PREDICTING RUNNING MOVEMENTS FROM MOTOR CONTROL PRINCIPLES

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We aim to predict running movements from motor control principles. Specifically, the central nervous system minimizes an objective related to energy efficiency when planning movements. We replicate this minimization in optimal control problems to create running simulations that predict running movements in new situations. Here, we will introduce how we create predictive simulations using optimal control, and we show how we used these to gain insight into the effect of running shoe midsole properties on running movements. We show that we can successfully predict the change in metabolic cost between different shoe conditions, but that our outcomes are limited when balance is important. Furthermore, we show that metabolic cost changed even though the kinematic and kinetic changes were small. Finally, we discuss some future directions of this simulation approach.

KEYWORDS: optimal control, effort minimization, running shoes, gait simulations.

INTRODUCTION: Predictions of human movement can improve our ability to prevent injuries and maximize performance, since we can get insights into the effect of a specific intervention without requiring time-consuming and potentially harmful human experiments. However, these predictions are challenging since human dynamics are highly redundant, both on the muscle and on the skeletal level. Therefore, we have to find the correct movement out of the many different options that exist. In humans, this choice is made through motor control by the central nervous system. Therefore, we have to replicate the central nervous system's approach to movement planning and execution, which we have to replicate. The central nervous system plans movements by optimizing an objective (Bertram & Ruina, 2001). For walking and running, this objective is related to energy or effort minimization, but it can vary between individuals and tasks (Mombaur & Clever, 2017).
By replicating this optimization digitally using optimal control, we can predict movements. Optimal control finds simulations (i.e., the control input and resulting movement) that minimize an objective for a dynamic model. We have previously used optimal control on musculoskeletal dynamics models to investigate the effect of ankle exoskeletons on walking movements (Weiss et al., 2024) and the effect of running shoe midsole properties on running movements (Dorschky et al., 2019; Nitschke et al., 2021; Wang et al., 2023), among others.
Here, we will give an overview of how we have used motor control principles to predict sports movements, specifically running. We have investigated the effect of running shoe materials on energy efficiency and running movements, since a small increase in energy efficiency can change the outcome of the competition especially in marathon running. Specifically, we have retrospectively investigated if we can predict the metabolic cost reduction of a soft midsole material, we have investigated the contributions of the midsole energy return and stiffness separately, and we have investigated the effect of stack height at the same time as an experimental investigation.

METHODS: We solve optimal control problems to predict human movement, to replicate the movement planning process of the central nervous system. When we simulate walking and running, we create simulations by solving the following optimal control problem:

minimize $$J(x,u,t) = \int_{t=0}^{T} c\big(x(t),u(t)\big)\mathrm{d}t \qquad (1)$$

subject to
$$f(x(t), \dot{x}(t), u(t)) = 0 \quad (2)$$
$$x(T) = x(0) + vTx_{hor}(0) \quad (3)$$

where $J(x, u, t)$ is the objective, T the movement duration, v the movement speed, $x(t)$ the system's state at time t and $u(t)$ its input, and $c(x(t), u(t))$ the cost function that is evaluated at each time point. $f(x(t), \dot{x}(t), u(t))$ represents the musculoskeletal dynamics including a ground contact model, and x_{hor} the states which require a horizontal translation.
The dynamics are defined by the musculoskeletal model and the contact model that describes the interaction between the model (i.e., the feet) and the ground. For straight walking and running, it is sufficient to use a sagittal plane musculoskeletal dynamics model, since most movement happens in the sagittal plane. We have used a model with 9 degrees of freedom: the position and orientation of the trunk, as well as a hip angle, a knee angle, and an ankle angle for each leg. This skeletal model is operated by eight Hill-type muscles in each leg, consisting of a contractile element to represent active muscle fibre, a series elastic element to represent the tendon and other passive tissues connected in series, and a parallel elastic element to represent the passive tissues connected in parallel to the active muscle fibre (Dorschky et al., 2019). The ground contact model includes the running shoe midsole properties, such as the softness and energy return of the material. The model's equations are based on dynamic loading tests on shoe samples. The model determines the ground reaction force from the midsole deformation and deformation rate (Dorschky et al., 2019). We also include the stack height in the location of the contact points with respect to the ankle joint.
To predict running movements, we use a cost function that consist of two main terms: tracking of typical joint angles and ground reaction forces and effort minimization. For running, we have used a publicly available dataset of male runners (Fukuchi et al., 2017). We minimize effort by minimizing the square of muscle stimulation. The weighting between these terms depends on the exact problem that is solved and the available data. We weigh the tracking objective with respect to the effort objective. If the variance of the tracking data is known, it is also used in the weighting, such that data points with a large variance are tracked less strictly than data points with small variance. The size of the variance also depends on whether it is a variance of a single participant or if it is across participants.
Here, we present how we have used this simulation approach to investigate the effect of running shoe midsole properties on metabolic cost, kinematics, and kinetics of running. Specifically, we investigated (1) the decrease in metabolic cost when using a soft midsole material compared to ethylene-vinyl acetate (EVA), (2) the effect of the soft material's softness and energy return on metabolic cost separately, and (3) the effect of a change in stack height.

RESULTS: In our first study, we investigated if we could predict the decrease in metabolic cost of a soft midsole material compared to EVA. The predicted reduction in metabolic cost was 0.7% (Dorschky et al., 2019), which was similar to the 1.2% reduction in oxygen consumption that was measured in an overground running experiment (Worobets et al., 2014).
In our second study, we separately investigated the increased softness and increased energy return of the soft midsole material used in study one. We found that the increased softness yielded a six times larger decrease in metabolic cost than the increased energy return. The effect was additive when combining both (Nitschke et al., 2021).
In our third study, we investigated if we could accurately predict changes in running due to an increase in stack height. We accurately predicted metabolic cost changes of shoes with a stack height of 40 mm and 45 mm compared to a shoe with 35 mm stack height, but we could not accurately predict the metabolic cost change for a 50 mm stack height (Wang et al., 2023).
When analysing movement kinematics and kinetics, we often found only small changes. Figure 1 shows that running kinematics between a reference midsole material and one that has increased softness cannot be distinguished (Nitschke et al., 2021). We found similar small differences when simulating running with different stack heights. Though the changes were smaller than in the experiment, we predicted the trends of the changes in ankle kinematics and kinetics, and knee kinetics correctly (Wang et al., 2023).

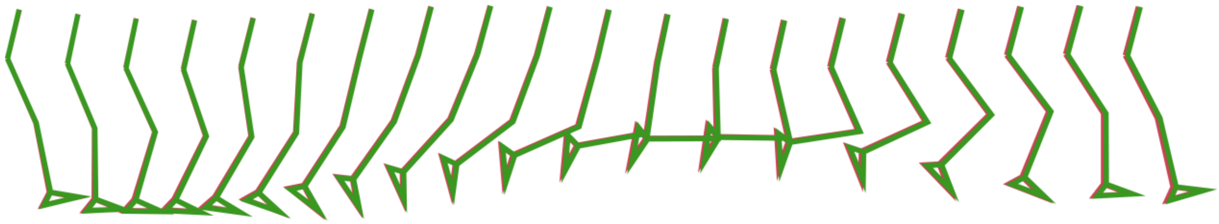

Figure 1: Stick figures of two simulations with different midsole materials.

DISCUSSION: We found that we can use principles of motor control to predict changes in running movements, by replicating the optimization performed by the central nervous system when planning and executing movements. We showed that we could predict the effect of running shoe midsole properties on metabolic cost, kinematics, and kinetics of running. We were not able to predict the change in metabolic cost accurately for shoes with a large stack height, which we suspect to be related to the deterministic nature of the simulations. Because the simulations are deterministic, we cannot use simulations to investigate balance, which is relevant for larger stack heights. This limitation should be kept in mind when simulations are used to investigate injury prevention, where unexpected movements could be relevant. Still, simulations provide an important advantage over experiments, since they allow us to investigate interventions, such as new shoes or other devices and muscle strength training, without requiring prototypes or a human experimental study.

An important open question is the accuracy that is required to make useful prediction from simulations. The required accuracy is dependent on the question that is answered. Therefore, it is important that predictive simulations are properly validated for each application, such that it is known for which applications they can be used with confidence. Generally, we are able to predict trends of changes well, but not absolute values. For example, we were able to predict the trends in kinematic and kinetic changes (Wang et al., 2023), even though the absolute peaks differed. This result shows that we could use simulations to predict an increase in, e.g., the peak knee moment, but we cannot predict the value of the peak knee moment.

Currently, our simulations are not purely predictive, because we require a tracking term in our predictions. Recordings of typical movements are always available, and, even though a bias might be introduced, the tracking term increases realism and variation between simulations, similar to movement variation between runners. The tracking term can be explained in two ways. The first way is that it represents an objective of the central nervous system to look "normal", which is an objective that seems important for humans. For example, looking normal is important for prosthesis users (Plettenburg, 1998). The second way to explain this term is that it adds prior information to the optimization to help it find the correct solution. There will always be a gap between simulation and reality due to the assumptions and simplifications in the musculoskeletal model and the differences between a central nervous system optimization and a computer optimization. The tracking term is one way to account for these differences and help the optimization find the correct solution. Instead of adding a tracking term, walking simulations have also been created by using a hand-crafted movement objective (Falisse et al., 2019). We advise to use this approach when locomotion principles are investigated, since then the possible bias from the tracking term might lead to incorrect insights.

While we have mainly focused on predictions of periodic movements like walking and running, we have recently also used optimal control simulations to investigate other movements, such as cutting movements (Nitschke et al., 2023). Such movements are relevant when investigating approaches for injury prevention through simulations, for example by investigating if strengthening a certain muscle will lead to a safer movement technique. Furthermore, we can use simulations as a safe approach to simulate movements that lead to an injury. One important aspect of movements on a sports field, such as a cutting movement, is that the central nervous system's objective might not be energy minimization, since for a cut, the goal is to put a defender on the wrong foot, while another objective could be to change direction as fast as possible. Therefore, we should update the objective for these movements. For example,

inverse optimal control (Mombaur & Clever, 2017), in which the objective is found based on experimental recordings, could be used to find an objective for cutting movements.
There is a huge potential of using simulations for individual predictions. Then, running shoes and other wearable devices could be optimized for each individual based on their body parameters and running goals, while also individualized training programs could be created to improve movement technique and prevent injuries. So far, we have made generalized predictions, over an average population of runners. Recently, we have started investigating individual predictions for exoskeleton walking, but found that we were not able to predict individual changes, even when the general effect was predicted correctly (Weiss et al., 2024). Therefore, we need to further explore how we can improve accuracy on an individual level. To do so, we should investigate both aspects of the simulations that are representative of a person, which are the movement objective and the musculoskeletal body parameters. It is known that movement objectives vary between individuals (Mombaur & Clever, 2017), while also different people have, e.g., different weight distributions and muscle strength.

CONCLUSION: We conclude that we can use motor control principles to predict sports movements. We created running simulations by solving optimal control problems that replicate the central nervous system's optimization for movement planning and execution. Using these simulations, we predicted the effect of running shoe midsole properties on running metabolic cost, kinematics, and kinetics. We identified a limitation, since we are currently not able to account for balance in our simulations. Future directions include predictions of other sports movements to aid injury prevention, for example during cutting movements, and personalized predictions, to enable shoes and other wearable devices to be optimized for individual athletes.

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