1. Introduction

Linking biomechanical work to physiological work for the purpose of developing a multi-model of fatigue i.e., reduction in performance capacity as observed by an increase in oxygen consumption at a constant work rate (Gastin, 2001) is a complex problem that cannot be solved easily by conventional biomechanical analysis. The purpose of the study was to determine if two nonlinear analysis methods can address the fundamental issue of utilizing kinematic data to track oxygen consumption from a prolonged walking trial: we evaluated the effectiveness of dynamical systems and fractal analysis in this study. Further, we selected, oxygen consumption as a measure to represent the underlying physiological measure of fatigue. Three male US Army Soldier volunteers (means: 23.3 yr; 1.80 m; 77.3 kg) walked for 120 min at 1.34 m/s with a 40-kg load on a level treadmill. Gait kinematic data and oxygen consumption (VO$_2$) data were collected over the 120-min period. For the fractal analysis, utilizing stride interval data, we calculated fractal dimension. For the dynamical systems analysis, kinematic angle time series were used to estimate phase space warping based features at uniform time intervals: smooth orthogonal decomposition (SOD) was used to extract slowly time-varying trends from these features. Estimated fractal dimensions showed no apparent trend or correlation with independently measured VO$_2$. While inter-individual difference did exist in the VO$_2$ data, dominant SOD time trends tracked and correlated with the VO$_2$ for all volunteers. Thus, dynamical systems analysis using gait kinematics may be suitable to develop a model to predict physiologic fatigue based on biomechanical work.

2. Methods

2.1. Participants

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warping based features estimate the amount of deformation (warping) in the fast-time (quickly changing) kinematics trajectory. This warping is caused by slow-time changes in fast-time kinematic system’s parameters that are related to slow-time physiologic fatigue variables as reflected by oxygen consumption. Smooth orthogonal decomposition is the process used to extract deterministic trends (i.e., smooth in time) from high to low dimensional space (Chelidze and Liu, 2005, 2006, 2008). Assuming physiologic fatigue is governed by a deterministic model, the extracted smooth trends are expected to reflect slow variations in fatigue variables.

Nonlinear analysis has been applied to examine gait for short durations (Miller et al., 2006; West and Griffin, 1998); both studies demonstrated that gait kinematics contain non-random patterns within the gait cycle. Limited knowledge exists on how these nonlinear properties change over time or relate to physiological parameters associated with prolonged exercise.

Dynamical systems analysis may enable the linking of mechanical work to physiological work. Chelidze and Liu (2005) utilized dynamical systems analysis to predict damage accumulation and failure in mechanistic systems. This analysis was extended to study kinematic data in human inclined treadmill walking (Dingwell et al., 2006) and stationary cycling (Song et al., 2009). If the dynamical systems analysis can be further developed incorporating biomechanical measures to track measures of fatigue, it would be a very important first step toward the development of models to predict physiologic fatigue. The purpose of this study was to determine if dynamical systems analysis (Chelidze and Liu, 2005) or fractal analysis (West and Griffin, 1998) can address the fundamental issue of using kinematic data to track oxygen consumption (a selected measure to represent the underlying physiological measure of fatigue) during a prolonged load carriage walking task.

2. Methods

Three US Army enlisted men (age = 23.3 ± 4.2 yr; height = 1.80 ± 0.2 m; body mass = 77.3 ± 4.2 kg) took part in the study. Informed consent was obtained and the study was approved by the Institutional Review Board and conducted in accordance with Federal Policy for the Protection of Human Subjects, Department of Defense, 32 CFR Part 219. All volunteers were healthy and without injuries.

Volunteers walked for 120 min with a 40-kg load on a level treadmill (AMTI, Watertown, MA) set at 1.34 m/s. The 40-kg load consisted of soldier clothing, protective equipment, and a rucksack. Gait kinematic data were collected at 60 Hz (Qualysis, Gothenburg, Sweden) in sequential five-minute bins throughout the 120-min walking period. Approximately 30’s existed between the sequential bin collections.

Breath by breath VO2 (L/min) data were collected over the 120 min using a COSMED (Rome, Italy) K4B刁 metabolic system. We calibrated the COSMED device according to the manufacturer’s instructions. For the VO2 data, an outlier filter for data greater than 3 standard deviations was applied and then we smoothed the data using a convolution-based triangular smoothing function to obtain a slowly varying trend. To compare the VO2 data to the fractal dimension values and to the smooth orthogonal coordinates, appropriate averaging was done to match the respective nonlinear data points.

2.1. Fractal dimension analysis

Within each 5-min bin, unfiltered knee angle data were calculated utilizing body segment markers located on the shank and thigh. Time between maximal knee flexion angles of each stride was computed to determine stride interval time for gait cycle. Data were processed using Visual3D (C-Motion, Rockville MD, USA). The analysis yielded an average 270.3 (SD 8.1) stride time intervals per bin. For each bin, the fractal dimension (D) of the stride interval time series data was computed, following previously described methods (West and Griffin, 1998).

For this particular measure of fractal dimension, data that is completely random with no correlation in the time series is represented by D = 1.5 and data that is regular and perfectly correlated is represented by D = 1.0, such as simple periodic motion. West and Griffin (1998) have previously demonstrated that the fractal property of gait data differs from random noise. Similar to West and Griffin, we randomly shuffled the original time series data to create random data, surrogate data: we found that the fractal property of gait across all volunteers and bins significantly differed from the fractal property of the surrogate data 1.30 (SD 0.12) vs. 1.53 (SD 0.02) with a p-value of less than 0.05.

2.2. Dynamical systems

For this analysis, it is assumed that the underlying hierarchical dynamical system has changes in VO2 (i.e., physical fatigue) as a slow-time process causing nonstationarity in a fast-time motion (kinematics). The measured kinematics are used to identify slow-time change related trends in two steps: (1) phase space warping (PSW) based feature vectors are estimated from time series; and (2) smooth orthogonal decomposition (SOD) is used to extract deterministic or smooth in time trends from these features (Chelidze and Liu, 2005, 2006, 2008).

The PSW describes the alteration or deformation of fast-time motion trajectory caused by slow drift in parameters triggered by underlying drift process (fatigue or VO2, in our case). For relatively small changes in slow-time variables, PSW-based metrics are in one-to-one map to the actual change in these variables (Chelidze and Liu, 2005, 2006, 2008). The PSW feature vectors are composed of estimated average deformation in small hyper-volumes of the reconstructed motion phase space for each time window. The time sequence of these feature vectors are analyzed using SOD that extracts smooth orthogonal coordinates (SOCs) from multivariate data. This is accomplished by identifying the subspace of the feature space that maximizes the variance of data while minimizing their local time fluctuations.

We assume that changes in VO2 vs. time (e.g. physical fatigue) are a smooth deterministic process and expect the dominant SOCs to dynamically reconstruct the actual VO2 trajectory (Chelidze and Liu, 2005, 2006). Thus, the smooth orthogonal coordinates (SOCs) were verified against the processed VO2 data. Statistical analyses were accomplished using SPSS 13.0 (SPSS Inc., Chicago, IL, USA). Pearson Product Moment Correlations were calculated for fractal dimension and averaged VO2 value across the bins and for SOCs and averaged VO2 over the walking period. Alpha was set at 0.05.

3. Results and discussion

On average, volunteers experienced an increase in oxygen consumption in walking two hours, from an initial 1.46 to 1.73 L/min at the completion (Fig. 1). The dynamical systems technique tracks the oxygen consumption data for all the volunteers (Fig. 2). The dynamical systems technique is a technique that can track and, given the right information, may predict increases in oxygen consumption to ultimately predict physical fatigue. This finding extends previous work that examined mechanical failing or fatiguing features indirectly (Chelidze and Liu, 2005, 2006, 2008; Song et al., 2009). In the current study, the kinematic measures track the oxygen consumption regardless of the presence of a specific trend (e.g., an increase in oxygen consumption over time). Linking mechanical work to physiological work is a novel contribution to a recognized complex problem of the field (Noakes, 2000).

The fractal dimension does not correlate with oxygen consumption (Fig. 3). However, the fractal dimension does decrease over time on average from an initial 1.43 to 1.12 at completion.
The limitation of our analysis is we examined only knee angle data. Other gait variables, kinematic, kinetic, or electromyographic, may contain nonlinear fluctuations that are related to changes in oxygen consumption.

With regards to dynamical systems, dominant smooth orthogonal coordinates (SOCs) extracted from the knee angle time series analysis correlated with the VO2 trends, yielding an $r^2 = 0.898$, a significant finding. The SOC trend closely tracks the VO2 data (Fig. 5). To illustrate the correlation of the identified SOC trends with the observed VO2 trends, the SOCs were projected in the least squares sense onto the VO2 data (Fig. 2). The SOCs correlated with the VO2 trends for each of the volunteers, regardless of the direction of the VO2 trend (Fig. 2). The results obtained from knee angle time series are shown in the same figure as solid red lines. Since the task load was approximately constant, we expect the systemic physiologic fatigue to accumulate monotonically. Since the dominant SOC identifies the most monotonic trend in the feature space, we expect it to identify this systemic physiologic fatigue: therefore, we would expect only one dominant SOC to be needed to closely track VO2. However, this was the case for only one volunteer. For two of the volunteers, 15 dominant SOCs were needed to closely track the VO2 data. This was attributed to the fact that their VO2 did not show the expected monotonic increase, possibly reflecting other physiologic changes in the system. However, by including more SOCs it was still possible to track the VO2 data.

The dynamical systems method appears to be robust, given its ability to track for three different volunteers, each with a different trend in the VO2 data. The methodology demonstrates that changes in the SOCs for kinematic variables correlates with changes in VO2 regardless of the overall trend of the VO2 data over time. This is an important step towards the ability to link biomechanical work to physiological work. The demonstrated feasibility of the dynamical systems approach presented provides a step towards developing an energy prediction model using only biomechanical data.

**Conflict of interest statement**

There are no known conflicts of interest.

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innovative teacher, mentor, mathematician, and friend. In the present study, Lou helped propose and formulate the creative and intellectual facets of this project, as well as contributed to the methodology but passed away before this paper was completed. His many friends and scientific colleagues will miss his unique insights and analytical skills.

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References


