TRACKING SLOW-TIME-SCALE CHANGES IN MOVEMENT COORDINATION

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INTRODUCTION

Diseases like osteoarthritis and repetitive strain injuries lead to changes in coordination that develop slowly over time. It is important, but often very difficult, to track the progression of these disease processes. By contrast, changes in movement coordination patterns can be easily measured. Our goal is to develop methods to track changes in underlying (i.e. "hidden") disease states from easily obtainable biomechanical data.

METHODS

We borrowed a method for tracking similar hidden damage processes in mechanical systems [1,2]. We assume our system can be modeled as a hierarchical dynamic system of the form:

$$\dot{x} = f(x, \mu(\phi)), \qquad \dot{\phi} = \varepsilon\, g(\phi, x) \tag{1a, 1b}$$

where $x \equiv$ the *observable* states of the fast-time-scale system, $\phi \equiv$ the *hidden* slowly-varying dynamics, $0 < \varepsilon << 1$, and $\mu(\phi)$ $\equiv$ the parameters in (1a). If $\varepsilon = 0$, $\mu(\phi)$ would be constant. We form a topologically valid state space from a single measured time series, $x(n)$, using delay embedding (Figure 1*A*):

$$y(n) = \left[x(n), x(n+\tau), \ldots, x(n+(d-1)\tau)\right] \tag{2}$$

where τ is a time delay and d is the embedding dimension [3]. Data from the unperturbed system are used to build a locally linear model of the system behavior (Figure 1*B*). Drift in ϕ leads to "errors" ($\mathbf{E}_k$) between actual and predicted behavior. If our model is good, the model error ($\mathbf{E}_k^M$) will be small and $\mathbf{E}_k \approx \varepsilon_k$ $\equiv$ the true error or drift in the system dynamics. $\mathbf{E}_k$ can then be used to define the following *tracking metric*:

$$\varphi = \left\langle F \left\| \mathbf{E}_k\left(y(n), \phi\right) \right\| \right\rangle \approx \left\langle \left\| \varepsilon_k\left(y(n), \phi\right) \right\| \right\rangle \tag{3}$$

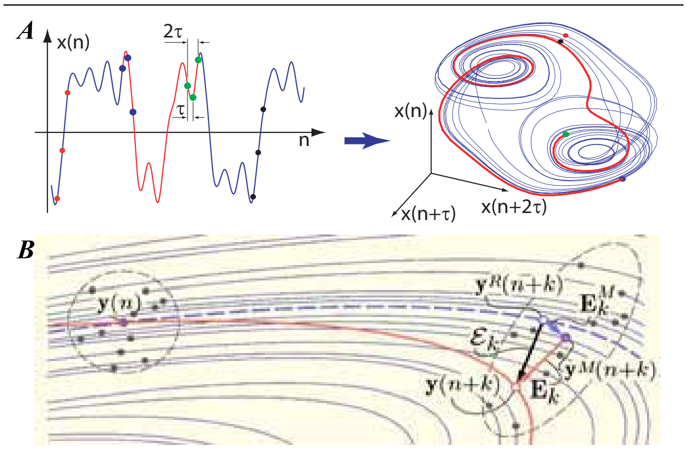

Figure 1. ***A:*** "Embedding" a 1-dimensional time series in a multi-dimensional vector space defining equivalent states of the system. ***B:*** Tracking function estimation: (—) is the current trajectory. (– –) is the corresponding model trajectory. $\mathbf{E}_k$ is the estimated error, $\mathbf{E}_k^M$ is the modeling error, and ε_k is the true error, or drift in the system.

where $\langle\cdot\rangle \equiv$ the RMS over the index n and F is an appropriate filter [2]. Thus, this metric essentially tracks the average error, over time, in the predicted fast-time-scale dynamics that is introduced by the slow-time-scale dynamics.

Five healthy subjects walked on a motorized treadmill at their self-selected pace. The treadmill incline was increased from 0° to +8° slowly over 25 minutes. Kinematic data were recorded (Vicon-612, Oxford Metrics, Oxford, UK) continuously at 60 Hz to obtain sagittal plane hip, knee and ankle angles. These joint kinematics defined $x(n)$, the fast-time-scale dynamics. Tracking metrics (φ) were computed from joint angle data and regression analyses were used to determine how well these metrics tracked the "hidden" treadmill incline angle.

RESULTS AND DISCUSSION

Basic patterns of joint kinematics changed little across trials. Tracking metrics (φ) generally increased with treadmill angle (Fig. 2). Regressions yielded adj-r^2 of 86% to 98%. Although these predictions were not perfect, no attempt was made to adjust or alter the original algorithm of [2]. By accounting for additional features specific to biological systems (e.g. noise, multiple time scales, etc.), better results may be obtained.

By using a state space formulation, the proposed method yields valid measures of slow-time-scale dynamics, without the need for "guessing" or for highly detailed first-principles models of system dynamics [2]. We anticipate this approach can be used to track other "hidden" biological processes like muscle fatigue, repetitive strain injury, or disease progression.

REFERENCES

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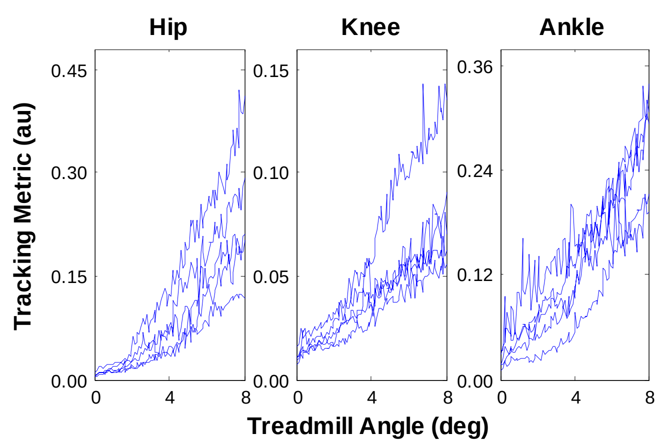

Figure 2: Tracking metrics computed from joint kinematic data as a function of treadmill angle (85.6% $\le r^2 \le$ 98.4%).