Movement Onset Time Detection

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Defining Initiation Time as Hand-reaching Movement Onset Time

Researchers have recently shown interest in improving their standard practices with the aim of producing reliable and comparable data (Schoemann, Lüken, Grage, Kieslich, & Scherbaum, 2019). The common characterization and implementation of hand-reaching movement onset is then important as initiation time is typically conceptualized as the time elapsed from stimulus presentation to movement initiation. In order to clarify the notion of movement onset time, I distinguish between two definitions: kinematic and computational. The first type relates to the kinematic features of movement onset. The second type describes how movement onset is identified in a discrete time series. The definitions are the following:

- *Kinematic definition:* movement onset time is the point in time of the transition between an initial static period and the period of initial motion in the trajectory movement. The static period is ideally characterized by zero velocity, whereas the period of initial motion evolves as a function of a power of time and a constant jerk value that minimizes acceleration.
- *Computational definition:* movement onset time is the closest data sample to the time calculated by estimating the minimum jerk that reduces a measure of the differences between the time series and the kinematic model of the trajectory. The model consists of a static phase characterized by a velocity close to zero (due to tracking noise), and a movement phase modelled as a function of a power of time and a constant jerk value.

Based on the computational definition, a method to detect movement onset in one-dimensional reaching trajectories has been presented before Botzer and Karniel (2009). I have extended such a method to consider two-dimensional reaching trajectories to put forward an alternative to the classic threshold-based methods. The details are introduced in the next section.

A New Movement Onset Time Detection Method for 2D Time Series

Botzer and Karniel (2009) proposed a method to detect the time of movement onset in one-dimensional time series of reaching trajectories by using a motor control model and linear regression to estimate the point of change between a motionless period and a movement period. This method has proved to be useful to detect movement onset in direct reaching trajectories (Botzer & Karniel, 2009; Nisky, Hsieh, & Okamura, 2013). However, some of the reaching trajectories of the Simon task in virtual reality have one characteristic that makes such an algorithm not suitable for these data. As participants are not forced to start the movement towards a target, a forward hand movement can be initiated between the two targets. The algorithm would then fail to detect movement onset in those trajectories given that it only uses the time series of one of the position components of the reaching movement.

In this section, I present how I have addressed the problem just presented by extending the movement onset detection method developed by Botzer and Karniel (2009) to consider two-dimensional time series. The movement period used in the original work is modelled based on the dominant factor at the beginning of the arm movement in the one-dimensional version of the Minimum Acceleration Criterion with Constraints (MACC). This model can be easily extended to consider two-dimensional time series as MACC was formulated for the general case of an n-dimensional space (Ben-Itzhak & Karniel, 2008). According to MACC, a two-dimensional hand-reaching movement can be described by

$$\vec{p}(t) = \vec{p}(0) + \frac{1}{L} r(t) \left(\vec{p}(T) - \vec{p}(0)\right) \tag{1}$$

where $\vec{p}(t) = [x(t), y(t)]$ is the hand position vector, T is the total movement duration, L is the total movement length, $\vec{p}(0)$ is the initial movement point, $\vec{p}(T)$ is the end movement point, and $r(t)$ is the time-dependent function specified by

$$r(t) = \begin{cases} \frac{1}{6}U_m t^3 & 0 \leq t \leq t_1 \\ \frac{1}{6}C_0 t^3 - \frac{1}{6}C_1 t^2 + \frac{1}{6}C_2 t + C_3 & t_1 \leq t \leq t_2 \\ \frac{1}{6}U_m t^3 - \frac{1}{2}U_m T t^2 + \frac{1}{2}U_m t T^2 - \frac{1}{6}U_m T^3 + L & t_2 \leq t \leq T \end{cases} \tag{2}$$

where U_m is a constant jerk, $C_i = f(U_m, T, L)$, for $i = 1, 2, 3, 4$, are constant term, and t_1 and t_2 are optimal switching times. As pointed by Botzer and Karniel (2009), this equation indicates that early in the movement, i.e. before the first switching time t_1, the position only depends upon the constant jerk, U_m, and the cubic power of time.

As stated by Botzer and Karniel (2009), the problem of movement onset detection can be seen as the problem of estimating the point of the change between a static phase and a phase describing the initial motion of the trajectory movement. Following this, the joint model I proposed is constructed by:

- a static phase modelled by two constant terms that indicate the location of the hand prior to the initiation of the movement, and
- a movement phase modelled by two third-order polynomial functions that indicate how the initial motion of the hand evolves as a function of the cubic power of time and depends upon a constant jerk as indicated when $0 < t < t_1$ in Equation (2).

The joint model I used is then specified by

$$x(t) = \begin{cases} x_0 & t \le t_0 \\ x_0 + \frac{1}{6} U_m^x (t - t_0)^3 & t_0 \le t \le t_1 = t_0 + \Delta t \end{cases}$$
$$y(t) = \begin{cases} y_0 & t \le t_0 \\ y_0 + \frac{1}{6} U_m^y (t - t_0)^3 & t_0 \le t \le t_1 = t_0 + \Delta t \end{cases} \tag{3}$$

where x_0 and y_0 are the initial static position along the x and y axes, respectively, U_m^x and U_m^y are the initial jerks in those respective dimensions, t_0 is the time onset, and Δt is a time interval. Thus, the parameters x_0, y_0, U_m^x, U_m^y and t_0 are to be estimated, whereas Δt is the minimum time length of the movement phase in the model in Equation (3).

To estimate the parameters, let $\{t,\ x,\ y\}$ be a two-dimensional time series of length N sampled at a constant time interval T_s. The trajectory is segmented into equal-sized segments, $\vec{t_l}$, $\vec{x_l}$, and $\vec{y_l}$ each with m data points, such that $m < N$ and $m < \Delta t / T_s$, as indicated by

$$\begin{aligned} \vec{t_l} &= \{t_{l-m+1}, t_{l-m}, ..., t_l\} \\ \vec{x_l} &= \{x_{l-m+1}, x_{l-m}, ..., x_l\} \\ \vec{y_l} &= \{y_{l-m+1}, y_{l-m}, ..., y_l\} \end{aligned} \tag{4}$$

where $t_l \in [t_s, t_f]$ such that $m{\cdot}T_s = t_m \le t_s < t_f \le t_N$ and t_N is total movement duration. The data segments that best fit the first terms of the joint model, $\vec{x}_q$, $\vec{y}_q$, $\vec{t}_q$, $t_q \in [t_s, t_{f-m+1}]$, and the adjacent segments that best fits the second terms $\vec{x}_{q+m-1}$, $\vec{y}_{q+m-1}$, $\vec{t}_{q+m-1}$, $t_{q+m-1} \in [t_{s+m-1}, t_f]$, are to be estimated. The method then has one free parameter, m, which defines the duration of both the static and movement trajectory segments.

The first terms of the model in Equation (3) are calculated according to

$$\begin{aligned} \widehat{x}_0(q) &= \overline{\vec{x}_q} = \frac{1}{m} \sum_{i=q-m+1}^{q} x_i \\ \widehat{y}_0(q) &= \overline{\vec{y}_q} = \frac{1}{m} \sum_{i=q-m+1}^{q} y_i \end{aligned} \tag{5}$$

In the case of the second term of the model, $\widehat{x}_0(q)$ and $\widehat{y}_0(q)$ are calculated according to the Equation (5). The onset time, t_0, is calculated as the end point, t_q, of the segment $\vec{t}_q$. U_m^x and U_m^y are individually estimated as the best root-mean-square solution that fits the data of the segment $\vec{t}_{q+m-1}$ as specified by

$$\begin{aligned} \widehat{U}_m^x(q) &= Argmin\left\{ \frac{1}{m} \sum_{i=q}^{q+m-1} \left[x_i - \left(\widehat{x}_0(q) + U_m \left(t - \widehat{t}_0(q) \right)^3 \right) \right]^2 \right\} \\ \widehat{U}_m^y(q) &= Argmin\left\{ \frac{1}{m} \sum_{i=q}^{q+m-1} \left[y_i - \left(\widehat{y}_0(q) + U_m \left(t - \widehat{t}_0(q) \right)^3 \right) \right]^2 \right\}. \end{aligned} \tag{6}$$

The RMS error between the data and the model is calculated as described by the following equation:

$$\epsilon(q) = \frac{1}{2m-1}\sqrt{\epsilon_x(q) + \epsilon_y(q)} \tag{7}$$

where

$$\begin{aligned}
\epsilon_x(q) &= \sum_{i=q-m+1}^{q} \big[x_i - \widehat{x}_0(q)\big]^2 + \sum_{i=q}^{q+m-1} \Big[x_i - \Big(\widehat{x}_0(q) + U_m\big(t - \widehat{t}_0(q)\big)^3\Big)\Big]^2 \\
\epsilon_y(q) &= \sum_{i=q-m+1}^{q} \big[y_i - \widehat{y}_0(q)\big]^2 + \sum_{i=q}^{q+m-1} \Big[y_i - \Big(\widehat{y}_0(q) + U_m\big(t - \widehat{t}_0(q)\big)^3\Big)\Big]^2
\end{aligned} \tag{8}$$

The estimated onset point, $\hat{t}_0$, is then the point at which the error is minimized, provided a local minimum exists, as indicated by

$$\widehat{t_0} = Argmin\{\epsilon(q)\}. \tag{9}$$

If no local minimum is found, the trial is excluded. If more than one local minima exists, the latter is selected as the onset point. The algorithm then compares the estimated movement onset time with the time threshold, t_{th}, calculated as the point in time when the trajectory leaves the starting sphere of radius 0.04 m in the virtual experimental setup. If there is more than one minima and $\widehat{t_0} > t_{th}$, the estimated movement onset time is adjusted by selecting the time associated with the latter minima prior to the time threshold if such a minima exists.

Given that the onset time cannot be found close to the maximum velocity of the trajectory, a threshold can be used to limit the extent to which the time series is segmented. I defined the threshold as

$$t_f = 0.6 \cdot ArgMin\{ArgMax\{\dot{x}\}, ArgMax\{\dot{y}\}\} \tag{10}$$

where $\dot{x}$ and $\dot{y}$ are the first derivatives of x and y, respectively, that were estimated using the numerical differentiation method presented in the previous section.

References

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