EFFECTS OF RUNNING SHOE STACK HEIGHT ON MOVEMENT VARIABILITY – A SHARED BIOMECHANICAL AND MOTOR CONTROL PERSPECTIVE

Bernd J. Stetter[1], Cagla Fadillioglu[1], Stefan Sell[1,2], Thorsten Stein[1]

Institute of Sports and Sports Science, Karlsruhe Institute of Technology, Karlsruhe, Germany[1]
Joint Center Black Forest, Hospital Neuenbuerg, Neuenbuerg, Germany[2]

Understanding how shoe features affect motor control processes is crucial for designing targeted running shoes. The purpose of this study was to investigate adaptations of coupled movement components, i.e. kinematic synergies (kSYNs), when running with different shoe stack heights (19 mm, 35 mm, and 50 mm). The applied analysis combined a principal component analysis, support vector machine classifiers, and stride-to-stride variability (SSV) calculations. The results showed classification rates ranging from 82.9% to 94.4% across different stack heights. Notably, only the 50 mm stack height demonstrated increased SSV for the kSYNs that highly contribute to separating the two stack heights when compared to the 19 mm condition. The findings suggest that the motor control system adjusts to variations in stack height within certain limits by regulating task-relevant kSYNs.

KEYWORDS: running shoes, movement analysis, modular control, machine learning.

INTRODUCTION: Running is a popular sport worldwide, bringing many health benefits, but it can also lead to injuries in the musculoskeletal system. Footwear manufacturers have dedicated research efforts to develop running shoes focused on enhancing performance and preventing injuries during running. Stack height is a critical feature of running shoes (Esculier et al., 2015), and ongoing debates persist regarding its effects on biomechanics and motor control mechanisms (Hébert-Losier & Pamment, 2023). In this context, motor variability is a central issue and it is currently unknown how for example shoe features influence the variability of running movements (Cowin et al., 2022).
Optimal feedback control models suggest that variability in task-relevant movement components are controlled, whereas variability in task-irrelevant components remain uncontrolled, since corrections involve a certain amount of effort and therefore causes costs. Accordingly, only corrections that are absolutely necessary to minimize costs should be made (Todorov, 2004). Analyzing these aspects in running is complex due to the numerous degrees of freedom involved in human locomotion. The concept of kinematic synergies (kSYNs) is an approach to quantify the covariation of joint motions, as angular movements in various joints tend to be coupled (Daffertshofer et al., 2004). Such kSYNs have been proposed as movement components that could simplify the construction and explanation of motor behaviour (Stetter et al., 2020). By applying such an approach, Maurer et al. (2013) demonstrated that speed-variant movement components are more tightly controlled during running, as evidenced by a lower degree of variability across running cycles, referred to as stride-to-stride variability (SSV), compared to the speed-invariant ones.
Related to differences caused by shoe features, such as midsole hardness, effects are known to be small, and machine learning approaches, such as support vector machines (SVMs), have proven effective in identifying and characterizing systematic changes (Nigg et al., 2012). Previous research has also shown that changes in shoe characteristics are more likely to be present in higher-order kSYNs (Nigg et al., 2012). So far, there hasn't been a combined application of kSYNs and machine learning specifically focusing on shoe stack height. However, such analysis may contribute to a deeper understanding of control mechanisms related to variations in running shoe features and related concepts, e.g. the preferred movement path paradigm (Nigg et al., 2015). This understanding is important for grasping how the motor control and biomechanical systems interact.
Therefore, the aim of this study was to determine differences in kSYNs when running with various stack heights using SVMs, and to evaluate the impact of the stack height on the SSV.

METHODS: This study used data from 17 healthy injury-free male experienced runners (age: 25.7 ± 3.9 years, height: 177.7 ± 3.9 m, weight: 68.1 ± 6.0 kg, shoe size: EU 42-43, running activity per week: 4.2 ± 1.8 days, and 33.7 ± 22.4 km). After a warm-up and familiarization, all participants performed treadmill running at 15 km/h with running shoes of different stack heights (S19 = 19 mm, S35 = 35 mm, and S50 = 50 mm). Kinematic data from 26 reflective markers were collected using a motion-capture system (Vicon Motion Systems, 200 Hz). Ten consecutive right strides were extracted and time normalized to 100 data points for S19, S35, and S50 of each participant.

The further data processing was subdivided in three primary steps: 1. Extraction of kSYNs, 2. Building of classification models, and 3. Calculation of the SSV.

1. Extraction of kSYNs: The details of PCA to extract kSYNs are explained elsewhere (Daffertshofer et al., 2004; Maurer et al., 2013). In summary, the kinematic data matrix (M1) for this study consisted of the 3D positions of the markers in space (26 markers x 3 dimensions = 78 marker positions). All markers were shifted in the anterior-posterior and medial-lateral direction to the centre of the pelvis as well as normalized to the body height of the participants. M1 stored the data of all strides that were extracted for all 17 participants and all 3 stack heights and was used in a PCA. The length of M1 was 51000 (17 participants x 3 stack heights x 10 strides x 100 time points). kSYNs were obtained by projecting the kinematic data stored in M1 onto the principal component vectors and represent correlated deviations from the mean pattern computed by the PCA applied to M1 (Figure 1) (Maurer et al., 2013).

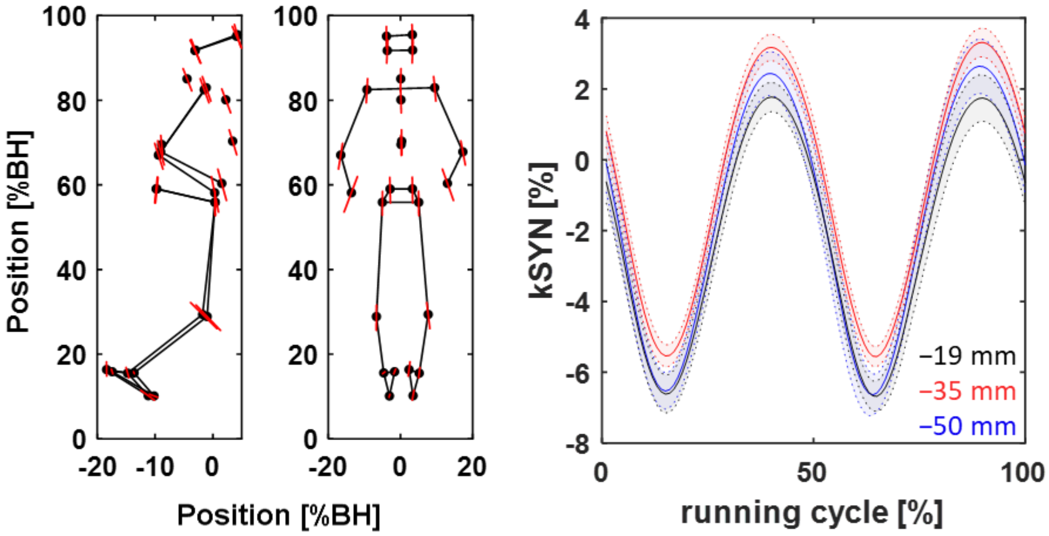

Figure 1: Left: Visualization of the second kSYN for one participant with S35 as stick figures in the sagittal and frontal plane (red = deviations from the mean positions). This kSYN primary characterizes the vertical movement of the upper body. Note that the direction of the kSYN is the same for all participants and stack heights, however, the range, is participant and condition specific. Right: Alternative representation as waveforms (mean and standard deviation) of the second kSYN for S19, S35, and S50 of the same participant. BH = body height.

2. Building of classification models: Three additional matrices (M2, M3, and M4) were created based on the first 37 obtained kSYNs that explain 99% of the variance in M1. Each of these matrices reflected the time evolution of kSYNs (3700 columns = 37 kSYNs x 100 time points) across observations (340 rows = 17 participants x 10 strides x 2 stack heights) of two stack heights (M2 = S19 and S35, M3 = S19 and S50, M4 = S35 and S50). A linear-kernel SVM was separately applied to M2, M3, and M4 to classify shoes of different stack height by determining the optimal separating hyperplane, which maximized separation between the data of two shoes under consideration (Eskofier et al., 2013). The leave-one-subject-out cross-validation method was used to assess the generalization of each SVM. The classification rate (CR) was determined for each cross-validation iteration, as the number of correctly predicted test

observations divided by the number of strides. A single CR was computed for each SVM by averaging the CR from the 17 cross-validation iterations. Binomial test were used to assess whether the CR were statistically higher than chance. In order to assess the contribution of individual kSYNs to the separability of stack heights, absolute mean loadings of kSYNs waveforms were calculated based on the returned discriminant vector (i.e. vector pointing in the direction of highest separability) for each pairwise SVM model.
3. Calculation of the SSV: Mean and standard deviation of each time point of the kSYN waveforms were calculated across the ten strides for each stack height and each participant. The SSV was calculated as the root mean square of each standard deviation waveform and reflects a measure of the variability in the movement between different strides (Maurer et al., 2013). SSV were summed for the kSYNs above the average discriminant loading (SSVhigh) and for the kSYNs below the average discriminant loading (SSVlow) of each pairwise SVM model and compared using dependent t-tests with a significance alpha level of 0.05. Cohen's d was used as effect size and interpreted as $0.5 \le d > 0.2$ a small effect, $0.8 \le d > 0.5$ a moderate effect, and $d > 0.8$ a large effect.

RESULTS: Together, the first 37 kSYNs explained 99% of the variance in the kinematic data. According to the cross-validations, 92.7%, 82.9% and 94,4% of strides were classified correctly when comparing S19-S35, S19-S50, and S35-S50, respectively. All of these classification rates were significant. $kSYN_2$ serves as an example kSYN that contributed to the separability of stack heights and was primary characterized by the vertical movement of the upper body (Figure 1). Figure 2 presents the contribution of individual kSYNs to separate between stack heights. $kSYN_2$ and $kSYN_{34}$ contributed to the separation of all stack heights. Considering the SSV, S50 showed an increased SSVhigh compared to S19 (4.73 ± 1.31 vs 3.99 ± 0.87, p = 0.04, d = 0.54). All other comparison showed no differences for SSVhigh and SSVlow, with no or small effects.

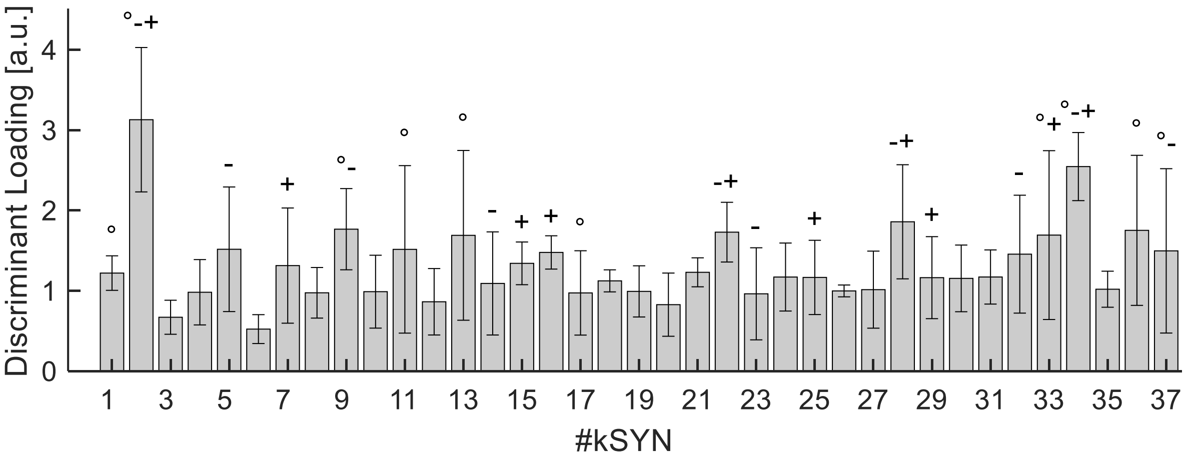

Figure 2: Mean and standard deviation of the absolute discriminant loading. The symbols indicate the ten kSYNs that contributed the most to the separation of S19-S35 (°), S19-S50 (-), and S35-S50 (+).

DISCUSSION: The aim of this study was to identify differences in kSYNs during running with various stack heights using SVMs, alongside evaluating the influence of stack heights on motor control through SSV analysis. Results showed a high level of accuracy in classifying strides when comparing different stack heights ranging from 82.9% to 94.4%. This underscores distinct differences in kSYNs linked to varying stack heights, aligning with prior research for example on midsole hardness, i.e. 86.0% to 99.5% for hard, medium, and soft midsoles (Nigg et al., 2012). Observations revealed a significant contribution to distinguishing between stack heights across the entire spectrum of kSYNs, from low-order to high-order (Figure 2). Certain kSYNs (e.g. $kSYN_2$) contributed to multiple separations, while others did not (Figure 2). This suggests potential adjustments in motor control strategies based on stack height variations, highlighting the adaptability of the motor control system (Maurer et al., 2013; Todorov, 2004).

Interestingly, only S50 showed increased SSV for the kSYNs that are attributed to task-relevant movement components (i.e. SSVhigh) compared to S19. This suggests that particularly high stack heights (i.e. 50 mm) may introduce more variability into running patterns. This variability could be attributed to the recently discussed increased effort required for balancing associated with a stack height of 50 mm (Wang et al., 2023). Understanding such differences in variability is crucial for assessing the consistency of movement patterns across variations in shoes and comprehending the effects of stack height on running biomechanics.
Overall, from a motor control and biomechanical perspective, the findings underscore the intricate relationship between shoe features, whole-body kinematics, and variability in running. The utilization of SVMs in classifying the effects of stack height on kSYNs proved to be helpful in this context. Further research in this area could explore additional factors contributing to SSV and refine shoe features aimed at enhancing movement efficiency.

CONCLUSION: The findings of this study indicate a significant distinction in kSYNs across various stack heights, alongside minimal alterations in SSV. One possible interpretation is that the motor control system adjusts movement execution based on specific stack height characteristics, tightly regulating task-relevant kSYNs within certain limits. From a practical standpoint, the motor control system may effectively compensate for moderate variations in stack height. However, more extreme designs may exceed compensatory capabilities, evidenced by a higher degree of variability across running cycles, potentially leading to adverse effects on running biomechanics and its control.

REFERENCES

Cowin, J., Nimphius, S., Fell, J., Culhane, P., & Schmidt, M. (2022). A Proposed Framework to Describe Movement Variability within Sporting Tasks: A Scoping Review. *Sports Med Open*, *8*(1), 85. https://doi.org/10.1186/s40798-022-00473-4

Daffertshofer, A., Lamoth, C. J., Meijer, O. G., & Beek, P. J. (2004). PCA in studying coordination and variability: a tutorial. *Clin Biomech (Bristol, Avon)*, *19*(4), 415-428. https://doi.org/10.1016/j.clinbiomech.2004.01.005

Esculier, J. F., Dubois, B., Dionne, C. E., Leblond, J., & Roy, J. S. (2015). A consensus definition and rating scale for minimalist shoes. *J Foot Ankle Res*, *8*, 42. https://doi.org/10.1186/s13047-015-0094-5

Eskofier, B. M., Federolf, P., Kugler, P. F., & Nigg, B. M. (2013). Marker-based classification of young-elderly gait pattern differences via direct PCA feature extraction and SVMs. *Comput Methods Biomech Biomed Engin*, *16*(4), 435-442. https://doi.org/10.1080/10255842.2011.624515

Hébert-Losier, K., & Pamment, M. (2023). Advancements in running shoe technology and their effects on running economy and performance - a current concepts overview. *Sports Biomechanics*, *22*(3), 335-350. https://doi.org/10.1080/14763141.2022.2110512

Maurer, C., von Tscharner, V., Samsom, M., Baltich, J., & Nigg, B. M. (2013). Extraction of basic movement from whole-body movement, based on gait variability. *Physiol Rep*, *1*(3), e00049. https://doi.org/10.1002/phy2.49

Nigg, B. M., Baltich, J., Hoerzer, S., & Enders, H. (2015). Running shoes and running injuries: mythbusting and a proposal for two new paradigms: 'preferred movement path' and 'comfort filter'. *Br J Sports Med*, *49*(20), 1290-1294. https://doi.org/10.1136/bjsports-2015-095054

Nigg, B. M., Baltich, J., Maurer, C., & Federolf, P. (2012). Shoe midsole hardness, sex and age effects on lower extremity kinematics during running. *Journal of Biomechanics*, *45*(9), 1692-1697. https://doi.org/10.1016/j.jbiomech.2012.03.027

Stetter, B. J., Herzog, M., Mohler, F., Sell, S., & Stein, T. (2020). Modularity in Motor Control: Similarities in Kinematic Synergies Across Varying Locomotion Tasks. *Front Sports Act Living*, *2*, 596063. https://doi.org/10.3389/fspor.2020.596063

Todorov, E. (2004). Optimality principles in sensorimotor control. *Nat Neurosci*, *7*(9), 907-915. https://doi.org/10.1038/nn1309

Wang, C., Nitschke, M., Wannop, J. W., Stefanyshyn, D., Luckfiel, T., Schlarb, H., & Koelewijn, A. (2023). Prediction of the effect of stack height on running biomechanics using optimal control simulation. *Footwear Science*, *15*(sup1), S78-S79. https://doi.org/10.1080/19424280.2023.2199295