FORCE-TIME CURVE ALIGNMENT FOR FUNCTIONAL PRINCIPAL COMPONENT ANALYSIS IN VERTICAL JUMPING

MARK WHITE[1], NEIL BEZODIS[1], JONATHON NEVILLE[2], HUW SUMMERS[3]

[1] Applied Sports, Technology, Exercise and Medicine Research Centre, Swansea University, UK
[2] Sport Performance Research Institute New Zealand, AUT University, Auckland, NZ
[3] Systems and Process Engineering Centre, College of Engineering, Swansea University, UK

Functional principal component analysis (FPCA) can be used to extract key features from time series data for use in statistical models. This study evaluated time normalisation in combination with curve registration prior to performing FPCA. Using vertical ground reaction force data from countermovement jumps, evaluation was based on linear regression for predicting peak power and jump height, and logistic regression for classifying jump type (arm swing or not). Datasets not subject to time normalisation generally produced better results with the highest accuracy being achieved when using registration with peak power as a landmark (peak power R^2 = 99.3%, jump height R^2 = 94.9%). Classification of jump type benefited in some cases from registration (87.0% to 91.2%). These techniques could be applied to data from wearable sensors to improve prediction and classification.

KEYWORDS: countermovement jump, curve registration, classification, functional data analysis, regression, time normalisation.

INTRODUCTION: Time series data from force platforms, wearable sensors and other biomechanical equipment typically exhibit a sequence of characteristic features which can be used for predicting performance or classifying movement patterns (Halilaj et al., 2018). Whilst, traditional discrete point analysis can discard potentially important information, as has been noted by several authors (e.g. Preatoni et al., 2013), functional principal component analysis (FPCA) can identify a more complete set of features which can be understood intuitively (Ramsay & Silverman, 2005). Functional data analysis requires all time series to be of equal length but they typically vary in duration between trials and participants. This is often addressed with time normalisation using a suitable linear compression or extension of the whole timeframe for each curve. However, such linear transformations can shift the temporal positions of features relative to those same features in other curves, increasing phase variance rather than reducing it (Page & Epifanio, 2007). Consequently, where features do not align cross-sectional standard deviations over certain periods may be inflated (Chau et al., 2005). This can be addressed with curve registration (also known as time warping) which aligns certain common features (i.e. landmarks) using a suitable non-linear function, $h(t)$ for each curve such that $f(t) \quad f(h(t))$(Ramsay & Li, 1998). Registration effectively separates out the variation between curves into amplitude and phase variance so they can be analysed independently or together. It preserves the harmonic content of cyclical movements (Sadeghi et al., 2000), but in discrete movements, such as vertical jumping, it does not necessarily improve predictions of jump height (Moudy et al., 2018). Establishing the most effective data pre-processing techniques may help produce feature sets for statistical models that yield higher levels of accuracy, which is vitally important for machine learning (Halilaj et al., 2018). The aim of this study is to use gold standard vertical ground reaction force (VGRF) data to evaluate time normalisation compared to a simple padding technique, both with and without curve registration, when applied to the countermovement jump for the purposes of performance prediction and jump type classification.

METHODS: Fifty-five healthy volunteers (36 males, 19 females: respective body mass 76.8 ± 12.4 kg, 62.2 ± 7.2 kg (mean ± SD); height 1.79 ± 0.08 m, 1.64 ± 0.08 m; and age 21.4 ± 3.4 years, 22.5 ± 4.1 years) gave their written informed consent for the study which was approved by the host University's Research Ethics and Governance Committee. All but four played sport either at recreational (13), club (34) or national (8) level. The participants performed eight CMJs each, divided equally between jumps with (CMJ_A) and without arm swing (CMJ_{NA}) with approximately one minute between jumps. All jumps were performed on two portable 400 × 600 mm force platforms (9260AA, Kistler, Winterthur, Switzerland), which recorded the vertical component of the ground reaction force (VGRF) at a sampling frequency of 1000 Hz. The unfiltered VGRF data, summed from both platforms, was normalised to body mass and used to calculate the peak power output (W kg^{-1}) and jump height (Owen et al., 2014; Street et al., 2001), two performance measures commonly used in applied practice.

Since functional data analysis requires all time series to have the same number of points, two methods were evaluated to standardise the length of the VGRF time series: linear time normalisation (LTN) using cubic interpolation to resample the data, and padding (PAD) the time series by inserting a series of 1's (equal to bodyweight) at the beginning. The standard length for LTN was 1340 points, the mean length to minimise changes to the timeframe, and 2000 points for PAD. Jumps with long execution times (> 2 s) were excluded as some but not all involved the use of practice arm swings (revised n = 394, 187 CMJ_A and 207 CMJ_{NA}). The time series were then converted into smooth continuous functions constructed from 5^{th}-order, b-spline basis functions with a 3^{rd} order roughness penalty ($\lambda = 10^{-10}$), determined by generalised cross-validation. There were 200 b-splines for PAD datasets and 134 for LTN datasets to ensure the same density of functions.

A series of different landmark registrations (Ramsay & Li, 1998) were performed on both datasets. To align each curve's landmarks, the time domain was transformed using a smooth, monotonic continuous function using 10 1^{st}-order, b-spline basis functions ($\lambda = 10^{-8}$). The same landmarks used by Moudy et al. (2018), which represent changes of phase or direction in the jump, were tested: VGRF minimum (designated 'L_1'), power minimum ('L_2'), the start of the propulsion phase ('L_3') and peak power ('L_4'). A baseline case with no registration was also included for both LTN and PAD. For each of the 32 datasets, FPCA was performed to extract the functional principal components (FPCs) from the VGRF curves (15 'amplitude' FPCs) and from the time warping function (5 'temporal' FPCs), each of which together explained > 99% of the variance in their respective curves. The associated FPC scores indicated the relative presence of each characteristic pattern described by the FPC in each jump.

The efficacy of using PAD or LTN in addition to curve registration (or no registration) were then evaluated by using common statistical models for each of the 32 datasets. Stepwise linear regression was used to estimate peak power and separately jump height using the amplitude and temporal FPC scores as the predictor variables. Stepwise logistic regression was used to classify the jump type (i.e. the presence of arm swing or not) with FPC scores standardised to Z-scores. Accuracy was taken to be the percentage of concordant matched pairs. The models were re-run with the temporal FPC scores removed to gauge the effect of registration by comparison with the full models. All data processing was performed in MATLAB R2019b (Mathworks, Natick, MA, USA) using bespoke scripts calling FDA library functions (Ramsay, 2012). The statistical models were generated using SAS University Edition 3.8 (SAS Institute, Cary, NC, USA).

RESULTS: The peak power outputs were 45.2 ± 7.2 W kg^{-1} for CMJ_{NA} and 51.6 ± 8.6 W kg^{-1} for CMJ_A, while the jump heights attained were 39.9 ± 8.2 cm and 47.7 ± 9.6 cm, respectively. The regression models generally achieved higher accuracy (R^2) when using FPC scores based on PAD compared with LTN (Figures 1A & 1B). The best regression model for peak power achieved an accuracy of 99.3% and for jump height of 94.9% (both P2 models; Table 1). These models were based on PAD and registration with peak power as the sole landmark (L_4), which was an improvement on the baseline models using the unregistered FPCs (P1), raising accuracy by 0.9% for peak power and 1.8% for jump height. However, registration was generally to the disadvantage of the PAD regression models with a few exceptions (P2 and P3). Registration benefited the LTN models in most cases, which for the best case raised their accuracy above baseline (Q1) by 3.7% for peak power (Q2) and 4.1% for jump height (Q3).

The classification models benefited from registration in some cases, more so for the LTN models, but the PAD models produced the best classifiers (Figure 1C). The best classification model (P4) achieved an accuracy 91.2%, an improvement on the baseline of 4.3% (Table 1). This was based on PAD FPCs with registration using two landmarks: VGRF minimum (L_1) and the propulsion phase start (L_3).

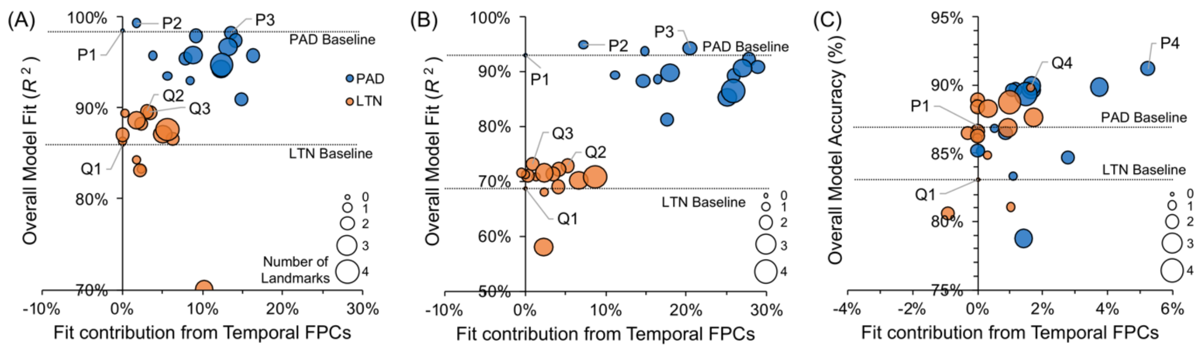

Figure 1: Model fit for (A) peak power, (B) jump height and (C) classification accuracy for PAD (blue) and LTN (orange) models indicating the contribution from temporal FPCs introduced by registration. Number of landmarks indicated by size of bubble. See Table 1 for details on the models identified: P1–P4, Q1–Q4.

Table 1: Registration landmarks, explained variance/accuracy for selected models identified in Figure 1

Model	Data set	Landmark Registration L_1	L_2	L_3	L_4	Peak Power R^2	Jump Height R^2	Classification Accuracy
P1	PAD	×	×	×	×	98.5%	93.1%	87.0%
P2	PAD	×	×	×	✓	**99.3%**	**94.9%**	86.8%
P3	PAD	×	×	✓	✓	97.9%	94.3%	89.6%
P4	PAD	×	✓	✓	×	95.7%	89.3%	**91.2%**
Q1	LTN	×	×	×	×	86.0%	68.8%	83.0%
Q2	LTN	×	✓	×	✓	89.6%	72.2%	88.9%
Q3	LTN	✓	×	×	✓	89.5%	72.9%	86.3%
Q4	LTN	×	×	✓	×	86.3%	71.3%	89.8%

L_1: VGRF minimum; L_2: Power minimum; L_3: Start of propulsion phase; L_4: Power maximum

DISCUSSION: This study evaluated the efficacy of using either time normalisation or padding in combination with curve registration for the purposes of performance prediction and activity classification pertaining to a CMJ, a movement widely used for athlete testing and monitoring in sport. Time normalisation resizes the time series to fit a standard length, which involves a uniform adjustment to the time domain. Padding achieves this more simply by extending the quiet standing period of the jump. Registration keeps the length unchanged but varies time's rate of progress in order to line up the landmark(s) across all curves. The regression models predicting peak power and jump height, two widely used performance measures, generally achieved greater accuracy when the VGRF time series was padded out to a standard length rather than using linear time normalisation. The best regression model used the PAD dataset in combination with registration which warped the time domain so that peak power was achieved at the same instant across all jumps (model P2). The VGRF curves were also aligned at take-off, an implicit second landmark. For other PAD models, registration usually yielded a less accurate model indicating that as a general rule the time domain should be preserved which may be expected given that jump height and peak power depend on the integration of the force time series, and noting that the FPC scores are directly proportional to the impulse. The fact that registration was able to improve upon this may be because the FPCs described either amplitude or temporal variance rather than having to do both in the case of no registration. Consequently, the registration models reported higher *t*-statistics for the regression coefficients and often included more predictors. For the peak power model, without registration (P1) the model included 12 amplitude FPCs, but with registration (P2) it included 14 amplitude FPCs and 2 temporal FPCs. Moudy et al. (2018) took a similar approach combining amplitude and temporal FPCs in their regression models for jump height, finding that one registration landmark (VGRF minimum) achieved the best results.

For classification, more PAD and LTN models benefited from registration although in some cases there was a negative contribution from the temporal FPCs indicating the model was better using only amplitude FPCs. The PAD models achieved the top three results overall with the best model, P4, using the power minimum (L_2) and the start of the propulsion phase (L_3) as landmarks. The results were based on FPC scores without varimax rotation, but as interpretation of the FPCs was not the purpose of this study, and the best models using the unrotated scores outperformed the best models using the varimax scores, outputs using rotated data were not presented.

The CMJ was chosen as the test case because the jump is well understood, can take two different forms suitable for classification, and the performance measures are widely used in practice as well as being highly valid when obtained from VGRF data. Since the performance measures were impulse-dependent it may be expected that any modification to the time domain would produce a less accurate model but that was not always the case. The results suggest it may be possible to improve model accuracy in other applications if the curves are aligned in the key phase of movement, upon which the outcome variable depends, such as the timing of peak power as evident in the current results. For classification, registration could improve accuracy by up 4.3% for the PAD models or up to 6.8% for the LTN models (from a lower baseline). This is relevant to activity recognition that often take time series data of fixed duration, typically from wearable sensors. Such systems may benefit from the decomposition of amplitude and temporal features helping to recognise the activities in question.

CONCLUSION: The results show that curve registration can improve predictions of performance in the CMJ (peak power or jump height) based on FPCA features, and also enhance activity classification accuracy with the appropriate choice of landmarks. Accuracy was generally higher for models based on padded time series compared to linear time normalisation. More research is needed to establish whether these findings, based on gold-standard VGRF data and common statistical methods, could translate favourably to applications where performance prediction or activity classification are based on data that is not directly representative of centre of mass motion, such as from wearable sensors in more ecologically valid settings, and where advanced machine learning models could be employed.

REFERENCES

Chau, T., Young, S., & Redekop, S. (2005). Managing variability in the summary and comparison of gait data. *Journal of NeuroEngineering and Rehabilitation*, 2(22).

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. *Journal of Biomechanics*, 81, 1–11.

Moudy, S., Richter, C., & Strike, S. (2018). Landmark registering waveform data improves the ability to predict performance measures. *Journal of Biomechanics*, 78, 109–117.

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.

Page, A., & Epifanio, I. (2007). A simple model to analyze the effectiveness of linear time normalization to reduce variability in human movement analysis. *Gait & Posture*, 25(1), 153–156.

Preatoni, E., Hamill, J., Harrison, A. J., Hayes, K., Van Emmerik, R. E. A., Wilson, C., & Rodano, R. (2013). Movement variability and skills monitoring in sports. *Sports Biomechanics*, 12(2), 69–92.

Ramsay, J. O., & Li, X. (1998). Curve registration. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 60(2), 351–363.

Ramsay, J. O., & Silverman, B. W. (2005). Functional data analysis (2nd ed). Springer.

Sadeghi, H., Allard, P., Shafie, K., Mathieu, P. A., Sadeghi, S., Prince, F., & Ramsay, J. (2000). Reduction of gait data variability using curve registration. *Gait & Posture*, 12(3), 257–264.

Street, G., McMillan, S., Board, W., Rasmussen, M., & Heneghan, J. M. (2001). Sources of error in determining countermovement jump height with the impulse method. *Journal of Applied Biomechanics*, 17(1), 43–54.