Advancing Clinical Evaluation of Musculoskeletal Impairment with a Robust Kinematic Composite Score

Erin S. Archibeck[1], Reece Huff[1], Ryan Halvorson[2], Abel Torres Espin[3], Jessica Ornowski[2], Karim Khattab[2], Robert P. Matthew[4], Grace D. O'Connell[1,2], Jeannie F. Bailey[2]

[1]Department of Mechanical Engineering, University of California, Berkeley, [2] Department of Orthopaedic Surgery, University of California, San Francisco, [3]Department of Neurological Surgery, University of California, San Francisco, [4]Department of Physical Therapy, University of California, San Francisco

Email of Presenting Author: erinarchibeck@berkeley.edu

Disclosures: JFB has stock options with Bioniks LLC

INTRODUCTION: Musculoskeletal disorders cause severe reduction in biomechanical function and are the leading contributor of global disability [1]. The existing options for assessing patient biomechanics are: 1) static goniometry for joint range of motion, 2) functional testing that measures the total duration of time to complete a maneuver, and 3) 3D biomechanical testing that is both time intensive and generates large and complex datasets for each body segment. Options 1 and 2 lack quantitative robusticity of movement biomechanics. Further, option 3 is not practical in a clinical setting, and the overall clinical utility of the resulting variables is unclear. It is critical to develop a quantitative approach for evaluating movement quality across multiple joints to capture compensatory patterns of patients with musculoskeletal impairments. Principal Component Analysis (PCA) is a popular strategy for dimensionality reduction to quantify full-body movement control [2-6] in which the three-dimensional joint positions are analyzed at a single time point to identify patterns across the entire group of patients. This technique was applied to previous work in our lab, which developed a novel composite metric, Kinematic Deviation Index (KDI), for quantifying movement control [2]. While the technique has promising clinical utility, using PCA as described overlooks the temporal data, a crucial aspect of motion analysis. Further, the use of PCA and other machine learning techniques require large patient sample sizes to improve data robustness. Therefore, the objective of this study was to formulate a data science approach that distills full-body postural and dynamic patterns into a single metric that has robustness and clinical utility, defined by changes in multi-joint kinematics over time and independence of sample size. This would provide a full-body movement quality composite score that could be used as a biomechanical outcome for assessing movement impairment and monitoring recovery.

METHODS: With IRB approval and informed consent, participants were recruited, including healthy adults who served as the control (n=6), preoperative total hip arthroplasty patients (THA, n=10), and patients with chronic low back pain for > 3 months and > 50% of days (LBP, n=10). Participants performed the sit-to-stand motion for five continuous repetitions. Eleven landmarks were used as inputs (base of spine, mid-spine, neck, shoulders, hips, knees, and ankles), and a non-invasive three-dimensional markerless depth camera (Azure Kinect, Microsoft) was used to systematically record positional data (Figure 1A). For all landmark data, repetitions were averaged to increase the signal-to-noise ratio. The data was temporally normalized to ensure uniform data points across all patients. PCA was separately performed for each patient's data, encompassing all averaged landmark positions in 3D for every normalized time point. Applying PCA independently for each patient addressed the challenge of detecting variation in temporal data and diminished the influence of patient sample size. To align the data across patients, Generalized Procrustes Analysis was applied to the PCA-transformed data using the transformation calculated at the resting position (t=0). The control group's average was chosen as the reference frame to ensure that the scores remained consistent regardless of the inclusion of patient-specific data. The Kinematic Profile (K-Profile), which captures the most prominent patterns across all landmarks, was calculated using the weighted sum of the PCA scores at every time point. A single metric for each activity, the Kinematic Composite Score (K-Score), was established by calculating the total difference between the individual's score and the control average. To incorporate patient speed, the K-Score was adjusted by multiplying the ratio of the average time to complete an individual activity to the control average time. Further, all values were transformed using a 100-point scale, with 100 representing an ideal movement trajectory, to enhance comprehensibility amongst patients and clinicians. The K-Score allows insight into the extent of alignment to the "ideal trajectory" and "ideal pace", which are defined by healthy subjects with no movement impairment. Kruskal-Wallis test was conducted on the K-Scores to account for the small sample sizes and nonparametric nature of the THA data (confirmed with the Shapiro-Wilk Normality Test). Dunn's post hoc analysis was performed to make pairwise comparisons when significance was found ($p \leq 0.05$).

RESULTS: The absolute value of the mean K-Profile was highest for the control group, indicating stronger alignment of joint positions with the principal components (Figure 1B). Specifically, controls exhibited well-defined postural patterns, while the patient groups were less defined. Notably, the variance in the control group was less than the patient groups, indicating more consistent movement patterns among controls. The comprehensive activity metric, K-Score, demonstrated statistically significant differences ($p<0.001$, $H=13.9$) between controls (Median:94.5, IQR:2.8), THA (Median: 81.5, IQR: 27.0), and LBP (Median:54.7, IQR: 34.6) (Figure 1C). The THA and LBP groups exhibited a 13.8% ($p=0.04$), and 42.1% ($p<0.001$) decrease in median K-Scores compared to the controls, respectively, and there were no statistical differences between the two patient groups ($p=0.12$).

DISCUSSION: This study developed a methodology to assess movement quality for musculoskeletal conditions by distilling full-body postural patterns into a composite score that addresses limitations in commonly used approaches, including limited temporal analysis, neglection of speed, and reliance on patient sample size. The results suggested that the control group displayed defined and consistent movement patterns for sit-to-stand, as indicated by the K-Profile magnitudes and lower overall standard deviation. Further, the K-Score, an intuitive and user-friendly metric, effectively distinguished between controls, THA, and LBP patients. The study is currently limited by the sample sizes and the specific sit-to-stand activity, restricting the statistical power and confirmation of broader utility, respectively. With the promising preliminary results, future research aims to increase sample size, diverse musculoskeletal conditions, and activities.

SIGNIFICANCE/CLINICAL RELEVANCE: The developed metrics are a promising avenue for assessing and differentiating heterogeneous musculoskeletal conditions based on objective postural and temporal patterns. The K-Score can ultimately be employed to aid in diagnosis and quantify rehabilitation progress.

REFERENCES: [1] World Health Organization, 2022 [2] Halvorson et al., *PLOS Dig. Health*; 2022 [3] Federolf et al.,*J. Biomech.*; 2012 [4] Troje, *J.Vis*; 2002 [5] Van Andel et al., *Front. Bioeng. Biotech.*; 2022 [6] Daffertshofer et al., *Clin. Biomech. Bristol. Avon*; 2004

ACKNOWLEDGEMENTS: This work was supported by NSF (GRFP #DGE 2146752) and NIH NIAMS (U19 AR076737).

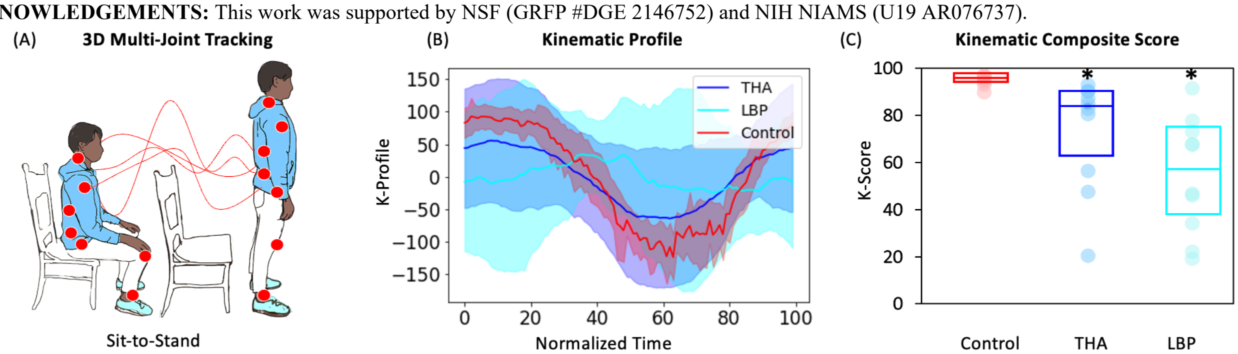

Figure 1: (A) Schematic of multi-joint markerless motion capture, (B) K-Profile over the normalized time as mean (solid line) and standard deviation (shaded region), and (C) K-Score as a box-and-whisker plot indicating median, IQ1, and IQ3. * Represents $p \leq 0.05$