Synchronization and Music

A different paradigm & new perspective on leader-follower interactions

Kit Armstrong 2024-08-07

Tapping synchronization → Music ensemble

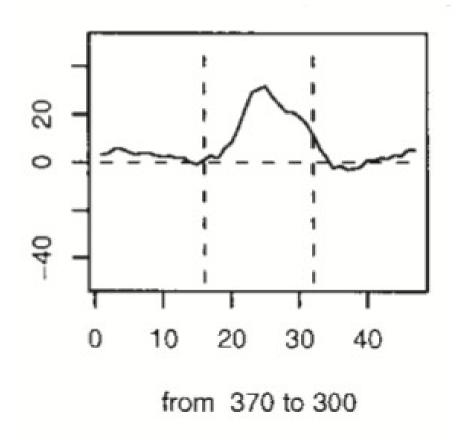
- Recall: Kuramoto model
 - for tapping: Continuous → Discrete
 - for music:
 - Variable rhythms
 - Non-constant tempo
 - Real-time causality

Schulze et al. (2005)

 Motivating scenario: tapping at non-constant tempo (accelerando & ritardando)

Schulze et al. (2005)

• We measure asynchrony A_i at each step



Schulze et al. (2005)

- Input:
 - "Metronome" C_{i}
- Primary elements of the model:
 - Timekeeper (random variable T_{i})
 - Motor noise (random variable M_{i})
 - Attention to asynchrony: error decays exponentially

Schulze et al. (2005)

- We wish to model A_{i}
- $A_{i-1} + T_{i-1} C_{i-1}$ is the "expected asynchrony"
- To this we add:
 - Motor noise M_{i}
 - Active correction factor $-\alpha A_{i-1}$

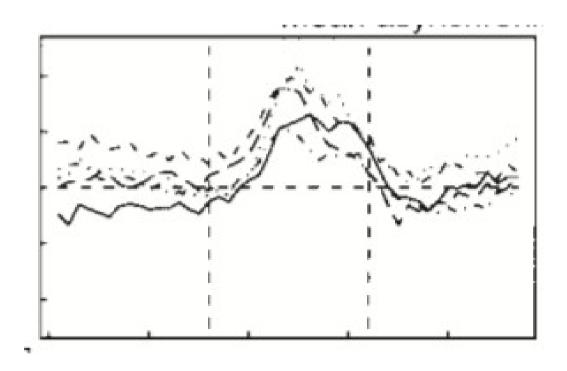
Schulze et al. (2005)

We also update the timekeeper T at each step

•
$$t_i = t_{i-1} - \beta A_{i-1}$$

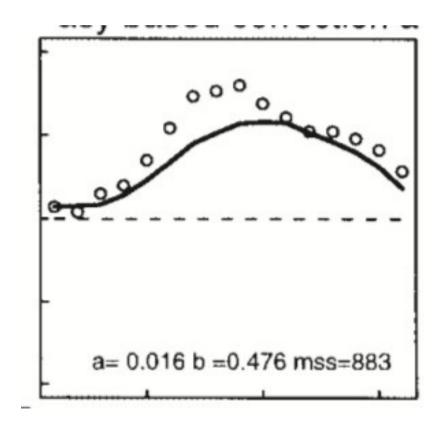
Schulze et al. (2005)

• Now estimate α & β to best fit the observed A_{i}



Schulze et al. (2005)

Result (by least-SSE criterion):



Schulze et al. (2005)

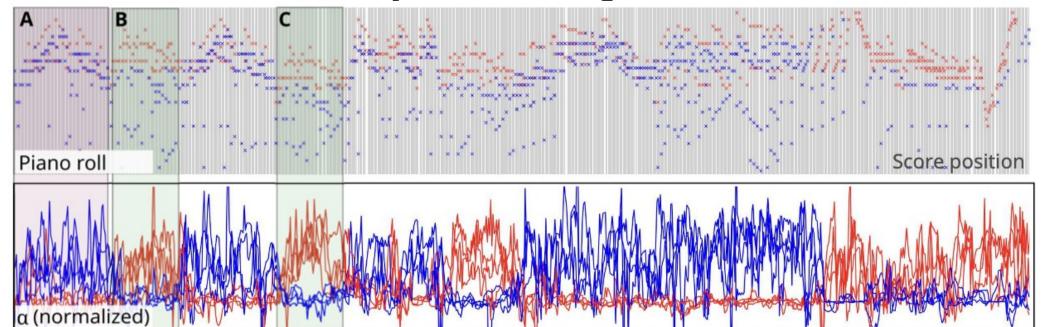
- Properties/Advantages:
 - Naturally discrete
 - Deals with changing tempo
- NB this is a model for *post hoc* analysis. In real-time, A < 0 cannot be implemented.

- Piano duet
- Rhythm quantized (32nd note)
- Linear interpolation when there is no onset

Maezawa (2024)

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- If the pair of musicians act like this model, we can treat one as the "metronome" and compute the local α , β of the other one.
- The result is very interesting:



- α, β are not constants.
- Maezawa's hypothesis: they depend on the score.
- Let's also consider $\sigma_{\!_M}$, $\sigma_{\!_T}$ to be functions of the score.

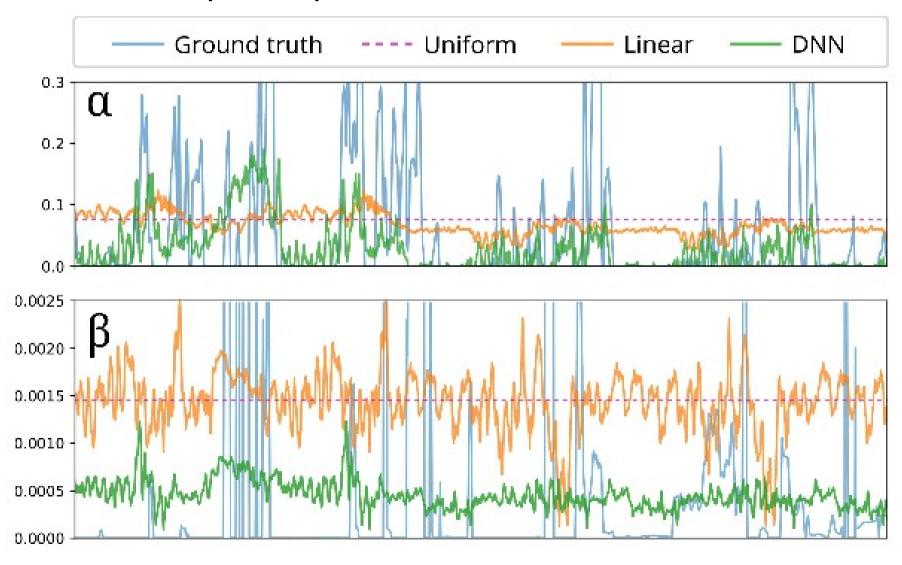
- Cut the score into frames (1 per 32nd note)
- We look at "slices" composed of 32 frames, centered around each sequential frame.
- Create a model:

INPUT
$$\rightarrow$$
 OUTPUT Score slice $\alpha, \beta, \sigma_{M}, \sigma_{T}$

Maezawa (2024)

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 It learns "hidden variables" which determine how to extract them from a score.
- Evaluation: compare model-computed α , β , σ_{M} , σ_{T} to observation.



Maezawa (2024)

• Mean absolute error: (recall that $0 < \alpha < 1$)

Condition	$ \alpha $	eta	σ_T	σ_M
Uniform-train	7.43E-2	2.85E-3	2.05E-2	2.76E-2
Uniform-valid	7.43E-2	2.84E-3	1.71E-2	2.74E-2
Linear	6.56E-2	1.77E-3	1.39E-2	2.42E-2
DNN	5.65E-2	1.80E-3	1.19E-2	1.82E-2

Discussion

- A way to approach the leader-follower problem
- General idea: the AI, having looked at the score, generates a "map" of the parameter values to be applied at each point of the score. It has learnt how to do this by analyzing how humans have performed other scores.
- We should be able to apply this concept to add another layer to our real-time ensemble player.
- However, its specificity w.r.t. certain salient musical features is probably low.