



# The effects of curve registration on linear models of jump performance and classification based on vertical ground reaction forces

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## ABSTRACT

Functional principal components define modes of variation in time series, which represent characteristic movement patterns in biomechanical data. Their usefulness however depends on the prior choices made in data processing. Recent research showed that better curve alignment achieved with registration (dynamic time warping) reduces errors in linear models predicting jump height. However, the efficacy of registration in different preprocessing combinations, including time normalisation, padding and feature extraction, is largely unknown. A more comprehensive analysis is needed, given the potential value of registration to machine learning in biomechanics. We evaluated popular preprocessing methods combined with registration, creating 512 models based on ground reaction force data from 385 countermovement jumps. The models either predicted jump height or classified jumps into those performed with or without arm swing. Our results show that the classification models benefited from registration in various forms, particularly when landmarks were placed at critical points. The best classifier achieved a 5.5 percentage point improvement over the equivalent unregistered model. However, registration was detrimental to the jump height models, although this performance variable may be a special case given its direct relationship with impulse. Our meta-models revealed the relative contributions made by various preprocessing operations, highlighting that registration does not generalise so well to new data. Nonetheless, our analysis shows the potential for registration in further biomechanical applications, particularly in classification, when combined with the other appropriate preprocessing operations.

## 1. Introduction

Principal Component Analysis (PCA) is a statistical technique that preserves variability in a multivariate dataset while reducing dimensionality (Jolliffe and Cadima, 2016). In its functional form, PCA accounts for the sequential dependence of time series data. Functional Principal Components (FPCs) describe independent modes of variation that typically have an intuitive appeal (Ramsay and Silverman, 2005). The technique also yields scores quantifying the extent to which each curve expresses characteristic features described by the FPCs. The associated scores can be used as inputs to models to reveal underlying relationships in the data that might otherwise have remained obscured

with traditional statistical methods (Halilaj et al., 2018).

Functional PCA (FPCA) has become established in biomechanics as a valuable tool for identifying characteristic features of kinematic and kinetic data (Dannenmaier et al., 2020; Harrison, 2014). Typical examples include using FPCs to discriminate between performance levels and identify chronic injury movement patterns (Donà et al., 2009; Ryan et al., 2006; Warmenhoven et al., 2017). FPCs represent a more complete, continuous description of curve characteristics compared to a collection of salient features defined with domain expertise, such as maxima or minima, because those methods discard potentially valuable information (Dowling and Vamos, 1993; Halilaj et al., 2018; Richter et al., 2014a). Some describe variations in magnitude, others reveal

*Abbreviations:* ACP, Analysis of Characterising Phases; CMJ<sub>A</sub>, Countermovement Jump (with arm swing); CMJ<sub>NA</sub>, Countermovement Jump (without arm swing); FPC, Functional Principal Component; FPCA, Functional Principal Component Analysis; PCA, Principal Component Analysis; LTN, Linear Time Normalisation; PAD, Padding (at the start); RMSE, Root Mean Squared Error.

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comparative differences across the time domain, and a few may represent phase variance (Brandon et al., 2013). The original curves can be reconstructed from a weighted sum of FPCs, where the weights are the FPC scores.

FPCA has limitations when the curves are misaligned with one another, as may arise from timing differences due to natural variability, movement strategies, chronic injury or impaired motor control (Epifanio et al., 2008; King et al., 2021; Sadeghi et al., 2003). In those situations, FPCA and other cross-sectional statistical measures are likely to understate amplitude variance at the turning points and overstate it elsewhere (Chau et al., 2005; Marron et al., 2015). Consequently, some FPCs may represent phase variance whilst also incorporating an element of amplitude variance (Brandon et al., 2013). This issue can be addressed with a suitable nonlinear transformation of the time domain using dynamic time warping (Wang and Gasser, 1997). The idea is that time advances in a nonlinear fashion unique to each curve rather than at a universal constant rate. Thus, jump execution may progress at different rates. For functional data, warping functions may be defined using one or more curve registration procedures (Ramsay and Silverman, 2005). Landmark registration seeks to align salient features (landmarks) at their cross-sectional mean positions (Gasser and Kneip, 1995; Kneip and Gasser, 1992), while continuous registration aligns the curves over their whole length (Ramsay and Li, 1998). FPCA can then be applied to the registered curves yielding amplitude FPCs with the time-warping curves generating phase FPCs. A model can be built from a linear combination of those FPC scores, analogous to the reconstruction of the original curves.

Registering VGRF curves from the countermovement jump (CMJ) improved the fit for a model of jump height based on amplitude and phase components (Richter et al., 2014b). Moudy et al. (2018) found some landmarks could be helpful for the CMJ, although not all landmark combinations were considered. However, Marron et al. (2015), in their review of registration, concluded that analyses depend on prior choices made in data processing. In the two studies cited above, Richter et al. (2014b) and Moudy et al. (2018) both employed the Analysis of Characterising Phases (ACP) to obtain features derived from PCA (Richter et al., 2014a). ACP identifies a key phase using a varimax rotation of the FPC that emphasises its most prominent feature, but introduces correlations between the FPC scores (Ramsay and Silverman, 2005). In addition, both investigations employed time normalisation to standardise curve length, as is often the case (e.g. Godwin et al., 2010; Kipp et al., 2012; Ryan et al., 2006). However, padding the data to a fixed length (e.g. Page et al., 2006) may be more appropriate for discrete movements like the CMJ. More research is needed to investigate the different possibilities of data preprocessing and registration concerning FPCA models.

Therefore, this paper aims to extend the understanding of curve registration by examining the impact of landmark and continuous registration on VGRF data from the countermovement jump, an archetypal movement in biomechanics. Using padded and time-normalised data, we consider the direct effect registration has on the decomposition of amplitude and phase variance and the indirect effects on regression and classification models based on PCA or ACP components. Our aim is to present a comprehensive analysis to establish the efficacy of different data processing combinations.

## 2. Methods

Fifty-five physically active adults (36 males, 19 females: body mass  $71.8 \pm 13.1$  kg (mean  $\pm$  SD); age  $21.6 \pm 3.6$  years) volunteered for the study, which was approved by the local ethics committee. The participants each performed eight CMJs with maximal effort, with and without arm swing (4 CMJ<sub>A</sub>, 4 CMJ<sub>NA</sub>). The order of jumps was randomised to minimise potential learning effects. All jumps were performed on two portable force platforms (9260AA, Kistler, Winterthur, Switzerland), which recorded the vertical component of the ground reaction force

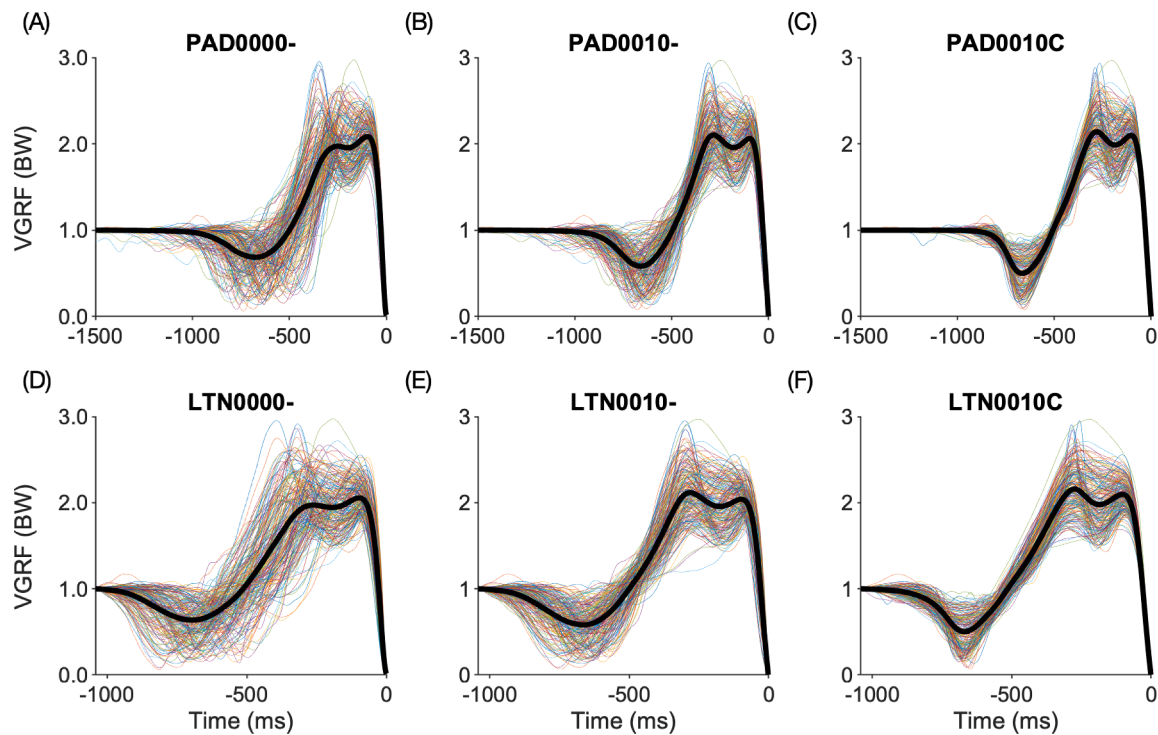
(VGRF) at 1000 Hz, separately under each foot.

The unfiltered VGRF data, summed from both platforms, were normalised to body weight. The time series were integrated from jump initiation to take-off (VGRF < 10 N) to compute the take-off velocity, from which the jump height was obtained. Adapting the two-step procedure of Owen et al. (2014), jump initiation was a backwards time offset from where VGRF deviated 8% from BW. The detection point was moved back to where VGRF passed through BW nearest take-off, provided the VGRF deviation was always < 2.5% BW prior to this point. From 440 jumps recorded, 385 met this criterion, 12 were rejected as unrepresentative, and a further 43 were excluded as outliers (>1799 ms, 90th percentile). Longer time series would have unduly biased the comparison of time normalisation and padding. Outliers below the 10th percentile (<439 ms) were retained because they were close to the median valid jump time (1096 ms), reflecting the skewed distribution.

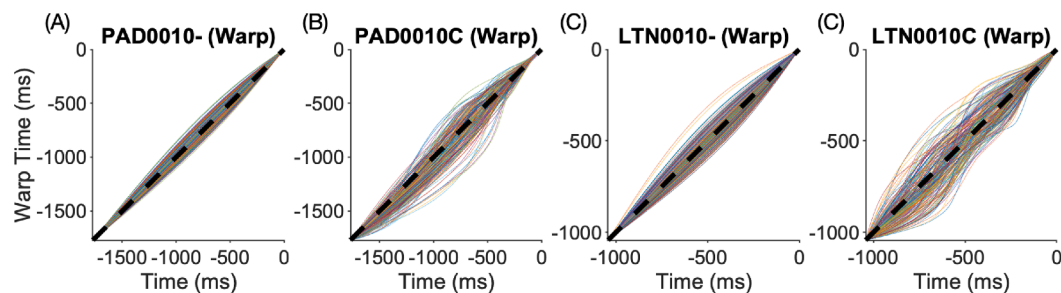
The cropped VGRF times series were standardised to a fixed length using padding (PAD) or linear time normalisation (LTN). The standard length for PAD was set to the longest series (CMJ<sub>A</sub>: 1797 ms; CMJ<sub>NA</sub>: 1773 ms) by padding out each series with 1's at the start, equivalent to bodyweight. The LTN method, based on cubic interpolation, set the standard length to the median (CMJ<sub>A</sub>: 1096 ms; CMJ<sub>NA</sub>: 1043 ms), thereby minimising temporal shifts. Fourth-order b-spline basis functions were fitted, subject to a second-order roughness penalty,  $\lambda = 10^0$  (i.e. penalising high curvature), determined using Generalised Cross Validation (GCV). PAD used 130 b-splines, the minimum required for jump height computed from the smoothed PAD series to have an RMSE < 0.1% with respect to jump height obtained from the raw data. LTN required 105 b-splines, the minimum needed to match PAD's GCV error. This approach reduced the number of basis functions required, lowering the computational cost of registration.

The smoothed curves were processed using multiple combinations of landmark registration, followed by continuous registration. For landmark registration, we used all 16 combinations of the four landmarks proposed by Moudy et al. (2018): VGRF minimum, peak negative power, the start of the concentric phase, and peak positive power. For continuous registration, the alignment criterion was the log eigenvalue ratio (Ramsay and Silverman, 2005). There were 32 registration combinations, including no change. In reporting, each landmark combination is abbreviated in binary notation (1 = landmark included) based on their sequential order, e.g. 0000 (no registration), 0100 (negative peak power alone), 0101 (negative and positive peak power). An appended letter 'C' indicates continuous registration. Registrations were performed recursively up to four times or until a convergence criterion was met:  $\Delta C < 0.001$ , where  $C$  is the independence constant (Kneip and Ramsay, 2008). Cumulative warping functions were updated following each registration by warping the previous warp functions. The time-warping functions for registration were based on 13 third-order b-splines with  $\lambda = 10^0$ . However, the total warp required fifth-order b-splines, sometimes in greater numbers, to maintain monotonicity. Further details on these procedures can be found at <https://github.com/markgewhite/jumpSFDA>.

FPCA was applied to the resulting VGRF and time-warped curves, retaining 15 amplitude components and eight phase components, which accounted for > 99% of curve variances in all cases. Sets of PCA and ACP scores were obtained separately from varimax (V) and the original unrotated components (U). (Standard ACP uses varimax components.) The ACP score was the mean VGRF over the key phase where  $|FPC| > 90\%$  of its absolute peak value (Richter et al., 2014a). The PCA or ACP scores were used as predictors in separate linear regression models to estimate jump height using the CMJ<sub>NA</sub> dataset. Logistic regression models classified jumps into those with and without arm swing using the combined CMJ<sub>A</sub> and CMJ<sub>NA</sub> datasets. The models were fitted using repeated 5-fold cross validation ( $4 \times 5$ ), partitioned at the participant level. Altogether, there were 512 models: two standardisation methods (PAD/LTN), 16 landmark registration combinations, two continuous registration options (applied or otherwise), two model types (jump



**Fig. 1.** Plots of the VGRF curves for the CMJ without arm swing for PAD data (top row) and LTN (bottom row). The original curves are shown without registration (A & D) compared to an exemplar two-stage registration using landmark registration (B & E) with the start of the concentric phase as the single landmark, followed by continuous registration (C & F). Take-off is at time zero. The solid black line is the cross-sectional mean.



**Fig. 2.** Plots of the cumulative time warping curves for the CMJ without arm swing for the exemplar registrations in Fig. 1. Initially, landmark registration (A, C) with the start of the concentric phase as a single landmark ('0010'), followed by continuous registration (B, D). The dashed black line indicates linear time advancement without warping. A steeper gradient indicates that the movement is being executed faster than average, or conversely, a shallower slope reveals a slowing in execution. At various times the movement may be further advanced than average (above the dashed line) or less advanced (below the dashed line). All timelines begin together but must converge at take-off.

height/classification) and two predictor types (PCA/ACP), each having two rotations (unrotated/varimax).

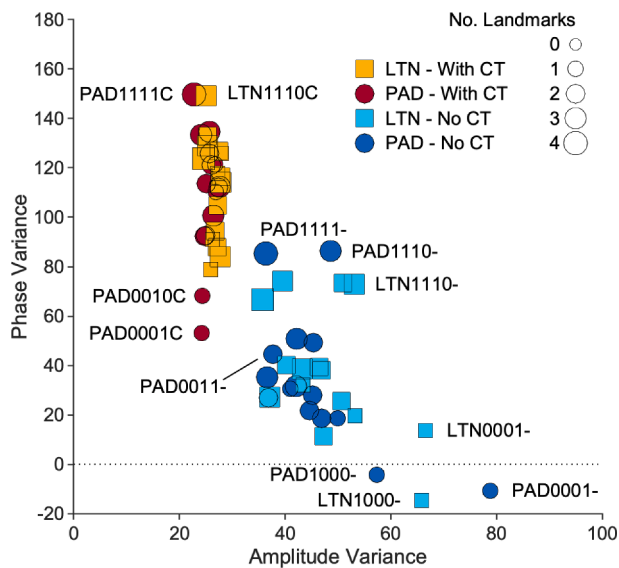
The effect of each preprocessing operation was determined using ANOVA applied to the models' predictive errors (RMSE for jump height and the proportion incorrect for classification). These meta-models used the same predictors as above, plus a term for partition (training/validation) and all interactions. Backwards stepwise selection removed terms according to the Bayesian Information Criterion. The meta-models used a gamma distribution, reflecting the chi-squared distribution of predictive errors. All processing was performed in MATLAB R2022a (MathWorks, Natick, MA, USA).

### 3. Results

The jump heights attained were  $29.0 \pm 7.6$  cm (mean  $\pm$  SD) for CMJ<sub>NA</sub> and  $33.0 \pm 7.9$  cm for CMJ<sub>A</sub>. The effect of registration brought more regularity to the VGRF curves, yielding a mean curve that became

more noticeably bimodal over the final concentric phase (Fig. 1). The warping functions for landmark registrations were typically bowed and were made more variable with continuous registration (Fig. 2). Nearly half of the 120 registrations involved two iterations (58), 39 took three iterations and 22 used the maximum of four. Continuous registration was more effective in extracting phase variance whilst reducing amplitude variance to an apparent minimum level (Fig. 3).

The top ten jump height models by RMSE all used PAD datasets (Table 1), where the best model (PCA with unrotated FPCs) involved no registration (RMSE = 0.92 cm). The second-ranked model employed peak power as a landmark (RMSE = 0.99 cm), whilst the best ACP model using varimax was third (RMSE = 1.04 cm). Generally, these models were less accurate the more extensive the registration became. In contrast, the top classification models all relied on registration, including continuous registration (Table 2). These models still used padding (PAD0011-|PCA(U), RMSE = 16.8%) but three out of the top five employed LTN. In comparison, the unregistered ACP(V) and PCA(U)



**Fig. 3.** Registration decomposition into amplitude and phase variance for different combinations of time normalisation (PAD, LTN), landmark registrations (LM: NNNN) and continuous registrations (CT).

**Table 1**

Top ten jump height models ranked by predictive error using the validation data, showing the contributions from amplitude and phase components in terms of explained variance,  $R^2$ .

Top 10 Jump Height Models	Validation RMSE (cm)	Validation $R^2$ (Amplitude FPCs)	Validation $R^2$ (Phase FPCs)
PAD0000- PCA (U)	0.92	98.7%	-
PAD0001- PCA (U)	0.99	96.8%	1.7%
PAD0000- ACP (V)	1.04	98.3%	-
PAD0010- PCA (U)	1.63	93.9%	2.5%
PAD0100- PCA (U)	1.96	87.2%	7.1%
PAD0011- PCA (U)	2.21	83.2%	10.2%
PAD0010- ACP (V)	2.41	90.3%	0.4%
PAD0000- ACP (U)	2.45	91.5%	-
PAD1000- PCA (U)	2.49	79.0%	10.8%
PAD1011- PCA (U)	2.54	51.5%	38.6%

PAD/LTN = Time Normalisation; NNNN = Landmark Registration; -/C = Continuous Registration; PCA/ACP = Component Type; (U)/(V) = Component Rotation (Unrotated/Varimax).

The binary notation for registration indicates which landmarks were used (in order: VGRF minimum, peak negative power, the start of concentric phase, peak positive power).

NB. Models using PCA(V), that is PCA with varimax rotation, were excluded because they gave identical results to PCA(U) without rotation to this level of precision.

models were ranked 22nd and 26th, respectively, with errors of 21.7% and 22.3%. Hence, registration improved classification performance by up to 5.5 percentage points. The best classification model also relied on phase components more than any other (17.8% vs 13.1% for the next highest, which was 29th in the error ranking – see [Supplementary Material](#)).

**Table 2**

Top ten classification models ranked by predictive error using the validation data, showing the contributions from amplitude and phase components in terms of explained variance,  $R^2$ .

Top 10 Classification Models	Validation Error (%)	Validation $R^2$ (Amplitude FPCs)	Validation $R^2$ (Phase FPCs)
PAD0011- PCA(U)	16.8	34.3%	17.8%
LTN0010- ACP(V)	18.4	42.5%	1.0%
LTN0010- ACP(U)	18.7	40.2%	1.9%
PAD1001C PCA(U)	19.0	39.9%	2.3%
LTN0010- PCA(U)	19.1	39.8%	3.7%
PAD0010- ACP(U)	19.3	42.0%	0.8%
PAD0010- PCA(U)	19.8	33.6%	9.5%
PAD0011- ACP(V)	19.9	42.5%	1.9%
PAD1010C PCA(U)	20.1	36.8%	4.5%
PAD0000C ACP(V)	20.2	32.2%	8.1%

PAD/LTN = Time Normalisation; NNNN = Landmark Registration; -/C = Continuous Registration;

PCA/ACP = Component Type; (U)/(V) = Component Rotation (Unrotated/Varimax).

The binary notation for registration indicates which landmarks were used (in order: VGRF minimum, peak negative power, the start of concentric phase, peak positive power).

NB. Models using PCA(V), that is PCA with varimax rotation, were excluded because they gave identical results to PCA(U) without rotation to this level of precision.

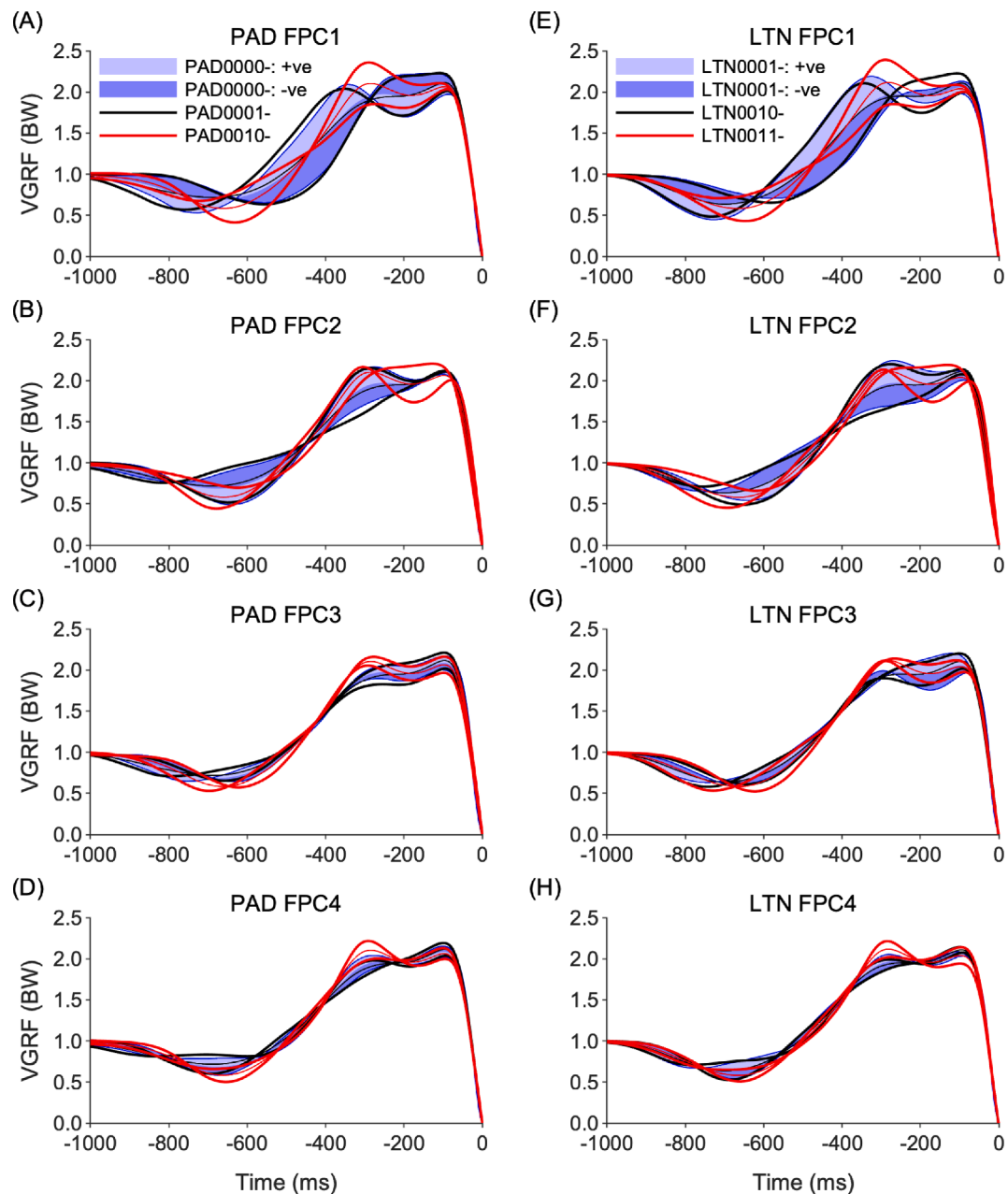
Registration changed the shape of the FPCs compared to the unregistered PCA components. For instance, padding with only peak power as a landmark (PAD0001-) modified the FPCs in minor ways, but padding with a landmark at the start of the concentric phase (PAD0010-) had a more substantial effect (Fig. 4A–D). FPC1 and FPC4 developed high variance around this landmark, whereas FPC2 captured variance more in the mid-to-late concentric phase (red lines). Similar characteristics can be observed in the LTN curves (Fig. 4E–H). Consequently, the explained variance in the outcome variable associated with each component could vary substantially (Fig. 5). For the best models, the components’ contributions were often outside the interquartile range.

The meta-models estimated the typical effects of preprocessing operations with standard errors  $\leq 0.1$  cm for jump height models and  $\leq 0.7\%$  for classification models (Fig. 6). According to the meta-models, LTN produced higher errors than PAD (+2.1 cm and +2.1%, respectively), and ACP was more error-prone than PCA (+0.8 cm and +1.2%). Varimax rotation in general had no effect. Validation errors were larger than training errors (+0.4 cm and +5.7%). Landmark registration increased jump height model errors (up to 2.8 cm), but its effect on classification error varied (-4.7% to +4.9%). Continuous registration was detrimental to jump height models (+2.3 cm) but beneficial to classification (-0.6%). Some interactions were favourable to several classification models, more than offsetting adverse effects, but they could not do so fully in jump height models – see [Supplementary Material](#) for the meta-model coefficients.

#### 4. Discussion

This paper aimed to extend our understanding of the effects of curve registration in a biomechanical context. We analysed the effect of registration on amplitude and phase variance, the functional principal components and the consequential impact on linear models with a view to their future application in machine learning. Our robust methods included repeating registration to ensure close alignment (Kneip and Ramsay, 2008; Marron et al., 2015). Five-fold cross validation balanced model selection (maximising the likelihood of identifying the true best model) with model evaluation (producing a low-biased expectation of the model’s performance) (Zhang and Yang, 2015). Partitioning at the participant level ensured the errors were not biased by models being trained and validated on data from the same individual (Halilaj et al.,





**Fig. 4.** Key functional principal components for PAD and LTN datasets showing the unregistered components indicating a  $2 \times$  SD range (shaded blue) for positive and negative PC scores. Overlaid with an outline only (black and red lines) are the components for two registrations ranked in the top ten (Table 1). The landmarks employed here are 0001 (peak power only), 0010 (start of the concentric phase) and 0011 (start of the concentric phase and peak power). For reference, FPC3 explained the highest proportion of variance in jump height, while FPC4 was the most important for classification.

2018). In addition, since time series length is critical to LTN, we paid particular attention to identifying jump initiation.

Registration was detrimental to the jump height models but beneficial to classification. Landmarks at the start of the concentric phase and at the instant of peak power were most effective in discriminating between the jump types (PAD0011-PCA(U)). These two landmarks, by definition, maximised amplitude variance at these points in jump execution (Fig. 4), as captured by the associated FPCs. Previous research has reported distinctive differences in VGRF curves between  $CMJ_A$  and  $CMJ_{NA}$  at the start and towards the end of the concentric phase (e.g. Feltner et al., 2004). Peak power was a convenient point to place a landmark late in the concentric phase, consistently and unambiguously across all jumps. The VGRF curves, which could be unimodal or bimodal, offered no consistent alternative landmark in this region. The

success of this model can also be attributed to its reliance on phase components, indicating arm swing alters the sequential timing of the jump.

The best jump height model, in comparison to classification, used no registration at all. Generally, predictive errors were higher in jump height models using more extensive registrations. These detrimental effects can be understood by considering impact of registration on the area under the curve, which for VGRF data is directly proportional to the mechanical impulse. The take-off velocity can be obtained directly from impulse using the conservation of momentum since the participant initially stood still. This matters for jump height because the linear models were effectively a weighted sum of curve areas described by the FPCs, plus the intercept, equivalent to the mean curve area. Given these relationships, PAD was strongly favoured over LTN by the jump height

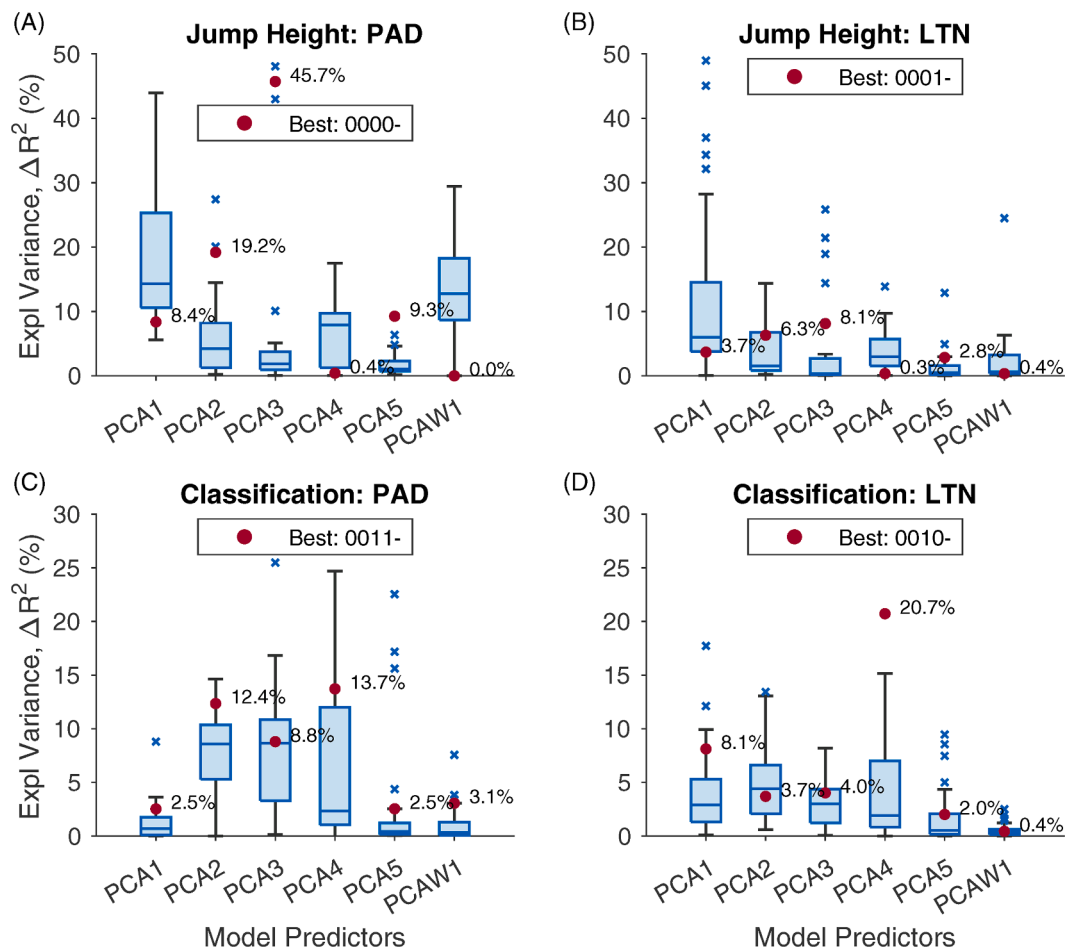


Fig. 5. Distributions of the variance explained across all PCA registrations for each of the first five PCA amplitude components (PCA1-5) and the first warp component (PCAW1). The red dots reveal where the best model sits in each distribution. The ACP models are excluded because they depend on varimax, which reallocates variation across the components in an inconsistent fashion.

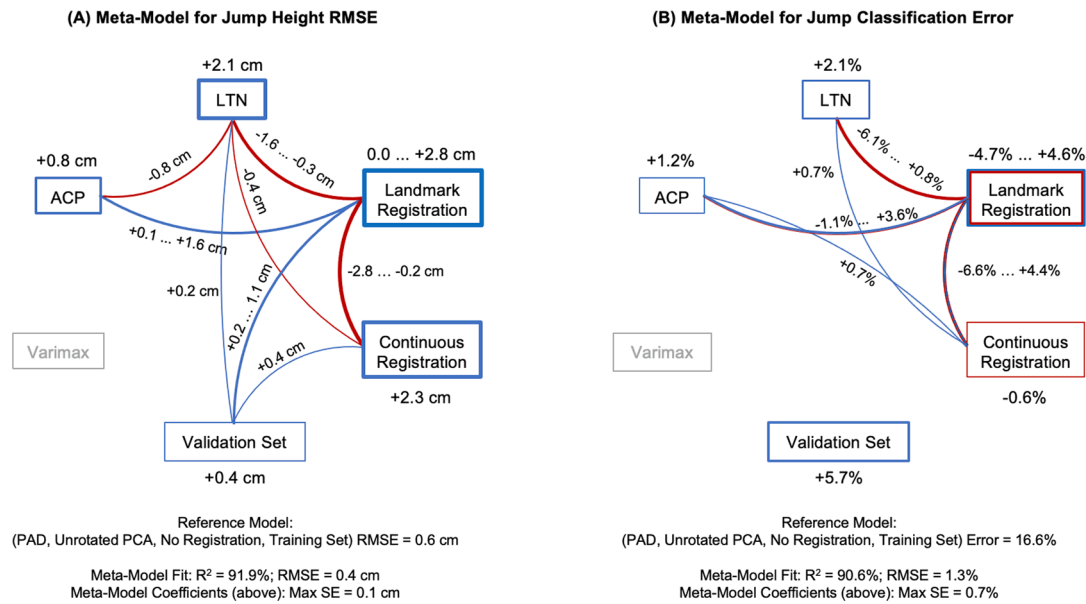
model since time normalisation would alter the area under the curve. As the meta-model showed, registration improved the LTN models, but it could not sufficiently compensate for the distortions first introduced by time normalisation.

Moudy et al. (2018) found a single landmark at the beginning of the CMJ concentric phase (LTN0010-|ACP(V) in our notation) yielded the best jump height model ( $R^2 = 86\%$ ). Our corresponding model also had  $R^2 = 85.8\%$  for training, which appears to be the most appropriate comparator, suggesting that similar results for registration may be obtained from different data collections. When cross validation was applied in our study,  $R^2$  dropped to 75.4%, placing it 33rd in our ranking. The padding-equivalent ACP model was ranked 7th (validation  $R^2 = 90.7\%$ ), whilst the corresponding PCA(U) model was fourth (validation  $R^2 = 96.4\%$ ). The validation figures provide reasonable estimates of how a model is likely to perform when applied to new data. These comparisons demonstrate the advantages of padding over time-normalisation and PCA over ACP, specifically in this case and more generally, as our meta-model showed. In the only other comparison of ACP and PCA in the literature, Richter et al. (2014b) reported that ACP models explained a higher proportion of variance in CMJ jump height than their PCA counterparts (99% vs 78%). In contrast, our results showed training  $R^2$  was quite similar for ACP and PCA: 99.0% vs 99.2% for PAD, respectively, and 84.2% vs 84.6% for LTN. Richter et al. (2014b) analysed only the time-normalised concentric phase using only four FPCs, whereas we included all jump phases and 15 FPCs in our models.

The decomposition analysis revealed registration reduced the

amplitude variance while increasing phase variance as intended (Fig. 3). Repeating registration was beneficial because phase variance increased with every iteration, albeit with diminishing returns. Four iterations were sometimes advantageous, although two were often sufficient, as Ramsay & Silverman (2005) also noted. We learned that it was essential to use fifth-order basis functions to track the overall warp, which was more complex than any single warping, otherwise the total warp could lose regularity and monotonicity. In the decomposition, some information was lost in the jump height models because the phase components could not fully compensate for the reduced contribution from the amplitude FPCs. In these situations, the FPCs ostensibly describing phase variance may be preferable even if they also capture an element of amplitude variance (Brandon et al., 2013). As our results suggest, this interaction may matter less for the classification models and perhaps for other models where the outcome measure is not overly time-dependent.

The spread of component contributions to the models revealed how distinct the best models were from their counterparts (Fig. 5). Their FPCs' explained variances typically stood apart from the interquartile range. The unregistered PAD model illustrated this well as it relied on three components in particular, especially PCA3 which explained 45.7% of jump height variance (Fig. 4A). This FPC described a late surge in VGRF before take-off, which has been identified previously with ACP (Richter et al., 2014a). These observations help explain how jump height models are particularly sensitive to registration since any warping would precipitate a substantial drop in explained variance. Given jump height has a precise relationship with curve area, these models may well be the worst-case scenario for registration. In comparison, the



**Fig. 6.** Meta-models' effects for jump height RMSE (A) and classification error (B) with respect to a reference model. Each box or node represents an effect (meta-model coefficient estimate). The associated figures state the adjustment to the reference model's error while the arcs reveal the interactions (blue positive, red negative). Since landmark registration has 16 levels, min–max ranges are quoted. Stepwise selection eliminated several interactions, and in (B), it also eliminated rotation (varimax). Example: using LTN instead of PAD in the reference model adds 2.1 cm to the jump height RMSE, increasing it from 0.6 cm to 2.7 cm. Introducing continuous registration adds a further 2.3 cm, less 0.2 cm for the interaction, giving an RMSE of 4.8 cm. These figures are the meta-models' coefficients, which have an associated standard error (SE). This is distinct from the meta-models' RMSE in predicting the various models' errors.

classification models depended on a broader number of components, an artefact partly of a logistic model. Registration was beneficial when it aligned curves in regions pertinent to the outcome variable, as noted above for jump type. It also follows that registration would lead to higher errors with validation sets, perhaps because registration attends to the peculiarities in the data, which do not generalise so well.

We had chosen VGRF data to determine how well the models performed in ideal circumstances. To consider less favourable situations, we re-ran the analysis with jump height computed from the total work done instead. It includes the height gain before take-off and has an imperfect relationship to impulse ( $r = 0.979$ ). Although the adjustment was minor, in all cases the jump height work-done models had significantly higher validation errors than the equivalent take-off velocity models (2.65 cm vs 0.92 cm for the best models). However, further analysis revealed peak power models had a similar fit to the jump height work-done models (validation  $R^2 = 98.2\%$  vs 0.98.8%), despite peak power having a lower impulse correlation ( $r = 0.929$ ). Therefore, the relationship with the curve area is not always a critical factor. These findings suggest that registration may be helpful in other applications where the curve area strongly correlates with the performance outcome. This may well be the case with inertial sensor applications in sport or clinical practice. It would be reasonable to suppose that the area under an inertial acceleration curve would in some sense be related to the impulse generated.

## 5. Conclusions

Our analysis shows registration can be advantageous for classification models, specifically when placing landmarks at critical points in the movement. We observed that models based on unrotated PCA components typically yielded smaller errors than those using ACP. Padding the data was often better than time-normalisation, although the classification models were more tolerant of adjustments to the time domain. The most accurate classifier used landmarks at the start and towards the end of the concentric phase when instantaneous power reached its peak. Maximising curve variance at these points proved pivotal to the model, which drew on amplitude and phase components. In contrast, registration was detrimental to the jump height models, owing to their critical

dependence on impulse – they were otherwise accurate when using padded, unregistered curves. Notwithstanding these limitations, registration may be helpful in applications where the outcome is not heavily dependent on time-dependent cues.

## CRediT authorship contribution statement

**Mark G E White:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jonathon Neville:** Writing – review & editing, Supervision, Conceptualization. **Paul Rees:** Writing – review & editing, Supervision, Conceptualization. **Huw Summers:** Writing – review & editing, Supervision, Conceptualization. **Neil Bezodis:** Writing – review & editing, Supervision, Conceptualization.

## 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.

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## Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jbiomech.2022.111167>.

## References

Brandon, S.C.E., Graham, R.B., Almosnino, S., Sadler, E.M., Stevenson, J.M., Deluzio, K. J., 2013. Interpreting principal components in biomechanics: Representative

- extremes and single component reconstruction. *J. Electromyogr. Kinesiol.* 23, 1304–1310. <https://doi.org/10.1016/j.jelekin.2013.09.010>.
- Chau, T., Young, S., Redekop, S., 2005. Managing variability in the summary and comparison of gait data. *J. NeuroEngineering Rehabil.* 2 (1).
- Dannenmaier, J., Kaltenbach, C., Kölle, T., Krischak, G., 2020. Application of functional data analysis to explore movements: walking, running and jumping - A systematic review. *Gait Posture* 77, 182–189. <https://doi.org/10.1016/j.gaitpost.2020.02.002>.
- Donà, G., Preatoni, E., Cobelli, C., Rodano, R., Harrison, A.J., 2009. Application of functional principal component analysis in race walking: An emerging methodology. *Sports Biomech.* 8, 284–301. <https://doi.org/10.1080/14763140903414425>.
- Dowling, J.J., Vamos, L., 1993. Identification of Kinetic and Temporal Factors Related to Vertical Jump Performance. *J. Appl. Biomech.* 9, 95–110. <https://doi.org/10.1123/jab.9.2.95>.
- Epifanio, I., Ávila, C., Page, Á., Atienza, C., 2008. Analysis of multiple waveforms by means of functional principal component analysis: normal versus pathological patterns in sit-to-stand movement. *Med. Biol. Eng. Comput.* 46, 551–561. <https://doi.org/10.1007/s11517-008-0339-6>.
- Feltner, M.E., Bishop, E.J., Perez, C.M., 2004. Segmental and Kinetic Contributions in Vertical Jumps Performed with and without an Arm Swing. *Res. Q. Exerc. Sport* 75, 216–230. <https://doi.org/10.1080/02701367.2004.10609155>.
- Gasser, T., Kneip, A., 1995. Searching for Structure in Curve Sample. *J. Am. Stat. Assoc.* 90, 1179. <https://doi.org/10.2307/2291510>.
- Godwin, A., Takahara, G., Agnew, M., Stevenson, J., 2010. Functional data analysis as a means of evaluating kinematic and kinetic waveforms. *Theor. Issues Ergon. Sci.* 11, 489–503. <https://doi.org/10.1080/14639220903023368>.
- Halilaj, E., Rajagopal, A., Fiterau, M., Hicks, J.L., Hastie, T.J., Delp, S.L., 2018. Machine learning in human movement biomechanics: Best practices, common pitfalls, and new opportunities. *J. Biomech.* 81, 1–11. <https://doi.org/10.1016/j.jbiomech.2018.09.009>.
- Harrison, A.J., 2014. Applications of Functional Data Analysis in Sport Biomechanics, in: Dyson Lecture. Presented at the 32nd International Conference of Biomechanics in Sports, Johnson City, TN, USA, p. 9.
- Jolliffe, I.T., Cadima, J., 2016. Principal component analysis: a review and recent developments. *Philos. Trans. R. Soc. Math. Phys. Eng. Sci.* 374, 20150202. <https://doi.org/10.1098/rsta.2015.0202>.
- King, E., Richter, C., Daniels, K.A.J., Franklyn-Miller, A., Falvey, E., Myer, G.D., Jackson, M., Moran, R., Strike, S., 2021. Biomechanical but Not Strength or Performance Measures Differentiate Male Athletes Who Experience ACL Reinjury on Return to Level 1 Sports. *Am. J. Sports Med.* 49, 918–927. <https://doi.org/10.1177/0363546520988018>.
- Kipp, K., Redden, J., Sabick, M., Harris, C., 2012. Kinematic and Kinetic Synergies of the Lower Extremities During the Pull in Olympic Weightlifting. *J. Appl. Biomech.* 28, 271–278. <https://doi.org/10.1123/jab.28.3.271>.
- Kneip, A., Gasser, T., 1992. Statistical Tools to Analyze Data Representing a Sample of Curves. *Ann. Stat.* 20 <https://doi.org/10.1214/aos/1176348769>.
- Kneip, A., Ramsay, J.O., 2008. Combining Registration and Fitting for Functional Models. *J. Am. Stat. Assoc.* 103, 1155–1165. <https://doi.org/10.1198/016214508000000517>.
- Marron, J.S., Ramsay, J.O., Sangalli, L.M., Srivastava, A., 2015. Functional Data Analysis of Amplitude and Phase Variation. *Stat. Sci.* 30, 468–484. <https://doi.org/10.1214/15-STS524>.
- Moudy, S., Richter, C., Strike, S., 2018. Landmark registering waveform data improves the ability to predict performance measures. *J. Biomech.* 78, 109–117. <https://doi.org/10.1016/j.jbiomech.2018.07.027>.
- Owen, N.J., Watkins, J., Kilduff, L.P., Bevan, H.R., Bennett, M.A., 2014. Development of a criterion method to determine peak mechanical power output in a countermovement jump. *Journal of Strength and Conditioning Research* 28 (6), 1552–1558. <https://doi.org/10.1519/JSC.0000000000000311>.
- Page, A., Ayala, G., León, M.T., Peydro, M.F., Prat, J.M., 2006. Normalizing temporal patterns to analyze sit-to-stand movements by using registration of functional data. *J. Biomech.* 39, 2526–2534. <https://doi.org/10.1016/j.jbiomech.2005.07.032>.
- Ramsay, J.O., Li, X., 1998. Curve registration. *J. R. Stat. Soc. Ser. B Stat. Methodol.* 60, 351–363. <https://doi.org/10.1111/1467-9868.00129>.
- Ramsay, J.O., Silverman, B.W., 2005. Functional data analysis, 2nd ed. ed, Springer series in statistics. Springer, New York.
- Richter, C., O'Connor, N.E., Marshall, B., Moran, K., 2014a. Analysis of Characterizing Phases on Waveforms: An Application to Vertical Jumps. *J. Appl. Biomech.* 30, 316–321. <https://doi.org/10.1123/jab.2012-0218>.
- Richter, C., O'Connor, N.E., Marshall, B., Moran, K., 2014b. Comparison of discrete-point vs. dimensionality-reduction techniques for describing performance-related aspects of maximal vertical jumping. *J. Biomech.* 47, 3012–3017. <https://doi.org/10.1016/j.jbiomech.2014.07.001>.
- Ryan, W., Harrison, A.J., Hayes, K., 2006. Functional data analysis of knee joint kinematics in the vertical jump. *Sports Biomech.* 5, 121–138. <https://doi.org/10.1080/14763141.2006.9628228>.
- Sadeghi, H., Mathieu, P.A., Sadeghi, S., Labelle, H., 2003. Continuous curve registration as an intertrial gait variability reduction technique. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 24–30. <https://doi.org/10.1109/TNSRE.2003.810428>.
- Wang, K., Gasser, T., 1997. Alignment of curves by dynamic time warping. *Ann. Stat.* 25 <https://doi.org/10.1214/aos/1069362747>.
- Warmenhoven, J., Cobley, S., Draper, C., Harrison, A.J., Bargary, N., Smith, R., 2017. Considerations for the use of functional principal components analysis in sports biomechanics: examples from on-water rowing. *Sports Biomech.* 18, 317–341. <https://doi.org/10.1080/14763141.2017.1392594>.
- Zhang, Y., Yang, Y., 2015. Cross-validation for selecting a model selection procedure. *J. Econom.* 187, 95–112. <https://doi.org/10.1016/j.jeconom.2015.02.006>.