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**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 Autoregressive 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

2540 Physiological Processes

## 1 *1. INTRODUCTION*

2 During shod running it is well established that rear-foot strikers typically exhibit a vertical  
3 ground reaction force (VGFR) profile with two peaks: the first is usually referred to as the  
4 impact peak, the second as the active peak, for example, see Nigg (2001). The impact peak has  
5 been implicated in injury processes originating from mechanical loading (Lieberman et al.,  
6 2010), and the absence of this peak in some forefoot strikers has driven the minimalist shoe  
7 movement (Daoud et al., 2012). However, moving to minimalist footwear has unfortunately not  
8 provided a simple solution to the problem of running injuries since injuries still occur while  
9 using such footwear (Daoud et al., 2012), and not all runners adopt a forefoot strike pattern when  
10 wearing this footwear (Squadrone, Rodano, Hamill, & Preatoni, 2014). Investigating the  
11 patterns of the impact peaks of rear-foot strikers during running is therefore of ongoing interest.

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

24 Identifying the structure of a time series offers insight into the control and regulation of many  
25 biological processes (Cusumano & Dingwell, 2013). For example, long-range correlations have  
26 been shown to exist in step or stride length, and their timings for both walking (Dingwell &  
27 Cusumano, 2010), and running (Jordan, Challis, & Newell, 2006), and alterations in the structure  
28 of these time series have been identified with age (Hausdorff et al., 1997), fatigue (Meardon,

29 Hamill, & Derrick, 2011) and running speed (Jordan, Challis, & Newell, 2007). Such changes in  
30 the structure of gait cycle parameters are suggested to indicate the extent to which variations in  
31 that parameter are controlled from cycle to cycle (Dingwell & Cusumano, 2010).

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

55 The purpose of this study was therefore to use ARFIMA models and the DFA approach proposed  
56 by Ton and Daffertshofer (2016) to identify whether long-range correlations existed in the  
57 magnitudes and timings of the peak impact and active vertical ground reaction forces during  
58 running in healthy recreational runners who were rear-foot strikers. It was hypothesised that

59 different control mechanisms for the two peaks would manifest as different structural behaviour  
60 in the associated time series, such that the capacity for within-step adjustment would result in an  
61 absence of long-range correlations in the active peak time series, whereas the lack of capacity for  
62 within-step adjustments to control the impact peak would result in long-range correlated  
63 behaviour of the associated time series.

64

65

## 66 **2. METHODS**

67 Twelve healthy experienced recreational runners mean ( $\pm$ SD) age  $26.5 \pm 6.1$  years, mass  $70.0 \pm$   
68  $11.7$  kg, were recruited. All experimental procedures were approved by The Pennsylvania State  
69 University Institutional Review Board; all subjects provided written informed consent. All  
70 runners in this study were rear-foot strikers.

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

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

93 The refined method proposed by Ton and Daffertshofer (2016) aims to confirm that a linear fit  
94 for the log-log plot used to estimate the scaling parameter, alpha, is indeed the best model. Full



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

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

125 test that an ARFIMA model is preferable to an ARMA model due to less false positives indicated  
126 by a DFA exponent for the same time series of 0.5.

127 The method of Wagenmakers et al. (2005) is based on using information criterion (IC) weights  
128 instead of the raw IC score, since the latter can be difficult to interpret. The IC is calculated for 9  
129 ARMA ( $p, q$ ) and 9 ARFIMA ( $p, d, q$ ) models, where  $0 \leq p, q \leq 2$ . The weights for each of the  
130 18 candidate models are then calculated by subtracting the minimum IC value from the IC value  
131 for each model and then normalising this difference to the sum of all differences for the 18  
132 models. The sum of the weights for a given set of models is 1. The original algorithm confirmed  
133 the presence of long range dependence if 1) the ‘best’ model (with the highest weight) is an  
134 ARFIMA ( $p, d, q$ ) model and 2) the sum of the normalised weights for the ARFIMA models are  
135  $>0.9$ . Here a slight refinement of this process was used, such that the ‘best’ model was one with  
136 good residuals and the  $d$  parameter was practically different from 0 in order to reflect typical  
137 practice in statistical model selection. Therefore, the presence of long-range correlations was  
138 only confirmed for the ARFIMA analysis if, 1) the BIC weights for the ARFIMA models added  
139 to  $> 90\%$  of the proportion of weights for all ARFIMA and ARMA models screened, 2) the  
140 ‘best’ ARFIMA model identified using BIC and residual checks had a significant  $d$  parameter  
141 ( $p<0.05$ ), and 3) the value of the  $d$  parameter was  $> 0.05$  (Torre et al., 2007).

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

$$145 \quad H = \frac{(2 \times d + 1)}{2} \quad [1]$$

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

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

152 **3. RESULTS**

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

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

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

178 Conversely, the APM time series exhibited long-range correlations for most subjects, and often  
179 for both legs (Table 1 and Figure 2) on the basis of the ARFIMA / ARMA test. The procedure  
180 of Ton and Daffertshofer (2016) confirmed that a linear model was the best fit for the log-log

181 plot of the DFA in 9 out of the 24 time series, and for 9 out of the 12 subjects (Table 2). The  
182 mean Hurst exponent was significantly greater than 0.5 ( $p < 0.001$ , for the ARFIMA / ARMA  
183 based test). In a further 5 APM time series the Ton and Daffertshofer (2016) procedure resulted  
184 in an approximate tie between the linear fit model and another model (usually a second order  
185 model). In two of these cases the best fitting ARFIMA model was a  $(0, d, 0)$  model. In the  
186 remaining three cases the best fitting ARFIMA model was either a  $(1, d, 0)$  or a  $(0, d, 1)$  model,  
187 with the  $p$  or  $q$  parameter estimate  $\sim 0.1$ .

188 **4. DISCUSSION**

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

202 A key feature of this study is that different methods were used to confirm the presence or  
203 absence of long-range correlations, and to estimate the alpha value (Hurst exponent) of the time  
204 series. This approach has been widely suggested in order to increase the robustness of  
205 identification of long range correlations (Dingwell & Cusumano, 2010; Marmelat & Delignieres,  
206 2011; Torre et al., 2007; Wagenmakers et al., 2005), since the use of the DFA alone may result  
207 in the spurious identification of long-range correlations (Wagenmakers et al., 2005). Here the  
208 procedure of Ton & Daffertshofer (2016) has been used to confirm whether a linear regression  
209 line fits the data on the DFA log-log plot. Short term correlations can mimic the power spectrum  
210 of a fractal series (Wagenmakers, Farrell, & Ratcliff, 2004), since unambiguous detection of the  
211 latter from the spectrum often depends on the presence of very low frequencies that it may not be  
212 physiologically possible to measure. The ARFIMA model fitting process described by  
213 Wagenmakers et al. (2004) has a tendency to favour the selection of ARIMA models (Torre et  
214 al., 2007), hence the additional checks imposed in the present study, and the use of BIC weights  
215 instead of AIC weights (Torre et al., 2007). In general the agreement between the DFA and  
216 ARFIMA procedures for the presence or absence of long-range correlations, and in the  
217 estimation of the Hurst exponent, was reasonably good for the APM, TIP and TAP time series,

218 but the agreement was less consistent for the IPM time series, because short-range correlations  
219 are present alongside or instead of long-range correlations in the IPM time series. For the APM  
220 time series the classical DFA and the ARFIMA / ARMA test procedure indicated the presence of  
221 long-range correlations more frequently than the Ton and Daffertshofer (2016) procedure (21  
222 versus 14 of the 24 time series). However, a problem that we encountered with the latter  
223 procedure is that, while simulated data often produces a clearly superior model in that the  
224 minimum BIC or AIC is clearly lower than other candidate models, experimental data can  
225 produce several models with similarly lowest BIC or AIC values. The procedure when two  
226 models produce approximately equal BIC or AIC values is typically to look at the statistical  
227 significance of the estimates for the model parameters, and to examine the residuals produced by  
228 each model, in order to choose the best model, and where this step produces no clear distinction,  
229 typically the most parsimonious model is selected. This is because the BIC and AIC values are  
230 calculated from the data used in the model, and very small changes in the value of the  
231 experimental data can change the value of the log likelihood. In the present study there were 5  
232 APM time series for which the BIC / AICc for the linear model were approximately equal to that  
233 for one of the other models (typically a second order model). Given the results for the ARFIMA  
234 /ARMA test we would conclude that we cannot exclude the possibility that a linear fit for the  
235 log-log plot is an appropriate model in at least two of these cases.

236 The results of the present study support the hypothesis of Nigg (2001) that in rear-foot strikers  
237 the nature of the control mechanism for the magnitude of the impact peak is different to the  
238 control mechanism for the control of the active peak force. He proposed that the impact forces  
239 are controlled by pre-foot-strike tuning of muscle activity. This is because the impact peak  
240 occurs in the first 70ms after initial contact (Bobbert, Yeadon & Nigg, 1992) and this is widely  
241 regarded to be the minimum time to record an increase in muscle force after activation (Nigg,  
242 1986), therefore changes in muscle force arising from changes in muscle activation after initial  
243 contact occur too slowly to have an effect on the impact peak magnitude. Conversely, changes  
244 in muscle activation after initial foot contact to control movement can result in changes in  
245 muscle force that could conceivably lead to alterations in the active peak magnitude. Impact  
246 force control therefore can only use information from previous steps, but not the current step,  
247 whereas active force control can also use information from the current step. Long range

248 correlations indicate the structure of the variability of the time series. Strong correlations  
249 (indicated by an alpha value further from 0.5) indicate a more predictable, regular time series  
250 whereas weaker correlations (values closer to 0.5) indicate a less predictable time series where  
251 any given stride interval is less dependent on the stride intervals preceding it. In the present  
252 study the APM time series usually exhibited long range correlations, whereas the IPM time  
253 series typically did not.

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

278 suggesting that in running the, potentially injurious, loading rate is controlled by moderation of  
279 the timing of the magnitude of the ground reaction forces.

280 Conversely, Dingwell and Cusumano (2010) suggested that the presence of strong long-range  
281 correlations represented a parameter for which fluctuations are allowed to persist, and are likely  
282 to arise due to the interaction of different components of the control system (e.g. central nervous  
283 system, afferent feedback) across multiple time scales. If this is true then the magnitude of the  
284 active peak, which is often the larger of the two peaks, is not closely regulated. This may be a  
285 somewhat surprising finding, since Nigg (2001) hypothesised that control over active forces may  
286 be exerted on a step by step basis to preserve movement control. However, it may be that a  
287 different parameter is more directly controlled by the neuro-muscular system since it is more  
288 directly associated with some task-oriented goal (Dingwell & Cusumano, 2010). This line of  
289 reasoning would lead to the conclusion that the neuro-muscular system does not directly control  
290 the peak forces experienced by the musculo-skeletal system on a step by step basis during  
291 treadmill running at the participant's preferred speed. There are a number of candidate  
292 parameters that might be controlled, for example, simulations suggest that human running can be  
293 produced using criteria related to minimizing the metabolic cost of locomotion (e.g., Miller et al.,  
294 2012), doing this on a step by step basis may influence the pattern of the ground reaction forces.

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

304 The impact forces are most often considered to cause running injuries due to the high loading  
305 rate associated with this peak. The lack of long-range correlations in the impact peak magnitude  
306 may have implications for injury rates. It would be potentially informative to examine whether



307 the behaviour of these time series is different for different running styles, performance levels,  
308 footwear styles, and injury history. For example, it is possible that random behaviour in the  
309 magnitude of the impact peak, indicating strict step by step control around a mean, is associated  
310 with absence of injury.

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

317

318 **6. CONCLUSIONS**

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

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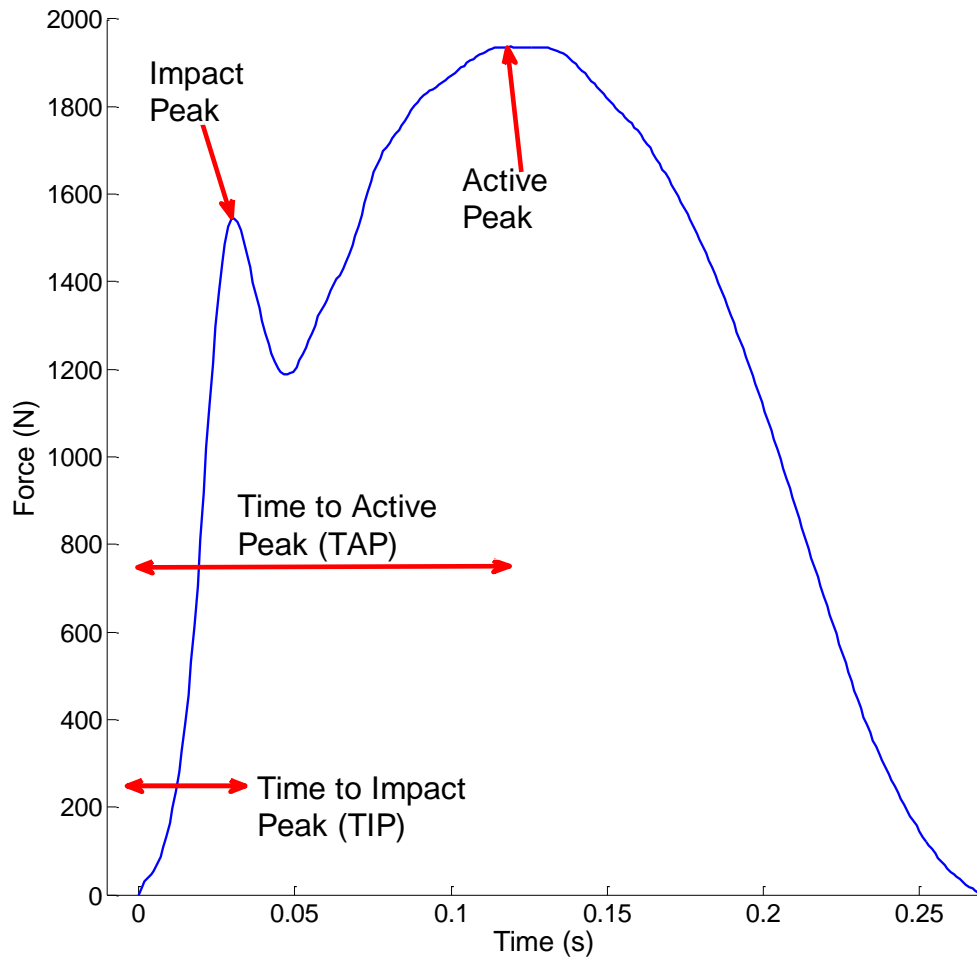
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## LIST OF TABLES

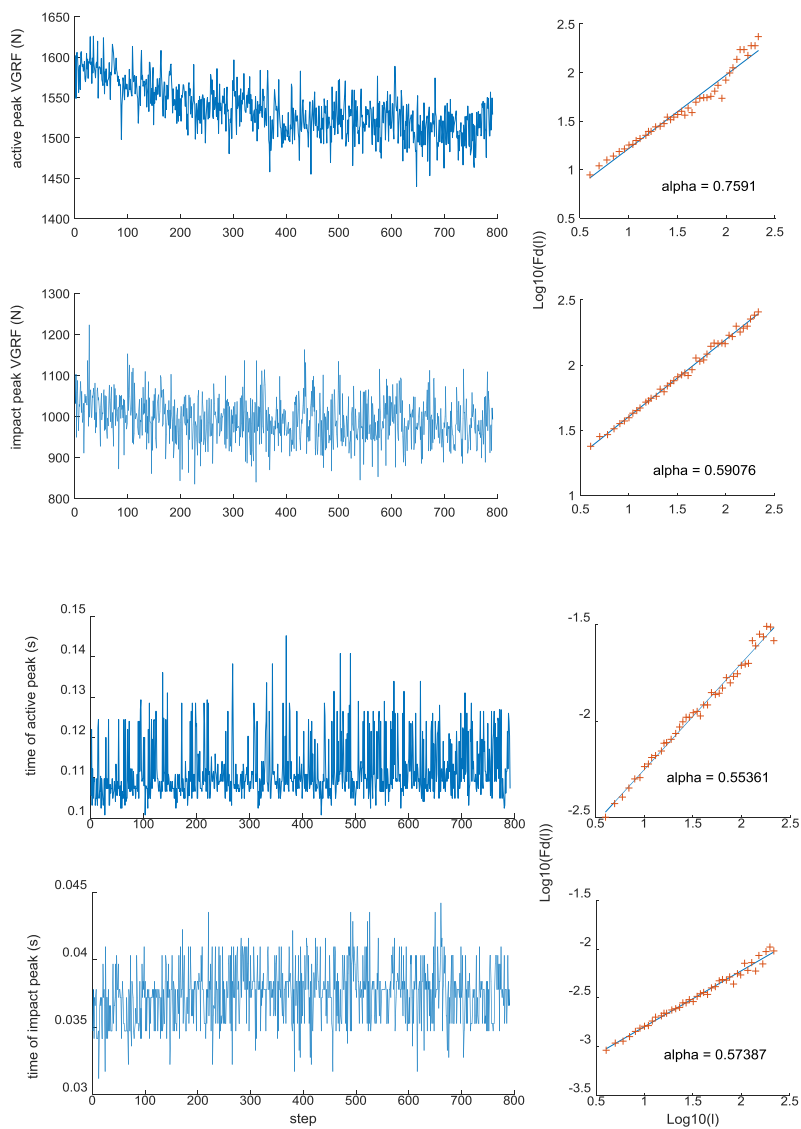
**Table 1:** The frequency of the identification of the long-range correlations in the times series for analysis of the vertical ground reaction forces and their timings during running. Long-range correlations were identified using ARFIMA considering the proportion of the BIC weights, and the  $d$  parameter 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.

	<u>Test</u>	<u>Impact Peak Magnitude</u>	<u>Active Peak Magnitude</u>	<u>Time of Impact Peak</u>	<u>Time of Active Peak</u>
<b>Participant</b> <b>(n = 12)</b>	<u>BIC weights &gt;90% for ARFIMA</u>	<u>10</u>	<u>12</u>	<u>11</u>	<u>12</u>
	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
<b>Trials</b> <b>(n = 24)</b>	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

## LIST OF FIGURES



**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).