Beat Tracking and Reaction Time

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Centre for Music and Science Faculty of Music University of Cambridge UK To investigate the weaknesses of current generation (real-time, causal) computational beat trackers:

Reaction time at phase/period jumps due to changing stimuli

Signal representation and phase alignment

Reference	Stimuli	Task	Reaction times (seconds)	Notes
Moelants and McKinney [2004]	polyphonic audio	tapping the beat	2-3	data set from the refer- enced paper. First tap taken as indicator, (pre- liminary results)
Toiviainen and Synder [2003]	Bach MIDI organ	"tap the beat of the music"	1.6-2.4	"do not begin tapping un- til you have found the beat mentally"
Dixon and Goebl [2002]	Mozart pi- ano sonatas	"tap the beat in time"	1.3 to 1.87	synchronisation time cal- culated from average re- sponses in beats and aver- age IBIs of stimuli
Repp [2001]	isochronous tones	tapping to a step tempo change to slower rate	up to 4 beats, around 2.1s	time to adaptation
Repp [2001]	isochronous tones	tapping to a step tempo change to faster rate	up to 7 beats, around 3.325s	time to adaptation
Pouliot and Grondin [2005]	Chopin pi- ano prelude	detect abrupt 1-5% tempo change	1.45- 4.76	

Table 1: Reaction time measurements from the rhythm perception and production literature

Exploring ecologically valid stimuli, ie pop/dance music with a mixture of transient rich drum heavy material and smoother, more pitch cued instrumentation.

The sort of polyphonic music I need computational beat trackers to follow in concert situations.

Subject tapping was assessed with respect to a given ground truth prepared with an Annotation GUI: 5 possible tapping modes.

Find the tapping mode with minimal error:

error score = $\frac{\text{numfalsepositives}}{\text{numtaps}} + \frac{\text{numfalsenegatives}}{\text{numground}}$ (1)

With a match tolerance:

tolerance =
$$\frac{0.125}{\text{extract tempo in bps}}$$
 (2)

Reaction time is taken as first of three consecutive subject taps matched to ground truth in that mode.

Experiment 1: Phase Determination from Degraded Signals

12 musicians/11 non-musicians

Between factor: subject type

musician/non-musician

Within factor: stimulus type

three signal qualities: 1-band vocoded white noise, 6-band vocoded white-noise and CD (Scheirer 1998).

15 source extracts of around 10 seconds length (15.8 beats, starting phase of 0.2), tempi from 100-130 bpm. From Blur's *Girls and Boys* to John William's *Indiana Jones*.

Each presented twice in each signal quality condition. Thus 90 trials, 20 minute experiment.

Dependent variable: minimum phase error, averaged over the two repeats and fifteen tracks, for each condition.

Experiment run using the SuperCollider software (quick demo)

Analysed with a 1-within, 1-between ANOVA using SuperANOVA

<u>Results</u>

Significant effect of subject type (F(1,21)=7.949, p=0.0103)

Significant effect of stimulus type (F(2,42)=9.863, p=0.0004) (G-G correction)

No significant interaction.

Interaction Plot Effect: subject-type Dependent: score With 95% Confidence error bars.



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Least Squares Means Table Effect: stimtype Dependent: score

	Vs.	Diff.	Std. Error	t-Test	P-Value
one-band	six-band	.035	.021	1.661	.1041
	CD	.096	.022	4.398	.0001
six-band	CD	.061	.022	2.737	.0091

Means Table Effect: stim type Dependent: reaction time

	Count	Mean	Std. Dev.	Std. Error
one band	23	2.097	.499	.104
six band	23	2.104	.443	.092
CD [23	1.888	.426	.089

Experiment 2: Reaction Time After Abrupt Transitions

13 mus/9 non-mus

Between factor: subject type

musician/non-musician

Within factors:

transition type

 $T{\rightarrow}T,\ T{\rightarrow}S,\ S{\rightarrow}S,\ S{\rightarrow}T$ where T is a transient rich signal and S is smoother

repetition

first and second presentation.

20 source extracts of around 6 seconds length (11.25 beats, starting phase of 0.0), tempi from 100-130 bpm. All sources were different to experiment 1, and in a mixture of styles.

Each subject took the test twice to also consider repetition as a factor.

Dependent variable: reaction time after transition averaged over the transitions in each category.

Experiment run using the SuperCollider software

Analysed with a 2-within, 1-between ANOVA using SuperANOVA

<u>Results</u>

Significant effect of transition type (F(3,60)=25.987, p=0.001 (G-G correction))

No significant main effect of subj type or repeat. There was a subject type/repeat interaction (F(1,20) = 6.397, p=0.02 (G-G)).



transitiontype

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Least Squares Means Table Effect: transitiontype Dependent: reaction time

	Vs.	Diff.	Std. Error	t-Test	P-Value
T->T	T->S	463	.106	-4.386	.0001
	S->S	431	.110	-3.924	.0002
	S->T	.378	.116	3.271	.0018
T->S	S->S	.032	.070	.462	.6458
	S->T	.841	.110	7.656	.0001
S->S	S->T	.809	.112	7.194	.0001

Means Table Effect: transitiontype * subj type Dependent: reaction time

	Count	Mean	Std. Dev.	Std. Error
T->T, musician	26	1.587	.462	.091
T->T, non-musician	18	1.548	.514	.121
T->S, musician	26	1.969	.325	.064
T->S, non-musician	18	2.128	.542	.128
S->S, musician	26	2.020	.596	.117
S->S, non-musician	18	1.976	.857	.202
S->T, musician	26	1.123	.298	.058
S->T, non-musician	18	1.294	.395	.093

As a side analysis: same set-up, but using dependent variable of phase error score, and a three way between test on musician/non-musician/computer where computational beat trackers (Auto-Track (adapted from Davies and Plumbley 2005) and DrumTrack (Collins 2005)) are assessed as one group.

Significant effect of subject type (F(2,21)=13.751, p=0.0002)



Least Squares Means Table Effect: subj type Dependent: score

	Vs.	Diff.	Std. Error	t-Test	P-Value	
musician	non-musician	155	.064	-2.440	.0236	
	computer	567	.111	-5.083	.0001	
non-musician	computer	411	.115	-3.586	.0017	



Computer reaction times:

- Sometimes lucky priors from a previous extract
- Mostly no adequate reaction within the short extract after a transition

Demo of computational beat tracker vs best human musician, rendering taps live.

<u>Conclusions</u>

Can't say that reaction time of humans faster than computational beat trackers, but certainly more reliable, even for nonmusicians

Humans perform significantly less well on white noise vocoded signals; so why should we expect Scheirer's representation to be the best one for computer trackers?

Reaction times average around 1-2s; some individual musicians are faster than this.

More speculatively:

Event cues based on sound object recognition and pitch segmentation are an important mechanism; a lack of computational auditory scene analysis is holding back beat induction techniques. Event cues are degraded in energy envelope representations, particularly for classical smooth signals; the same problems are seen in computational onset detection.

Long correlation windows are not the answer for effective humanlike beat tracking!

Need to spot overt piece transitions to force fast re-evaluation based on new information only (without tainting from the previous material), from knowledge of dominant instruments etc Some support:

D. Perrot and R. O. Gjerdingen, "Scanning the dial: An exploration of factors in the identification of musical style," abstract only, presented at Society for Music Perception and Cognition, 1999.

computational transcription studies: Hainsworth 2004, Klapuri 2005

Thankyou for listening