Continuous similarity analysis in patient populations

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ABSTRACT

Decreased movement symmetry is associated with injury risk and accelerated disease progression. Methods to analyze continuous data either cannot be used in pathologic populations with abnormal movement patterns or are not defined in terms easily incorporated into clinical care. The purpose of this study was to develop a method of describing symmetry and movement quality in continuous time-series data that results in scores that can be readily incorporated into clinical care. Two scores were developed: (1) the symmetry score (SS) which evaluates similarities in time-series data between limbs and (2) the closeness-to-healthy score (CTHS) which evaluates the similarity of time-series data to a control population. Kinetic and kinematic data from 56 end-stage unilateral ankle arthritis (A-OA) patients and 56 healthy older adults, along with 16 anterior cruciate ligament reconstruction (ACLR) patients and 16 healthy young adults were used to test the ability for SS and CTHS to differentiate between healthy and patient groups. Unpaired t-tests, Cohen's D effect sizes, and receiver-operating-curve analyses assessed group differences [SPSS, V27, $\alpha = 0.05$]. Patients had worse SS than controls and A-OA patients had worse CTHS compared to controls. SS had strong predictive capability, while the predictive capability of CTHS varied. Combined with clinically accessible data collection methods, the SS and CTHS could be used to evaluate patients' baseline movement quality, assess changes due to disease progression, and during recovery. Results could be utilized in clinical decision making to assess surgical intervention urgency and efficacy of surgical interventions or rehabilitation protocols to improve side-to-side limb symmetry.

1. Introduction

Poor movement symmetry has been associated with injury risk (Bredeweg et al., 2013; Ciacci et al., 2013; Zifchock et al., 2008a, 2006) and accelerated disease progression (Mills et al., 2013; Shakoor et al., 2003), making it important for clinical assessment. Movement symmetry during activities such as walking, running, and landing can be described as inter-limb kinetic and kinematic differences. Objective evaluation of movement symmetry often relies on the collection of continuous kinetic and kinematic time-series data. Despite collected data being continuous, symmetry is commonly analyzed using discrete points obtained from the continuous curves such as peaks and values at specific time points.

There are several commonly used discrete methods to identify gait symmetry. Some investigations assess between limb asymmetries as inter-limb differences (Brown et al., 2009; Edwards et al., 2012; Lee et al., 2009; Sinsurin et al., 2017). Other studies utilize symmetry metrics expressing the degree of symmetry in a single measure such as the limb symmetry index, symmetry ratio, symmetry angle, or normalized symmetry index (Herzog et al., 1989; Patterson et al., 2012; Queen et al., 2020; Robinson et al., 1987; Rohman et al., 2015; Zifchock et al., 2008b). Although there are advantages to commonly used discrete analysis methods including direct statistical comparison between limbs and easy interpretation, these methods rely on data discretization. Instead of investigating the entire movement cycle and all points within, analysis and interpretation is limited to only a few points within the movement cycle. All potentially meaningful characteristics of the movement patterns outside of the selected discrete points are lost with this approach.

Analyzing continuous data expands the scope of analysis to the entire time-series and prevents the loss of potentially important data. Previously utilized methods of continuous data analysis include the Coefficient of Multiple Determination (CMD) (Kadaba et al., 1989; Milner et al., 2011; Shi et al., 2019; Vickers et al., 2008) and Statistical Parametric Mapping (SPM) (Hughes-Oliver et al., 2019; King et al., 2018b, 2018a; Mueske et al., 2019), among others. This is not an exhaustive list of existing methodologies, but instead includes measures that have

limitations when analyzing continuous biomechanical data. The CMD, which is numerically equivalent to an adjusted R-squared value for evaluating waveforms and is also commonly known as the Coefficient of Multiple Correlation (CMC), has been used as a measure of repeatability and similarity between time-series curves across multiple independent variables (Kadaba et al., 1989; Røislien et al., 2012) ; in the case of assessing symmetry, limb is the independent variable of interest. The computation determines the proportion of variation in the dependent variable that can be predicted from the independent variables. While the CMD is a valuable tool for many applications due to its ease of interpretation, its computation requires the assumption that the curves being compared move in the same direction throughout the time-series. This assumption is violated at time points in which the curves move in opposite directions, which results in increasingly inaccurate similarity estimations with greater proportions of opposing slope directions throughout the time-series. The potential to violate this assumption makes the use of the CMD unreliable in clinical populations where this opposing directionality is more likely, especially in the frontal and transverse planes, thereby limiting the use of the CMD in assessing symmetry across a wide variety of healthy and pathologic populations.

Statistical parametric mapping (SPM) is another tool that has been used to assess inter-limb differences in continuous kinetic and kinematic biomechanical data (Hughes-Oliver et al., 2019; King et al., 2018a; Pataky, 2010; Pataky et al., 2013). SPM is based on random field theory and enables the identification of regions of difference between curves along the time-series (Friston et al., 1994; Pataky et al., 2013; Robinson et al., 2014). SPM avoids the previously described limitation of the CMD by performing well across healthy and pathologic populations as long as the data is time normalized and there is a balanced study design. While SPM is a valuable tool for extracting detailed information regarding inter-limb differences throughout the time-series, its output does not facilitate quick interpretation, which would be ideal in a clinical environment. SPM output includes test statistic curves comparing variation in the dependent curves to random data. Regions of significant difference based on the independent variable(s) are indicated on these output graphs. Additional details of statistical comparison of the time-series curves are also available in output variables. Despite the value of this detailed analysis, interpretation of SPM results necessitates visualization and conceptualization of the time-series curves and the identified regions of difference, along with the direction of differences between curves. Such interpretation is more challenging for integration within a clinical environment due to time constraints, so SPM is mostly restricted to use in research settings. SPM also directly compares the curves at each time point, which may generate inaccurate or misleading results in populations for which there is a time shift between curves.

Although previously used methods of analyzing continuous biomechanical data avoid pitfalls associated with the analysis of discrete data, they either cannot be used reliably across a wide variety of populations or are not defined in concise enough terms to be quickly interpreted and incorporated into clinical decision making and outcome assessment. Additionally, most analyses of movement symmetry or inter-limb differences focus only on differences between limbs without providing context into the degree of movement normality or quality. This is particularly problematic in cases where both limbs may be affected by pathology; these cases would reflect high symmetry scores, but the bilateral abnormality of the movement pattern would be missed without context into movement quality. The purpose of this study was to develop an alternative method of describing movement symmetry, while providing context for movement quality, in continuous kinetic and kinematic time-series data that can be quickly utilized in clinical care. End-stage, unilateral ankle arthritis (A-OA) patients and anterior cruciate ligament reconstruction (ACLR) patients were used as the clinical test cases. We hypothesized that the developed scores would be able to differentiate between healthy individuals and patient populations (A-OA and ACLR patients) with good to excellent predictive capability.

2. Methods

2.1. Participants

Kinetic and kinematic data was collected A-OA and ACLR patients along with control populations for each patient group. All participants signed informed consent approved by the University's Institutional Review Board prior to study participation.

Three-dimensional motion capture and force plate data during walking from 56 end-stage, unilateral A-OA patients scheduled for total ankle replacement was obtained from a previously collected data set (Queen et al., 2012) (61 ± 11 years) (Table 1). Exclusion criteria for this prior data set include inability to walk without an assistive device and having pain at more than one lower extremity joint or limb. Motion capture and force plate data was also collected from 56 healthy adults (walking controls) matched by age and sex to the A-OA sample as closely as possible (59 ± 12 years) (Table 1). Walking control participants were included if they had no lower extremity injuries in the past 12 months, had no history of major lower extremity injury or surgery, were able to walk unassisted for 10 min, were able to speak and read English, and were not blind or pregnant.

Sixteen unilateral ACLR patients (14–30 years old) were recruited between 6 and 12 months after surgery (17 ± 1 years)(Table 1). Additional inclusion criteria included planning to return to a sport that involves jumping and/or cutting and having no preexisting condition which limits physical activity. Sixteen healthy control participants (18–30 years old) (landing controls) were recruited for comparison with the ACLR patients (24 ± 3 years)(Table 1). Inclusion criteria for landing control participants included being recreationally active, defined as participating in physical activity at least three times per week for at least thirty minutes, having prior experience playing a sport involving jumping, no injury in the previous three months and not having any current pain limiting mobility, having no prior major lower extremity injury or surgery, and having no preexisting condition limiting physical activity.

2.2. Data collection

Walking control participants and A-OA patients completed seven barefoot walking trials at self-selected speeds along a 10-meter walkway with four embedded force plates (AMTI, Watertown, MA) (Queen et al., 2012). Thirty-five bilateral lower extremity markers were placed, and 3D motion capture (120 Hz) (Oqus, Qualisys, Gothenburg, Sweden) and force plate data (AMTI, Watertown, MA) were recorded. Walking control and A-OA patient force plate data was collected at 1920 Hz and 1200 Hz, respectively. All data was processed in Visual 3D (C-Motion, Germantown, MD). The following outcome measures were assessed in A-OA patients and walking controls: vertical ground reaction force (vGRF), sagittal plane ankle angle (AA), and center of pressure traces in the anterior-posterior (COP_{AP}) and medial–lateral (COP_{ML}) directions. All outcome measures were time-normalized to stance phase between heel strike and toe off, which were defined systematically using a threshold of 25 N and confirmed by visual inspection. Vertical ground reaction forces were normalized to body mass, and center of pressure measures were normalized to foot length and width.

Data collection was completed for ACLR patients in a local rehabilitation facility, while data collection for landing controls was completed in a university athletic center (Peebles et al., 2021). All participants wore standardized neutral cushioning running shoes (Air Pegasus, Nike Inc., Beaverton, Oregon). Participants completed seven bilateral drop vertical jumps, with a forward distance of half the participant's body height, and seven unilateral drop landings on each limb, during which participants dropped off of a 31 cm high box, landed on a single limb and held the unilateral landing for two seconds (Peebles et al., 2021). Plantar impact forces were measured bilaterally using loadsol® sensors (Novel Electronics, St. Paul, Minnesota), which were calibrated

Table 1
Demographic data from control and patient participants in each comparison group. Mean (SD).

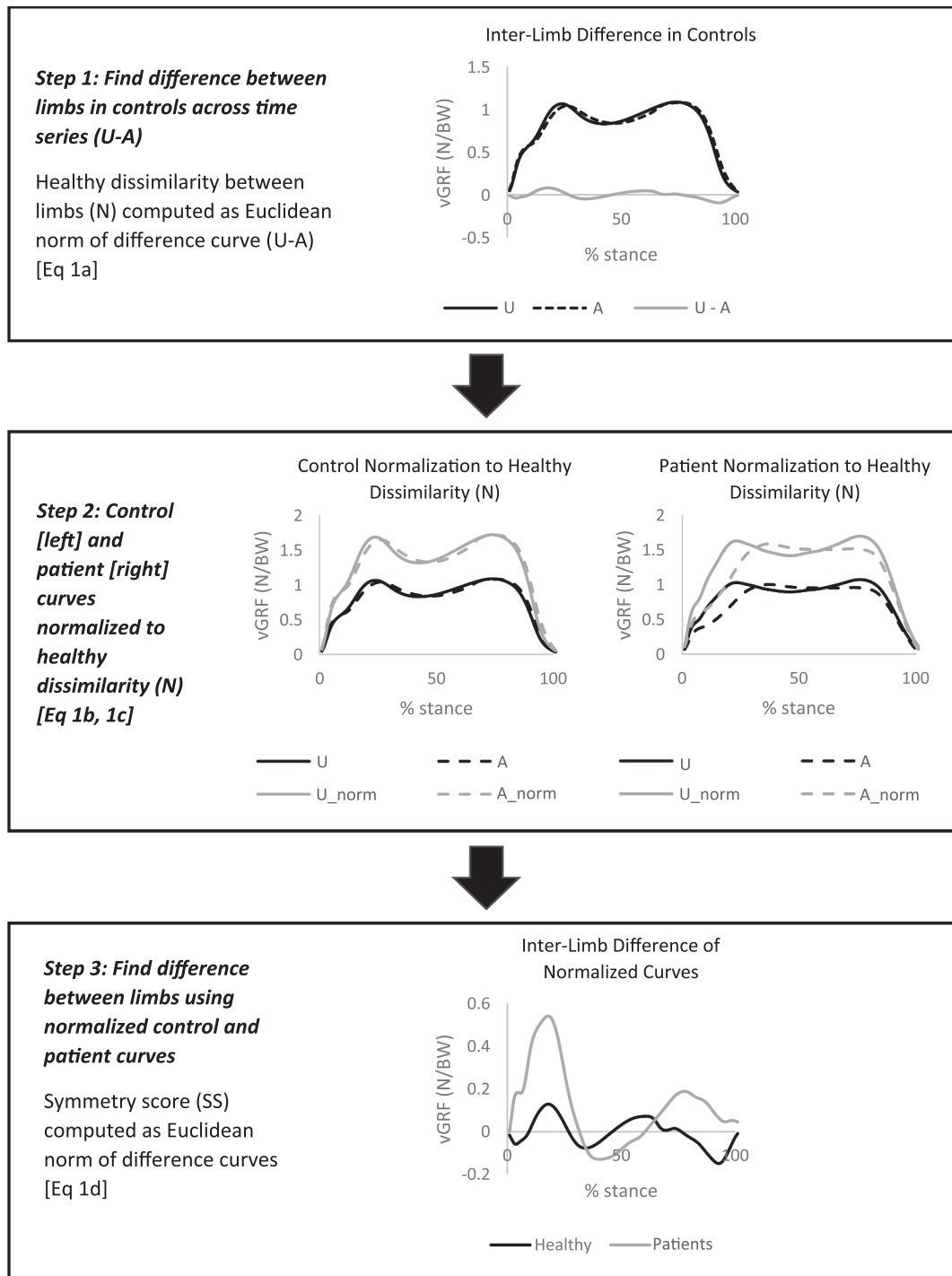|	Walking			Landing		
	Controls (13 M,43F)	A-OA Patients (13 M,43F)	p-value	Controls (7 M, 9F)	ACLR Patients (7 M, 9F)	p-value
Age	59 (12)	61 (11)	0.304	24 (3)	17 (1)	<0.001*
Height (m)	1.67 (0.08)	1.68 (0.09)	0.496	1.77 (0.08)	1.72 (0.11)	0.136
Weight (kg)	69.45 (12.06)	72.79 (12.02)	0.144	71.90 (16.47)	73.81 (14.96)	0.734

* difference between control and patient group

Fig. 1. Process used to compute Symmetry Score (SS) using vertical ground reaction force example data from walking controls and A-OA patients. U = Unaffected limb (dominant limb in controls, non-surgical limb in patients). A = affected limb (non-dominant limb in controls, surgical limb in patients). '_norm' indicates normalization by healthy dissimilarity (N).

based on manufacturer guidelines (Peebles et al., 2018), at 100 Hz and 200 Hz for the landing controls and ACLR patients, respectively. The difference in sampling frequency between groups was due to an advancement in the loadsol® technology; ACLR data was down-sampled to 100 Hz to enable accurate comparison. Plantar loading data used for kinetic analysis was analyzed using the Load Analysis Program (LAP) open-source MATLAB user interface, which can be downloaded here: https://github.com/GranataLab/LAP. Bilateral data was time-normalized between ground contact and toe off, which were identified when plantar force rose above and fell below 50 N. Unilateral data was time-normalized to the first 500 ms after ground contact. The following outcome measures were assessed in ACLR patients and landing controls: vGRF during bilateral landing ($vGRF_B$) and vGRF during unilateral landing ($vGRF_U$).

In both control groups, the dominant limb was defined as the limb used to kick a soccer ball. In all groups and for each measure, normalized curves were averaged across trials for each limb and each participant prior to analysis.

2.3. Score computation

For computational purposes, each continuous time-series curve was conceptualized as 101 points, equally spaced in time. Two scores were developed and computed using a custom MATLAB script (MathWorks, Natick, MA) to assess symmetry and movement quality: the symmetry score (SS) and closeness-to-healthy score (CTHS), respectively. These scores were computed separately for the walking and landing comparisons. Surgical (S) and non-surgical (NS) limbs in patients were compared to non-dominant (ND) and dominant (D) limbs, respectively, in control participants. 'A' denotes the affected limb, which is the surgical limb in patients and the non-dominant limb in controls, and 'U' denotes the unaffected limb, which is the non-surgical limb in patients and the dominant limb in controls. This score computation can be used with any continuous dataset, denoted as 'DV'.

The symmetry score (SS) evaluated similarity of the time-series curves between limbs. First, dissimilarity between limbs was computed for each control participant as the Euclidean norm of the difference between limbs across the time-series. This value was then averaged across control participants to define a healthy amount of dissimilarity (N) (Equation (1a)). The curved data from the control participants and patients were normalized to the amount of dissimilarity observed in the control population (N) in order to maximize interpretability of results (Equation (1b)-c). The symmetry score (SS) was computed as the Euclidean norm of the difference between limbs across the time-series (Equation (1d)). A small SS indicates greater side-to-side symmetry, while a large SS indicates less side-to-side symmetry. The process used to compute the SS is shown in Fig. 1.

$$InControls : N = norm\left(\overrightarrow{DV_U} - \overrightarrow{DV_A}\right) \tag{1a}$$

$$InControlsandPatients : \overrightarrow{A}_{norm} = \frac{\overrightarrow{DV_A}}{N} \tag{1b}$$

$$InControlsandPatients : \overrightarrow{U}_{norm} = \frac{\overrightarrow{DV_U}}{N} \tag{1C}$$

$$InControlsandPatients : SS = norm\left(\overrightarrow{A}_{norm} - \overrightarrow{U}_{norm}\right) \tag{1d}$$

where A = affected limb (surgical or non-dominant), U = unaffected limb (non-surgical or dominant), DV = dependent variable

The closeness-to-healthy score (CTHS) evaluated the similarity of a single curve to the average curve of the control participants. First, the average curve in the control participants across both limbs was computed; the control average curve was then normalized by its Euclidean norm (Equation (2a)). Curves of all control participants and

patients were also normalized by their respective Euclidean norms (Equation (2b)-c). The CTHS was computed on each limb separately as the dot product (that is, the inner product in function space) of the normalized average control curve and the normalized curve of interest subtracted from 1 (Equation (2d)-e). A small CTHS indicates a curve similar to the average curve of the control participants, while a large CTHS indicates a curve dissimilar to what would be expected in a healthy individual. The process used to compute the CTHS is shown in Fig. 2.

$$InControls : \overrightarrow{N} = \frac{\overrightarrow{healthy_{average}}}{norm(\overrightarrow{healthy_{average}})} \tag{2a}$$

$$InControlsandPatients : \overrightarrow{DV_A} = \frac{\overrightarrow{DV_A}}{norm(\overrightarrow{DV_A})} \tag{2b}$$

$$InControlsandPatients : \overrightarrow{DV_U} = \frac{\overrightarrow{DV_U}}{norm(\overrightarrow{DV_U})} \tag{2C}$$

$$InControlsandPatients : CTHS_A = 1 - \overrightarrow{DV_A}\hat{A}\cdot\overrightarrow{N} \tag{2d}$$

$$InControlsandPatients : CTHS_U = 1 - \overrightarrow{DV_U}\hat{A}\cdot\overrightarrow{N} \tag{2e}$$

where A = affected limb (surgical or non-dominant), U = unaffected limb (non-surgical or dominant). DV = dependent variable

The SS and CTHS were compared between control participants and patients for each comparison using unpaired t-tests and Cohen's D effect sizes. Cohen's D effect sizes were described as small (0.2–0.39), medium (0.4–0.59), or large (>0.6) (Cohen, 1988) with positive effect sizes indicating larger values in patients. To further analyze the ability for the scores to differentiate between healthy individuals and patients, receiver operator curves (ROC) were generated using sensitivity and specificity of group categorization for each score. Sensitivity refers to the ability of the score to correctly identify patients (true positive rate), while specificity refers to the ability of the score to correctly identify healthy individuals (true negative rate). Resulting ROC curves plotted sensitivity against 1-specificity, and the optimal operating point of the ROC curve was defined using the '*perfcurve*' MATLAB function. Cutoff values were defined as the value of the score at the identified optimal operating point. The area under the ROC curve (AUC), which exists between 0 and 1, was computed for each ROC curve. Higher AUC values indicate better predictive capability and more accurate classification between control and patient groups. AUC values were described as excellent (>0.9), good (0.8–0.89), fair (0.7–0.79), or poor (0.6–0.69) (Hodt-Billington et al., 2012). All statistics were performed in SPSS Statistics (SPSS, V27 [IBM, Chicago, IL], α = 0.05).

3. Results

Score trends matched expectations from visual inspection of time-series curves. Curves resulting in low (good) SS and CTHS are visibly more symmetric and similar to the shape and magnitude of the movement pattern in a healthy individual (Figs. 3 and 4).

A-OA patients had higher (worse) SS and CTHS on both limbs compared to walking controls in almost all measures (Table 2), indicating worse symmetry and movement quality in the A-OA patients. The only measures that did not follow this trend were the COP_{ML} SS and the AA CTHS on the unaffected limb, which were not different between groups (Table 2). All significant differences between A-OA patients and walking controls reflected medium to large Cohen's D effect sizes, further emphasizing potential clinical importance of these observed differences and indicating clearer differentiation between groups. Differences in AA CTHS on the affected limb and COP_{AP} CTHS on the unaffected limb reflected medium effect sizes ($CTHS_A$ AA: d = 0.48, $CTHS_U$ COP_{AP}: d = 0.41), while all other significant differences reflected large
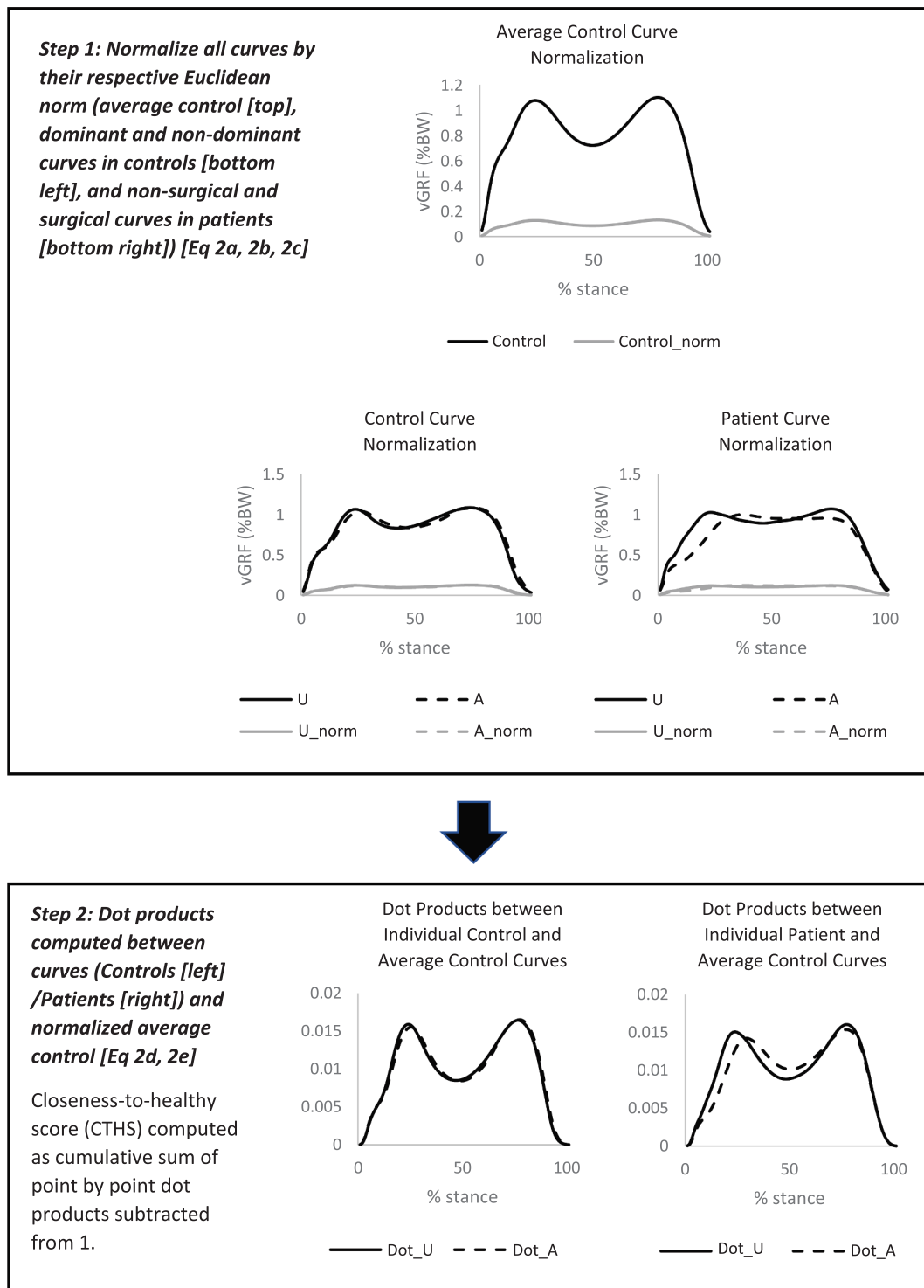
Fig. 2. Process used to compute Closeness-to-healthy score (CTHS) using vertical ground reaction force example data from walking controls and A-OA patients. Control = average control. U = Unaffected limb (dominant limb in controls, non-surgical limb in patients). A = affected limb (non-dominant limb in controls, surgical limb in patients). '_norm' indicates normalization by Euclidean norm. 'Dot_' indicates product between curve and average control. Note: Final CTHS is cumulative sum of the points displayed in the Step 2 graphs of the point by point dot product computation.

effect sizes (d = 0.66 – 1.73) (Table 2). ACLR patients had higher (worse) $vGRF_B$ and $vGRF_U$ SS compared to landing controls with both differences reflecting large effect sizes (unilateral: p = 0.018|d = 0.88, bilateral: p = 0.003|d = 1.12). CTHS did not differ between ACLR patients and landing controls on either limb.

All SS indicated good to excellent accuracy of group classification between walking controls and A-OA patients (AUC:0.85–0.94) (Table 3).

Similarly, the COP_{ML} and COP_{AP} CTHS on the affected limb and the COP_{ML} CTHS on the unaffected limb indicated good predictive capability (AUC:0.82–0.89). The COP_{AP} CTHS on the unaffected limb indicated fair predictive capability (AUC = 0.76), while the $vGRF_B$ and $vGRF_U$ CTHS indicated poor accuracy (AUC:0.65–0.67) and the CTHS of AA on the affected limb had no predictive capability (AUC = 0.56). In differentiating between landing controls and ACLR patients, the $vGRF_B$
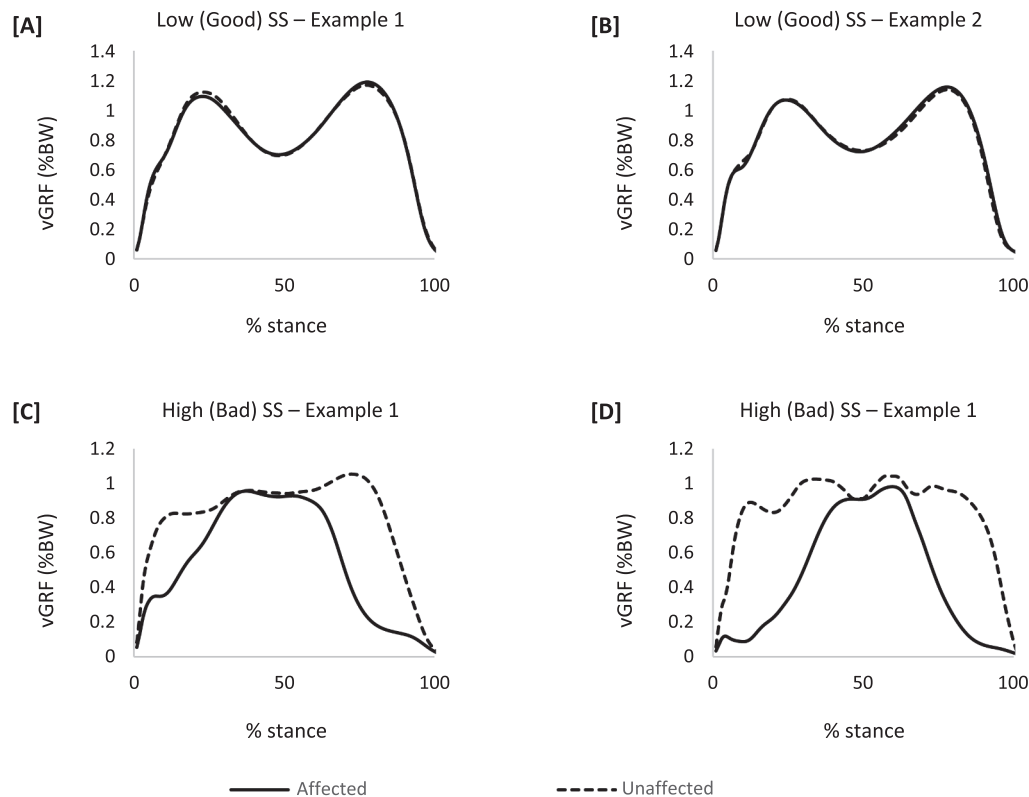
Fig. 3. Examples of vertical ground reaction force time series curves resulting in low (good) [A-B] and high (poor) [C-D] symmetry scores (SS) in walking controls and A-OA patients, respectively. [A-B] (healthy controls): curves represent non-dominant (affected) and dominant (unaffected) limbs. [C-D] (A-OA patients): curves represent surgical (affected) and non-surgical (unaffected) limbs.

and vGRF$_U$ SS had good (AUC = 0.87) and fair (AUC = 0.75) predictive capability, respectively (Table 3). Further details regarding specificity, sensitivity, and score cutoff points are reported in Table 3.

4. Discussion

Most scores were able to differentiate between healthy adults and both A-OA and ACLR patients with medium to large effect sizes, although predictive capability varied. Differences in gait symmetry between healthy adults and A-OA patients observed in the current study align well with findings in prior literature (Creaby et al., 2012; Mills et al., 2013; Schmitt et al., 2015; Valderrabano et al., 2007). Similarly, landing asymmetries reflected in prior literature between healthy athletes and ACLR patients align well with those observed in the current study (Paterno et al., 2007; Peebles et al., 2021; Schmitt et al., 2015).

Both the SS and CTHS could have important clinical implications when evaluating disease progression and surgical recovery. Large and medium effect sizes between groups and good to excellent predictive capability of several scores defined by the AUC suggests that the scores were able to differentiate between controls and patient groups at both a statistically and clinically significant level. Despite the inclusion of two very different patient groups being assessed during different movement tasks, the SS showed strong differentiation and predictive capability, particularly when used with kinetic measures, with both A-OA and ACLR patients. Although the CTHS did not show as much consistency in differentiation between groups or strength of predictive capability, these scores can act as a supplement to the SS to provide additional interpretive context for movement normality. It should also be noted that the ACLR data was collected 6–12 months post-surgery when the patient had already been cleared for return to sport. In comparison with the A-OA data that was collected prior to ankle replacement surgery, these

ACLR patients had likely regained more normal movement patterns by the collection period, which may be why CTHS did not differ between ACLR patients and landing controls. Additionally, landing timing is more variable than the timing of a gait cycle. Although all ACLR patients and landing controls were given the same instructions, participant interpretation and movement strategies could impart variation in the time-series curves, which would influence the average control curve included in the computation of the CTHS. This is an area for further score development with one future possibility being the introduction of time shifts to the data as necessary to maximize alignment across trials and participants.

While the walking control and A-OA data were collected in a motion capture research laboratory, the landing control data was collected in a university athletic facility and the ACLR data was collected in a local clinic. This further reinforces the ability for these scores to be evaluated using data collected in a laboratory or real-world settings, including clinical environments (Peebles et al., 2021). Combined with clinically accessible movement assessments such as the in-shoe load sensors used to collect the ACLR data in the current study, both scores could be used to evaluate symmetry and movement quality in a clinical setting. Such evaluations could be performed prior to disease diagnosis, to evaluate disease progression, and during rehabilitation to monitor recovery. Resulting scores could be utilized in clinical decision making to assess urgency for surgical intervention and whether a rehabilitation protocol can effectively target specific asymmetric movement patterns. The SS identified differences in symmetry during unilateral landing that were not previously identified by evaluating only peak vGRF symmetry in the same dataset, further emphasizing the utility of a continuous analytical approach as a supplement to discrete analysis. These scores are not meant to replace more detailed analytical methods or to be a final tool for evaluation and decision making. However, they could serve as
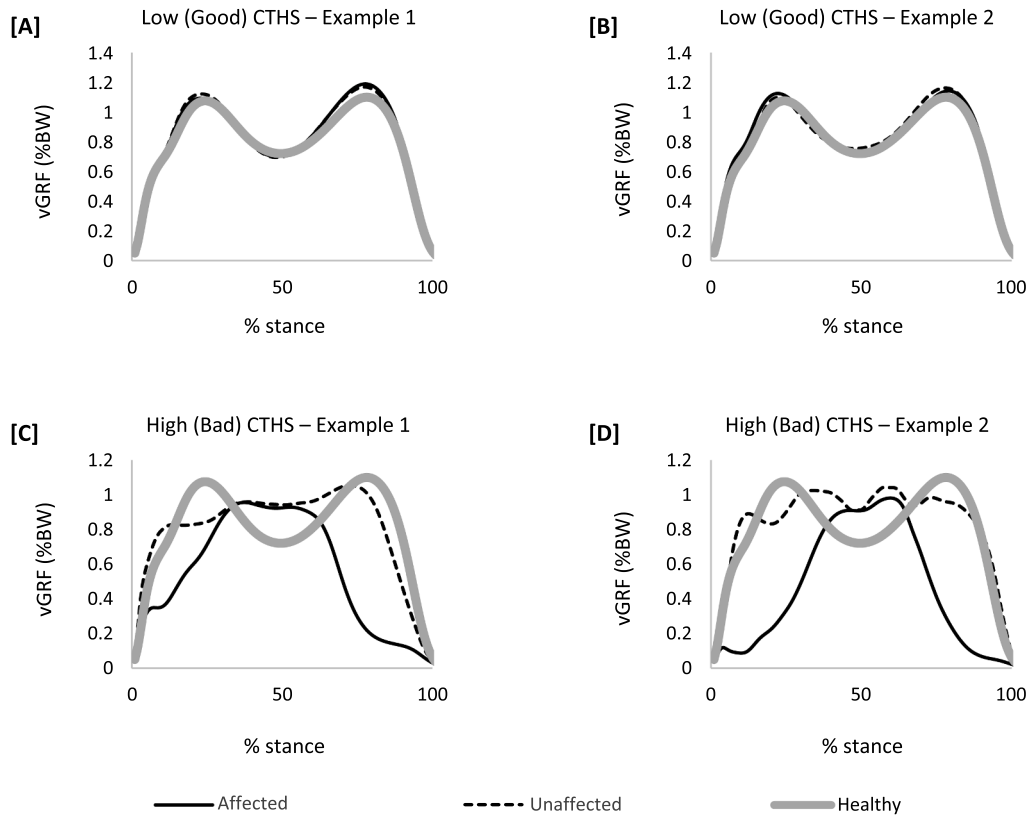
Fig. 4. Examples of vertical ground reaction force time series curves resulting in low (good) [A-B] and high (poor) [C-D] closeness-to-healthy scores (CTHS) in walking controls and A-OA patients, respectively. [A-B] (healthy controls): curves represent non-dominant (affected) and dominant (unaffected) limbs. [C-D] (A-OA patients): curves represent surgical (affected) and non-surgical (unaffected) limbs.

Table 2
Mean(SD), 95% confidence intervals (lower limit, upper limit), p-values, and Cohen's D effect sizes (d) for each score. *: significant difference between controls and patients ($p < 0.05$). †: small effect size ‡: medium effect size. ††: large effect size. A: affected limb (non-dominant limb in controls and surgical limb in patients). U: unaffected limb (dominant limb in controls and non-surgical limb in patients). vGRF: vertical ground reaction force during walking. AA: sagittal plane ankle angle. COP_{ML} and COP_{AP}: center of pressure in medial–lateral and anterior-posterior directions. $vGRF_U$: vertical ground reaction force during unilateral landing. $vGRF_B$: vertical ground reaction force during bilateral landing.

Walking							
Score	**Measure**	**Mean (SD)**		**95% Confidence Interval**		**p**	**d**
		Control	**A-OA Patients**	**Control**	**A-OA Patients**		
Landing							
Score	**Measure**	**Mean (SD)**		**95% Confidence Interval**		**p**	**d**
		Control	**ACLR Patients**	**Control**	**ACLR Patients**		
SS	vGRF	1.000 (0.337)	3.091 (1.673)	0.912,1.088	2.653,3.529	<0.001*	1.73††
	AA	1.000 (0.839)	2.215 (1.320)	0.780,1.220	1.869,2.561	<0.001*	1.10††
	COP_{ML}	1.000 (0.469)	0.884 (0.529)	0.877,1.123	0.746,1.023	0.223	–
	COP_{AP}	1.000 (0.535)	2.763 (2.116)	0.860,1.140	2.209,3.318	<0.001*	1.14††
CTHS (A)	vGRF	0.005 (0.004)	0.011 (0.012)	0.004,0.006	0.007,0.014	0.001*	0.66††
	AA	0.121 (0.082)	0.226 (0.302)	0.099,0.142	0.147,0.305	0.013*	0.48‡
	COP_{ML}	0.176 (0.165)	0.509 (0.353)	0.133,0.219	0.416,0.601	<0.001*	1.21††
	COP_{AP}	0.002 (0.005)	0.011 (0.012)	0.001,0.004	0.008,0.014	<0.001*	0.97††
CTHS (U)	vGRF	0.004 (0.003)	0.008 (0.007)	0.003,0.005	0.006,0.010	0.001*	0.65††
	AA	0.153 (0.163)	0.181 (0.276)	0.110,0.195	0.109,0.254	0.502	–
	COP_{ML}	0.143 (0.222)	0.574 (0.384)	0.085,0.201	0.473,0.675	<0.001*	1.37††
	COP_{AP}	0.003 (0.005)	0.007 (0.015)	0.001,0.004	0.003,0.011	0.032*	0.41‡
SS	$vGRF_U$	1.000 (0.305)	1.512 (0.763)	0.851,1.149	1.138,1.886	0.018*	0.88††
	$vGRF_B$	1.000 (0.297)	2.088 (1.337)	0.855,1.145	1.433,2.743	0.003*	1.12††
CTHS (A)	$vGRF_U$	0.024 (0.014)	0.022 (0.023)	0.017,0.031	0.010,0.033	0.706	–
	$vGRF_B$	0.021 (0.013)	0.025 (0.019)	0.015,0.027	0.016,0.034	0.515	–
CTHS (U)	$vGRF_U$	0.027 (0.016)	0.019 (0.012)	0.019,0.035	0.013,0.025	0.127	–
	$vGRF_B$	0.022 (0.014)	0.025 (0.017)	0.015,0.028	0.016,0.033	0.547	–

Table 3

Results of Receiver-Operator Curve analysis for each score that was significantly different between controls and patients. ACU: area under the curve. ††: excellent predictive capability. ‡: good predictive capability. †: fair predictive capability. ¥ poor predictive capability. vGRF: vertical ground reaction force during walking. AA: sagittal plane ankle angle. COP_{ML} and COP_{AP}: center of pressure in medial–lateral and anterior-posterior directions. $vGRF_U$: vertical ground reaction force during unilateral landing. $vGRF_B$: vertical ground reaction force during bilateral landing.

Walking					
Score	Measure	AUC	Optimum Point		Cutoff Point
			1-Specificity	Sensitivity	
Landing					
Score	Measure	AUC	Optimum Point		Cutoff Point
			1-Specificity	Sensitivity	
SS	**vGRF**	0.94 ††	0.07	0.84	1.517
	AA	0.86 ‡	0.14	0.79	1.402
	COP_{AP}	0.85 ‡	0.23	0.77	1.283
CTHS (A)	**vGRF**	0.67 ¥	0.32	0.64	0.005
	AA	0.56	0.00	0.16	0.318
	COP_{ML}	0.82 ‡	0.23	0.71	0.242
	COP_{AP}	0.86 ‡	0.25	0.84	0.002
CTHS (U)	**vGRF**	0.65 ¥	0.23	0.55	0.005
	COP_{ML}	0.89 ‡	0.18	0.88	0.200
	COP_{AP}	0.76 †	0.18	0.57	0.003
SS	$vGRF_U$	0.75 †	0.38	0.81	0.968
	$vGRF_B$	0.87 ‡	0.13	0.75	1.342

valuable metrics to quickly assess movement symmetry and normality, determine whether more in-depth motion analysis is warranted, and assess general trends across time such as during rehabilitation or disease progression.

Positive analytic results of these newly developed symmetry and movement quality measures warrant more in-depth validation and application to investigate the robustness and potential limitations of the SS and CTHS. While the current study included several kinetic and kinematic measures in two patient-control comparisons, there are numerous additional measures and populations for which the utility of these scores could be assessed. As shown by the current study results, these scores are not restricted to gait and may be utilized to evaluate symmetry and movement quality during other tasks such as running, jumping, and landing. As previously discussed, however, time shifts between curves being compared should be noted and potentially accounted for prior to computation to limit effects on results. Further validation of these scores could include evaluating gait data of a patient population both pre-operatively and post-operatively at various points within the rehabilitation and recovery process. Their utility could potentially be taken a step further with the establishment of bounds indicative of injury and disease risk, which would increase the ability for clinicians and researchers to quickly interpret results in a comparative manner. Currently, the scores are not bound since the present dataset is not of sufficient size or breadth to define a meaningful and realistic worst case; this definition would be needed to inform an upper bound that would maintain validity across other populations instead of being study-specific. As unbound scores can be more difficult to interpret, this is an important area for future development. Aggregate healthy data to inform what is deemed normal along with a breadth of clinical data is necessary to define meaningful score bounds and risk thresholds, both of which will increase the strength and broad utility of these scores in future iterations.

The current study provides new scores reflective of symmetry and movement quality across the stance phase of two movements, which could be useful for both researchers and clinicians. However, there are limitations to the interpretation and application of study findings. First, the walking control participants included in the study were likely healthier and more physically active than average middle-aged adults,

which may limit functional comparisons with the A-OA patients. However, the walking control group enabled comparison of the A-OA group to a healthy group with no health complications or gait limitations. Another limitation is that neither score is bound, which could present a challenge for easy interpretation, as previously discussed. Lastly, the influence of self-selected walking speed on these outcome scores was not investigated and should be included in a future analysis. The relationship between walking speed and the SS and CTHS may indicate that patients who walk extremely slowly likely have compromised gait symmetry and normality. This relationship should be investigated further and taken into consideration during interpretation of study findings and use of these symmetry and normality scores.

5. Conclusions

Scores related to movement symmetry and movement quality have been developed. These scores were able to differentiate between healthy controls and A-OA and ACLR patients with varying predictive capability and medium to large effect sizes. These scores could provide clinicians with another quick and simple tool to objectively assess movement symmetry and quality from continuous kinetic and kinematic data in various patient populations. These scores could also be used to track symmetry and movement quality throughout disease progression and during recovery following injury or surgery as supplements to more in-depth analytic methods.

CRediT authorship contribution statement

Cherice N. Hill: Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft preparation, Visualization. **Shane Ross:** Methodology, Software, Validation, Resources, Writing - review & editing, Supervision. **Alexander Peebles:** Investigation, Writing - review & editing. **Robin M. Queen:** Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Writing - review & editing, Visualization, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Code Availability

The code used to perform this analysis is available upon request and can be found on the Virginia Tech Granata Lab GitHub page.

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