Landmark registering waveform data improves the ability to predict performance measures

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Abstract

The purpose of this study was to investigate the benefit of landmark registration when applied to waveform data. We compared the ability of data reduced from time-normalised and landmark registered vertical ground reaction force (vGRF) waveforms captured during maximal countermovement jumps (CMJ) of 53 active male subjects to predict jump height. vGRF waveforms were landmark registered using different landmarks resulting in four registration conditions: (i) end of the eccentric phase, (ii) adding maximum centre of mass (CoM) power, (iii) adding minimum CoM power, (iv) adding minimum vGRF. In addition to the four registration conditions, the non-registered vGRF and concentric phase only were time-normalised and used in subsequent analysis. Analysis of characterising phases was performed to reduce the vGRF data to features that captured the variability of each waveform. These features were extracted from each condition's vGRF waveform, time-domain (time taken to complete the movement), and warping functions (generated from landmark registration). The identified features were used as predictor features to fit a step-wise multilinear regression to jump height. Features generated from the best performing registration condition were able to predict jump height to a similar extent as the concentric phase (86-87%), while all registration conditions could explain jump height to a greater extent than time-normalisation alone (65%). This suggests waveform variability was reduced as phases of the CMJ were aligned. However, findings suggest that over-registration can occur when applying landmark registration. Overall, landmark registration can improve prediction power to performance measures as waveform data can be reduced to more appropriate performance related features.

Introduction

Biomechanical analysis of kinetic and kinematic waveforms has traditionally identified 'key' features that have been related to the performance of a movement or to injury mechanisms. This process is commonly referred to as discrete point analysis and reduces the dimensionality of a waveform to a number of selected features (commonly chosen prior to analysis) for magnitude and timing comparisons (van Emmerik et al., 2016). However, discrete point analysis has significant limitations as it can a) discard valuable information (Dona et al., 2009; Donoghue et al., 2008), b) compare features with unrelated neuromuscular capacities (Richter, Marshall et al., 2014), c) result in biased non-directed hypothesis testing (e.g., testing of every feature found in previous research; Pataky et al., 2013), and d) limit the ability to predict performance outcomes or injury mechanisms (Grabowski et al., 2010; Hewett et al., 2005). In response to these limitations, research has analysed continuous waveforms as features outside the current discrete points could provide more meaningful performance or injury related measures (Hamill et al., 2000; Schöllhorn et al., 2002).

Currently, waveform analysis does not often account for the inherent timing/phase variability within and between subjects' and this can limit direct magnitude comparisons of physiological events (Chau et al., 2005; Godwin et al., 2010). Without decreasing the phase variability, significant findings may not truly reflect the movement physiology (Sadeghi et al., 2000). The main approach to address this limitation is to linearly time-normalise data to match the duration of different trials by converting the time-domain (frames or seconds) to a percentage of time (0-100%; Page and Epifanio, 2007). However, it has been seen that time-normalisation does not fully discard all time/phase variability (Buzzi et al., 2003). Therefore, magnitude comparisons can consequently be performed across different phases of a movement. Figure 1A depicts time-normalised vertical ground reaction force (vGRF) curves for two subjects' when performing the take-off phase of a countermovement jump (CMJ). The end of the eccentric phase (denoted by a red dot) differs between subjects. Subsequent waveform analysis would result in magnitude comparisons during two distinctly different physiological phases of a CMJ. Results may therefore be wrongly interpreted as magnitude differences rather than as a result of comparing different physiological phases of the movement due to differences in timing. Additionally, time-normalisation changes the original timing of the movement, which may be an important aspect in assessing efficiency of a movement or the risk of injury. To examine the timing differences across participants, the time-domain (i.e., the time taken to complete a movement) can be extracted (Figure 1B). This would provide greater insight into waveform data as differences in the timing of an event or phase has been thought to be as important as magnitude differences (Levitin et al., 2007).

A possible solution to account for timing/phase variability in waveforms is to landmark register the signal to meaningful events inherent within the movement. Landmark registration is a technique that 'stretches' or 'shortens' phases of a movement that occur between specified landmarks (i.e. landmarks, key frames) while maintaining each curve's individual shape and amplitude (Crane et al., 2010; Levitin et al., 2007). Registering to specific landmarks (e.g., peak centre of mass power) might allow for a more valid waveform magnitude analysis by aligning the signal to distinct physiological events. In addition to more direct comparisons of magnitude, landmark registration also creates a time-warping function. This function represents the time manipulation required to align the specified landmarks and can be further examined to assess timing differences of physiological events within a movement (Levitin et al., 2007; Ramsay, 2006). No research has been conducted on the practical benefit of landmark registration on waveform data. Additionally, no research has suggested the number of landmarks necessary to allow for valid magnitude analysis without over-fitting the data.

This study aims to examine the benefit of landmark registration when applied to waveform data. Reducing waveform data that has been landmark registration, as compared to time-normalised data, could provide more appropriate features that have a greater ability to predict performance measures or injury mechanisms. To assess this aim, a vertical CMJ will be used as it has a good performance indicator (jump height), is well-researched, and the vGRF can theoretically describe 100% of jump height by the impulse-momentum relationship. Landmark registering to align phases in a vGRF waveform during a CMJ is implemented in order to decrease the inherent timing/phase variability, thereby, increasing the ability of the vGRF waveform features to describe jump height. It is hypothesised that features extracted from the magnitude-domain, time-domain (time taken to complete the CMJ), and time-warping function in a landmark registered vGRF will increase the prediction power to jump height over features extracted from a time-normalised waveform. Additionally, it is hypothesised that increasing the number of landmarks will continue to increase prediction power.

Methods

This cohort study was captured as a normative data set in the Sports Surgery Clinic, Dublin as part of an anterior cruciate ligament study. The study received ethical approval from the University of Roehampton, London (LSC 15/122) and the Sports Surgery Clinic Hospital Ethics committee (25AFM010) and was registered on clinicaltrials.gov (NCT02771548).

All subjects were male athletes, aged between 18 and 35 years, recreationally participating in multidirectional field sports (i.e. Gaelic Football, Soccer, Hurling, Rugby). The dataset consists of 53 subjects (mean ± SD; age = 24.8 ± 4.8 years, mass = 84 ± 15.2 kg, height = 180 ± 8.0 cm) who were free from lower limb injury at the time of testing. Subjects wore their own athletic footwear during the testing protocol.

Before data collection, subjects undertook a standardised warm-up including a 2-minute jog, 5 bodyweight squats, and 2 submaximal and 3 maximal CMJs. Each subject then performed 3 maximal trials with a 30-second rest between trials. The testing took place in the biomechanics laboratory of the clinic using two AMTI force platforms (1000Hz; BP400600, AMTI, USA). Force data were collected for each leg on a separate platform and were subsequently summed for further analysis. Analysis of the data was completed in the following order: data processing, landmark registration of the data, data reduction to discrete features utilising the analysis of characterising phases (ACP), and statistical analysis between data conditions.

Data Processing

Maximal jump trials for each subject were analysed. A custom MATLAB code (The MathWorks, Natick, USA) was used to perform all data processing and analysis. Force data were low-pass filtered using a fourth-order Butterworth filter (15Hz cut-off frequency). CoM velocity was calculated by the integration of the body weight adjusted vGRF divided by the mass of the subject. CoM velocity at take-off was used to calculate jump height for each trial. CoM power was further calculated as the dot product of vGRF and CoM velocity. The vGRF and CoM power curves were normalised to body mass and time-normalised to 100% from start of the countermovement to take-off. Start of the countermovement was determined when vGRF fell below 97.5% of body weight, and take-off occurred when vGRF fell below 25N. The time-domain, that is the time taken (seconds) to complete the take-off phase, was extracted and time-normalised. Lastly, as the gold-standard in the literature, the vGRF concentric phase (CON) was also analysed as the impulse generated during this phase is a key determinant of jump height and provides most of the information necessary to describe jump height (Kirby et al., 2011). CON was extracted and time-normalised from the end of the eccentric phase, determined as the first positive point in the CoM power curve, to take-off.

Landmark registration

Four different landmarks (Figure 2A) were determined from the time-normalised (TN) vGRF and CoM power curves: minimum GRF (1), minimum CoM power (2), end of the eccentric phase (3), and maximum CoM power (4). These discrete points represent a change in phase or movement direction of the jump (Aragón-Vargas and Gross, 1997; Cormie et al., 2009; Dowling and Vamos, 1993; Morrissey et al., 1998; Petushek et al., 2010). These events were added one at a time resulting in four different registration conditions: warped^3, warped^4, warped^5, and warped^6 (Figure 2B). The first and last landmarks were the start of the CMJ and take-off, respectively, for every registration condition.

To register each curve to the specified landmarks, a warping function was applied to the TN vGRF and time-domain curves. First, a time-warping function was created, based on each trial, that determined whether the phase between two successive landmarks should be 'stretched' or 'shortened'. The landmark registration approach applied in this study was based on adjusting the differentiation of time (dTime) using a piecewise velocity registration rather than a piecewise linear or spline registration. This study did not use a piecewise linear registration (as employed by Ramsay, 2006) because it generates sharp corners at landmarks (Figure 3; zoomed in red time signal). Additionally, a piecewise spline registration approach can result in "backward flowing" time (Figure 3; blue signal), which is not possible and hence should not be used. The reader should note that other spline methods have been developed to keep the time function strictly increasing (Page et al., 2006). However, the approach utilised in the current study registers the dTime which alters the integral of the dTime within set phases (Figure 3). This approach conformed to the following rules:

- The value of the dTime was set to 1 at the requested landmarks.
- A magnitude of the midpoint of each phase was then estimated using equation 1 and spline filled.

$$\text{est. mag.} = \int_{i}^{n} \text{dTime}(x)$$

  with *i* (start) and *n* (end) representing the knots of a phase. The actual value of the integral was then computed and the magnitude of the midpoint was adjusted until the value of the integral was within .01% of the requested magnitude.

- If negative values were observed, these values were set to 0. While this case was not observed, if the desired integral magnitude could not be reached the start and endpoints of the phase were lowered in .01 steps for all knots (start and end points of phases) that do not represent the start and end of the dTime. This could accommodate a phase in which no change in time was required.

The specified landmarks were determined as the average time point at which the landmark occurred across all trials. The warping function curve created for each trial was used in subsequent analysis as an added predictor feature.

Data Analysis

Analysis was completed on the TN vGRF and its time-domain, the CON vGRF and its time-domain, and each of the four registration conditions vGRF curves and their corresponding time-domain and warping function curves. To assess the effect of landmark registration, features were extracted and their ability to predict jump height was assessed. The idea of ACP was utilised to compute features based on phases of variation (similar to Richter, O'Connor et al., 2014). First, key phases of variation were identified using varimax rotated principal components (PCs) that represented more than 1% of the total curve variation (Richter, McGuinness et al., 2014). Key phases were determined as the time period representing 90% of the peak magnitude of each PC. Each key phase was extracted from the vGRF, time-domain, and warping function curves for all condition (TN, CON, and each registration condition). Key phases are highlighted in figures 5 and 6. Finally, features were calculated as the mean of each key phase.

Following ACP, Pearson's correlations were performed for all conditions between the calculated features and jump height. A p-value level of 0.05 was chosen to indicate a significant relationship. Last, step-wise multiple linear regression analyses were performed to assess the relationship between jump height and the features extracted for the vGRF, time-domain, and, where applicable, warping function for all conditions. The number of steps allowed in the regression was limited by the 10:1 rule resulting in no more than 5 features selected[1] (Austin and Steyerberg, 2015; Peduzzi et al., 1996). To assess the prediction power of the regression model, the mean absolute error (MAE) for each condition was calculated between the predicted jump height from the regression model equation and the actual jump height achieved.

Results

Average jump height was 30.3 ± 5.0 cm ranging from 21.4 cm to 41.6 cm. Strong prediction powers to jump height were found in all conditions as indicated by high adjusted R^2 values (Table 1). Each condition generated between 5-13 PC key phases in total from the vGRF, time-domain, and, where applicable, warping function curves (Table 1). Of these, 5 PC key phases were found for all conditions as significant predictors of jump height in the regression model (Table 1†; Figures 5 and 6).

MAE for each condition of the final regression model with all significant predictors added ranged from 1.37 to 2.04 cm (Table 1 & Figure 4). A stronger prediction power was associated with a lower MAE (Table 1). Warped[3] registration (Adj. R^2 = 0.86, $p \leq 0.001$; MAE = 1.39 cm) and CON (Adj. R^2 = 0.87, $p \leq 0.001$; MAE = 1.37 cm) had the greatest prediction powers. The lowest prediction power and greatest MAE was TN (Adj. R^2 = 0.65, $p \leq 0.001$; MAE = 2.04 cm). Warped[4], warped[5], and warped[6] increased prediction power by 6-8% and reduced MAE by 0.1 - 0.21 cm relative to TN.

Figure 5 presents the vGRF and time-domain for the TN and CON conditions with key phases of variation highlighted. Figure 6 presents similar information for each registration condition

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[1] When additional features were allowed (15:1 rule), only the TN condition was affected and increased the R^2 value to 0.81. All other conditions were unaffected suggesting landmark registration reduces timing/phase variability. Landmark registration reduces the need for many features to be selected as the important information is concentrated into a fewer number features. This limits the possibility of over-fitting the data.

with the addition of warping function curves. TN, CON and warped^3 vGRF curves had two significantly correlated key phases between ~81-97% of the jump (r = 0.29-0.51, $p < 0.05$; Table 1), whereas warped^4, warped^5, and warped^6 registrations had only one significantly correlated vGRF key phase between ~83-91% of the jump (r = 0.30-0.33, $p < 0.05$; Table 1). All conditions found vGRF key phases and the time-domain key phase from ~84-100% as significant predictor features that best described jump height (Table 1†). Each registration condition additionally found warping function key phases as significant predictor features.

Discussion

The purpose of this study was to examine the benefit of landmark registration by utilising the features identified from a vGRF waveform captured during a CMJ to predict jump height. The features generated from the landmark registered waveforms were more appropriate as they had a greater ability to predict a performance measure. The primary findings of the present study were: 1) landmark registration could increase the prediction power to a performance indicator over TN, 2) registration conditions found warping function key phases as important predictor features, and 3) over-registration of a waveform may occur if inappropriate landmarks are used.

Findings highlighted the benefit of landmark registration in identifying more appropriate features contained in the waveform as the prediction power increased by (+22%) while the MAE decreased (-0.67 cm). The regression model MAE was inversely related to the prediction power of each condition indicating a good fit of the data to the regression model. All registration conditions could explain jump height to a greater extent (6-22%) than time-normalisation (TN) alone (Table 1). Reducing the waveform variability allowed for the waveform data to be reduced to more appropriate performance related features, thereby, increasing the ability to predict jump height. Of the registration conditions, warped^3 had the greatest prediction power (Adj. R^2 = 0.86, $p \leq 0.001$) by landmark registering to account for the end of the eccentric/start of the concentric phase of the CMJ. These phases represent the stretch-shortening cycle, and warped^3 registration aligned these phases to compare directly across all trials. This is similar to analysing only the concentric phase in the CON condition. The results of the current study, in line with previous research, demonstrate that the concentric phase had the greatest influence on jump height (Aragón-Vargas and Gross, 1997; Dowling and Vamos, 1993; McErlain-Naylor et al., 2014). All conditions, regardless of registration, found the most significant predictor of jump height was the significantly correlated GRF key phases (~83-97%), representing magnitude variation in the concentric phase (p<0.001, Adj. R^2 = 0.07 – 0.23). Richter, Marshall et al. (2014), utilising the ACP technique on CON only, also found this phase as the most significant predictor of jump height (Adj. R^2 = 0.54). In addition, CON prediction power was similar to warped^3 (1% more) and 22% greater than the TN vGRF curve. This suggests that analysis on the specific phase associated with performance related measures can be just as powerful without registration. However, warped^3 maintains the influence between the eccentric and concentric phases by representing the time-shift required to align the phases (warping function key phase from 53-72%, Table 1†).

Additional registration to include the peak CoM power in the concentric phase (warped^4, warped^5, and warped^6) decreased the prediction power of the model as compared to warped^3 by 10-12%. This suggests that over-registration can occur. By over-registering, the significantly correlated vGRF key phase during propulsion disappeared (95-96%) and was replaced by the corresponding peak CoM power warping function key phase (~87-93%) as a significant predictor feature. The warping function variation provided reduced prediction power to jump height denoting that over-registration can occur when neuromuscular requirements, such as rapid unloading, often described as decay-rate, are warped too much. Decay-rate during the propulsive phase has been found to have significant negative correlations with jump height from peak vGRF to take-off (r = -0.274) and from peak CoM power to take-off (r = -0.41; Dowling and Vamos, 1993). Decay-rate was also found to be a significant predictor of jump height (Adj. R^2 = 0.17; Richter, Marshall et al., 2014). Consistent with the findings in this study, timing variation prior to take-off (~90-100%; Table 1†) was a significant predictor in all conditions.

Registration of the eccentric phase was performed in the warped^{5} and warped^{6} conditions at minimum CoM power and minimum vGRF. Increased alignment of the eccentric phase was found to slightly overcome the over-registration of the concentric phase associated with warped^{4}. This resulted in the slightly higher prediction power over warped^{4} (1-2%). For warped^{5}, registration was performed at minimum CoM power, which has been seen to negatively correlate with jump height (r = -0.3; Dowling and Vamos, 1993). This resulted in only slightly better prediction power than warped^{4} (1%) and a 14% decrease compared to warped^{3}. This was possibly due to the loss of vGRF key phase from ~95-96%. Warped^{6} had similar significant predictor features as warped^{5} (varying by 1-2% change in time), explaining only 2% more variation than warped^{4} and 13% less than warped^{3}. This increased prediction power over warped^{5} suggests the additional time warping from the minimum vGRF landmark increased the alignment of each phase between landmarks. This change in alignment could be due to the landmark residing within the vGRF waveform itself, or the wide time range in which minimum vGRF occurred (12-54%) resulting in considerable time warping changes. Past research has suggested that a shorter eccentric phase is associated with increases in jump height (Komi, 2000; Laffaye and Wagner, 2013; Moran and Wallace, 2007), however this was not found in the current study as the eccentric phase time-domain and warping function key phases were not significant predictors of jump height in any condition. This possibly due to either variability still exists in the eccentric phase in the TN and warped^{3} conditions and/or the over-registration occurring in the concentric phase as a result of warped^{4}.

A secondary analysis was performed to assess the relationship between jump height and the eccentric phase using only eccentric landmarks: minimum vGRF, minimum CoM power, and end of the eccentric phase. The results demonstrate an increased prediction power of jump height to 88%, a 1-2% increase from warped[3] and CON, and 23% greater than the TN curve (Figure 7). A MAE of 1.32 cm was found for the regression model, the lowest of all conditions. In addition, this registration condition also re-introduced the later vGRF key phase (95-97%) during propulsion as a significant predictor and had a greater correlation to jump height (r = 0.40, p = 0.003) than all other conditions. The significant predictor features were all concentric key phases including magnitude, time and warping function variation. The significant predictor features selected were identical to warped[3] (1-2% time variation in key phases). Therefore, it may not be necessary to register to more than three events for the take-off phase of a CMJ.

Limitations/Further Work

A possible limitation of dynamical time warping in comparison to linear registration is that the relative timing of events within a waveform may be compromised. To mitigate the loss of morphological information, time-domain and warping function features were utilised within the analysis. Secondly, appropriate event selection is essential to allow for consistent comparisons of physiologically meaningful phases across participants for multiple variables. For example, if assessing running gait, the anterior-posterior GRF could be used to align the propulsive and braking phases of stance. This landmark would then be applied to all variables of interest (e.g., joint angular motion). Lastly, we only explored the application and validation of landmark registration in jumping, a movement with a clear performance indicator (jump height); applications to other movements without performance indicators were not considered. Landmark registration can be applied to other movements and may provide information on risk of injury, movement efficiency, or stability, as key physiological time points are aligned and the phase shifts can be examined using the warping functions.

Conclusions

The results from this study suggest that landmark registration may be able to improve prediction power of extracted features to performance related outcomes (jump height), but caution should be used when selecting the landmarks and the number of events chosen for registration. This was true for both a linear and dynamical approach. Three landmarks provide the greatest ability to align phases of waveform without the risk of over-registration. In addition, the landmarks chosen should represent distinct phases within the movement. Future work should assess the effect of landmark registration across a variety of movements to determine if similar conclusions can be drawn.

Conflict of Interest

None of the authors declare any conflicts of interest.

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