DATA-TRACKING AND PREDICTIVE SIMULATIONS OF SPRINT RUNNING

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The sprint running literature contains recommendations for how athletes should consider modifying their technique, yet, very few studies have documented their affect on performance. We used a musculoskeletal modelling and simulation approach to initially perform a data-tracking simulation to evaluate the outputs against experimental data. A predictive simulation with limited constraints was then performed to assess the influence of technique modications on performance. The data-tracking simulation tracked the experimental data well, particularly the ground reaction forces (largest RMSE = 0.04 BW). The predictive simulation resulted in the model covering 2.79 m in 0.325 s through an increase in step frequency, and this was a time duration improvement of 6.9% in comparison to the athlete's own performance. In this preliminary work we have managed to track experimental sprint running data, and provided a promising basis to further explore hypothetical modifications in technique.

KEYWORDS: technique, optimal control, modelling.

INTRODUCTION: The mechanics of sprint running have been studied extensively. Most studies have concentrated their efforts on understanding how to improve sprint running performance by assessing ground reaction forces (GRFs), joint kinetics and kinematics, and spatiotemporal parameters (e.g. Mann & Sprague, 1980; von Lieres und Wilkau *et al.*, 2018). Such studies have undoubtedly improved the scientific understanding of factors governing sprint running performance. However, a limitation of the current studies is that they have typically focused on identifying key aspects of technique from group level analyses, and thus, they may have neglected individualised aspects of technique that may be critical to performance. Furthermore, the existing literature provides various suggestions for improving performance through modifications in technique, although there is a sparsity of studies that have attempted to assess technique modifications, especially in elite athletes.

Advancements within musculoskeletal modelling and predictive simulation approaches have opened the possibility of exploring how hypothetical modifications in technique can lead to improvements in performance on an individualised basis. However, prior to performing predictive simulations, it is necessary to ensure that the model can produce realistic outputs by evaluating them against experimental data. Consequently, the first aim of the current study was to assess the capability of reproducing experimental sprint running GRFs, and joint kinematics and kinetics by performing a data-tracking simulation. The second aim was to develop a predictive simulation framework and to use it to explore technique changes in relation to performance.

METHODS: *Data Collection:* One male sprinter (age: 24 years; height: 1.79 m; mass: 72.2 kg; 100 m PB: 10.33 s) provided written informed consent to participate in the current study which was approved by the local research ethics committee. The athlete was asked to complete a maximal effort sprint on an indoor track whilst three-dimensional kinematics (250 Hz, Oqus, Qualisys AB, Sweden) and GRFs (2000 Hz, Kistler, Switzerland) were collected between the 15-20 m mark. The data from a stance phase were used for the data-tracking simulation, whilst data from a step and a successive stance phase (right contact, flight and left contact) were used as a reference to compare the output from the predictive simulation. The marker trajectories and GRFs were filtered at 20 Hz using a fourth-order low-pass Butterworth filter.

Musculoskeletal Model: A generic full-body 37 degrees of freedom musculoskeletal model (Hamner *et al.*, 2010) was linearly scaled in OpenSim 3.3 (Delp *et al.*, 2007) using marker positions acquired during a static trial. The knee flexion range of motion was increased to 145° to accommodate the range observed during sprint running. The lower-limbs and trunk were actuated by 92 muscles, and the upper-limbs were driven by 14 ideal joint actuators (pelvis residual actuators were also included). Each muscle was represented as a Hill-type muscle-tendon unit with muscle contraction and activation dynamics described using the formulations in Falisse *et al.* (2019). Furthermore, each muscle's length, velocity and moment arm was defined as a polynomial function of joint position and velocity (Falisse *et al.*, 2019). A smoothed Hunt-Crossley contact model (Serrancolí *et al.*, 2019) was used to model the foot-ground interaction by means of attaching 4 and 2 spheres to each calcaneus and toe segment, respectively. A compliant foot-ground contact model was used to avoid unrealistic foot-ground penetrations following the work of Allen *et al.* (2012).

Tracking Data: An inverse kinematics analysis was performed within OpenSim using the filtered marker data and scaled model. The resulting kinematics were fitted using B-spline interpolation. Velocities and accelerations were determined by calculating the time derivatives of the splines. An inverse dynamics analysis was also performed to calculate the joint moments and pelvis residuals using OpenSim. The splined kinematics, joint moments and filtered GRFs served as the experimental data for which the simulated model outputs were evaluated against by calculating the root mean square error (RMSE).

Optimal Control Framework: The data-tracking and predictive simulations were formulated as optimal control problems, and converted to nonlinear programming problems using the direct collocation method to determine the optimal states, controls and static parameters (Table 1). The time horizon for the data-tracking simulation was discretised across 40 equally spaced mesh intervals using the Legendre-Gauss-Radau discretisation scheme (Garg *et al.*, 2011), with 4 collocation points per mesh interval.

Table 1: List of the different variables included within each type of optimal control problem.

State	Joint positions and velocities, muscle activations, normalised tendon forces
Control	Upper-limb and pelvis actuators, ground reaction forces, time derivative of normalised tendon forces, time derivative of muscle activations, joint accelerations
Parameters	*Contact model parameters (location of each sphere, and uniform sphere stiffness and damping) and &time interval between each phase

*unique to data-tracking, &unique to predictive

The states were parameterised with third-order Lagrange polynomials within each mesh interval, whilst the controls were parameterised at the beginning of each mesh interval and assumed to be piecewise constant during a given mesh interval. Implicit multibody and muscle contraction dynamics formulations were used (Falisse *et al.*, 2019), which required the introduction of additional control variables. This enabled the equations of motion and Hill-equilibrium to be enforced as equality path constraints at the beginning of each mesh interval. Muscle activation dynamics were enforced as inequality path constraints at the beginning of each mesh interval using the formulations described in De Groote *et al.* (2009), which required the introduction of an additional control variable. Constraints were also included to ensure the continuity of state variables between each mesh interval and the continuity of state derivatives at the collocation points within each mesh interval (Serrancolí *et al.*, 2019). The cost functional included terms to track the experimental kinematics (positions and velocities), joint moments and GRFs, minimisation of pelvis residuals, and the minimisation of untracked controls were included to improve the convergence rate and reduce redundancy. The predictive simulation was formulated similarly to the data-tracking simulation, although several additional equality and inequality path constraints had to be included to ensure the model's limbs did not penetrate each other for example and to match the experimental data at the beginning. The predictive simulation cost functional featured terms to maximise the vertical and anterior-posterior GRFs whilst each foot was in contact with the ground, and to minimise the duration of each phase, joint accelerations and muscle activations. Both problems were formulated in MATLAB (2017b, MathWorks Inc., Natick, USA) using CasADi (Andersson *et al.*, 2019), and solved using IPOPT

(Wächter & Biegler, 2006). Direct methods (e.g. direct collocation) for solving optimal control problems necessitate the calculation of derivatives to determine a new search direction, which can be computationally expensive. To increase computational efficiency we used the recently released modified versions of OpenSim and Simbody (Falisse *et al.*, 2019) for the purposes of evaluating the multibody equations of motion. These versions are interfaced with CasADi, which permits the calculation of derivatives using algorithmic differentiation as opposed to conventional finite difference methods.

RESULTS AND DISCUSSION: The data-tracking simulation was able to accurately track the experimental GRFs (largest RMSE = 0.04 BW) to the detriment of the kinematics and kinetics. The tracked kinematics showed the largest RMSE for pelvis anterior-posterior translation (3.3 cm), pelvis rotation (10°), and right hip internal-external rotation (5°) for the lower-limbs. The tracked flexion-extension joint moments for the right lower-limb had a RMSE of 35.5, 27.5 and 42.9 N·m for the hip, knee and ankle, respectively. Although the kinematics errors were larger than anticipated, their patterns were similar to the experimental kinematics (Figure 1), and this was also observed for the joint moments. The marked differences in the errors are likely to be explained by the weighting term of each variable in the cost functional. A heuristic approach was taken to determine the weights, and we placed a greater weighting on the variables to be tracked that we believed were closer to the ground-truth (e.g. GRFs). Nevertheless, in the future a more objective approach may be necessary to determine the weights, such as inverse optimal control. A further means of refining our data-tracking simulation could involve the parameterisation of the control variables with Lagrange polynomials, which would lead to the controls having more freedom at the expense of increasing the number of design variables and constraints. The aforementioned approach has not been extensively explored from a biomechanical perspective and warrants further investigation.
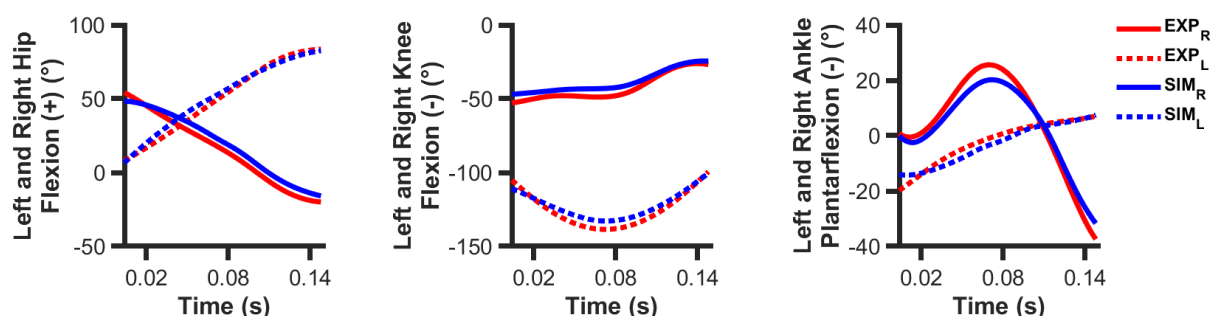

Figure 1: Simulated (solid and dashed blue line) and experimental (solid and dashed red line) left and right lower-limb joint angles during the stance phase of the right foot.

The predictive simulation resulted in the model covering 2.79 m in 0.325 s whilst the athlete covered 2.78 m in 0.348 s. This equates to a 6.9% improvement in time duration across a step and a successive contact phase. The model was also found to have a step frequency and length of 5.38 Hz and 1.66 m, respectively, whilst the athlete had a step frequency and length of 4.18 Hz and 1.89 m, respectively. The step frequency from the predictive simulation is currently not within the range reported in the sprint running literature (3.60 – 4.80 Hz) (von Lieres und Wilkau *et al.*, 2018), and therefore different bounds on the contact and flight phase durations may be necessary to ensure the model does not achieve an infeasible step frequency. Differences in the lower-limb kinematics were also observed (Figure 2), with discernible differences in the patterns of knee flexion-extension and ankle plantarflexion-dorsiflexion. For example, the predictive simulation was found to exhibit a greater range of knee flexion-extension in comparison to the athlete, and this may have contributed to the improved performance of the model. In the current predictive simulation we gave the model a large amount of freedom to accomplish the task set. Future work will therefore feature investigating specific modifications in technique, and testing coach-driven hypotheses. This will involve the use of constraints based upon measures of coordination, with the idea to avoid individual joint changes in technique which are unlikely to happen in the real world.
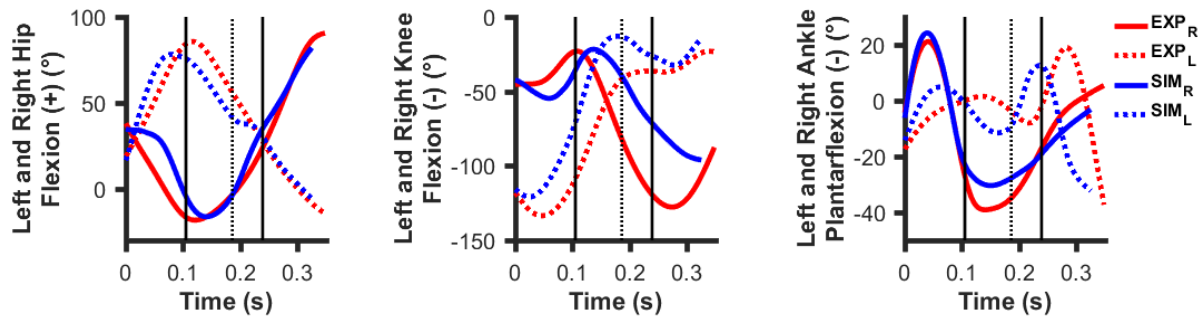
Figure 2: Predicted (solid and dashed blue line) and experimental (solid and dashed red line) left and right lower-limb joint angles during a step and a successive contact phase. Both steps begin with right foot touch-down and end at left foot take-off. The first solid black vertical line marks right foot take-off (both predicted and experimental occurred at the same instant in time). The next solid black vertical line marks left foot touch-down for the experimental data, whilst the dashed black vertical line marks left foot touch-down from the predicted simulation.

CONCLUSION: The data-tracking results are very promising and give confidence that the model and simulation framework are capable of reproducing sprint running experimental data to a sufficient degree of accuracy. Furthermore, with the suggestions mentioned above we anticipate improved data-tracking performance. The predictive simulation aspect still requires further improvements to ensure predicted outputs are feasible. Nevertheless, this is the first study to perform a predictive simulation of sprint running using a three-dimensional musculoskeletal model, and the initial results obtained give further hope that modifications in technique alongside changes in muscle properties can be explored.

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