Multidimensional Similarity Modelling of Complex Drum Loops using the *GrooveToolbox*

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In this paper we present the *GrooveToolbox*, a Python library for analysing *symbolic* drum loops. It provides a new centralised resource for researchers working with drum loops, along with new models for analysing microtiming and measuring similarity. We also perform an evaluation to test our new features' ability to model perceptual similarity between drum loops.

The *GrooveToolbox* currently contains: 20+ models, both re-implementations of existing ones and new ones (listed in red). They are in 3 sets:

- **Rhythm features:**
  - Syncopation, density, periodicity, complexity +more
- **Microtiming features:**
  - Swing-ness/Triplet-ness
  - Microtiming style: laidback-ness, timing accuracy
- **Similarity measures:**
  - Hamming distance
  - Fuzzy Hamming distance
  - Structural similarity

Take a look!

https://github.com/fredbru/GrooveToolbox

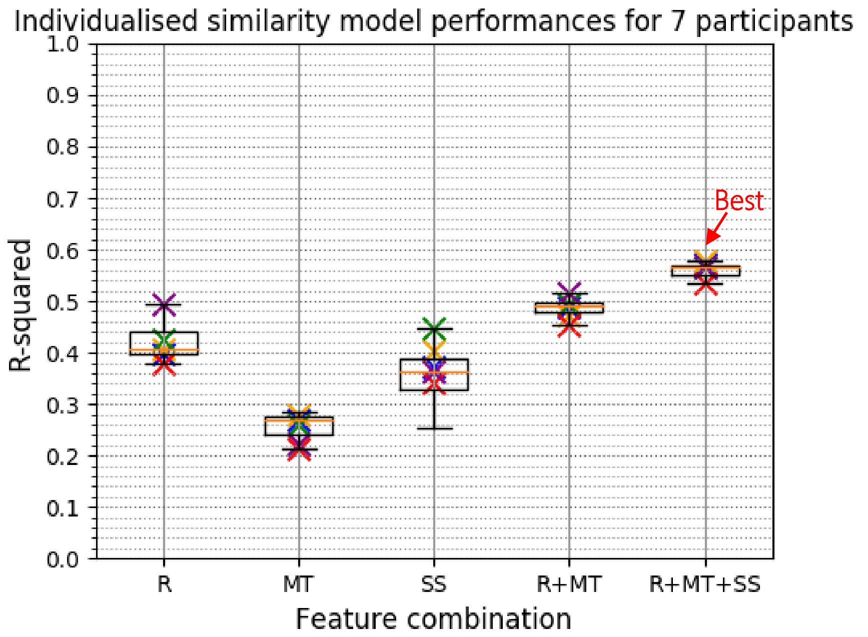
EVALUATION

1. *Should models of drum loop similarity rely on rhythm similarity, microtiming and rhythm feature sets or all three?*
2. *Can our new models of microtiming improve similarity models?*
3. *How do the new similarity models compare to the Hamming distance?*

Part 1: To test feature feature performance we compared their correlation to perceptual data – mean similarity ratings for pairs of drum loops from 21 participants.

The structural similarty measure correlated higher to the similarity ratings than the Hamming distance, with the fuzzy Hamming distance approximately the same as the Hamming distance. All four microtiming features correlated to the perceptual data to a statistically signifiant extent.

Part 2: To find the best way to combine the 3 model types – fit regression models to individuals for a subset of participants, using each set individually, and each combination of the three.



Model performance as R-squared value for rhythm R feature set, microtiming MT feature set, structural similarity feature SS and all three combined for each participant. The best performance is found when the three are combined (see paper for full diagram).

KEY FINDINGS:

1. *Models of drum loop similarity perform best when using similarity models* ***in combination with*** *rhythm features*
2. *Modelling microtiming (swing, microtiming style)* ***improves*** *similarity models*
3. *Structural similarity performs* ***better*** *than Hamming distance*