us how a particular melody should continue. On the other hand, learned factors are due to exposure to music throughout our lives and familiarity with musical styles and particular melodies. According to Narmour, any two consecutively perceived notes constitute a melodic interval, and if this interval is not conceived as complete, it is an *implicative interval*, i.e., an interval that implies a subsequent interval with certain characteristics. That is to say, some notes are more likely than others to follow the implicative interval. Two main principles recognized by Narmour concern *registral direction* and *intervallic difference*. The principle of registral direction states that small intervals imply an interval in the same registral direction (a small upward interval implies another upward interval and analogously for downward intervals), and large intervals imply a change in registral direction (a large upward interval implies a downward interval and analogously for downward intervals). The principle of intervallic difference states that a small (five semitones or less) interval implies a similarly sized interval (plus or minus two semitones), and a large interval (seven semitones or more) implies a smaller

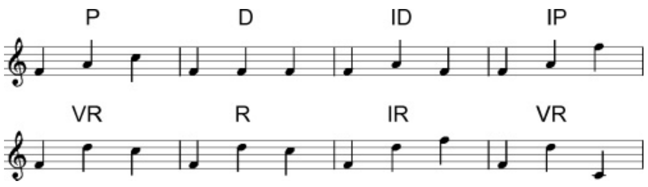


Figure 3. Prototypical Narmour structures.

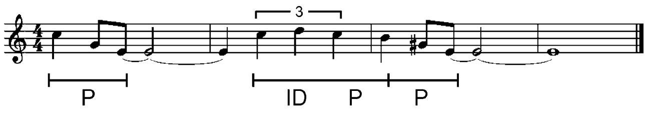


Figure 4. Narmour analysis of All of Me.

interval. Based on these two principles, melodic patterns or groups can be identified that either satisfy or violate the implication as predicted by the principles. Such patterns are called structures and are labeled to denote characteristics in terms of registral direction and intervallic difference.

Figure 3 shows prototypical Narmour structures. A note in a melody often belongs to more than one structure. Thus, a description of a melody as a sequence of Narmour structures consists of a list of overlapping structures. We parse each melody in the training data to automatically generate an implication/realization analysis of the pieces. Figure 4 shows the analysis for a fragment of a melody.

Extraction of Intra-Note and Transition Features

Once we segment the audio signal into notes, we perform a characterization of each of the notes in terms of its internal features, and of each of the note-to-note transitions based on the intra-note features extracted for both notes involved in the transition.

The intra-note segmentation method is based on the study of the energy envelope contour of the note. Once onsets and offsets are located, we study the instantaneous energy values of the analysis frames corresponding to each note. This study is carried out by analyzing the envelope curvature and characterizing its shape to estimate the limits of the intra-note segments under consideration. The model used is schematically represented in Figure 5. To extract the limits of the three characteristic segments, we perform automatic search by looking for the energy envelopes' second-derivative extrema in a way similar to that presented in Jensen (1999). However, in Jensen, partial amplitude envelopes are modeled for isolated sounds. Here, we instead analyze the global energy envelope of notes in their musical context, considering two (*attack* and *release*) or three (*attack*, *sustain*, and *release*) linear segments, depending on the appearance of sustain segment. Transition segments are considered as including release and attack segments of adjacent notes. We described in detail and evaluated the procedure for carrying out intra-note segmentation in Maestre and Gomez (2005).

Once we have found the intra-note segment limits, we describe each one by its duration (absolute and relative to note duration), start and end times, initial and final energy values (absolute and relative to note maximum), and slope. We also extract two spectral descriptors corresponding to the sustain segment: spectral centroid and spectral tilt (Peeters 2004). These are computed as an average along the sustain segment, or else as a single value at the end of the attack segment when a sustain segment has not been detected. Figure 6 shows the linear approximation of energy envelope of a real excerpt obtained by using the methods presented here.

To characterize note detachment, we also extract some features of the note-to-note transitions describing how two notes are detached. For two consecutive notes, we consider the transition segment starting at the beginning of the first note's release and finishing at the end of the following note's attack. Both the energy envelope and the fundamental-frequency contour (schematically represented by E_{XX} and f_0 in Figure 7) during transitions are studied to extract descriptors related to articulation. We measure the energy envelope minimum position t_c (see also Figure 7) with respect to the transition duration as Equation 1. This descriptor has proven useful when reconstructing amplitude envelopes during transitions.

$$E_{TPOS_{min}} = \frac{t_c}{t_{end} - t_{init}}. \tag{1}$$

We then compute a legato descriptor as described next. First, we join start and end points on the energy-envelope contour by means of a line L_t

Figure 5. Schematic view of the energy-envelope-based intra-note segmentation that is used in this work.

Figure 6. Energy envelope of a real excerpt with intra-note segment and transition limits depicted, where the linear approximation has been superimposed.

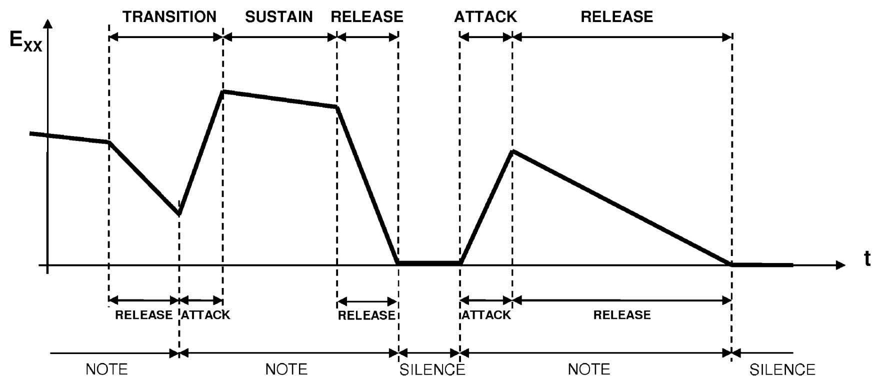


Figure 5

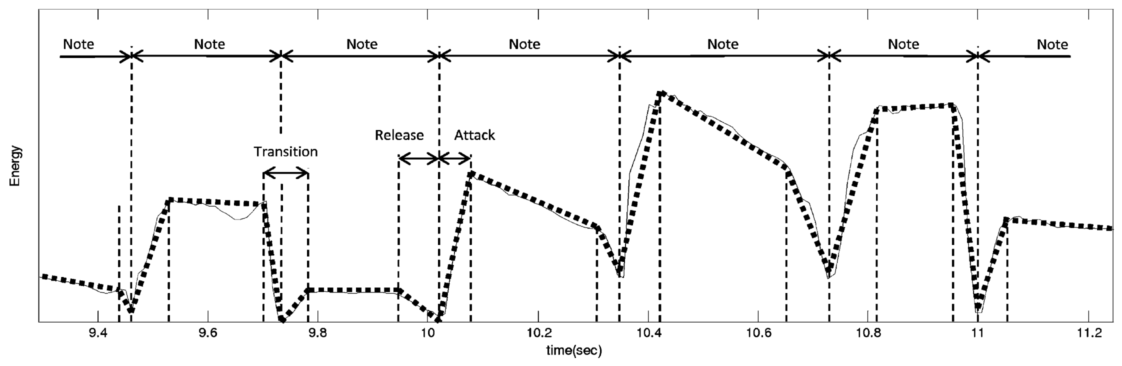


Figure 6

representing the smoothest (least detached) case of articulation. Then, we compute both the area A_2 below the energy envelope and the area A_1 between the energy envelope and the joining line L_t and define our legato descriptor as shown in Equation 2. The legato descriptor has a value of 0.0 when it is smoothest and 1.0 when it is most detached. In Maestre and Gomez (2005), we evaluate the validity of this descriptor.

$$LEG = \frac{A_1}{A_1 + A_2} = \frac{\int_{t_{init}}^{t_{end}} (L_t(t) - E_{XX}(t))dt}{\int_{t_{init}}^{t_{end}} L_t(t)dt} \qquad (2)$$

After observing fundamental-frequency contours from the recordings, pitch transitions are considered to be linear for this study (see lower part Figure 7), being characterized by measuring width and translation with respect to the position of the energy-envelope minimum and the transition length. (*Portamento* transitions, i.e., transitions incurring pitch glides significantly slower than the linear pitch transitions in our study, are not considered, as they are not present in the recordings used for constructing the database.) Pitch-transition center time t_{FC} and width W_{PT} are measured by finding the boundaries of pitch steps, studying pitch derivatives along the transition. To do so, we followed an approach analogous to the one followed for describing the energy envelope of a note: We characterize pitch contour by three linear segments using automatic segmentation adapted from the method introduced in Maestre and Gomez (2005). Pitch-transition center time t_{FC} is estimated as the midpoint of the pitch step width W_{PT}. Pitch-step width W_{PT} enriches a legato descriptor in terms of fundamental-frequency description, and it is also used for helping in the final concatenation step during the synthesis stage.

Figure 7. Schematic view of the transition-segment characterization.

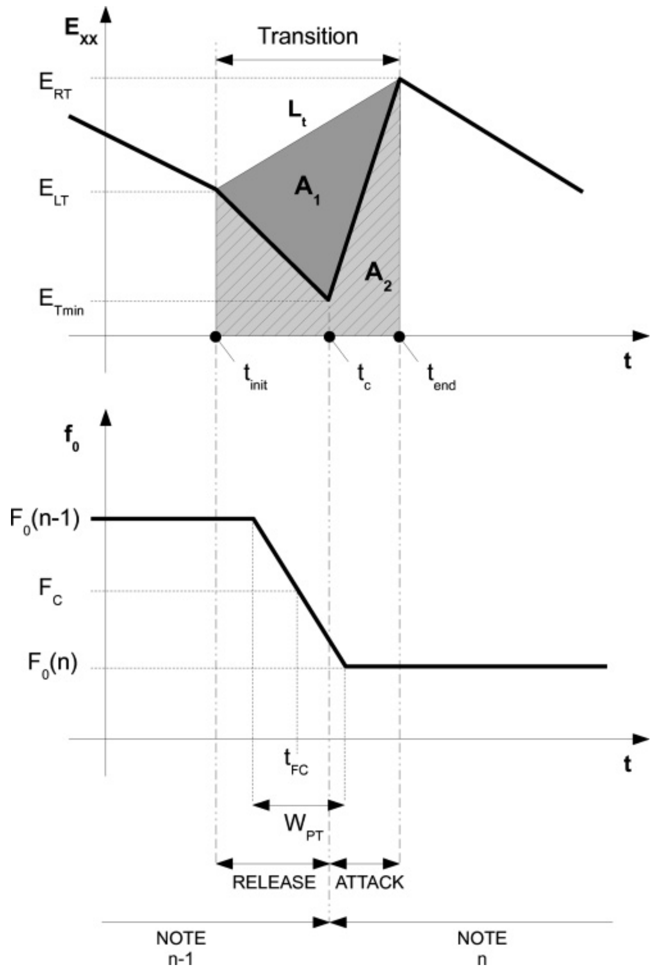
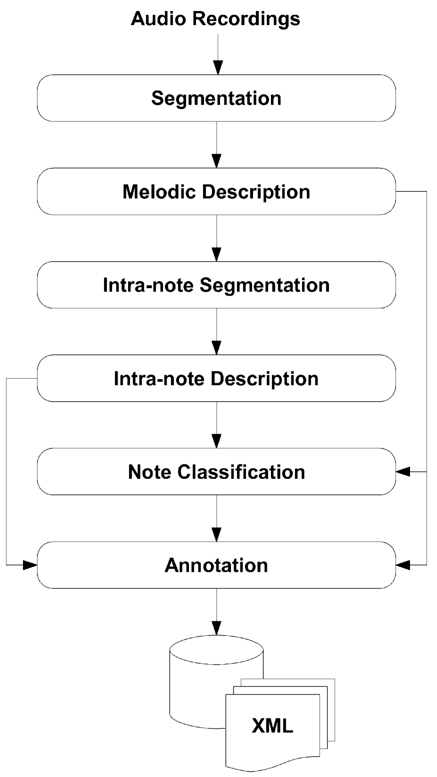


Figure 8. Database construction steps. Once the melodic description has been obtained, intra-note and transition segment annotations are attached to each note sample together with their melodic description.



Database Construction

Although currently employed in a synthesis context, the database used in this work was recorded for analysis purposes. Previous studies carried out by the authors focused on studying timing and dynamics deviations occurring during jazz saxophone performances at different tempi (Gomez et al. 2003), obtaining significant results. Later, we found it interesting to apply the obtained expressive-performance models for audio synthesis (Ramirez, Hazan, and Maestre 2006a, 2006b). In addition to using the audio recordings for inducing expressive performance models, we also aim at exploring the possibilities of using the performance-recordings database for rendering new performances using concatenative synthesis. Such a possibility became one of the key points of the methodology introduced by this work. An important issue here is the fact that dynamics or timbre nuances and ornamentations were not given any emphasis during the recordings (the performer was able to freely use such resources in each context), which led us to be able induce expressivity knowledge with no constraints, making the analysis extensible to any performance recording.

We used an audio database consisting of four jazz standards played by a professional musician at eleven different tempi around the nominal one. Most phrases were repeated to test consistency among performances. The jazz standards recorded were *Body and Soul*, *Once I Loved*, *Like Someone in Love*, and *Up Jumped Spring*—approximately 1.5 hours of recording distributed among approximately 5,000 notes. The different steps followed for the construction of the database are sketched in Figure 8.

Out of the performance recordings, we carry out both segmentation into notes and a melodic description for each phrase. Then, starting from the note segmentation, we perform intra-note segmentation into attack, sustain or release segments for each note, thus also obtaining the note-to-note transition limits. Intra-note segments and transitions are then characterized in a fourth step, following also the techniques for audio analysis outlined previously. Then, we classify notes based on their context in the performance, and also based on their amplitude envelope and timbral features. Finally, we store audio files of recorded phrases along with their corresponding XML annotation files including segmentation and extracted features for each note at the different temporal levels considered in the analysis.

Note Classification

We group notes in two different steps. First, we classify notes from the recorded phrases into four different articulation classes, depending on their context, by looking at the adjacent segments. Referring to the note under consideration as *n* and to a silence as to *SIL*, the four classes are (1) *SIL–n–SIL*, (2) *SIL–n–NOTE*, (3) *NOTE–n–SIL*, and (4) *NOTE–n–NOTE*. This information will be used as a strict constraint during the sample-retrieval stage to match the original articulation context of the notes used for synthesizing the output performance. Once the expressive component predicts the output note sequence, the resulting articulation group for each note is used for fulfilling this requirement. We observed notable improvements in the synthesis results when forcing the sample-search algorithm to strictly match the articulation group.

As a second step, we divide, for each set of notes corresponding to one of the four articulation groups, all notes (as segmented from the recordings) into several clusters. This is done by characterizing each note by a set of intra-note features representing the internal structure of the note. The set of intra-note features consists of the note's attack level, sustain duration (relative to the duration of the note), sustain slope, spectral centroid, and spectral tilt. That is, each performed note is characterized by the tuple (*AtackLev, SustDur, SustSlo, SpecCen, SpecTilt*). These intra-note features provide an amplitude and timbre description for each note in the database. Based on this note characterization, we apply *k*-means clustering to group together notes that are likely to be perceptually similar. The choice of the value for *k* was chosen according to the predictive accuracy of the classifiers described later in the section entitled "Transition Level Prediction": $k = 2$ for articulation groups *SIL–n–SIL*, *SIL–n–NOTE*, and *NOTE–n–NOTE*, and $k = 3$ for group *NOTE–n–SIL*.

We also consider transformations consisting of alterations to the melody (as specified in the score) by introducing or suppressing notes. Thus, we annotate the notes in the recordings to indicate whether a note alters the melody. We have categorized these transformations as consolidations, fragmentations, and ornamentations. A consolidation represents the agglomeration of multiple score notes into a single performed note, a fragmentation represents the performance of a single score note as multiple notes, and an ornamentation represents the insertion of one or several short notes between two performed notes.

Database Annotation Overview

Table 1 summarizes the descriptors attached to each note in the database. The table shows a logical grouping of descriptors, as well as the context in which each descriptor is used in our system.

Expressive Performance Modeling

In this section, we describe our inductive approach to learning expressive-performance models for different expressiveness-related dimensions such as duration transformation, onset, energy, melody alteration (e.g., ornamentations), inter-note transitions, and/or note-class estimation. These models are applied at different stages to automatically synthesize expressive audio. First, ornamentation and rhythm variation relative to the input score are predicted, together with the note's mean energy. Then, subsequent predictions (transition level and intra-note level) are performed for each of the notes present in the obtained sequence (see Figure 9).

Note that the term "prediction" here does not refer to any anticipation of future notes in

Table 1. Database Annotation Overview

Logical Group	*Descriptor Name*	*Short Name*	*Type (units)*	*Context Usage*		
				Note Classification	*Expression Modeling*	*Concatenative Synthesis*
Melody/Dynamics	Pitch	Pitch	real (Hz)		x	x
	Onset time	t_{on}	real (sec)		x	x
	Duration	Dur	real (sec)		x	x
	Alteration	Alt	Label	x	x	
	Mean Energy	EnergyM	real (dB)		x	x
Context	Metrical Strength	MetStr	Label		x	
	Narmour group (pos 1)	Nar1	Label		x	
	Narmour group (pos 2)	Nar2	Label		x	
	Narmour group (pos 3)	Nar3	Label		x	
	Articulation group	ArtGroup	Label	x	x	x
	Duration (previous)	PrevDur	real (sec)		x	
	Duration (next)	NextDur	real (sec)		x	
	Pitch (previous)	PrevPitch	real (Hz)		x	x
	Pitch (succ)	NextPitch	real (Hz)		x	x
Timbre	Mean spectral centroid	SpecCen	real (Hz)	x	x	
	Mean spectral tilt	SpecTilt	real (dB/oct)	x	x	
Intra-Note	Attack level	AttackLev	real (dB)	x	x	
	Sustain relative duration	SustDur	real (ratio)	x	x	
	Sustain slope	SustSlo	real (dB/sec.)	x	x	
	Legato (previous)	LegLeft	real (ratio)		x	
	Legato (next)	LegRight	real (ratio)		x	
	Note change time	t_c	real (sec)			x
	Transition init time	t_{init}	real (sec)			x
	Transition end time	t_{end}	real (sec)			x
	Pitch step width time	W_{PT}	real (sec)			x
	Pitch step center time	t_{pc}	real (sec)			x
Classification	Cluster number	Clus	Label		x	x

the performance, but rather to the output of our performance model, which "predicts" the expressiveness-related dimensions as relative to the input score. A more detailed description of the model induction process can be found in Ramirez, Hazan, and Maestre (2006b).

Training Data

The training data used to induce the expressive performance model is the data described in the section entitled "Database Construction"—monophonic recordings of jazz standards performances at different tempi. Each note in the musical score is characterized by a set of features representing the musical context in which the note appears. This set of features consists of the note's pitch, duration, and metrical strength; relative pitch and duration of the neighboring notes (i.e., previous and following notes); and the Narmour structures to which the note belongs (see Figure 10). Thus, each score note is contextually characterized by the tuple (*Pitch, Dur, MetStr, PrevPitch, PrevDur, NextPitch, NextDur, Nar1, Nar2, Nar3*).

In addition, each performed note is characterized by a set of intra-note and transition features. The intra-note and transition features represent the internal structure of a note, specified as intra-note

Figure 9. Overview of the learning task.

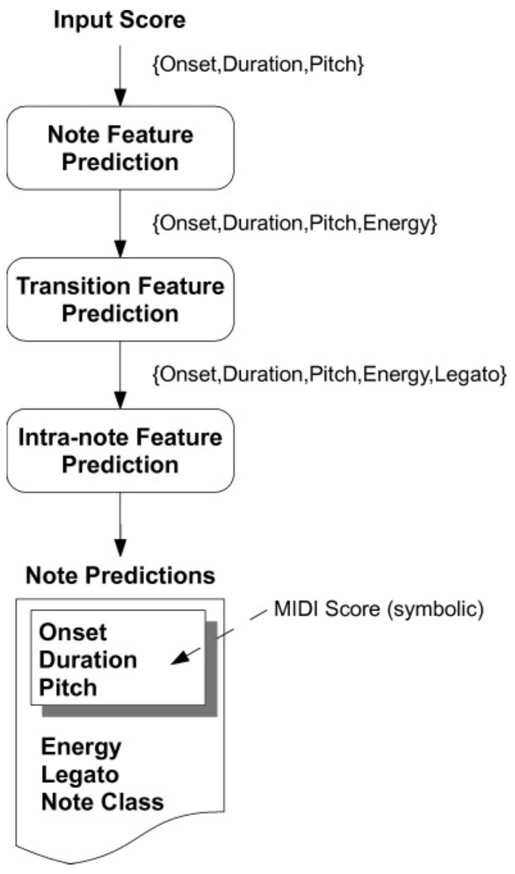
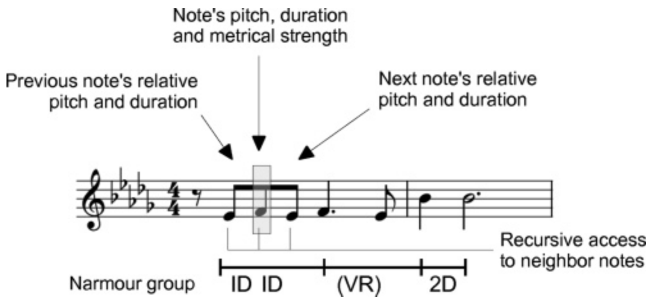


Figure 10. Overview of the note's musical context characterization.



Note's pitch, duration and metrical strength
Previous note's relative pitch and duration
Next note's relative pitch and duration
Recursive access to neighbor notes
Narmour group
ID ID
(VR)
2D

and transition characteristics extracted from the audio signal. These consist of the note's attack level, sustain relative duration, sustain slope, amount of legato with respect to the previous note, amount of legato with respect to the following note, mean energy, spectral centroid, and spectral tilt. That is, each performed note is characterized by the tuple (*AttackLev, SustDur, SustSlo, LegLeft, LegRight, EnergyM, SpecCen, SpecTilt*).

Algorithm

To obtain the expressive performance models, we apply inductive logic programming techniques, in particular Tilde's inductive algorithm (Blockeel et al. 1998). Tilde's algorithm can be considered as a first-order logic extension of the C4.5 decision-tree algorithm: Instead of testing attribute values at the nodes of the tree, the algorithm tests logical predicates. This provides the advantages of both propositional decision trees (i.e., efficiency and pruning techniques), the use of first-order logic (i.e., increased expressiveness), and the possibility of including background knowledge in the learning process. The increased expressiveness of first-order logic not only provides a more elegant and efficient specification of the musical context of a note, but it provides a more accurate predictive model (Ramirez, Hazan, and Maestre 2006b).

Temporal sequencing of notes is captured by including a predicate $succ(X, Y)$ in the learning process. The predicate $succ(X, Y)$ means "the successor of X is Y." Note that $succ(X, Y)$ also means "X is the predecessor of Y." The $succ(X, Y)$ predicate allows the specification of arbitrarily sized note contexts by chaining a number of successive notes: $succ(X1, X2)$, $succ(X2, X3) \ldots, succ(X_{n-1}, X_n)$, where X_i $(1 \leq i \leq n)$ is the note of interest.

Note-Level Prediction

At the note level, we are interested in predicting duration transformation, onset deviation, energy variation, and any note alterations (e.g., ornamentations). These expressive transformations are respectively represented by the parameters *duration, onset, energy,* and *alteration.* Duration is expressed as a percentage of the note score duration (e.g., a value of 1.1 represents a prediction of 10% lengthening for a particular note). Onset is expressed as a fraction of a quarter note (e.g., 0.2 represents a delay in onset of 0.2 of a quarter note). Energy is expressed as a percentage of a predefined average energy value extracted from the whole set of recordings.

Table 2. Correlation Coefficient (CC), Relative Absolute Error (RAE), and Root Relative Squared Error (RRSE) for the Duration, Onset, and Energy Models

	CC	*RAE (%)*	*RRSE (%)*
Onset	90.02	70.12	87.45
Duration	80.37	45.25	76.96
Energy	79.80	36.61	71.52

Alteration assumes one of the following classes: *consolidation*, *fragmentation*, *ornamentation*, and *none*. By applying the Tilde inductive logic programming algorithm (see the previous section), we learn a predicate definition (i.e., a set of first-order rules) for each of the expressive transformations. The accuracies obtained by applying inductive logic programming techniques to the data are higher than the accuracies obtained by other machine-learning techniques, including support vector machines, (propositional) decision trees, *k*-nearest neighbor, and artificial neural networks. Details of the resulting models, which were evaluated by means of 10-fold cross validation, can be found in Ramirez, Hazan, and Maestre (2006b).

Transition-Level Prediction

At the inter-note level, we are interested in predicting the type of transition (legato/staccato) between two neighboring notes. To do this, we assign each performed note to a one of four articulation groups depending on whether the note is preceded/followed by silence or a note. For the group of notes preceded and followed by a silence (i.e., *SIL–n–SIL*), there is no need to predict any type of transition; for the groups of notes preceded by a note (i.e., *NOTE–n–SIL* and *NOTE–n–NOTE*), we predict the transition with the previous note; and for the groups followed by a note (i.e., *SIL–n–NOTE* and *NOTE–n–NOTE*), we predict the transition with the subsequent note. The transition-level prediction consists then of a real number in [0, 1], with 0 representing a maximum staccato transition and 1 representing a maximum legato transition. Table 2 shows the obtained correlation coefficient (CC), and relative absolute error (RAE) for the legato prediction model. The RAE is a relative measure of the average absolute prediction error and the average absolute deviation of the real performance data values from their mean.

From the results shown in Table 2, we can see how the models involving silences (*NOTE–n–SIL* and *SIL–n–NOTE*) show a CC and RAE consistently higher than those not involving silences (*NOTE–n–NOTE*). One possible cause for this difference would simply appear to be related to inherent limitations of the learning task: it might remain more "difficult" to model legato in *NOTE–n–SIL* and *SIL–n–NOTE* transitions. However, we attribute the observed difference to database sparseness: the space is less populated with *NOTE–n–SIL* and *SIL–n–NOTE* transitions than with *NOTE–n–NOTE* transitions, so a smaller set of examples (e.g., a less rich variety of context parameters) is used when training the first two models, keeping the accuracy from reaching equivalent levels.

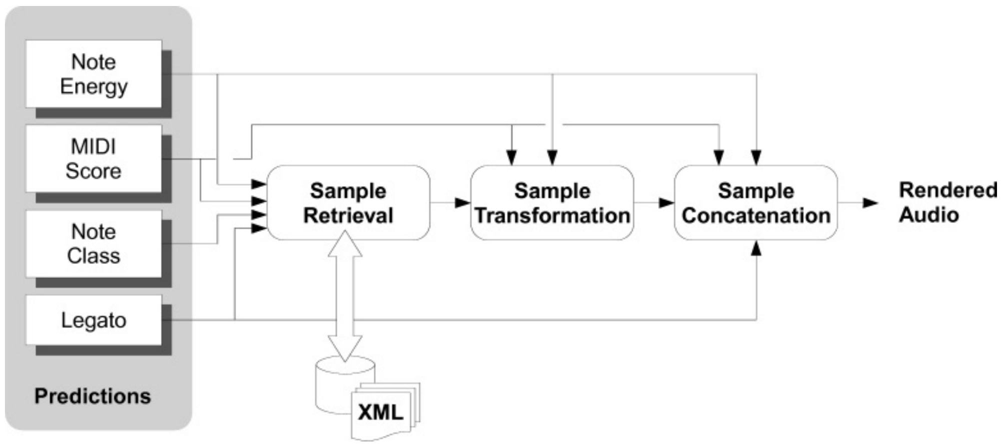
Table 3. Correctly Classified Instances (CCI), Relative Absolute Error (RAE), and Root Relative Squared Error (RRSE) for the Melody-Alteration Model

	CCI (%)	*RAE (%)*	*RRSE (%)*
Melody alteration	80.37	45.25	56.96

Intra-Note Level Prediction

For each of the articulation groups described above (i.e., *SIL–n–SIL*, *SIL–n–NOTE*, *NOTE–n–SIL*, and *NOTE–n–NOTE*), we are interested in predicting several intra-note properties, e.g., attack level. We apply *k*-means clustering to all the notes in a particular articulation group using the intra-note features. This divides the notes within a particular articulation group into a set of clusters, each containing notes with similar intra-note features. For each articulation group, we train a classifier that, given the musical context of a note, predicts a cluster. Table 3 shows the number of clusters

Figure 11. Overview of the audio-synthesis engine.



considered and the ratio of correctly classified instances for each articulation group. We have selected the number of classes based on comparing their relative classification accuracies.

Audio Synthesis

The system generates the audio sequence based on the predictions of the expressive performance model and the annotated sample database. An overview of the process is illustrated in Figure 11. First, the expressive-performance modeling component is fed with the input score, and a prediction of an enriched note sequence is obtained (see the previous section). For each note in the new sequence, a candidate list containing possible matching samples from the database is generated. Then, the best note sample sequence is determined by paying attention both to the "cost" of the transformations to be applied (as explained subsequently) and also to the concatenations involved. Selected samples are analyzed in the spectral domain, and a representation of their spectral regions (Bonada and Loscos 2003; Laroche 2003) is extracted. Such a representation allows us to apply phase-vocoder techniques for time, amplitude, and frequency transformations, along with equalizations needed in the concatenations.

For the synthesis part of this work, we adapted a generic concatenative-synthesis framework currently being developed at Music Technology Group (*GenConcatSynth*) and being used in different sample-based synthesis applications. Notes (samples) are transformed to fit the predicted note characteristics applying global note amplitude transformation, pitch shift, and non-linear time stretch for matching, respectively, dynamics, fundamental frequency, and duration of the target sequence. After that, samples are concatenated by means of amplitude, pitch, and spectral-shape interpolation applied to the resulting note transitions to obtain a smooth reconstruction from release and attack segments of adjacent notes. Amplitude reconstruction is carried out by taking into account the legato prediction coming from the expressive-performance modeling component.

Sample Retrieval

The output of the expressive performance-modeling component carries time (onset and duration), fundamental-frequency (pitch), and dynamics (energy) information at a global note level. In a subsequent step, the note-class prediction (cluster) containing information about energy envelope and spectral shape is provided, along with a prediction of the *legato* feature for each of the involved transitions. With this information, the best possible combination of notes from the database is determined.

We recall here the recurrent problem of database sparseness in sample-based systems for which high-dimensional descriptions are attached to each sample. We used four songs—each one played at eleven different tempi, implying lower coverage in pitch-related dimensions than in duration and timbre-related features. Even though we did not formally check how populated the different areas of the feature space are, we devised a clustering step during database analysis and a further cluster prediction step prior to synthesis to avoid predictions in too high-dimensional of a space. The advantage of compacting information by means of such a classification and class-prediction process is that a set of dimensions potentially causing sparseness in the feature space (e.g., energy-envelope or timbral features) are instead modeled as areas in such the space from which note samples will be retrieved, mostly based on dimensions for which interpolation is available. This therefore implies a constrained high-dimensional prediction, ensuring that interpolation is not needed for all dimensions, because an actual sample will be retrieved and no transformations will be applied in the dimensions used in this dual "classification–class prediction" process. Thus, a number of other features (those used for distance computation within the predicted cluster) configure a space for which interpolation is indeed performed (e.g., global energy, duration, or pitch transformation).

Now, an overview of the sample-retrieval process is given. First, a list of all possible candidates for each note in the sequence is generated, attending to the constraints given by database note classification (see subsequent discussion). Then, a computational "cost" is computed for every possible path, considering the limitations of involved sample transformations and concatenations. It is important to clarify here that by "cost" we do not refer to computational efficiency, but to a distance between samples (see the next section) that provides an estimation of the potential degradation of candidate samples when transforming and concatenating them. The most suitable combination of samples is found as the notes belonging to the path presenting the minimum total cost (see Figure 12 and the section entitled "Computation of Costs"). Depending on the computation requirements, the candidate lists may be truncated by attending to pre-computed transformation and applying some thresholds. We use dynamic programming techniques, by means of the so-called Viterbi algorithm (Viterbi 1967) to speed up the search.

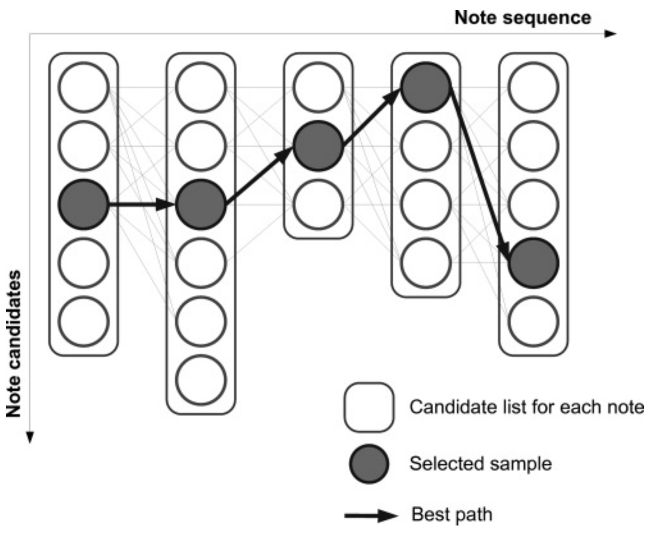


Figure 12. Illustration of the path search. Once the candidate sample list is generated for each note, all possible paths are searched, and the path presenting the minimum total cost is selected.

Candidate Sample List Generation

Based on the articulation class of each of the notes in such an output sequence, and also on the predicted note class (cluster), a list containing all possible candidates from the database is generated. Candidates must match the articulation class and must also belong to the predicted class cluster. With the goal of reducing the number of computations needed during the search (especially for large databases or long sequences with no silence in between notes), the candidate list might be truncated by pre-computing sample transformation costs (see the next section) and retaining the n best candidates.

Computation of Costs

A set of heuristic formulas adapted to our application context has been devised for satisfying our needs for cost computation during the sample-retrieval stage. It remains difficult to formally assess the quality and validity of such a set of ad hoc cost formulas. Even though we aimed at designing them as general and independent of the algorithms used, some consideration was given to a subjective quality measure of the techniques available for transformation (see for instance the duration-transformation and frequency-transformation costs). Moreover, we carried out a manual calibration of applied weights by listening to synthesis results for a set of ad hoc input scores by supervising sample retrieval and transformation processes. Ultimately, a formal calibration of cost formulas and weights would need of an extensive set of perceptual listening tests.

The total path cost C_P is computed in Equation 3 as a weighted sum of two components: the total sample transformation cost C_T and the total concatenation cost C_C.

$$C_P = w_T C_T + w_C C_C \tag{3}$$

Transformation Cost

We compute the total transformation cost C_T as the sum of the transformation costs for each of the N_S note samples of the path. We obtain the estimation of the transformation cost from a weighted sum of three different sub-costs (Equation 4): the duration transformation cost C_D, the frequency transformation cost C_F, and the energy transformation cost C_E.

$$C_T = \sum_{i=1}^{N_S} w_D C_D(i) + w_F C_{F(i)}(i) + w_E C_E(i) \tag{4}$$

The duration transformation cost C_D is computed as a weighted average of time-stretch transformation costs C_{TS}, computed from the time-stretch factor F_{TS} values to be applied along the note sample to match the predicted duration. This is expressed in Equation 5, where N_f corresponds to number of frames of the database sample. Time stretching is not applied linearly for the whole note, but rather according to a variable-shape function. The shape of such functions can vary to avoid stretching critical sections, such as attack or release segments. (Their limits are annotated.) For weighting, we use the time-stretch transformation cost C_{TS} itself, so that high values penalize the total cost.

$$C_D = \frac{\sum_{i=1}^{N_S} C_{TS}^2(i)}{\sum_{i=1}^{N} C_{TS}(i)} \tag{5}$$

In Equation 6, a logarithmic function is used for computing the time-stretch transformation cost C_{TS} to make its value equal to unity for time-stretch factors of 2 or 0.5. This decision is based on prior knowledge on the quality of our time-stretch transformation algorithm (see next section), assuming near-lossless time-stretch transformations for stretching factors of 0.5–2.

$$C_{TS} = |log_2(F_{TS})| \tag{6}$$

For the frequency transformation cost C_F, we use a logarithmic function that depends on the relation of the fundamental frequencies expressed in Hz, as it is expressed in Equation 7. A transposition of one octave up or down would correspond to a cost of unity. Again, the decision adapting the cost formula to arbitrary limits of transposition transformation (one octave) is based on prior knowledge of the quality of the pitch-shifting technique that we used (See the next section).

$$C_F = \left| log_2 \left(\frac{F_{0\,Pred}}{F_{0\,DB}} \right) \right| \ldots . \tag{7}$$

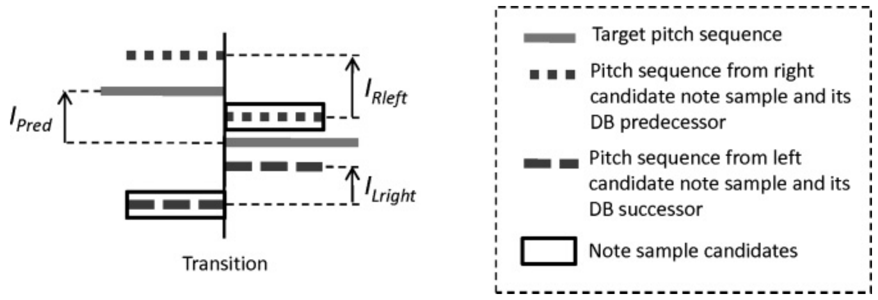
The energy transformation cost C_E is computed from the relation of the predicted mean energy E_{Pred} and the mean energy of the database sample E_{DB} expressed in a linear scale (RMS), using again a logarithmic function for which a global amplitude transformation of ± 12dB would correspond to a cost of unity (Equation 8).

$$C_E = \frac{1}{2} \left| log_2 \left(\frac{E_{Pred}}{E_{DB}} \right) \right| \ldots . \tag{8}$$

Concatenation Cost

The concatenation cost C_C of the path is computed as a sum of all N_C involved sample-to-sample concatenations. Again, we compute it as a weighted sum of three sub-costs: the legato cost C_L, the interval cost C_I, and the continuity cost C_P, as

Figure 13. Illustration of the intervals involved in the interval cost computation.


I_{Pred}
I_{Rleft}
I_{Lright}
Transition
Target pitch sequence
Pitch sequence from right candidate note sample and its DB predecessor
Pitch sequence from left candidate note sample and its DB successor
Note sample candidates

expressed in Equation 9:

$$C_C = \sum_{i=1}^{N_C} w_L C_L(i) + w_I C_I(i) + w_P C_P(i)) \qquad (9)$$

For computing the legato cost C_L, taking into account that its value ranges from zero to unity, we use the difference between the predicted value LEG_{Pred} and a pre-computation of the legato descriptor LEG_{DBrec} resulting from concatenating the two samples involved in the transition into consideration (Equation 10).

$$C_L = |LEG_{Pred} - LEG_{DBrec}| \qquad (10)$$

We compute an interval cost C_I of the notes involved in the transition (see Figure 13) as expressed in Equation 11:

$$C_I = \left| \frac{|I_{Pred} - I_{Lright}| + |I_{Pred} - I_{Rleft}|}{I_{Pred}} \right| \qquad (11)$$

Here, I_{Pred} corresponds to the target interval, I_{Rleft} corresponds to interval from the candidate sample at the right side of the transition to its predecessor sample in the database, and I_{Lright} corresponds to interval from the candidate sample at the left side of the transition to its successor sample in the database.

Finally, we reward sample choices for which notes that were consecutive in the database recordings appear as consecutive in the synthesis sequence, by including a continuity cost C_P. This cost is set to zero if such a condition is satisfied, and unity otherwise.

Sample Transformation

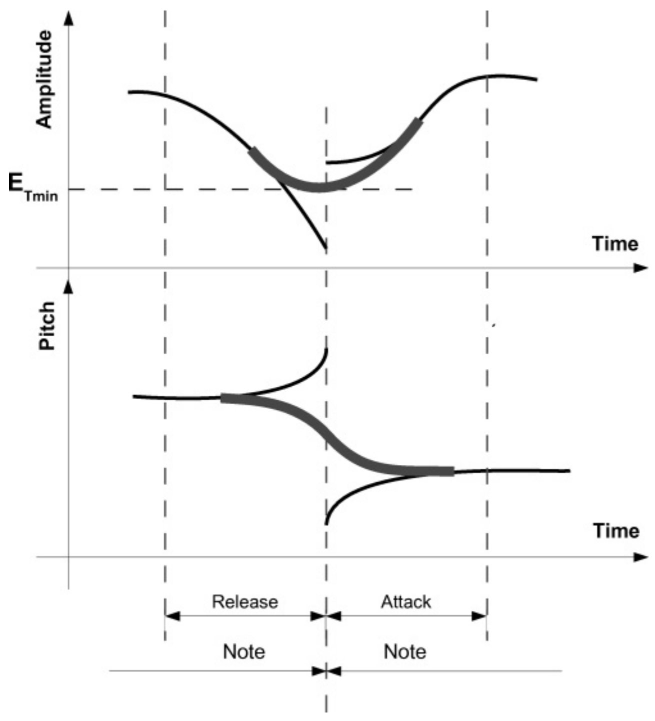
Once the best sequence of note samples has been determined, samples are analyzed in the spectral domain, obtaining a frame representation array based on spectral peaks and harmonic regions. Using spectral-processing techniques based on the phase-vocoder (Amatriain et al. 2002; Bonada and Loscos 2003; Laroche 2003), each retrieved note is transformed in terms of amplitude, pitch, and duration to match the target description given at the output of the performance model.

To match the energy prediction, a note global-energy transformation is applied to the sample as a global amplitude transformation, because the energy-envelope quality, spectral centroid, and spectral tilt are already represented by the note class (cluster) prediction. (See the previous section entitled "Transition Level Prediction.")

Then, a pitch transformation is applied to the sample by shifting harmonic regions of the spectrum by an amount equal to the fundamental frequency ratio between the retrieved sample and the value appearing in the sample sequence, preserving spectral shape (Laroche 2003).

In a final step, a duration transformation is carried out by applying a time stretch with variable stretch-factor values along the note's length. The frame insertion/dropping rate is not constant along the note, as it is governed by an ad hoc function constructed from the intra-note segmentation annotations. This prevents inserting or dropping frames outside the limits of the sustain segment so that blurring of attacks or transitions is avoided. The fundamental frequency and spectral shape of the new frames are obtained by linearly

Figure 14. *Amplitude and pitch corrections applied during the transition-reconstruction stage. The value* E_{Tmin} *is adjusted to match the* legato *prediction for such a transition.*



interpolating the surrounding frames (Amatriain et al. 2002).

Sample Concatenation

Finally, sample concatenation is performed by restoring the possible amplitude, pitch, and timbre discontinuities occurring within the resulting transitions in the neighborhood of the junction point between each pair of consecutive notes (i.e., those with no silence in between them). On one side, amplitude and pitch contours are reconstructed (see Figure 14) by means of smoothing curves (we use cubic splines) spanning several frames. For the case of amplitude reconstruction, the shape of the curve is adapted by means of controlling the minimum energy value E_{Tmin} so that it matches the prediction of *legato* (its value is computed following the procedure outlined in the previous section, "Extraction of Intra-Note and Transition Features") coming from the expressive-performance modeling component. Timbre discontinuities are smoothed around the junction point by spectral-shape interpolation (Bonada and Loscos 2003) while maintaining overall energy.

Conclusion

We have presented an approach to synthesizing expressive jazz-saxophone performances that is based on concatenating note samples (recordings of notes). We used a set of expressive saxophone recordings both for training the performance model and for constructing the database used for synthesis. We have carried out tests synthesizing pieces in the training set and pieces not included in the training set and obtained promising results. The presence of subtle timbral and loudness discontinuities in the synthesized pieces has led us to consider using samples of transitions in our future work. It is always difficult to evaluate formally a model that captures subjective knowledge, as is the case with an expressive music synthesis model. The ultimate evaluation may consist of listening to the resulting synthesized pieces.

Further work includes studying pitch contour to model portamento-like transitions and pitch modulations (e.g., vibrato) occurring within a sustain segment. Moreover, owing to the difficulties of evaluating the synthesized performance's expressivity and naturalness, we must carry out more extended auditory tests to be able to tune and improve our system. This work should be considered as a step toward a methodology for the automatic creation of both the performance model and the sample database needed to carry out expressive synthesis. The application of the proposed methodology to other instruments, together with the exploration of other classification techniques, can only inspire the expansion and further improvement of high-level, sample-based instrumental sound synthesis.

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