Clinical Biomechanics 56 (2018) 61–69

Contents lists available at ScienceDirect

Clinical Biomechanics

journal homepage: www.elsevier.com/locate/clinbiomech

Low-dimensional dynamical characterization of human performance of cancer patients using motion data☆

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ARTICLE INFO

Keywords:
Human performance
Patient fitness
Motion capture

ABSTRACT

Background: Biomechanical characterization of human performance with respect to fatigue and fitness is relevant in many settings, however is usually limited to either fully qualitative assessments or invasive methods which require a significant experimental setup consisting of numerous sensors, force plates, and motion detectors. Qualitative assessments are difficult to standardize due to their intrinsic subjective nature, on the other hand, invasive methods provide reliable metrics but are not feasible for large scale applications.
Methods: Presented here is a dynamical toolset for detecting performance groups using a non-invasive system based on the Microsoft Kinect motion capture sensor, and a case study of 37 cancer patients performing two clinically monitored tasks before and after therapy regimens. Dynamical features are extracted from the motion time series data and evaluated based on their ability to i) cluster patients into coherent fitness groups using unsupervised learning algorithms and to ii) predict Eastern Cooperative Oncology Group performance status via supervised learning.
Findings: The unsupervised patient clustering is comparable to clustering based on physician assigned Eastern Cooperative Oncology Group status in that they both have similar concordance with change in weight before and after therapy as well as unexpected hospitalizations throughout the study. The extracted dynamical features can predict physician, coordinator, and patient Eastern Cooperative Oncology Group status with an accuracy of approximately 80%.
Interpretation: The non-invasive Microsoft Kinect sensor and the proposed dynamical toolset comprised of data preprocessing, feature extraction, dimensionality reduction, and machine learning offers a low-cost and general method for performance segregation and can complement existing qualitative clinical assessments.

1. Introduction

In oncologic practice, clinical assessments of performance stratify patients into subgroups and inform decisions about the intensity and timing of therapy as well as cohort selection for clinical trials. The Karnofsky performance status (KPS) (Karnofsky and Burchenal, 1948) and the ECOG/World Health Organization (WHO) performance status (Oken et al., 1982) are two equally prevalent measures of the impact of disease on a patient's physical ability to function. The Karnofsky score is an 11-tier measure ranging from 0 (dead) to 100 (healthy) whereas the ECOG score is a simplified 6-tier score summarizing physical ability, activity, and self-care: 0 (fully active), 1 (ambulatory), 2 (no work activities), 3 (partially confined to bed), 4 (totally confined to bed), 5 (deceased) (Oken et al., 1982).

☆ Declarations of interest: none.

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https://doi.org/10.1016/j.clinbiomech.2018.05.007
Received 28 December 2017; Accepted 8 May 2018

Although these metrics have been employed for many decades due the practicality, standardization of patient stratification, and speed of assessment, prospective studies have revealed inter- and intra-observer variability (Péus et al., 2013), gender discrepancies (Blagden et al., 2003), sources of subjectivity in physician assigned performance assessments (Péus et al., 2013), and a lack of standard conversion between the two different scales (Buccheri et al., 1996). Nevertheless performance status provides clinical utility because it is able to differentiate patient survival (Kawaguchi et al., 2010; Radzikowska et al., 2002). Consequently, the existing protocol of assigning a performance status based on an inherently subjective assessment must be refined to achieve a more objective classification of a patient's physical function.

In contrast to the qualitative and relatively practical nature of physician assessments in the clinic, laboratory based invasive methods have been developed to biomechanically quantify elements of human performance. Many of these efforts have conducted gait analysis using accelerometer, gyroscope and other types of wearable sensors and motion capture systems (Tao et al., 2012) to detect and differentiate conditions in patients with osteoarthritis (Turcot et al., 2008), neuromuscular disorders (Frigo and Crenna, 2009), and cerebral palsy (Desloovere et al., 2006). The shortcomings of more extensive assessments such as gait analysis include high cost, time required to perform tests, and general difficulty in interpreting results (Simon, 2004). The need for new technologies has been emphasized, particularly in the oncology setting (Kelly and Shahrokni, 2016), to bridge the gap between subjective prognostication using KPS or ECOG performance status and objective, yet cumbersome assessments of performance.

To this end, we propose a non-invasive motion-capture based performance assessment system which can (i) characterize performance groups using solely kinematic data and (ii) be trained to predict ECOG scores by learning from various physicians in order to reduce bias and intra-observer variability. The Microsoft Kinect is used as the motion-capture device due to its low cost, and ability to extract kinematic information without the need of invasive sensors. We describe and test a data processing and analysis pipeline using a cohort of 40 cancer patients who perform two clinically supervised tasks before and after therapy at USC Norris Comprehensive Cancer Center, Los Angeles County + USC Medical Center, and MD Anderson Cancer Center.

2. Methods

A set of dynamical analysis and machine learning tools is developed to gather kinematic information from recordings of patients performing tasks (Fig. 1) with the goal of validating the experiment design by performing unsupervised classification of performance categories (Fig. 1, step 4a), as well as supervised learning of physician assigned ECOG performance status (Fig. 1, step 4b). Although we illustrate the use of the toolset by exploring its application to an oncology cohort, the following methods are general and may be used to characterize patient performance in other settings.

2.1. Experimental setup

The Kinect depth sensor employs an infrared laser projector to detect a representative skeleton composed of 25 anatomical points (Fig. 2A) and recordings are post-processed using Microsoft Kinect SDK (v2.0) to extract 3-dimensional displacement time series data for the 25 points. The Microsoft Kinect sensor is used in the clinical setting to record patients performing two tasks: (i) task-1 requires patients, who start from a sitting a position, to stand up and sit down on an adjacent elevated medical table (Fig. 2B), (ii) task-2 requires patients to walk 8 ft towards the Kinect sensor, turn, and return to the original position (Fig. 2C). Both tasks are performed by each patient before and after a therapy cycle, providing two samples for each task for a total of four time series per patient. In both tasks the Kinect camera is secured to a tripod on a table, and oriented so as to capture the entire figure. Details about the data collection, skeletal data extraction, and experimental setup are described by Nguyen and Hasnain in Nguyen et al. (2017).

2.2. Data preprocessing

Due to irregularities in the positioning of the Kinect camera across different experiments, time series for task-2 is distorted such that a level plane (e.g. clinic floor) appears sloped in the recordings. To resolve this, an automated element rotation about the x-axis is performed. The angle of distortion θ ranges between 5 and 20° in the time series studied. The second preprocessing step involves manually segmenting the series to trim irrelevant data in the beginning and end of each task while the patient is stationary.

2.3. Feature extraction

The position vector, $\vec{r_i}(t) = \langle x_i(t), y_i(t), z_i(t) \rangle$ for an anatomical joint i is used to calculate its velocity magnitude,

$$v_i(t) = \|\dot{\vec{r_i}}(t)\| \tag{1}$$

and acceleration magnitude,

$$a_i(t) = \|\ddot{\vec{r_i}}(t)\| \tag{2}$$

using the mean-value theorem. In the absence of distribution of mass information, specific kinetic energy,

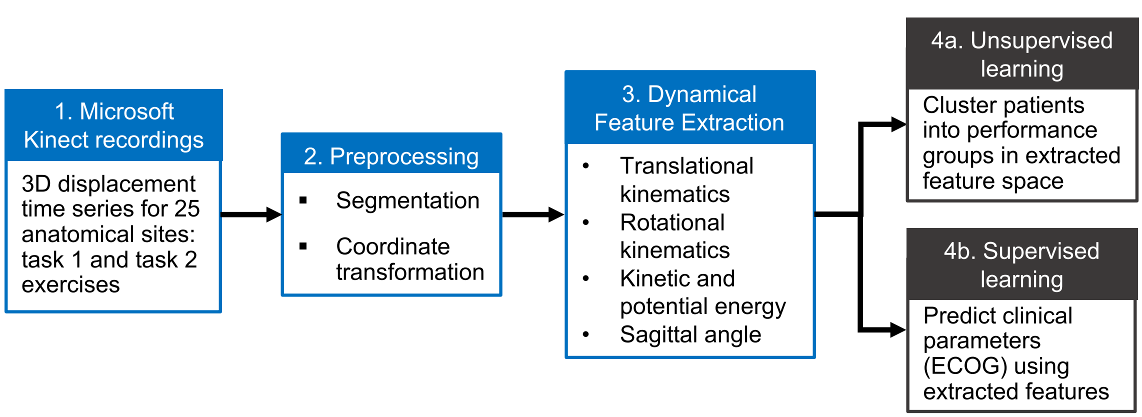

Fig. 1. Schematic of dynamical and machine learning analysis pipeline. Raw skeletal displacement data (step 1) from two clinically monitored tasks are preprocessed (step 2) before feature extraction (step 3) and two mutually exclusive machine learning analyses are performed. Unsupervised clustering (step 4a) of patients in a low dimensional space reveals the degree to which performance groups can by stratified using solely motion data. Supervised classification (step 4b) tests the ability of motion data to evaluate patients similar to physician ECOG performance status.