Title: Classifying the variability in impact and active peak vertical ground reaction forces during running using DFA and ARFIMA models.

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ABSTRACT

The vertical ground reaction force (VGRF) during rear-foot striking running typically exhibits peaks referred to as the impact peak and the active peak; their timings and magnitudes have been implicated in injury. Identifying the structure of time-series can provide insight into associated control processes. The purpose here was to detect long-range correlations associated with the time from first contact to impact peak (TIP) and active peak (TAP); and the magnitudes of impact (IPM) and active peaks (APM) using a Detrended Fluctuation Analysis, and Auto-Regressive Fractionally Integrated Moving Average models. Twelve subjects performed an 8 minute trial at their preferred running speed on an instrumented treadmill. TIP, TAP; IPM, and APM were identified from the VGRF profile for each footfall. TIP and TAP time-series did not demonstrate long-range correlations, conversely IPM and APM time-series did. Short range correlations appeared as well as or instead of long range correlations for IPM. Conversely pure powerlaw behaviour was demonstrated in 11 of the 24 time series for APM, and long range dependencies along with short range correlations were present in a further 9 time series. It has been hypothesised that control mechanisms for IPM and APM are different, these results support this hypothesis.

Keywords

Variability Measurement; Running; Motor Processes

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1. INTRODUCTION

During shod running it is well established that rear-foot strikers typically exhibit a vertical ground reaction force (VGRF) profile with two peaks: the first is usually referred to as the impact peak, the second as the active peak, for example, see Nigg (2001). The impact peak has been implicated in injury processes originating from mechanical loading (Lieberman et al., 2010), and the absence of this peak in some forefoot strikers has driven the minimalist shoe movement (Daoud et al., 2012) However, moving to minimalist footwear has unfortunately not provided a simple solution to the problem of running injuries since injuries still occur while using such footwear (Daoud et al., 2012), and not all runners adopt a forefoot strike pattern when wearing this footwear (Squadrone, Rodano, Hamill, & Preatoni, 2014). Investigating the patterns of the impact peaks of rear-foot strikers during running is therefore of ongoing interest.

A common assumption is that the impact peak occurs so early during foot contact that it cannot be controlled during the stance phase, but instead is controlled by planning before foot strike (Nigg, Denoth, & Neukomm, 1981). It is suggested that feedforward control affecting joint configuration before foot strike (Nigg, 2001) and deformation of passive structures on impact (Challis & Pain, 2008) allows control of the impact peak forces. Conversely the active peak occurs much later during stance, so it is considered that feedback control by active muscle contraction of this peak can occur after foot strike (Nigg et al., 1981). This reasoning implies the two peaks are subject to different control mechanisms. It is likely that this difference is reflected in the time dependent structure of the time series associated with each peak (Torre & Wagenmakers, 2009). For example, if the peak forces experienced during the active phase were under step by step active muscular control, it could be hypothesised that the time series of active peak forces would display no auto-correlated behaviour or at most only short-range correlations.

Identifying the structure of a time series offers insight into the control and regulation of many biological processes (Cusumano & Dingwell, 2013). For example, long-range correlations have been shown to exist in step or stride length, and their timings for both walking (Dingwell & Cusumano, 2010), and running (Jordan, Challis, & Newell, 2006), and alterations in the structure of these time series have been identified with age (Hausdorff et al., 1997), fatigue (Meardon, Hamill, & Derrick, 2011) and running speed (Jordan, Challis, & Newell, 2007). Such changes in the structure of gait cycle parameters are suggested to indicate the extent to which variations in that parameter are controlled from cycle to cycle (Dingwell & Cusumano, 2010).

The Detrended Fluctuation Analysis (DFA) (Peng et al., 1993) is a commonly used analysis for identifying the structure of biological time series, but may result in the spurious identification of long-range correlations (Wagenmakers, Farrell, & Ratcliff, 2005). A recently proposed confirmatory procedure for the DFA (Ton and Daffertshofer, 2016) is based on using information criteria such as the Bayesian Information Criterion (BIC) or the Akaike Information Criterion (AIC) to choose between candidate models generated using a maximum likelihood estimation of model parameters and so confirm the linear fit that the DFA depends on. Also, Auto-Regressive Fractionally Integrated Moving Average (ARFIMA) modelling has been proposed as a complementary method to DFA procedures to confirm the presence of long-range correlations (Marmelat & Delignieres, 2011; Torre, Delignieres, & Lemoine, 2007). The advantage of using both approaches simultaneously is that the presence of long-range correlations, and more specifically, pure powerlaw behaviour, may be more reliably identified, and that the particular nature of these long-range correlations may be more precisely identified. Alterations in the presence or the nature of long range correlations indicate a change in the dynamics of the processes causing the time series, and so offer insight into the control of the time series. For example, Dingwell and Cusumano (2010) suggested that the presence of long range correlations in the time series for a parameter suggested that variations were not corrected on a cycle by cycle basis but were allowed to persist over time. Conversely random behaviour suggests that a parameter is tightly controlled at a mean value with random errors. To date the magnitudes of the impact and active ground reaction forces and their timings during human running have not been subjected to such an analysis to determine if long-range correlations exist in these data. The appearance, or not, of long-range correlations in such data will provide insight into the control mechanisms in human running.

The purpose of this study was therefore to use ARFIMA models and the DFA approach proposed by Ton and Daffertshofer (2016) to identify whether long-range correlations existed in the magnitudes and timings of the peak impact and active vertical ground reaction forces during running in healthy recreational runners who were rear-foot strikers. It was hypothesised that different control mechanisms for the two peaks would manifest as different structural behaviour in the associated time series, such that the capacity for within-step adjustment would result in an absence of long-range correlations in the active peak time series, whereas the lack of capacity for within-step adjustments to control the impact peak would result in long-range correlated behaviour of the associated time series.

2. METHODS

Twelve healthy experienced recreational runners mean (±SD) age 26.5 ± 6.1 years, mass 70.0 ± 11.7 kg, were recruited. All experimental procedures were approved by The Pennsylvania State University Institutional Review Board; all subjects provided written informed consent. All runners in this study were rear-foot strikers.

Each subject performed an eight minute trial at their preferred running speed, established using a standard procedure (Jordan et al., 2007), on a Gaitway instrumented treadmill (Kistler Instrument Corp., Orchard Park, NY). Force plates under the treadmill belt were used to record the vertical ground reaction forces (VGRF) throughout each trial, at a 250 Hz sampling frequency. Four variables were extracted from the VGRF for each foot step: impact peak magnitude (IPM), time from initial contact to impact peak (TIP), active peak magnitude (APM), and time from initial contact to active peak (TAP) (Figure 1). A time series for each variable was created separately for the left and right feet.

A classical DFA analysis (Peng et al., 1994) calculated the alpha value (or scaling exponent) for each time series. Briefly, the DFA analysis proceeds by first integrating the time series and dividing the integrated time series into non-overlapping boxes (for a time series of n data points the largest box size is $n/4$, and the smallest box size is 4 data points). The local linear trend in each box is then subtracted. The average root mean square error across all boxes of the same size is calculated. This process is repeated over a range of time scales or box sizes to provide a relationship between box size and the average root mean square error (RMSE) for that box size. The RMSE essentially represents the characteristic size of the fluctuation for a given time scale. The slope of the line relating the log of the box size to the log of the average RMSE determines the scaling parameter, alpha. For uncorrelated, completely random white noise the integrated time series represents a random walk process and alpha = 0.5. When 0 < alpha < 0.5, anti-correlations are present and when 0.5 < alpha < 1 long-range correlations of a power law form are present. When alpha > 1, long-range correlations exist but they cease to be of a power law form. Brown noise is indicated by alpha = 1.5.

The refined method proposed by Ton and Daffertshofer (2016) aims to confirm that a linear fit for the log-log plot used to estimate the scaling parameter, alpha, is indeed the best model. Full details of the procedure are given by Ton and Daffertshofer (2016), but briefly, the procedure uses information criteria to select the best model fit. The information criteria are the commonly used corrected Akaike Information Criterion (AICc) and the BIC. The former is a version of the AIC that adds a penalty term for additional model parameters that attempts to overcome problems of overfitting associated with the standard AIC. The information criteria are calculated for 10 candidate models, including the linear fit, all polynomials up to order three, two exponential models derived from variance expressions for linear stochastic dynamics and a linear piecewise model. The model taken to be the best fitting model is the one that produces the minimum (in a number line sense) AICc or BIC. In order to achieve this, the fluctuations for each interval size are treated as stochastic variables and the associated probability densities are estimated in order to provide maximum likelihood estimates of candidate model parameters. The procedure of Ton and Daffertshofer (2016) was slightly modified so that the box sizes matched that of the classical DFA analysis.

Subsequently, ARFIMA and Auto-regressive Moving Average (ARMA) models were fitted to each de-trended time series using the "fracdiff" package in R 3.0.2 (www.r-project.org/). The general ARMA(p, q) model has two components (p and q) and the ARFIMA(p, d, q) model has three components (p, d and q). An autoregressive component determines the present value using a weighted sum of the previous p observations. A moving average component determines the present value based on random fluctuations for the q previous observations. In the ARFIMA model the d parameter, which is the integrated component, can take on fractional values (between -0.5 and 0.5). This parameter determines whether values are modelled directly or whether d differences between observations are modelled, and in the latter case this provides the model with long-range dependencies. Standard errors associated with the parameter estimates allow for statistical tests of whether the d parameter is significantly different from zero. Use of an information criterion allows the identification of the best model from a series of potential models with different value components. ARFIMA models in the present study were screened according to the algorithm proposed by Wagenmakers et al. (2005), but using the BIC instead of the AIC as the former has been shown to give superior results (Torre et al., 2007) in terms of choosing the most parsimonious model. The BIC was used as our experience with our data agreed with the work of Torre et al. (2007): that the BIC essentially provides a more stringent test that an ARFIMA model is preferable to an ARMA model due to less false positives indicated by a DFA exponent for the same time series of 0.5.

The method of Wagenmakers et al. (2005) is based on using information criterion (IC) weights instead of the raw IC score, since the latter can be difficult to interpret. The IC is calculated for 9 ARMA (*p, q*) and 9 ARFIMA (*p, d, q*) models, where $0 \le p, q \le 2$. The weights for each of the 18 candidate models are then calculated by subtracting the minimum IC value from the IC value for each model and then normalising this difference to the sum of all differences for the 18 models. The sum of the weights for a given set of models is 1. The original algorithm confirmed the presence of long range dependence if 1) the 'best' model (with the highest weight) is an ARFIMA (*p, d, q*) model and 2) the sum of the normalised weights for the ARFIMA models are >0.9. Here a slight refinement of this process was used, such that the 'best' model was one with good residuals and the *d* parameter was practically different from 0 in order to reflect typical practice in statistical model selection. Therefore, the presence of long-range correlations was only confirmed for the ARFIMA analysis if, 1) the BIC weights for the ARFIMA models added to > 90% of the proportion of weights for all ARFIMA and ARMA models screened, 2) the 'best' ARFIMA model identified using BIC and residual checks had a significant *d* parameter ($p<0.05$), and 3) the value of the *d* parameter was > 0.05 (Torre et al., 2007).

For the DFA analysis alpha values between 0 and 1 correspond to the Hurst exponent (also known as the scaling exponent) (Wagenmakers et al., 2005). The Hurst exponent (*H*) can be calculated from the fractional *d* parameter of an (0, d, 0) ARFIMA model using,

$$H = \frac{(2 \times d + 1)}{2} \qquad [1]$$

If the d parameter is not significant then *H* is taken to be 0.5. A surrogate analysis performed on the data using the method of Theiler et al. (1992) showed that all results were due to the temporal structure of the data ($p < 0.05$).

Confidence intervals for the Hurst exponent, where reported, were calculated using the average of both legs for each subject. One sample t-tests were conducted to determine whether the mean Hurst exponents for the time series was significantly different from 0.5.

3. RESULTS

The preferred running speed was (mean ± SD) 3.52 ± 0.97 m/s. Over the eight minute running trials the subjects experienced 1,663 ± 79 footfalls. Exemplar data for each of the four time series (IPM, TIP, APM, TAP) are shown in Figure 2.

The results of all of the analyses indicated that the time series of the timings of the impact (TIP) and active peaks (TAP) did not demonstrate long-range correlations: only a very few trials exhibited Hurst exponents that were different from 0.5 on the basis of the classical DFA analysis. The ARFIMA/ ARMA based test did not lead to a (0, d, 0) ARFIMA model being chosen with a significant and practically meaningful (>0.05) d parameter in 40 out of the 48 time series (Table 1), and the mean Hurst exponents were not significantly different from 0.5 for either TIP or TAP ($p>0.05$ for both time series). It was notable that testing for a significant d parameter excluded many time series that passed the criterion that BIC weights for ARFIMA models exceeded 90% (Table 1). The procedure of Ton and Daffertshofer (2016) resulted in selection of a non-linear model (most frequently a 3rd order polynomial) to describe the log-log fluctuation plots in 41 out of the 48 time series associated with the timings of the impact and active peaks (Table 1). Inspection of the ARMA models that obtained the minimum BIC showed that the best fitting models typically contained up to 3 parameters (autoregressive or moving average or both).

The classical DFA analysis suggested that the IPM time series contained long range correlations in approximately half of the participants. However, this was not confirmed using the Ton and Daffertshofer (2016) procedure (Table 1). Only 3 of the 24 IPM time series resulted in linear plots. While the ARIMA / ARMA test procedure suggested that ARIMA models were preferable, inspection of the 'best' models selected for IPM showed that only two of the best fitting ARFIMA models were (0, d, 0) models. The remaining models were (p, d, q) models with either $p>0$ and / or $q>0$, and the associated coefficient significantly different from 0. This indicates that the IPM time series generally have long-range dependencies but that they do not scale in a pure power-law manner.

Conversely, the APM time series exhibited long-range correlations for most subjects, and often for both legs (Table 1 and Figure 2) on the basis of the ARFIMA / ARMA test. The procedure of Ton and Daffertshofer (2016) confirmed that a linear model was the best fit for the log-log plot of the DFA in 9 out of the 24 time series, and for 9 out of the 12 subjects (Table 2). The mean Hurst exponent was significantly greater than 0.5 ($p<0.001$, for the ARFIMA / ARMA based test). In a further 5 APM time series the Ton and Daffertshofer (2016) procedure resulted in an approximate tie between the linear fit model and another model (usually a second order model). In two of these cases the best fitting ARFIMA model was a (0, *d*, 0) model. In the remaining three cases the best fitting ARFIMA model was either a (1, *d*, 0) or a (0, *d*, 1) model, with the *p* or *q* parameter estimate ~0.1.

4. DISCUSSION

This study has shown for the first time that the magnitudes of the active peak and of the impact peak exhibit long range correlations, and that the magnitude of the active peak exhibits powerlaw behaviour in approximately half of the cases. This result does not agree with our hypotheses based on the capacity for within step adjustments of each of the two peaks. Furthermore it has been shown that long range correlations are absent from both time series representing the timing of each peak, and that these timings vary in a more random way, or with at most short range correlated behaviour. Jordan et al. (2007) previously analysed the peak VGRF time series for running using the DFA and reported the presence of long range correlations, but did not distinguish whether this peak was associated with the active or impact peak. In addition, they did not report the specific alpha values. The magnitude of the impact and active peak ground reaction forces is typically 1.5 to 5 times body weight depending on running velocity and style (Nigg, 2001). These forces are very much greater than those typically experienced during walking and standing, and are hypothesised to play a role in injury mechanisms (Hreljac, 2004).

A key feature of this study is that different methods were used to confirm the presence or absence of long-range correlations, and to estimate the alpha value (Hurst exponent) of the time series. This approach has been widely suggested in order to increase the robustness of identification of long range correlations (Dingwell & Cusumano, 2010; Marmelat & Delignieres, 2011; Torre et al., 2007; Wagenmakers et al., 2005), since the use of the DFA alone may result in the spurious identification of long-range correlations (Wagenmakers et al., 2005). Here the procedure of Ton & Daffertshofer (2016) has been used to confirm whether a linear regression line fits the data on the DFA log-log plot. Short term correlations can mimic the power spectrum of a fractal series (Wagenmakers, Farrell, & Ratcliff, 2004), since unambiguous detection of the latter from the spectrum often depends on the presence of very low frequencies that it may not be physiologically possible to measure. The ARFIMA model fitting process described by Wagenmakers et al. (2004) has a tendency to favour the selection of ARIMA models (Torre et al., 2007), hence the additional checks imposed in the present study, and the use of BIC weights instead of AIC weights (Torre et al., 2007). In general the agreement between the DFA and ARFIMA procedures for the presence or absence of long-range correlations, and in the estimation of the Hurst exponent, was reasonably good for the APM, TIP and TAP time series, but the agreement was less consistent for the IPM time series, because short-range correlations are present alongside or instead of long-range correlations in the IPM time series. For the APM time series the classical DFA and the ARFIMA / ARMA test procedure indicated the presence of long-range correlations more frequently than the Ton and Daffertshofer (2016) procedure (21 versus 14 of the 24 time series). However, a problem that we encountered with the latter procedure is that, while simulated data often produces a clearly superior model in that the minimum BIC or AIC is clearly lower than other candidate models, experimental data can produce several models with similarly lowest BIC or AIC values. The procedure when two models produce approximately equal BIC or AIC values is typically to look at the statistical significance of the estimates for the model parameters, and to examine the residuals produced by each model, in order to choose the best model, and where this step produces no clear distinction, typically the most parsimonious model is selected. This is because the BIC and AIC values are calculated from the data used in the model, and very small changes in the value of the experimental data can change the value of the log likelihood. In the present study there were 5 APM time series for which the BIC / AICc for the linear model were approximately equal to that for one of the other models (typically a second order model). Given the results for the ARFIMA /ARMA test we would conclude that we cannot exclude the possibility that a linear fit for the log-log plot is an appropriate model in at least two of these cases.

The results of the present study support the hypothesis of Nigg (2001) that in rear-foot strikers the nature of the control mechanism for the magnitude of the impact peak is different to the control mechanism for the control of the active peak force. He proposed that the impact forces are controlled by pre-foot-strike tuning of muscle activity. This is because the impact peak occurs in the first 70ms after initial contact (Bobbert, Yeadon & Nigg, 1992) and this is widely regarded to be the minimum time to record an increase in muscle force after activation (Nigg, 1986), therefore changes in muscle force arising from changes in muscle activation after initial contact occur too slowly to have an effect on the impact peak magnitude. Conversely, changes in muscle activation after initial foot contact to control movement can result in changes in muscle force that could conceivably lead to alterations in the active peak magnitude. Impact force control therefore can only use information from previous steps, but not the current step, whereas active force control can also use information from the current step. Long range correlations indicate the structure of the variability of the time series. Strong correlations (indicated by an alpha value further from 0.5) indicate a more predictable, regular time series whereas weaker correlations (values closer to 0.5) indicate a less predictable time series where any given stride interval is less dependent on the stride intervals preceding it. In the present study the APM time series usually exhibited long range correlations, whereas the IPM time series typically did not.

Dingwell and Cusumano (2010) hypothesised that uncorrelated or anti-persistent behaviour in time series may indicate tight regulation whereas long-range persistence indicates a lack of close regulation: they used the example that normal walking exhibits long range correlations in the stride time, whereas walking in time to a metronome, which has to be controlled very tightly step by step under enhanced spinal control ((Scafetta, Marchi & West, 2009), actually exhibits anti-persistent behaviour. Dingwell and Cusumano (2010) measured stride speed during treadmill running, which must obviously be closely controlled on a stride to stride basis in order to remain on the treadmill. They found that, while stride length and stride time exhibited strongly persistent behaviour, stride speed exhibited slightly anti-persistent behaviour. Using their original hypothesis, the timing of the two peaks here, may reflect a form of tightly regulated, step by step control such that there are random fluctuations around a constrained mean value. This explanation is feasible given that participants were running on a treadmill, and the timing of foot-strikes during treadmill running has been shown to exhibit constrained behaviour compared with over-ground running (Dingwell & Cusumano, 2010). It is possible that the timings of the impact peak and the active peak reflect the constrained control pattern of foot-strike timings. This is very likely for the impact peak timing since the impact peak during running is associated with passive mechanisms such as heel pad deformation (Nigg, 2001). The vertical ground reaction force loading rate has been implicated in running related injuries (e.g., Milner et al., 2006), where the loading rate depends on two factors: the magnitude of the force (signal with long-range correlations), and the time to generate the force (random signal). With increasing running speed the magnitudes of the impact and active peaks of the VGRF increase, while their timings decrease and thus loading rate increases (Hamill et al., 1993; Nigg et al., 1987). The increases in ground reaction forces with increased running speed arise from the mechanics of the task suggesting that in running the, potentially injurious, loading rate is controlled by moderation of the timing of the magnitude of the ground reaction forces.

Conversely, Dingwell and Cusumano (2010) suggested that the presence of strong long-range correlations represented a parameter for which fluctuations are allowed to persist, and are likely to arise due to the interaction of different components of the control system (e.g. central nervous system, afferent feedback) across multiple time scales. If this is true then the magnitude of the active peak, which is often the larger of the two peaks, is not closely regulated. This may be a somewhat surprising finding, since Nigg (2001) hypothesised that control over active forces may be exerted on a step by step basis to preserve movement control. However, it may be that a different parameter is more directly controlled by the neuro-muscular system since it is more directly associated with some task-oriented goal (Dingwell & Cusumano, 2010). This line of reasoning would lead to the conclusion that the neuro-muscular system does not directly control the peak forces experienced by the musculo-skeletal system on a step by step basis during treadmill running at the participant's preferred speed. There are a number of candidate parameters that might be controlled, for example, simulations suggest that human running can be produced using criteria related to minimizing the metabolic cost of locomotion (e.g., Miller et al., 2012), doing this on a step by step basis may influence the pattern of the ground reaction forces.

A limitation of this study is that the participants were running on a treadmill and not over-ground. Previous work has measured the behaviour of the inter-stride intervals for over-ground gait, e.g. Hausdorff et al. (1997), however, these studies were able to use footswitches to establish timings. Presently there is no equivalent portable technology that exists for the measurement of vertical ground reaction forces. In shoe pressure measurement has been shown to achieve errors of less than 10% in quantifying mean vertical ground reaction force (Forner Cordero, Koopman, & van der Helm, 2004). However, the accuracy with which such systems can quantify specific ground reaction force events, such as the impact and active peaks, has yet to be established.

The impact forces are most often considered to cause running injuries due to the high loading rate associated with this peak. The lack of long-range correlations in the impact peak magnitude may have implications for injury rates. It would be potentially informative to examine whether the behaviour of these time series is different for different running styles, performance levels, footwear styles, and injury history. For example, it is possible that random behaviour in the magnitude of the impact peak, indicating strict step by step control around a mean, is associated with absence of injury.

The different methods used in the present study to identify long range dependencies and to confirm the presence of powerlaw behaviour showed clearly that the classical DFA analysis often results in spurious identification of powerlaw behaviour. Using the procedure of Ton and Daffertshofer (2016) to confirm the linearity of the DFA log-log plot, and the ARFIMA / ARMA test in a complementary way meant that richer conclusions about the nature of the time dependent structure of the time series could be drawn.

6. CONCLUSIONS

In conclusion, a DFA and ARFIMA / ARMA model fitting procedures were applied to the time series associated with the impact and active peak magnitudes and timings, and both procedures showed that the time series associated with the timings of the peaks did not demonstrate long-range correlations, conversely the time series associated with the magnitudes of the active peaks did for the majority of subjects. Differences between the nature of the long-range correlations for the impact and active peaks reinforced the idea that different control processes may exist for these two peaks. This work also shows the importance of not relying solely on the classical DFA for the detection of long range correlations.

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Table 1: The frequency of the identification of the long-range correlations in the times series for analysis of the vertical ground reaction forces and their timings during running. Long-range correlations were identified using ARFIMA considering the proportion of the BIC weights, and the *d* parameter from the ARFIMA. A time series had to pass both ARFIMA tests for long-range correlations to be identified. These frequencies are reported by subject (only one of their legs had to pass the tests), and by trial.

	Test	**Impact Peak Magnitude**	**Active Peak Magnitude**	**Time of Impact Peak**	**Time of Active Peak**
Participant (n = 12)	BIC weights >90% for ARFIMA	10	12	11	12
	Significant *d* parameter for best ARFIMA model, value of *d* parameter > 0.05	9	12	3	3
	Ton & Daffertshofer (2016) procedure resulted in linear fit	3	9	2	5
Trials (n = 24)	BIC weights >90% for ARFIMA	17	21	15	18
	Significant *d* parameter for best ARFIMA model, value of *d* parameter > 0.05	15	20	4	4
	Ton & Daffertshofer (2016) procedure resulted in linear fit	3	9	2	5

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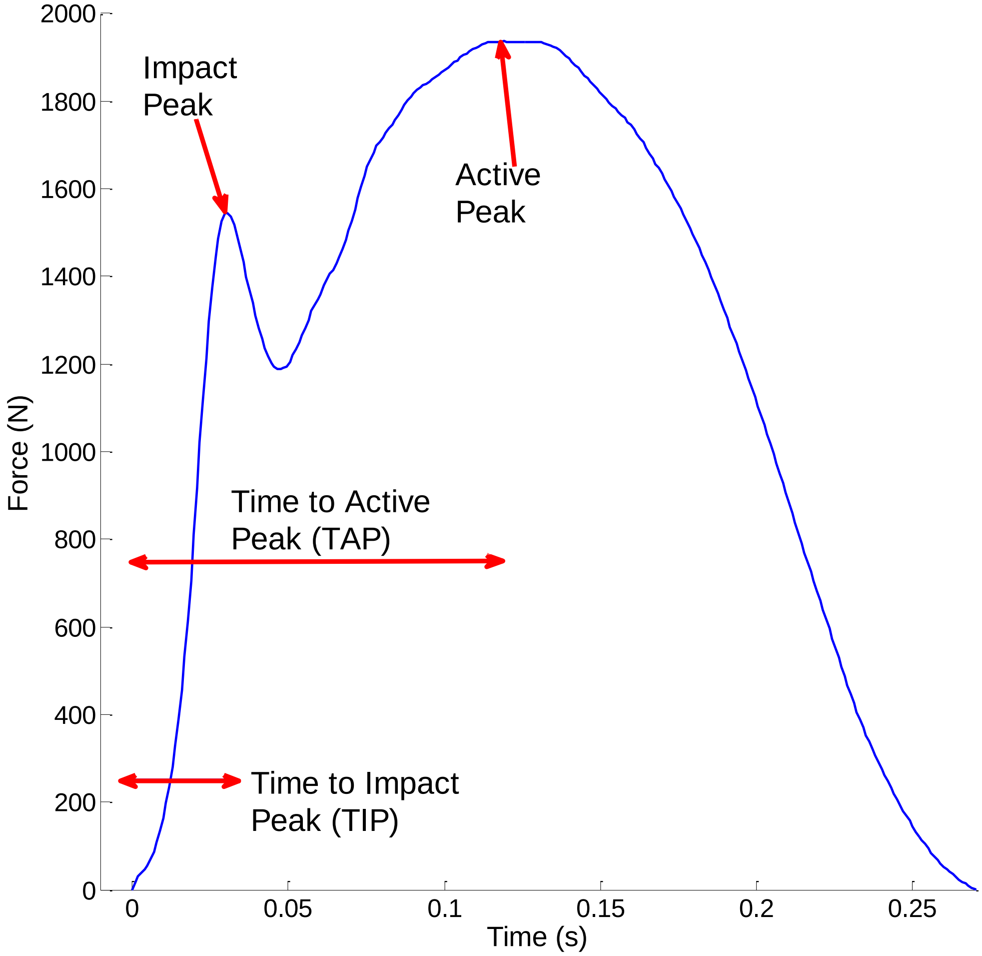

Figure 1: The four variables identified for each running step: impact peak magnitude (IPM), active peak magnitude (APM), time from initial contact to impact peak (TIP), and time from initial contact to active peak (TAP).

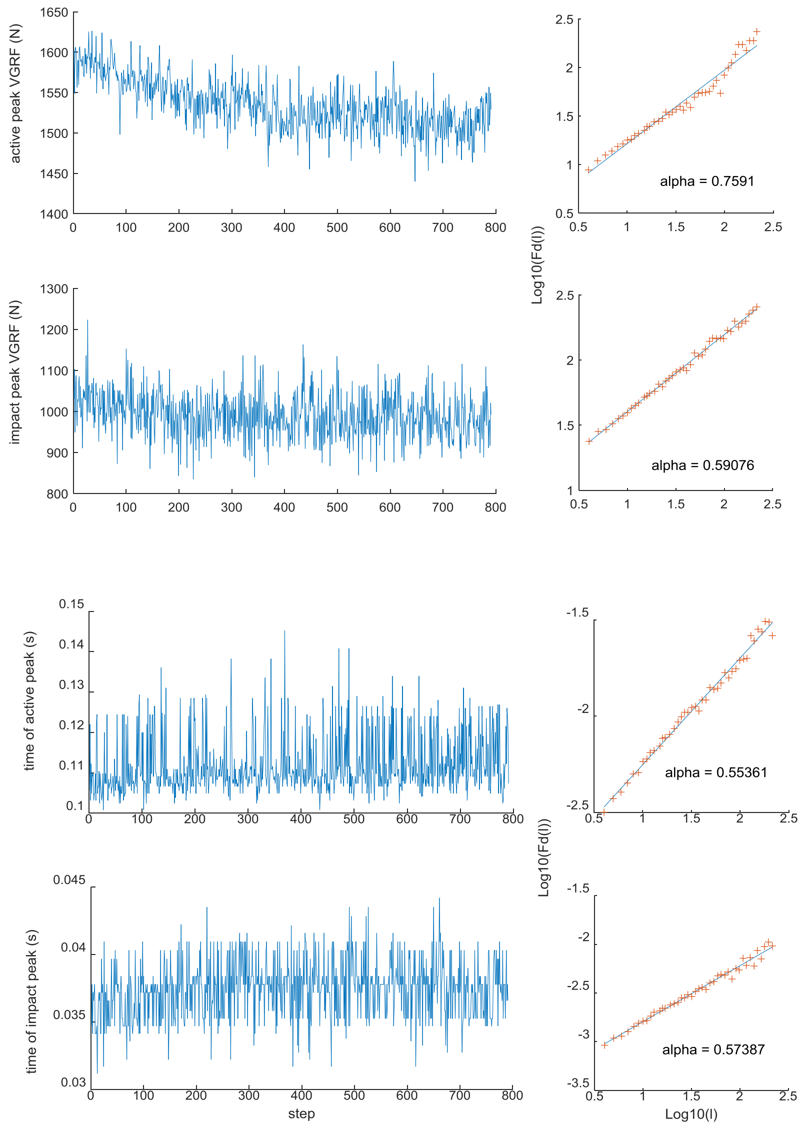

Figure 2: Exemplar time series for APM, IMP, TAP and TIP and the associated DFA plots: only the APM time series resulted in a linear fit using the procedure of Ton and Daffertshofer (2016).