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A NOVEL 1D STATE SPACE FOR EFFICIENT MUSIC RHYTHMIC ANALYSIS

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Motivations / Contributions

➢ **Motivations:**

- **Music Rhythmic Analysis (MRA)** includes several essential Music Information retrieval (MIR) tasks e.g. beat, downbeat, tempo, meter, and rhythmic pattern detection.
- Many state of the art models for MRA tasks are computationally expensive and are not applicable for real life on-device or large scale industrial setups.
- Widely used Bar Pointer models are not optimal. They require many states leading to computationally expensive inferences.

➢ **Contributions:**

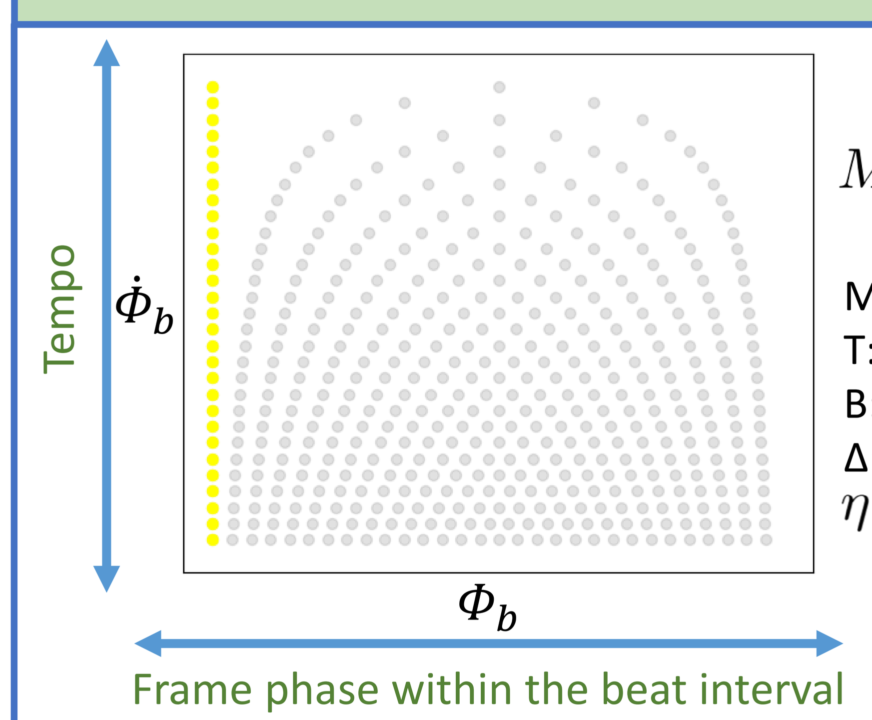
✓ We propose a novel 1D state space and transition model a super efficient alternative for widely used bar pointer models for music rhythmic analysis.

✓ We introduce a semi-Markov jump back reward inference technique.

✓ We Implement the proposed methods into a causal joint beat, downbeat, tempo and meter tracking system.

✓ Our model achieves more than 30X speed up, delivers state of the art beat tracking and comparable downbeat tracking results.

Baseline Efficient Bar Pointer Model



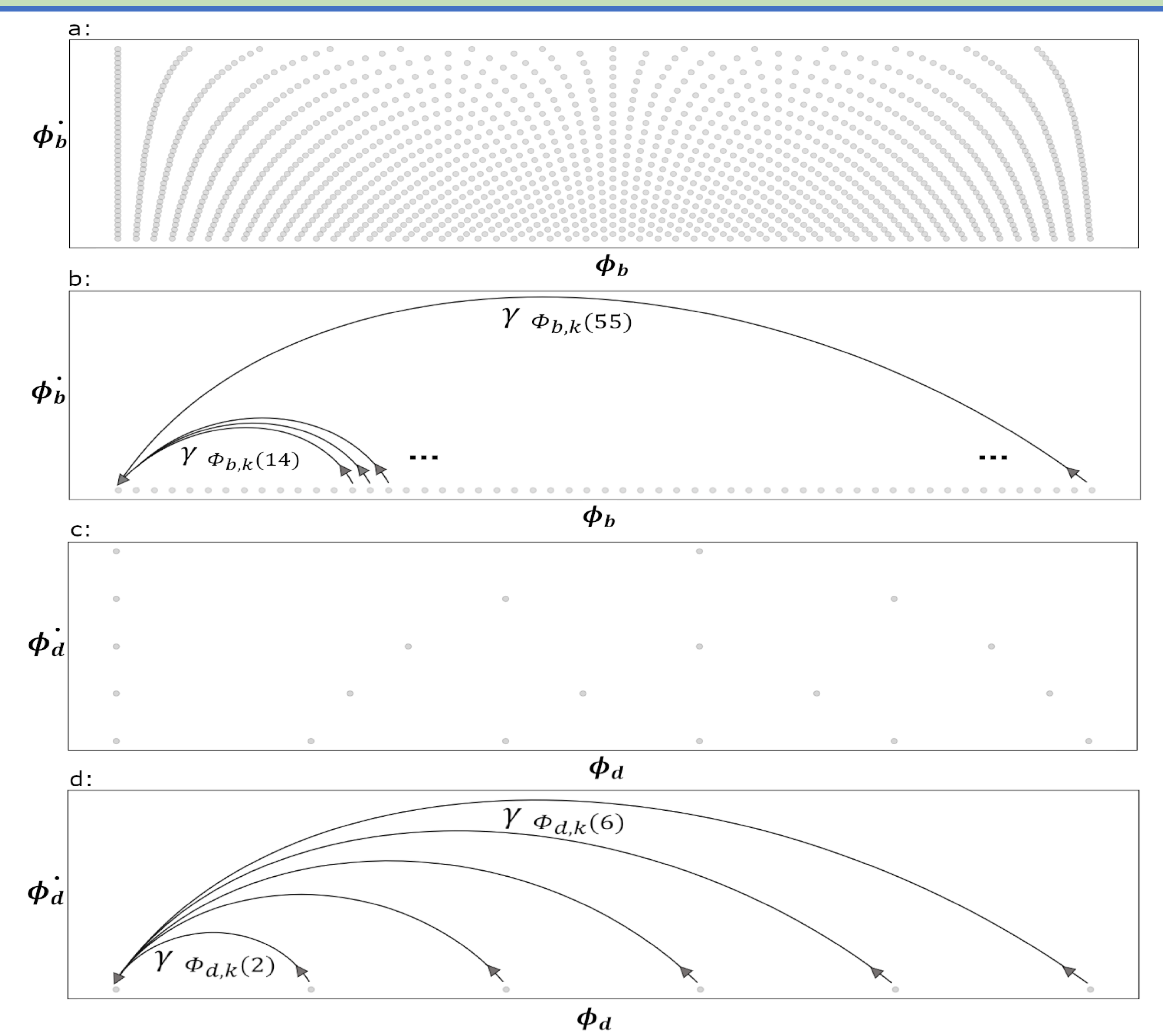
$$M(T) = Round(\frac{B \times 60}{T \times \Delta}), \quad (1)$$

M: Number of positions within a bar
T: Tempo in BPM
B: Number of beats per bar
Δ: Frame length in seconds
η: Diffuse Constant

$$\phi_k = (\phi_{k-1} + \dot{\phi}_{k-1}) \mod (\phi^{max} + 1), \quad (2)$$

$$p(\dot{\phi}_k|\dot{\phi}_{k-1}) = \begin{cases} \exp\left(-\eta\left|\frac{\dot{\phi}_k}{\dot{\phi}_{k-1}}\right|\right) & \text{if } \phi_k = 0 \\ \mathbb{1}(\dot{\phi}_k = \dot{\phi}_{k-1}) & \text{if } \phi_k > 0 \end{cases}, \quad (3)$$

Proposed 1D State Spaces



a: Efficient Beat pointer for Beat/Tempo level analysis
b: Proposed 1D state space for Beat/Tempo level analysis
c: Efficient Beat pointer for Bar/time-signature level analysis
d: Proposed 1D state space for Bar/time-signature level analysis

Jump Back Reward Inference

❖ Motion Step:

$$p(\phi_{k+1}|y_{1:k}) = \sum_{\phi_k} p(\phi_{k+1}|\phi_k)p(\phi_k|y_{1:k}), \quad (4)$$

$$p(\phi_{k+1}|\phi_k) = \begin{cases} \gamma(\phi_k) & \text{if } \phi_{k+1} = 1 \\ 1-\gamma(\phi_k) & \text{if } \phi_{k+1} = \phi_k + 1 \\ 0 & \text{otherwise} \end{cases}, \quad (5)$$

❖ Correction Step:

$$p(\phi_{k+1}|y_{1:k+1}) = \frac{1}{Z_{k+1}} p(y_{k+1}|\phi_{k+1})p(\phi_{k+1}|y_{1:k}), \quad (6)$$

$$p(y_{k+1}|\phi_{k+1}) = \begin{cases} b_{k+1} & \text{if } \phi_{k+1} = 1 \text{ and } b_{k+1} \geq T \\ \epsilon & \text{otherwise} \end{cases}, \quad (7)$$

Where b_{k+1} is the beat activation at frame k+1 and ϵ is a small constant.

Jump Update Using The Reward Function

❖ Jump back weights' Update :

$$\gamma(\phi_{k+1}) = \lambda\gamma(\phi_k) + (1-\lambda)\Gamma(\phi_{k+1}), \quad (8)$$

Where $\gamma(\phi_{k+1})$ and $\Gamma(\phi_{k+1})$ are the jump back weight and state reward at frame k+1 and λ is the forget factor.

❖ Reward function :

$$\Gamma(\phi_{k+1}) = \begin{cases} p(\phi_{k+1}|y_{1:k}) - p(\phi_{k+1}|y_{1:k+1}) & \text{if } b_{k+1} \geq T \\ -(p(\phi_k|y_{1:k}) - p(\phi_{k+1}|y_{1:k})) & \text{if } b_{k+1} < T \text{ and } \phi_{k+1} = 1 \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

Evaluation

Table 1. Performance and speed comparison of several online beat and downbeat tracking models on the GTZAN.

Method	*F-Measure Beats*	*F-Measure Downbeats*	*Comp. Time (Seconds)*
Aubio [19]	57.09	—	0.1
BeatNet [8]	75.44	<u>46.49</u>	8.87
Böck ACF [22]	64.63	—	7.01
Böck FF [20]	74.18	—	2.19
DLB [5]	73.77	—	21.30
IBT [6]	68.99	—	4.89
1D state space	<u>76.48</u>	42.57	0.29

Advantages :

- ☑ General approach (Applicable to multiple rhythmic analysis tasks)
- ☑ More than 30X computationally efficient than the previous SOTA model
- ☑ Robust against tempo fluctuation
- ☑ Delivering SOFA Beat tracking results

Drawbacks :

- ☒ Worse downbeat tracking results
- ☒ Not the fastest model

References

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