



Artificial Intelligence 79 (1995) 387–398

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**Artificial  
Intelligence**

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## Book Review

Peter Todd and D. Gareth Loy, eds.,  
*Music and Connectionism*

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Received June 1995

Before jumping too far into this review, it is probably important that I “come clean” and describe the particular perspective I used when reading this book. I am not a researcher investigating aspects of human intelligence with a computer, nor am I one of the growing number of cognitive philosophers who use the machine as a springboard for philosophical speculation. I am a composer who happens to use computers to realize my musical goals. As such, I am somewhat of a dilettante in a variety of computer-related research areas, including the artificially-intelligent use of computers to model human behavior. My primary concern, however, is not with the research itself, but with discovering tools I can adapt to aid in my pursuit of musical art. Most of my criticisms of this book spring from this “what’s in it for me” filter.

This perspective is not meant to be pejorative towards pure research into musical behavior. Indeed, music can serve as an excellent area of inquiry into how humans operate. Because of the special problems posed by the practice of music, researchers such as Terry Winograd [11] and Marvin Minsky [8] have seen fit to use music as a vehicle for explorations in cognitive science. It is important to realize, though, that music has an extremely broad definition in contemporary society and that research using music as a toy domain (however rich that domain may be) must necessarily make some large and narrowing assumptions about what music is.

Thus, my first overarching criticism of this book is that the authors seem too often unaware that using music as a toy domain generally means working with toy music. Although the scaling problem is discussed in several of the papers, it is presented chiefly as a problem of quantitative complexity. The musical scaling problem—especially when talking about music in the broad sense—will require some significant qualitative changes, however. The path from the low-level

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musical results presented in this book to a high-level musical cognition/creation system is most probably nonlinear and possibly quite discontinuous. Some of the papers in this collection imply that these qualitative changes will perhaps occur as an emergent phenomenon of hierarchically organized or more broadly structured neural nets. After reading through this book, I still remain unconvinced.

The second general criticism relates to the format and scope of the book. The collected papers represent a scatter-shot approach to the moving target of music perception and creation. The editors acknowledge this in the preface, stating that the “authors do not always concur or present a unified world view but rather demonstrate the disagreement and diversity of opinion characteristic of a dynamic young field” (p. x, Preface). Gareth Loy (one of the editors of the book) said that one of the primary objectives in publishing the book was to get the research out to people in a variety of disciplines and hopefully stimulate work in the area. While this is certainly a worthy goal, it would have been nice to see a bit more “connective tissue” in the book explicating some of the assumptions and points of contact within and between the papers. To be sure, this is a tall order for an emerging field of research, and too much editorial influence might have run counter to Loy and Todd’s stated mission. I don’t think that a slightly more polemical stance by the editors would have harmed the book’s impact, and it might have made some of the underlying assumptions about “what music is” more apparent to the reader.

### **1. Introducing connectionism in music**

The book is organized into four sections. The first part of the book deals with the background of neural net research in music. Mark Dolson gives a lucid explanation of some of the basic principles behind neural net operation, complete with an example of a simple network designed to evaluate and classify rudimentary rhythmic patterns. Dolson does a marvelous job of describing the problems he encountered when implementing his example network. He does not discuss in much detail how he arrived at the particular network configuration he used for the rhythm classifier, however. I get the impression that settling upon a network topology for a given task is still an intuitive process.

In an addendum to his original paper (all papers in this book had been previously published in several issues of the *Computer Music Journal*), Dolson discusses the potential use of network models to synthesize sound. He correctly concludes that neural nets are probably not well-suited for the direct creation of a sound waveform, but that they do show some promise as an interface mechanism to low-level synthesis algorithms. I think this might prove to be an exciting area for connectionist applications, especially given the performance complexity (but highly realistic sound!) of some of the new physical model synthesis algorithms being developed in the computer music research community.

Gareth Loy closes the introductory section of the book with an historical overview of efforts to create musically intelligent systems. Using this survey, Loy

builds some strong arguments for a connectionist approach in musical research. Talking about “the problem of formal specification of music”, Loy claims that:

The position of the composer . . . is really in the cracks between categories of formal description. Describing the compositional process within the framework of a strictly formal representation will necessarily miss this dimension of the composer’s art. And yet a computable approach is perforce necessarily strictly formal. This is the dilemma shared by all computer models of music. (p. 30)

“Traditional”, formal AI techniques (rule-based systems, probabilistic and algorithmic methods, etc.) fall into this trap when modelling musical activity. Loy feels that connectionism, being a “very pragmatic theory” using the neuronal basis of the brain as a model, holds promise for circumventing this difficulty (p. 32). Connectionist systems appear able to generalize and extract rules in complex contexts where formal descriptions may be at best difficult. Connectionism might prove to be the best methodology for building models of music cognition. Real (human) composers and listeners alike are often quite unaware of any general rules or strategies (if any) used in their musical experience.

Loy concludes his paper with some interesting philosophical speculations about the artistic nature of automatic music systems. Loy finishes by saying that his comments “only focus on the philosophical level of machine models of human artistic expression” (p. 34). He further states that there are many other perspectives from which to view music, psychology, computer science, musicology, etc. each with separate sets of questions and objectives. Unfortunately, Loy did not elaborate these different perspectives. I certainly would have enjoyed more of this discussion. Loy’s “philosophical level” could have helped situate some of the musical attitudes implicit in this work within a wider context. I also wish that some of these philosophical questions had played a larger role in the rest of the book, and that there were more interpenetration of the different perspectives.

## 2. Perception and cognition

### 2.1. *Modelling “low-level” perception*

A case in point is a paper by Hajime Sano and B. Keith Jenkins which opens the next section of the book (the “Perception and Cognition” section). Sano and Jenkins have devised a network model of pitch perception which they take great pains to ground in the physiology of human hearing. Their network model is able to extract pitch from the harmonic information of complex tones, even multiple complex tones using an extension to the basic model described in an addendum by Jenkins. This is no small feat, and certainly very useful for a variety of computer music applications. However, statements such as “the majority of chordal emotional affect is related to the relative positions of notes within an octave, not

to which octaves they are in” (p. 47) and “modelling the emotional effect of chords would most likely require several pitch perception networks tied together feeding into a chord classification, heteroassociative neural network” (p. 49) suggest that the authors have an overly-simplified view of pitch perception (and certainly perception in general). Their scheme for reducing frequency data into equal-tempered note data, despite the qualification that moving from JND discriminations<sup>1</sup> to 12-tone pitch classes “is culturally dependent” (p. 45), assumes *a priori* that pitch perception is a straightforward act of mapping stimuli onto fixed categories. This questionable premise leads to the somewhat bizarre situation where the network model natively exhibits absolute pitch perception rather than relative pitch perception. The underlying assumption that music fundamentally consists of notes has biased the entire design of the model—not a healthy situation if the project is intended to model aspects of biological perception.

In “Connectionist Models for Tonal Analysis”, Don Scarborough, Ben Miller and Jacqueline Jones attack the problem of the induction of tonality: how do we determine the key in a piece of tonal music? Their model presupposes the existence of a lower-level system for parsing incoming acoustic stimuli into pitch categories (such as the Sano and Jenkins model). From the vantage point of this higher-level process, the authors are able to make some cogent observations about music perception in general. Although their simple linear network model does a “more than creditable job” in extracting tonality from simple monophonic or polyphonic music (p. 56), Scarborough et al. harbor no illusions about modelling actual human perception: “It is not clear how well this network simulates human performance because we know very little about how people identify tonality” (p. 56). The authors also seem very aware of the particular cultural filters they have adopted in designing their model, this again is probably a consequence of the higher-level phenomenon they are investigating.

In the addendum to the original paper, Scarborough et al. discuss some of the advantages and disadvantages of their simple linear network approach. They note that their network model is based upon the concept of pitch classes, “an example of the cognitive assumption that the mind codes experiences in an abstract symbolic code” (p. 63). They can speculate that (at least in musical perception) this assumption may be wrong.

Bernice Laden and Douglas Keefe confront this issue directly in their paper comparing several different methods for representing pitch in a neural network model. This is done in the context of a network intended to classify chords as major, minor or diminished triads. Laden and Keefe contrast “cognitive” approaches relying upon the explicit symbolic representation of notes with “psychoacoustic” approaches using harmonic [3] or subharmonic [9] spectral complexes. They conclude that a spectral representation of pitch is preferable in

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<sup>1</sup> “JND” is an abbreviation for “Just Noticeable Difference”. In this case a JND discrimination is the amount of pitch-shift necessary for people to notice that the pitch is different. This is much less than the amount of pitch change between notes in a 12-tone equal-tempered (the piano keyboard) scale.

network models because it is tied more closely to the actual acoustic content of musical sound, and it preserves much of this cognitively important information.

Because I read the book from front to back, probably the way most books are read, I wish that the editors had placed Laden and Keefe's paper closer to the beginning of this section of the book. Laden and Keefe investigate several network architectures and give empirical results for various numbers of hidden units and learning epochs used. This 'hands-on' information and the ensuing discussion was very useful for my learning how network models are constructed, especially when coupled with Mark Dolson's paper at the beginning of the book. In addition, I would have preferred to read Sano and Jenkin's paper on pitch extraction after the discussion of different approaches given by Laden and Keefe, or at least have had some way of connecting the two papers more directly.

## 2.2. "Higher-level" musical cognition

I also wish that Jamshed Bharucha's paper "Pitch, Harmony, and Neural Nets: A Psychological Perspective" had opened the "Perception and Cognition" section. Although I disagree with Bharucha's criticisms of Laden and Keefe (especially his decoupling of pitch perception from a spectral representation of pitch), his discussion of the issues involved in modelling pitch and harmony is quite enlightening. Bharucha has done some seminal work in musical connectionism, and his admonishments to consider known constraints, both theoretical and empirical, when modelling human perception should inform nearly all of the work being done in this field.

In this paper, Bharucha presents a model extending his MUSACT system [1] for recognizing keys and chords from tones. Bharucha focuses on how this capability is learned, certainly a primary concern when attempting to model human performance. The strength of relying upon "real-world", psychological models (in this case, Bharucha's insistence that learning should occur through passive exposure to music; an hypothesis which may or may not be true) is revealed by the development of a robust model of pitch cognition, exhibiting human characteristics such as transposition invariance (a melody sounds more or less the same no matter what key is used) and key-distance effects (essential for the development of tonal relationships).

Mark Leman tackles the question of tonal relationship development using a neural network self-organization technique known as the Kohonen Feature Map [5]. While I don't completely buy into Leman's assertion that the notion of a "cognitive map" is "essential for the explanation of cognitive processes" (p. 103), I certainly endorse his stated intention of adopting what he calls a *subsymbolic* approach:

This implies, among other things, that the system should exhibit what we call "responselike" behavior to stimuli in the environment. This criterion embodies the idea that a system develops tonal semantics only in virtue of the response of the system to the environment. Stated differently, the tones

encountered acquire meaning solely because they are relevant for the action of the organism in the environment. (p. 103)

While I'm certainly not a hard-core (nor necessarily even a soft-core) behaviorist, I like this approach because of the relative lack of assumptions about "how music should go" imbedded in a model based on this design criterion.

Unfortunately, Leman is forced to abandon his "ultimate goal . . . to start from the raw acoustic data" in favor of a "more modest approach" to pitch representation "over which strict control could be more easily exercised" (p. 106). Leman settled upon an input pitch coding scheme, based upon Terhardt's subharmonic spectral complex theory [9] (an approach grounded in the actual acoustic signal rather than some *a priori* abstract representation scheme), for similar reasons to those outlined in Laden and Keefe's paper. The self-organized KFMs resulting from exposure to major, minor and dominant seventh chords (the most common chords in Western tonal music) show some remarkable emergent features which can be correlated with Western listeners' experience of tonality (i.e. chords and keys closely related through the "circle of fifths" lie close together on the resultant KFM). My fear is that this may be more a consequence of the particular input coding adopted by Leman. Leman reduces much of the spectral information from the Terhardt representation into a single equal-tempered octave, a move which certainly has some tonal implications. It would be terrific if Leman could operate on raw acoustic data. If such a model were constructed, then it would be fascinating to see the KFMs resulting from non-Western musics using instruments with a large number of non-harmonic partials.

Bharucha and Peter Todd take a more time-oriented approach to the problem of tonal structure development. The authors present a sequential memory network designed to work in conjunction with Bharucha's MUSACT model [1]. Bharucha and Todd use this network memory to learn schematic and veridical expectancies for sequences of chords. Schematic expectancies are musical commonalities existing within a cultural tradition, and veridical expectancies are built from an individual's knowledge of specific pieces of music. The network ultimately learns a set of heavily contextualized probabilities for a given chord occurring in an on-going musical passage. The interesting feature of this model is the authors' consideration of how these expectancies are learned, especially given a particular cultural environment. As in Bharucha's earlier work, this model learns through passive exposure, simply by "hearing" the music. The assumption behind this approach is that most people learn listening strategies through the passive immersion in a musical culture.

The biggest difficulty I have with this model of human perception is the implicit assertion that the violation or fulfillment of harmonic expectancies is a major (if not *the* major) component in our hearing of music. Taken to the extreme, this view suggests that we are either shocked or bored when listening to music. I believe that this aesthetical stance, generally attributed to Leonard Meyer [7], is more an artifact of the compartmentalization of musical parameters and narrow focus upon the pitch parameter which has developed in the Western musical

tradition. What does the expectancy/violation theory tell us about other musical features? Timbre is a fundamental part of my own experience of music—what is a timbral expectancy, and how is it violated? I would argue for a more holistic approach to musical perception, involving timbre, sonic density, rhythm, time, etc. not as separate musical parameters but instead as essential and interconnected parts of a unified perceptual entity.

### 2.3. Coding of musical features and patterns

Robert Gjerdingen attempts to address some of these problems in the coding of input to his adaptive resonance theory [2,4] network model. Gjerdingen's ART model (which he calls *L'ART pour l'art*) learns to recognize abstract musical patterns from relatively complex music (early Mozart). *L'ART pour l'art* constructs musical memories by representing a set of 34 input features as activations which decay or become reinforced as new inputs are introduced. Gjerdingen's input features include items such as the melodic scale degree, the bass and melody contour (up or down), melodic "inflections", etc. Ostensibly the learned feature vectors can be used to parse new music, in a somewhat more complex version of Bharucha and Todd's harmonic expectancy model.

Although Gjerdingen included many other features of music besides simple pitch and harmony in his input coding scheme, these features are all tied almost exclusively to pitch. Gjerdingen also grounds his work firmly in the harmonic expectancy/violation theory of Meyer—my criticisms of Bharucha and Todd's model apply equally here. By using Gjerdingen's selected features for input, I suspect that *L'ART pour l'art* may be learning more about what Gjerdingen thinks is important in music than general musical principles.

With this decaying feature activations, however, Gjerdingen did include a more explicit concept of the flow of musical time in his model; musical time being more-or-less represented in previous models as a shifting "context". Peter Desain and Henkjan Honing focus exclusively on time problems in their connectionist approach to recognizing musical rhythms. From a purely utilitarian standpoint, this paper is noteworthy. The parsing of music into rhythms is badly needed by musicians working with real-time interactive computer music systems. It would also be extremely useful in the automatic transcription of human-performed music by computer.

The model works by using "interaction cells" to bias "basic cells" towards small integer relationships. The basic cells contain the inter-onset intervals measured between incoming musical events. A refinement of the model introduces "sum cells" to assist the interaction cells. The sum cells account for complex rhythms in which short durations are intermingled with long durations (i.e., eighth or sixteenth notes with half or whole notes).

Even though the basic topology of Desain and Honing's model is fairly simple, the interactions of the cells can become quite complex. Desain and Honing describe several techniques for analyzing network behavior—the clamping of all cell states except one to study the functioning of the single cell, and the use of

“state space” graphs (discussed in the addendum) to observe global network activity. Again from a purely utilitarian standpoint, these discussions are quite useful, as is the listing of LISP code implementing the model which is included with the article.

### 3. Applications of connectionism

#### 3.1. Melodic composition

I was disappointed in the next major section of the book, “Applications”. From my “what’s in it for me” perspective, I was looking forward to seeing how neural network models could be used as compositional tools. With one exception, all of the papers dealt almost exclusively with the automatic composition of melodies, and only one of these papers generated polyphonic music (melodies with an explicit harmonic accompaniment). Being more of a timbre-oriented composer, this work was not particularly useful to me personally. This heavy emphasis on the production of melody-generating systems is symptomatic of the narrow view of music as consisting mainly of a sequence of pitches, an idea which pervades most of the research presented in this book.

As I described earlier, I am also allergic to the “parameterization” of music that goes hand-in-hand with this approach to musical modelling. What is the pitch sequence of the famous motto of Beethoven’s *5th Symphony* without the characteristic rhythm and accent patterns? More to the point, what is this simple theme without the incredible intellectual and emotional context built by Beethoven? Is it even truly possible for contemporary listeners to hear this theme without the “Beethoven” context? I don’t believe that the various parameters of music can be so cleanly separated from each other and investigated as independent entities. I’m not even convinced of the primacy of pitch perception, at least for my own experience of music. If music were nothing more than a sequence of pitches conjoined with some rhythmic templates, overlaid by a set of timbres, then listening would be a dreary experience indeed. It could be argued that the intellectual and emotional excitement of music comes at higher levels of processing, but I don’t subscribe to a strongly-ordered, hierarchical model of mental processing. My vote goes instead for a more integrated, a more *connected* approach. My worry is that by working with a restricted, toy-domain music these integrated connections are severed and the phenomena under investigation become simplified right out of the model.

With this jeremiad aside, however, Peter Todd presents a good overview of many issues involved in melodic composition in the opening paper of this section, “A Connectionist Approach to Algorithmic Composition”. Todd describes various systems using network models, his intention being to “present alternative approaches and tangential ideas [which] are included throughout as points of departure for further efforts” (p. 173). Todd then discusses a model which can



learn from sequences of pitches and rhythms given one or more simple melodies as input. The network accomplishes this through the construction of contextualized “plan vectors”, or schemes for putting together melodic sequences. Todd can then manipulate the plans in various ways to produce new melodies.

One problem with this approach derives from the local view of pitch transition built into the model. This limits the size of the pitch sequences which can be manipulated by the model. I also suspect that longer sequences would tend to “wander” without a clear musical direction because the network cannot readily learn higher-level knowledge of large-scale musical structure. In an addendum to his paper, Todd discusses the hierarchical organization of several sequential network models to overcome these problems. How hierarchical knowledge might be learned by this super-network is an unresolved question.

Michael Mozer concentrates on the construction of sequences of pitches only with his CONCERT network. No representation of rhythm or any other parameters are included in the model. Mozer is careful to work within psychophysical constraints (such as judgements of “closeness” of one pitch to another made by human observers, or relative amounts of consonance and dissonance between different pitches) in the representation of pitch in his model. His feeling is that the creation of “melodies peoples perceive as pleasant” must be tied to a “psychologically-motivated representation of pitch” (p. 202). Mozer uses a pitch coding scheme which, rooted in psychophysics or not, emphasizes diatonic relations developed in the Western tonal tradition. As presumptuous as this assumption is, I find more disturbing Mozer’s assertion that “a complete model of music composition should describe each note by a variety of properties—pitch, duration, phrasing, accent—along with more global properties such as tempo and dynamics” (p. 195). This statement says much about what Mozer means by “composition”. If his intention is to model human creativity, then his conception of that activity is extremely constricted. I realize that it is necessary to begin modelling a complex activity with some basic set of assumptions about that activity, but I think that Mozer’s view of what composition entails is overly constrained. I don’t believe that a robust model of general composition can be ‘scaled-up’ by simply adding note-properties.

Mozer does show how network models can capture dimensions of context in ways which are not possible with “traditional” algorithmic compositional paradigms. Mozer also raises an interesting question concerning how to judge the success of a network model:

One potential pitfall in the research area of connectionist music composition is the uncritical acceptance of a network’s performance. It is absolutely essential that a network be evaluated according to some objective criterion. One cannot judge the enterprise to be a success simply because the network is creating novel output. (p. 195)

This statement stands in direct contrast to Peter Todd’s remark that the melodies generated by his network model, “while incorporating important elements of the training set, remain more or less unpredictable and therefore musically interest-

ing” (p. 188). My own view is something like the adage “the proof of the pudding is in the eating”. The problem with a musical Turing test is that the sonic pudding may taste radically different to different people. Of course, if arguments about the success of a compositional model become arguments about musical taste and style, then the model has probably succeeded.

### 3.2. Musical judgement and style

J.P. Lewis actually tries to imbed some notion of musical taste in his compositional model. Lewis uses a technique he calls “creation by refinement”, in which “a standard supervised gradient descent learning algorithm trains a network to be a ‘music critic’ (preferentially judging musical examples according to various criteria)” (p. 212). This acquired critical knowledge is then used to refine a haphazardly created composition, until the network decides it is “good”. Lewis also recognizes the difficulties encountered by relatively low-level models when attempting to capture a larger-scale musical structure. His solution is similar to Todd’s in employing a hierarchical design strategy. The hierarchy uses a scheme of grammar rewriting rules, such as sequence  $ABC$  being expanded to  $AxBYC$ . Lewis makes no claim that this *really* captures any deep musical structure, his primary motivation being to make longer musical passages computationally manageable.

Teuvo Kohonen, Pauli Laine, Kalev Tiits, and Kari Torkkola describe a non-neural network algorithm for capturing compositional “style”. The relation of this work to the other models presented in this book is through its treatment of an unfolding musical context. The algorithm uses Kohonen’s dynamically expanding context (DEC) algorithm [6] to specify the succession of notes as loosely as possible. The grammar learned through this technique becomes specific only when a controversy or conflict is found in the parsed data. Like the other compositional models in this book, Kohonen et al. apply the DEC learning algorithm to several pieces and then use the acquired grammar to generate new pieces in the same style. The refreshing aspect of this paper is that the authors applied the technique to polyphonic music instead of simply generating rather abstract pitch sequences. However, this approach suffers from an inability to capture any deep musical structure, as the examples in the paper humorously demonstrate.

The final paper in the “Applications” section is actually one of the best examples of an ‘application’ of connectionism in music. Samir Sayegh uses a network implementing Viterbi’s algorithm [10] to find optimal paths for guitar fingering. Sayegh uses observed solutions of expert guitarists to construct cost functions which are learned by the network. These are then used to compute fingerings for other guitar pieces. It would have been nice if Sayegh had included some evaluations of the generated fingerings by practicing guitarists but the paper seems more focussed upon the application of the algorithm as a computer science problem rather than a music problem.

#### 4. Debated conclusions

The book ends with a very short “Conclusions” section containing a Letter to the Editor of the *Computer Music Journal* by Otto Laske commenting upon connectionist composition, responses to the letter by Loy and Todd, and a brief paper outlining some possible directions for future research by Todd. Laske criticizes connectionist musical systems as representing *model-based composition*, this being opposed to *rule-based composition*. Laske states that “connectionist models of composition seem to come attached with an aesthetics that is more suited to pedagogy and musicology in the orthodox sense than to compositional thinking and composition theory” (p. 260). Laske points to the lack of knowledge about the deep structure of music in network models as a symptom of this regressive approach. While I don’t subscribe to Laske’s notion that we composers must operate from within a “compositional theory”, I do endorse the related idea that computer music algorithms should have appropriate handles for compositional manipulation. I do think, however, that many of the systems described in this book—especially some of the pitch perception and rhythm quantizing models—would be excellent tools “to be added to the composer’s toolbox to further the creative effort” (Todd’s words, p. 261). In this light, I can appreciate Loy’s intention “to bring these techniques to the attention of composers so that they may be validated in practice” (p. 262).

Todd concludes his response to Laske by saying:

Finally, it is ridiculous to speak of “a primitive notion of composition” as if there were an established, universal aesthetic hierarchy of means, let alone ends. The fact that the connectionist approach shows “a lack of notions of composition theory” is one of its virtues, freeing the composer as it does from remembered compositional theories of the past—if not “remembered musics of the past.” (p. 261)

I don’t agree that connectionist approaches show a lack of notions of composition theory. I believe that many of the connectionist systems discussed in this book have very particular notions of composition theory, and that this compromises their claims to higher-level generality. When I read about systems which represent music as a set of discrete and virtually independent parameters, then I realize that a very strong concept of compositional theory has been implicitly and irrevocably imbedded in the model. When I read about attempts to capture the deep structure of music through the hierarchical organization of low-level models, then I realize that the authors have a relatively clear concept of how to construct music. This bothers me, because the deep structure of music is itself not a very clear concept. In fact, there is considerable disagreement among us humans as to what makes a piece of music cohesive or coherent, or even whether it needs to be. As I said earlier in this review, the “musical scaling problem” is not a simple matter of computational scaling. It is more a matter of modelling intelligence in general. This is probably what makes music such an attractive area for AI research.

My big caveat is that there are some fundamental pitfalls which must be recognized when Science intersects with Art. The goals of the researcher can be diametrically opposed to the goals of the artist. Blanket, cross-boundary pronouncements about either pursuit should be viewed with a healthy degree of skepticism.

It is easy for a reviewer to wax critical of an endeavor as young as this. Many of my criticisms are a bit “nit-picky”. Probably the fundamental task for the reviewer, however, is to recommend the purchase (or non-purchase) of the book under review. In this case, my answer is easy: I have already recommended to a number of students that they get this book. Even though the collection is somewhat scattered—after all, it is covering a broad range of topics in an emerging field—the book does give a good overview of the initial research being done in connectionist music modelling. If the editors’ intentions were indeed to stimulate and intrigue a potential audience of composers and music researchers, then they have succeeded admirably.

## References

- [1] J. Bharucha, MUSACT: a connectionist model of musical harmony in: *Proceedings Ninth Annual Conference of the Cognitive Science Society* (Erlbaum, Hillsdale, NJ, 1987) 508–517.
- [2] G.A. Carpenter, and S. Grossberg, ART 2: self-organization of stable category recognition codes for analog input patterns, *Applied Optics* **26** (1987) 4919–4930.
- [3] J.L. Goldstein, An optimum processor theory for the central formation of the pitch of complex tones, *J. Acoustical Soc. Am.* **63** (1973) 486–497.
- [4] S. Grossberg, Adaptive pattern classification and universal recording, II: feedback, expectation, olfaction, and illusions, *Biol. Cybern.* **23** (1976) 187–202.
- [5] T. Kohonen, *Self-organization and Associative Memory* (Springer-Verlag, Berlin, 1984).
- [6] T. Kohonen, Dynamically expanding context. Report TKK-F-A592, Helsinki University of Technology, Helsinki, Finland (1985).
- [7] L. Meyer, *Emotion and Meaning in Music* (University of Chicago Press, Chicago, IL, 1956).
- [8] M. Minsky, Music, mind and meaning, *Computer Music J.* **5** (3) (1981) 28–44.
- [9] E. Terhardt, Pitch consonance, and harmony, *J. Acoustical Soc. Am.* **55** (1974) 1061–1069.
- [10] A. J. Viterbi, Error bounds for convolutional codes and an asymptotically optimum decoding algorithm, *IEEE Trans. Inf. Theory* **13** (2) (1967) 260–269.
- [11] T. Winograd, Linguistics and the computer analysis of tonal harmony, *J. Music Theory* **12** (1968) 2–49.