

Modeling Human Timing Behavior

Dominic Noy

*Center of Mathematics (CMAT), School of Science, Department of Basic Psychology,
School of Psychology, University of Minho, Portugal,
dominic.noy@gmail.com*

Raquel Menezes

*Center of Mathematics (CMAT), School of Science, University of Minho,
rmenezes@math.uminho.pt*

Palavras-chave: Cognitive Modeling, Sensorimotor Synchronization, Timing, Extended Linear Model, Parameter Estimation

Resumo: Humans coordinate their movements with nearby moving objects with a remarkable ease. This requires a highly timed processing of the perception-action systems underpinning the movement control. In order to investigate the underlying timing mechanisms, employed by the Central Nervous System (CNS), researchers study individuals that attempt to synchronize their movements with repetitive environmental events. Synchronization can be understood as a simplified type of coordination because it is constrained in space and time. It is particularly important in activities such as music, sports, and manufacturing. For its inquiry, it was mostly focused on the motion of effectors like the fingers, the forearms, or the feet. As external events were presented simple auditory metronomes, light displays, or the movements of interaction partners [1, 2].

To successfully synchronize with rhythmically repeating events, the individual must perceive a) the event onsets, to compute an asynchrony between the event and movement onsets and b) the temporal structure of the event sequence, to predict upcoming events. Based on these perceptual and cognitive processes, appropriate motor commands can be computed that control the rhythmical effector displacement so that future asynchronies are minimized [3]. When the external event is presented in (relatively) constant temporal intervals, this paradigm is called Sensorimotor Synchronization (SMS) [4].

There are cognitive models accounting for the empirical findings obtained from SMS. Cognitive models have usually a formal mathematical representation as an approximation to the organization of the particular process at hand. Here, this means that there are assumptions about the cognitive architecture underlying movement timing. This is formalized as a system of equations that receives variables as input and predicts output based on the input, the mathematical expression, and the parameters [5]. These models can be challenged by comparing their analytical or simulated output (for a given input and set of parameters) with experimental observations. By systematically manipulating

the input, it can be validated whether such processes—as postulated by the particular model—underpin the information processing of the CNS.

Because in experiments, there are always variables that can neither be manipulated nor controlled—i.e., there is noise within and beyond the CNS—these problems are usually approached in a probabilistic manner. Within the framework of probability theory, a model can be defined as a parametric family of probability distributions. The combination of probability distributions (indexed by parameters) determines the distribution of the input. This implies that the probability of occurrence is associated with each output value [6].

In order to understand human motor synchronization processes, Schulze & Vorberg (2002) developed such a probabilistic cognitive model, called the *Linear Phase Correction model* (LPC). It describes the asynchrony dynamics obtained in SMS tasks:

$$A_{n+1} = (1 - \alpha)A_n + T_n + M_{n+1} - M_n - C_n,$$

where A_n is the asynchrony at cycle n , C_n is the corresponding metronome interval, M_n is the motor delay ($M_n \sim N[\mu_M, \sigma_M^2] \forall n$), and T_n is the Time Keeper interval ($T_n \sim N[\mu_T, \sigma_T^2] \forall n$). Thus, the LPC describes the dynamics of the observed asynchronies as linear combination of the preceding asynchronies A , a cognitive representation of the external event structure T , and of the information processing delays within the CNS M . The model received vast empirical evidence [5]

However, all presented approaches require that the asynchronies are generated from weak stationary processes and that the time series samples are very large ($n > 30$). Many natural situations require initializing synchronization within short periods of time when the movements are initially not synchronized. In dance, dyads alternately synchronize the motion of their body segments; in manufacturing work, the demand to coordinate with machines and other workers may be repetitive but short lasting; in a symphony orchestra, instruments such as cello, viola, or violin, double bass, piano, and celesta stand alone or together for very short time periods. Although the musicians know the correct tempo in advanced—this is a crucial role of the concertmaster—there still exist larger asynchronies when entering into the ensemble. Also, the observations of amateur musicians or athletes who try to “get into pace” highlight that a precise and accurate initial synchronization is quite challenging. Decomposing and quantifying its underlying information processes is crucial to capture, understand, and improve human motor timing.

Our main goal is to provide a method of parameter estimation of the LPC built on multiple short asynchrony series. Figure 1 shows series of asynchronies that are observed when an individual attempts to synchronize (here $m=20$ times) discrete events of one’s movements (here finger tapping on a

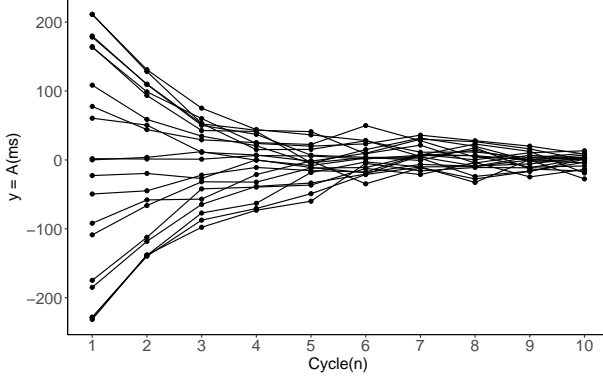


Figure 1: Illustration of 20 asynchrony times series (A in milliseconds, each with length $n=10$). Each line segment represents one independent series. The absolute value of μ_y and σ_y decreases as a function of cycle number n revealing its non-stationarity.

surface) with isochronous sequences of 10 discrete events. Our approach includes all empirical series within an *Extended Linear Model* that allows for serially correlated errors [8].

$$y = Bx + Z,$$

where

$$y = \begin{bmatrix} A_1 - E(A) \\ \vdots \\ A_N - E(A) \end{bmatrix}, x = 1 - \alpha, Z = \begin{bmatrix} H_0 \\ \vdots \\ H_{N-1} \end{bmatrix}, B = \begin{bmatrix} A_0 - E(A) \\ \vdots \\ A_{N-1} - E(A) \end{bmatrix},$$

where A_n is the asynchrony between movement and event at cycle n , $N = \sum_{i=1}^m n_i$ is the sum of the length of each series n_i .

The asynchrony in the next cycle is linearly related to the asynchrony in the previous cycle captured by Bx , because the individual attempts to correct the perceived asynchrony by a correction coefficient α . However, there is also an additional error Z . This error is supposed to arise from the CNS processes (timekeeper, motor and perceptual processes, $Z = [H_0, H_1, \dots, H_{N-1}]^T$, $H_k = T_k + M_{k+1} - M_k - E(T)$, see LPC model [7]). This implies that the variance of A is $\sigma_A^2 = \gamma_A(0) = 2\sigma_M^2 + \sigma_T^2$ and the autocovariance at lag 1 $\gamma_A(1)$ is $-\sigma_M$. Thus, $Z \sim MVN(0, \Sigma)$, where Σ is an $N \times N$ variance-covariance matrix determined by the autocovariance functions $\gamma_A(0)$ and $\gamma_A(1)$.

Our estimation procedure consists of two steps: first, a global cubic spline removes the non-stationary aspect of the asynchronies. Second, the unknown

parameters of x and Σ (i.e., α , σ_T^2 , σ_M^2) are obtained by iteratively maximizing a log-likelihood function departing from some initial values for the parameters x or Σ . We are currently running Monte Carlo simulations of the model to validate the estimation approach. Also, we attempt to implement a Generalized Least Square fitting technique to include both estimation steps within a single model. Subsequently, these approaches may be validated on experimental observations.

Bibliografia

- [1] Schmidt, R. C., Richardson, M. J. Dynamics of interpersonal coordination. In *Coordination: Neural, behavioral and social dynamics (p. 281-308)*. Springer, 2008.
- [2] van Ulzen, N. R., Lamoth, C. J., Daffertshofer, A., Semin, G. R., Beek, P. J. (2008). Characteristics of instructed and uninstructed interpersonal coordination while walking side-by-side. *Neuroscience Letters*, 432(2), 88–93, 2008.
- [3] Grush, R. The emulation theory of representation: Motor control, imagery, and perception. *Behavioral & brain sciences*, 27(03), 377–396, 2004.
- [4] Repp, B. H. Sensorimotor synchronization: a review of the tapping literature. *Psychonomic bulletin & review*, 12(6), 969–992, Repp2005.
- [5] Jacoby, N., Tishby, N., Repp, B. H., Ahissar, M., Keller, P. E. Parameter estimation of linear sensorimotor synchronization models: phase correction, period correction, and ensemble synchronization. *Timing & Time Perception*, 3(1-2), 52–87, 2015.
- [6] Myung, I. J. Tutorial on maximum likelihood estimation. *Journal of mathematical Psychology*, 47(1), 90–100, 2003.
- [7] Schulze, H.-H., Vorberg, D. Linear phase correction models for synchronization: Parameter identification and estimation of parameters. *Brain & Cognition*, 48(1), 80–97, 2002.
- [8] Pinheiro, J., Bates, D. Mixed-effects models in s and s-plus. Springer, New York. Repp, B. H. (2005). Sensorimotor synchronization: a review of the tapping literature. *Psychonomic bulletin & review*, 12(6), 969–992, 2000.