

# Technical Appendix for *The ACCompanion: Combining Reactivity, Robustness, and Musical Expressivity in an Automatic Piano Accompanist*

Carlos Cancino-Chacón<sup>1</sup>      Silvan Peter<sup>1</sup>      Patricia Hu<sup>1</sup>  
Emmanouil Karystinaios<sup>1</sup>      Florian Henkel<sup>2</sup>      Francesco Foscarin<sup>1</sup>  
Nimrod Varga<sup>1</sup>      Gerhard Widmer<sup>1</sup>

<sup>1</sup>Johannes Kepler University Linz, Austria

<sup>2</sup>SiriusXM + Pandora, USA

Version: May 20, 2023

## 1 Sensorimotor Synchronization Models

This section follows the notation introduced in Section 3 (in particular Figure 3 in the paper), but we drop the superscript  $p$  of performed onsets to unclutter notation. In order to make this document more readable on its own, we include Figure 3 in the paper here (Figure 1). In the following description of the tempo models, we denote the observed performed onset time of the  $n$ -th onset in the score as  $o_n$  and the onset time predicted by the synchronization models as  $\hat{o}_n$ . The asynchrony between these onsets is denoted as  $A_n = \hat{o}_n - o_n$  and the observed beat period is given as  $\tau_n = \frac{\delta_n^{\text{perf}}}{\delta_n^{\text{score}}}$ , with  $\tau_0$  being the initial tempo set by the performer as a hyper parameter.

### 1.1 Reactive Sync Model (R)

The next accompaniment onset is "estimated" at the same time as the last observed performed onset, making this model purely reactive.

$$\hat{o}_{n+1} = o_n + b_n \delta_n^{\text{score}} \quad (1)$$

$$b_{n+1} = \tau_n \quad (2)$$

### 1.2 Moving Average Sync Model (MA)

This model is very similar to the first baseline, except for its estimation of the global

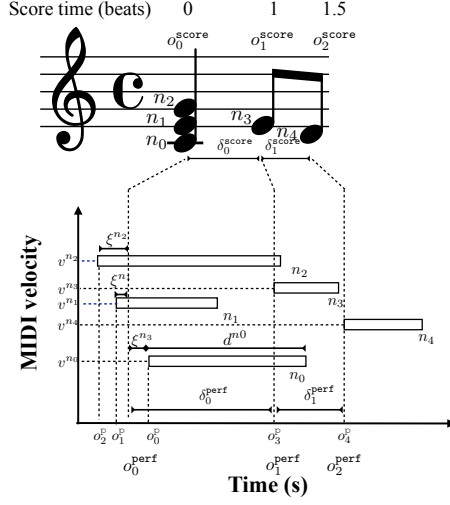


Figure 1: Excerpt of a MIDI performance (as a piano roll where the x-axis describes performance time in seconds and the y-axis is the MIDI velocity of the note) and its corresponding score, showcasing the elements for encoding/decoding an expressive performance. **This figure is identical to Figure 3 in the paper.**

tempo, which uses a weighted average of the last and current tempo estimate.

$$\hat{o}_{n+1} = o_n + b_n \delta_n^{\text{score}} \quad (3)$$

$$b_{n+1} = \eta_{\text{MA}} b_n + (1 - \eta_{\text{MA}}) \tau_n \quad (4)$$

where  $\eta_{\text{MA}}$  is a constant parameter.

### 1.3 Linear SMS Model (L)

Onset and beat period estimates  $o_{n+1}$  and  $b_{n+1}$  are computed as follows:

$$\hat{o}_{n+1} = \hat{o}_n + b_n \delta_n^{\text{score}} - \eta^o A_n \quad (5)$$

$$b_{n+1} = \begin{cases} b_n - \eta^b A_n, & \text{if } A_n < 0, \\ b_n - 2\eta^b A_n, & \text{else} \end{cases} \quad (6)$$

where  $\eta^o$  and  $\eta^b$  are the learning rates for the onset and beat period, respectively.

### 1.4 Linear Tempo Expectation Model (LTE)

This model is similar to the previous one, but includes an anticipation (expectation)

term in the computation of the beat period:

$$\hat{o}_{n+1} = \hat{o}_n + b_n \delta_n^{\text{score}} - \eta^o A_n \quad (7)$$

$$b_{n+1} = \phi(o_{n+1}^{\text{score}}) - \eta^b A_n, \quad (8)$$

where  $\phi(o_n^{\text{score}})$  is a function that computes an estimate of the beat period at score onset time  $o_n^{\text{score}}$  based on the tempo of the reference performance(s) and  $\eta^o$  and  $\eta^b$  are constant parameters that represent the learning rates for the onset and beat period, respectively.

## 1.5 Joint Adaptation Anticipation Model (JADAM)

This model includes both an error-correction term (the adaptation part) and a moving average estimate of the observed beat period (the anticipation part).

### 1. Adaptation Module

$$\hat{o}_{n+1}^{\text{ad}} = \hat{o}_n + b_n \delta_n^{\text{score}} - \eta_J^o A_n \quad (9)$$

$$b_{n+1} = b_n - \eta_J^b A_n \quad (10)$$

### 2. Anticipation Module

$$\hat{\tau}_n = \eta_J^b (2\tau_n - \tau_{n-1}) + (1 - \eta_J^b) \tau_n \quad (11)$$

$$\hat{o}_{n+1}^{\text{an}} = o_n + \hat{\tau}_n \delta_n^{\text{score}} \quad (12)$$

### 3. Joint Module

$$\hat{A}_n = \hat{o}_{n+1}^{\text{ad}} - \hat{o}_{n+1}^{\text{an}} \quad (13)$$

$$\hat{o}_{n+1} = \hat{o}_{n+1}^{\text{an}} - \eta_J^a \hat{A}_n \quad (14)$$

Parameters  $\eta_J^o$  and  $\eta_J^a$  and  $\eta_J^b$  are learning rates for the prediction of the onset of the adaptation and joint modules and the learning rate for the beat period, respectively.

## 1.6 Kalman Tempo Model (KT)

The observed variable of the Kalman filter is the performed onset time, and the beat period is the latent variable. The updates are computed as follows:

$$\hat{b}_n = \alpha_K b_n \quad (15)$$

$$v_n = \gamma_K^2 \hat{v}_n + \beta_K \quad (16)$$

$$\hat{A}_n = \delta_n^{\text{perf}} - \hat{b}_n \delta_n^{\text{score}} \quad (17)$$

$$\kappa_n = \frac{v_n \delta_n^{\text{score}}}{v_n \delta_n^{\text{score}^2} + \lambda_K} \quad (18)$$

$$b_{n+1} = \hat{b}_n + \kappa_n \hat{A}_n \quad (19)$$

$$\hat{v}_{n+1} = (1 - \kappa_n \delta_n^{\text{score}}) v_n \quad (20)$$

$$\hat{o}_{n+1} = \hat{o}_n + b_{n+1} \delta_n^{\text{score}} \quad (21)$$

where  $\alpha_K$ ,  $\beta_K$ ,  $\gamma_K$  and  $\lambda_K$  are the parameters of the model.