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JOURNAL OF BIOMECHANICS

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Short communication

A nonlinear approach to tracking slow-time-scale changes in movement kinematics

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Accepted 28 June 2006

Abstract

Degenerative processes like repetitive strain injuries (RSIs) cause normal movement patterns to change slowly over time. Accurately *tracking* how these disease/injury processes evolve over time and *predicting* their future progression could allow early intervention and prevent further deterioration. However, these processes often cannot be measured directly and first-principles models of these processes and how they affect movement control are highly complex and difficult to derive analytically. This study was conducted to determine if algorithms developed to track damage accumulation in mechanical systems without requiring first-principles models or direct measurements of the damage itself could also track a similar "hidden" process in a biomechanical context. Five healthy adults walked on a motorized treadmill at their preferred speed, while the treadmill inclination angle was slowly increased from 0° (level) to approximately +8°. Sagittal plane kinematics for the left hip, knee, and ankle joints were computed. The treadmill inclination angle was independently recorded and defined the "damage" to be tracked. Scalar tracking metrics were computed from the lower extremity walking kinematics. These metrics exhibited strong cubic relationships with treadmill inclination ($88.9\% \leqslant r^2 \leqslant 98.2\%$; $p < 0.001$). These results demonstrate that the proposed approach may also be well suited to tracking and predicting slow-time-scale degenerative *biological* processes like muscle fatigue or RSIs. This possibility is potentially quite powerful because it suggests that easily obtainable biomechanical data can provide unique and valuable insights into the dynamics of "hidden" biological processes that cannot be easily measured themselves.

Keywords: Coordination; Time series analysis; Nonstationarity; Tracking

1. Introduction

The movement patterns people exhibit when performing different tasks often change over time due to degenerative processes like muscle fatigue and/or repetitive strain injuries (RSIs) (Sparto et al., 1997; Côté et al., 2002; Rodgers et al., 2003). Accurately *tracking* how these disease/injury processes evolve over time and *predicting* their future progression would allow the earliest possible identification and intervention to prevent further deterioration. One primary impediment to achieving this goal is the inherent complexity of deriving first-principles models of these processes. Such models need to include *at the very least* the geometries of the biological structures involved, the material properties of relevant tissues, the motions and external loads applied to those structures, and some description of how the neuromuscular control system responds to the initiation of any muscle fatigue and/or tissue damage that occurs. Thus, constructing a single comprehensive model of any specific disease/injury process poses a highly complex problem. In the absence of firm pathophysiological models of how these processes develop over time, it has been largely impossible to

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0021-9290/$ - see front matter © 2006 Elsevier Ltd. All rights reserved.
doi:10.1016/j.jbiomech.2006.06.019

Please cite this article as: Jonathan B. Dingwell, et al., A nonlinear approach to tracking slow-time-scale changes in movement kinematics, Journal of Biomechanics (2006), doi:10.1016/j.jbiomech.2006.06.019

derive specific means of accurately predicting which individuals will develop such degenerative conditions or when. The purpose of the present study was to determine if methods recently developed for tracking and predicting damage accumulation in mechanical systems might provide a useful alternative approach for addressing these complex questions.

Engineers have long tried to predict how damage accumulates in mechanical systems prior to failure (Qu et al., 1993; Ma and Li, 1995). Many researchers have used heuristic (i.e., data-based) approaches to define predictive feature vectors (Messina et al., 1998; Luo et al., 2000; Worden et al., 2000). However, this often requires testing many subjectively chosen candidate metrics to determine which one(s) work. There is also usually no direct connection between the final feature vector and the actual damage mechanism. Finally, heuristic feature vectors are generally *only* valid for *the* specific context in which they were derived.

Our approach originates from a novel nonlinear damage tracking method (Chelidze et al., 2002; Cusumano et al., 2002) that avoids the limitations of both heuristic and model-based approaches. This approach has been successfully applied to various mechanical systems with different notions of "failure" (Chelidze et al., 2002; Cusumano et al., 2002). However, biological systems are fundamentally different in several important ways. They are typically inherently noisier, they "fail" at multiple levels (e.g., cellular, tissue, etc.), and they can *adapt* by voluntarily changing their behavior and/or by healing themselves. If this approach is also valid for biological systems, it could be used to predict future disease/injury onset and/or to track disease/injury progression without requiring complex first-principles models of the underlying (and often un-observable) disease/injury processes themselves.

2. Methods

Five healthy adults (ages 21–36) with no musculoskeletal or neurological deficits participated after providing written informed consent. Subjects walked on a motorized treadmill (Woodway USA, Waukesha, WI) at their preferred walking speed (PWS) (Dingwell and Marin, 2006), which averaged 1.18 m/s (range: 1.07–1.43 m/s). Each subject spent ~15–20 min acclimating to the treadmill while their PWS was determined. They then performed a single trial where the treadmill inclination angle was steadily increased from 0° (level) to approximately +8° over 25 min. Subjects were instructed to walk normally, look straight ahead, and to resist extraneous movements. The 25 min trial length was chosen to minimize potential fatigue effects. All subjects reported no fatigue after testing.

Kinematic data were recorded continuously at 60 Hz using a six-camera Vicon-612 motion analysis system (Oxford Metrics, Oxford, UK). Reflective markers (14 mm diameter) were attached to the left leg over the anterior-superior (ASIS) and posterior-superior iliac spines (PSIS) of the pelvis, greater trochanter, lateral epicondyle of the knee, lateral maleolus of the ankle, heel, and fifth metatarsal head (toe). Sagittal plane hip, knee, and ankle joint angles were computed from these marker coordinates. Two 35 mm diameter markers were placed on the front and rear left side of the treadmill to compute the treadmill inclination angle.

Our goal was to track the "hidden" (i.e., not directly observed) slow-time-scale process (i.e., the treadmill inclination angle) directly from the observed walking kinematics. The approach used is described in detail elsewhere (Cusumano and Chatterjee, 2000; Chelidze et al., 2002; Cusumano et al., 2002). The essential features are summarized here. Data were not filtered because of the complications associated with filtering nonlinear data (Mees and Judd, 1993; Kantz and Schreiber, 2004).

First, we assume our system is a hierarchical dynamical system, where a slow-time process causes parameter drift in a subsystem describing the dynamics of the fast-time system:

$$\dot{\mathbf{q}}(t) = \mathbf{f}(\mathbf{q}, \boldsymbol{\mu}(\boldsymbol{\phi}), t), \tag{1a}$$

$$\dot{\boldsymbol{\phi}}(t) = \varepsilon\, \mathbf{g}(\boldsymbol{\phi}, \mathbf{q}, t), \tag{1b}$$

where $\mathbf{q} \in \Re^n$ is the directly observable, fast-time state (i.e., walking kinematics); $\boldsymbol{\phi} \in \Re^m$ is a hidden, slow-time damage state (i.e., treadmill angle); $\boldsymbol{\mu} \in \Re^s$ is a function of $\boldsymbol{\phi}$ representing the parameters in Eq. (1a); and $0 < \varepsilon \ll 1$ defines the time-scale separation between the fast-time and slow-time dynamics. For $\varepsilon \neq 0$, Eq. (1a) is nonstationary due to the evolution of $\boldsymbol{\phi}$. Over time scales of order ε, Eq. (1a) can be considered quasi-stationary, since drifts in $\boldsymbol{\mu}$ are negligible. This formulation is appropriate for systems where the slow-time dynamics is several orders of magnitude slower than the observed fast-time dynamics.

Given a single measured time series from the fast-time system, $x(n)$, we reconstruct a topologically equivalent phase space for the system's dynamics using delay embedding (Fig. 1B) (Takens, 1981; Sauer et al., 1991; Kantz and Schreiber, 2004):

$$\mathbf{y}_n = [x(n), x(n+\tau), \ldots, x(n+(d-1)\tau)]^{\mathrm{T}}, \tag{2}$$

where $\mathbf{y}_n \in \Re^d$ is the embedded phase space, τ is a suitable delay time (Fraser and Swinney, 1986) and d is the embedding dimension (Kennel et al., 1992). Thus, a valid phase-space representation of the fast-time dynamics is obtained without having to derive the associated physics-based analytical model (Kantz and Schreiber, 2004). These reconstructed state vectors are governed by an unknown map:

$$\mathbf{y}_{n+1} = \mathbf{P}(\mathbf{y}_n; \phi). \tag{3}$$

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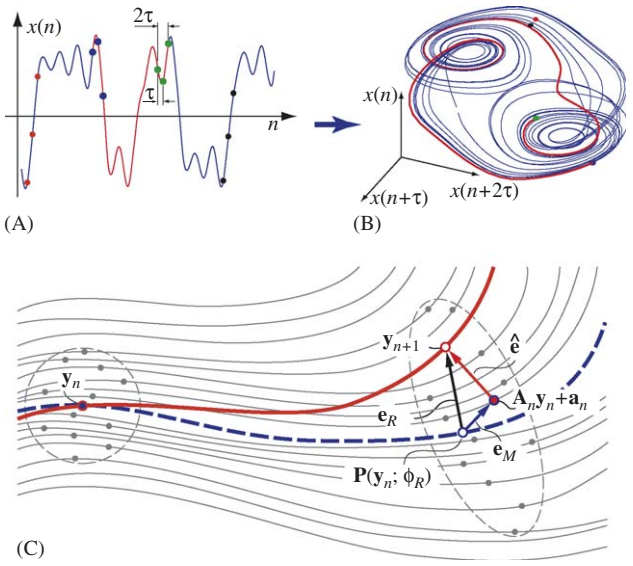

Fig. 1. (A, B) Schematic diagram of phase-space reconstruction. The original one-dimensional time series (A) is "embedded" in a multi-dimensional vector space defining equivalent states of the system (B). Note that each triplet of three points in A maps onto a single point in the 3D phase space shown in B. (C) Phase-space warping (PSW) tracking function estimation. The solid line is the current trajectory. The dashed line is the corresponding reference trajectory. The tracking metric (Eq. (7)) is derived from the relative error in the current trajectory as measured from the true and estimated reference trajectories (Eq. (6)). Fig. 1C was adapted from Chelidze et al. (2002).

Drift in the damage variable ϕ in Eq. (3) causes distortions in the phase space that alter the evolution of trajectories. This is termed *phase-space warping* (PSW). The *PSW tracking function* is defined for every point in the reconstructed phase space as

$$\mathbf{e}_{\mathrm{R}}(\phi;\mathbf{y}) = \mathbf{P}(\mathbf{y};\phi) - \mathbf{P}\left(\mathbf{y};\phi_{\mathrm{R}}\right), \tag{4}$$

where ϕ is the current state of the damage variable and ϕ_{R} is the reference state. The first term in Eq. (4) is already available from the current data record (Eq. (3)). Thus one only needs a model for $\mathbf{P}(\mathbf{y};\phi_{\mathrm{R}})$ for the undamaged or reference system. In the reconstructed reference phase space, $\mathbf{P}$ can be approximated using local models that describe how neighborhoods about each data point are mapped forward in time. The simplest such model is a local linear model:

$$\mathbf{y}_{n+1} = \mathbf{A}_n\mathbf{y}_n + \mathbf{a}_n, \tag{5}$$

where the model parameter matrix $\mathbf{A}_n$ and a parameter vector $\mathbf{a}_n$ are determined by least-squares regression at each point n in the data set (Chelidze et al., 2002).

The process for defining an appropriate *PSW tracking function* to estimate this drift is summarized in Fig. 1C. First, an "undamaged" reference data set is used to reconstruct the reference phase space. Then, a sufficiently large number of initial points $\mathbf{y}_n(n = 1, 2, \ldots)$ is obtained, together with the corresponding future points, $\mathbf{y}_{n+1}$, for the "changed" system. The nearest neighbors of each point $\mathbf{y}_n$ are also looked up, along with the corresponding points one time step later. These points are used to build the local linear reference model for each point $\mathbf{y}_n$ as described above. Then, the *PSW tracking function* can be written as

$$\mathbf{e}_{\mathrm{R}}(\phi;\mathbf{y}) = \hat{\mathbf{e}}_{\mathrm{R}}(\phi;\mathbf{y}) + \mathbf{e}_{\mathrm{M}}(\mathbf{y}), \tag{6}$$

where $\mathbf{e}_{\mathrm{M}}$ is the modeling error and $\hat{\mathbf{e}}_{\mathrm{R}}$ is the *estimated tracking function*. The use of $\hat{\mathbf{e}}_{\mathrm{R}}$ as a tracking function instead of $\mathbf{e}_{\mathrm{M}}$ is justified if $\mathbf{e}_{\mathrm{M}}$ is sufficiently small compared to the true error, $\mathbf{e}_{\mathrm{R}}$ (Chelidze et al., 2002; Cusumano et al., 2002).

However, $\hat{\mathbf{e}}_{\mathrm{R}}$ still defines a *vector* tracking function. A single scalar measure for the drift, or *tracking metric*, can be obtained from the set of all values of the estimated tracking function by computing a weighted average root-mean-square magnitude of $\hat{\mathbf{e}}_{\mathrm{R}}$ (Chelidze et al., 2002):

$$\hat{e}^2 = \left\langle \hat{\mathbf{e}}_{\mathrm{R}}^{\mathrm{T}}\hat{\mathbf{e}}_{\mathrm{R}} \right\rangle \approx \frac{\sum_{n=1}^{M} q(n)\left\|\hat{\mathbf{e}}_{\mathrm{R}}\left(\phi;y_n\right)\right\|^2}{\sum_{n=1}^{M} q(n)}, \tag{7}$$

where $\left\langle \hat{\mathbf{e}}_{\mathrm{R}}^{\mathrm{T}}\hat{\mathbf{e}}_{\mathrm{R}} \right\rangle$ denotes the average computed across different regions of the phase space, $\mathbf{a}^{\mathrm{T}}$ denotes the transpose of $\mathbf{a}$, and $q(n)$ is an appropriate weighting function (Chelidze et al., 2002).

This procedure was applied to the lower extremity walking kinematics recorded from each subject. An embedding dimension of $d = 5$ was found to be sufficient to fully unfold the walking dynamics, consistent with previous studies (Dingwell and Cusumano, 2000). The first 1500 samples (25 s) of each data record were used to construct the local linear reference model (Eq. (5)). The entire data record (25 min) was then divided into 100 equal-sized bins (~900 samples each). Scalar tracking metrics (Eq. (7)) were computed for the data from each bin. These tracking metrics were then compared directly to the independently recorded treadmill inclination angles, which defined the slow-time-scale "drift" in this experiment. Relationships between tracking metrics and treadmill inclination angles were quantified using standard polynomial regression.

3. Results

The basic patterns exhibited by the lower extremity kinematics (Fig. 2) exhibited some subtle changes, but remained largely similar across the duration of each trial. The tracking metrics (Eq. (7)) increased monotonically, but nonlinearly, with treadmill angle (Fig. 3). The tracking metrics were therefore scaled to the treadmill angles using cubic polynomial fits. These scaled tracking metrics yielded highly significant predictions of the treadmill inclination angles (Fig. 4). Thus,

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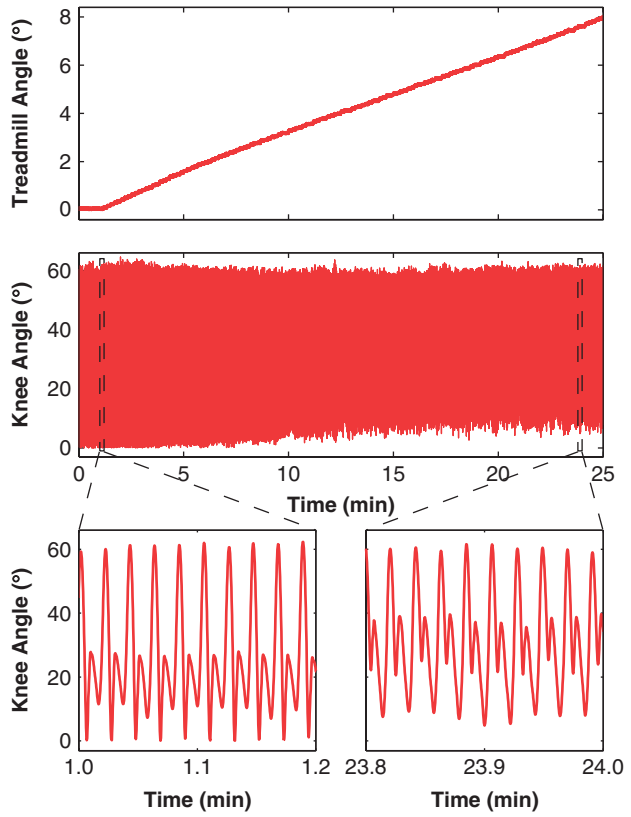

Fig. 2. Example plots of the kinematic data recorded from the treadmill (top) and from the knee joint (middle) of a typical subject (S#1). The bottom panel shows expanded views of two brief windows of the knee data towards the beginning and end of the trial. The knee joint kinematics exhibited subtle changes, but the overall pattern of motion remained largely in tact. Similar results were obtained for the other joint angles recorded for all five subjects.

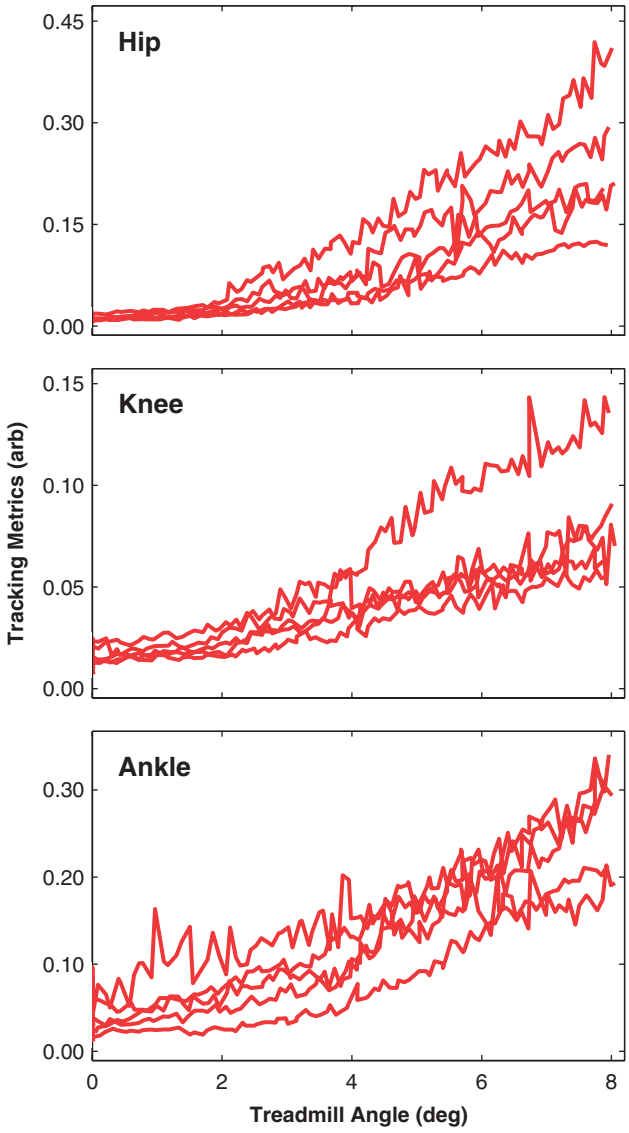

Fig. 3. Tracking metrics (Eq. (7)) computed from the fast-time-scale walking kinematics as a function of the independently recorded treadmill angle. Each line in each sub-plot represents the results from one subject. These tracking metrics exhibited generally monotonic, although nonlinear, increases with increasing treadmill angle.

the algorithm was able accurately track, to within a static nonlinear transformation, the slow-time-scale changes in treadmill inclination angles directly from the observed fast-time-scale walking kinematics.

4. Discussion

We used readily observable kinematic data to successfully track slow-time-scale changes in a functionally relevant variable that was not directly observed. While the predictions of treadmill inclination angle were not perfect, the tracking algorithm was applied in its original form, as designed to analyze purely mechanical systems. This allowed us to determine if the algorithm *itself* could work using *bio*mechanical data in a context where an unequivocal "gold standard" for comparison was obtained. The tracking algorithm worked quite well, yielding monotonic responses in all cases (Fig. 3). The nonlinearities observed between the tracking metrics and treadmill angle may have resulted from subtle neuro-muscular adaptations to low-level muscle fatigue in addition to changing task demands. More detailed multi-dimensional damage tracking analyses (Chelidze, 2004) might differentiate these various influences on movement kinematics.

It is possible that, had we tested enough candidates (e.g., amplitudes, maxima/minima, frequencies, etc.), we might have found some other, seemingly much simpler variable that predicted the treadmill inclination angle just as well. However, there would be no a ;priori theoretical justification for any such heuristically derived measure and that measure would be valid *only* for *this* experiment. The approach adopted here is superior because the choice of tracking variable ;is well

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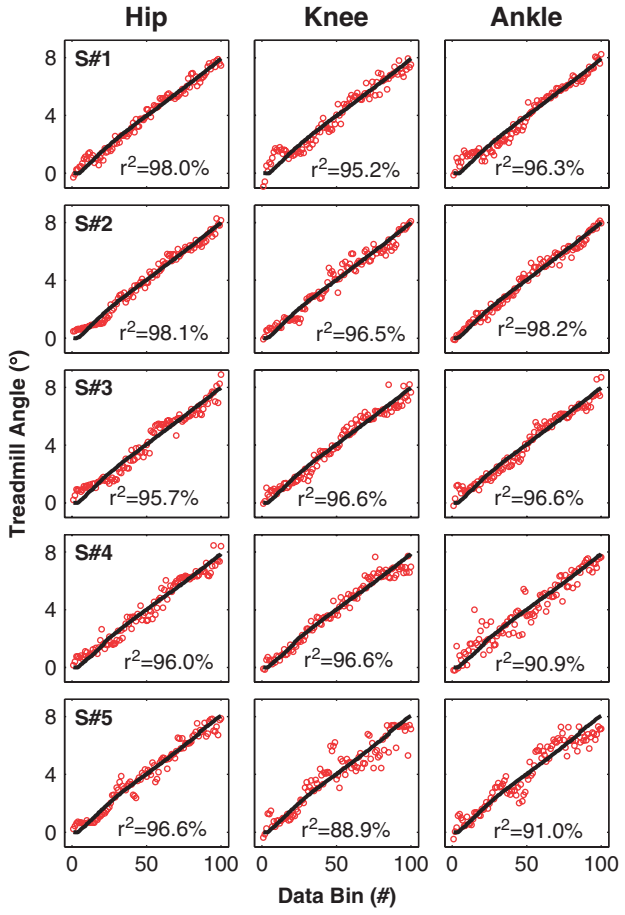

Fig. 4. Cubic polynomial fits of scalar tracking metrics (Eq. (7)) to treadmill inclination angles for each subject (S#) for each joint recorded. Circles are the scaled tracking metrics. The solid black lines are the measured treadmill angles. The r^2 values corresponding to each regression equation ($88.9\% \leqslant r^2 \leqslant 98.2\%$) are shown in each sub-plot. The tracking algorithm demonstrated similar predictive capacity across all subjects and for all three joint angles. All polynomial regressions were highly statistically significant ($p < 0.001$).

defined, theoretically justified, and validly applicable to a wide range of experimental paradigms.

Our results suggest that this approach is likely to also be effective for tracking slow-time-scale *biological* processes, like muscle fatigue or repetitive strain injury. A principle advantage of our approach is that we do not need to develop detailed first-principles models of the underlying damage process (Chelidze et al., 2002). By offering the potential to yield insight into such "hidden" biological processes, these methods could provide a means to detect how pathophysiological changes at the *biological* level affect the system dynamics at the *biomechanical* (i.e., observable) level at very early stages of disease progression. Such early identification of damage/disease onset should in turn allow much earlier intervention and prevention of further deterioration. Future work will adapt these tracking algorithms to deal directly with aspects unique to biological systems and use them to track *biological* slow-time-scale processes.

Acknowledgments

Partial funding for this research was provided by a research grant from the National Institutes of Health (EB003425).

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