A Live Performance Rule System Informed by Irish Traditional Dance Music

Marco Amerotti[1], Steve Benford[2], and Bob L. T. Sturm[1] and Craig Vear[2]*

[1] Speech, Music and Hearing, KTH Royal Institute of Technology, Stockholm Sweden
[2] University of Nottingham {amerotti,bobs}@kth.se, {steve.benford, craig.vear}@nottingham.ac.uk

Abstract. This paper describes ongoing work in programming a live performance system for interpreting melodies in ways that mimic Irish traditional dance music practice, and that allows plug and play human interaction. Existing performance systems are almost exclusively aimed at piano performance and classical music, and none are aimed specifically at traditional music. We develop a rule-based approach using expert knowledge that converts a melody into control parameters to synthesize an expressive MIDI performance, focusing on ornamentation, dynamics and subtle time deviation. Furthermore, we make the system controllable (e.g., via knobs or expression pedals) such that it can be controlled in real time by a musician. Our preliminary evaluations show the system can render expressive performances mimicking traditional practice, and allows for engaging with Irish traditional dance music in new ways. We provide several examples online.[3]

Keywords: Music performance modeling, traditional music, Irish

1 Introduction

The performance of an Irish traditional dance tune involves ornamentation and variation over repetitions. Some practitioners employ small variations where the tune is always recognizable (e.g., Irish accordionist Derek Hickey calls these "microvariations" of the "bones"[4]), while others move far away from the tune (e.g., the fiddler Tommy Potts is well-known as an extreme example). The ornamentation and variation employed in a performance are often guided by the instrument one is playing, which certain choices are made based on the accessibility of pitches, physical constraints, range, and so on.

* Portions of this work are outcomes of projects that have received funding from the European Research Council under the European Union's Horizon 2020 research and innovation program: DigiScore (Grant agreement No. 101002086) and MUSAiC (Grant agreement No. 864189).

[3] See this website: https://www.kth.se/profile/bobs/page/research-data.

[4] Private communication in a lesson with author Sturm.

Irish traditional music is by and large an aural tradition, where notated music ("the dots on the page") is passed over in favor of listening to master musicians interpreting tunes and then imitating their creative choices. When Irish traditional dance music is notated, the convention is one of writing what one thinks are the most important notes, leaving ornamentation and variation to the performer. Computer playback of such notated music thus lacks important elements of the traditional music performance: how might we program a performance system so that its rendition is closer to real-life performance?

While there is much research in modeling expressive music performance, e.g., classical piano, we do not find work devoted to traditional music. This paper presents a performance system focused on Irish traditional dance music aiming to render performances that mimic the practice. Our system operationalizes expert knowledge into a set of rules binding musical elements, such as ornamentation and dynamics, to performance parameters for controllable MIDI synthesis. The lack of explicit performance data in the context of Irish music motivates an expert-knowledge-driven, rule-based approach, which is both computationally efficient and sufficient to create at least a baseline model for Irish traditional music performance. Furthermore, since the performance of Irish traditional dance music can involve heterophony (multiple musicians playing their own versions of the same tune together), we make our system real-time and controllable such that one can play *with* it in a live performance scenario. In the next sections we review existing work in music performance modeling, as well as conventions in Irish traditional music performance. We describe our system and how its components operationalize expert knowledge. We then provide some preliminary evaluation of its output, and discuss its use in the context a live performance. Future research is discussed in the conclusion.

2 Background

We now review research in the modeling of music performance. We then discuss specific characteristics in the performance of Irish traditional dance music.

2.1 Existing work in modeling music performance

Music performance modeling [4] is aimed at making machines perform music in expressive ways. This is accomplished by translating musical elements, such as pitches, phrases, and timing, into expressive parameters, such as articulation, loudness, dynamics, and phrasing. One example is the "KTH rule system" for musical performance [5], which applies a user-weighted rule-based estimation of expressive parameters for each note of a piece. The set of rules has been implemented in the software package *Director Musices* [6], which allows one to inspect the generated expressive contours.

Most work in music performance modeling is aimed at the performance of classical music, but a growing number of studies focus on popular music and jazz performance [4]. While there exists research in the analysis of traditional music practice, we do not find any attempting to generate such performances. For traditional music, computational approaches are usually employed for performance *analysis* rather than *synthesis* [12,16,15,13].

The most commonly modeled parameters among performance systems include loudness, tempo, ornamentation and articulation, and so the MIDI protocol is often used since it allows some amount of modeling of the above through velocity, timing, pitch, and control messages (e.g., pitch bend). Expressive parameters are often modeled jointly since they can be highly related, e.g., tempo and dynamics [17]. Moreover, since human performance can go beyond the written score, such as ornamentation and style-specific musical practices, some work has explored the modeling of such performance conventions, e.g., ornamentation of lead sheets in the performance of jazz standards [7]. Another example is the MusicTransformer system [9], which can generate realistic accompaniments and performances given only melody input. Improvisation and variation are usually ignored when modeling classical music performance, but other styles (jazz and some folk traditions) consider them essential aspects of expressive performance.

2.2 Performance of Irish traditional dance music

Irish traditional dance music has a history going back a few centuries at least [3,18,8]. A dance tune consists of parts, each typically built from simple musical ideas unfolding over two to four beats. These parts are often repeated in performance, as is the whole tune. Common dances are the reel, jig, hornpipe, and polka, each executed with characteristic rhythms. Tunes are modal, most often in major, mixolydian, dorian or minor, and typically involve melodic motion that combines stepwise movement with arpeggiated chords. Ornamentation is an essential aspect of traditional performance, contributing to the rhythmic drive of a dance tune.

Irish traditional music is an aural practice, the expert performance of which does not involve playing tunes “as written”. Figure 1 notates the A part of the well-known jig, *The Connachtman’s Rambles*, as printed in “O’Neill’s 1001” [14], along with a transcription of one of its repetitions performed by master musician Máirtín O’Connor. This shows his variation of the jig rhythm, playing with the timing of quavers within each beat. He uses a variety of “cuts” (a grace note ornament emphasizing the attack of the following note), some of which provide tonal value to establish a counter melody (bars 11–12).

O’Connor’s performance of this tune demonstrates how the practice of the music involves “microvariations”, which lends itself well to performance in “sessions” where musicians of varied abilities gather informally to play tunes together. While varying greatly, sessions tend to exhibit some common characteristics including [2] performers joining and leaving throughout, numerous and diverse melody instruments playing in unison (often accompanied by a few guitars, citterns and bouzoukis), musicians with different skills – from beginners to seasoned experts – playing alongside one another, and playing and learning by ear more often than playing from printed music. Furthermore, sessions feature tunes linked together in “sets” of two or more, each repeated a number of times. This structure allows tunes to be learned by ear or recalled to the fingers before then being embellished on subsequent repeats. There is also a degree of improvisation in selecting tunes that fit well together as sets and in guessing which tunes other players might or might not know and/or be able to pick up.

Fig. 1. The A part of *The Connachtman's Rambles*. Top: as printed in "The Dance Music of Ireland: O'Neill's 1001". Middle: as performed by Máirtín O'Connor on accordion in 1979 (transposed down to D from Eb). Bottom: as interpreted by our performance model. The performance hyperparameters were set to create a performance similar to Máirtín O'Connor's.

3 Performance System

We now present our performance system, which processes MIDI input and outputs control parameters to synthesize an expressive MIDI performance that can be exported on its own without human interaction, or input in real-time to any software or hardware with MIDI input capabilities. The resulting performance incorporates style-specific ornaments, time deviations, and dynamics to reflect conventions of Irish traditional dance music practice. The performances of each of these three aspects (ornamentation, dynamics, tempo) are modeled with expert-knowledge-based rules and functions, user-specified performance parameters, and metadata in the MIDI file itself (e.g., the key signature MIDI meta-message).

The expert-knowledge-based rules and functions are motivated not only by our own practical knowledge of Irish traditional dance music performance, but also that of noted Irish musician and theorist Tomás Ó Canainn [18]. In his analysis of Irish music, Ó Canainn presents a formalism of note importance in which he assigns points to each note appearing in a tune:

> 1) a note frequency count giving a point for each appearance of the note; 2) the addition of a further point (a) to a note which occurs on a strong beat, (b)

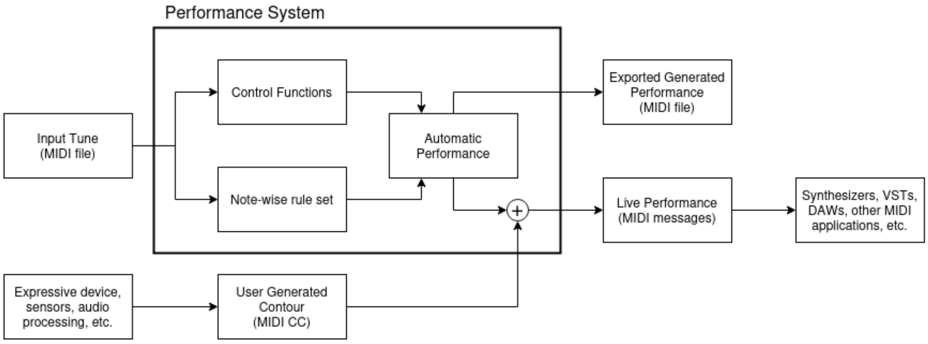

Fig. 2. The performance system pipeline. An input MIDI tune is processed by computing control functions to guide the performance and by evaluating rule-sets for each note (e.g. to generate ornamentation). The performance can be live, and optionally steered in real-time, or otherwise exported to a MIDI file.

to the highest note on its first appearance, (c) to the lowest note on its first appearance, (d) to a note proceeded to by a leap greater than a fifth, (e) to the first stressed note, (f) to a long note (e.g., a dotted crotchet in a jig).

Inspired by Ó Canainn our system assigns five scores to each note in a tune, and then uses these to derive and apply control functions to guide the resulting performance. For each note-on event of a MIDI source, we compute the following scores:

1. a number of points equal to the number of occurrences of that pitch class in the entire tune (*frequency score*);
2. if the note occurs on a strong beat, it gets a number of points equal to the number of times the pitch occurs on a strong beat; otherwise zero (*beat score*);
3. a point if it is either the highest or the lowest pitch of the tune (*ambitus score*);
4. a point if the interval leading to it is greater or equal to a fifth (*leap score*);
5. a point if its duration is longer than the mode of the note durations of the tune (*length score*).

To generate control functions the system normalizes these scores and linearly combines them to manifest particular musical qualities relevant to the three modeled performance aspects. We hand-craft these linear combinations through a combination of formalizing our musical experiences and expectations, as well as trial and error, e.g., that a cut is more likely to occur between a repetition of a pitch and on a strong beat. Table 1 shows the weightings involved, which have proven to be sufficient at this preliminary stage, but work is required to determine their sufficiency for modelling real performance. Finally, we apply smoothing to these functions to reduce extreme sudden variations that make the performance erratic. In particular, we employ a third-order Savitzky–Golay filter with a window size of 15 notes, and use mean-value padding at the edges.

To illustrate the procedure of generating control functions, consider the A part of *The Connachtman's Rambles* from Fig. 1. Figure 3 show the five series of scores derived

Control function	frequency	beat	ambitus	leap	length
Ornaments	0.2	0.3	0.15	0.15	0.2
Dynamics	0.1	0.25	0.25	0.2	0.2
Tempo	0.25	0.1	0.3	0.25	0.1

Table 1. Score weighting for computing control functions. For instance, the ornament score is given by the sum $0.2 \cdot \textit{frequency score} + 0.3 \cdot \textit{beat score} + 0.15 \cdot \textit{ambitus score} + 0.15 \cdot \textit{leap score} + 0.2 \cdot \textit{length score}$.

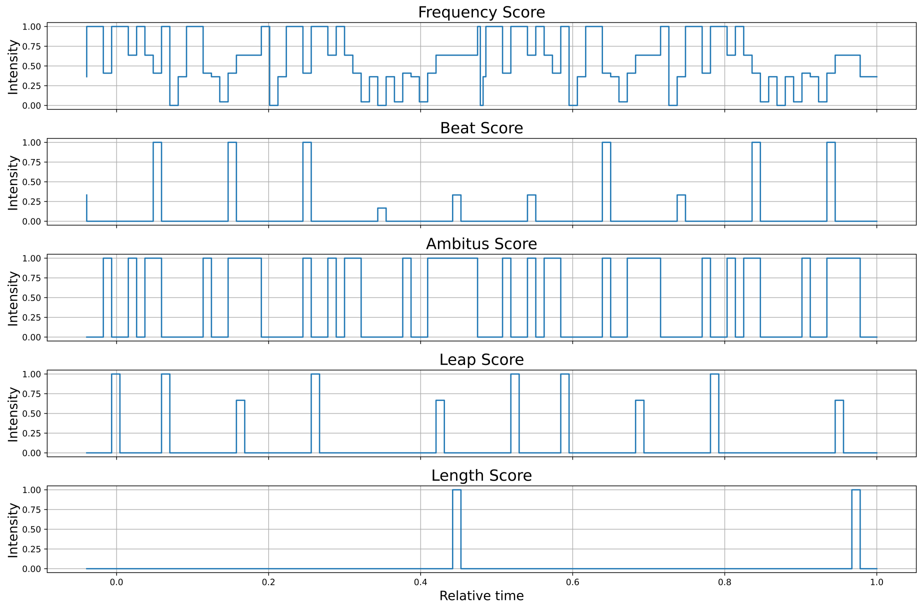

Fig. 3. Individual scores used to generate control functions for each modeled aspect for the A part of *The Connachtman's Rambles* (Fig. 1). The single note-wise scores are summed and weighted according to Table 1 to generate the control functions.

using the above method. Figure 4 show the control functions resulting from the linear combination and smoothing for each performance model aspect. For each note in the input melody, the system uses the corresponding value of the control functions to affect its performance according to each modeled aspect.

Being intended not only as a performance generator, but also as an agent capable of performing live with another musician, we make our system responsive to an external user-defined control signal to steer the performance, e.g., an accompanying guitarist with an expression pedal. The following subsections describe how our system models each of the three performance aspects and how each of those is influenced by a control function.

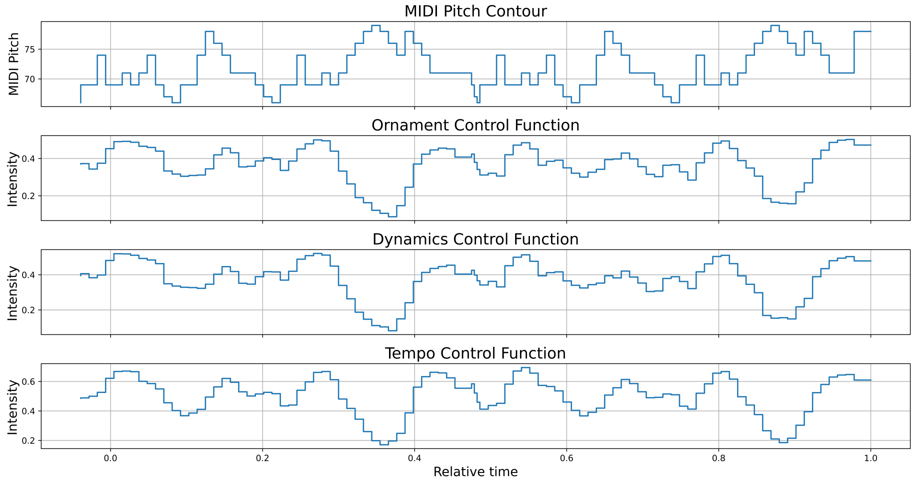

Fig. 4. From the top, MIDI Pitch contour and generated ornament, dynamics, and tempo control functions for the A part of *The Connachtman's Rambles* (Fig. 1). The ornament control function is directly mapped to the probability of ornamenting a note; the dynamics control function is mapped to note velocity in the range [0, 127]; the tempo control function is mapped to a tempo drift percentage with 0.5 being the original tempo, higher/lower values meaning a faster/slower tempo.

3.1 Performing Ornamentation

Ornaments in Irish traditional music are partly dependent on the physical characteristics of the traditional instruments [18] (e.g., sliding between pitches on the fiddle, "tapping" on the tin whistle to articulate repeated notes) and musical characteristics (e.g., to accentuate beats in accordance with traditional dancing). On top of that, musicians may impose personal stylistic preferences and improvisational elements. We focus on the modeling of three of the most common ornaments which can be easily modeled with MIDI, and are not exclusive to particular instruments by and large. The particular ornaments performed by our system are slides, cuts and rolls:

– A slide entails approaching a note from a lower pitch. We create a slide ornament by using a series of MIDI pitch-bend messages between a notes and next lowest scale degree.
– A cut is like a grace-note that emphasizes the attack of a note, or separates repeated notes. We create a cut by adding a short note one scale degree above the note.
– A roll is a decoration of three quavers that involves separating each with cuts, similar to the classical "gruppetto" or "turn", and consist in approaching the pitch from above and then from below. We create a roll by adding the appropriate notes.

In our system, the pitches of rolls and cuts are drawn from the mode of the tune.

For each note of a MIDI file, the system determines if it is a candidate for ornamentation with a probability computed from the ornament control function and user-specified parameters. If it is a candidate, the system selects one of the ornaments, or possibly drops the note (a “humanizing” of the performance), at random.

3.2 Performing with dynamics and tempo deviations

Our systems models dynamics via MIDI note velocity using the dynamics control function, which is scaled to the range [0,127] and applied directly to the note velocity parameter. Notes falling on a beat are further accentuated by increasing their velocity. To humanize the performance, the system implements tempo deviations around a user-specified tempo by locally warping the performance tempo using the tempo control function. The motivating idea is that musicians will tend to speed up or slow down at times the melody has certain characteristics, e.g., ornamentation, repeated notes, and melodic leaps.

3.3 Human Interaction

Our system is capable of continuously reading an external MIDI control change signal on a specified MIDI control number during a performance with an accompanying musician. This signal is scaled to $[0, 1]$ and interpolated with the control functions with a user-defined weight. For instance, the musician can make the performance system play without ornamentation at first, and then gradually make it more adventurous. While basic, this approach can be quite versatile since any kind of user-generated control function can manipulate the MIDI control signal processed by the system. Possibilities include conventional controls, e.g., MIDI pedals and knobs, but also unconventional ones such as body sensors.

4 Preliminary Evaluation

We now conduct a preliminary evaluation of our performance system to determine its effectiveness and chart future work for development. We first compare an expert performance of *The Connachtman's Rambles* (Fig. 1) with that of our system to determine acceptable parameters. We then apply the performance system to a novel tune generated by Folktune-VAE [1] – a model trained on Irish traditional music – and gauge its plausibility with respect to traditional practice. Audio examples of generated performances are available on our website.

Figure 1 shows transcriptions of two performances of the A part of *The Connachtman's Rambles*, one by an expert and another generated by our system. We see that the system is able to mimic some of the ornamentation of the expert, with a general difference in the pitch used to cut. Most of O'Connor's cuts are pitches a third above – which are convenient to do on the accordion because of the physical distribution of its pitches. Our system at this time is not instrument-specific and produces “generic” cuts within the mode of a tune. In terms of rhythm, our model accentuates the beats using cuts as in the human performance. Rhythmic swing is clear in the human performance (emphasizing the jig rhythm), while the performance system shows none since it is only subtly adjusting tempo at this time. The performance system stays with a steady

Fig. 5. A tune generated by the model *Folktune-VAE* [1]. Top: original tune as generated by the model. Bottom: as interpreted by the performance system. A rolled note is notated with a tilde.

tempo but introduces subtle drifts. While still far from the human performance, our system generates stylistically coherent elements that are more expressive than basic MIDI synthesis.

We now analyze how our system performs the machine-generated tune shown at top of Fig. 5. There is of course no reference performance for this tune, but we can gauge the stylistic coherence of our system's performance. The transcription, shown at the bottom of Fig. 5, shows the system mainly employs cuts and occasional slides and dropped notes. Cuts are placed appropriately, e.g., on the start of bars or between repeated notes. The system generates a roll at the start of the B part on a dotted crochet, which is also consistent with the practice. Listening to the performance, the reel rhythm is clear and the dynamics are varied throughout.

While preliminary, this evaluation shows our system shows some success in rendering a performance of melodies in ways that are consistent with the practice of Irish traditional dance music. Linking probabilistic decisions with higher-level control signals derived from the music content make expressive and varied renditions that are more interesting than straight MIDI playback. Furthermore, adding interactivity makes for a dynamic playing partner.

5 Discussion: The system as a musician

The inspiration for our system arose from an ongoing project to explore how human and AI musicians might perform together. Our distinctive focus was on how humans might accompany AI, specifically on how a human guitarist might improvise an accompaniment to AI-generated and performed tunes. First, a human musician (Benford) used the

FolkRNN system[5] to generate around twenty tunes, from which eight were selected and segued to form two sets – a set of four reels and a set of four jigs. While this yielded sets of tunes potentially interesting to accompany, the automated playback of the resulting MIDI files through a standard digital audio workstation was, unsurprisingly, flat and immediately striking for its lack of variation when tunes were repeated. There was no sense of the system pushing the performer or vice versa, and the human accompanist was left to do all of the work in making the performance dynamic and interesting.

Our preliminary exploration involved a series of scripts generating ornamentation, micro timing, and pitch errors[6] based on random chances alone; with those, a human musician generated twelve variations of each tune with different parameters (three levels of ornamentation, note pitch error, micro timing, and three combinations of all of them with the scripts applied in sequence). The human musician listened to and compared these, selecting three versions of each tune to be sequenced together as part of the overall set. This process already led to some immediate insights and inspirations for further developments.

The traditional ornamentations of rolls, cuts, and slides worked to introduce aesthetically pleasing variation. Timing errors and dropped notes on the other hand gave a sense of the agent struggling to play the tune, or being tentative, giving the impression that it was learning it or trying to recall it back to its fingers. Pitch errors were sometimes heard as mistakes, but sometimes as more as attempted 'jazzy' (chromatic) improvisations, especially if the system was otherwise performing fluidly (*e.g.*, was introducing odd pitched without obvious timing errors).

These observations led to the idea that the system might have a persona that would support a narrative through the performance that would make sense of their variations. For example, they might be a learner struggling to learn new tunes and/or to master their instrument, or alternatively, a skilled and proficient player quickly trying to recall 'out of practice' tunes. The latter felt particularly appealing, as a skilled musician might conceivably play with various embellishments, but also errors depending on their situation, and might even be expected to vary these through a performance. The journey through such a narrative should be interactive, *i.e.* the human should be able to influence it. This inspired the idea of a simple control based on an expression of musical intensity; that the human musician should be able to signal that they would want their skilled AI collaborator to play with more or less intensity. This might be interpreted in various ways. Lowering intensity might signal the AI to back off, perhaps playing more solidly (if boringly) and ultimately more tentatively (as if trying to recall a tune). Raising intensity might cause it to introduce more traditional embellishments, and eventually introduce jazzy improvisations or even take risks that would lead to mistakes. Intensity might be signaled explicitly (*e.g.* through the expression pedal) or perhaps detected automatically from the accompanist's own playing. In this case, our performance system allows us to hear a tune that is foreign to the tradition and which would have to be physically learned and played by a musician to be heard otherwise.

[5] `https://folkrnn.org`

[6] The pitch errors were not included in the system presented here as we felt that more work was needed in modeling this aspect.

In summary, the variations introduced by our performance system felt potentially productive in inspiring accompaniment, but might benefit from the creation of an underlying musical persona and narrative for the system that would help make sense of them and enable them to be influenced during the performance. Our goal was to generate a performance an authentic performance, more than an ideal one: such a performance cannot be modeled without having an underlying musician, or an idea of them.

6 Conclusion

To the best of our knowledge, this is the first work explicitly modeling the performance of folk music, and Irish traditional dance music in particular. We have operationalized expert knowledge to form a rule-based performance system that is able to render a melody expressed in MIDI as an expressive and dynamic performance that exemplifies conventions of the practice. Performance aspects that we have modeled include various ornaments, tempo variations and dynamics. Our preliminary evaluation demonstrates the effectiveness of our system and points to its usefulness in human-AI co-performance. The system has clear limitations, however. For example, its parameters and hyperparameters are currently set by trial and error, but could be estimated from expert performances. Another limitation is the performances it generates are not instrument specific, possibly rendering a performance on a synthetic instrument that would not be typical or even possible on a real instrument. More work should thus be conducted to improve this baseline system, e.g., further humanizing the performance, introducing melodic variation and extemporization, and modeling specific instruments. Another aspect deserving of further work is the rendering of a *session* performance, where two or more artificial performers play a melody together.

While the task of creating a performance system presents common elements across styles, datasets, and approaches [4], a main difference in the modeling of folk music performance is *performance creativity* [11], not limited to creativity in planning the performance, but ranging from adding ornamentation and micro timing to explicitly playing wrong notes and drifting in tempo. This is in contrast to the performance of classical music, where one must play a score as written without mistakes, but taking liberties with phrasing, dynamics, articulation, and tempo. It might seem at first that modeling the performance of just a melody is a trivial matter, but the conventions of the practice of Irish traditional dance music bring subtle and interesting challenges. Folk music is more complex than it appears at first. The modeling of folk music performance presents challenges that are different from those when modeling other styles, and in our opinion should be pursued to enrich opportunities engaging with music traditions.

Of the performance systems dealing with performance creativity listed in [11], most of them present very limited evaluation, if any at all. An obvious way of evaluating a performance system is through listening tests, RENCON [10] being a key example. Our preliminary evaluation analyzes generated performances from an expert-knowledge-based perspective, but future work can conduct listening tests as done at RENCON, both of the system's output and its application in the context of human-AI co-performance. This latter aspect brings ambiguity, however: if a performance system is difficult to play with, it could be a bad performance system, or a good emulation of a bad musician. Nonetheless, we aim for rendering performances that are expressive and faithfully reflect practical conventions.

References

1. AMEROTTI, M. *Latent representations for traditional music analysis and generation*. Tesi di laurea, Università di Bologna, Oct. 2022.
2. BENFORD, S., TOLMIE, P., AHMED, A. Y., CRABTREE, A., AND RODDEN, T. Supporting traditional music-making: designing for situated discretion. In *Proc. of the ACM 2012 Conf. on Computer Supported Cooperative Work* (2012), pp. 127–136.
3. BREATHNACH, B. *Folk Music and Dances of Ireland: A comprehensive study examining the basic elements of Irish Folk Music and Dance Traditions*. Ossian, 1971.
4. CANCINO-CHACÓN, C. E., GRACHTEN, M., GOEBL, W., AND WIDMER, G. Computational Models of Expressive Music Performance: A Comprehensive and Critical Review. *Frontiers in Digital Humanities 5* (2018).
5. FRIBERG, A., BRESIN, R., AND SUNDBERG, J. Overview of the KTH rule system for musical performance. *Advances in Cognitive Psychology 2* (2006), 145–161.
6. FRIBERG, A., COLOMBO, V., FRYDÉN, L., AND SUNDBERG, J. Generating Musical Performances with Director Musices. *Computer Music J. 24*, 3 (Sept. 2000), 23–29.
7. GIRALDO, S., AND RAMÍREZ, R. A machine learning approach to ornamentation modeling and synthesis in jazz guitar. *J. of Mathematics and Music 10*, 2 (May 2016), 107–126.
8. HALLMHURÁIN, G. O. *A pocket history of Irish Traditional Music*. The O'Brien Press, 1998.
9. HUANG, C.-Z. A., VASWANI, A., USZKOREIT, J., SHAZEER, N., HAWTHORNE, C., DAI, A. M., HOFFMAN, M. D., AND ECK, D. Music transformer: Generating music with long-term structure. *arXiv preprint arXiv:1809.04281* (2018).
10. KATAYOSE, H., HASHIDA, M., DE POLI, G., AND HIRATA, K. On evaluating systems for generating expressive music performance: The RENCON experience. *J. of New Music Research 41* (12 2012), 299–310.
11. KIRKE, A., AND MIRANDA, E. R. *Handbook of Artificial Intelligence for Music: Foundations, Advanced Approaches, and Developments for Creativity*. Springer, 2021, ch. Performance Creativity in Computer Systems for Expressive Performance of Music, pp. 521–584.
12. LERCH, A., ARTHUR, C., PATI, A., AND GURURANI, S. An interdisciplinary review of music performance analysis. *arXiv preprint arXiv:2104.09018* (2021).
13. MÜLLER, M., GROSCHE, P., AND WIERING, F. Automated analysis of performance variations in folk song recordings. In *Proc. Int. Conf. on Multimedia Information Retrieval* (Mar. 2010), pp. 247–256.
14. O'NEILL, F. *The Dance Music of Ireland: O'Neill's 1001*. Chicago, 1907.
15. RAMIREZ, R., MAESTRE, E., PEREZ, A., AND SERRA, X. Automatic performer identification in celtic violin audio recordings. *J. of New Music Research 40*, 2 (2011), 165–174.
16. REN, Y., KOOPS, H. V., BOUNTOURIDIS, D., VOLK, A., SWIERSTRA, W., VELTKAMP, R. C., HOLZAPFEL, A., PIKRAKIS, A., ET AL. Feature analysis of repeated patterns in Dutch folk songs using principal component analysis. In *Proc. of the 8th International Workshop on Folk Music Analysis* (2018), pp. 86–88.
17. TODD, N. P. M. The dynamics of dynamics: A model of musical expression. *The J. of the Acoustical Society of America 91*, 6 (June 1992), 3540–3550.
18. Ó CANAINN, T. *Traditional Music in Ireland*. Routledge and Kegan Paul Ltd., 1978.