Anticipation in collaborative music performance using fuzzy systems: a case study *

Oscar Thörn[1], Peter Fögel[2], Peter Knudsen[2],
Luis de Miranda[3], and Alessandro Saffiotti[1]

[1] School of Science and Technology, Örebro University, Sweden
oscar.thorn@aass.oru.se, alessandro.saffiotti@aass.oru.se
[2] School of Music, Theatre and Art, Örebro University, Sweden
peter.fogel@oru.se, peter.knudsen@oru.se
[3] School of Humanities, Education and Social Sciences, Örebro University, Sweden
luis.de-miranda@oru.se

Abstract. In order to collaborate and co-create with humans, an AI system must be capable of both reactive and anticipatory behavior. We present a case study in jazz improvisation, in which a human pianist is accompained by a synthetic drummer controlled by an AI system.

1 Introduction

The creation and performance of music has inspired AI researchers since the very early times of artificial intelligence [8], and there is today a rich literature of computational approaches to music [11], including AI systems for music composition and improvisation [10]. As pointed out by Thom [14], however, these systems rarely focus on the spontanous interaction between the human and the artificial musician. We claim that such interaction demands a combination of *reactivity* and *anticipation*, where by the latter we mean the ability to act based on a predictive model of the companion player [12]. This paper reports our initial steps in the generation of collaborative human-machine music performance, as a special case of the more general problem of anticipation and creative processes in mixed human-robot, or *anthrobotic* systems [3].

2 Methodology

We focus on the collaborative execution between a human musician and a robotic performer. We assume that the robotic performer is capable of autonomous execution, whose modalities are controlled by a fixed number of parameters. We addresses the problem of controlling these parameters to obtain a harmonious joint performance between the human and the robotic performer.

Figure 1 illustrates our concept. A human musician plays freely, and an AI system controls the parameters of a robotic performer. We use "robot" here in a broad sense to mean any agent that generates physical actions: this could be

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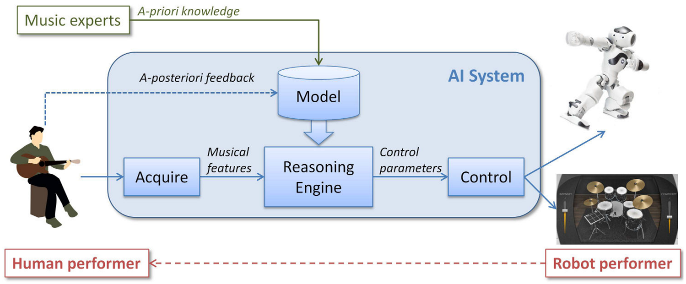

Fig. 1. The proposed methodology to control a robotic music partner

a dancing robot, a virtual drummer, or a sound agent that spatializes music in the concert hall. In the case presented in this paper, the musician is a jazz pianist and the robot perormer is a Strike 2 virtual drummer [2].The drums parameters controlled by the AI system include patterns, intensity, complexity, fills, instruments used, and enter or exit sequences.

Discussions with the musicians revealed that heuristic knowledge of how the drummer's parameters depend on the pianist's play is available, and that it can be express in terms of approximate rules using vague linguistic terms, like:

If the rhythmic complexity on the lower register is *high*,
then the rhythmic complexity of the drums should increase *strongly*.

This type of knowledge is suitably encoded in fuzzy logic, and this was therefore the modeling and reasoning tool of choice for our system. Note that, while rule-based systems have often been used for music composition and improvisation [13], the use of fuzzy logic in this field is much less explored [9].

3 System Design

The core of our system is a multiple-input multiple-output Fuzzy Inference System (FIS) [6], which implements the "Reasoning engine" block in Figure 1. The system runs at a fixed clock cycle, and it resembles the structure of a classical fuzzy controller. It takes as input a set of music parameters extracted in real time that describe the human execution, and it produces as output a set of control parameters for the virtual drummer. Differently from most conventional fuzzy controllers, the rules' conditions are not simply conjunctions of positive literals, but general formulas in fuzzy propositional logic. This gives us greater expressive power in representing the musician's knowledge.

Below we briefly list the main elements of the overall system. A more detailed technical description can be found in the full version of this paper [15].

Input features. The interface between the software and the piano relies on MIDI. The system continually polls the input port for MIDI messages, and extracts both explicit and implicit features from these. These include: velocity $v(t)$, rhythmic density $d(t)$, time since last note $T(t)$ and beat couter $b(t)$.

Temporal filters. Some aspects of the knowledge expressed by the musicians implicitly refers to a temporal dimension, e.g., the relative change in rythmic density. We use a second FIS to extract relevant temporal features in a way that explicitly reflects the knowledge of the musician, e.g., on what counts as a "sudden drop in intensity". This FIS is a recurrent fuzzy system [1] that takes as input the current features at time t plus its own output at time $t-1$. The extracted temporal features include: $\bar{v}(t)$ (average velocity), $\bar{d}(t)$ (average density), $\Delta_v(t)$ (velocity slope), $\Delta_d(t)$ (density slope), and $\delta(t)$ (step change).

Anticipation. Anticipation plays an important role in joint musical performance. We have encoded a simple predictive model in the above temporal FIS to infer a coming climax or anti-climax from a change in intensity and complexity. The main FIS includes anticipatory rules that use these forecasted features, e.g., to anticipate a climax by starting a drums fill-in; or anticipate an anti-climax by muting the kick first, and then the snare once the change occurs.

Output parameters. The Strike 2 virtual drummer allows us to control its behaviour and settings by sending MIDI messages. Currently our software controls the intensity and complexity of the drummer as well as starting, stopping and changing the pattern (e.g., verse, bridge, chorus, fills, intros and outros) and muting individual parts of the kit.

Fuzzy inference. The main inferece system is a FIS based on the above input and output variables. It usese the usual fuzzify-inference-defuzzify pipeline [6].

4 Development and Testing

System development. The system has been implemented using Python 3.6.8 and the MIDO library (1.2.9). We used Strike 2 (2.0.7) as virtual drummer. The input comes from a MIDI piano, or from a MIDI file for debugging purposes.

Knowledge elicitation. The project includes people from computer science, music performance, audio engineering and philosophy. This strong inter-disciplinarity requires a careful process for the conceptual and practical development. Throughout the project, participants have kept journals on their thoughts, and relied on a variety of interaction means — discussions, workshops, shared documents, examples of piano performance, and system demos. In the initial phases, piano recordings were analyzed by the performer himself through a process of open coding, where different features of the playing were identified and described; e.g. "phrase with high intensity", "build up in velocity", etc. These indications then provided a basis for identifying the relevant musical parameters and fuzzy rules in the AI system. Interestingly, the interaction has led to mutual enrichment of the participants in all directions. For example, the need to describe music performance in logical terms led to the development of a new analytical perspective on how, when and why different styles are being chosen and used. On the other hand, the fuzzy models had to be enriched to meet the complexity of human musical performance, e.g., to change the feeling of intensity in the music using density of notes, change of notes registries, sustain pedal, or dynamics.

Testing. Development was done in a tight loop between the musicians and the software developers: musicians could test the system at all times during development, starting from a very simple but usable one, and provide continuous feedback for incremental improvement. The system has been demostrated in several public concerts, with very positive reactions. Videos of some concerts, as well as the project code, are available from the CREA website [4].

5 Next Steps

So far we have used a pure knowledge-based approach. This allowed us to go through an open, modular and incremental development loop together with the music experts. We next plan to integrate this approach with a data-driven approach, e.g., to complete and/or adapt the rules as done, e.g., in [7].

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