USE OF STATISTICAL PARAMETRIC MAPPING TO REVEAL NOVEL ATHLETE-SPECIFIC KINETIC DETERMINANTS OF SPRINT START PERFORMANCE

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The powerful development of force largely determines sprint start performance. However, to date, block phase kinetics have only been examined using discrete (0D) variables. One male sprinter completed 16 sprint starts whilst the ground reaction forces applied by each limb were measured. Kinetic predictors of horizontal external power were identified using Pearson *r* for 0D variables and statistical parametric mapping (SPM) to assess entire force curves. Pearson's correlations revealed fast horizontal force production to result in better performance, but maximum forces appeared important only for the rear leg. Conversely, SPM results suggested that horizontal forces in the early push phase (initial 15-30%) were important for both legs. Testing entire force curves using SPM can supplement 0D analysis to identify kinetic factors which would otherwise be undetected.

KEY WORDS: 1D analysis, forces, power, sprinting, within-athlete

INTRODUCTION: Elite sprint start performances are realised through the generation of high horizontal power, which is determined by an athlete's ability to produce high forces across very short time frames. Many studies have attempted to unpick the force-time variables which differentiate elite from sub-elite or novice performers during the sprint start, with the intention to inform coaching practices and ultimately improve performance. To date, this research has involved the identification of discrete (0-dimensional, 0D) determinants either through correlations with performance (Willwacher et al., 2013) or by assessing differences between sprinters of varying abilities (Mero et al., 1983). Additionally, the effects of training or experimental block modifications on performance are typically evaluated using these 0D variables (Fortier et al., 2005; Mero et al., 2006). Utilising instrumented blocks (Willwacher et al., 2013) or starting blocks placed on separate force plates (Salo et al., 2016), studies have assessed the forces applied by each leg during the sprint start. Comparisons across sprinters of varying abilities have revealed higher rear block peak forces for elite vs. sub-elite performers with similar (or even lower in some cases which involved elite athletes) front block peak forces reported (van Coppenolle et al., 1989; Fortier et al., 2005). Thus, it seems to be that force production of the rear leg better differentiates the level of athletes compared with that of the front leg.
Whilst these studies have contributed substantially to our understanding, the use of discrete force-time variables could potentially neglect important information. Moreover, it is plausible that force production strategies differ between athletes and important information may be masked by group-based analyses. Statistical parametric mapping (SPM) allows entire one-dimensional (1D) data sets to be analysed; preserving the dimensionality of the data and overcoming aforementioned problems with data reduction (Friston et al., 1994). This technique can be used to assess for differences between sets of curves and/or associations between these curves and a discrete outcome measure (either within one athlete or across multiple athletes). The aim of this study was to demonstrate the potential for SPM analyses to identify novel kinetic determinants of sprint start performance within an individual athlete.

METHODS: One university-level male sprinter (age: 21 years, height: 1.82 m, mass: 74.6 kg, 100-m PB: 10.84 s) provided informed consent to participate in two data collection sessions separated by four weeks. Four force plates (900 mm x 600 mm, sampling at 1000 Hz, model 9287BA; Kistler Instruments Ltd, Switzerland) positioned in a 2-by-2 formation were covered with synthetic rubber mats. To allow forces from each leg to be collected separately,

competition blocks were set as described in Salo et al. (2016) whereby two separate spines were used; one on each force plate with the foot plates positioned so that the lateral space between them equalled the width of the spine. The remaining two force plates captured hand force production. The athlete conducted a brief warm-up including some practice starts. Preferred block settings were used and spikes were worn throughout. At each session, eight maximal-effort sprint starts were performed with a four-minute recovery between each trial. An experienced starter provided normal starting commands followed by an electronic beep, which synchronously triggered the force plate data collection and provided a starting signal.
The force data were analysed using a custom-written Matlab script (The MathWorks, USA), which firstly filtered the data using a fourth-order Butterworth filter (103 Hz cut-off frequency based on residual analysis). Ground reaction forces from the four platforms were summed in the vertical and anterior-posterior directions. The average and standard deviation of vertical force was then calculated across the first 50 ms from the starting signal. Onset of movement was defined as the instant when vertical force exceeded a two standard deviation threshold above the average. Block exit was set at the instant vertical force fell below 20 N. The impulse-momentum relationship was then used to calculate vertical and horizontal block exit velocities. The time between onset of movement and block exit was defined as total push duration and combined with horizontal block exit velocity to provide horizontal external power as the criterion (Bezodis et al., 2010). Subsequently, average horizontal and total (resultant) forces were calculated across the push duration and used to calculate ratio of forces (Morin et al., 2011). Maximum forces (horizontal and vertical) were also computed for each leg (front and rear). Finally, peak rate of horizontal force development for each leg was calculated across the first 150 ms of force production using a 30-ms moving window.
Statistical analysis took a two-part approach: discrete tests were firstly conducted whereby Pearson correlations assessed the relationships between the above discrete variables and horizontal external power. A 0.1 threshold was set for the smallest practically important correlation (Hopkins et al., 2009) through which clear (positive or negative) and unclear relationships were defined using 90% confidence intervals (CI). Open-source SPM software (Pataky, 2012) was then used to assess the relationship between force curves and horizontal external power. Force traces were temporally normalised from 0 to 100% of total push duration before linear regression models were applied to each of the 101 nodes resulting in a SPM{*t*} curve. Using random field theory, which describes probabilistic behaviour of random curves and accounts for the smoothness of the data, a critical threshold was set (α = 0.05). If the SPM{*t*} curve exceeded this critical threshold, force was deemed to be significantly related to the discrete outcome measure (horizontal external power) at these specific nodes.

RESULTS: The athlete exited the block with a horizontal velocity of 3.32 ± 0.04 $m \cdot s^{-1}$ (mean ± SD) after pushing against the block for 0.399 ± 0.023 s. Consequently, a mean body mass-normalised horizontal external power of 13.81 ± 0.69 $W \cdot kg^{-1}$ was achieved. Vertical velocity at block exit was 0.66 ± 0.07 $m \cdot s^{-1}$. Recorded values for the other discrete variables, along with their associations with horizontal external power, are presented in Table 1.

Table 1. Discrete kinetic variables and associations (Pearson *r*) with horizontal external power

	Mean	SD	*r*	±90% CI
Average total force (N)	1085	22	0.84*	0.14
Average horizontal force (N)	621	32	0.95*	0.05
Ratio of forces (%)	57	2	0.96*	0.04
Maximum horizontal force rear leg (N)	727	36	0.35*	0.38
Maximum vertical force rear leg (N)	671	39	0.25	0.40
Maximum horizontal force front leg (N)	843	26	0.09	0.42
Maximum vertical force front leg (N)	986	29	-0.13	0.42
Peak rate of horizontal force production rear leg ($N \cdot s^{-1}$)	15980	2262	0.78*	0.19
Peak rate of horizontal force production front leg ($N \cdot s^{-1}$)	7250	967	0.53*	0.32

CI = confidence intervals. *denotes clear association between variable and horizontal external power. Correlations can be considered statistically significant (p < 0.05) if the 90% CI of r do not cross zero.

The relationships between horizontal external power and horizontal force production of the rear and front leg (1D analysis) are provided in Figure 1. The SPM{*t*} curves (bottom panels) indicate statistically significant relationships ($p < 0.001$) between horizontal force production in the early phases of force production for both legs (between 15 and 22% of the block phase for rear leg and between 16 and 30% of the block phase for the front leg). For vertical forces, the SPM{*t*} curves did not reach statistical significance.

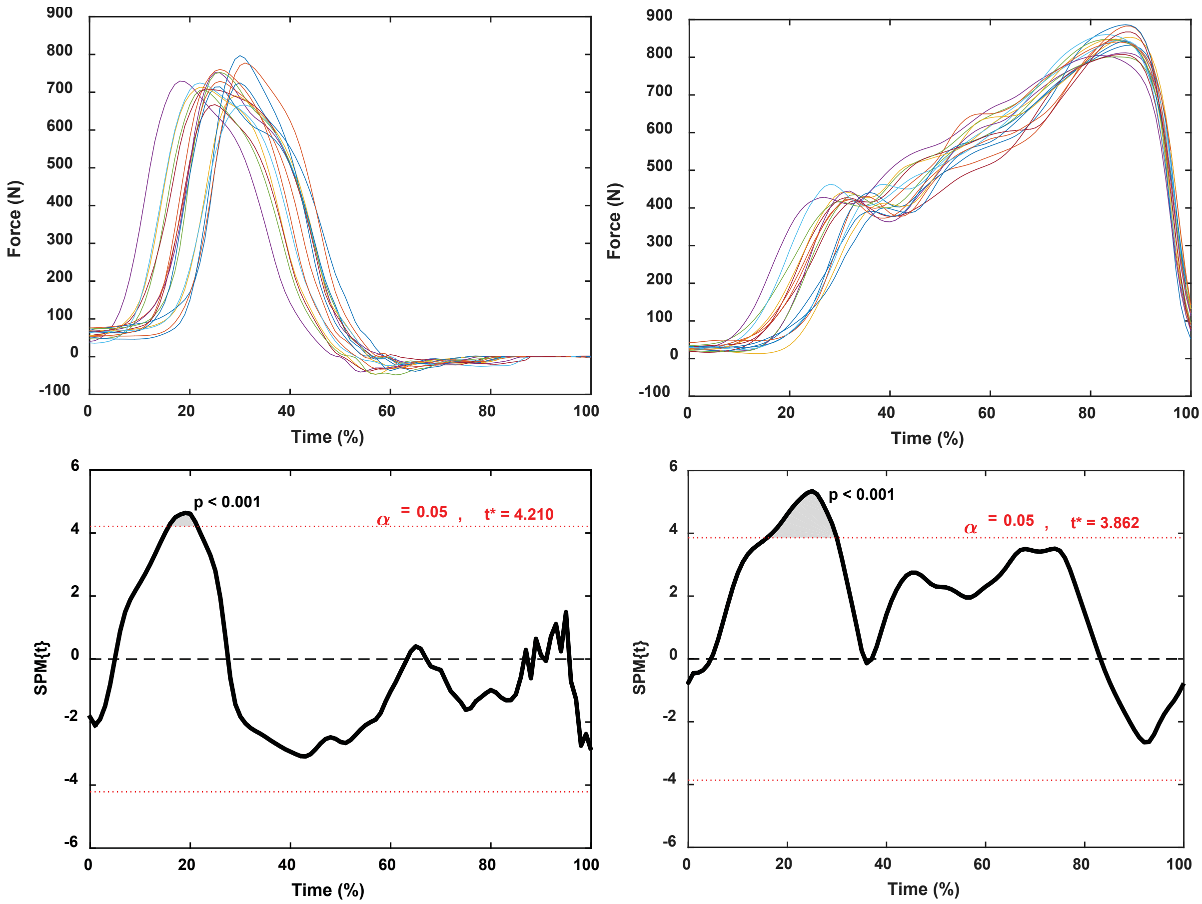

Figure 1. Horizontal force production for 16 sprint start trials from the same athlete (upper left: rear leg, upper right: front leg) and SPM results (*t* curves) depicting the relationships between force curves (lower left: rear leg, lower right: front leg) and horizontal external power across the block phase. Grey shaded areas indicate a significant relationship between force and horizontal external power at those time nodes.

DISCUSSION: This study used SPM to assess kinetic determinants of sprint start performance and make comparisons with those obtained using conventional discrete (0D) analysis. Pearson correlations (0D force variables) revealed statistically significant and clear, positive associations (r ± 90% CI) between horizontal external power and average total force (0.84 ± 0.14), average horizontal force (0.95 ± 0.05) and the ratio of forces (0.96 ± 0.04). Thus, block performance seems to be associated with the ability to orientate the force vector horizontally, as observed in the acceleration phase (Morin et al., 2011). The SPM results provide further support for this as horizontal force production was positively associated with horizontal external power, whereas, vertical force production was not (either positively or negatively). Additionally and as in Willwacher et al. (2013), the ability to rapidly generate horizontal force in the initial push phase seems to be important to this sprinter's overall block performance (r ± 90% CI = 0.78 ± 0.19 for the rear leg and 0.53 ± 0.32 for the front leg).
When maximum forces were extracted for each leg, the only variable which was clearly associated with block performance was maximum horizontal force of the rear leg (r ± 90% CI = 0.35 ± 0.38). This appears to support previous studies (van Coppenolle et al., 1989; Fortier

et al., 2005), which have shown faster sprint starters to generate greater maximum horizontal forces on the rear block but not on the front. However, when data were analysed using the 1D SPM approach, horizontal force production on both blocks was found to be significantly ($p < 0.001$) related to horizontal external power from 15-30% of the push phase (Figure 1). At these points in time, front leg forces were considerably less than maximum and this perhaps explains the apparent discrepancy between 0D and 1D results. Only when the force data were analysed using 1D SPM, did it become apparent that it is important for this sprinter to increase horizontal force production on both blocks in the initial push phase.
This study highlights the potential utility of SPM to analyse sprint start performance alongside the more conventional discrete tests. Further 1D analyses, which have potential in this setting, include *t* tests and ANOVA to assess for differences between curves (either inter- or intra-athlete) in response to training or technique intervention, for example. An ongoing consideration with SPM, however, is the requirement to time-normalise, which may temporally distort the data and analysis. Nonetheless, variation in push duration was small in the current study (SD = 0.023 s), and thus, this was not anticipated to be problematic.

CONCLUSION: Traditional discrete 0D analyses of the sprint start can certainly provide important insight regarding a sprinter's start performance. However, by focussing on maximum forces or similar scalar variables, practitioners and coaches may overlook meaningful information, which can potentially be detected using 1D SPM. We encourage researchers to assess the variation in push duration before conducting SPM and perhaps combine 0D and 1D analyses to fully characterise and examine sprint start performance.

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Acknowledgement
The authors thank S. Page, A. Davies, P. Chen and M. Morgan for their assistance with data collection. This investigation was funded by CAMERA, the RCUK Centre for the Analysis of Motion, Entertainment Research and Applications, EP/M023281/1.