Towards Deconstructivist Music: Reconstruction paradoxes, neural networks, concatenative synthesis and automated orchestration in the creative process

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Since the 1980s, deconstruction has become a popular approach for designing architecture. In music, however, the term has not been absorbed as well by the related literature, with a few exceptions. In this article, ways to find ideological groundings for deconstructivism in music are introduced through the concepts of *enchaînement* and reconstruction paradoxes. Similar to the Banach–Tarski paradox in mathematics, reconstruction paradoxes occur when reconstructing the parts of a whole no longer yields the same properties as the whole. In music, a reconstruction paradox occurs when a piece constructed from tonal segments no longer yields a perceived tonality. Deconstruction in architecture heavily relies on computer-aided design (CAD) to realise complex ideas. Similarly in music, computer-aided composition (CAC) techniques such as neural networks, concatenative synthesis and automated orchestration are used. In this article, we discuss such tools in the context of this advocated new aesthetics: *deconstructivist music*.

1. INTRODUCTION

The role of the composer as an artist who has been bestowed the Atlantean burden of choosing notes and sounds (Murail 2005) has led to many formalisations and theories about music. From stochastic and spectral music to neo-Riemannian and transformational theories, different schools of thought have proposed different solutions and techniques, to the benefit of the novice composer who can now choose or unchoose among different paths. Notes can be picked randomly from some scale (a sieve in the sense of Xenakis or a partials reconstruction in the sense of Murail), a series (in the sense of the serial school), a process (in the sense of process music) or by an algorithm (in the sense of algorithmic and generative music). This paper describes the deconstructivist aesthetics that emerges from techniques for generating music that have emerged in new music, notably concatenative synthesis, neural networks, random walks, transformational techniques and variants. It discusses various reconstruction paradox instances in which parts do not reconstruct the whole. We then discuss three case studies: first, random walks in neo-Riemannian spaces learned from a corpus; second, automated orchestration of piano rolls based on distance spaces learned from a corpus; and finally, the use of recursive neural networks (RNN) to generate polyphonic multichannel sketches (i.e., orchestral) based on a learned corpus and steering input data. This article is an exploratory walk in the lands of (this so-called) deconstructivist music, not an exhaustive survey in the field. Other papers have served this purpose (Roads 1985; Edwards 2011; Briot, Hadjeres and Pachet 2020; Ji, Luo and Yang 2020).

2. BACKGROUND AND RELATED WORK

2.1. Deconstruction in architecture

Deconstruction in philosophy, as a late structuralist declination by French philosopher Jacques Derrida, has had a long legacy in the arts since as early as the 1980s (Wigley 1993; Vitale 2019). In the fine arts, architecture is perhaps the field in which deconstruction has been the most successfully applied as a technique with palpable and visible aesthetic results, as may be exemplified through the works of architects Daniel Libeskind, Zaha Hadid, Peter Eisenman, Bernard Tschumi, Rem Koolhaas, Frank Gehry, Coop Himmelblau or Morphosis, among many others (Figure 1). About destruction and architecture in a harrowing vision of a lost Europe (in his work *Danube*), Claudio Magris writes:

> It is comforting that travel should have an architecture, and that it is possible to contribute a few stones to it, although the traveller is less like one who constructs landscapes for that is a sedentary task than like one who destroys them … But even destruction is a form of architecture, a deconstruction that follows certain rules and calculations, an art of disassembling and reassembling, or of creating another and different order. (Magris 2001)

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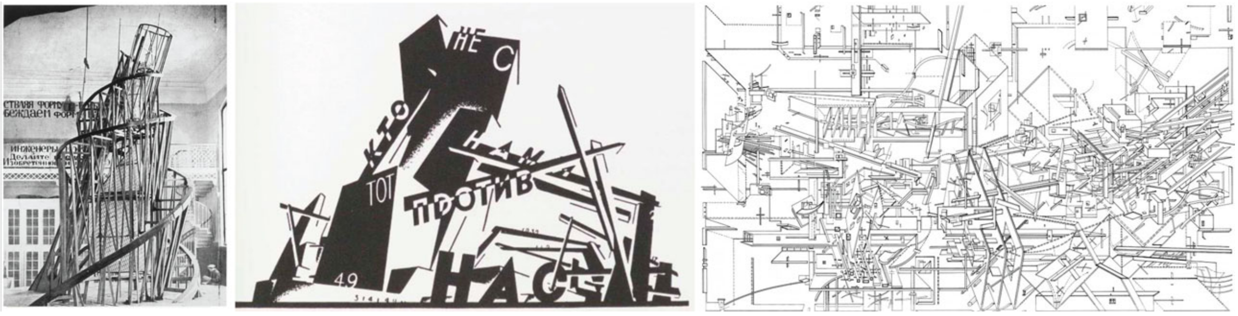

Figure 1. (left) Vladimir Tatlin, *Project for a Monument to the Third International*, 1919 (The Museum of Modern Art/ Licensed by SCALA/Art Resource, NT); (centre) *Constructive Theatrical Set* by Iakov Chernikhov (1889–1951) (figure reproduced from his book *The Construction of Architectural and Machine Forms* (Chernikhov 1931)); (right) *Micromegas, drawings* (1979) by Daniel Libeskind (Image Courtesy © Daniel Libeskind). The literature indicates that the term 'deconstructivist architecture' (inspired from early Russian constructivism and avant-garde of the twentieth century) was first popularised in the MOMA exposition catalogue *Deconstructivist Architecture* (Johnson and Wigley 1988).

In architecture and the visual arts, the deconstructivist movement of the 1980s and 1990s found its inspiration partly from the Russian Constructivism of the early twentieth century (Johnson and Wigley 1988; Wigley 1993) and partly from challenging new designs coming from computer-generated art (Boden 2009). The patterns used for the windows of Libeskind's *Jewish Museum* in Berlin are reminiscent of some of Malevitch's paintings; as are the random geometries early personal computers could generate.

We can describe the deconstructivist works of the 2000s and forward as part of a post-deconstructivist or late deconstructivist era in architecture, where, inspired by the early deconstruction of the 1980s, form has been effectively liberated from the straight line. A myriad of designs has been imagined and built following this initial drive. Computer-aided design and physical models in the design of complex shapes have been instrumental in this artistic movement by allowing greater technical possibilities and greater control over the rendered product. Generative art (e.g., using machine learning) has been a trend in computer graphics and visual arts since at least the 1960s (Boden 2009; Audry 2021).

2.2. Deconstruction in music

Deconstruction has also been explicitly applied to the theory of music and its meanings (philosophical and sociological). Rose Subotnik seemed to have coined the term in music and used critical theory to provide a new interpretation of classical music (e.g., Mozart, Chopin) (Subotnik 1995). Deconstuctivism in architecture relates to a set of techniques, effective processes with aesthetic and 'palpable' results. In music, however, existing work on deconstructivist approaches is scattered among different niches of contemporary music with diverse labellings.

No deconstructivist school of thought effectively exists in music and association with a heuristic idea of deconstruction may be more of an impression left on an auditor by some work rather than an intentional process.

This being said, the so-called parametric music of serialism and high modernism was an early example of deconstruction (of a piece into its parameteric models). The generative material is represented as a set of tweakable parameters with which a piece can be reconstructed. It was commonplace among composers of the era to believe that once the series was chosen, the rest of the piece would follow and could be reconstructed. Koblyakov's analysis of Boulez's *Marteau sans maître* undeniably demonstrates the parametric and generative aspects of Boulez's work for instance (Koblyakov 1993). Also, composer Iannis Xenakis is known to have parametrised the stochastic generation of some of his most famous pieces, yielding results that still today can surprise and impress (Solomos 2015). Edwards (2011) lists the following examples as forerunners of the current day algorithmic music: Guillaume Dufay's (1400–74) isorhythmic motet *Nuper rosarum flores*; evidence of Fibonacci relationships in the music of Bach, Schubert and Bartók; Mozart's *Musikalisches Würfelspiel* (1792); and the *Quadrille Melodist* sold by Professor J. Clinton of the Royal Conservatory of Music, London (1865) (a set of cards that allowed a pianist to generate quadrille music).

The music of Brian Ferneyhough and the visual scores of John Cage or Sylvano Bussotti are also proto-deconstructions (Ferneyhough 1981; Attinello 1992; Bogue 2014; Hidalgo and Ipinza 2016). Figure 2 shows several such examples of deconstruction in music. In Ferneyhough's work, the serial use of rhythm trees (i.e., in the sense of the Patchwork or OpenMusic softwares) disjuncts the time dimension;

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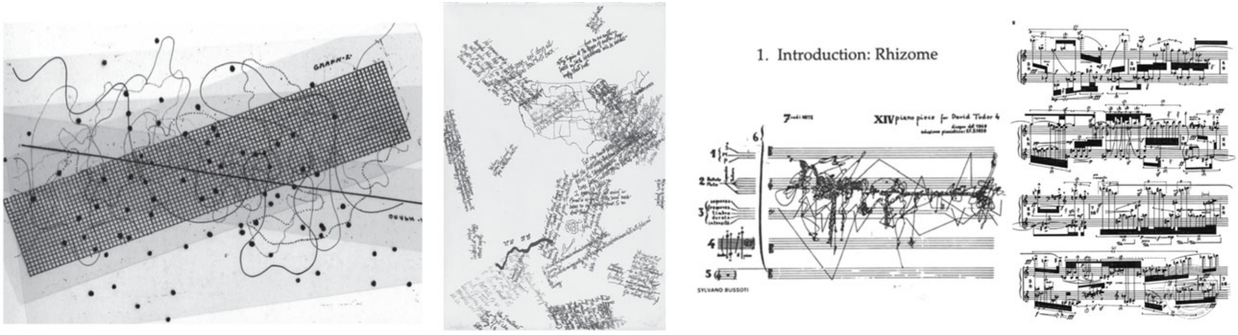

Figure 2. (left) *Fontana Mix* by John Cage (1958) (© 1958 by Henmar Press Inc. Permission by C. F. Peters Corporation. All rights reserved); (centre-left) John Cage, *II from Mushroom Book* 1972 (image courtesy @ John Cage Trust; digital image © The Museum of Modern Art/Licensed by SCALA/Art Resource, NT); (centre-right) *Introduction: Rhizome – From Five Piano Pieces for David Tudor Music* by Sylvano Bussotti (© 1959 Casa Ricordi Srl, a division of Universal Music Publishing Classics & Screen. International Copyright Secured. All Rights Reserved. Reprinted by permission of Hal Leonard Europe BV (Italy)); (right) *Lemma-Icon-Epigram* by Brian Ferneyhough (© 1981 by Hinrichsen Edition, Peters Edition Limited. Permission by C. F. Peters Corporation. All rights reserved).

for John Cage, the deconstruction of the time domain comes from the use of indeterminacy and chance composition; for Bussotti, the deconstruction is visual (as it relates to deconstruction in the visual arts) – the straight line, like in architectural deconstruction, is literally perturbated. The work *Piano Pieces for David Tudor: 1. Rhizome* by Bussotti was incidentally inspired by the 'rhizome' concept of post-structuralist philosopher Gilles Deleuze (2013): a 'rhizome' (a concept borrowed from botany and dendrology) is a structure of constant splitting, such that synthesis (in a Hegelian sense) of the parts is no longer possible. Corbussen (2002) describes a work by Gerd Zacher, *Die Kunst seiner Fuge* (1968) – a set of ten variations of *Contrapunctus I* by Bach where the composer interprets the piece in various ways – as deconstructivist. Variations are a musical form that adequate well with the idea of deconstruction or parametric music in general. Generated content and reconstructions can be obtained by slightly varying some parameters, yielding significantly different results.

Granular synthesis – deconstructing (segmenting into 'grains') and reordering audio signals (often with additional parametric signal processing) – is a technique notably pioneered by Xenakis (Solomos 2015). The same process applied to music notation (via MIDI) is at the source of techniques such as concatenative synthesis – which could be performed on audio or MIDI (Zils and Pachet 2001; Schwarz 2004, 2005; Maestre, Ramírez, Kersten and Serra 2009).

The work on real-time generative accompaniment and concatenative synthesis (Dannenberg 1993; Lewis 2000; Thom 2000; Young 2007; François Pachet, Roy and d'Inverno 2013; Carsault 2017; Nika, Déguernel, Chemla-Romeu-Santos and Vincent 2017) could also be described as a form of musical deconstruction. In the OMax project (Dubnov, Assayag and El-Yaniv 1998; Assayag, Bloch, Chemilliera, Cont and Dubnov 2006; Assayag and Bloch 2007), segments are classified in a suffix tree using the Oracle Factor algorithm. These research systems segment musical sources and reconstruct them out of place based on different heuristics. In the DYCI2 project (Nika et al. 2017), the musical material is broken into memories that are triggered in real time by an instrumentalist. The work *Ex Machina* by saxophonist Steve Lehman and artistic director Frédéric Maurin is a hallmark of the use of DYCI2. Interestingly, most of these systems have parameters designed to improve the continuity of the reconstructed pieces, or their contextual/genre readability. These parameters can, however, be tweaked to their extremities and yield completed *deconstructed*, *disjuncted* results. The work of Umberto Eco (1965) on open works can be noted, but also indeterminacy as pioneered by John Cage and the New York School (Iddon and Thomas 2020).

3. RECONSTRUCTION PARADOXES

A fundamental concept in the construction of tonal music, which is often overlooked when considering other such concepts such as tonality, harmony, counterpoint and timbre, is the *enchaînement* concept. Simplistically speaking, *enchaînement* is to music what the straight line is to architecture. As a related concept, voice leading and its perception was extensively studied in the cognitive sciences (Huron 2016). *Enchaînement* is thus the composition of the rules defining what comes before and what comes after a given musical event (e.g., a certain chord, a dissonance, an incomplete melodic pattern), the actualisation of harmony and tonality in a temporal structure. In neo-Riemannian theory, or transformational theory, some chords occur with higher probability after some other chords based on their position in some neo-Riemannian embedding space. In Hollywoodian music, this syntax has been made evident (Lehman 2018). It is our opinion that *enchaînement conventions* define musical order in at least as pervasive a manner as tonality or timbre.

In the piece *Morphogenesis* (2022) (Figure 3), we used as source material Beethoven's Symphony no. 9 (4th movement), or *Bee9*, and a recursive neural network to reconstruct the material using Boulez's *Notations* for orchestra as a steering material. The reconstructed pieces were composed of reordered (tonal) segments from *Bee9*, and they sound atonal.

In a sense, this relates to the Banach–Tarski paradox where reconstruction from the parts does not yield the whole. Sets in complex spaces (a 3D ball or a musical piece) may not always follow expected behaviours. The following quote gives a description of the Banach–Tarski paradox (de Rauglaudre 2017: 37):

> [The] Banach-Tarski Paradox states that a ball in 3D space is equidecomposable with twice itself, i.e. we can break a ball into an infinite number of pieces, and with these pieces, build two balls having the same size as the initial ball. This strange result is actually a Theorem which was proven in 1924 by Stefan Banach and Alfred Tarski using the Axiom of Choice.

In music, we could call this a reconstruction paradox. In the same way, the reverse transformation or rotations in post-romantic and serial music could be seen as generative techniques (e.g., Rachmaninov's *Variations on a Theme by Paganini*). Breaking the *enchaînement* conditioning of musical sources effectively generates new sonorities and aesthetics. We will discuss the details of these compositional processes in later sections.

Figure 4 demonstrates a reconstruction paradox using an example from Rachmaninov's Piano Concerto no. 2. In the study sketch for the piece *Morphogenesis* (2022) (Figure 3), a neural network was used to learn associations between segments of *Rach2* and their MIDI representations. The neural network was then used to transform segments from Boulez's *Notations* for orchestra into multitrack polyphonic MIDI signals (i.e., orchestral segments). Judging from the atonality of the resulting sequences, the perceived sense of tonality is not the consequence of choosing notes from a tonal scale but rather an artefact of tonal *enchaînement* patterns (i.e., tonally syntactic chord progressions, dissonance resolution conventions and so on).

4. PIECES, SLABS, WEDGES, CASES AND STUDIES

4.1. Learning generative transformations in neo-Riemannian spaces

At least two trends in algorithmic music and composition can be distinguished in the massive grove of new music techniques and technologies: on one hand, generative techniques, such as OMax, DYCI2, Somax (Assayag et al. 2006); and on the other hand, a perpetual search for understanding inner structures of musical composition through neo-Riemannian and transformational theories (some examples include Lewin 1987; Lerdahl 1996; Tymoczko 2011; Cohn 2012). Concepts from transformational theories, such as chordal distance and spatial embeddings, have been used in generative techniques to steer the generation of music from pure randomness to some sense of coherent aesthetics. The ability to choose notes among the infinitude of possible assemblies of frequencies has been at the core of contemporary music research since Xenakis's exploration into stochasticity and his development of sieve theory (Xenakis 1992; Solomos 2015), Messiaen's quest for modes of limited transposition (Messiaen 2000), and Cage's chance music, to the usage of partials and microtonality generated from sound analyses in the spectral school (Murail 2004, 2005). The quest for theories of compositional choice is foundational to the design of algorithms and processes of generative music.

Figure 5 shows the embeddings-into-nearest-neighbour graphs of segments obtained from distance matrices using the Spiral Array distance (Chew 2014) and computed for different works (i.e., *Rach2* and Schoenberg's *Klavierstücke*, op.11, no. 3). Different pieces yield different structures (which is reminiscent of the work on generative meshing in the new architectural geometry field). These graphs and structures can be used as terrain for a random walk steered by the concavities and convexities of the terrain. We start from an input chord and the algorithm chooses some optimal path based on the data it has learned from the different works. Reproducing the genre or style of the piece is not the primary goal of such methods. Following the concept of reconstruction paradoxes, we can say that the reconstituted wholes rarely display all the properties of the original works. Figure 6 shows examples of such reconstructions. Figure 7 shows a piece generated from a random walk in a space learned from 'O Fortuna' from *Carmina Burana* by Carl Orff. The random walks generated on a single channel were then orchestrated using Orchidea, a software developed at IRCAM (Maresz 2013).

The generated random walks sometimes preserve some characteristics of the original corpus (in 'O Fortuna', the grandiloquence could still be perceived), however, reconstruction paradoxes (in the perception of tonality and metric rhythm especially) still occur in the generated artefacts. The random walk algorithms are described in Algorithms 1 and 2.

Figure 3. Sketch for the work *Morphogenesis* (2022): reconstruction of *Bee9* using a segmentation window of length on average μ = 2.0512s steered using Boulez's *Notations* for orchestra. The result reminds the pointillism of early serial post-Webernian music.

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Figure 4. (a) An excerpt of the piano part (MIDI layout) of the first movement of Rachmaninov's Piano Concerto no. 2 (bb. 38–42); (b) a reconstruction of the piano part of Rachmaninov's Piano Concerto No. 2 steered using Boulez's *Notations* for orchestra. Multitrack polyphonic MIDI files are reconstructed using neural networks (for simplicity, only the piano parts are shown here). Syncopations and disjunctions are introduced in the reconstruction. While (a) is clearly tonal (post-romantic), (b) is clearly modern: a reconstruction paradox occurs when a reconstruction from the parts of a whole no longer yields the same properties as the whole.

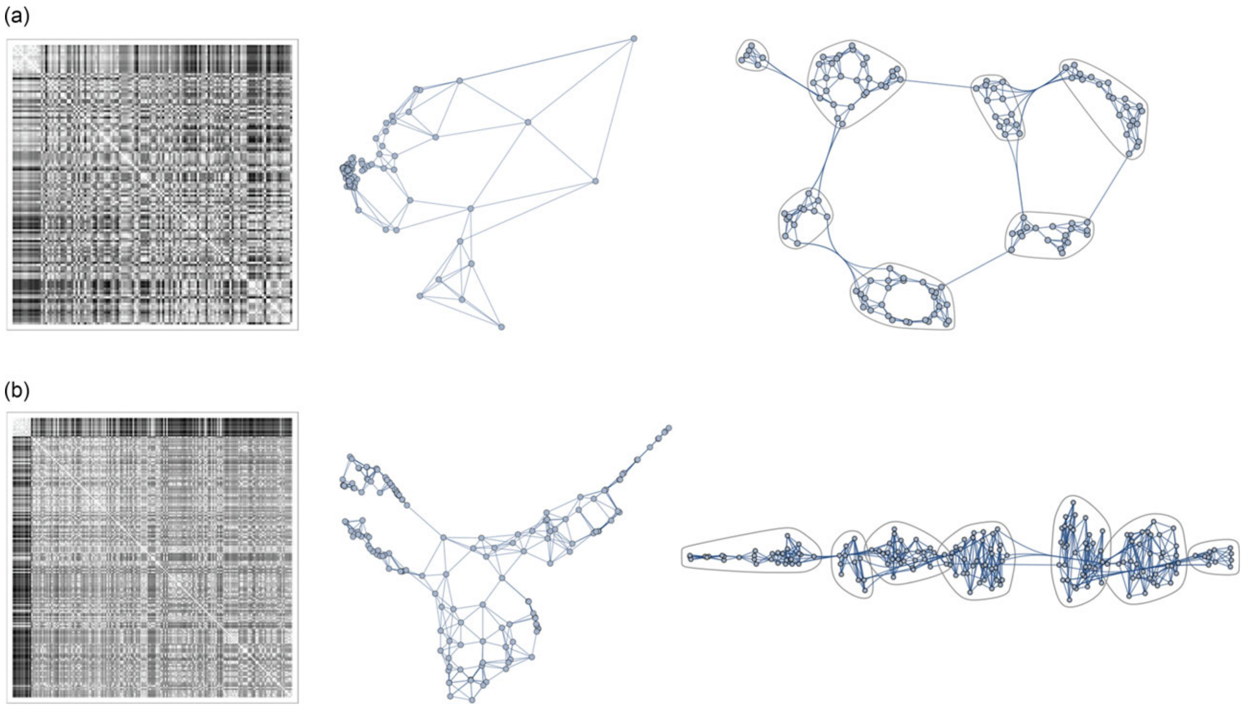

Figure 5. (left) A generative transformation learning algorithm is learned from transformation matrices (i.e., similarity distance matrices); (centre) two-dimensional Euclidean space embedding using the multidimensional scaling (MDS) algorithm; (right) the network community graphs for (a) segments generated from Schoenberg's *Klavierstücke*, op. 11, no. 3 and (b) segments generated from *Rach2*.

4.2. Distance-based automated orchestration

Automated orchestration designs have offered a smaller number of candidates for review than algorithmic composition. Orchidea, the latest creation of the Orch* series developed at IRCAM by Carmine-Emanuele Cella, uses a customisable database of sounds to output an optimal instrumentation using genetic algorithms (Maresz 2013). IRCAM has also developed another

Figure 6. (a) A random walk based on Schoenberg's *Klavierstücke*, op. 11, no. 3; (b) a random walk based on a piano reduction of *Rach2*. Both random walks were steered by chordal distance measures (e.g., chromagrams, Estrada distance, Costère distance and Chew distance).

piece of software, Orchestral Piano by Leopold Crestel (Crestel and Esling 2017), where orchestration rules are learned from real orchestration of piano reductions. The machine-learning algorithms then learn association predictions from the piano reduction and orchestration data using variants of Restricted Boltzmann Machines (RBM, cRBM and FGcRBM). Finally, Handelman and Sigler (2012) proposed an automated orchestration method based on the concept of z-chains.

We demonstrate a technique that is based on some chordal distance measure (e.g., chromagrams, Estrada distance, Costère distance and Chew distance) that has a lightweight learning phase (i.e., updating a distance matrix) and that can therefore be used in real time with minimal footprint (storing a transformation matrix, which in the case of subsets of 12 notes is 4096×4096). A first learning phase where an existing MIDI orchestration of some work A is segmented and tagged by its pitch-class content (i.e., the multichannel MIDI signal is collapsed, and duplicate pcs across all octaves are deleted) is performed. A second-generation phase is performed with MIDI from some work B that is used for generating sketches: each segment of work B is matched to some segment in Work A and a reconstruction of A is generated, steered by B.

This process is explained in Algorithms 1 and 3 (in Figure 8). Algorithm 1 is shared between the random walk algorithm and the distance-based automated orchestration algorithm; as the generation of a transformation matrix uses the same techniques. This process can be used to handle timbre as well in the distance-based automated orchestration algorithm. Timbre, here, is extracted from the information on the channels/instruments provided in the MIDI file. Creating a distinct transformation matrix for the channel information in addition to the note information (pitch-class sets, or harmony) is possible. Joining both transformation matrices using a weighing strategy is also possible.

4.3. Recursive neural networks for steered orchestral concatenative synthesis

Neural networks in music synthesis have been studied extensively since the idea was first put forth (Lewis and Todd 1988; Lewis 1998). Also, more recent RNN, ConvNets, GAN, VAE and concatenative synthesis-based techniques in music synthesis have notably been experimented with in IRCAM's automated accompaniment libraries (e.g., OMax, DYCI2, Somax).

Here we demonstrate the use of a robust and well-tested technique used in speech recognition/classification (the so-called spoken digit classification problem) using RNNs and apply it to music synthesis. As usual, neural networks are sensible to input data and training parameters.

We generated three sets of input data using Beethoven's Symphony no. 9 (4th movement) or *Bee9*. One with an average segment length of $\mu = 0.137405$s (a short segment length corresponding to a segment generated at each onset of the MIDI file modulo a precision parameter handling notes not hitting the same exact onset), one with an average $\mu = 1.04207$s (a coarse segment length where segments could contain many onsets – motifs) and a coarser segmentation with average $\mu = 2.05122$s.

Different datasets used to train the RNN yielded different properties in the generated music. Shorter segments yielded less diversity in the generated segments. Coarser segments yielded more diversity in the segments. Coarser segments also increased the recognisability of the input corpus. Reconstruction paradoxes are clear in the generated material, even in longer segments in the *Bee9* example. This is illustrated in Figure 9.

5. ALGORITHMS

Algorithm 1 is identical for the random walk and distance-based orchestration algorithms and one can

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Figure 7. Excerpt from the cantata for choir and piano *The Fall of Rome*, *1. The Last Harangue* (2022). The source material used for training the model was 'O Fortuna' from Carl Orff's *Carmina Burana*. From the model, a random walk was generated and the result was orchestrated using the software Orchidea developed at IRCAM (Maresz 2013).

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Algorithm 1 Feature extraction algorithm from a MIDI segmentation algorithm (notes, duration, velocities, channels/instruments)

procedure EXTRACT($durations, chords$)

  $window$ = some constant in ms ▷ initialize a window size in ms

  n_1, c_1 = some scaling constants for the decay function δ_1 ▷ initialize to some constant

  n_2, c_2 = some scaling constants for the decay function δ_2 ▷ initialize to some constant

  Read the ($durations[i], chords[i]$) tuple at index i ▷ if multichannel, collapse and delete duplicates

  $t = 0$

  $j = i + 1$

  $\mathbf{M} = \mathbf{1}$

  while $t < window$ **do** ▷ iterate over the window length

    $i1$ = index of $chords[i]$ in distance matrix ▷ index in subset order

    $i2$ = index of $chords[j]$ in distance matrix

    $\mathbf{M}[i1, i2] = \mathbf{M}[i1, i2]\ \delta_1(t)\ \delta_2(d(chords[i], chords[j]))$ ▷ using some distance measure

    $t = t + durations[j - 1]$

    $j = j + 1$

  Return $\mathbf{M}$

Algorithm 2 Generation/synthesis algorithm given an input chord, a transformation matrix and a segmentation

procedure GENERATE($initchord$, $\mathbf{M}$, $noteson$)

  r = constant (possibly a list) defining the radius of the random walk

  o = constant (possibly a list) defining the order chosen in the nearest neighbor ordering

  i = random index from r-nearest neighbors in all chords minimizing a distance to $initchord$

  $chordNumber$ = random index from the r-nearest neighbors of order o on row $\mathbf{M}[i]$

  seg = segment in $noteson$ matching the $chordNumber$ index

  Return seg

Algorithm 3 Orchestral generation/synthesis algorithm given an input midi file

procedure GENERATE(MIDI input **I**)

  r = constant (possibly a list) defining the radius of the random walk

  o = constant (possibly a list) defining the order chosen in the nearest neighbor ordering

  while $window$ in **I** **do**

    i = random index from r-nearest neighbors in all chords minimizing a distance to $initchord$

    $chordNumber$ = random index from the r-nearest neighbors of order o on row $\mathbf{M}[i]$

    (n, v, d, c) = segment in $noteson$ matching the $chordNumber$ index

    Append (n, v, d, c) to $(notes, velocities, durations, channels)$

  Return $(notes, velocities, durations, channels)$

Algorithm 4 RNN for Orchestral Concatenative Synthesis given a trained RNN with audio input and classified segment output

procedure GENERATE(MIDI input **I**, trained RNN rnn)

  while $window$ in **I** **do**

    $segment = rnn(windows)$

    $(n, v, d, c) = get(segment)$ ▷ get segment info from parsed data

    Append (n, v, d, c) to $(notes, velocities, durations, channels)$

  Return $(notes, velocities, durations, channels)$

Figure 8. Algorithms 1–4 discussed in this article.

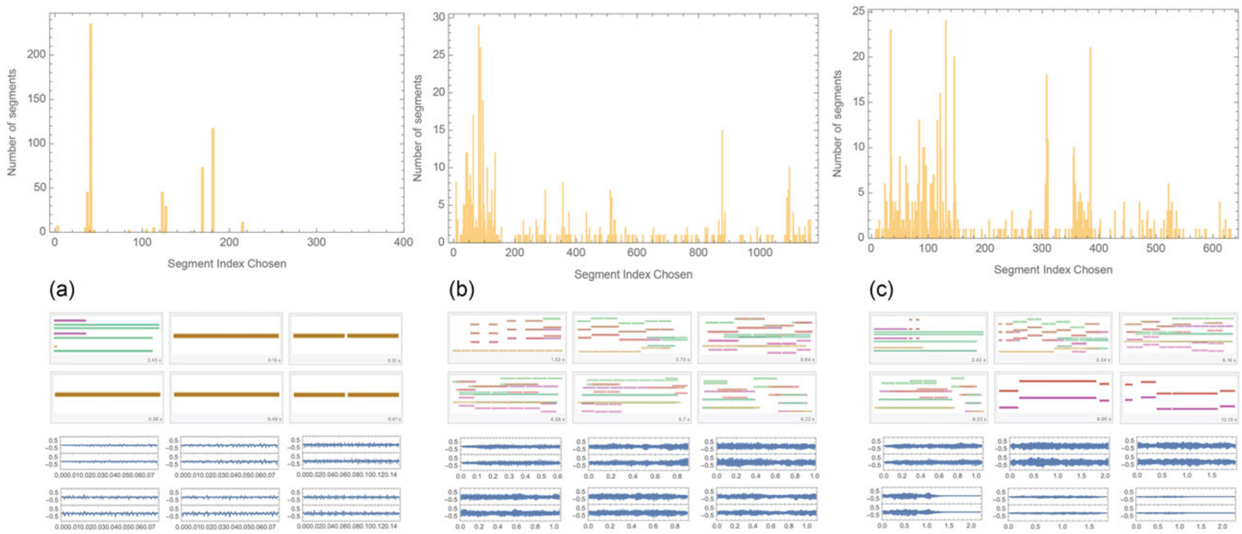

Figure 9. (a) Histogram showing the index of the chosen segments (i.e., such an index is the label of some set of notes/channels/onsets/durations with duplicate notes deleted) and the number of such indices returned by a recursive neural network trained on a fine-grained segmentation (the average segment size was μ = 0.1374s) – the fine-grained segmentation corresponded to a segmentation where each new onset generated a segment; (b) histogram for a coarse segmentation (μ = 1.0420s); (c) histogram for a coarser segmentation (μ = 2.0512s). Coarse segmentations could contain multiple onsets where a given segment contained a continuous succession of segments from the source material (i.e., *Bee9*), effectively increasing continuity. Finer segmentations yielded less diversity in the segments chosen and more repetition. Coarser segmentations yielded more diversity with the coarsest segmentation producing a Gaussian mixture. These neural networks were trained for the piece *Morphogenesis* (2022).

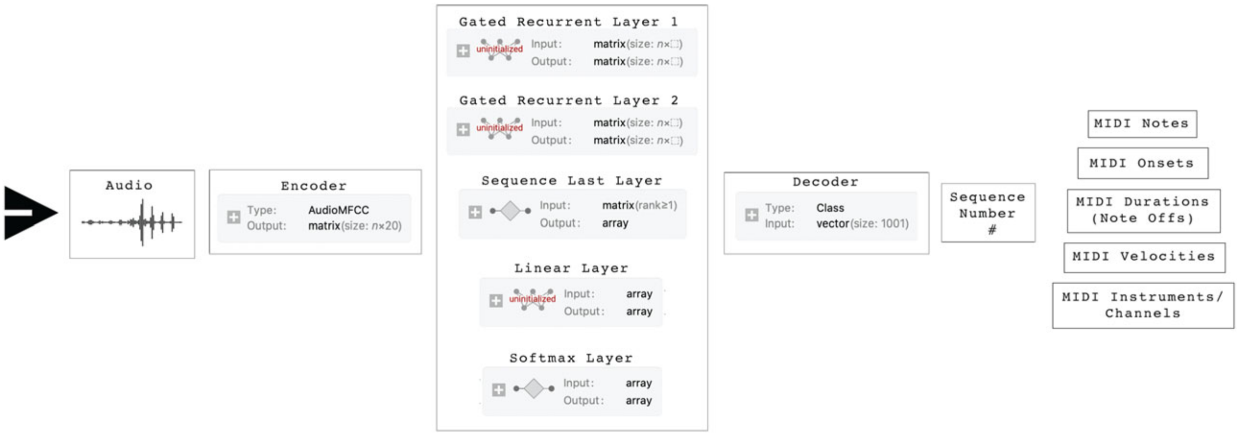

Figure 10. Example of architecture from the Wolfram Language and Mathematica software for a recursive neural network trained on audio segments and their corresponding MIDI segments. Audio inputs are encoded into MFCC coefficients. A segment number is decoded. The segment number corresponds to the MIDI data of the segment.

overload the other. When dealing with orchestration, the MIDI files used are multichannel: the feature extraction and embedding algorithm (Algorithm 1) learns the pitch-class space and collapses the channel information to keep only the pc-set data (note that this technique can be extended by learning the timbral embedding space and storing the MIDI channel information on another segment).

Algorithms 2 and 3 assume that a transformation matrix was learned using Algorithm 1. In the case of Algorithm 2, a single channel segment is returned. In the case of Algorithm 3, multichannel information is returned.

Algorithm 4 assumes a trained RNN of the type described in Figure 10. The RNN effectively classifies orchestral audio segments to their MIDI polyphonic

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multichannel counterparts (additional technicalities are necessary to handle MIDI files with more than 16 channels).

6. CONCLUSION

The study of deconstruction in music promises to be a testbed for many new works. Reconstruction paradoxes are real consequences of many generative and algorithmic music techniques that are being studied in new music (e.g., neural networks, random walks, concatenative synthesis, variational autoencoders, machine learning). When comparing Figures 4a (*Rach2* non-deconstructed) and 4b (*Rach2* deconstructed), we can see that the excerpt generated by AI has an embedded deconstructivist 'logic' to it: the traditional patterns of *enchaînement* do not seem to hold. The AI deconstructivist creations may share some traits and parameters with their component parts and the original pieces these parts were extracted from (mostly at the microtemporal domain); but they demonstrate unique aesthetical features, distinguishable by the absence of traditional *enchaînement* conventions – resulting from the dismantling of their original syntactic tonal/metric contexts. As we continue to research and create in the area of deconstructivist AI music, other paradoxes, phenomena and epiphanies are bound to be discovered, leading to a growing body of works and theoretical base.

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