Unraveling the Effects of Expertise and Fatigue on Kinematics and Stride-to-Stride Variability in Running

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Summary

Our body enables us to perform complex movements without significant effort. Due to the multitude of degrees of freedom (DoF) in the musculoskeletal system, our body is a highly redundant system. Therefore, for every conceivable movement, there are several possible solutions which in turn lead to a variety of movement executions. In recent years, there has been growing awareness that analysis of this trial-to-trial variability could lead to valuable insights.

From the outside, one could say that within a cyclic motion, like running, the same movement cycle is performed over and over again. This could lead to the assumption that analysis of one running gait cycle would be sufficient to analyze the biomechanics of running. In doing so, one would miss the information hidden in the slight variations between consecutive strides during movement execution. In fact, a pure reproduction of the same stride under the same conditions could lead to injuries, since always the same structures would be under repeated loads. However, it cannot be assumed that the state of the runner and his environment are identical from stride to stride, so an exact reproduction of the same movement pattern is unlikely. One example for this kind of change could be fatigue, which is inevitable in endurance sports. The multitude of equivalent movement solutions and the resulting variability between individual strides are therefore valuable features and an important topic for research in the context of human motion coordination.

Within the research field of movement variability, promising approaches have been developed and applied to biomechanical data. Namely, there is the uncontrolled manifold approach (UCM) and the tolerance noise covariation approach (TNC). The UCM has its origin in the field of motor control whereas the TNC comes from the field of motor learning. The UCM and TNC approaches have been used to analyze how variability at the level of joint angles relates to the variability of the goal-relevant variable. They have mainly been applied to restricted movements with only a few DoF and hardly ever to the study of whole-body movements such as running. So far, there is no study that investigated running by applying these approaches. Analyzing walking, it was found that even though there is stride-to-stride variability (SSV) at one level, e.g. joint angles, it can be channeled to ensure that a goal-relevant variable, e.g. the center of mass (CoM), is relatively constant over various strides.

This thesis extends the knowledge of how expertise and fatigue affect running kinematics based on five studies, not only by performing a joint angle analysis but also by applying complex approaches analyzing movement variability. Since these approaches have rarely been applied in international sports science research so far, the present thesis also examines whether these approaches, originally developed based on simple experimental paradigms of basic research, can be effectively transferred to sports science problems.

In the first study, the effects of expertise on the stride-to-stride variability of the CoM during running were analyzed at 10 and 15 km/h. Novices were found to show greater variability than experts at 15 km/h. In the second study, a classical biomechanical approach was chosen to characterize the reactions to fatigue of expert runners. Changes were found in spatiotemporal and stiffness parameters, as well as in joint kinematics. These results show that kinematics are considerably altered in a fatigued state. The third study extended these findings by use of the UCM approach, where a subject-specific 3D model of the human body was applied to accurately calculate the whole-body CoM. Using the UCM, only minor changes were found with increasing fatigue. This shows that experienced runners are able to control their CoM trajectory in a fatigued state. In the fourth study, these findings were extended by the application of the TNC approach. It was found that variability of the CoM increases with fatigue in both the medio-lateral and vertical directions. In the fifth study, a classical biomechanical approach was again chosen to characterize the reactions to fatigue, this time in novice runners. No changes were found in spatiotemporal or stiffness parameters, though joint kinematics were affected by fatigue. These results indicate that novices might lack strategies to keep up a fixed running speed under fatigue.

With this series of studies, the knowledge of expertise and fatigue effects on kinematics and SSV in running will be expanded. Having demonstrated the fundamental applicability of relatively new approaches such as the UCM and TNC to complex sports science problems, the foundation was built to further test and improve these approaches in the application to real-world problems in applied sports science.

Zusammenfassung

Unser Körper ermöglicht es uns, ohne große Anstrengung komplexe Bewegungen auszuführen. Aufgrund der Vielzahl von Freiheitsgraden (DoF) im Muskel-Skelett-System ist unser Körper ein hochredundantes System. Für jede denkbare Bewegung gibt es daher mehrere Lösungsmöglichkeiten, welche wiederum zu einer Vielzahl an Bewegungsausführungen führen.

Von außen betrachtet liegt die Vermutung nahe, dass innerhalb einer zyklischen Bewegung, wie z.B. dem Laufen, immer wieder der gleiche Bewegungsablauf ausgeführt wird. Dies führt oft zu der Annahme, dass die Beobachtung eines einzigen Laufzyklus ausreicht, um die Biomechanik des Laufens zu analysieren. Dabei werden allerdings Informationen übersehen, die in den Variationen zwischen aufeinanderfolgenden Zyklen liegen. Tatsächlich könnte eine reine Reproduktion desselben Laufzyklus unter gleichen Bedingungen zu Verletzungen führen, da immer dieselben Strukturen in demselben Maße belastet werden würden. Jedoch ist der Zustand des Läufers und seiner Randbedingungen von Laufzyklus zu Laufzyklus nicht immer identisch, daher ist eine exakte Reproduktion desselben Bewegungsmusters unwahrscheinlich. Eine mögliche Veränderung der Randbedingungen könnte das Auftreten von Ermüdung sein, welche bei Ausdauersportarten unvermeidlich ist. Die Vielzahl gleichwertiger Bewegungslösungen und die daraus resultierende Variabilität zwischen einzelnen Laufzyklen eines Läufers sind daher wertvolle Merkmale und ein wichtiges Thema für Forschungsarbeiten im Kontext der menschlichen Bewegungskoordination.

Auf dem Forschungsgebiet der Bewegungsvariabilität wurden zwei vielversprechende spezifische Methoden entwickelt und auf biomechanische Daten angewendet: die Uncontrolled Manifold-Methode (UCM) und die Tolerance Noise Covariation-Methode (TNC). Die UCM hat ihren Ursprung im Forschungsfeld der motorischen Kontrolle, wohingegen die TNC aus dem Bereich des motorischen Lernens kommt. Mit Hilfe der UCM und der TNC Methoden wird analysiert, wie die Variabilität auf der Ebene der Gelenkwinkel mit der Variabilität der Zielgröße zusammenhängt. Sie wurden hauptsächlich auf eingeschränkte Bewegungen mit nur wenigen DoF angewendet und kaum zur Untersuchung von Ganzkörperbewegungen, wie z.B. des Laufens, genutzt. Bei Untersuchungen des Gehens wurde festgestellt, dass trotz Zyklus-zu-Zyklus Variabilität (SSV) auf unterschiedlichen Ebenen (z.B. Gelenkwinkel) diese so kanalisiert werden kann, dass eine Zielgröße (z.B. Körperschwerpunk, CoM) über die Zyklen hinweg annähernd konstant bleibt.

Diese Arbeit erörtert auf der Basis von fünf Studien, wie sich Expertise und Ermüdung auf die Laufkinematik auswirken, indem sie nicht nur eine biomechanische Analyse der Effekte von Ermüdung auf die Lauf-Kinematik durchführt, sondern auch komplexe Methoden zur Analyse der Bewegungsvariabilität anwendet. Da diese Methoden in der internationalen sportwissenschaftlichen Forschung bisher kaum Anwendung gefunden haben, wird mit der vorliegenden Arbeit auch geprüft, ob sich die anhand von einfachen, experimentellen Paradigmen der Grundlagenforschung entwickelten Methoden, gewinnbringend auf sportwissenschaftliche Problemstellungen übertragen lassen.

In der ersten Studie wurden die Auswirkungen von Expertise auf die SSV des CoM beim Laufen bei 10 und 15 km/h analysiert. Novizen zeigten bei 15 km/h eine größere Variabilität als Experten. In der zweiten Studie wurde ein klassischer biomechanischer Ansatz gewählt, um die Ermüdungsreaktionen von erfahrenen Läufern zu untersuchen. Dabei wurden Veränderungen sowohl in Raum-Zeit- und Steifigkeitsparametern, als auch in der Gelenkkinematik gefunden. Diese Ergebnisse zeigten, dass die Kinematik im ermüdeten Zustand deutlich verändert ist. Die dritte Studie erweiterte diese Erkenntnisse durch die Verwendung der UCM-Methode. Dabei wurde ein probandenspezifisches 3D-Modell für den menschlichen Körper eingeführt, um den Ganzkörper-CoM genau berechnen zu können. Es wurden geringe Veränderungen bei Ermüdung gefunden. Dies zeigte, dass erfahrene Läufer in der Lage sind, ihre CoM-Trajektorie auch in einem ermüdeten Zustand zu kontrollieren. In der vierten Studie wurden diese Ergebnisse durch die Verwendung der TNC-Methode erweitert. Es zeigte sich, dass die Variabilität des CoM sowohl in medio-lateraler als auch in vertikaler Richtung mit Ermüdung zunimmt. In der fünften Studie wurde wieder ein klassischer biomechanischer Ansatz gewählt, um die Reaktionen auf Ermüdung zu charakterisieren, dieses Mal bei Lauf-Novizen. Es wurden keine Veränderungen in den Raum-Zeit- und Steifigkeitsparametern gefunden, obwohl die Gelenkkinematik durch die Ermüdung beeinflusst wurde. Diese Ergebnisse deuten darauf hin, dass Novizen möglicherweise Strategien fehlen, um eine konstante Laufgeschwindigkeit unter Ermüdung beizubehalten.

Mit dieser Studienreihe wird das Wissen über die Auswirkungen von Expertise und Ermüdung auf die Kinematik und SSV beim Laufen erweitert. Nachdem die grundsätzliche Anwendbarkeit von neuen Ansätzen, wie der UCM oder der TNC Methode, auf komplexe sportwissenschaftliche Probleme gezeigt wurde, können diese Methoden bei der Anwendung auf praxisorientierte Probleme in der Sportwissenschaft geprüft und zu verbessert werden.

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Abbreviations

CNS	Central nervous system
CoM	Center of mass
CV	Coefficient of variation
DoF	Degrees of freedom
EV	Execution variables
FS	Fatigue speed
GEM	Goal equivalent manifold
PRE	Rested state
POST	Fatigued state
RoM	Range of motion
RRI	Running-related injuries
RV	Result variable
SPM	Statistical parametric mapping
SSV	Stride-to-stride variability
TNC	Tolerance noise covariation
UCM	Uncontrolled manifold
$UCM_{\parallel}$	Variability parallel to the UCM
$UCM_{\perp}$	Variability orthogonal to the UCM
UCM_{Ratio}	Ratio of parallel and orthogonal variability

1. Introduction

1.1 Preface

In everyday life, we unconsciously perform a multitude of extremely complex actions. We control our body with ease, despite the fact that it is a highly redundant multi-segmental system (Bernstein, 1967). This redundancy allows a variety of possible movement executions, which in turn lead to variability between different executions. Even though this variability is not suppressed, it is controlled and channeled in a way which is still not fully understood (Sternad, 2018). Several sophisticated approaches have been developed to understand how this channeling or structuring of variability is controlled and how to extract information regarding human motor control out of this variability. These approaches comprise, among others, the Uncontrolled Manifold (UCM, Scholz and Schöner, 1999) approach and the Tolerance Noise Covariation (TNC) approach (Müller & Sternad, 2004). These approaches have been applied to a variety of movements, however only a few studies apply these approaches to whole-body sports movements (Black et al., 2007; Koh et al., 2020; Morrison et al., 2016; Qu, 2012).

During running, athletes perform the same movement, e.g. a stride, innumerable times. Although these strides do not vary a lot from an exterior perspective, there is always variability between strides. Thus, running seems to be a good model to study variability in sports. Several factors are known to affect running kinematics and variability, such as age, running speed, level of experience or fatigue (Boyer et al., 2014; Brughelli et al., 2011; Fukuchi et al., 2011; Williams et al., 1991) and it was hypothesized that common running-related injuries (RRI) are related to the variability of the movement (Heiderscheit et al., 2002).

Within this framework, this thesis comprises five studies conducted within an ongoing project investigating the effects of expertise and fatigue on running kinematics and stride-to-stride variability (SSV) (see Table 1). Research in this project is an ongoing process.

Fatigue is an inherent phenomenon of endurance sports such as running. Even though fatigue affects running kinematics (Winter et al., 2017), there is no coherent picture about the dimensions of fatigue effects, or how fatigue can influence the SSV. However, these fatigue influences can have the potential to influence injury risk in runners or occur as an isolated risk factor during running (Clansey et al., 2012; Radzak & Stickley, 2020). Also, expertise has been identified as a risk factor concerning RRI as shown by a higher incidence among novice runners (Kemler et al., 2018; Videbæk et al., 2015).

Table 1: Scheme of the research project with the published and planned studies. Studies not included in this thesis are grayed out

Unraveling the effects of expertise and fatigue on kinematics and SSV in running		
Topic A **Expertise**	**Topic B** **Fatigue in experts**	**Topic C** **Fatigue in novices**
• Effects on Stability of the CoM *(UCM analysis, Möhler et al., 2020)* • Changes in Running Style Between 10 and 15 km/h *(TNC analysis, work in progress)*	• Effects on Spatiotemporal Parameters, Stiffness and Joint Angles *(biomech. analysis, Möhler et al., 2021a)* • Effects on Stability of the CoM *(UCM analysis, Möhler et al., 2019)* • Effects on CoM Trajectory and its Variability *(TNC analysis, Möhler et al., 2021b)* • Identification of Kinematic Differences Using a Support Vector Machine *(Stetter et al., 2020)*	• Effects on Spatiotemporal Parameters, Stiffness and Joint Angles *(biomech. analysis, under review)* • Effects on the CoM Trajectory and its Variability *(UCM/TNC analysis, work in progress)*

In this framework, this thesis contributes important knowledge and findings about the interplay between expertise or fatigue and motor control by analyzing how both novice and experienced runners are affected by fatigue occurring during a middle-distance run. Thereby, the effects of expertise on SSV and the effects of fatigue on joint kinematics and SSV were analyzed. From these results, implications for injury prevention and training will be deduced.

1.2 Outline of the Thesis

The dissertation at hand comprises nine main chapters. The second chapter provides an overview of relevant theoretical background and the state of research (2.1 - 2.5). Subsequently, the aims and scope of the thesis are presented (2.6). The approaches for analyzing SSV are described in section 2.2. Chapters three through seven represent the studies published in peer-reviewed journals (one is currently under review). The second and fifth studies (chapters 4 and 7) follow the approach of classical biomechanical analysis by determining the effects of fatigue on joint kinematics and spatiotemporal parameters. The first, third and fourth studies (chapters 3, 5 and 6) make use of more sophisticated approaches to gain extended insight into the mechanisms occurring with fatigue:

Chapter 3: *Topic A – Expertise*
Möhler, F., Marahrens, S., Ringhof, S., Mikut, R., & Stein, T. (2020). Variability of running coordination in experts and novices: A 3D uncontrolled manifold analysis. European Journal of Sport Science, 20(9), 1187–1196.

Chapter 4: *Topic B – Fatigue in experts*
Möhler, F., Fadillioglu, C., & Stein, T. (2021). Fatigue-Related Changes in Spatiotemporal Parameters, Joint Kinematics and Leg Stiffness in Expert Runners During a Middle-Distance Run. In Frontiers in Sports and Active Living, 3, 23.

Chapter 5: *Topic B – Fatigue in experts*
Möhler, F., Ringhof, S., Debertin, D., & Stein, T. (2019). Influence of fatigue on running coordination: A UCM analysis with a geometric 2D model and a subject-specific anthropometric 3D model. Human Movement Science, 66, 133–141.

Chapter 6: *Topic B – Fatigue in experts*
Möhler, F., Stetter, B., Müller, H., & Stein, T. (2021). Stride-to-Stride Variability of the Center of Mass in Male Trained Runners After an Exhaustive Run: A Three Dimensional Movement Variability Analysis With a Subject-Specific Anthropometric Model. Frontiers in Sports and Active Living, 3, 124.

Chapter 7: *Topic C – Fatigue in novices*
Möhler, F., Fadillioglu, C., & Stein, T. (2021). Changes in Spatiotemporal Parameters,

Joint and CoM Kinematics and Leg Stiffness in Novice Runners During a High-Intensity Fatigue Protocol. PLoS one, submitted

Chapter 8 summarizes the main findings and outlines their implications. Furthermore, the use of the UCM and TNC approaches in applied sport science is discussed and recommendations for further research are given.

2. Theoretical Background

2.1 Movement Redundancy and Variability

Due to the highly redundant musculoskeletal system, movement variability is a feature which is inherent to human motion (Sternad, 2018). Even though single aspects, e.g. the end position of the hand, are more or less constant over several movement executions, one execution will always differ from another: no execution is willingly reproducible (Bernstein, 1967). While this may look like a weakness, e.g. when attempting to hit a target, this can be a strength, e.g. when having to react flexibly to unforeseen events. Although skilled behavior, which is known to be controlled to a high degree, is characterized by a low variability, a certain amount of variability is necessary to react to unforeseen perturbations or serves as a prerequisite for adaptations (Müller & Sternad, 2009). In fact, a stereotyped movement execution with a very low variability can indicate impaired movement (Hamill et al., 1999). Therefore, it is hypothesized that there is an optimal window of variability (Stergiou, Harbourne and Cavanaugh 2006). This is underlined by the fact that learning enhances precision, but does not eliminate variability (Bartlett et al., 2007). Therefore, variability is not suppressed but is made to matter less (Sternad, 2018).

When analyzing variability within human motion, one has to distinguish between variability on different levels. On one hand, there is variability on the level of variables which describe movement execution, the execution variables (EV). One common example of EV is the angles between adjacent body segments, the joint angles. On the other hand, there might be variability on the level of the end point of the movement, the result level, which is described by a result variable (RV). Variability on the level of EV might be beneficial since it ensures a distribution of the loads on several structures, e.g. during the heel strike of a running stride (Hamill et al., 2012), and offers flexibility and adaptability. Therefore, the term “motor abundance” was introduced, to underline the positive attributes (Latash et al., 2002). Even though variability at the execution level might be desired to a certain degree, variability on the level of RV might impair the result and thus has to be controlled (Müller & Sternad, 2004). As the dimension of EV is mostly higher than the dimension of RV, the system is redundant. In a space spanned by all possible combinations of EV, a subspace can be found which includes all solutions keeping the RV constant. This subspace is referred to as solution space or solution manifold - in robotics it is named null space (Khatib, 1987). Since solutions within this subspace do not affect the RV, and since variability among the EV is possibly beneficial, variability within this subspace is supposed to be uncontrolled (Scholz & Schöner, 1999). The movement executions in the null space are referred to as equivalent movement executions. The movement executions orthogonal to that null space are however detrimental to performance, since they affect the movement outcome (Scholz & Schöner, 1999). This performance-relevant part of movement variability is further broken down within the TNC approach (Müller & Sternad, 2004). Thereby, three distinct components influencing this portion of variability can be determined, and will be described below.

Humans execute highly complex movements with great elegance, e.g. during gymnastics. This is proof that our musculoskeletal system is well controlled despite the imposed challenges, e.g. the high redundancy. The abundance of equivalent movement solutions might be used in motor control to ensure a stable and reliable movement execution. Impairments such as injuries might alter control due to changes in the available movement solutions, and might thus result in an altered movement variability (Hein et al., 2012). By observing the reactions of the system to introduced perturbations like age, disease, expertise or fatigue, further insight into the functioning of motor control and the role of movement variability can be gained.

2.2 Analysis of Stride-to-Stride Variability

Since the focus of human movement analysis has moved away from solely analyzing mean values and towards analyzing the information contained in variability, different approaches have been developed (Sternad, 2018). We will focus here on two approaches which were previously used to characterize SSV: UCM (Scholz and Schöner, 1999) approach and the TNC (Müller and Sternad, 2004) approach. While the UCM approach originates from the motor control domain, the TNC approach was developed in the context of motor learning.

Both approaches agree that analysis of trial-to-trial-variability can lead to important insights into the mechanisms of motor control (Latash et al., 2002; Müller & Sternad, 2009). As stated above, by the mid-20th century Bernstein found that even though no movement can be replicated exactly, certain parts of the movement, such as the RV, are more invariant than others (Bernstein, 1967). In the context of both the UCM and TNC approaches, these invariant parts of the movement are thought to be of high importance for the particular movement and are thus more closely controlled. To control the RV, there has to be a non-random interplay among the EV. Hence, there must be a structure in the variability of this movement over several repetitions. Analysis of this structure could reveal insights into the characteristics of motor control.

2.2.1 Choice of Variables

Although every movement can be described in different but equivalent variables or reference frames, the results obtained with the UCM and TNC are tied to the chosen variables (Scholz & Schöner, 2014; Sternad et al., 2010). One has to keep in mind that this dependency is not a drawback of these approaches, but inherent physics. When thinking of a body which moves with respect to a fixed reference frame, the same body is stationary with respect to a reference frame moving with the body (Müller et al., 2007). The choice of variables and thus reference system is a crucial step. Within the UCM and TNC approaches, there are two levels of description for which suitable variables have to be chosen (Müller et al., 2007). The first is the execution level, the level of the EV, where the execution of the actual movement is described. The second is the result level, the level of the RV, where the result or movement outcome is described.

As described above, in both the UCM and the TNC approaches, a certain task-relevant variable, the RV, is thought to be controlled in a way that its value is held constant over several movement executions. Known examples are the dart throwing or skittles task (Müller & Sternad, 2004) and the finger pressing task (Latash et al., 2002). In the present thesis, we applied these approaches to running movement.

Over years of training, runners adapt their specific running style to optimize economy (Moore, 2016; van Oeveren et al., 2021). To run as economically as possible, deviations from this personal running style are minimized, which means that we should observe a low SSV. Since the running movement has been successfully modeled using spring-mass models (Blickhan, 1989), the CoM trajectory can be regarded as a task-relevant variable (van Oeveren et al., 2021). This variable is controlled in such a way that it is reproducible over strides even under the presence of disturbances (Girard et al., 2013). A stable running style should therefore be characterized by a CoM trajectory which shows little variability over strides. The CoM was consequently chosen as the RV in the present thesis. Having chosen the RV, the variables on the execution level, the EV, have to be defined. The majority of existing studies agree that the joint angles represent a suitable choice (Hamacher et al., 2019; Papi et al., 2015; Rosenblatt et al., 2015).

In the following paragraphs, the reasoning and calculation steps necessary for the UCM and TNC approaches are presented. Afterwards, their commonalities and differences are discussed.

2.2.2 UCM

The UCM approach was first published in 1999 as an approach to assess the stability and the level of control of kinematic variables (Scholz & Schöner, 1999). Herein, stability is seen as the ability of a system to return to a given state after a perturbation. This view is similar to its definition in the field of dynamic systems theory (Latash et al., 2007). As kinematic regularities are interpreted as a sign of control (more regular equals tighter control), control is closely related to the notion of stability.

Despite the uncertainties inherent motor control, certain variables show low variability over multiple repetitions. The presence of such a kinematic regularity can only be ensured if there is a stabilizing mechanism which compensates flexibly for perturbations. This regular kinematic feature would be chosen as RV and the stabilization could be done by non-random covariation among EV. Through these covariations, a multitude of equivalent movement solutions exists. These movement solutions are considered equivalent in that they lead to the same value of RV.

The variability over trials among EV can be partitioned in two quantities: the part which does not change the values of the RV and the part which does. All movement solutions which do not change the RV are supposed to be equivalent and are thus not controlled. This first portion of variability is also referred to as parallel variability, $\mathrm{UCM}_{\parallel}$. The second portion, consisting of the solutions changing the RV, lies in a subspace orthogonal to the solution manifold and is referred to as orthogonal variability, $\mathrm{UCM}_{\perp}$ (Scholz & Schöner, 1999). If the amount of $\mathrm{UCM}_{\parallel}$ is greater than the amount of $\mathrm{UCM}_{\perp}$, the control hypothesis about the chosen RV is accepted (Latash et al., 2007).

To analyze a hypothesis about an RV, it has to be expressed as a function of the EV:

$$\mathrm{RV} = f(\mathrm{EV}), \tag{2.1}$$

where f is also referred to as forward model. In the present thesis, where the CoM was chosen as RV and the joint angles where chosen as EV, a 3D anthropometric model was developed based on the Hanavan model (Hanavan, 1964) to calculate the CoM as a function of the joint angles (Möhler et al., 2019). The forward model consists of 17 segments with 50 DoF, which comprise 47 joint angles linking the segments and 3 segment angles of the pelvis. Details of the definitions of the segments can be found in the appendix, section 9.2. As a supplement to the Hanavan model, a neck and a hip segment were included and details such as the shape of the trunk were modified (see Figure 5). To model the segments, 36 anthropometric measures were used. A constant mass density was assumed (Ackland et al., 1988). The mass of each segment was determined via volume integration so that the CoM coordinates ($\boldsymbol{r}_{\mathrm{CoM}}$) result from a weighted sum:

$$\boldsymbol{r}_{\mathrm{CoM}} = \frac{1}{\sum_{i=1}^{N} V_i} \cdot \sum_{i=1}^{N} r_i V_i, \qquad (2.2)$$

where N denotes the number of segments, V_{i} the volume of segment i and $\boldsymbol{r}_{\mathrm{i}}$ the vector of the center of gravity of segment i.

When addressing research questions with the UCM approach, these forward models are highly redundant or abundant (Latash et al., 2010). This results in the fact that several combinations of EV lead to the same RV. The subspace in which all of these equivalent solutions lie is named the solution manifold. Mathematically, the solution manifold is the null space of the Jacobian of f (Khatib, 1987, see equation (2.3). Thereby, the curved solution manifold is linearized around a reference configuration. Usually, the mean configuration for the task at hand is chosen. This linearization is only admissible when the EV show small dispersion over trials (Müller & Sternad, 2003).

$$\mathbf{0} = \boldsymbol{J}\boldsymbol{e}_{\mathrm{i}} \text{ where } \boldsymbol{J} = \left.\frac{\partial f(\boldsymbol{EV})}{\partial EV}\right|_{\boldsymbol{EV}_0} \text{ and } i = 1 \dots n - d. \qquad (2.3)$$

$\boldsymbol{EV}_0$ are the mean values of the EV over trials, $\boldsymbol{e}_i$ are the vectors defining the null space, n is the number of DoF of EV and d is the number of DoF of the RV. The Jacobian $\boldsymbol{J}$ shows the effects of changes in the EV on the RV. Therefore, all EV must have the same respectively compatible units (Müller & Sternad, 2009). In case of EV with different units, a transformation must be performed to compare these EV and their effects. All deviations from the mean joint configuration $\boldsymbol{EV}_0$ can now be projected into the subspace parallel to the solution manifold ($\sigma_{k,\parallel}$) and orthogonal to it ($\sigma_{k,\perp}$):

$$\sigma_{\mathrm{k},\parallel} = \sum_{i=1}^{n-d}\left[\left(\boldsymbol{e}_{\mathrm{i}}^{\mathrm{T}}(\boldsymbol{EV}_{\mathrm{k}} - \boldsymbol{EV}_0)\right)\boldsymbol{e}_{\mathrm{i}}\right], \text{ and} \tag{2.4}$$

$$\sigma_{\mathrm{k},\perp} = (\boldsymbol{EV}_{\mathrm{k}} - \boldsymbol{EV}_0) - \sigma_{\mathrm{k},\parallel}. \tag{2.5}$$

Here, k signifies the current trial with N_{trial} as the number of trials. Subsequently, the variance over all trials in each subspace is computed. Thereby, the variance is normalized per DoF and $\mathrm{UCM}_{\parallel}$ and $\mathrm{UCM}_{\perp}$ are calculated as follows:

$$\mathrm{UCM}_{\parallel} = \sqrt{\frac{1}{(n-d)*N_{\mathrm{trial}}}\sum_{k=1}^{N_{\mathrm{trial}}}\sigma_{\mathrm{k},\parallel}^2}, \text{ and} \tag{2.6}$$

$$\mathrm{UCM}_{\perp} = \sqrt{\frac{1}{d*N_{\mathrm{trial}}}\sum_{k=1}^{N_{\mathrm{trial}}}\sigma_{k,\perp}^2}\ . \tag{2.7}$$

Afterwards, the ratio between these two quantities is calculated as a measure for the degree of control or stability (Latash et al., 2002; Scholz & Schöner, 1999):

$$\mathrm{UCM}_{\mathrm{Ratio}} = \mathrm{UCM}_{\parallel}\ /\ \mathrm{UCM}_{\perp} \tag{2.8}$$

Different modes of calculation for the $\mathrm{UCM}_{\mathrm{Ratio}}$ have been proposed (Latash et al., 2010). Common to all variants is the assumption that when there is more $\mathrm{UCM}_{\parallel}$ than $\mathrm{UCM}_{\perp}$, the control hypothesis about the RV is accepted, resulting in the assumption that there is a synergy stabilizing the RV (Latash et al., 2007). Thereby, this synergy has a certain stability, e.g. resistance against perturbations, which is quantified by $\mathrm{UCM}_{\mathrm{Ratio}}$, and a certain flexibility, e.g. for adaptations, which is quantified by $\mathrm{UCM}_{\parallel}$.

The UCM analysis is an analysis of posture. To apply this analysis to time series data, one has to time-normalize the data and perform a separate analysis for each posture, e.g. each time step. In our case, when analyzing running strides, one stride is seen as a concatenation of postures (Scholz & Schöner, 1999).

To explain the core idea of the approach more clearly, Figure 1 shows an illustrative 2-DoF example. We modelled the leg of a runner consisting of the shank and the thigh, with the foot flat on the ground. Thus, we can define the sagittal plane ankle and knee joint angles (θ_{ankle} and θ_{knee}) as EV, and the height of the hip joint (h_{hip}, red cross) as RV. The movement goal is to keep the height of the hip constant over trials. Our forward model can be expressed as:

$$h_{\text{hip}} = \sin(\theta_{\text{ankle}}) \cdot l_{\text{shank}} + \sin(\theta_{\text{knee}} - \theta_{\text{ankle}}) \cdot l_{\text{thigh}} \tag{2.9}$$

where l_{shank} and l_{thigh} are the lengths of the shank and thigh, respectively. When observing the values of h_{hip} over repetitions (Figure 1 C), there are several combinations which lead to the same value of RV. As the data point cloud formed by the movement executions is elongated in the direction of the isolines, it can be concluded that there is more $\text{UCM}_{\parallel}$ than $\text{UCM}_{\perp}$. Hence, the $\text{UCM}_{\text{Ratio}}$ is greater than one and there is a synergy stabilizing the height of the hip.

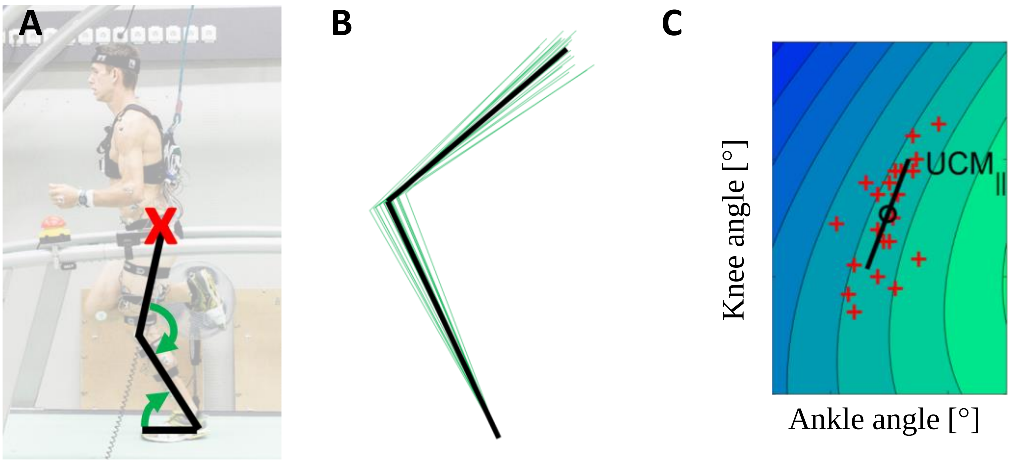

Figure 1: Exemplary illustration of the UCM analysis on a 2 DoF model. (A): The model consists of the foot (flat on the ground), the shank and the thigh; sagittal knee and ankle joint angles are the EV; the height of the hip joint (red cross) is the RV. (B): Several movement executions (thin green lines) and their mean value (thick black line) are illustrated. (C): Sagittal knee angles are plotted vs. ankle angles; the isolines represent constant values of the RV. Several movement executions are shown as red crosses. The black circle represents the mean value and the direction of the solution manifold ($\text{UCM}_{\parallel}$) is depicted as a straight black line.

2.2.3 TNC

Since the human musculoskeletal system is highly redundant, covariation among the EV might be a method to ensure a constant value of RV. However, the classical measure of covariance only compares two variables, which is insufficient to characterize the complex mechanisms underlying movement coordination. In this context, Müller and Sternad (2003) developed an approach to determine the covariation between a multitude of variables by applying randomization methods. By incorporating the additional components tolerance and noise, they extended their approach in their subsequent publication (Müller & Sternad, 2004).

The first of these three components, tolerance (T), describes the fact that there are combinations of EV which are more error-tolerant than others. This means that neighboring positions in the EV space may still lead to the same value of the RV. So, one possible way to improve the consistency of the RV might be to move to a different position in the EV space.

The second component, noise (N), describes the dispersion of the EV. It appears reasonable that by decreasing the dispersion of the EV, the consistency of the RV can be improved. Thus, a functional search in a learning process might cause a temporary increase in N and possibly also in T. Once an optimal position in EV space is found, a smaller dispersion of the EV will again be more favorable (Müller & Sternad, 2009).

The third component, covariation (C), describes compensatory mechanisms among the EV. For example, an increase in one joint could be compensated by a complementary change in other joints.

Within the TNC approach, a difference in performance Δp between two points of time, in the following referred to as PRE and POST, can be described by changes in the three components T, N and C described above (Müller & Sternad, 2004):

$$\Delta p = \Delta T + \Delta N + \Delta C \tag{2.10}$$

To calculate these three components, a forward model has to be defined (equations (2.1) and (2.2)).

Five different data sets of EV (D1 – D5) are needed for the calculation of T, N and C. For each data set the value of the RV has to be calculated and a measure of performance has to be determined to quantify the changes in performance. In the example introduced above (see Figure 1), this measure of performance can be formulated as the standard deviation of the height of the hip joint. The first data set, D1, consists of the values of the EV recorded in PRE (see Figure 2). Even though it might be possible to measure the value of RV and the performance in this case, it has to be determined using *f* (Müller & Sternad, 2004).

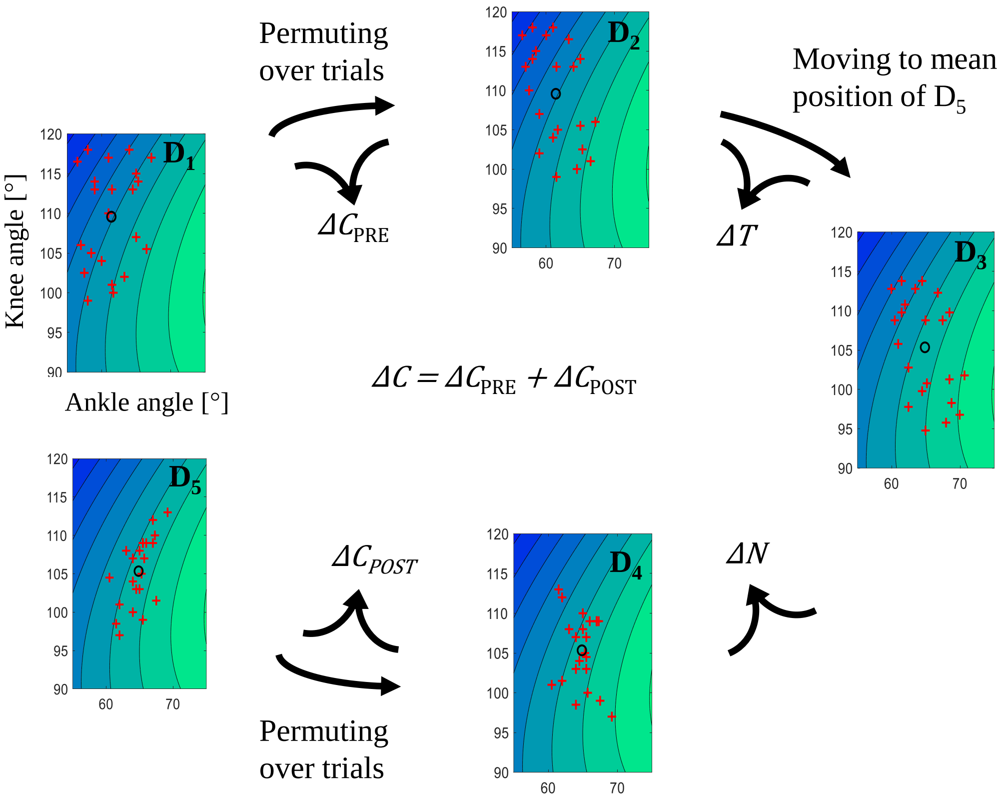

Figure 2: Illustration of the TNC approach. The five datasets which are needed for the calculation of T, N and C are shown. D_1 and D_5 are representative data recorded before and after an intervention. D_2 and D_4 are obtained from D_1 and D_5, respectively, by performing a permutation procedure. D_3 is obtained by moving D_2 to the position of D_4 and D_5.

Analogous to D_1, D_5 consists of the values of the EV recorded in POST (after the learning/intervention).

D_2 is obtained by permuting the values of D_1 over trials, so that all possible covariation is removed. Therefore, D_2 has the same mean value and dispersion as D_1, but no covariation since all compensatory effects are removed. This permutation has to be performed numerous times and a mean performance will be used in the subsequent calculations.

Analogously, D_4 is obtained by permuting the values of the EV from D_5 over various trials so that the data in D_4 have the same mean value and dispersion as the data in D_5 without covariation. Using the performance obtained with D_1, D_2, D_4 and D_5 the value of ΔC can be determined:

$$\Delta C = \Delta C_{PRE} + \Delta C_{POST} = p(D_5) - p(D_4) + p(D_2) - p(D_1). \tag{2.11}$$

Where $p(D_i)$ signifies the performance of D_i.

The third dataset, D_3, is obtained by moving D_2 to the position of D_4 in EV space. This means that the mean value of the EV of D_1, which describes the position of D_1 and D_2 in the execution space, is subtracted and the mean value of D_4 is added. Therefore, D_3 is a dataset with no covariation but with the same dispersion as D_1 and D_2 and the same mean values as D_4 and D_5. Since the only difference between D_2 and D_3 is their position in the execution space (see Figure 2), ΔT can be calculated by comparing the performances of these two data sets:

$$\Delta T = p(D_3) - p(D_2). \tag{2.12}$$

ΔN can be calculated by comparing the performances of D_3 and D_4. Since both data sets are at the same position and have no covariance, they differ only in their dispersions:

$$\Delta N = p(D_4) - p(D_3). \tag{2.13}$$

Having calculated ΔT, ΔN, and ΔC, changes in variability or performance between PRE and POST can now be attributed to different mechanisms. Since the analysis is performed in the RV space, changes in variability among the EV which do not affect the RV (captured in the UCM approach in the component $UCM_{\parallel}$) cannot be seen. Just like the UCM approach, the TNC approach is an analysis of posture. So, when performing a TNC analysis, separate analyses for each time step are performed.

2.2.4 Commonalities and differences of the presented approaches

Both the UCM and the TNC approach are based on a common assumption: for each movement, there is an important variable which is closely controlled and thus shows a relatively low variability over movement repetitions (Scholz & Schöner, 1999). As outlined above, this variable is chosen as the RV. To ensure the low variability of the RV, there have to be compensatory mechanisms at the level of the EV. The main difference between the UCM and the TNC approaches is based on the different levels of analysis. The UCM analyzes the SSV on the level of the EV, whereas the TNC analyzes it at the level of the RV. Most conclusions about differences between the two approaches are based on this main difference (Müller & Sternad, 2009; Schöner & Scholz, 2007).

Since the UCM analyzes variability on the level of EV, the analysis can only be performed if all EV have compatible units (Müller & Sternad, 2009). In case of EV with different units, a transformation must be performed to compare these EV and their effects. The forward model *f* used in the calculation of the RV within a UCM analysis has to be differentiable with respect to the EV to be able to determine the Jacobian $\boldsymbol{J}$. Additionally, in the process of calculating $\mathrm{UCM}_{\parallel}$ and $\mathrm{UCM}_{\perp}$, a linearization is performed. Even though this approximation might often be negligible, non-linear relationships cannot be analyzed using the UCM (Müller & Sternad, 2009). The possible errors induced by the linearization are difficult to quantify but have to be kept in mind (Müller & Sternad, 2009; Scholz & Schöner, 1999).

In contrast to the UCM approach, the TNC approach performs the analysis in the result space. This means that variability over trials is not analyzed on the level of EV, as done in the UCM. Instead, the EV are manipulated and the effects on the RV are observed. This has the advantage that EV with different units can be combined within *f* and *f* does not have to be differentiable. Additionally, no linearization has to be performed (Müller & Sternad, 2009). However, only variability which affects the RV is visible so the variability among the EV which does not affect the RV is not seen. Furthermore, since T, N and C show possible developments, they can only describe changes from one point in time to another, e.g. in a learning process. A single point in time cannot be analyzed. This limitation was however addressed by developing a numerical method to determine an “optimal reference” (Cohen & Sternad, 2009).

Apart from these methodological differences, further interpretation-related points should be mentioned. After performing a UCM analysis, one can make statements about the stability or the degree of control of an RV (Latash et al., 2007). This is not possible after a TNC analysis, since the components T, N and C are not able to explain why and how the distribution of EV and the consistency of the RV change. What they can do is to find three different mechanisms which underlie changes in variability. Besides these differences, some parallels can be drawn between the results obtained with both approaches. Changes in the component N should also be visible as changes in $\mathrm{UCM}_{\perp}$. Changes in the component C should represent changes in the distribution of variability into $\mathrm{UCM}_{\perp}$ and $\mathrm{UCM}_{\parallel}$ and thus in the $\mathrm{UCM}_{\mathrm{Ratio}}$. In a one-dimensional space, it was shown that the results concerning covariation obtained with the two approaches are equivalent (Verrel, 2011). Changes in the component T will not be visible in the results of a UCM approach, just as changes in $\mathrm{UCM}_{\parallel}$ will not be visible in a TNC approach.

When thinking about an appropriate approach for analyzing SSV, one should have in mind the specificities of the two approaches. As outlined above, the two approaches should not be seen as in rivalry with each other, but as based on the same conceptual assumption, using distinct procedures and thus having different fields of application.

2.3 Expertise

In the following two paragraphs, findings regarding the effects of expertise on both running kinematics and SSV will be summarized. It might be of interest to mention that expertise can be defined differently, e.g. based on years of running experience, weekly mileage or running performance. Here, no distinction was made between the different definitions.

2.3.1 Effects of Expertise on Running Kinematics

A number of studies have looked at the effects of expertise on running kinematics, of which most are cross-sectional. Nelson and Gregor (1976) however performed a longitudinal study. They observed that both stride time and time of support decreased with increasing experience. This decrease in stride time was not found in other studies (Agresta et al., 2018; Cavanagh et al., 1977). Also, the decrease in ground contact time was not found again (Gómez-Molina et al., 2017; Padulo et al., 2012). This contradiction might be explained by a non-fixed running speed in the study of Nelson and Gregor (1976). Stride length, however, seems to be clearly influenced by running experience. Only one study found an increase in stride length (Padulo et al., 2012), whereas several others found a shorter stride length in more experienced runners (Cavanagh et al., 1977; Gómez-Molina et al., 2017; Nelson & Gregor, 1976; Slawinski & Billat, 2004). Since stride time was mostly found to be unaffected, but stride length seems to be reduced, one might expect an increase in stride frequency with experience. This was indeed found in several studies (Cavanagh et al., 1977; Gómez-Molina et al., 2017; Nelson & Gregor, 1976; Slawinski & Billat,

2004) while only one study found a lower cadence in more experienced runners, which is in accordance with the increase in stride length observed in their study (Padulo et al., 2012).

Concerning joint kinematics, the results are less clear. Cavanagh et al. (1977) found qualitative differences in plantarflexion whereas Agresta et al. (2018) found no differences in the observed kinematic parameters. Using machine learning approaches, Clermont et al. (2017) could separate competitive from recreational runners using a support vector machine. The separation was mainly based on pelvic tilt, knee flexion and ankle eversion. The classification rate of 100% suggests that there are distinct running patterns for competitive and recreational runners. In another study by Boyer et al. (2014), a principal component analysis method was used to look for differences in coordination between runners with different mileages. They conclude, mainly based on hip and knee kinematics, that the coordination of the lower extremities differs between higher and lower mileage runners.

Overall, there are differences in running kinematics depending on experience. These differences are visible in both spatiotemporal parameters and joint kinematics. Due to the limited number of studies and the influence of running speed, more highly standardized studies are needed to draw clear conclusions about the effects of experience on running kinematics.

2.3.2 Effects of Expertise on Stride-to-Stride Variability

Only a few studies have analyzed the effect of expertise on SSV in running. Using a detrended fluctuation analysis, Nakayama et al. (2010) showed that stride interval variability was smaller in more experienced runners, indicated by a lower scaling exponent. This is contradictory to the results of Mo and Chow (2018a), who found a higher scaling exponent in the more experienced runners and no differences in stride interval variability. However, running speed differed between experts and novices in both studies. There are two studies quantifying coordination variability using either a continuous relative phase approach (Floría et al., 2018) or a coupling angle approach (Mo & Chow, 2018b). Mo and Chow (2018b) found a higher variability in the more experienced runners, whereas Floría et al. (2018) found a lower variability in the more experienced group.

Overall, there is no consensus on how SSV is affected by expertise. This might be due to the limited number of studies and to the different methodologies applied.

2.4 Fatigue

Fatigue is an important topic for chronically sick people or during daily physical labor, but also during sports (McKenna & Hargreaves, 2008). Running, as an endurance sport, involves fatigue by definition. When talking about the effects of fatigue one has to keep in mind that there are different definitions of fatigue (Gandevia, 2001). Fatigue basically starts right from the onset of the task and increases progressively until task failure, which will here be described as exhaustion. Therefore, an exemplary definition from Barry & Enoka (2007) claims that fatigue is an exercise-induced reduction in the ability of the muscle to produce force or power, whether or not the task can be sustained. This definition is often extended by a term referring to the reversibility of this reduction (Gandevia, 2001). Even if fatigue undoubtedly directly affects the functioning of the muscles (Place et al., 2010), one has to keep in mind that is it ultimately the brain which tells us when to stop (Secher et al., 2008). Fatigue can thus be seen as a combination of subjectively perceived fatigability and objectively measurable performance fatigability. Therefore, objective measures of fatigue are not sufficient, and an additional subjective judgement is needed (Enoka & Duchateau, 2016).

Fatigue effects can be separated into those happening before and beyond the neuromuscular junction, referred to as central and peripheral fatigue (Enoka & Stuart, 1992). This differentiation is however not always useful, since performance is not limited by one isolated factor, but rather by the interaction of physiological and psychological factors (Barry & Enoka, 2007; Nybo & Secher, 2004). Central fatigue may be seen as a protection mechanism of the muscles to prevent further peripheral fatigue by hindering muscle excitation, since further exercise could lead to the impairment of other essential processes such as temperature regulation or respiration (Gandevia, 2001). Thereby fatigue is not only a negative phenomenon but also has a positive connotation (McKenna & Hargreaves, 2008). The fatigue-induced impairments on different levels of the neuromuscular system probably affect running kinematics as well as movement variability, which will be further discussed in the following paragraphs.

2.4.1 Effects of Fatigue on Running Kinematics

Most of the current studies addressing the effects of fatigue on running kinematics focus on long distance running (Kim et al., 2018; Winter et al., 2017). Even though the studies clearly show that running kinematics are affected by fatigue, no coherent findings can be formulated.

This may be due to the differences in samples, running surface and the underlying fatigue protocol. Research concerning middle-distance running is even more limited. Schütte et al. (2018) found a decreased step frequency and an increased contact time in recreational runners after a maximal effort run of 3200 m. These findings were however confounded by running speed, and therefore cannot solely be attributed to fatigue (Schütte et al., 2018). This underlines the importance of keeping the running speed constant, so that only fatigue is varied. When focusing on studies with high level runners running at a fixed speed, the research gap becomes even more apparent. Hayes et al. (2014) analyzed sub-elite middle-distance runners at a constant speed during an exhaustive run (6.9 ± 1.3 min) and found that their leg stiffness decreased, even though the vertical stiffness did not. The decrease in leg stiffness was correlated with the ground contact time and the step length. The ground contact time, step length and the vertical CoM displacement increased with fatigue. Fourchet et al. (2015) found increases in contact time, peak vertical ground reaction force and CoM displacement after an exhaustive run of 8.8 ± 3.4 min in highly trained adolescents. Leg stiffness and flight time decreased. Rabita and colleagues (2011) analyzed elite triathletes during a run to exhaustion (10.7 ± 2.6 min) at a constant velocity on an indoor track, and found a decrease in leg stiffness and vertical and propulsive ground reactions forces but no changes in vertical stiffness. Additionally, they found an increase in step frequency and contact time as well as a decreased step length - which contrasts the findings of Hayes et al. (2014). This difference might be explained by the difference between treadmill running and running on an indoor track.

There are only a few studies analyzing the effects of fatigue on joint kinematics in competitive runners. Radzak et al. (2020) analyzed participants of the Army Reserve Officers Training Corps and found increases in hip adduction angles, hip internal rotation velocities, knee adduction and knee internal rotation velocities. However, the study had methodological weaknesses in their measurement protocol. Abt and colleagues (2011) analyzed competitive runners during an exhaustive run of 17.8 ± 5.7 min. Using triaxial accelerometers, no effects of fatigue on knee flexion or ankle pronation were found. Hayes et al. (2004) found no changes in hip and knee angles after a run until exhaustion (6.9 ± 1.3 min) in sub-elite runners.

Maas et al. (2018) studied the effects of an exhaustive run at a pace previously ran during a 3200 m time trial on joint kinematics in both novice and competitive runners. In the competitive group, they reported increases in pelvic tilt, range of motion (RoM) and ankle plantarflexion; and decreases in hip adduction. Effects in novices were greater. Increases were seen in pelvic tilt, pelvic rotation RoM, ankle plantarflexion, trunk forward lean and hip abduction. Using a wearable sensor system, Strohrmann et al. (2012) performed an exhaustive 45 min run. They found a decrease in step frequency across different skill levels and an increase in vertical oscillation, shoulder rotation and forward lean in novices. One study focusing on the effects of fatigue in novice runners (Koblbauer et al., 2014) found increases in trunk inclination and increases in ankle eversion after a fatigue protocol (19.7 ± 7.8 min). Derrick et al. (2002) found a more flexed knee and a more inverted rearfoot angle at heel strike after a run to exhaustion (15.7 ± 1.7 min) in recreational runners. A recent study by Yu et al. (2021) found several changes after a fatiguing running protocol in the lower limbs in novice runners. However, as the running speed was not controlled, the results might have been compromised by the effects of different running speeds (van Oeveren et al., 2021).

To date, there is a lack of studies analyzing the effects of fatigue on both novice and experienced runners, especially during middle-distance runs. Even though a consensus might exist concerning single discrete parameters, e.g. decreases in stiffness or increases in ground contact time in expert runners, there is a lack of knowledge concerning the effects of fatigue on joint kinematics. In novices, the effects of fatigue on spatiotemporal parameters are even less well understood.

2.4.2 Effects of Fatigue on Stride-to-Stride Variability

When thinking of sports movements, cyclic motion is a special case since the actual movement is performed innumerable times. This is similar to former studies on craftsmen (Côté et al., 2002, 2005, 2008) and thus might be an ideal example of “repetition without repetition” (Bernstein, 1967). Cignetti et al. (2009) analyzed cross country skiing and found more variability, noise and instability in a fatigued state. They argued that in the beginning, a flexible behavior might be favorable since it enables the athlete to adapt for possible perturbations. This ability degraded with fatigue, which is manifested by more random fluctuations. Nielsen et al. (2018) found compensatory mechanisms under peripheral/muscular fatigue during cycling. Due to these mechanisms, the (effective) orientation of the pedal force could be kept constant throughout fatigue. Looking at the effects of fatigue on SSV during running, Meardon et al. (2011) found a more variable stride time in recreational runners after a fatiguing run of about 27 min. Chen et al. (2020) found more variability in several coupling angles (pelvis vs. thigh and shank vs. rearfoot in the frontal plane) after a half marathon in recreational runners. Schütte et al. (2018) showed that throughout an exhaustive run of 3200m, the vertical step regularity decreased in recreational runners. Using a modified vector coding technique, Hafer et al. (2017) found no differences in coordination variability (thigh vs. shank in the sagittal plane, pelvis vs. thigh in the frontal plane, thigh in the sagittal vs. shank in the transverse plane) after an exhaustive run of about 25 min.

The few studies which analyzed the effects of fatigue on the SSV in running mostly looked at the variability of single parameters or at the combination of two parameters. Even though these results are valuable, they do not allow conclusions to be drawn about the effects of fatigue on the interplay between the many DoF in the human body. Hence, there is a lack of studies using complex analyses incorporating more DoF when analyzing the effects of fatigue on movement variability during running.

2.5 Stride-to-Stride Variability and Running Related Injuries

There are a number of current reviews discussing reasons for running related injuries (RRI) (Ceyssens et al., 2019; Vannatta et al., 2020). Ceyssens et al. (2019) focused on prospective studies and stated that biomechanical factors are thought to play an important role. This would be promising, since these factors are modifiable. For example, greater peak hip adduction and greater peak knee internal rotation could lead to more stress on the iliotibial band and the patellofemoral joint, and smaller peak knee flexion could be a sign of less shock absorption. These relationships are in line with retrospective studies; however, conflicting results are obtained for other biomechanical variables. Neither trunk nor pelvis kinematics were studied in the existing prospective studies. Vannatta et al. (2020) confirm the findings of Ceyssens and colleagues (2019) and extend their results by a meta-analysis. As done by Ceyssens et al. (2019), they only consider prospective studies. At least in female runners, several biomechanical factors concerning the lower limbs, like increased peak hip adduction, knee internal rotation and femoral external rotation and a decreased peak eversion, may favor the development of iliotibial band syndrome and patellofemoral pain syndrome. A higher step rate was assumed to be related to shin injuries.

RRI are mostly overuse injuries (Ceyssens et al., 2019), which emphasizes the importance of variability. More variability allows the possibility of distributing stresses, since various different structures are loaded. Hamill et al. (2012) show in their review that a higher variability is related to a healthier state. However, this is only shown by retrospective studies and not as a causative relationship. So, it is not clear whether the observed reductions in variability lead to or result from injury. Studies analyzing the variability in the context of RRI found a reduced variability in runners with lower back pain (Seay et al., 2011). Heiderscheit (2002) found a reduced variability for the thigh-leg rotation coupling around heel strike in a patellofemoral pain group. They hypothesize that the lower variability might lead to a reduced ability to adapt to unanticipated perturbations. Other studies found no differences (Schütte et al. 2018: medial tibial stress syndrome, Hafer et al., 2017 and Hein et al. 2012: iliotibial band syndrome) or even a higher variability in the injured group (Cunningham et al. 2014: patellofemoral pain and Desai and Gruber, 2021 in a prospective study).

Fatigue might favor the development of RRI since several risk factors are modified under fatigue (Clansey et al., 2012; Mizrahi et al., 2000; Radzak & Stickley, 2020). Some studies analyzed the effects of fatigue on variability in the context of RRI. Meardon et al. (2011) found a tendency to a lower stride time variability in the injured group, as well as Miller et al. (2008), who found less variability in several couplings in a fatigued state in a group with iliotibial band syndrome. So, fatigue might favor movement patterns which increase the risk of RRIs.

Independent of aspects of SSV, novices might be at an increased risk of injury compared to more experienced runners. Buist et al. (2010) found that running experience was the most important risk factor in their study. The fact that experience is a risk factor for RRI is supported by other studies (Kemler et al., 2018; Videbæk et al., 2015).

RRI are closely related to movement variability, and fatigue might favor RRI through disadvantageous effects on joint kinematics. Novices seem to be more prone to injuries than more experienced runners. Therefore, it is necessary to gain further insights into the consequences of a fatiguing mid-distance run on running kinematics and SSV in experts as well as novices.

2.6 Aims of This Thesis

Based on the above-mentioned unanswered questions in the field of movement variability, this thesis aims to reveal the differences in SSV between experts and novices, and to unravel the effects of fatigue on kinematics and SSV in middle-distance running. Special attention is given to SSV by using complex models which incorporate dependencies between the multiple (and redundant) DoF of the human body. A subgoal of this thesis was thereby to verify the applicability of the UCM and the TNC approaches to problems from applied sport science. To address this issue, three experiments were conducted, providing the data that were analyzed in five studies (four studies published in peer-reviewed journals, the fifth study is currently under review) as the core of this thesis. Each of these five studies has a specific aim:

I. To analyze the effects of expertise on the structure of SSV in expert and novice runners using the UCM approach with a subject-specific 3D model.

II. To analyze the possible effects of fatigue on spatiotemporal parameters, leg and vertical stiffness, 3D joint kinematics time series as well as the CoM trajectory during a middle-distance run in competitive runners.

III. To analyze the effects of fatigue on the structure of SSV during running using the UCM approach. Two different models were used to better understand their influence on the outcome of the analysis.

IV. To investigate if and how runners adjust their CoM trajectory and its variability during a run to fatigue. Additionally, the results obtained here with the TNC approach were compared with those obtained with the UCM approach.

V. To analyze the possible effects of fatigue on spatiotemporal parameters, leg and vertical stiffness, 3D joint kinematics time series as well as the CoM trajectory during a middle-distance run in novice runners.

Chapters 3 to 7 comprise the detailed elaboration of the studies while addressing these specific aims.

3. Topic A – Expertise: Variability of Running Coordination in Experts and Novices: a 3D Uncontrolled Manifold Analysis

Slightly modified version of the paper published as:

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3.1 Abstract

The UCM approach has been widely used in recent studies to examine variability in daily tasks; however, it has not yet been used to study running or the effects of expertise. Therefore, the aim of this study was to analyze the synergy structure stabilizing the CoM trajectory in experts compared to novices during running at two different speeds using a subject-specific 3D model.

A total of 25 healthy young adults (13 experts, 12 novices) participated in the study. All subjects ran at 10 and 15 km/h on a treadmill. In each case, kinematics of 20 consecutive strides were recorded and the effects of expertise and gait cycle phase on the synergy structure were investigated at both speeds. Specifically, the variance affecting the CoM ($\mathrm{UCM}_{\perp}$), the variance not affecting the CoM ($\mathrm{UCM}_{\parallel}$), and their ratio ($\mathrm{UCM}_{\mathrm{Ratio}}$) were analyzed.

Descriptively, in both groups there was a synergy stabilizing the CoM trajectory in running. However, the ANOVA showed no differences in $\mathrm{UCM}_{\mathrm{Ratio}}$ between the two groups. In novices, $\mathrm{UCM}_{\perp}$ and $\mathrm{UCM}_{\parallel}$ were significantly higher compared to experts at the 15 km/h condition. In both groups, there was more variability in the stance phase compared to the flight phase in the majority of cases.

The results indicate that experts adopted a more consistent running style. The SSV was diminished but not abolished. This difference was only visible at the 15 km/h condition. Furthermore, variability was less constrained in the stance phase compared to the flight phase.

3.2 Introduction

All movements in sports have goals (e.g. win the running competition) but also costs (e.g. energy consumption). Therefore, athletes undergo long-term practice to optimize the cost-benefit ratio of their movements. This idea is reflected in the framework of optimal feedback control (Todorov, 2004; Todorov & Jordan, 2002). Against this background, a naive assumption with regard to motor coordination could be that all aspects of an athlete’s movement are consistent across repeated executions, because they are the result of deliberate practice (Anders Ericsson et al., 1993). However, due to redundancy of the motor system, consistency in goal achievement could theoretically be accomplished by a variety of kinematic patterns as shown by Bernstein’s (1967) famous analysis of blacksmiths.

Sports biomechanics research has in fact found that athletes produce variable kinematic patterns (Bartlett et al., 2007). The degree of variability seems to depend on the importance of the movement for the desired outcome: aspects contributing directly to the desired outcome are more consistent, while other aspects of the movement are variable (Todorov & Jordan, 2002).

An approach quantifying this observation is the UCM approach (Scholz & Schöner, 1999). The UCM approach provides a computational approach to analyze how the central nervous system (CNS) deals with the abundant degrees of freedom. More specifically, the UCM approach tests the hypothesis whether variability on the level of EV, e.g. joint angles is structured in a way to stabilize a variable on the level of RV, e.g. CoM trajectory. In this regard, several combinations of EV produce the same RV outcome. Therefore, observed movement variability over several repetitions can be separated into $\mathrm{UCM}_{\perp}$, which changes the RV; and $\mathrm{UCM}_{\parallel}$, which does not (Latash et al., 2007; Scholz & Schöner, 1999). This $\mathrm{UCM}_{\parallel}$ is thought to stabilize the RV by representing multiple ways to successfully achieve a consistent performance and reach additional goals (e.g. a constant stride length and frequency in running). The ratio between $\mathrm{UCM}_{\parallel}$ and $\mathrm{UCM}_{\perp}$ ($\mathrm{UCM}_{\mathrm{Ratio}}$) indicates whether there is a “synergy” stabilizing the RV (Latash et al., 2002, 2007). If $\mathrm{UCM}_{\parallel}$ is greater than $\mathrm{UCM}_{\perp}$, the subject is able to stabilize the performed movement through a multitude of equivalent movement solutions. This can be seen as a quantification of the minimum intervention principle, since $\mathrm{UCM}_{\parallel}$ represents movement variability, which does not need to be corrected since it does not compromise the movement goal.

Previous research showed that the two components of variability are affected differently by practice, resulting in a decrease or sometimes an increase in total variability (Wu & Latash, 2014). Iino et al. (Iino et al., 2017) and Nisky et al. (Nisky et al., 2014) studied the differences in the synergy-structure between experts and novices in table tennis forehand and in a surgical movement, respectively. Both found higher $\mathrm{UCM}_{\mathrm{Ratio}}$ in experts due to a lower $\mathrm{UCM}_{\perp}$.

Studies using the UCM approach to analyze human locomotion used different variables to represent successful task fulfilment and thus which might be controlled by the CNS. Some studies focused on the position of the swing foot (Krishnan et al., 2013), others assumed the total angular momentum to be the PV (Robert et al., 2009) and still others looked at head position (Black et al., 2007). However, most of the studies agree that control of the CoM trajectory is one of the most important RVs (Black et al., 2007; Papi et al., 2015; Vito et al., 2018). These studies used either a purely geometrical model (Papi et al., 2015; Vito et al., 2018) or a segmented-mass model (Black et al., 2007; Qu, 2012) to calculate the CoM. Common to all these models is a restriction to two dimensions. However, as suggested by Papi et al. (2015), there is a strong need for three dimensional analysis. Finally, although different walking velocities have been analysed (Vito et al., 2018), yet no study has analyzed running with the UCM approach. Besides studies underlining the effects of expertise on spatio-temporal parameters (Padulo et al., 2012) and joint kinematics (Leskinen et al., 2009), there exist studies which analyzed the effects of expertise on running coordination and its variability. While Floría et al. (2018) and Mo & Chow (2018b) analysed the interplay of two degrees of freedom, Boyer et al. (2014) took into account the motion of the whole body. However, none of these studies can answer the question if coordination variability is structured according to the minimum intervention principle.

Against this background, we are interested in the question whether movement variability is structured differently in experienced athletes compared to novices in running. Therefore, the purpose of the present study was to analyze the effects of expertise on the synergy structure stabilizing the CoM trajectory in two groups: experienced runners (experts) compared to none-runners (novices). Participants were analysed during running at two different speeds (10 km/h and 15 km/h) using an UCM approach with a subject-specific 3D model and the CoM trajectory serving as the RV. We hypothesized that at higher running speed, experts show stronger synergies compared to novices because of the long-term training at a wide range of speeds. This should be reflected by a higher $\mathrm{UCM_{Ratio}}$ due to a lower amount of $\mathrm{UCM_{\perp}}$.

3.3 Methods

3.3.1 Subjects

A total of 25 healthy young adults, 13 experts and 12 novices, participated in the study (see Table 2). The inclusion criteria for the experts were a 10 km record below 35 min (run within the last year), a minimum of distance covered of 50 km/week during the eight weeks preceding the experiment and membership of a running club for at least two years. The inclusion criteria for the novices were a maximum of two training sessions per week, including a maximum of one running session, and having never trained in a running club or for a running event. Exclusion criteria for both groups were recent injuries or pain in the lower limbs. All subjects provided written informed consent. The study was approved by the ethics committee of the Karlsruhe Institute of Technology.

Table 2: Sample characteristics (mean ± standard deviation); BMI: body mass index; VL3: running speed at 3 mmol/L lactate; p values as revealed by independent t-tests, * p< 0.05

	Experts	Novices	p
Sample size [N]	13	12	-
Age [years]	23.5 ± 3.6	23.9 ± 3.8	0.769
Height [m]	1.80 ± 0.06	1.83 ± 0.07	0.361
Weight [kg]	66.8 ± 5.4	72,2 ± 6,6	0.044*
BMI [kg/m²]	20.6 ± 1.7	21,6 ± 1,5	0.143
Physical activity [h/week] (including running)	8.2 ± 1.9	0.8 ± 0.6	< 0.001*
Running [h/week]	6.5 ± 1.7	0.2 ± 0.2	< 0.001*
Running training [years]	7.2 ± 3.2		
10 km record [min:sec]	32:59 ± 01:19		
VL3 [m/s]	4.67 ± 0.29		

3.3.2 Experimental Protocol

All subjects started with a familiarization on the treadmill (h/p/cosmos Saturn, Nussdorf-Traunstein, Germany). This consisted of 6 minutes of walking (Matsas et al., 2000) followed by 6 minutes of running (Lavcanska et al., 2005). At the end of the familiarization, the treadmill was accelerated up to 15 km/h and held at this speed for 15 seconds, followed by a 2-minute break.

Then, the measurement itself began: all subjects were asked to run at 10 and 15 km/h for 1 minute to collect 20 consecutive strides in each case. Previous studies revealed that spatio-temporal parameters as well as joint kinematics are sensitive to running speed (Jordan et al., 2007; Padulo et al., 2012). In addition, Cazzola et al. (2016) found changes with speed in coordination variability in race walking. For this reason, we asked experienced runners about their usual training speeds and chose to perform our analysis at two different running speeds: 15 km/h, which is a usual training speed for the experts and 10 km/h, which should be comfortable for the novices and not too slow for the runners.

The two conditions were performed in a counterbalanced order. Between the two conditions, subjects had 2 minutes of rest. Subjects were instructed to look ahead and to not perform undesired movements like looking at their wristwatch during their performance. One subject of each group at the 10 km/h condition had to be excluded from analysis due to unwanted movements. To prevent falls, all subjects were held in a safety harness during the experiment, which did not interfere with the subjects.

3.3.3 Data Collection and Processing

A total of 22 anthropometric measurements of each subject were taken manually followed by the attachment of 41 reflective markers. Both steps were conducted according to the ALASKA (Advanced Lagrangian Solver in kinetic Analysis) modelling system (Härtel & Hermsdorf, 2006). Then, the subjects had to complete the treadmill protocol as described above. Subjects' kinematics were recorded by 11 Vicon MX cameras at 200 Hz (Vicon Motion Systems; Oxford Metrics Group, Oxford, UK).

After data collection, the kinematic data were processed using Vicon Nexus software V1.8.5 and filtered using a fourth order low-pass Butterworth filter with a cutoff-frequency of 10 Hz using MATLAB R2017b (The MathWorks, Natick, MA, USA). Marker trajectories and anthropometric measurements (22 measured manually, 43 determined from the reflective markers according to the requirements of the ALASKA modelling system) allowed segment angles to be calculated using inverse kinematics with the full-body Dynamicus model (ALASKA, insys GmbH, Chemnitz, Germany; Härtel and Hermsdorf, 2006).

For each subject and condition, the 20 strides captured were each divided into stance phase and flight phase. Stance phase was further divided into absorption and propulsion (Novacheck, 1998). The absorption phase is characterized by a downward motion of the CoM, whereas the CoM rises during propulsion. We calculated the mean for each of the phases and for each of the UCM variables.

For each subject and condition, the 20 consecutive strides were time-normalized (from right foot strike to right foot strike) to 100 time steps using custom-made MATLAB routines. Following Leitch et al. (2011), foot strike was determined as the timeframe where the speed of the heel or foot marker changed its sign; and toe off was determined using the peak acceleration of the toe marker.

3.3.4 Uncontrolled Manifold Approach

We applied the UCM approach to our data with the whole body CoM trajectory serving as the RV. We therefore developed an anthropometric model of the human body which allowed us to calculate the subject-specific whole-body CoM as a weighted sum of the body segments. This gives us the relationship between the EV (joint angles) and the RV (CoM). Building on this, we decomposed the variability into the proportion that affected the RV ($\mathrm{UCM}_{\perp}$) and the proportion that did not ($\mathrm{UCM}_{\parallel}$) (Latash et al., 2007; Scholz & Schöner, 1999).

Anthropometric Model of the Human Body

Based on the model of Hanavan (1964), we developed a 3D anthropometric model of the human body, consisting of 17 segments and 50 degrees of freedom (47 segmental angles and 3 hip rotations). Compared to the model developed by Hanavan (1964), ours included the neck and hip as segments and modified segments (e.g. the shape of the trunk was changed using more subject-specific measurements) assuming a constant density (Ackland et al., 1988). The dimensions of the segments were determined via 36 subject-specific anthropometric measurements (21 measured manually, 15 determined through the reflective markers). Each segment's mass was determined via volume integration.

The whole-body CoM ($\boldsymbol{r}_{\mathrm{CoM}}$) was calculated as a weighted sum:

$$\boldsymbol{r}_{\mathrm{CoM}} = \frac{1}{\sum_{i=1}^{N} V_{\mathrm{i}}} * \sum_{i=1}^{N} \boldsymbol{r}_{\mathrm{i}} V_{\mathrm{i}} \tag{3.1}$$

With N as the number of segments; V_{i} as the volume of the segment i; and $\boldsymbol{r}_{\mathrm{i}}$ as the position vector of the center of gravity of segment i.

UCM-based Decomposition of Stride-to-Stride Variability

Since we hypothesized that the CoM trajectory is the variable being controlled during walking and running (Black et al., 2007; Papi et al., 2015), we needed to link changes in joint angles (θ, EV) with changes in the CoM ($\boldsymbol{r}_{\text{CoM}}$, RV). Therefore, we expressed the RV as a function of the EV: RV $= \boldsymbol{r}_{\text{CoM}} = f(\text{EV}) = f(\boldsymbol{\theta})$. Then, following the UCM approach (for details see Black et al., 2007; Scholz & Schöner, 1999), we calculated the null space of the Jacobian (Khatib, 1987), representing the space in which alterations of the EV do not cause alterations of the PV:

$$0 = \boldsymbol{J}\boldsymbol{e}_{\text{i}}; \boldsymbol{J} = \left.\frac{\partial f(\boldsymbol{\theta})}{\partial \theta}\right|_{\boldsymbol{\theta}_0}; i = 1 \dots n - d. \tag{3.2}$$

$\boldsymbol{\theta}_0$ are the mean values of the EV over the 20 strides, $\boldsymbol{e}_{\text{i}}$ are the vectors defining the null space. n is the number of dimensions of EV and d is the number of dimensions of the PV (here: $n = 50$ and $d = 3$).

The deviation of the mean joint configuration ($\boldsymbol{\theta}_0$) was separated into deviations that were parallel to the UCM (those stabilizing the PV, $\sigma_{\text{k},\parallel}$) and deviations that were orthogonal to the UCM (those that stabilize the PV, $\sigma_{\text{k},\perp}$). These calculations were performed for every percent of the gait cycle.

$$\sigma_{\text{k},\parallel} = \sum_{i=1}^{n-d}\left[\left(\boldsymbol{e}_{\text{i}}^{\text{T}}(\boldsymbol{\theta}_{\text{k}} - \boldsymbol{\theta}_0)\right)\boldsymbol{e}_{\text{i}}\right] \tag{3.3}$$

$$\sigma_{\text{k},\perp} = (\boldsymbol{\theta}_{\text{k}} - \boldsymbol{\theta}_0) - \sigma_{\text{k},\parallel}; k = 1 \dots N_{\text{trial}} \tag{3.4}$$

The variability parallel and orthogonal to the UCM was than calculated as the variance over the $N_{\text{trial}} = 20$ strides:

$$UCM_{\parallel} = \sqrt{\frac{1}{(n-d)*N_{\text{trial}}}\sum_{k=1}^{N_{\text{trial}}}\sigma_{\text{k},\parallel}^2} \tag{3.5}$$

$$UCM_{\perp} = \sqrt{\frac{1}{d*N_{\text{trial}}}\sum_{k=1}^{N_{\text{trial}}}\sigma_{\text{k},\perp}^2} \tag{3.6}$$

We calculated the quotient between these two quantities as

$$UCM_{Ratio} = \frac{2*UCM_{\parallel}{}^{2}}{UCM_{\parallel}^{2}+UCM_{\perp}{}^{2}} - 1 \tag{3.7}$$

to quantify to which degree the CoM trajectory is controlled. This ratio lies between -1 and 1. A ratio > 0 is interpreted as a synergy, whereas a ratio ≤ 0 indicates no synergy (Papi et al., 2015).

Accordingly, our dependent variables were $\mathrm{UCM_{Ratio}}$, $\mathrm{UCM_{\parallel}}$ and $\mathrm{UCM_{\perp}}$.

3.3.5 Statistics

Statistical analyses were performed using JASP (jasp-stats.org). We specifically looked for differences in $\mathrm{UCM_{Ratio}}$, $\mathrm{UCM_{\parallel}}$ and $\mathrm{UCM_{\perp}}$ between the two groups (experts and novices). A 2 x 3 ANOVA with group [experts, novices] and gait cycle phase [absorption, propulsion, flight] as factors was calculated for each parameter and for each of the two speed conditions (10 km/h and 15 km/h). In case of significant phase effects, dependent t-tests were used for further analysis. Independent t-tests were used as post-hoc tests when a significant group effect was observed. The conditions for the application of ANOVA were tested a priori and Greenhouse-Geisser correction used if necessary. Multiple t-tests are presented as corrected t-tests using the Holm-Bonferroni-correction (Holm, 1979). The significance level was set to p = 0.05. Partial eta square (η_p^2) and Cohen's d were used to indicate effect size for the ANOVA and t-tests, respectively, with large effect sizes indicated by $\eta_p^2 > 0.14$ or $d > 0.8$ (Cohen, 1992), respectively.

3.4 Results

Figure 3 shows the time-normalized time courses of $\mathrm{UCM_{Ratio}}$, $\mathrm{UCM_{\parallel}}$ and $\mathrm{UCM_{\perp}}$. In all conditions, $\mathrm{UCM_{Ratio}}$ was > 0, indicating that a synergy was present and stabilizing the CoM trajectory.

3.4.1 10 km/h Condition

There were no group or interaction effects for the three UCM variables in the 10 km/h condition.

For UCM_{Ratio} (seeTable 3), the 2 x 3 ANOVA showed a significant phase effect ($p = 0.006$, $\eta_p^2 = 0.215$). However, post-hoc tests showed no significant differences between phases neither for experts nor for novices.

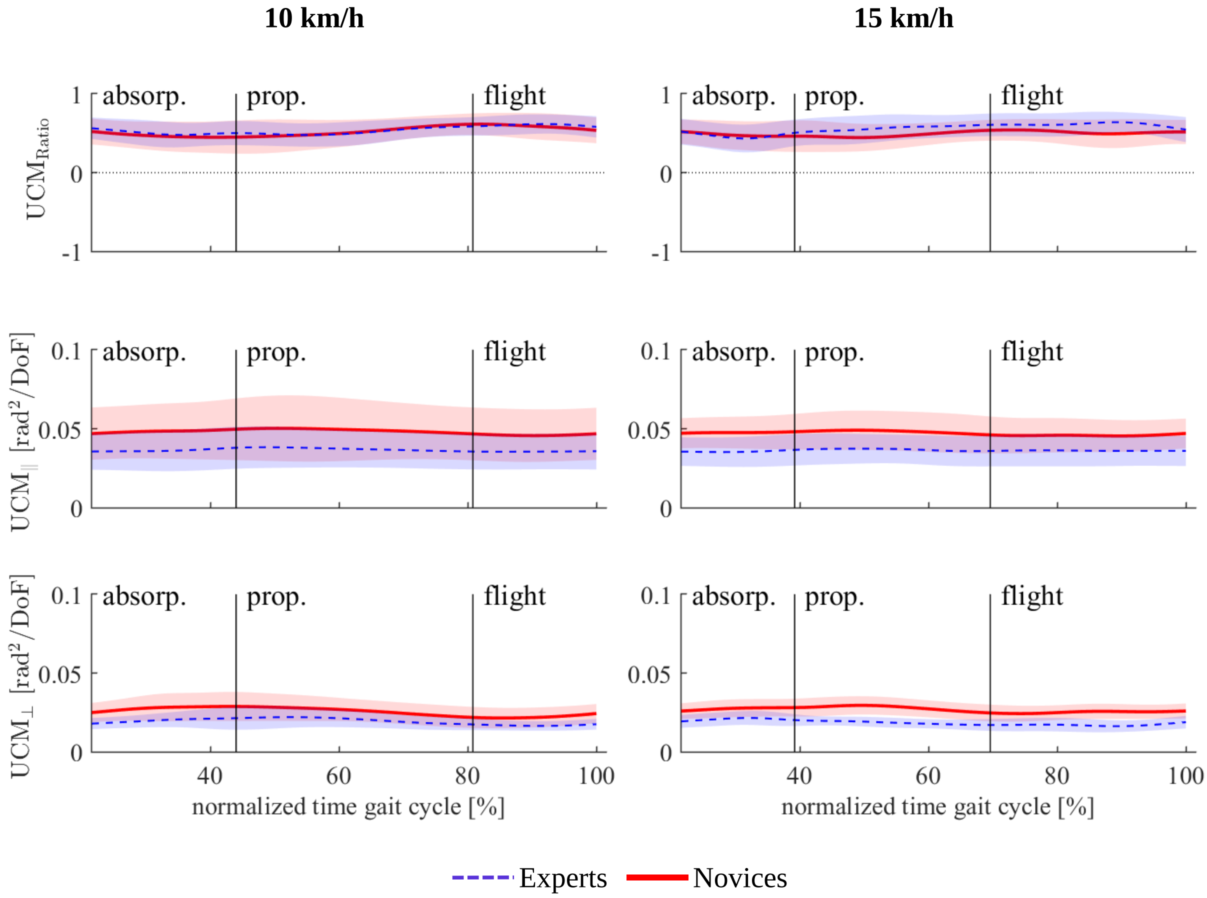

Figure 3: Time courses for UCM_{Ratio} (top row), $UCM_{\parallel}$ (middle row) and $UCM_{\perp}$ (bottom row), time-normalized to 100% of the gait cycle. Values for the right and left side are averaged. Data are presented as mean ± standard deviations. Vertical lines define the different phases of the gait cycle: 'abs.' stands for absorption phase, 'prop.' Stands for propulsion phase and 'flight' stands for flight phase.

For the parallel component ($UCM_{\parallel}$), the 2 x 3 ANOVA showed a significant phase effect ($p < 0.001$, $\eta_p^2 = 0.343$). Post-hoc tests showed that $UCM_{\parallel}$ was significantly higher during propulsion phase compared to flight phase in the expert group ($p = 0.003$, $d = 1.080$). In the novice group, $UCM_{\parallel}$ was significantly higher during both absorption phase ($p = 0.001$, $d = 1.367$) and propulsion phase ($p = 0.003$, $d = 1.194$) compared to flight phase.

For $UCM_{\perp}$, the 2 x 3 ANOVA showed a significant phase effect ($p < 0.001$, $\eta_p^2 = 0.356$). Dependent t-test showed that in experts and in novices, $UCM_{\perp}$ was smaller during flight compared to absorption (experts: p = 0.013, d = 0.852; novices: p = 0.003, d = 1.191) and to propulsion (experts: p = 0.015, d = 0.831; novices: p = 0.023, d = 0.811).

Table 3: Mean ± standard deviation for stance and swing phase for the two running conditions (10 and 15 km/h) Significant post-hoc tests for the group comparisons are highlighted in bold. p-values and effect sizes for the ANOVAs and post-hoc t-tests are given for the corresponding phases. The values for the phase effects can be found in the text.

	Speed [km/h]	Phase	Experts	Novices	ANOVA p (η_p^2)	Post-hoc t-tests p (d)
UCM_{Ratio}	10	Abs.	0.632 ± 0.102	0.629 ± 0.147	Interaction n.s.	
		Prop.	0.640 ± 0.075	0.664 ± 0.133		
		Flight	0.693 ± 0.076	0.675 ± 0.160	Group n.s.	
	15	Abs.	0.620 ± 0.120	0.596 ± 0.172	Interaction 0.023 (0.151)	0.683 (0.165)
		Prop.	0.669 ± 0.091	0.615 ± 0.146		0.272 (0.451)
		Flight	0.712 ± 0.104	0.616 ± 0.167	Group n.s.	0.095 (0.697)
$UCM_{\parallel}$ [$Rad^2 \cdot DoF^{-1}$]	10	Abs.	0.035 ± 0.012	0.045 ± 0.016	Interaction n.s.	
		Prop.	0.037 ± 0.009	0.046 ± 0.017		
		Flight	0.035 ± 0.011	0.043 ± 0.015	Group n.s.	
	15	Abs.	**0.035 ± 0.009**	**0.050 ± 0.013**	**Interaction 0.032 (0.139)**	**0.005 (1.242)**
		Prop.	**0.037 ± 0.009**	**0.050 ± 0.014**		**0.010 (1.126)**
		Flight	**0.036 ± 0.009**	**0.047 ± 0.011**	**Group 0.008 (0.271)**	**0.011 (1.108)**
UCM_{Ratio}	10	Abs.	0.016 ± 0.003	0.020 ± 0.004	Interaction n.s.	
		Prop.	0.017 ± 0.004	0.019 ± 0.004		
		Flight	0.014 ± 0.004	0.017 ± 0.004	Group n.s.	
	15	Abs.	**0.016 ± 0.003**	**0.024 ± 0.004**	Interaction n.s.	**<0.001 (2.090)**
		Prop.	**0.016 ± 0.002**	**0.023 ± 0.004**		**<0.001 (2.350)**
		Flight	**0.014 ± 0.002**	**0.022 ± 0.003**	**Group <0.001 (0.637)**	**<0.001 (2.707)**

3.4.2 15 km/h Condition

For $\mathrm{UCM_{Ratio}}$ (see Table 3), a significant phase effect ($p < 0.001$, $\eta_p^2 = 0.301$) and a significant phase x group interaction were observed ($p = 0.023$, $\eta_p^2 = 0.151$). Independent t-test showed no significant differences between the two groups. Dependent t-test showed that $\mathrm{UCM_{Ratio}}$ was higher in flight compared to absorption ($p < 0.001$, $d = 1.255$) and propulsion ($p = 0.001$, $d = 1.188$) and higher in propulsion compared to absorption ($p = 0.016$, $d = 0.773$) in the expert group. Post-hoc tests for the novices were not significant.

For $\mathrm{UCM_{\parallel}}$, a significant group effect ($p = 0.008$, $\eta_p^2 = 0.271$), a significant phase effect ($p = 0.001$, $\eta_p^2 = 0.249$) and a significant phase x group interaction ($p = 0.032$, $\eta_p^2 = 0.139$) were observed. Post-hoc tests showed higher $\mathrm{UCM_{\parallel}}$ for the novices compared to the experts in all three phases (absorption: $p = 0.005$, $d = 1.242$; propulsion: $p = 0.010$, $d = 1.126$; flight: $p = 0.011$, $d = 1.108$). Dependent t-test showed that in the expert group, $\mathrm{UCM_{\parallel}}$ was significantly lower in flight phase compared to propulsion phase ($p = 0.004$, $d = 0.983$).

For $\mathrm{UCM_{\perp}}$, the 2 x 3 ANOVA showed a significant group effect ($p < 0.001$, $\eta_p^2 = 0.637$) and a significant phase effect ($p < 0.001$, $\eta_p^2 = 0.435$). $\mathrm{UCM_{\perp}}$ was higher in novices in all three gait cycle phases (all three $p < 0.001$, absorption: $d = 2.090$, propulsion: $d = 2.350$, flight: $d = 2.707$). Dependent t-tests showed that in the experts and in the novices, $\mathrm{UCM_{\perp}}$ was smaller during flight compared to absorption (experts: $p < 0.001$, $d = 1.415$; novices: $p = 0.001$, $d = 1.235$) and for the experts also compared to propulsion ($p < 0.001$, $d = 1.360$).

3.5 Discussion

This study was the first to analyze the effects of expertise on the synergy structure in running using an UCM approach. To account for different anthropometries of runners compared to non-runners (Virmavirta & Isolehto, 2014), a subject-specific 3D model (Möhler et al., 2019) was used within the UCM framework for the analysis of locomotion patterns. We chose two different running speeds: a) 10 km/h, which is supposed to be somewhat comfortable for the novices, and b) 15 km/h, which is quite fast and thus uncomfortable for the novices, but it represents a comfortable speed for the experts. We found no differences in $\mathrm{UCM_{Ratio}}$ during running between the two groups. Therefore, our hypothesis, saying that experts show stronger synergies at higher running speed, had to be rejected. However, an interesting finding was the significant differences between experts and novices in both $\mathrm{UCM}_{\parallel}$ and $\mathrm{UCM}_{\perp}$ and between different gait cycle phases.

3.5.1 Differences in Running Coordination Between Experts and Novices

We found no differences in $\mathrm{UCM}_{\mathrm{Ratio}}$ between experts and novices during running. Experts revealed higher $\mathrm{UCM}_{\mathrm{Ratio}}$ in the flight phase than during stance. This might not reflect an increase in the degree of control but more likely reflect the fact that the position of the CoM is not influencable during flight phase since its trajectory is predetermined at toe-off. Thus, the amount of $\mathrm{UCM}_{\perp}$ is diminished, which leads to the observed increase in $\mathrm{UCM}_{\mathrm{Ratio}}$.

Both $\mathrm{UCM}_{\perp}$ and $\mathrm{UCM}_{\parallel}$ were higher in novices compared to experts in the 15 km/h condition. Probably, the 10 km/h condition was not sufficiently demanding to provoke differences between the two groups. In general, a greater $\mathrm{UCM}_{\parallel}$ offers flexibility and helps to stabilize an assumed RV (Latash et al., 2007). Since not only $\mathrm{UCM}_{\parallel}$ but also $\mathrm{UCM}_{\perp}$ was higher in the novices, there was a higher variability but not a higher degree of stabilization of the CoM trajectory. This is in contradiction to the results of Nisky et al. (2014) and Iino et al. (2017). They found a higher amount of $\mathrm{UCM}_{\parallel}$ and a higher $\mathrm{UCM}_{\mathrm{Ratio}}$ in experienced surgeons and experienced table tennis players, respectively, compared to novices. In contrast to the employed arm movements, we studied a rhythmic, whole-body movement task (Wolpert et al., 2013). This might explain the fact that we found different effects of expertise on the synergy structure. Moreover, we analyzed the structure of variability with respect to the control of the CoM trajectory. However, there might be additional important variables, which are controlled by the CNS during running. Finally, besides offering flexibility, a high $\mathrm{UCM}_{\parallel}$ might be detrimental to performance due to deviations to an optimal running style (Moore, 2016).

$\mathrm{UCM}_{\perp}$ is reported to decrease with improved performance (Latash et al., 2002), so it seems reasonable that it was higher in the novices. During years of practice, experts might have adapted a running style which is optimized for a variable like energy consumption (Joyner & Coyle, 2008; Moore, 2016). This is reflected by the more consistent locomotion style observed in the experts in the 15 km/h condition. This decrease in variability with expertise is consistent with recent studies (Mo & Chow, 2018b; Nakayama et al., 2010).

Considering the phase effects, $\mathrm{UCM}_{\parallel}$ and $\mathrm{UCM}_{\perp}$ were significantly higher during the stance phases than during flight phase in most of the cases. The lower amount of $\mathrm{UCM}_{\perp}$ during flight phase is probably due to the fact that CoM trajectory during this phase of the gait cycle is determined at toe off. Since a higher $\mathrm{UCM}_{\parallel}$ indicates higher flexibility, an increased value during stance possibly reflects the fact that the CNS tries to ensure a certain flexibility during interaction with the ground (Mo & Chow, 2018a). Even if experts show lower variability due to a more consistent running style, a certain amount of variability during stance phase is possibly desirable, since this could alter the impact of foot strike and toe off to hypothetically prevent over-use injuries (Hamill et al., 2012).

3.5.2 The Uncontrolled Manifold Approach

Research in sports biomechanics has revealed that athletes do not repeatedly produce precise kinematic patterns (Bartlett et al., 2007). However, variability seems to be channelled: aspects contributing directly to the desired outcome are more consistent than aspects that are less relevant (Todorov & Jordan, 2002). In recent years, this observation has been formalized with different approaches (Sternad, 2018). In this paper we used the UCM approach (Scholz & Schöner, 1999) to analyze the motor coordination of experienced and less experienced runners. This approach enabled us to test a control hypothesis by comparing the variability affecting the CoM ($\mathrm{UCM}_{\perp}$), and the variability not affecting the CoM ($\mathrm{UCM}_{\parallel}$). If there is more variability not affecting the CoM trajectory and thus stabilizing it, the control hypothesis is accepted. Since the $\mathrm{UCM}_{\mathrm{Ratio}}$ was always > 0 for both conditions, our data indicate that there was a continuous synergy stabilizing the CoM trajectory. Therefore, we suggest that the CoM trajectory can be interpreted as a RV not only during walking (Black et al., 2007; Papi et al., 2015; Vito et al., 2018) but also during running.

Besides the UCM approach, there have been several attempts to address the question of coordination variability (Sternad, 2018). One approach developed in the context of motor abundance is the Goal Equivalent Manifold (GEM) approach (Cusumano & Cesari, 2006). The GEM analyses the relationship between variability at the execution level, compared to the result level, using a quantitative task-specific goal function (Cusumano & Dingwell, 2013). Another approach to study coordination variability is the TNC approach (Müller & Sternad, 2003, 2004). The TNC approach analyses variability in result space. Thereby the influence of the chosen position in execution space, noise and covariation on the stability of the movement outcome, for example the endpoint trajectory, can be differentiated. The UCM approach takes into account the influence of covariation, but additionally the influence of individual variability

(Schöner & Scholz, 2007; Verrel, 2011). Since we wanted to test the hypothesis about a synergy structure stabilizing the CoM trajectory, the UCM approach was the appropriate approach.

3.5.3 Limitations

In the framework of the UCM approach, different RV can exist. Accordingly, different RV have been proposed for human locomotion (Krishnan et al., 2013; Robert et al., 2009). Thereby, one has to keep in mind that not all of these RV might be controlled by the CNS but could be a result of the UCM-model or reflect the effect of the control of other parameters. Another important goal during running on a treadmill could be to stay on the treadmill, since its speed is prescribed (Dingwell et al., 2010). However, we chose the CoM trajectory as a RV and we are of the opinion that this choice is reasonable (Black et al., 2007; Papi et al., 2015).

In order to investigate the variability of running locomotion, we captured our data while participants were running on a motorized treadmill. It is well known that movement patterns may differ between overground and treadmill running (e.g. Wank, Frick, & Schmidtbleicher, 1998). On the other hand, measurements taken overground would prohibit the capture of cyclic locomotion patterns, since one would have to analyse concatenated rather than consecutive strides. Therefore, we chose to use the treadmill and to provide all of the subjects with sufficient time for familiarization with the treadmill (Lavcanska et al., 2005; Matsas et al., 2000). Consequently, movement patterns are likely to be stable, if not identical to ones from overground running (Riley et al., 2008), although the constant speed of the treadmill might decrease variability (Lindsay et al., 2014).

This is the first study using a 3D model to study human locomotion within the UCM approach. Unfortunately, our current model does not allow for a separate analysis in each of the three dimensions. This would be a valuable extension of the model.

3.6 Conclusions

This was the first study comparing SSV of CoM trajectory control in experts and novices using a 3D-model of the CoM within the UCM framework. Athletes are a special anthropometric group (Virmavirta & Isolehto, 2014), which requires specific anthropometric models. We thus used a subject-specific 3D model to calculate the CoM serving as RV. There were no differences in $\mathrm{UCM}_{\mathrm{Ratio}}$ between experts and novices. Since $\mathrm{UCM}_{\mathrm{Ratio}}$ was always > 0, it can be assumed that the CoM trajectory is an important RV during running. In the majority of cases, the variability (both $\mathrm{UCM}_{\parallel}$ and $\mathrm{UCM}_{\perp}$) was less constrained in absorption and propulsion phase compared to the flight phase. Differences between experts and novices were only visible at 15 km/h. Our results showed that expert runners have adopted a more consistent running style, as shown by the smaller variability (both $\mathrm{UCM}_{\parallel}$ and $\mathrm{UCM}_{\perp}$). These changes in the synergy structure are consistent with the effects of learning previously reported (Latash et al., 2002).

4. Topic B – Fatigue in Experts: Fatigue-Related Changes in Spatiotemporal Parameters, Joint Kinematics and Leg Stiffness in Expert Runners During a Middle-Distance Run

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4.1 Abstract

Fatigue with its underlying mechanisms and effects is a broadly discussed topic and an important phenomenon, particularly in endurance sports. Although several studies have already shown a variety of changes in running kinematics with fatigue, few of them have analyzed competitive runners and even fewer have focused on middle-distance running. Furthermore, the studies investigating fatigue-related changes have mostly reported the results in terms of discrete parameters, e.g. RoM in the frontal or sagittal plane, and therefore potentially overlooked effects occurring in subphases of the stride or in the transverse plane. On this basis, the goal of the present study was to analyze the effects of exhaustive middle-distance running on expert runners by means of both discrete parameters and time series analysis in 3D. In this study, 13 runners ran on a treadmill to voluntary exhaustion at their individually determined fatigue speed (FS) which was held constant during the measurements. Kinematic data were collected by means of a 3D motion capture system. Spatiotemporal and stiffness parameters as well as the RoM of joints and of the CoM within the stance and flight phases were calculated. Independent t-tests were performed to investigate any changes in means and coefficients of variation (CV) of these parameters between the rested (PRE) and fatigued (POST) state. Statistical parametric mapping method was applied on the time series data of the joints and the CoM. Results from this exploratory study revealed that during a middle-distance run, expert runners change their stance time, rather than their step frequency or step length in order to maintain the constant running speed as long as possible. Increased upper body movements occurred to counteract the increased angular moment of the lower body possibly due to longer stance times. These findings provide insights into adaptation strategies of expert runners during a fatiguing middle-distance run and may serve as valuable information particularly for comparisons with other group of runners (e.g. females or non-athletes) as well with other conditions (e.g. non-constant speed or interval training), and might be useful for the definition of training goals (e.g. functional core training).

4.2 Introduction

Fatigue is a complex phenomenon that develops during both high- and low-intensity exercise, and its origin depends on the intensity and duration of exercise (Millet & Lepers, 2004). Fatigue is therefore inherent in endurance sports, e.g. in running. Several studies have shown that fatigue causes changes in running kinematics (Kim et al., 2018; Winter et al., 2017), which in turn may decrease performance and increase injury risk (Hreljac et al., 2000). Deeper understanding of fatigue-related changes is therefore essential for optimization of training loads or prevention of injuries.

Most previous studies investigated the influence of fatigue during long-distance runs (> 3000 m or an equivalent time, Winter et al., 2017; Kim et al., 2018; García-Pinillos et al., 2020; Willwacher et al., 2020), and only a few analyzed biomechanical alterations of competitive-level runners under exhaustive effort. Sanno et al. (2018) compared competitive with recreational runners over a 10 km run and found an increased knee flexion at touchdown in both groups as well as increases in maximal knee flexion and decreases in plantar flexion at toe off in the recreational runners (Sanno et al., 2018). Willwacher et al. (2020) observed kinematic adaptations in both recreational and competitive runners during a 10 km treadmill run in the non-sagittal planes. They reported changes between the pre- and post-fatigue state, particularly in hip adduction, ankle eversion and in knee valgus angle, although they did not consider spatiotemporal parameters or changes in the sagittal plane. García-Pinillos et al. (2020) analyzed spatiotemporal parameters and stiffness changes in trained male endurance runners during a 60 min treadmill run, but did not include any results concerning joint kinematics in their study. They reported an increased contact time and step variability as well as decreased flight time and leg stiffness in fatigued runners.

To date, only a limited number of studies have examined kinematic alterations related to fatigue over middle-distance runs (≤ 3000 m or an equivalent time). Rabita et al. (2013) evaluated the changes in spring-mass behavior of runners during an effort with a mean time to exhaustion of 5:53 min. They reported decreased leg stiffness and altered spatiotemporal parameters, although they did not include joint kinematics in their analysis. Derrick et al. (2002) examined kinematic adjustments and their influences on shock attenuation potential during an exhaustive run (average time 15:42 min) of recreational runners by means of mobile sensors, and suggested that kinematic adaptations may lead to increased metabolic cost. A recent study by García-Pinillos et al. (2019) analyzed kinematic adaptations during two high-intensity interval programs using a high-speed camera, and reported no changes in the spatiotemporal and kinematic variables studied. In another study examining joint angle alterations and changes in shock absorption capacity after a brief exhaustive run, no significant differences between pre- and post-fatigue states were found (Abt et al., 2011). Maas et al. (2018) analyzed both experienced and novice runners during a run to exhaustion during a 3200 m time trial pace using a 3D motion capture system. They reported increases in pelvic tilt, pelvic RoM and knee abduction as well as decreases in hip adduction and ankle plantar flexion. Furthermore, they showed that novice runners exhibit larger kinematic adjustments than experienced runners. Another group of researchers also analyzed novice runners in comparison to experienced runners focusing on SSV (Mo & Chow, 2018a) and coordination variability (Mo & Chow, 2018b) for prolonged treadmill run at anaerobic threshold speed. They reported that novice and experienced runners differ from each other particularly in terms of both SSV and coordination variability.

Several studies only analyzed motion in 1D or 2D (Kim et al., 2018; Winter et al., 2017), which could limit the scope of the results. As suggested by Willwacher et al. (2020), fatigue may cause alterations in non-sagittal planes. Therefore, analyses should comprise all of the relevant and anatomically-possible DoF. In addition, including upper body kinematics could improve the explanatory value of results, since upper body rotation has been found to increase with fatigue in long distance runs and was hypothesized to be detrimental for performance and to increase injury risk (Strohrmann et al., 2012). In addition, García-Pinillos et al. (2020) argued that robust conclusions regarding coordination, injury prevention and sports performance depend not only on the mean values of spatiotemporal parameters but also their variability, which in their study was operationalized as the CV. They reported increased variability with fatigue, whereas Hanley and Tucker (2018) found only moderate changes in variability between successive testing distances in their study. Variability of movement patterns is all in all an important and widely discussed topic in a wide range of disciplines, among others in sports biomechanics, since it helps to understand adaptation strategies as well as flexibility of the motor system in movement production (Meardon et al., 2011; Mo & Chow, 2018a, 2018b). In addition, movement variability is speed-dependent (Meardon et al., 2011), so different running distances may lead to different variability characteristics since running speed changes with running distance. Similarly, the expertise of the runners is a factor influencing movement variability. Accordingly, different groups of participants as well as different study designs may provide different results (Mo & Chow, 2018a, 2018b). Stiffness is another important biomechanical parameter in analyses of running gait because of its close relationship to injuries and performance (Butler et al., 2003) as well as to fatigue (García-Pinillos et al., 2020; Rabita et al., 2013), however a clear consensus regarding the relationship between these parameters is still lacking. Butler et al. (2003) reported that increased stiffness may be beneficial to sports performance and decreased stiffness may be associated with soft tissue injuries. On the other hand, Lorimer and Hume (2016) concluded that high lower body stiffness may be associated with Achilles tendon injuries, particularly in association with training on surfaces with low stiffness properties. All in all, leg and vertical stiffness might be important aspects for performance as well as for injury prevention (Pappas et al., 2014).

In summary, existing studies have used a multitude of fatigue protocols, measurement devices, and dependent variables with participants from a broad range of expertise levels. Accordingly, there is no consensus about the effects of fatigue on the biomechanics of middle-distance running. The goal of the present study was to analyze the possible effects of fatigue on spatiotemporal parameters, leg and vertical stiffness, 3D joint kinematics as well as the CoM trajectory during a middle-distance run by expert runners. In addition, this study aimed to conduct an explorative analysis of entire time series data by means of statistical parametric mapping (SPM) and important discrete parameters (spatiotemporal parameters and RoM). The presented results may provide informative data concerning biomechanical adaptations of competitive-level runners during an exhaustive middle-distance run and may be useful for future research particularly for comparisons with different expertise levels (e.g. non-athletes) or other running distances.

4.3 Materials and Methods

4.3.1 Data Set

Data from a previously published study (Möhler et al., 2019) were re-analyzed. The participants were 13 male runners (age: 23.5 ± 3.6 years, BMI: 20.6 ± 1.7 kg/m²). Inclusion criteria were a 10 km record below 35 min (32:59 ± 01:19 min), a minimum mileage von 50 km/week during the 8 weeks preceding the measurement and an active membership in a running club for at least 2 years (7.2 ± 3.2 years). Exclusion criteria were pain in the lower limbs or recent injuries. All participants provided written informed consent. The study was approved by the ethics committee of the Karlsruhe Institute of Technology. Each participant came to the laboratory on two different days one week apart. The tests were performed on a motorized treadmill (h/p/cosmos Saturn, Nussdorf-Traunstein, Germany). For safety reasons, subjects wore a safety harness which was connected to an emergency stop. During the first visit, their individual FS was determined during an incremental lactate threshold test. The test started at 8 km/h, the duration per step was 3 min, there were 30 s of rest between the steps and the increment between the steps was 2 km/h. The individual FS was determined on the basis of lactate values and by means of the critical power concept developed by Monod and Scherrer (1965). The FS was defined as the speed that runners were potentially able to run for 10 min at most. This speed was at 110 % of their speed at 4 mmol/l lactate (19.27 ± 0.72 km/h). During the second visit, the actual measurement was performed. At first, a standardized treadmill familiarization (6 min of walking, 6 min of running, Matsas et al., 2000; Lavcanska et al., 2005) was performed. Afterwards, participants ran at their individually determined FS until voluntary exhaustion, which was reached after 4:06 ± 0:52 min (1.34 ± 0.27 km). Exhaustion was confirmed by a Borg-scale rating (Borg, 1982) of 19.6 ± 0.65. Participants wore their own running shoes. During running, 41 marker trajectories were captured by 11 infrared cameras at a recording frequency of 200 Hz (Vicon Motion Systems; Oxford Metrics Group, Oxford, UK). A total of 19 strides were captured at the beginning of the run (PRE measurement, non-fatigued state) and 19 strides immediately before exhaustion (POST measurement, fatigued state).

4.3.2 Data Processing

Data were preprocessed using Vicon Nexus software V1.8.5 (Vicon Motion Systems Ltd., UK). All subsequent data processing operations were performed with MATLAB R2020a (MathWorks, Natick, MA, USA). To obtain joint angles, an inverse kinematics calculation was conducted using a modified version of the full-body model Dynamicus (ALASKA) (Härtel & Hermsdorf, 2006). Foot strikes were identified using the vertical speed of the foot markers whereas toe-off was identified using the vertical acceleration (Leitch et al., 2011).

Duration of stance (time between right foot strike and right toe off), duration of flight (right toe off to left foot strike), and stride frequency (right foot strikes per second) were analyzed as spatiotemporal parameters in order to generally characterize the running kinematics of our participants. Vertical stiffness and leg stiffness were also included in the analyses because these parameters may change under neuromuscular fatigue (Dutto & Smith, 2002; García-Pinillos et al., 2020) and therefore be helpful to understand the general adaptation patterns in presence of fatigue, especially in relation to the spatiotemporal changes. Since the measurements were performed on a non-instrumented treadmill, the stiffness parameters were estimated based on kinematic data as suggested by Morin et al. (2005), who showed the validity of this method. For both spatiotemporal and stiffness parameters, the CV was calculated alongside the mean and standard deviation. The CV was included because it may reveal changes in the stability of the coordination pattern (Jordan et al., 2009). Furthermore, there are some studies indicating a relationship between step variability and injuries (Meardon et al., 2011) as well as endurance performance (Nakayama et al., 2010).

Joint kinematics were analyzed for the lower extremities (ankle, knee, and hip joints) and torso (lumbar spine and thoracic spine joints) in the sagittal (S), frontal (F), and transversal (T) planes to incorporate all important DoF and constraints. Time series data of joints were analyzed by means of SPM because it has been suggested to be superior to over-simplified discrete parameter analyses by being capable of identifying field regions which co-vary significantly with the experimental design (Pataky et al., 2013). As well as analysis of the entire time series, RoM was calculated as the difference between the maximum and the minimum joint angle for both stance (right foot strike to right toe off) and flight phase (right toe off to left foot strike). The RoM results could be helpful for understanding adaptations to fatigue, particularly in terms of injuries, because it literally manifests the limits of motions. Increases in RoM may indicate a higher risk of soft tissue damages because of potentially increased strains in these tissues. Similarly, analysis of the CoM was accomplished by considering both the time series and the RoM.

4.3.3 Statistics

For the spatiotemporal parameters and the RoM, the 19 PRE strides and the 19 POST strides were averaged for each participant for statistical analysis. The PRE and POST averages were compared using paired t-tests and Cohen's d was calculated as a measure of effect size. Normality distribution was verified using the Shapiro-Wilk-test. For all statistical tests, the level of significance was set a priori to $p = 0.05$. Cohen's d was classified as the following: $d < 0.5$ small effect, $0.5 < d < 0.8$ medium effect and $d > 0.8$ large effect (Cohen, 1992). The joint angle time series were time-normalized and compared using statistical non-parametric mapping (www.spm1d.org) due to non-normal distribution. All analyses were performed for the right side assuming that both legs would fatigue at a similar rate (Pappas et al., 2015).

4.4 Results

4.4.1 Spatiotemporal Parameters and Their Variability

Aiming at investigating spatiotemporal characteristics both in PRE and POST, stance time, time of flight, stride frequency, and their variability across multiple strides were estimated. The results are represented in Table 4. Analysis of the spatiotemporal parameters revealed a significantly higher stance time (PRE: 0.16 s, POST: 0.17 s, $p < 0.001$, $d = 3.016$) and shorter time of flight (PRE: 0.33 s, POST: 0.31 s, $p < 0.001$, $d = 2.077$). The CV of the spatiotemporal parameters did not show any significant changes (Table 4).

Table 4: Spatiotemporal parameters, vertical and leg stiffness together with corresponding coefficients of variation (CV). Values shown as mean ± standard deviation. p-values as calculated by the dependent t-test and Cohen's d as effect sizes are given. Significant differences are highlighted in bold ($p < 0.05$). Cohen's d effect sizes of 0.1−0.50, 0.5−0.8 and > 0.8 indicate small, medium and large effects, respectively.

	PRE	POST	p	d
Stance time [s]	**0.16 ± 0.02**	**0.17 ± 0.02 s**	**< 0.001**	**3.016**
Time of flight [s]	**0.33 ± 0.04**	**0.31 ± 0.03 s**	**< 0.001**	**2.077**
Stride frequency [1/s]	1.53 ± 0.07	1.54 ± 0.07 1/s	0.120	0.464
Vertical stiffness [kN/m]	**20.55 ± 3.98**	**18.01 ± 4.56**	**< 0.001**	**1.701**
Leg stiffness [kN/m]	**12.40 ± 2.62**	**10.56 ± 2.90**	**< 0.001**	**1.856**
Coefficients of variation				
Stance time	0.03 ± 0.01	0.03 ± 0.01	0.175	0.399
Time of flight	0.02 ± 0.01	0.01 ± 0.07	0.069	0.555
Stride frequency	0.01 ± 0.00	0.01 ± 0.00	0.230	0.351
Vertical stiffness	**0.08 ± 0.02**	**0.06 ± 0.02**	**0.045**	**0.619**
Leg stiffness	**0.08 ± 0.03**	**0.07 ± 0.02**	**0.047**	**0.613**

4.4.2 Vertical and Leg Stiffness and Their Variability

Vertical and leg stiffness were included in order to be able to explain changes in spatiotemporal parameters with respect to changes in stiffness, because stiffness is thought to exert a major effect on various athletic variables related to running kinematics (Brughelli and Cronin, 2008). In the POST, both the leg and the vertical stiffness decreased significantly with high effect sizes (PRE_{leg}: 12.40 kN/m, $POST_{leg}$: 10.56 kN/m, $p < 0.001$, $d = 1.856$; $PRE_{vertical}$: 20.55 kN/m, $POST_{vertical}$: 18.01 kN/m, $p < 0.001$, $d = 1.701$), which were in accordance with increased stance times. The CV of both stiffness parameters also decreased significantly with medium effect sizes indicating a less variable stiffness over strides in POST (PRE_{leg}: 0.08, $POST_{leg}$: 0.07, $p = 0.047$, $d = 0.613$; $PRE_{vertical}$: 0.08, $POST_{vertical}$: 0.06, $p = 0.045$, $d = 0.619$) (Table 4).

4.4.3 Analyses of Range of Motion

In the stance phase, the RoM predominantly increased with fatigue (Table 5). Both at the ankle and at the knee joint, RoM increased significantly in the sagittal plane with a high effect size (Ankle PRE_S: 51.15°, $POST_S$: 53.55°, $p < 0.001$, $d = 1.23$; Knee PRE_S: 37.81°, $POST_S$: 40.97°, $p < 0.001$, $d = 1.451$). The remaining joints, namely the hip (PRE_S: 53.55°, $POST_S$: 56.87°, $p < 0.001$, $d = 2.200$; PRE_F: 17.10°, $POST_F$: 18.82°, $p < 0.001$, $d = 1.282$; PRE_T: 9.39°, $POST_T$: 11.86°, $p < 0.001$, $d = 1.442$), the lumbar spine (PRE_F: 8.10°, $POST_F$ 10.05°, $p < 0.001$, $d = 1.513$, PRE_T: 3.78°, $POST_T$: 4.54°, $p < 0.001$, $d = 2.568$) and the thoracic spine (PRE_S: 5.45°, $POST_S$: 5.93°, $p = 0.009$, $d = 0.863$; PRE_F: 12.82°, $POST_F$: 14.89°, $p < 0.001$, $d = 2.989$; PRE_T: 18.71°, $POST_T$: 22.51°, $p < 0.001$, $d = 1.728$), showed significantly increased RoM with a high effect size in all three planes, except for the lumbar spine in the sagittal plane. Generally speaking, runners showed a tendency toward more joint motion especially in the sagittal plane. The RoM of the CoM increased significantly in the medio-lateral direction ($PRE_{medio-lateral}$: 4.60°, $POST_{medio-lateral}$: 5.11°, $p = 0.039$, $d = 0.641$), but decreased in the vertical direction ($PRE_{vertical}$: 61.85°, $POST_{vertical}$: 60.11°, $p = 0.043$, $d = 0.627$) with medium effect sizes. This means that runners moved more from side-to-side but less up-and-down.

Table 5: Range of motion of joints and of the CoM. Values of the joint angles in degrees (°) and of the CoM in mm are shown as mean ± standard deviation for stance and flight phases separately. p-values as calculated by the dependent t-test and Cohen's d as effect sizes are also given. Significant differences ($p<0.05$) are highlighted in bold. Cohen's d effect sizes of 0.1−0.5, 0.5−0.8 and >0.8 indicate small, medium and large effects, respectively. S, F and T signify the sagittal, the frontal and the transversal plane, respectively.

	PRE	POST	p	d
Stance phase				
Ankle – S [°]	**51.15 ± 4.38**	**53.55 ± 4.37**	**< 0.001**	**1.230**
Ankle – F [°]	17.32 ± 5.31	17.53 ± 5.36	0.568	0.163
Ankle – T [°]	11.11 ± 2.21	10.61 ± 2.41	0.363	0.262
Knee – S [°]	**37.81 ±5.23**	**40.97 ± 6.12**	**< 0.001**	**1.451**
Knee – F [°]	4.54 ± 3.54	4.78 ± 3.52	0.580	0.158
Knee – T [°]	7.16 ± 2.68	7.12 ± 3.35	0.953	0.017
Hip – S [°]	**53.33 ± 5.53**	**56.87 ± 6.24**	**< 0.001**	**2.200**
Hip – F [°]	**17.10 ± 3.60**	**18.82 ± 3.58**	**< 0.001**	**1.282**
Hip – T [°]	**9.39 ± 5.05**	**11.86 ± 5.35**	**< 0.001**	**1.442**
Lumbar Spine – S [°]	12.13 ± 1.98	12.86 ± 2.47	0.088	0.514
Lumbar Spine – F [°]	**8.10 ± 0.86**	**10.05 ± 1.12**	**< 0.001**	**1.513**
Lumbar Spine – T [°]	**3.78 ± 0.54**	**4.54 ± 0.68**	**< 0.001**	**2.568**
Thoracic Spine – S [°]	**5.45 ± 0.78**	**5.93 ± 1.01**	**0.009**	**0.863**
Thoracic Spine – F [°]	**12.82 ± 1.25**	**14.89 ± 1.34**	**< 0.001**	**2.989**
Thoracic Spine – T [°]	**18.71 ± 4.10**	**22.51 ± 22.51**	**< 0.001**	**1.728**
CoM ant-post [mm]	13.42 ± 1.62	14.14 ± 2.66	0.213	0.365
CoM med-lat [mm]	**4.60 ± 1.36**	**5.11 ± 1.61**	**0.039**	**0.641**
CoM vertical [mm]	**61.85 ± 6.87**	**60.11 ± 6.25**	**0.043**	**0.627**

Flight phase

Ankle – S [°]	13.03 ± 4.17	11.44 ± 4.42	0.059	0.579
Ankle – F [°]	5.17 ± 3.08	5.67 ± 2.44	0.223	0.356
Ankle – T [°]	6.54 ± 3.00	6.39 ± 3.35	0.751	0.090
Knee – S [°]	99.52 ± 10.62	96.65 ± 11.63	0.057	0.583
Knee – F [°]	7.44 ± 3.96	8.16 ± 4.21	0.224	0.355
Knee – T [°]	11.48 ± 8.00	13.12 ± 6.55	0.065	0.564
Hip – S [°]	**22.96 ± 6.14**	**20.75 ± 5.21**	**0.001**	**1.155**
Hip – F [°]	8.85 ± 2.20	8.91 ± 1.43	0.877	0.044
Hip – T [°]	10.55 ± 4.22	10.94 ±4.87	0.524	0.182
Lumbar spine – S [°]	11.03 ± 2.40	11.19 ± 2.36	0.584	0.156
Lumbar spine – F [°]	4.68 ± 1.33	4.33 ± 1.26	0.190	0.385
Lumbar spine – T [°]	**1.03 ± 0.45**	**1.28 ± 0.47**	**< 0.001**	**1.210**
Thoracic spine – S [°]	4.75 ± 0.97	4.94 ± 1.01	0.117	0.468
Thoracic spine – F [°]	1.99 ± 0.72	2.12 ± 1.11	0.424	0.230
Thoracic spine – T [°]	**9.85 ± 3.25**	**10.56 ± 3.31**	**0.025**	**0.710**
CoM ant-post [mm]	13.706 ± 2.78	12.94 ± 3.24	0.163	0.412
CoM med-lat [mm]	8.60 ± 3.10	8.15 ± 2.34	0.428	0.227
CoM vertical [mm]	**51.88 ± 14.76**	**46.92 ± 11.76**	**0.002**	**1.075**

In the flight phase, a smaller number of significant changes were detected compared to the stance phase. The RoM of the hip joint decreased significantly in the sagittal plane with a high effect size (PRE: 22.96°, POST: 20.75°, $p = 0.001$, $d = 1.155$), whereas those of the lumbar (PRE: 1.03°, POST: 1.28°, $p < 0.001$, $d = 1.210$) and the thoracic (PRE: 9.85°, POST°: 10.56, $p = 0.025$, $d = 0.710$) spine increased in the transverse plane. The effect sizes were high and medium, respectively, which means that upper body rotation increased. The RoM of the CoM decreased in the vertical direction with a high effect size (PRE: 51.88°, POST: 46.92°, $p = 0.002$, $d = 1.075$) but no significant changes were detected in the other planes (Table 5), which means that runners moved less up-and-down during flight.

In summary, the results revealed predominantly greater motion in the sagittal plane for the lower limbs and increased upper body motion especially in the transverse plane. Furthermore, the CoM showed less up-and-down-movement.

4.4.4 Time Series Analyses of Joint and CoM Movements

To prevent any over-simplification, the joint angle data were further analyzed by means of SPM. The trajectories of five joints as well as the CoM in all three planes are represented in Figure 4. The SPM analysis (Figure 4) revealed an increase in dorsiflexion and external rotation prior to right toe off.

The knee joint showed more flexion particularly during late swing and during stance, whereas it was more extended during early swing in the POST. In the remaining planes, there were no significant differences.

The hip joint was less flexed during early and mid-swing, and more flexed during stance and late swing, in the POST. There were several significant differences between the PRE and the POST in the frontal plane of the hip joint. The hip joint was more adducted in the middle of the right stance phase and more abducted in the beginning of the right flight phase. Contrarily, it was more abducted during mid swing.

The two joints representing trunk movement, in the lumbar and in the thoracic spine, showed less flexion in the sagittal plane, indicating a predominantly increased backwards tilt of the trunk in the POST. In the frontal plane, both the lumbar and the thoracic spine were more tilted to the left before left toe-off. After left toe-off, these areas were more tilted to the right and after right toe-off the thoracic spine was more tilted to the left. In the transverse plane, runners rotated to the right after left toe-off and rotated to the left after right toe-off. This occurred at both the lumbar and the thoracic spine joints, which overall indicates an increased rotation in the upper body.

During almost the entire stride, the position of the CoM was lower in the POST compared to the PRE. In the remaining two directions, anterio-posterior and medio-lateral, there were not any significant changes.

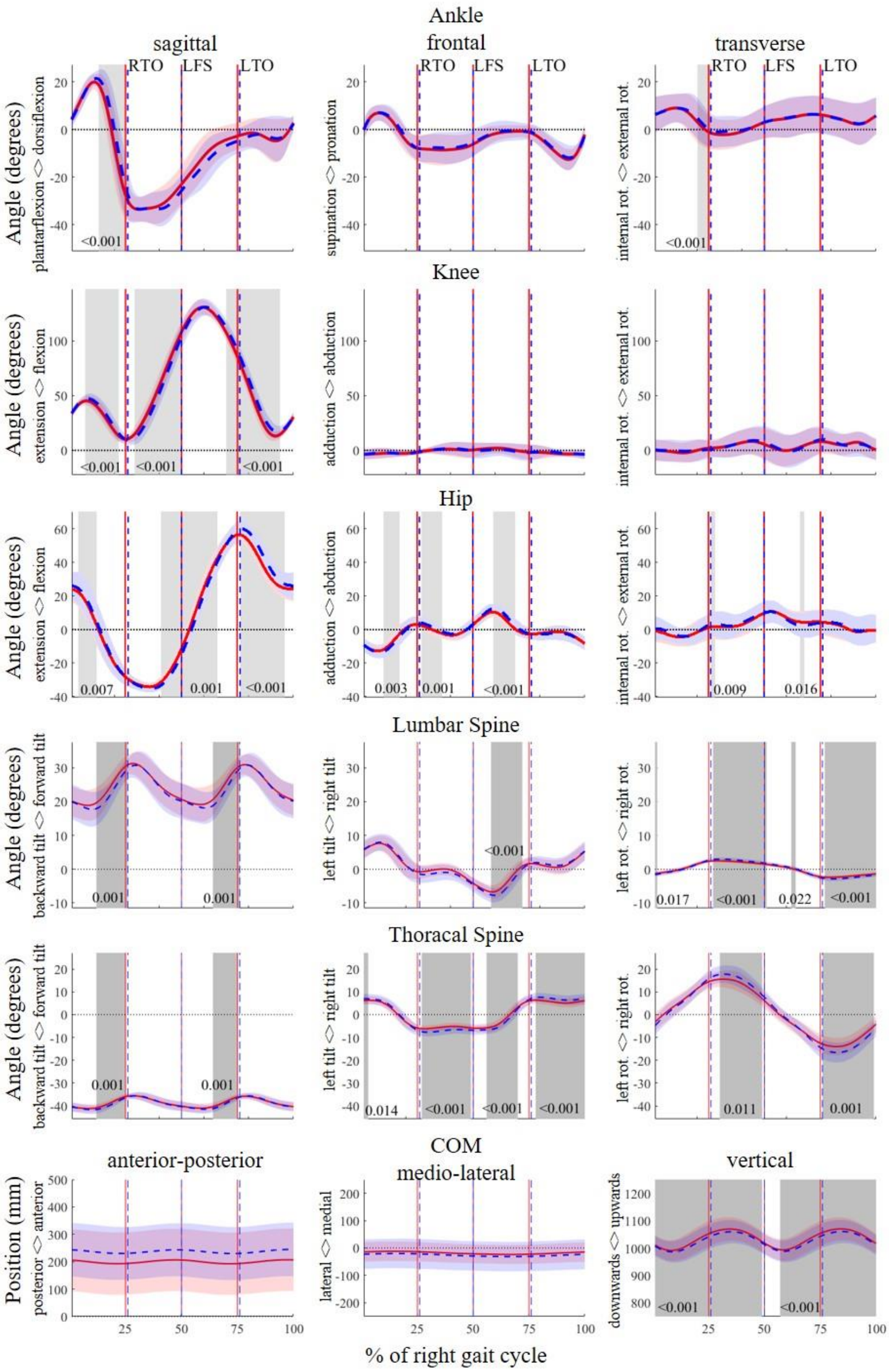

Figure 4: SPM analyses. Time courses for the angles of the ankle, knee, hip, lumbar spine and thoracic spine in degrees, and of the trajectory of the center of mass (CoM) in mm for the entire running stride of the right leg (from right foot strike to right foot strike) in 3D. The PRE and POST time series data are shown in red and blue, respectively. Significant differences ($p < 0.05$) are highlighted with gray areas and corresponding p-values are given. RTO signifies right toe off; LFS, left foot strike; LTO, left toe-off.

4.5 Discussion

This study is one of the first to investigate the effects of fatigue on expert runners during an exhaustive middle-distance run. The analysis was performed in 3D and entire time series were considered in the analysis by means of SPM. The results indicated that fatigue affects the spatiotemporal parameters, stiffness, CoM trajectories and joint kinematics throughout the stride.

4.5.1 Spatiotemporal Parameters and Their Variability

Between the PRE and POST, stride frequency fluctuated between 1.53 and 1.54 Hz (∼92 strides per min). Since the speed was fixed during the fatigue protocol and the stride frequency did not change, the step length had to remain unchanged because speed is the multiplication of stride frequency with stride length. Since stride frequency did not change from PRE to POST, one could assume that trained runners choose a stride frequency and a step length associated with the lowest energy cost and try to keep them up (Hunter & Smith, 2007; Williams & Cavanagh, 1987). The stride frequency chosen by the athletes in the present study (∼92 strides per min) was slightly higher than reported by Hunter and Smith (∼86–87 strides per min) who analyzed changes with fatigue during a 1 h high-intensity run. This increase might be due to the higher running velocity (Fletcher & Macintosh, 2017). Even though stride frequency was the same in PRE and POST, contact time increased which was compensated by a decreased flight time.

4.5.2 Vertical and Leg Stiffness and Their Variability

The results show that fatigued runners have a decreased leg and vertical stiffness in the POST, which leads to a longer contact time and shorter flight times. These results are in line with other studies (Dutto & Smith, 2002; García-Pinillos et al., 2020; Rabita et al., 2011, 2013). These decreases in stiffness may be explained by the reduced effectiveness of the stretch-shortening cycle and may possibly increase energy cost, which ultimately would decrease running performance (Hayes & Caplan, 2014; Pappas et al., 2014). The CV of both vertical and leg stiffness decreased with fatigue, which means that stiffness varied more from stride to stride in PRE compared to POST. In a study investigating relationships between coordinative variability and overuse injury (Hamill et al., 2012), a higher variability of a coordinative structure was related to a healthier state of athletes. However, a causal relationship between injury and variability was not yet found. Dutto and Smith (2002) also reported that the relationship between injury mechanisms and shifts in stiffness remained unclear.

4.5.3 Analyses of Range of Motion

Increases in RoM were observed, mainly during the stance phase, which was also reported by Maas et al. (2018). In the ankle, knee, and hip joints, RoM in the sagittal plane increased with fatigue. Since the running speed was fixed by the treadmill, the horizontal mechanical power that each runner had to generate remained unchanged during the entire run. Accordingly, it may be assumed that a tradeoff between mechanical torque and angular displacement has been maintained during the run (Günther & Blickhan, 2002). Consequently, increased angular displacement, which manifests itself as increases in RoM in this case, may be explained by decreased torques at joints, probably due to decreased muscle forces occurring with fatigue (Hanon et al., 2005).

At the hip, the lumbar spine and the thoracic spine, the RoM increased in the frontal and transverse planes. These changes are possibly due to a fatigued core musculature causing difficulties in stabilizing the trunk (Koblbauer et al., 2014), and may be considered to be counterproductive since they do not produce any effective contribution to forward propulsion. On the other hand, increased upper body motion may also be a result of motor control system which tries to compensate increased lower body angular moment by increasing the upper body moment in the reverse direction (for more details see section 4.4.4). During stance, the CoM showed more movement in the medio-lateral direction and less movement in the vertical direction; this is also in line with the decreased stiffness discussed earlier in section 4.5.1.

4.5.4 Time Series Analyses of Joint and CoM Movements

The SPM showed that the ankle was less plantarflexed during the second half of stance. This is in accordance with Mizrahi et al. (2000), who found a decreased activity of the tibialis anterior and hypothesized that this led to a pendant toe. The difference in both knee and hip flexion looks like a time shift in the signal: in the POST, the knee flexion curve is behind the PRE curve, which might be caused by the longer stance phase. There was an increased level of movement in the upper body in the POST. Runners leaned more to the side, which is in accordance with the increased medio-lateral CoM movement during stance (for more details see section 4.4.2). Additionally, an increased upper body rotation was detected, which means there was an increase in movements which do not support forward propulsion. This was probably due to a decrease in trunk stability and possibly led to a decrease in running efficiency.

The SPM showed that many joint movements are affected, not only around initial contact and toe off but also in other phases of the running stride. This finding is an indicator that the studies whose results are limited to discrete parameters may be missing some important aspects due to over-simplified treatments, as also mentioned by Pataky et al. (2013).

The significant changes between PRE and POST in the lower body mainly occurred in the sagittal plane, whereas the changes in the upper body were distributed in all three planes. Sagittal plane dominance within the changes in the lower body movements can be explained by the fact that forward propulsion is mainly associated with the extensions of hip, knee, and ankle joints. Increased level of lower body joint extensions leads to an increased lower body angular moment in vertical direction (e.g. moment due to rotation around the axis parallel to the direction of gravity). These increased rotational moments are counteracted by increased upper body moments around the same axis, which is predominantly done by increasing upper body rotation (Hinrichs, 1987). Ultimately, the total moment of the body around the vertical direction approaches zero, so that the runners can sustain an optimum level of horizontal speed. Significant differences in CoM trajectories were only seen in the vertical direction, indicating that the angular moments in the lower and upper body were balanced such that CoM trajectories related to rotation in vertical direction remained unchanged. These findings may be transferred into practical usage as an indicator for the importance of functional core training. A properly functioning tradeoff mechanism between upper and lower body would optimize the horizontal speed, therefore the performance of the runners as well (Hinrichs, 1987). Any weakness or lack of sufficient coordination in the core muscles may potentially decrease the movement efficiency or increase the injury risk. Main focus of a proper core training should therefore be on the training of movements and positions, rather than just single muscles without considering their synergic behaviors within the complete body (Fredericson & Moore, 2005).

4.5.5 Limitations and Outlook

There are some limitations of the present study that need to be mentioned. First, the use of a treadmill ensured a constant speed and thus enabled investigation of the effects of fatigue in isolation. However, one has to keep in mind that varying speed is a strategy which would be employed by runners when running overground. Besides, it should be noted that although the parameters estimated during treadmill running are comparable to those measured during overground running, they are not equivalent (Van Hooren et al., 2020). Since all participants underwent standardized treadmill familiarization, we can assume that participants had a stable running style. Second, the sample size could have been larger, although it is not easy to recruit a large sample of high-level runners. By using the results found in this exploratory study, subsequent studies may be able to formulate targeted hypotheses concerning the effects of fatigue on running performance or risk of injury. Third, participants of this study were chosen based on their 10 km performance, whereas fatigue protocol was considerably shorter (1.34 ± 0.27 km). This contrast may be considered as a limiting factor. However, even if it would have been preferable to select runners based on their 1500 or 3000 m performance, the goal of this study was to analyze fatigue-related changes during a middle-distance run of experienced runners.

4.6 Conclusion

Despite the number of studies conducted, there is still no clear consensus on how running patterns change in a fatigued state. Compared to long-distance running, middle-distance running has been less frequently studied until now. In this study, the fatigue changes in expert runners during a middle-distance run were investigated in a highly standardized laboratory study by analyzing not only discrete parameters but also time series in 3D. Ultimately, an extensive picture of running in a fatigued state was presented.

The key findings from this study highlight that expert runners increase stance time and decrease time of flight, but keep both the step frequency and the step length constant. Concerning kinematics, increased upper body movements became apparent with fatigue, which may be transferred into the field as an indicator for the importance of functional core training (e.g. total body trainings focusing on core strength) in middle-distance runners. In the fatigued state runners increased their stance time, which led to increased lower body angular moments. These moments were counteracted by increased upper body rotation. The presented results may be used in future research or for practical uptake, particularly when designing training programs (e.g. integrating proper kind of functional core training).

5. Topic B – Fatigue in Experts: Influence of Fatigue on Running Coordination: A UCM Analysis with a Geometric 2D Model and a Subject Specific Anthropometric 3D Model

Slightly modified version of the paper published as:

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5.1 Abstract

Although fatigue is a central issue in endurance sports little is known about the effects of fatigue on coordination. The UCM approach has been widely used in recent studies to examine coordination in human movement; however, it has not been used to study the effects of fatigue on running. Therefore, the aim of this study was to analyze the effects of fatigue on the synergy structure stabilizing the CoM trajectory in experienced runners during high-intensity running using the UCM approach.

A total of 13 healthy young experienced runners participated in the study. Based on a lactate threshold testing undertaken one week prior to the measurements, participants were asked to run on a treadmill at their individual FS until exhaustion. The kinematics of 20 consecutive strides were recorded at the beginning (PRE) and at the end (POST) of the protocol. The effects of fatigue on the synergy structure were investigated using a geometric 2D model and a subject-specific anthropometric 3D model. Specifically, the variance affecting the CoM ($\mathrm{UCM}_{\perp}$), the variance not affecting the CoM ($\mathrm{UCM}_{\parallel}$), and their ratio ($\mathrm{UCM}_{\mathrm{Ratio}}$) were analyzed for different gait cycle phases (absorption, propulsion and flight phase).

Three-way repeated-measures ANOVA tests revealed differences between the two models. Fatigue-induced changes in the UCM structure could only be detected using the 3D model. $\mathrm{UCM}_{\mathrm{Ratio}}$ did not change, but $\mathrm{UCM}_{\perp}$ increased during flight phase. In the 2D model, $\mathrm{UCM}_{\mathrm{Ratio}}$ and both components were higher during the propulsion phase than during the absorption phase in both the rested and the fatigued state.

Using a current concept for analyzing motor coordination, the UCM approach, only minor changes with fatigue were detected using the 3D subject-specific model. This indicates that the runners were able to control the position of their CoM when fatigued. As the 2D model was not able to detect these changes, our study emphasizes that future studies on the effects of fatigue should focus on 3D analyses.

5.2 Introduction

Running is widely enjoyed as both a recreational and a competitive sport. To maintain running performance over a long distance, economy and resistance to fatigue are key factors

(Hoogkamer et al., 2016). Since it can be assumed that experienced runners have spent many years developing a running style that ensures economy, one might suppose that they will try to maintain this running style in a fatigued state.

Studies on the effects of fatigue on running biomechanics have produced conflicting results (Winter et al., 2017). Most previous studies focused on spatiotemporal parameters or changes in isolated DoF (Chan-Roper et al., 2012; Maas et al., 2018; Strohrmann et al., 2012). In fatigued runners, Chan-Roper et al (2012) found significant changes decreases in knee flexion (decrease during support and increase during swing) and an increase in hip flexion and a decreases in hip extension (during swing). Maas et al. (2018) found an increased anterior pelvic tilt and increased pelvic rotation RoM during stance phase as well as increased ankle plantar flexion during swing phase. Koblbauer et al. (2014) also found changes in trunk flexion-extension, which indicates that upper-body kinematics are also affected during fatigue. However, to gain a deeper understanding of the effects of fatigue on running coordination, approaches are needed that are based on models of motor control, to capture coordination in terms of the interplay of different DoF (Cowley & Gates, 2017). Against this background, there is a lack of research.

The framework of the UCM hypothesis (Scholz & Schöner, 1999) is an established approach in the motor control literature for the analysis of motor coordination (Latash et al., 2007). The fundamental hypothesis of the UCM approach is that EV co-vary to stabilize a task-dependent RV (Scholz & Schöner, 1999). Several combinations of EV can lead to the same RV outcome Thus, stabilization of the RV is reflected through a multitude of combinations of EV across repetitions which lead to the same value of the RV. Hence, movement variability is split in two components: $\mathrm{UCM}_{\perp}$, which changes the RV, and $\mathrm{UCM}_{\parallel}$, which does not (Latash et al., 2007; Scholz & Schöner, 1999). The parallel component is thought to stabilize the RV by representing flexible solutions for the movement task. The ratio of $\mathrm{UCM}_{\parallel}$ and $\mathrm{UCM}_{\perp}$ ($\mathrm{UCM}_{\mathrm{Ratio}}$) is used as a measure of the degree of stability. Thus, if $\mathrm{UCM}_{\parallel}$ is greater than $\mathrm{UCM}_{\perp}$, there is a “synergy” that stabilizes the RV (Latash et al., 2002, 2007).

Within the UCM framework, some studies have assessed human walking (Black et al., 2007; Krishnan et al., 2013; Papi et al., 2015; Qu, 2012; Robert et al., 2009; Tawy et al., 2018; Vito et al., 2018; Yen & Chang, 2010) and the effects of fatigue on walking (Qu, 2012). This last study showed that $\mathrm{UCM}_{\mathrm{Ratio}}$ in the frontal plane decreased with fatigue, indicating that participants were less able to control their CoM when fatigued. In contrast to this result, research focusing on the effects of fatigue on movement coordination found changes in parts of the multi-element system, which compensated for the fatigue effects so that the stability of the movement outcome was not affected (Côté et al., 2008; Emery & Côté, 2012; Singh & Latash, 2011). This seems to be the case even in a finger force task with low redundancy (Singh et al., 2010). To date, however, no studies have analyzed the synergy-structure or the effects of fatigue on running.

Most previous studies that applied the UCM approach to analyze walking chose the body's CoM as a RV (Black et al., 2007; Papi et al., 2015; Qu, 2012; Tawy et al., 2018; Vito et al., 2018) and joint angles as EV, except Black et al. (Black et al., 2007) who used segment angles. Others focused on the foot trajectory during swing phase (Krishnan et al., 2013; Rosenblatt et al., 2015). However, there are differences between these studies in the modelling of the CoM: they used either a purely geometrical model limited to one limb (Papi et al., 2015; Tawy et al., 2018; Vito et al., 2018) or a segmented-mass model (Black et al., 2007; Qu, 2012) to calculate the CoM. Since all of these models are restricted to two dimensions, Papi et al. (2015), pointed out the need for the development of a three-dimensional model. The potential effects of models of different complexity on the outcome of UCM-analysis have not yet been investigated. Additionally, as stated above, fatigue leads to changes which do not exclusively take place in the sagittal plane or in the lower limbs (Maas et al., 2018; Qu, 2012). Thus, these effects might not be detectable by a simplified 2D-model.

Therefore, this study has two purposes: 1) to analyze the effects of fatigue on the synergy structure stabilizing the CoM during running and 2) to perform this analysis with two different models to better understand their influence on the outcome of the UCM analysis.

To this end, experienced runners were analyzed before and after a fatigue protocol using an UCM approach with two different models: a geometric 2D model developed by Papi et al. (2015) and a subject-specific anthropometric 3D model. We hypothesized that $\mathrm{UCM}_{\mathrm{Ratio}}$ would decrease with increasing fatigue due to an increase of $\mathrm{UCM}_{\perp}$. Since changes with fatigue do not exclusively happen in the sagittal plane, we hypothesized that the 3D model might detect these changes better than the geometric 2D model.

5.3 Methods

5.3.1 Participants

A total of 13 healthy young experienced male runners participated in the study (see Table 6). The inclusion criteria were a 10 km record below 35 min (run within the last year); a minimum distance covered of 50 km/week during the eight weeks preceding the experiment and an active membership of a running club for at least two years. Exclusion criteria were recent injuries or pain in the lower limbs. All participants provided written informed consent. The study was approved by the ethics committee of the Karlsruhe Institute of Technology.

Table 6: Sample characteristics (mean ± standard deviation); BMI: body mass index; VL3: running speed at 3 mmol/L lactate

Sample size [N]	13
Age [years]	23.5 ± 3.6
Height [m]	1.80 ± 0.06
Weight [kg]	66.8 ± 5.4
BMI [kg/m²]	20.6 ± 1.7
Physical activity [h/week] (including running)	8.2 ± 1.9
Running [h/week]	6.5 ± 1.7
Running training [years]	7.2 ± 3.2
10 km record [min:sec]	32:59 ± 01:19
VL3 [m/s]	4.67 ± 0.29

5.3.2 Experimental Protocol

All participants came to the lab twice to perform two types of tests. The tests were conducted one week apart and at a similar time of the day on a treadmill (h/p/cosmos Saturn, Nussdorf-Traunstein, Germany) with a slope of 1% (Jones & Doust, 1996).

On day 1, participants performed a lactate threshold test. The test started at 8 km/h, the step duration was 3 minutes, the step increment was 2 km/h and the pause between the steps was 30 seconds. Blood lactate concentration was measured at the right ear prior to the test and after each step. Based on the lactate values and the critical power concept (Monod & Scherrer, 1965), an individual FS was determined. This speed was calculated as the speed which participants should be able to run for a maximum of 10 minutes, and was used for the main measurement on day 2.

On day 2, the participants were first familiarized with the treadmill. The familiarization protocol consisted of 6 minutes of walking (Matsas et al., 2000) followed by 6 minutes of running (Lavcanska et al., 2005). Afterwards, participants ran at their individual FS until exhaustion. Measurements were taken at two time points: the first 15 seconds after the treadmill reached FS (PRE), and the second just before ultimate fatigue (POST). Participants were instructed to give notice about 20 seconds prior to exhaustion. In both states (PRE, POST), 20 consecutive strides were recorded.

Fatigue was confirmed using rating of perceived exertion on the Borg 15-grade scale (Borg, 1982). Participants were instructed to look ahead and to not perform undesired movements like looking at their wristwatch during their performance. To prevent falls, all participants were held in a safety harness during the experiment.

5.3.3 Data Collection and Processing

Prior to the measurements, 22 anthropometric measures were manually taken from each participant and 41 reflective markers were attached to participants' skin in accordance to the ALASKA modelling system (Advanced Lagrangian Solver in kinetic Analysis, insys GmbH, Chemnitz, Germany; Härtel and Hermsdorf 2006). During the treadmill protocol, 11 Vicon MX cameras (Vicon Motion Systems; Oxford Metrics Group, Oxford, UK) were used to record the marker trajectories at 200 Hz. Afterwards, data were preprocessed using Vicon Nexus software V1.8.5 and filtered using a fourth order low-pass Butterworth filter with a cutoff-frequency of 10 Hz using MATLAB R2017b (The MathWorks, Natick, MA, USA). The recorded trajectories along with the anthropometric measures (22 measured manually, 43 determined from the reflective markers according to the requirements of the ALASKA modelling system) were used to determine joint angles through inverse kinematics calculations using the ALASKA-full-body Dynamicus model (Härtel & Hermsdorf, 2006). The 20 consecutive strides were time-normalized (from right foot strike to right foot strike) to 100 time steps using custom-made MATLAB routines for each participant and condition. Foot strike was determined as the timeframe where the vertical speed of the heel or foot marker changed its sign and toe off was determined using vertical acceleration of the toe marker (Leitch et al., 2011).

5.3.4 Uncontrolled Manifold Approach

In line with other studies, we chose the CoM as our RV and joint angles as our EV (Black et al., 2007; Papi et al., 2015; Qu, 2012; Tawy et al., 2018; Vito et al., 2018). We chose two different models to calculate the CoM: a 2D geometric model (Papi et al., 2015; Tawy et al., 2018) and a subject-specific anthropometric 3D model. The 2D model approximated the CoM as a fixed point in the pelvis calculated along the leg. In the 3D model, the CoM was calculated as a weighted sum of the body segments. Each of these models provides the relationship between the EV (joint angles) and the RV (CoM). Building on this, we decomposed the variability into the proportion that affected the RV ($\mathrm{UCM}_{\perp}$) and the proportion that did not affect the RV ($\mathrm{UCM}_{\parallel}$) (Latash et al., 2007; Scholz & Schöner, 1999).

2D Geometric Model

The 2D model is based on the model of Papi et al. (2015) and was restricted to the leg in the sagittal plane (Figure 5, A). It consists of 4 segments and 4 DoF. The CoM is determined as the midpoint of the anterior and posterior superior iliac spines (Papi et al., 2015), which are indicated by the respective pelvis markers. The 2D position of the CoM $\boldsymbol{r}_{\mathrm{CoM\_2D}}$ can be expressed using the angles between the foot and the ground (θ_{G}), at the ankle (θ_{A}), at the knee (θ_{K}) and at the hip (θ_{H}). The angles are defined as shown in Figure 5, where A, K and H are the 2D positions of the ankle, knee and hip joint centers calculated by Dynamicus, C and M are the 2D positions of the heel and toe markers and α and β are the angles of the foot segment. A trigonometric analysis leads to:

$$\boldsymbol{r}_{\mathrm{CoM\_2D}} = \begin{pmatrix} x_{\mathrm{A}} - \|AK\| \sin(\theta_{\mathrm{G}}+\theta_{\mathrm{A}}) - \|KH\| \sin(\theta_{\mathrm{G}}+\theta_{\mathrm{A}}+\theta_{\mathrm{K}}) - \|HCoM\| \sin(\theta_{\mathrm{G}}+\theta_{\mathrm{A}}+\theta_{\mathrm{K}}+\theta_{\mathrm{H}}) \\ z_{\mathrm{A}} + \|AK\| \cos(\theta_{\mathrm{G}}+\theta_{\mathrm{A}}) + \|KH\| \cos(\theta_{\mathrm{G}}+\theta_{\mathrm{A}}+\theta_{\mathrm{K}}) + \|HCoM\| \cos(\theta_{\mathrm{G}}+\theta_{\mathrm{A}}+\theta_{\mathrm{K}}+\theta_{\mathrm{H}}) \end{pmatrix} \tag{5.1}$$

with

$$x_{\mathrm{A}} = \begin{cases} x_{\mathrm{C}} + \|CA\| \cos(\alpha+\theta_{\mathrm{G}}) & z_{\mathrm{M}} \geq z_{\mathrm{C}} \\ x_{\mathrm{M}} - \|MA\| \cos(\theta_{\mathrm{G}}-\beta) & z_{\mathrm{M}} < z_{\mathrm{C}} \end{cases} \text{ and } z_{\mathrm{A}} = \begin{cases} z_{\mathrm{C}} + \|CA\| \sin(\alpha+\theta_{\mathrm{G}}) & z_{\mathrm{M}} \geq z_{\mathrm{C}} \\ z_{\mathrm{M}} - \|MA\| \sin(\theta_{\mathrm{G}}-\beta) & z_{\mathrm{M}} < z_{\mathrm{C}} \end{cases}. \tag{5.2}$$

This model can only be used in the stance phase and therefore the appropriate leg (left/right) was used during calculations for the relevant stance phase. The difference between the 3D segment length and the projected segment length was found to be marginal.

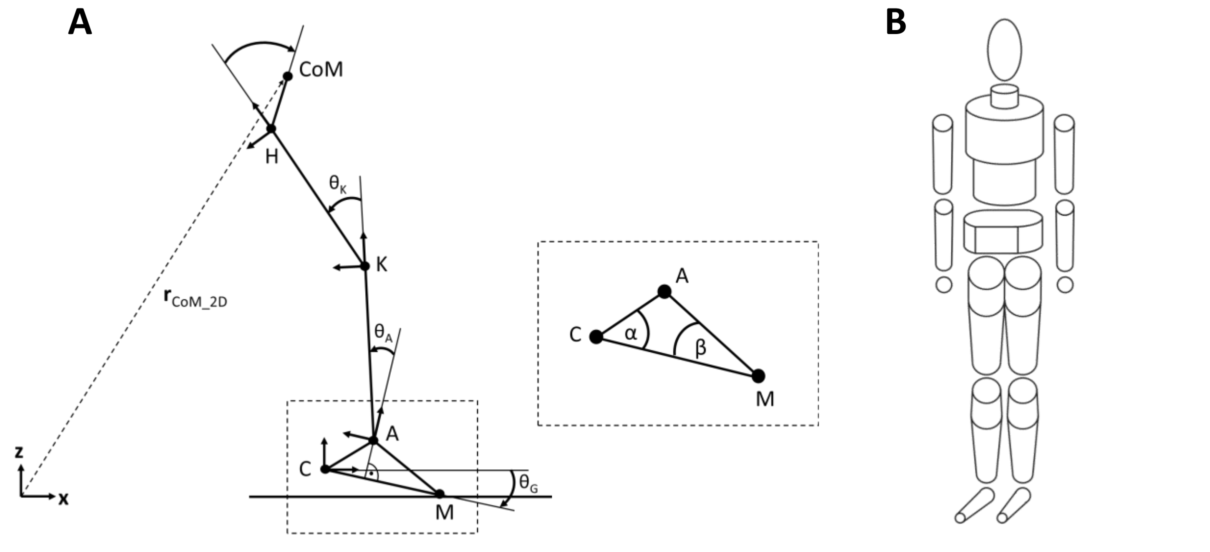

Figure 5: Models for calculating the CoM. (A): 2D geometric model; definition of the segment angles and positions used in the calculation of $\boldsymbol{r}_{\mathrm{CoM\_2D}}$. (B): 3D anthropometric model.

3D Anthropometric Model

The 3D model is based on Hanavan (1964) and consists of 17 segments and 50 DoF (47 segmental angles and 3 hip rotations, see Figure 5, B). In addition to the Hanavan-model (Hanavan, 1964), we included a neck and a hip segment and modified some segments (e.g. the shape of the trunk was changed using more subject-specific measurements), leading to a total of 36 subject-specific anthropometric measurements (21 measured manually, 15 determined through the reflective markers). A constant density was assumed (Ackland et al., 1988). Each segment's mass was determined via volume integration.

Finally, the whole-body CoM ($\boldsymbol{r}_{\mathrm{CoM\_3D}}$) was calculated as a weighted sum:

$$\boldsymbol{r}_{\mathrm{CoM\_3D}} = \frac{1}{\sum_{i=1}^{N} V_{\mathrm{i}}} * \sum_{i=1}^{N} \boldsymbol{r}_{\mathrm{i}} V_{\mathrm{i}} \tag{5.3}$$

With N as the number of segments; V_{i} as the volume of segment i; and $\boldsymbol{r}_{\mathrm{i}}$ as the vector of the center of gravity of segment i.

UCM-based Decomposition of Stride-to-Stride Variability

Since we chose the CoM as a RV (Black et al., 2007; Papi et al., 2015), changes in joint angles (θ, EV) were linked to changes in the CoM ($\boldsymbol{r}_{\mathrm{CoM}}$, RV). Therefore, the RV is expressed as a function of the EV: $\boldsymbol{RV} = \boldsymbol{r}_{\mathrm{CoM}} = f(\boldsymbol{EV}) = f(\boldsymbol{\theta})$. Following the UCM approach (Black et al., 2007; Scholz & Schöner, 1999), the null space of the linearized Jacobian, representing the space in which alterations of the EV do not cause alterations of the RV, is calculated as:

$$\mathbf{0} = \boldsymbol{J}\boldsymbol{e}_i; \boldsymbol{J} = \left.\frac{\partial f(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right|_{\boldsymbol{\theta}_0}; i = 1 \ldots n - d. \tag{5.4}$$

$\boldsymbol{\theta}_0$ are the mean values of the EV over the 20 strides, $\boldsymbol{e}_{\mathrm{i}}$ are the vectors defining the null space, n is the number of dimensions of EV and d is the number of dimensions of the RV (here: $n = 4$ and $d = 2$ for the 2D model and $n = 50$ and $d = 3$ for the 3D model).

Deviations from the mean joint configuration ($\boldsymbol{\theta}_0$) were separated into those parallel to the UCM (those stabilizing the RV, $\sigma_{\mathrm{k},\parallel}$) and those orthogonal to the UCM (those changing the RV, $\sigma_{\mathrm{k},\perp}$). These calculations were performed for every percent of the stride.

$$\sigma_{\mathrm{k},\parallel} = \sum_{i=1}^{n-d} \left[\left(\boldsymbol{e}_{\mathrm{i}}^{\mathrm{T}} (\boldsymbol{\theta}_{\mathrm{k}} - \boldsymbol{\theta}_0) \right) \boldsymbol{e}_{\mathrm{i}} \right] \tag{5.5}$$

$$\sigma_{\mathrm{k},\perp} = (\boldsymbol{\theta}_{\mathrm{k}} - \boldsymbol{\theta}_0) - \sigma_{\mathrm{k},\parallel}; k = 1 \ldots N_{\mathrm{trial}} \tag{5.6}$$

The variability parallel and orthogonal to the UCM was calculated as the variance over the $N_{\mathrm{trial}} = 20$ strides:

$$UCM_{\parallel} = \sqrt{\frac{1}{(n-d) * N_{\mathrm{trial}}} \sum_{k=1}^{N_{\mathrm{trial}}} \sigma_{\mathrm{k},\parallel}^2} \tag{5.7}$$

$$UCM_{\perp} = \sqrt{\frac{1}{d * N_{\mathrm{trial}}} \sum_{k=1}^{N_{\mathrm{trial}}} \sigma_{\mathrm{k},\perp}^{2}}. \tag{5.8}$$

The ratio between these two quantities was calculated as

$$UCM_{\mathrm{Ratio}} = \frac{2 * UCM_{\parallel}{}^{2}}{UCM_{\parallel}^{2} + UCM_{\perp}{}^{2}} - 1 \tag{5.9}$$

and quantifies the degree of stabilization of the CoM. This ratio lies between -1 and 1: a ratio > 0 is interpreted as a synergy, whereas a ratio ≤ 0 indicates no synergy (Papi et al., 2015; Tawy et al., 2018).

We divided one stride in stance and flight phases. Following Novacheck (1998), stance was further divided in an absorption phase, characterized by a downward motion of the CoM, and a propulsion phase, characterized by an upwards motion of the CoM. For each of the phases we calculated the mean of each of the dependent variables ($\mathrm{UCM_{Ratio}}$, $\mathrm{UCM_{\parallel}}$ and $\mathrm{UCM_{\perp}}$). For the 2D model, analyses could only be performed during stance.

5.3.5 Statistics

Statistical analyses were performed using JASP (http://www.jasp-stats.org). To test whether the control hypothesis about our RV ($\mathrm{UCM_{Ratio}} > 0$) was fulfilled, one-sample t-tests were conducted.

To test if an influence of the choice of model exists, a 2 x 2 x 2 ANOVA with factors state [PRE, POST], model [2D, 3D] and phase [absorption, propulsion] was calculated for each dependent variable. Dependent t-tests (differences between gait cycle phases and states) were used as post-hoc tests. For the 3D model, a dependent t-test was used to look for differences between the rested and fatigued state for the flight phase.

The conditions for the application of ANOVA were tested a priori. Multiple t-tests are presented as corrected t-tests using the Holm-Bonferroni-correction (Holm, 1979). The significance level was set to p = 0.05. Partial eta square (η_p^2) and Cohen's d were used to indicate effect size for the ANOVA and t-tests, respectively. A small effect size was < 0.06 (η_p^2) or < 0.5 (Cohen's d). A moderate effect size was between 0.06 and 0.14 (η_p^2) or between 0.5 and 0.8 (Cohen's d). A large effect size was indicated by $\eta_p^2 > 0.14$ or Cohen's d > 0.8 (Cohen, 1992), respectively.

5.4 Results

FS calculated from the lactate threshold test on day 1 was at 19.27 ± 0.72 km/h. Participants were able to run at this speed for 4:06 ± 0:52 minutes and reported their perceived fatigue as 19.6 ± 0.65 on the Borg Scale (Borg, 1982).

The times courses of the UCM parameters are shown in Figure 6. The mean values and standard deviations are listed in Table 7 and Table 8 for the 2D and 3D model, respectively. The three-way ANOVA showed no significant state effect or interactions involving the factor state for $\mathrm{UCM_{Ratio}}$ and $\mathrm{UCM_{\parallel}}$. For $\mathrm{UCM_{\perp}}$, the state effect showed a high effect size ($p = 0.110$, $\eta_p^2 = 0.199$). Significant model effects were detected for $\mathrm{UCM_{Ratio}}$ ($p < 0.001$, $\eta_p^2 = 0.627$) and $\mathrm{UCM_{\perp}}$ ($p < 0.001$, $\eta_p^2 = 0.633$) as well as a high effect size for $\mathrm{UCM_{\parallel}}$ ($p = 0.080$, $\eta_p^2 = 0.234$). For all three parameters, significant phase effects (all $p < 0.001$, $\eta_p^2 > 0.739$) and model x phase interactions were found (all $p < 0.001$, $\eta_p^2 > 694$). Since differences between the models occurred in all three dependent variables, the following results are presented separately for the 2D model and the 3D model.

5.4.1 Geometric 2D Model

The post-hoc tests following the main effect for the factor state [PRE, POST] for $\mathrm{UCM_{\perp}}$ showed no influence of fatigue for neither absorption phase nor propulsion phase.

Concerning the phase effect [absorption, propulsion], dependent t-tests showed that $\mathrm{UCM_{Ratio}}$ significantly increased from absorption to propulsion phase in both the PRE ($p < 0.001$, $d = 5.044$) and the POST ($p < 0.001$, $d = 3.113$) state.

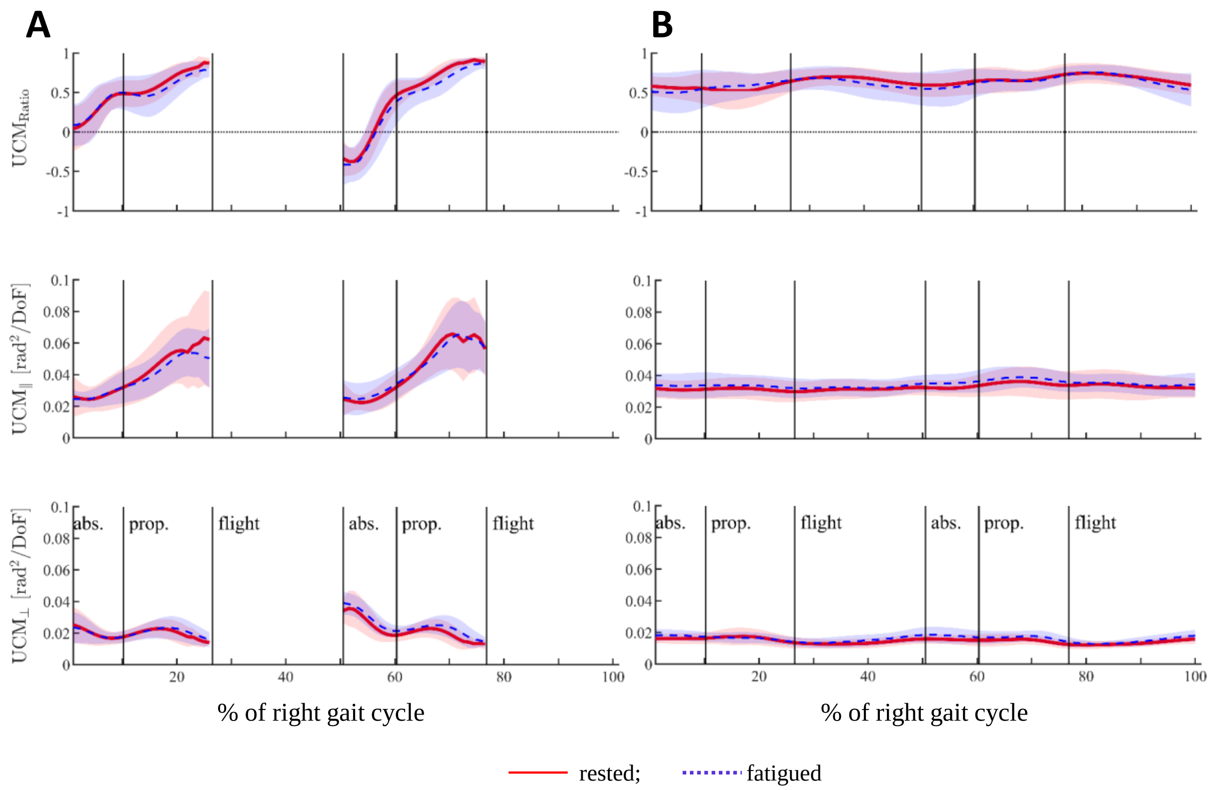

Figure 6: Time courses for the three dependent UCM variables. Mean ± sd, for both models: (A): 2D model (sagittal plane); (B): 3D model. "abs." denotes the absorption phase, "prop." denotes the propulsion phase and "flight" denotes the flight phase.

Moreover, the UCM_{Ratio} was significantly above zero for both phases of the PRE state (absorption: $p = 0.043$, $d = 0.627$; propulsion: $p < 0.001$, $d = 8.937$) and for the propulsion phase but not the absorption phase ($p = 0.245$, $d = 0.339$) of the POST state ($p < 0.001$, $d = 6.098$).

For $UCM_{\parallel}$, post hoc tests showed that in both the PRE and the POST state, $UCM_{\parallel}$ increased from absorption to propulsion (rested: $p < 0.001$, $d = 2.526$; fatigued: $p < 0.001$, $d = 2.067$).

For $UCM_{\perp}$, post-hoc tests showed a decrease from absorption phase to propulsion phase in both the PRE and the POST state (rested: $p < 0.001$, $d = 1.370$; fatigued: $p = 0.001$, $d = 1.269$).

Table 7: Values of the UCM variables for the 2D model. Mean ± sd for the three dependent variables, in the two stance phases (absorption, propulsion), calculated with the 2D geometric model.

		PRE	POST
UCM_{Ratio}	Absorption	0.044 ± 0.174	0.063 ± 0.187
	Propulsion	0.664 ± 0.074	0.627 ± 0.103
	Flight		
$UCM_{\parallel}$	Absorption	0.026 ± 0.008	0.026 ± 0.006
	Propulsion	0.049 ± 0.016	0.049 ± 0.011
	Flight		
$UCM_{\perp}$	Absorption	0.024 ± 0.007	0.025 ± 0.005
	Propulsion	0.019 ± 0.005	0.021 ± 0.004
	Flight		

5.4.2 Anthropometric 3D Model

Post-hoc tests following the main effect for the factor state [PRE, POST] for $UCM_{\perp}$ in the 2 x 2 x 2 ANOVA showed no influence of fatigue showed now significant results. The dependent t-tests for the flight phase showed a significant increase with fatigue, with a medium effect size ($p = 0.041$, $d = 0.635$).

Concerning the post-hoc tests for the phase effect [absorption, propulsion] for UCM_{Ratio}, there were no significant differences. One-sample t-tests showed that UCM_{Ratio} was significantly above zero throughout the stride in both the PRE and the POST states ($p < 0.001$ in all cases, $d \geq 2.542$). For $UCM_{\parallel}$, the post-hoc tests showed a significant increase with a medium effect size from absorption to propulsion phase in both the PRE ($p = 0.032$, $d = 0.671$) and the POST ($p = 0.020$, $d = 0.742$) state. For $UCM_{\perp}$ there were no significant effects.

Table 8: Values of the UCM variables for the 3D model. Mean ± sd values for the three dependent variables, in the three phases (absorption, propulsion, flight), calculated with the 3D anthropometric model.

		PRE	POST
UCM_{Ratio}	Absorption	0.582 ± 0.132	0.536 ± 0.211
	Propulsion	0.600 ± 0.160	0.615 ± 0.137
	Flight	0.679 ± 0.102	0.652 ± 0.127
$UCM_{\parallel}$	Absorption	0.032 ± 0.005	0.034 ± 0.006
	Propulsion	0.033 ± 0.007	0.036 ± 0.006
	Flight	0.032 ± 0.006	0.033 ± 0.005
$UCM_{\perp}$	Absorption	0.016 ± 0.003	0.018 ± 0.004
	Propulsion	0.016 ± 0.004	0.017 ± 0.003
	Flight	0.013 ± 0.002	0.015 ± 0.003

5.5 Discussion

This is the first study to analyze the effects of fatigue during running within the framework of the UCM hypothesis in experienced runners. We analyzed the synergy stabilizing the CoM trajectory in both a rested and a fatigued state. Neither of the two models detected fatigue effects for the UCM_{Ratio}. Therefore, our first hypothesis, stating that UCM_{Ratio} would decrease with increasing fatigue, had to be renounced. Our second hypothesis was partly confirmed: The 3D anthropometric model found a significant effect of the fatigue protocol in $UCM_{\perp}$ in the flight phase. Since the two models showed different results, the effects of fatigue are discussed for each model separately.

5.5.1 Fatigue Effects

All participants were considerably fatigued as indicated by their rating on the Borg scale (19.6 ± 0.65).

The 2D model showed an increasing UCM_{Ratio} throughout the stance phase. During the absorption phase, UCM_{Ratio} was not significantly different from zero in the fatigued state. In the propulsion phase for both the PRE and the POST state and in the absorption phase for the PRE state, $\mathrm{UCM_{Ratio}}$ was significantly above zero. This means that, during the absorption phase for the fatigued state, there was no synergy stabilizing the CoM trajectory. This is also reflected in the two variability components. $\mathrm{UCM}_{\parallel}$, which stabilizes the RV by offering flexible solutions (Latash et al., 2002), was higher during the propulsion phase than during the absorption phase. In contrast, $\mathrm{UCM}_{\perp}$, which changes the RV and is thus potentially detrimental for performance, was lower during propulsion compared to absorption. So, the geometric 2D model implies that exhausted runners were no longer able to stabilize their CoM trajectory during the absorption phase, although this development did not reach significance. In addition, it has to be kept in mind that the 2D model is restricted to the sagittal plane and does not take into account any parts of the upper body which are also affected by running-induced fatigue (Koblbauer et al., 2014).

Within the 3D model, $\mathrm{UCM_{Ratio}}$ was always above zero, indicating that there was a synergy present over the whole stride. For $\mathrm{UCM_{Ratio}}$ and $\mathrm{UCM}_{\perp}$, there was no difference throughout stance for either the rested or fatigued state. $\mathrm{UCM}_{\parallel}$ increased from absorption to propulsion, but to a smaller degree than in the 2D model. For both $\mathrm{UCM_{Ratio}}$ and $\mathrm{UCM}_{\parallel}$, there were no effects with fatigue. $\mathrm{UCM}_{\perp}$ increased with fatigue during the flight phase. Since $\mathrm{UCM}_{\perp}$ represents variability influencing the RV (Latash et al., 2002), it has to be avoided to reach a constant performance from stride-to-stride. The increase with fatigue might show that runners cannot maintain their stride-to-stride consistency in a fatigued state. The trajectory of the CoM during flight is largely determined at toe-off: alterations during flight are a result of alterations during toe-off. Since there were no fatigue effects detected during the propulsion phase, these might develop during the course of the flight phase. Since this effect only showed a medium effect size, it is questionable whether it is significant in practice.

Previous studies on the effects of fatigue on movement coordination frequently found an increase in $\mathrm{UCM}_{\parallel}$, indicating that variability increased without affecting the movement outcome (Côté et al., 2008; Emery & Côté, 2012; Singh & Latash, 2011). Common to these studies was that the fatigue protocol concerned one element of the multi-element system. The non-affected elements of the system seemed to compensate for this impairment. Similar to the fatigue protocol applied by Qu (2012), our fatigue protocol intended to induce a “whole-body-fatigue”. So there were no non-affected elements which could account for the fatigue-effects. This might explain the decreased $\mathrm{UCM_{Ratio}}$ in the frontal plane in the study by Qu (2012). In contrast to

Qu (2012), our study focused on running experts. Running experts are used to running in a fatigued state in training and competition. Accordingly, the athletes in our study are used to maintaining their running style in a fatigued state. Hoenig et al. (2019) studied the local dynamic stability during a 5000 m run in recreational and competitive runners and found an increase with fatigue in both groups. However, since the same kinematic pattern can be generated by different muscle activations due to the redundancy of the musculoskeletal system, it is possible that the effects of fatigue could be detectable at the muscle level (Hollman et al., 2012). Compensation strategies on a muscular level as observed by Singh et al. (2011) or Nielsen et al. (2018) might also be of importance in our study. Therefore, it might be promising to study fatigue effects in running within the UCM framework using modules calculated from EMG data as EV, like it was done before in a postural control task (Krishnamoorthy et al., 2003; Singh & Latash, 2011).

The fact that no fatigue effects were found in this study does not necessarily mean that they are not present in the studied kinematics. It could be speculated that runners adopted a different locomotion pattern in the fatigued state. Since the CoM is an important performance variable, it remains closely controlled and therefore changes are not detectable with the UCM approach. The use of a matrix factorization technique such as principal component analysis (Cowley & Gates, 2017; Daffertshofer et al., 2004) could help to detect such changes in kinematics while taking into account the interplay of the different DoF.

5.5.2 Modeling

We assumed the CoM to be a good choice of a performance variable in running (Black et al., 2007; Papi et al., 2015), since the running human body has been successfully modelled as a spring-mass model (Blickhan, 1989; Dutto & Smith, 2002). It has been shown that runners adjust their running speed rather than the vertical position of their CoM , so CoM-control seems to have a high priority (Girard et al., 2013). Our finding, that the control of the CoM is not impaired by fatigue, supports this assumption. In the UCM literature, two different approaches have been employed to link changes in the EV with changes in the RV. One can either build up a multi-body model or use a multiple linear regression technique, both techniques have been shown to produce equivalent results (Freitas et al., 2010; Freitas & Scholz, 2010). We chose an approach using a multi-body model.

As stated earlier, fatigue effects are observed in all three planes, in the lower and upper body and during stance and flight phase (Chan-Roper et al., 2012; Koblbauer et al., 2014; Maas et al., 2018). We therefore developed a 3D anthropometric whole-body model. Since athletes are a special anthropometric group (Virmavirta & Isolehto, 2014), the use of a subject-specific model seemed appropriate. We performed our analysis with this model and with a literature-based 2D model (Papi et al., 2015). Since there is no fixed support during flight phase, the geometric 2D model could only be used during stance. Because of that, an anthropometric 3D model should be used to study the effects of fatigue on running gait.

5.5.3 Limitations

To capture the natural variability over several repetitions of the same movement, consecutive strides were captured and measurements were therefore performed on a treadmill. However, running on a treadmill is not identical to running overground (Fellin et al., 2010). Since participants were given sufficient time for familiarization with the treadmill (Lavcanska et al., 2005; Matsas et al., 2000), it can be assumed that movement patterns were at least stable, if not identical to ones from overground running (Riley et al., 2008). The choice of the RV in the UCM framework is a subjective one. Different RVs have been used in studies dealing with human locomotion (Krishnan et al., 2013; Robert et al., 2009). There might not be one correct choice, but instead several important variables. However, as the CoM is highly controlled even in the fatigued state, CoM control seems to be a high priority for the CNS and thus is a reasonable choice.

5.6 Conclusions

The understanding of fatigue effects on running coordination is an important issue in sport science. Studies analyzing the effects of fatigue on running using discrete kinematic parameters show only limited evidence concerning the effects of fatigue (Winter et al., 2017). Applying current concepts from motor control to the field of sport science is a promising direction to gain deeper insights. The effects of fatigue might be better addressed at the level of motor coordination while taking into account the interplay of different DoF (Sternad, 2018). Using a current concept for motor coordination, the UCM approach, minor changes with fatigue could be detected using a 3D subject-specific model: the orthogonal component increased during flight phase, without affecting the $\mathrm{UCM}_{\mathrm{Ratio}}$. Runners thus seem to be able to control the position of their CoM under fatigue.

6. Topic B – Fatigue in Experts: Stride-to-Stride Variability of the Center of Mass in Male Trained Runners After an Exhaustive run: A Three-Dimensional Movement Variability Analysis with a Subject Specific Anthropometric Model

Slightly modified version of the paper published as:

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6.1 Abstract

The motion of the human body can be described by the motion of its CoM. Since the trajectory of the CoM is a crucial variable during running, one can assume that trained runners would try to keep their CoM trajectory constant from stride to stride. However, when exposed to fatigue, runners might have to adapt certain biomechanical parameters. The UCM approach and the TNC approach are used to analyze changes in movement variability while considering the overall task of keeping a certain task relevant variable constant. The purpose of this study was to investigate if and how runners adjust their CoM trajectory during a run to fatigue at a constant speed on a treadmill and how fatigue affects the variability of the CoM trajectory. Additionally, the results obtained with the TNC approach were compared to the results obtained with the UCM analysis in an earlier study on the same dataset. Therefore, two TNC analyses were conducted to assess effects of fatigue on the CoM trajectory from two viewpoints: one analyzing the CoM with respect to a lab coordinate system (RV_{lab}) and another one analyzing the CoM with respect to the right foot (RV_{foot}). Full body kinematics of 13 healthy young athletes were captured in a rested and in a fatigued state and an anthropometric model was used to calculate the CoM based on the joint angles. Variability was quantified by the CV of the length of the position vector of the CoM and by the components Tolerance, Noise and Covariation which were analyzed both in 3D and the projections in the vertical, anterior-posterior and medio-lateral coordinate axes. Concerning RV_{lab} we found that runners increased their SSV in medio-lateral direction (1%). Concerning RV_{foot} we found that runners lowered their CoM (4 mm) and increased their SSV in the absorption phase in both 3D and in the vertical direction. Although we identified statistically relevant differences between the two running states, we have to point out that the effects were small (CV ≤ 1%) and must be interpreted cautiously.

6.2 Introduction

One of the key questions in the field of motor control is how humans are able to perform skilled movements. Competitive sports might be seen as performing movements in perfection: a gymnast, for example, is able to perform complex movements with maximal aesthetics, and an endurance athlete performs his/her movements with maximal efficiency. With respect to that, variability might be seen as counterproductive, since it causes deviations from the singular "optimal movement" in a given situation. However, a certain amount of variability is desirable since it could avoid overload injuries (Hamill et al., 2012). So, the benefit of variability might depend on the variable we are looking at. It was shown that parameters such as movement speed, footwear, expertise and fatigue affect movement variability (Fuller et al., 2016; García-Pinillos et al., 2020; Jordan & Newell, 2008). Since fatigue is an unavoidable phenomenon in endurance sports, the question arises as to how fatigue affects motor variability and whether athletes are still able to perform their movements with the same consistency in a fatigued state.

Variability analyses are well established within the field of motor control, with different degrees of complexity (Sternad, 2018). Namely, these are the GEM (Cusumano & Cesari, 2006), the UCM (Scholz and Schöner 1999) and the TNC (Müller & Sternad, 2004) approaches, all of which allow analysis of functional structure and repartition of movement variability. Common to these approaches is the examination of a task-relevant RV. Its value should show low variability and stay close to the optimum over several movement repetitions to ensure successful task completion. The execution of the movement is described by EV. A main difference between the TNC approach and the UCM and GEM approach is the fact that the TNC analyses the variability on the level of the RV whereas the UCM and GEM analyze the variability on the level of EV. There exist different kinds of variability: If variability among the EV does not increase variability of the RV it is supposed to be "good", since this variability could be essential for adaptations or motor learning (Latash et al. 2010). On the other hand, variability among the EV which affects the RV is considered to be "bad" since it causes deviations from the desired RV-value. To analyze the effect of the variability of certain EV, the RV has to be formulated as a function of the EV. One example of a RV might be hitting a target, e.g. a specific field on a dartboard, with a dart. This RV could be described as a function of the EV release angle and velocity (Müller & Sternad, 2004).

The approaches mentioned above have mostly been applied to movements with a restricted number of degrees of freedom and far less often to whole-body movements. Some recent studies have analyzed walking using diverse analyses (GEM: Dingwell, Bohnsack-McLagan, and Cusumano 2018; UCM: Yamagata et al. 2019; and TNC: Hamacher et al. 2019). Using a GEM approach, Dingwell et al. (2018) showed that the structure of SSV was speed-dependent: variability affecting the RV decreased with speed. Yamagata et al. (2019) showed a relationship between incident falls and stride-to-stride-variability in older adults using an UCM approach. The study by Hamacher et al. (2019) investigated the SSV in walking by means of the TNC approach and has highlighted the usefulness of this approach for gaining deeper insight into related motor adaptations. Using the TNC approach, Hamacher et al. found decreases in gait variability during dual task walking due to the component "noise". However, there are only a few studies analyzing the SSV in running. Dingwell et al. (2018) found tighter control in running compared to walking as indicted by quicker corrections. In our earlier studies we found higher SSV in novices compared to experts and only slight changes due to fatigue using an UCM approach (Möhler et al., 2019, 2020). Brahms et al. (2020) analyzed the CV of several spatiotemporal parameters (stride time and length, contact time) and peak acceleration during an overground run with constant speed. They found no effects of fatigue, which is interpreted as a confirmation for the insensitivity of linear variability measures. Skowronek et al. (2021) investigated the effects of an aerobic running protocol on jump rhythm using the Optojump Next system. They found that the rhythm of movement is impaired by the anaerobic fatiguing protocol. To date, the TNC approach has not been used to study running.

As stated above, a RV has to be determined first in all mentioned approaches and should be kept constant between movement repetitions. In the case of endurance running, it can be assumed that runners adopted a subject-specific optimal running style over years of training (Moore, 2016; Williams & Cavanagh, 1987). This optimal running style should be kept constant from stride-to-stride if the ambient conditions do not change. The CoM trajectory can be used to describe this running style (Blickhan, 1989; Dutto & Smith, 2002) and is one of several biomechanical parameters which influence running economy (Moore, 2016; Tartaruga et al., 2012; Williams & Cavanagh, 1987). It has been shown that during a run to fatigue with self-selected speed, runners adjust their speed rather than their vertical CoM position, which underlines the importance of keeping this parameter constant (Girard et al., 2013). When running on a treadmill however, speed is mostly fixed and runners are thus not able to adjust their running speed. Consequently, the question is whether and how runners adjust their CoM trajectory when they are not able to adjust their speed when they become fatigued and how fatigue affects the variability of the CoM trajectory.

The CoM trajectory can be described with respect to different reference points when running on a treadmill. The origin of the lab coordinate system as a fixed reference point (Möhler et al., 2019) is one possible viewpoint. However, Moore et al. (2016) found that the alignment of the ground reaction force with the leg axis led to increases in running economy. This seems plausible, since the runner tries to accelerate his/her body (represented by the CoM) forwards and upwards against gravity by pushing his/her body over the legs (Heise & Martin, 2001), so the description of the CoM trajectory in a body-related coordinate system (e.g. relative to the pushing foot) might be better suited as a relevant RV during running than the CoM trajectory in a lab coordinate system (e.g. relative to an arbitrarily chosen point in the lab). Besides, even if a 3D analysis is desirable (Papi et al., 2015), the separate analysis of the three dimensions as complementary measures could provide valuable information since the observed variability could be repartitioned in the three directions. However, this is not easy to implement with an analysis in the execution space (as with the UCM analysis) since the EV must have the same units (e.g. joint angles in degrees vs. foot position in meters) and a new model has to be built up for each direction (Latash et al., 2007; Müller & Sternad, 2009). In contrast to the UCM approach, the TNC approach allows for the combination of EV with different units, since the analysis is performed in the result space (Müller & Sternad, 2009). Whereas UCM analysis is applicable to a single data set, TNC analysis can only reveal changes in movement variability between two states (Müller & Sternad, 2003, 2004). However, this is suitable for looking at differences between a fatigued and a non-fatigued state.

In this study, data from Möhler et al. (2019) were re-analyzed using the TNC approach to gain a deeper insight into changes in motor coordination due to running induced fatigue. Effects of fatigue on running mechanics were shown to be dependent on the type of fatigue, as Fischer et al. (2015) found clear effects of a high intensity short-time fatigue protocol on spatiotemporal parameters and Vernillo et al. (2016) found no effects of an extreme ultra-marathon on the spatiotemporal parameters observed. In our study, we analyze the effects of an anaerobic run to exhaustion. The purpose was to investigate if and how runners adjust their CoM trajectory due to high intensity anaerobic fatigue (~4 min at ~19 km/h) and how this fatigue affects the variability of the CoM trajectory. Additionally, we wanted to compare our results to the ones obtained with the UCM approach in our earlier study on the same dataset (Möhler et al., 2019). Therefore, we calculated the TNC approach for two RV: RV_{lab} as the CoM with respect to a fixed point in order to compare our results to the ones obtained with the UCM and RV_{foot} as the CoM with respect to the right foot in order to choose a RV which potentially better suited to functionally study running. So, we obtained two vectors which were described in dependence of the joint angles as EV. The CV of the length of these vectors was observed as a measure of variability of the CoM trajectory. Our hypotheses for the two RVs were: (1) According to our previous study (Möhler et al., 2019), the TNC analysis would reveal no effects of fatigue when looking at RV_{lab} in 3D. (2) Based on previous biomechanical studies which found effects of fatigue on different joint angles (Winter et al., 2017) as well as increases in variability with fatigue on spatio-temporal parameters and their variability (García-Pinillos et al., 2020) the TNC analysis looking at RV_{foot} would show changes in CoM trajectory as well as increases in variability with fatigue.

6.3 Methods

6.3.1 Used Dataset

A description of the study design is given in the following section. Further details can be found in Möhler et al. (2019). The sample consisted of 13 healthy young experienced male runners (age: 23.5 ± 3.6 years, BMI: 20.6 ± 1.7 kg/m², 7.2 ± 3.2 years of running training, 10 km record 32:59 ± 01:19 minutes). Inclusion criteria were an active membership in a running club for at least two years, a 10 km record below 35 min, a minimum training volume of 50 km/week during the eight weeks before the measurements. Exclusion criteria were recent injuries or pain in the lower limbs. A total of 22 anthropometric measures were taken manually from each participant and 41 reflective markers were attached to anatomical landmarks to perform an inverse kinematics calculation using the Alaska Dynamicus full body model (Härtel & Hermsdorf, 2006). One week prior to the biomechanical measurement, participants came to the lab to perform a lactate threshold test. Following the critical power concept (Monod & Scherrer, 1965), their individual fatigue-speed was determined. This speed was at 19.27 ± 0.72 km/h. On the day of the measurement, participants performed a standardized treadmill familiarization (6 min of walking, Matsas et al., 2000; and 6 min of running, Lavcanska et al., 2005). Afterwards, participants ran on the treadmill at their individual FS until voluntary exhaustion. Participants reached voluntary exhaustion at this speed after 4:06 ± 0:52 minutes. Their perceived fatigue was reported as 19.6 ± 0.65 on the Borg Scale (Borg, 1982). For each participant, a minimum of 20 consecutive strides were collected at the beginning, 20 seconds after the FS was reached (PRE state) and end of the run, when the participant indicated exhaustion (POST state). Due to data issues, only 19 consecutive strides per participant could be analyzed. Based on marker data (heel and toe marker, Leitch et al., 2011), the right stance phase was determined. Since the running mechanics could change with the foot strike pattern (Lieberman et al., 2010) we verified that foot strike patterns did not change from PRE to POST (angle between longitudinal foot axis and ground PRE: 3.16°, POST: 3.76°, $p = 0.164$). Data were cut to the right stance phase and time-normalized to 100 time points using a cubic spline interpolation. The time-normalized stance phase was then further divided into absorption phase

(1-50%) and propulsion phase (51-100%) (Cavanagh & Lafortune, 1980; da Rosa et al., 2019). These data serve as input for the following TNC analysis.

6.3.2 TNC Analysis

In order to perform a TNC analysis, one has to define EV and a RV and a forward model linking the EV with the RV. The joint angles were defined as EV. The RV is supposed to be a variable which is controlled in a way that its value remains constant over several trials (in our case: strides). The steps and choices necessary to perform a TNC analysis are described in the following sections. We first describe our EV, RV_{lab} and RV_{foot}, then our anthropometric model and finally the decomposition of variability in T, N and C.

$\boldsymbol{RV}_{\mathbf{lab}}$

In accordance with our previous UCM analysis (Möhler et al., 2019), we defined the CoM trajectory relative to a fixed point as RV_{lab} ($\boldsymbol{r}_{\mathrm{RV\_lab}}$), respectively the length of the vector (euclidean norm) pointing from this fixed point to it (see Figure 7 and equation (6.2). The chosen coordinate axes were classified as: pointing parallel to the treadmill belt (x-direction, anterior-posterior), vertical (z-direction) or perpendicular to these two axes (y-direction, medio-lateral). Therefore, x and z represent physically meaningful directions (running direction, gravity).

The CV was calculated as a measure for SSV. Thus, the degree to which the RV is kept constant over the 19 strides could be quantified. CVs were calculated for the 3D length of the vector and on the projections in the individual directions (anterior-posterior, medio-lateral and vertical direction).

$\boldsymbol{RV}_{\mathbf{foot}}$

We defined the CoM trajectory relative to the right foot as RV_{foot} ($\boldsymbol{r}_{\mathrm{RV\_Foot}}$), more precisely the length of the vector pointing from the right foot to the CoM (see Figure 7 and equation (6.3). The chosen coordinate axes were classified as: pointing parallel to the treadmill belt (x direction, anterior-posterior), vertical (z-direction) or perpendicular to these two axes (y direction, medio-lateral). The length of the vector pointing from the right foot to the CoM trajectory was then calculated (euclidean norm). CV of RV_{foot} were calculated in the same manner as for RV_{lab}.

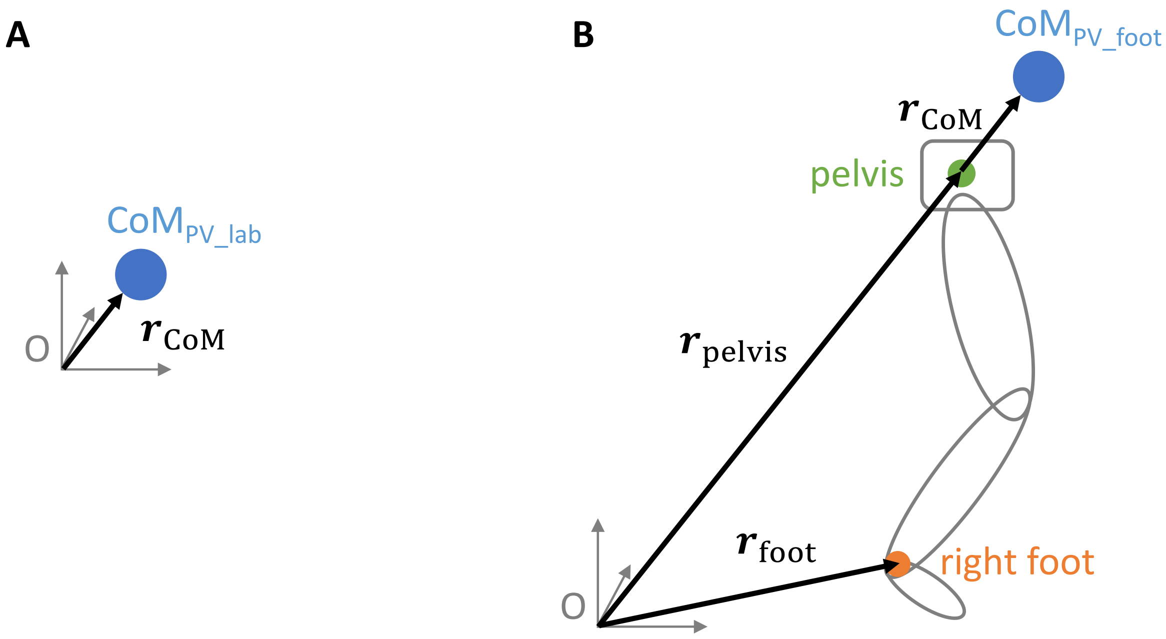

Figure 7: Drawing illustrating the calculation of the two RVs. The CoM is shown in blue. (A): definition of RV_{lab} as the CoM relative to the origin. (B): definition of RV_{foot}. The right leg is shown in grey with the midpoint of the malleolus markers (right foot) in orange and the midpoint of the pelvis in green.

3D Anthropometric Model

To perform a TNC analysis, a forward model is required which links the RV (CoM trajectory) with the EV (joint angles). We used the same subject-specific 3D forward model as used for our previous UCM analysis (Möhler et al., 2019) consisting of 17 segments and 50 degrees of freedom (47 joint angles and 3 hip rotations). The 50 degrees of freedom of the anthropometric model were defined as EV. The model is based on the Hanavan model (Hanavan, 1964) and was modified by including a neck and a hip segment. The shapes of the segments were defined using 36 subject-specific anthropometric measurements, thereof 21 measured manually and 15 determined through the marker data. By assuming a constant density distribution (Ackland et al., 1988), the segment's masses could be determined via volume integration. The whole-body CoM ($\boldsymbol{r}_{\mathrm{CoM}}$, see Figure 7) was calculated as a weighted sum:

$$\boldsymbol{r}_{\mathrm{CoM}} = \frac{1}{\sum_{i=1}^{N} V_{\mathrm{i}}} * \sum_{i=1}^{N} \boldsymbol{r}_{\mathrm{i}} V_{\mathrm{i}} \tag{6.1}$$

With N as the number of segments; V_{i} as the volume of segment i; $\boldsymbol{r}_{\mathrm{i}}$ as the vector of the center of gravity of segment i relative to the pelvis. $\boldsymbol{r}_{\mathrm{CoM}}$ is the vector from the origin to the CoM. In the case of RV_{lab}, the RV matches this vector:

$$\boldsymbol{r}_{\mathrm{RV\_lab}} = \boldsymbol{r}_{\mathrm{CoM}} \tag{6.2}$$

Since $\boldsymbol{r}_{\mathrm{CoM}}$ is defined in 3D, RV_{lab} has 3 degrees of freedom (three coordinates). In the case of RV_{foot}, the vector from the origin to the pelvis ($\boldsymbol{r}_{\mathrm{Pelvis}}$) is added and the one to the right foot ($\boldsymbol{r}_{\mathrm{RFoot}}$) is subtracted:

$$\boldsymbol{r}_{\mathrm{RV\_foot}} = \boldsymbol{r}_{\mathrm{CoM}} + \boldsymbol{r}_{\mathrm{Pelvis}} - \boldsymbol{r}_{\mathrm{RFoot}} = \frac{1}{\sum_{i=1}^{N} V_{\mathrm{i}}} * \sum_{i=1}^{N} \boldsymbol{r}_{\mathrm{i}} V_{\mathrm{i}} + \boldsymbol{r}_{\mathrm{Pelvis}} - \boldsymbol{r}_{\mathrm{RFoot}} \tag{6.3}$$

Since $\boldsymbol{r}_{\mathrm{CoM}}$, $\boldsymbol{r}_{\mathrm{Pelvis}}$ and $\boldsymbol{r}_{\mathrm{RFoot}}$ are defined in 3D, RV_{foot} has 3 degrees of freedom (three coordinates).

Decomposition of Variability in T, N and C

Within the TNC approach, changes in RV variability are assigned to changes in one of three components: Tolerance, Noise or Covariation. Tolerance (T) involves changes in the mean configuration of the EV so it could be seen as a measure for sensitivity; Noise (N) involves changes in the dispersion of the EV, so how changes in the scattering of the EV influence the RV; Covariation (C) involves changes in compensatory mechanisms among the EV so whether the EV co-vary in a manner that variability of the RV is diminished (or not) (Müller & Sternad, 2004). A TNC analysis is performed at one discrete point in time. Thus we time-normalized our stance phases and assumed, that over several repetitions, the same posture is specified at a specific percentage of the gait cycle (Scholz & Schöner, 1999). A separate TNC analysis was performed at each time point of the time-normalized stance phase. Afterwards, the means for the absorption and propulsion phase were calculated.

Using the TNC approach, changes in variability of the RV between the two states can be separated into changes due to T, N and C. To calculate the contributions of these components, five datasets (D_1 – D_5) are needed (Müller & Sternad, 2004). The CV as a measure of variability is determined for each of the datasets. By comparing the variability calculated with the different datasets, one can attribute changes in RV-variability to one of the three components. All of these datasets consist of the values for our EV for all subjects, all strides and all time points:

D_1: measured EV in the first (PRE) state.

D_2: Data from D_1 but permuted over repetitions so that all possible covariance is eliminated (Müller & Sternad, 2003). These data are on the position of D_1 in the EV space and have the same dispersion as D_1 but no covariation. We used 1000 permutations.

D_3: Data from D_2 but moved to the position of D_5 in the EV space (the mean values from D_1 are subtracted and the mean values from D_5 are added). These data are on the position of D_5 in the EV space but with the dispersion of D_1 and without covariation.

D_4: Data from D_5 but permuted over repetitions so that all possible covariance is eliminated. These data are on the position in the EV space of D_5 and have the same dispersion as D_5 but without covariation.

D_5: measured EV in the second (POST) state.

For each of these five datasets the CV as a measure of variability is calculated using our forward model (see equations (6.1 and (6.3). When comparing the errors obtained with the five datasets, changes in variability of the RV from the PRE state to the POST state can be analyzed with respect to T, N and C. By comparing the RV-variability for D_1 with the RV-variability for D_5, one can see if the variability of the RV changed between the PRE and the POST state. However, one cannot yet state by which component (T, N or C) this change is caused. It would even be possible that we have changes in the components without observing them on the RV level, because one component causes an increase and another a decrease in RV variability. To determine the changes due to T one has to subtract the RV-variability for D_2 from the RV-variability for D_3. Since the two data sets have the same dispersion and no covariation, the mean value of the EV (thus the position in EV space) is the only difference. If changes due to T are observed, the positions in EV space between the PRE and the POST state show difference in error-tolerance so in sensitivity. To determine whether the scattering of the EV cause changes in variability of the RV, the RV-variability for D3 is subtracted from the RV-variability for D_4. Since D_3 and D_4 have no covariation and the same mean value (both are on the POST-position in EV space), the scattering of the EV is the only difference. So, if changes due to N are observed, the scattering of the EV between the PRE and the POST state leads to changes in RV-variability. To calculate changes due to changes in covariation among EV due to fatigue, one has to calculate the differences in RV-variability between D_1 and D_2 as well as D_5 and D_4. The only difference between D_1 and D_2 as well as D_5 and D_4 is that the data in D_4 and D_2 were randomized to delete all covariation. So, if changes due to C are observed, changes in covariation among the EV lead to changes in RV-variability. A positive value for a component signifies that variability increased from state one to state two due to this factor, a negative value that it decreased.

6.3.3 Statistics

The independent variable is fatigue (PRE vs. POST). The dependent variables are the 3D-length of RV_{lab} and RV_{foot} and the lengths of the projections in the three coordinate axes. Further dependent variables are the CV of these lengths and the components T, N, C (in %). We calculated a mean value for each dependent variable for the absorption and propulsion phase separately. For the lengths and their CV we calculated dependent t-tests (between PRE and POST). For T, N and C we calculated one-sample t-tests to detect deviations from zero, since these values are a measure for the changes from PRE to POST. Cohen's d was used to indicate effect size for the t-tests. A small effect size was $d < 0.5$, a medium effect size was between 0.5 and 0.8 and a large effect size was $d > 0.8$ (J. Cohen, 1992). P values < 0.05 were considered statistically significant.

6.4 Results

The results are shown separately for the two RV. First, we show the results for RV_{lab} (CoM relative to the lab coordinate system), then we show the results for RV_{foot} (CoM relative to the right foot).

*RV*lab

Concerning RV_{lab} and its CV, there were no significant effects of fatigue in 3D (see Figure 8 and Table 9). Concerning T, N and C, only component N showed significant effects of fatigue. An increase in variability due to N with a medium effect size was seen in the absorption phase, although not reaching statistical significance ($p = 0.096$, $d = 0.501$).

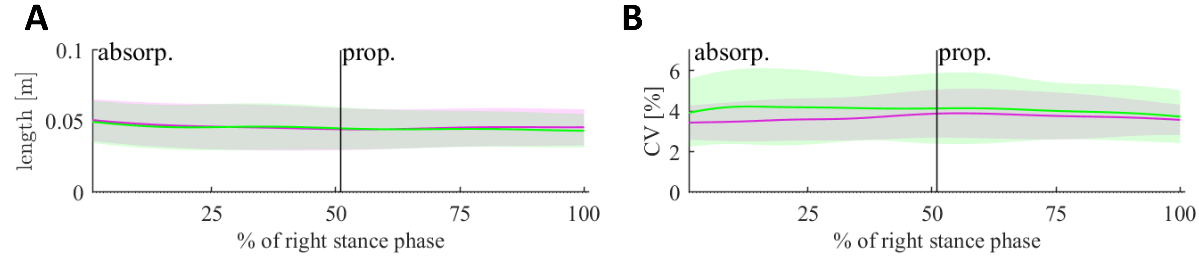

Figure 8: Length of the 3D vector for RV_{lab} in the PRE (magenta) and POST (green) state (A) and the CV of this length (B). The lines represent means and the shaded areas represent standard deviations.

In the anterior-posterior direction, there were no significant effects of fatigue.

In the medio-lateral direction, the CV increased with fatigue in the propulsion phase ($p = 0.012$, $d = 0.822$). Component N showed an increase in variability with a medium effect size in both phases, although not reaching statistical significance (both $p = 0.051$, $d = 0.602$). Component C showed a significant increase in variability during propulsion phase with a high effect size ($p = 0.012$, $d = 0.821$).

In the vertical direction, RV_{lab} decreased with fatigue with a medium effect size during propulsion phase, although not reaching statistical significance ($p = 0.092$, $d = 0.507$). There were no significant effects on the CV of RV_{lab}. Only factor N showed an increase with a medium effect size during absorption, although not reaching statistical significance ($p = 0.095$, $d = 0.502$).

Table 9: Variability for RV_{lab}. Variability of the dependent variables for RV_{lab} are shown here for PRE and POST (mean ± standard deviation). Moderate or strong effect sizes and significant p-values are highlighted in bold. There is only one value for T, N and C, since they describe the change from PRE to POST. A negative value signifies a decrease in variability, positive values an increase. CV represents the coefficient of variation and T, N, C the components tolerance, noise and covariation.

		Absorption				Propulsion			
		PRE	POST	p	d	PRE	POST	p	d
3D	Length [m]	0.047 ± 0.015	0.046 ± 0.015	0.748	0.091	0.045 ± 0.013	0.044 ± 0.012	0.459	0.212
	CV [%]	3.606 ± 0.909	4.147 ± 1.587	0.215	0.363	3.765 ± 0.994	4.000 ± 1.402	0.584	0.156

	T [%]	0.003 ± 0.014		0.553	0.169	0.004 ± 0.014		0.388	0.249
	N [%]	0.013 ± 0.025		0.096	**0.501**	0.007 ± 0.033		0.471	0.206
	C [%]	0.525 ± 1.411		0.222	0.357	0.224 ± 1.417		0.594	0.152
Anterior-posterior	Length [m]	0.033 ± 0.015	0.033 ± 0.015	0.673	0.120	0.035 ± 0.013	0.035 ±0.013	0.987	0.004
	CV [%]	4.668 ± 0.886	5.091 ± 1.970	0.368	0.259	4.289 ± 0.969	4.666 ± 1.555	0.358	0.265
	T [%]	0.002 ± 0.018		0.695	0.111	0.001 ± 0.014		0.753	0.089
	N [%]	0.008 ± 0.029		0.391	0.247	0.011 ± 0.030		0.234	0.347
	C [%]	0.413 ± 1.546		0.373	0.257	0.365 ± 1.339		0.363	0.262
Medio-lateral	Length [m]	0.022 ± 0.010	0.022 ± 0.009	0.796	0.073	0.010 ± 0.004	0.011 ± 0.005	0.131	0.450
	CV [%]	4.563 ± 1.145	4.796 ± 1.347	0.396	0.244	4.296 ± 0.712	5.292 ± 1.242	**0.012**	**0.822**
	T [%]	0.003 ± 0.013		0.474	0.205	0.001 ± 0.012		0.736	0.096
	N [%]	0.013 ± 0.021		0.051	**0.602**	0.025 ± 0.040		0.051	**0.602**
	C [%]	0.218 ± 0.896		0.417	0.233	0.970 ± 1.135		**0.012**	**0.821**
Vertical	Length [m]	0.019 ± 0.011	0.018 ± 0.010	0.179	0.395	0.023 ± 0.013	0.021 ± 0.011	0.092	**0.507**
	CV [%]	2.696 ± 0.462	3.143 ± 1.288	0.195	0.381	2.872 ± 0.755	3.257 ± 1.668	0.322	0.287
	T [%]	0.004 ± 0.009		0.130	0.450	0.005 ± 0.011		0.129	0.452
	N [%]	0.014 ± 0.026		0.095	**0.502**	0.011 ± 0.030		0.219	0.360
	C [%]	0.430 ± 1.104		0.203	0.374	0.369 ± 1.264		0.332	0.280

Summarizing these results, the only significant effects of fatigue on RV_{lab} are a decrease in vertical direction which does not reach statistical significance. Hypothesis (1) can thus be accepted.

$\boldsymbol{RV_{foot}}$

Concerning RV_{foot}, there was a significant decrease in the absorption phase ($p = 0.035$, $d = 0.658$) and a significant increase in the propulsion phase ($p = 0.045$, $d = 0.621$), both with a medium effect size. The CV of RV_{foot} increased during the absorption phase ($p = 0.027$, $d = 0.696$) with a medium effect size (see Figure 9 and Table 10). Concerning T, N and C, only component T showed significant effects of fatigue. A decrease in variability due to T was seen in the absorption phase ($p < 0.001$, $d = 1.488$) and in the propulsion phase ($p = 0.028$, $d = 0.693$). The component N showed an increase in variability during absorption with a medium effect size without reaching statistical significance ($p = 0.057$, $d = 0.583$).

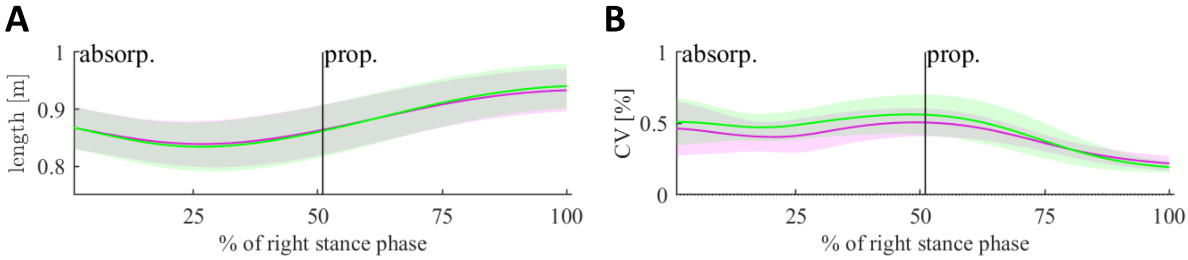

Figure 9: Length of the 3D vector for RV_{Foot} in the PRE (magenta) and POST (green) state (A) and the CV of this length (B). The lines represent means and the shaded areas represent standard deviations.

In the anterior-posterior direction, there was an increase in RV_{foot} in the propulsion phase ($p < 0.001$, $d = 1.621$). The CV of RV_{foot} was not affected by fatigue. Component T showed a decrease in variability during the absorption phase ($p < 0.001$, $d = 1.285$) and propulsion phase ($p < 0.001$, $d = 1.236$).

In the medio-lateral direction, there were no significant effects of fatigue on RV_{foot} or its CV. Component C showed a decrease in variability during propulsion with a medium effect size but without reaching statistical significance ($p = 0.061$, $d = 0.574$).

Table 10: Variability for RV_{foot}. The values of the dependent variables for RV_{foot} are shown here for PRE and POST and for absorption and propulsion (mean ± standard deviation). Moderate or strong effect sizes and significant p-values are highlighted in bold. There is only one value for T, N and C, since they describe the changes from PRE to POST. A negative value signifies a decrease in variability, positive values an increase. CV represents the coefficient of variation and T, N, C the components tolerance, noise and covariation.

		Absorption				Propulsion			
		PRE	POST	p	d	PRE	POST	p	d
3D	Length [m]	0.849 ± 0.038	0.846 ± 0.040	**0.035**	**0.658**	0.905 ± 0.039	0.908 ± 0.040	**0.045**	**0.621**
	CV [%]	0.451 ± 0.105	0.514 ± 0.109	**0.027**	**0.696**	0.363 ± 0.055	0.376 ± 0.096	0.618	0.142
	T [%]	-0.003 ± 0.002		**<0.001**	**1.488**	-0.001 ± 0.002		**0.028**	**0.693**
	N [%]	0.058 ± 0.096		0.057	**0.583**	0.026 ± 0.065		0.190	0.386
	C [%]	0.007 ± 0.061		0.688	0.114	-0.012 ± 0.062		0.517	0.185
Anterior-posterior	Length [m]	0.116 ± 0.010	0.118 ± 0.010	0.148	0.429	0.427 ± 0.031	0.440 ± 0.031	**<0.001**	**1.621**
	CV [%]	1.672 ± 0.673	1.476 ± 0.491	0.120	0.464	1.023 ± 0.234	0.959 ± 0.320	0.597	0.150
	T [%]	-0.004 ± 0.003		**<0.001**	**1.285**	-0.004 ± 0.003		**<0.001**	**1.236**
	N [%]	-0.193 ± 0.452		0.165	0.410	-0.034 ± 0.375		0.761	0.086
	C [%]	-0.027 ± 0.068		0.196	0.379	-0.026 ± 0.098		0.382	0.252
Medio-lateral	Length [m]	0.015 ±0.010	0.013 ± 0.009	0.599	0.150	0.015 ± 0.008	0.016 ± 0.011	0.684	0.116
	CV [%]	0.891 ± 0.222	0.851 ± 0.294	0.574	0.160	0.826 ± 0.179	0.794 ± 0.149	0.575	0.160
	T [%]	0.013 ± 0.044		0.314	0.292	0.043 ± 0.183		0.517	0.185
	N [%]	-0.036 ± 0.237		0.608	0.146	0.015 ± 0.229		0.823	0.064
	C [%]	-0.017 ± 0.067		0.403	0.241	-0.040 ± 0.067		0.061	**0.574**
Vertical	Length [m]	0.838 ± 0.037	0.834 ± 0.039	**0.041**	**0.634**	0.793 ± 0.035	0.789 ± 0.037	**0.009**	**0.865**

CV [%]	0.376 ± 0.103	0.474 ± 0.094	**0.004**	**0.994**	0.459 ± 0.099	0.535 ± 0.154	0.095	**0.503**
T [%]	-0.002 ± 0.223		**0.002**	**1.127**	-0.002 ± 0.001		**0.001**	**1.152**
N [%]	0.093 ± 0.104		**0.009**	**0.861**	0.065 ± 0.141		0.139	0.440
C [%]	0.006 ± 0.062		0.734	0.096	0.013 ± 0.047		0.356	0.266

In the vertical direction, RV_{foot} decreased during both absorption (p = 0.041, d = 0.634) and propulsion (p = 0.009, d = 0.865). The CV increased during absorption phase (p = 0.004, d = 0.994). In the propulsion phase, there was also an increase with a medium effect size but without reaching statistical significance (p = 0.095, d = 0.503). Significant changes were observed in components T in both phases (abs.: p = 0.002, d = 1.127; prop.: p = 0.001, d = 1.152) and N during absorption phase (p = 0.009, d = 0.861).

Since RV_{foot} was affected by fatigue in 3D and in anterior-posterior and in vertical direction, hypothesis (2) could be accepted.

6.5 Discussion

The purpose of this study was to investigate if and how runners adjust their coordination as reaction to fatigue when running at constant speed and how this fatigue affects the variability of the CoM. Additionally, we wanted to compare the results of the TNC analysis with results obtained with the UCM approach in an earlier study (Möhler et al., 2019). Therefore, we performed a TNC analysis with two different RV: RV_{lab} is the global CoM relative to the origin. This RV was chosen to be able to compare our results to the ones obtained with the UCM. RV_{foot} is the CoM relative to the right foot. This RV was chosen since we think that is functionally more relevant, since it describes the relation between the foot and the CoM which is crucial for the forward propulsion during running.

To be able to combine the position of the foot and the joint angles in our analysis, we chose the TNC approach, since this approach is performed in the results space and allows for the combination of EV of different units. Our hypotheses were confirmed, since we found no effects of fatigue for RV_{lab} in 3D, but there were effects of fatigue for RV_{foot} both in 3D and in the projections.

In the following, we will discuss the findings of the TNC analysis for RV_{lab} and RV_{foot} and then comment on some methodological consideration concerning the comparison between the UCM and the TNC approach. Afterwards, we will address the limitations of our study and comment on its contributions to the field.

6.5.1 Fatigue Effects on CoM Trajectory and its Variability

We analyzed the effects of fatigue on the CoM trajectory and its variability using two different RV: RV_{lab}, where the position of the CoM is described relative to a lab coordinate system and RV_{foot}, where the CoM is described relative to the right foot.

Concerning RV_{lab}, the only changes with fatigue visible in 3D were a non-significant increase in variability due to the component N with a medium effects size. There were no effects in anterior-posterior direction. In the medio-lateral direction, the SSV of the CoM trajectory increased during propulsion phase, due to increases in variability caused by the components N and C. In the POST state, the CoM was lower during propulsion phase than during the PRE state. These results show that relative to a fixed point, runners lowered their CoM slightly in the POST state and showed more SSV in the medio-lateral direction due to a less error-tolerant joint configuration and more variability in the joint angles.

Concerning RV_{foot}, the results show that in 3D, the distance between the right foot and the CoM decreased during absorption and increased during propulsion phase. The decrease in distance can be explained by a lower CoM (decrease in vertical direction). The increase was due to an increase in anterior-posterior direction. The SSV of the CoM trajectory increased during absorption phase, caused by more variability in the vertical direction, which was caused by an increase in component N. This means that changes in the dispersion of the joint angles caused this increase. Component T caused a decrease in variability in both absorption and propulsion phase in the anterior-posterior and vertical direction as well as in 3D. This means that runners had a less error-tolerant joint configuration, especially in the sagittal plane. The effects of this component however were considerably smaller than the ones of N and C, so the effects of T might have been hidden and are thus not visible as a decreased CoM variability.

At first sight, the changes in CoM trajectory in this study are contradicting the results of Girard et al. (Girard et al., 2013), who found that runners kept their CoM on the same height. However, it must be noted that runners were able to adapt their running speed in the study by Girard et al.

(2013), which they could not in the present study. So apparently, runners choose a different strategy when running at a constant speed. SSV of the CoM trajectory increased with fatigue. A high variability can indicate changes in running style, which potentially increase energy consumption caused by deviation from the individual's optimal running style (Moore, 2016; Williams & Cavanagh, 1987). Thus, runners were probably less economical in the POST state. The changes in the vertical direction might be explained by reductions in leg stiffness which are commonly observed in a POST state (Dutto & Smith, 2002; Girard et al., 2013; Rabita et al., 2011, 2013). Reductions in leg stiffness have also been linked to a lower running economy (Dalleau et al., 1998). A decreased stiffness could also explain the reduced distance from the right foot to the CoM during absorption phase, since runners would have a more compliant leg at touchdown, so the CoM was lowered (decreases in length in the vertical direction). Since the speed was fixed, runners had to push longer in order to keep up, which explains the increased distance in the propulsion phase visible in the anterior-posterior direction.

We find more changes with fatigue when analyzing RV_{foot} than when analyzing RV_{lab}, so changes with fatigue are more pronounced in the CoM trajectory relative to the right foot than in the CoM trajectory relative to a fixed point. This might be either caused by changes in foot position or in the position of the pelvis or both. Hoenig et al. (2019) found increases in local dynamic stability of the pelvis with fatigue, so one might assume that it was especially the foot motion which changed with fatigue. In the analysis using RV_{lab}, an increased variability in medio-lateral direction was detected which is not visible when analyzing RV_{foot}. So, it is only visible with respect to a fixed reference. This could mean that runners move medio-laterally on the treadmill. Since we focused on SSV, we cannot comment on effects of fatigue on the vertical oscillation or the medio-lateral movement of the CoM throughout the stride.

6.5.2 Methodological Considerations – References to the UCM Results

The TNC analysis with RV_{lab} as RV was performed to be able to compare the results obtained here with those obtained using an UCM analysis (Möhler et al., 2019). The results corroborated those obtained with the UCM analysis, as we found no effects on the RV_{lab} in 3D. The only effect we found for T, N or C was an increase in variability with a medium effect size due to N in the absorption phase which did not reach statistical significance ($p = 0.096$, $d = 0.501$). The analysis of SSV with respect to RV_{foot} would not be possible within the UCM, since we would have to combine the different units of the foot and pelvis location in meters with the joint angles in degrees or radians. This is not feasible within the UCM approach (Latash et al., 2007). When calculating the Jacobian, which is the core of the UCM analysis, the position of the foot or pelvis would disappear when performing the partial derivatives since they are not expressed in dependence on any EV (e.g. a constant term without any dependency). The CoM trajectory within the UCM approach is not suitable to describe its movement along its trajectory in a global coordinate system because it is rather a parameter representing fluctuation of the CoM around an arbitrary point in the coordinate system. Therefore, one should calculate the CoM trajectory of interest separately when an UCM analysis is performed.

With the TNC approach used in this study, the combination of different units within the EV does not pose a problem since the analysis is performed in the result space (Müller & Sternad, 2009). Although the possibility to analyze variability on the level of the whole human body is a big strength of these approaches, analyzing sub-systems can also lead to deeper insights. Within the TNC approach, the analysis of the projections in the three dimensions is possible since it is performed in the result space (Müller & Sternad, 2009). Within the UCM approach a separate model for each dimension would have to be built up.

There are some other differences between the two approaches. When performing an UCM analysis one should select a set of EV that show no task-independent covariation (Latash et al., 2007). Covariance inherent to the system will be detected by the UCM as parallel variance, although it might only be an artefact of the musculoskeletal system and might not arise from motor control processes. To determine the Jacobian necessary for the UCM analysis, the forward model has to be linearized. This means that only differentiable forward models can be implemented (Müller & Sternad, 2009). Whether this linearization is feasible could be studied by comparing the results of the linearized model with the full forward model (Scholz & Schöner, 1999). However, the influence of the linearization is rarely examined. The orthogonal variance is determined based on this linearization (Latash et al., 2007), but orthogonality is only given in a Euclidean space and it is hard to determine whether this assumption is valid. Performing an UCM analysis without having examined whether these requirements are met does not mean that the analysis will lead to wrong or unusable results, although the influence of violating these assumptions is hard to evaluate. While an UCM analysis tests a hypothesis concerning the degree of control or stability of a certain RV (Latash et al., 2007), a TNC analysis only quantifies the influence of components T, N and C on the variability of the result. Hypotheses about control have to be subsequently analyzed. Also, variability not affecting the RV (in the UCM context: parallel variability) is not detected within the TNC approach, since it is not captured by T, N or

C (Schöner & Scholz, 2007). Therefore, the two approaches are not in conflict, but are instead complementary since both look at a given problem from different perspectives. The UCM analysis can be performed on data from a single measurement. The TNC analysis was developed in the context of motor learning and always shows a development from one state to another, so it cannot be performed on single measurements.

Some parallels can be drawn between the results obtained with the two approaches. Changes in component N in a TNC analysis can be seen in an UCM analysis as changes in the orthogonal variance. Changes in component C could be seen as changes in the repartition of variance on the parallel and orthogonal components and so in the UCM ratio. Verrel (2011) showed that, in 1D, the measure for covariation is even equivalent between the two approaches. Changes in component T are not detectable in UCM since the forward model is linearized around the mean configuration, which has no effect on the UCM results.

6.5.3 Limitations

To capture consecutive strides, this study was performed on a treadmill. There are a number of studies showing differences between treadmill running and overground running (Fellin et al., 2010). Given the time of treadmill familiarization (Lavcanska et al., 2005; Matsas et al., 2000), it can be assumed that movement patterns were at least stable and differences from overground running were minimal (Riley et al., 2008). However, the constant speed of the treadmill is expected to result in less variability in the movement execution.

So far, the TNC approach, as well as the UCM approach have been mainly used to analyze postures at one specific moment in time. Here we apply these approaches to a whole-body continuous movement (comparable to Hamacher et al., 2019; Yamagata et al., 2019). In order to do so, we had to time-normalize our data, although we acknowledge the fact that this might mask certain variability in timing over the stance phase.

Even if we find statistically significant and thus systematic effect with fatigue on the CoM trajectory, one has to critically question the practical significance of the findings. The observed effects in this study have to be considered as small (differences in distance of ± 3mm, differences in CV < 1%). However, since we study trained runners we cannot expect huge changes. Also, since runners had to run at a high, fixed speed (19.27 ± 0.72 km/h), maintaining the speed has not allowed any major deviations. Due to the limitation to male runners and the relatively small sample size, our findings are not directly generalizable or transferable to other samples such as recreational athletes or female runners.

Since the TNC and other related variability analyses are always coordinate dependent, (Schöner & Scholz, 2007; Sternad et al., 2010) we have to emphasize that our results are only valid for the chosen coordinates. We analyzed the trajectory of the CoM with respect to two different coordinate systems during the stance phase and this analysis was performed in the coordinate space spanned by our EV - the joint angles. The results for an analysis performed in a different coordinate frame might differ. We chose the joint angles as EV since they are a possible control variable during motor control, in agreement with other studies (Hamacher et al., 2019; Papi et al., 2015; Yamagata et al., 2019).

6.6 Conclusion and Outlook

For the first time, the TNC analysis was used in the context of running as well as in combination with an 3D full body model. The results obtained with this approach were compared with results obtained with the UCM approach on the same dataset and their differences and similarities were outlined.

Concerning RV_{lab} we found that runners increased their SSV in medio-lateral direction by 1 %. Looking at RV_{foot} we found that runners lowered their CoM by 4 mm and increased their SSV in the absorption phase in both 3D and in the vertical direction. The lowering of the CoM might be explained by a reduced leg stiffness. Apparently, runners have to lower their CoM in order to maintain a fixed running speed throughout a fatiguing run.

Both the UCM and the TNC approach were developed and are mainly applied in well controlled lab movements with limited degrees of freedom, in contrast to our application to a complex whole body movement. Even though this is a necessary, results from these experiments are not always transferable to whole-body sports movements. In this study, we show that this transfer is feasible. Even though we only find minor effects in our study, these approaches are promising approaches to gain further insights into the SSV in running.

7. Topic C – Fatigue in Novices: Changes in Spatiotemporal Parameters, Joint and CoM Kinematics and Leg Stiffness in Novice Runners During a High-Intensity Fatigue Protocol

Slightly modified version of the paper submitted as:

Möhler, F., Fadillioglu, C., & Stein, T. (2021). Changes in Spatiotemporal Parameters, Joint and CoM Kinematics and Leg Stiffness in Novice Runners During a High-Intensity Fatigue Protocol. PLoS one, submitted

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7.1 Abstract

Even though running enjoys growing popularity, the effects of fatigue on the running kinematics of novices have rarely been studied. This is surprising, given the risk of RRI when detrimental movement patterns are adopted. Therefore, the goal of the present study was to characterize in an exploratory way the effects of fatigue induced by a high intensity running protocol on spatiotemporal and stiffness parameters as well as joint kinematics and CoM motion in novice runners. 14 novice runners volunteered to participate and ran on a treadmill at 13 km/h until voluntary exhaustion. Thereby, kinematics were captured by means of a 3D motion capture system. Independent t-tests for the comparisons of discrete parameters as well as statistical parametric mapping method for time series analyses were applied. Our results revealed that novice runners did not change spatiotemporal or stiffness parameters, but showed adaptations in joint kinematics. The results of this study might underline the importance of strengthening the ankle joint in order to prevent excessive pronation.

7.2 Introduction

Running is a popular sport activity chosen by several million people in the world from different backgrounds. The world health organization recommends a minimum of 150 minutes of aerobic physical activity per week to maintain a healthy life. On the other hand, the number of injuries related to running is also high. Although a direct connection could not yet be clearly defined (Ferber et al., 2009), there are several studies suggesting that injuries are related to atypical foot pronation (Ferber et al., 2009), inadequate hip muscle stabilization (Ferber et al., 2009; Schmitz et al., 2014), overuse (Van Gent et al., 2007) or lack of running experience (Buist et al., 2010). Thus, novice runners are especially at risk to injury. In a meta-analysis by Videbaek et al. (2015), it was shown that novice runners are at significantly higher risk of injury than recreational runners. In another study by Kemler et al. (2018) analyzing injury risk and characteristics between novices and experts based on 4621 runners, it was reported that incidence of RRI in novice runners is twofold higher than in expert runners. It is conceivable, that due to a lack of experience, there may be a low level of body awareness among novice runners, leading to an overlooking or misinterpretation of pain signals, particularly under fatigue.

Due to its effectiveness, training under high intensities is common among runners. One popular example is the high intensity interval training (HIIT) (Helgerud et al., 2007). During this type of training, runners perform shorter intervals at a high intensity rather than prolonged jogging at a low intensity. HIIT is widely chosen not only by experienced but also by recreational runners to improve performance (García-Pinillos et al., 2017). Having in mind the increased injury risk in novice runners, the question rises if the exhaustion experienced during these training sessions might constitute a risk of injury. A few studies focused on the effects of fatigue induced by a run with a shorter distance in novice runners. Maas et al. (2018) observed changes in kinematics both for novices and competitive runners (mean time to exhaustion 28 min and 16 min, respectively) and reported that novices had larger kinematic adjustments involving hip abduction, ankle plantar flexion, and kinematics of the pelvis and trunk. By analyzing kinematic changes after running induced fatigue (mean time to fatigue 19.7 ± 7.8 min), Koblbauer et al. (2014) found changes in trunk motion and changes in ankle eversion in novice runners. However, none of these studies analyzed the effects of a high intensity run. Since existing studies show that novice runners react differently to fatigue than more experienced runners (Maas et al., 2018), effects of fatigue on running kinematics found in expert runners (García-Pinillos et al., 2019; Möhler, Fadillioglu, et al., 2021) are not directly transferable to novice runners. Therefore, a global picture how high intensity fatigue affects basic parameters (running kinematics and spatiotemporal parameters) in novice runners is missing.

In summary, despite its practical relevance, the effects of fatigue induced by high intensity running on the kinematics have not yet been considered for novice runners. The goal of the present study was to analyze the effects of fatigue, induced by a high intensity run, on spatiotemporal parameters, leg and vertical stiffness, 3D joint kinematics as well as the CoM trajectory in novice runners. In addition, this study aimed to conduct an explorative analysis of entire time series data by means of SPM and important discrete parameters (spatiotemporal parameters and RoM). Since novices were found to show stronger reactions to fatigue as compared to experts in their kinematics after a run to fatigue at a moderate intensity (Maas et al., 2018) and as we found in our previous study (Möhler, Fadillioglu, et al., 2021) marked effects of fatigue in experienced runners, we assumed that novices would show pronounced reactions to fatigue in both joint kinematics and spatiotemporal and stiffness parameters. The results from this study may be helpful for the understanding of typical adaptation strategies of novice runners to the fatigue induced by a running at a high intensity.

7.3 Materials and Methods

7.3.1 Participants

Fourteen male healthy novice runners participated in the study (see Table 11). Inclusion criteria were participating in a sports activity once or twice a week, a BMI between 19 and 23 kg/m² and no more than two runs per week throughout the last year. Exclusion criteria were recent injuries or pain and performing a regular running training. All participants provided written informed consent and the study was approved by the ethics committee of the Karlsruhe Institute of Technology.

7.3.2 Experimental Design

The experiment was conducted on a motorized treadmill (h/p/cosmos Saturn, Nussdorf-Traunstein, Germany) with a slope of 1% (Jones & Doust, 1996). After having performed a standardized treadmill familiarization (6 min of walking, 6 min of running; Lavcanska et al., 2005; Matsas et al., 2000), an acceleration up to the test speed of 13 km/h was performed. This speed was held for 10 seconds. Then, participants had a break of 2 min before the actual measurement. During the measurement, participants had to run at a fixed speed of 13 km/h until voluntary exhaustion. After voluntary exhaustion was reached, participants were asked to rate their perceived exertion using the Borg scale (Borg, 1982). Participants were instructed to look ahead during the run. For safety reasons, participants were held by a safety harness which was connected to an emergency-off.

Table 11: Sample characteristics (mean ± standard deviation); BMI: body mass index

Sample size [N]	14
Age [years]	27.4 ± 4.2
Height [m]	1.82 ± 0.06
Weight [kg]	77,5 ± 10,3
BMI [kg/m²]	23.3 ± 2,63
Physical activity [h/week] (including running)	1.8 ± 1.2
Running [h/week]	0.2 ± 0.3

7.3.3 Data Acquisition and Processing

Kinematic data was recorded at 200 Hz using 16 Vicon cameras (Vicon Motion Systems, Oxford Metrics Group, Oxford, UK) throughout the whole run. Therefore, 42 reflective markers were attached to the participant's skin and anthropometric measures were taken according to the instructions of the Alaska Dynamicus modelling system (Advanced Lagrangian Solver in kinetic Analysis, insys GmbH, Chemnitz, Germany; Härtel and Hermsdorf, 2006).

After preprocessing of the marker data using Vicon Nexus 2.11.0 software, all further steps of data processing were performed in MATLAB R2020b (The MathWorks, Natick, MA, USA). Marker data was filtered using a second order 15 Hz low-pass butterworth filter. An inverse kinematics calculation was performed using the Alaska Dynamicus modelling system (Härtel & Hermsdorf, 2006).

Gait events were identified using the change of sign of the heel or forefoot-markers and the vertical acceleration of the toe marker for heel strike and toe-off, respectively (Leitch et al., 2011). 20 consecutive gait cycles in the beginning of the run (PRE) and 20 gait cycles at the end of the run (POST) were further analyzed. These gait cycles were time normalized to 101 time points each.

Similar to our previous work in expert runners (Möhler, Fadillioglu, et al., 2021), we analyzed time of stance (right foot strike to right toe off), time of flight (right toe off to left foot strike) and the stride frequency (right foot strikes per second) since these spatiotemporal parameters are used to generally characterize running gait. Vertical and leg stiffness were shown to be influenced by fatigue (Dutto & Smith, 2002; García-Pinillos et al., 2020) and were therefore also included in our analysis. Additionally, alterations in spatiotemporal parameters might be explained by concurrent alterations in stiffness parameters. Due to a lack of ground reaction force data, stiffness was calculated following the method evaluated by Morin and colleagues (Morin et al., 2005). Besides mean values and standard deviations, we also calculated CV in order to be able to quantify changes in variability of the running movement.

Since the aim of our study was to reveal the effects of fatigue on running kinematics in novices in an explorative manner, we performed a time series analysis by means of SPM (Pataky et al., 2013) in all three planes (sagittal (S), frontal (F), transversal (T) plane) on the relevant joints in the lower limb (ankle, knee, hip) and in the torso (lumbar and thoracic spine). Additionally, RoM was calculated separately for the stance and the flight phase. A higher RoM, as a measure for the occurring limits of motion, could be used as a precursor for a higher risk of soft tissue injury due to the higher stresses. The trajectory of the CoM was analyzed analogously to the analysis of the joint angles by performing both a time series analysis and the calculation of the RoM.

7.3.4 Statistics

For the analysis of the spatiotemporal parameters, their CV and the RoM, the results for the 20 gait cycles per condition were averaged for each participant for subsequent statistical analysis. Normality distribution was tested using the Shapiro-Wilk-test. In case of a given normal distribution, comparisons for these parameters were done using paired t-tests. In case of a non-normal distribution, Wilcoxon signed rank test were calculated. Due to the non-normal distribution of part of the data, the robust d (d_r) was calculated. This is done following the regular calculation of Cohen’s d while taking the 20% trimmed mean and in the 20% winsorized variance. Thereby, $0.2 < d_r < 0.5$ was interpreted as a small effect, $0.5 < d_r < 0.8$ as a medium effect and $d_r > 0.8$ as a large effect (J. Cohen, 1992).

The time-normalized joint angle and CoM time-series were compared using statistical non-parametric mapping (www.spm1d.org) due to non-normal distribution of the data. It was assumed that both legs would fatigue at a similar rate (Pappas et al., 2015), thus analyses were performed for the right side only. For all statistical analyses, the level of significance was set a priori to $p = 0.05$.

7.4 Results

7.4.1 Spatiotemporal Parameters, Vertical and Leg Stiffness and their Variability

The participants stopped running after 06:11 ± 02:27 minutes. Exhaustion was confirmed by a Borg scale rating of 18.7 ±1.0. Effects of fatigue were neither apparent in stance time, flight time, stride frequency, vertical stiffness or leg stiffness, nor in their CV (Table 12). However, joint angle RoM and time courses showed pronounced effects of fatigue. Therefore, our initial assumption was partly supported by our data.

Table 12: Mean ± standard deviation of spatiotemporal parameters, vertical and leg stiffness along with their corresponding coefficients of variation. p-values as calculated by the dependent t-tests and effect sizes are given. d_r values of 0.2 - 0.50, 0.5 - 0.8 and > 0.8 indicate small, medium and large effects, respectively. A superscript "nnd" behind the p-value signifies a non-normal distribution.

	PRE	POST	p	d_r
Time of support [s]	0.25 ± 0.02	0.25 ± 0.03	0.617	0.124
Time of flight [s]	0.20 ± 0.05	0.21 ± 0.04	0.301	0.189
Stride frequency [1/s]	1.43 ± 0.05	1.41 ± 0.06	0.087	0.557
Vertical stiffness [kN/m]	8.82 ± 1.83	9.02 ± 2.20	0.485	0.177
Leg stiffness [kN/m]	6.16 ± 1.42	6.31 ± 1.69	0.452	0.176
Coefficients of variation				
Time of support	0.02 ± 0.01	0.03 ± 0.01	0.761^{nnd}	0.115
Time of flight	0.06 ± 0.03	0.06 ± 0.02	0.855^{nnd}	0.248
Stride frequency	0.01 ± 0.01	0.02 ± 0.01	0.450	0.314
Vertical stiffness	0.06 ± 0.02	0.06 ± 0.02	0.715^{nnd}	0.166
Leg stiffness	0.06 ± 0.02	0.07 ± 0.02	0.670^{nnd}	0.149

7.4.2 Analyses of Range of Motion

The joint angle RoMs showed pronounced effects of fatigue, especially during stance phase. In the upper body, changes occurred in all three planes, whereas sagittal and frontal plane were most affected in the lower limbs. All changes with fatigue in RoM were increases (Table 14).

Stance phase

The RoM increased significantly in the knee joint in the sagittal plane with a high effect size (knee: PRE_S: 33.57°, $POST_S$: 37.68°, $p < 0.001$, $d_r = 1.605$) and in the hip joint in the sagittal plane with a high effect size and in the frontal plane with a medium effect size (hip: PRE_S: 46.70°, $POST_S$: 49.59°, $p < 0.001$, $d_r = 0.842$; PRE_F: 16.65°, $POST_F$: 18.86°, $p = 0.007$, $d_r = 0.602$). In the lumbar and thoracic spine, the RoM increased in all three planes significantly with high effect sizes (lumbar spine: PRE_S: 9.89°, $POST_S$: 10.97°, $p = 0.020$, $d_r = 0.802$; PRE_F: 8.27°, $POST_F$: 10.47°, $p < 0.001$, $d_r = 1.785$; PRE_T: 5.61°, $POST_T$: 6.99°, $p < 0.001$,

$d_r = 2.059$; thoracic spine: PRE_S: 5.00°, $POST_S$: 5.87°, $p < 0.001$, $d_r = 1.363$; PRE_F: 15.46°, $POST_F$: 20.01°, $p < 0.001$, $d_r = 3.773$; PRE_T: 32.71°, $POST_T$: 39.97°, $p < 0.001$, $d_r = 1.660$). The RoM of the CoM increased in the medio-lateral direction significantly with a high effect size ($PRE_{medio\text{-}lateral}$: 6.46 mm, $POST_{medio\text{-}lateral}$: 8.62 mm, $p = 0.009$, $d_r = 1.328$).

Table 13: Mean ± standard deviation of the range of motion of joints in degrees (°) and of the CoM in mm are shown as for stance and flight phases separately. p-values as calculated by the dependent t-test and Cohen's d as effect sizes are also given. Bold font indicates significant differences ($p<0.05$). d_r values of 0.2 - 0.50, 0.5 - 0.8 and > 0.8 indicate small, medium and large effects, respectively. A superscript "nnd" behind the p-value signifies a non-normal distribution. S, F and T signifies the sagittal, the frontal and the transversal plane, respectively.

	PRE	POST	p	d_r
Stance phase				
Ankle – S [°]	48.62 ± 4.18	49.28 ± 4.33	0.199	0.284
Ankle – F [°]	15.86 ± 3.94	15.35 ± 4.12	0.259	0.157
Ankle – T [°]	10.56 ± 2.84	10.70 ± 3.03	0.419	0.064
Knee – S [°]	**33.57 ± 4.52**	**37.68 ± 4.50**	**< 0.001**	**1.605**
Knee – F [°]	5.00 ± 2.42	5.83 ± 2.04	0.068^{nnd}	0.588
Knee – T [°]	10.89 ± 3.88	9.49 ± 3.36	0.244	0.544
Hip – S [°]	**46.70 ± 5.13**	**49.59 ± 5.45**	**< 0.001**	**0.842**
Hip – F [°]	**16.65 ± 3.44**	**18.86 ± 4.39**	**0.007**	**0.602**
Hip – T [°]	11.36 ± 3.77	12.61 ± 2.97	0.071	0.319
Lumbar Spine – S [°]	**9.89 ± 2.21**	**10.97 ± 2.94**	**0.020^{nnd}**	**0.802**
Lumbar Spine – F [°]	**8.27 ± 1.77**	**10.47 ± 1.83**	**< 0.001**	**1.785**
Lumbar Spine – T [°]	**5.61 ± 0.95**	**6.99 ± 1.41**	**< 0.001**	**2.059**
Thoracic Spine – S [°]	**5.00 ± 1.06**	**5.87 ± 1.58**	**$<0.001^{nnd}$**	**1.363**
Thoracic Spine – F [°]	**15.46 ± 2.14**	**20.01 ± 3.01**	**< 0.001**	**3.773**
Thoracic Spine – T [°]	**32.71 ± 6.66**	**39.97 ± 9.10**	**< 0.001**	**1.660**
COM ant-post [mm]	13.58 ± 1.61	15.30 ± 3.16	0.054	0.762

COM med-lat [mm]	**6.46 ± 2.08**	**8.62 ± 2.32**	**0.009**	**1.328**
COM vertical [mm]	68.96 ± 7.38	71.17 ± 8.79	0.243	0.319

Flight phase				
Ankle – S [°]	6.71 ± 2.88	5.76 ± 2.86	0.173^{nnd}	0.483
Ankle – F [°]	3.18 ± 1.27	2.73 ± 1.64	0.258	0.359
Ankle – T [°]	**2.14 ± 1.29**	**2.73 ± 1.64**	**0.009^{nnd}**	**0.696**
Knee – S [°]	44.66 ± 9.68	45.61 ± 10.34	0.389	0.151
Knee – F [°]	5.08 ± 2.19	5.69 ± 3.15	0.2142	0.225
Knee – T [°]	**6.91 ± 2.81**	**8.87 ± 3.51**	**0.002^{nnd}**	**0.904**
Hip – S [°]	6.95 ± 2.94	6.21 ± 2.67	0.179	0.282
Hip – F [°]	**6.59 ± 2.49**	**7.54 ± 2.58**	**0.009**	**0.489**
Hip – T [°]	8.46 ± 3.40	9.23 ±3.74	0.296^{nnd}	0.216
Lumbar spine – S [°]	4.88 ± 1.51	5.34 ± 2.07	0.208	0.316
Lumbar spine – F [°]	**2.64± 1.20**	**3.34 ± 1.19**	**0.002**	**0.640**
Lumbar spine – T [°]	1.48 ± 0.40	1.56 ± 0.47	0.204	0.206
Thoracic spine – S [°]	**2.59 ± 0.71**	**2.92 ± 1.01**	**0.048**	**0.427**
Thoracic spine – F [°]	4.19 ± 1.26	4.54 ± 1.32	0.129	0.334
Thoracic spine – T [°]	8.43 ± 2.07	8.86 ± 2.69	0.147	0.233
COM ant-post [mm]	8.30 ± 2.49	8.75 ± 2.29	0.235	0.343
COM med-lat [mm]	**3.47 ± 1.09**	**4.72 ± 1.18**	**<0.001**	**1.323**
COM vertical [mm]	25.32 ± 7.36	27.81 ± 7.75	0.051	0.331

Flight phase

There were less changes in the flight phase compared to stance. RoM increased significantly in the ankle joint as well as in the knee joint in the transversal plane with a medium and with a high effect size, respectively (ankle: PRE_T: 2.14°, $POST_T$: 2.73°, p = 0.009, d_r = 0.696, knee:

PRE_T: 6.91°, $POST_T$: 8.87°, $p = 0.002$, $d_r = 0.904$). In the hip joint and in the lumbar spine RoM increased significantly in the frontal plane with medium effect sizes (hip: PRE_F: 6.59°, $POST_F$: 7.54°, $p = 0.009$, $d_r = 0.489$; lumbar spine: PRE_F: 2.64°, $POST_F$: 3.34°, $p = 0.002$, $d_r = 0.640$). The RoM of the thoracic spine increased in the sagittal plane significantly having a medium effect size (PRE_S: 2.59°, $POST_S$: 2.92°, $p = 0.048$, $d_r = 0.427$). The RoM of the CoM increased in medio-lateral direction significantly with a high effect size ($PRE_{medio\text{-}lateral}$: 3.47 mm, $POST_{medio\text{-}lateral}$: 4.72 mm, $p < 0.001$, $d_r = 1.323$).

7.4.3 Time Series Analyses of Joint and CoM Movements

The time series of the joint angles and the CoM as well as the results of the SPM analysis are shown in Figure 10. The participants showed a higher dorsiflexion during stance in the POST and more plantarflexion during swing. Around heel strike, the knee joint showed greater flexion in the POST. The hip joint was more extended in the POST after toe-off and more flexed before right heel strike. In the POST, the thigh was more abducted during swing and more adducted around heel strike.

In the POST, participants showed a greater backward lean in the lumbar spine. Around the right heel strike, participants were more tilted to the right and rotated to the left. In the flight phase, after right toe-off, participants rotated more to the right. For the left heel strike and left toe-off the reactions were an increased tilt to the left and an increased rotation to the left. In the thoracic spine, there was a greater backward lean in the POST compared to PRE. Analogously to the effects seen in the lumbar spine, participants tilted to the right and rotated to the left during right heel strike and left toe-off. During right toe off and left heel strike, runners tilted to the left and rotated to the right.

The CoM showed a significantly lower trajectory in the POST, mainly after right and left heel strike. In the remaining planes, there were not any significant differences between the PRE and the POST trajectories of CoM.

The joint angle time series of the lower limbs showed significant effects of fatigue in the frontal and sagittal planes. Lumbar and thoracic spine were affected in all three planes. The CoM motion was affected in vertical direction, showing a lower trajectory.

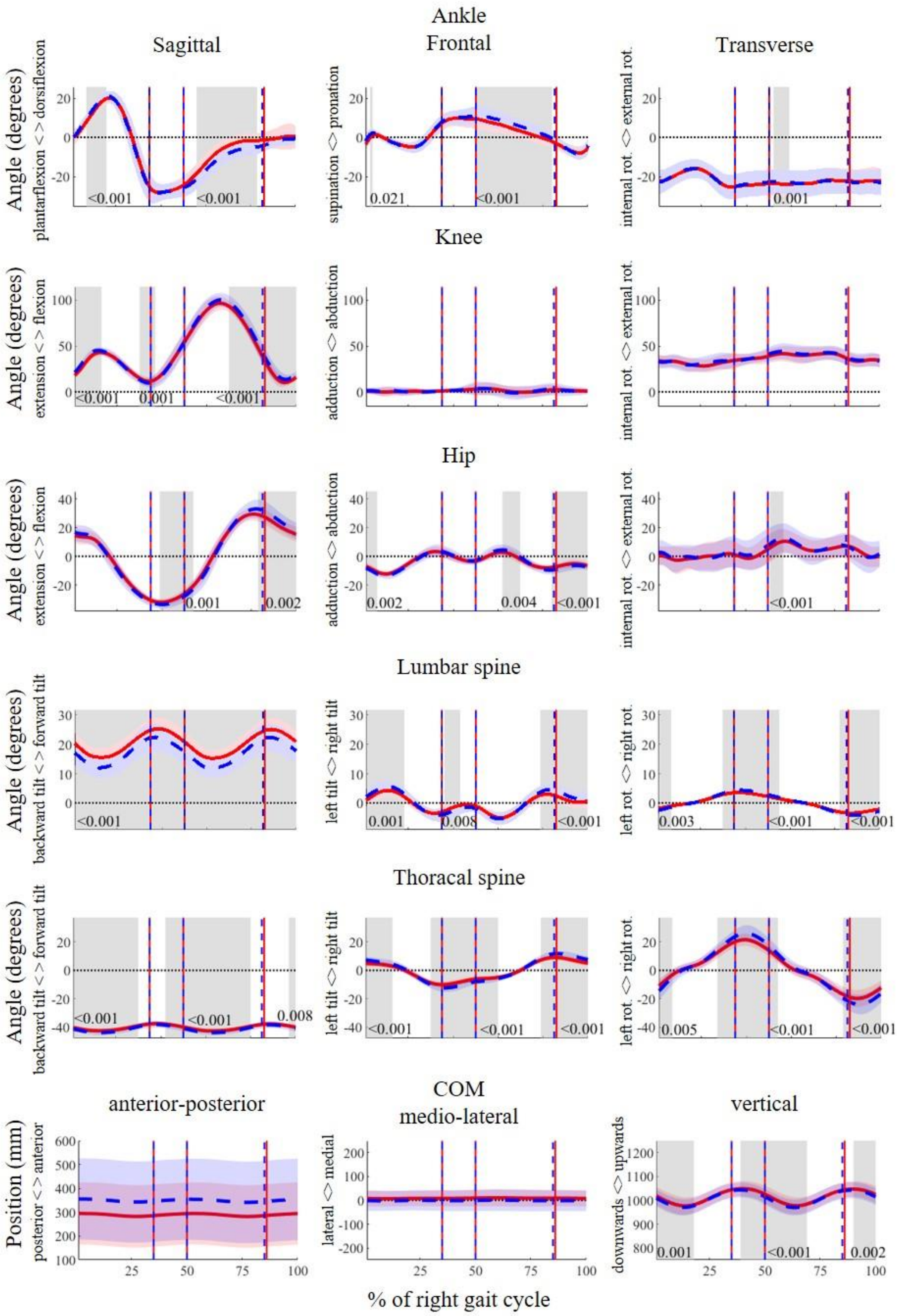

Figure 10: SPM analyses for the angles of the ankle, knee, hip (right side), lumbar spine and thoracic spine in degrees and of the trajectory of the center of mass (CoM) in mm for the entire running gait cycle (from right foot strike to right foot strike) in 3D. The PRE and POST time series data are shown in red and blue, respectively. Significant differences ($p < 0.05$) are highlighted with grey areas and corresponding p-values are given. RTO signifies right toe off, LFS left foot strike and LTO left toe-off.

7.5 Discussion

The aim of this study was to characterize the effects of fatigue induced by a high intensity run on the running kinematics of running novices in an exploratory manner. We hypothesized that we would find pronounced reactions to the induced fatigue. Since we found effects of fatigue on joint kinematics, but not on the spatiotemporal parameters, the stiffness and their CV in the present study, our hypothesis could only be partly accepted.

7.5.1 Spatiotemporal Parameters, Vertical and Leg Stiffness and their Variability

Similar to expert runners, novice runners kept their stride frequency constant (~85.2 Hz). This value is very close to the mean metabolically optimal stride frequency (84.8 ± 3.6 Hz) reported by Lieberman et al. (2015), who analyzed effects of stride frequency and foot position at landing on variety of biomechanical parameters. Nevertheless, the lack of changes in the remaining spatiotemporal and stiffness parameters as well as in their CV, was somewhat surprising having in mind the changes found in expert runners (Möhler, Fadillioglu, et al., 2021). This finding could possibly be explained by the fact that novice runners have missing strategies to further keep up the fixed running speed and thus ended the run earlier than expert runners. The analysis of coordination using methods taking into account the interplay of the joint angles could provide deeper insights (Maurer et al., 2013; Möhler et al., 2019).

7.5.2 Analyses of Range of Motion

As in our previous study (Möhler, Fadillioglu, et al., 2021), all significant changes in RoM were increases from PRE to POST which occurred mainly in the stance phase. Changes in the lower extremities happened mainly in the sagittal and frontal plane in the knee and hip. The observed increases in RoM could be caused by the tentative to generate the torque necessary to keep up with the treadmill speed. The increase in RoM in the hip joint, evoked through a greater abduction around heel strike followed by an increased adduction in the end of the stance phase might be caused by an increased need of shock absorption (Novacheck, 1998). These increases in RoM in the hip and knee could be a sign of an increased injury risk, since the tissues are more stretched. Increases in upper body RoM (lumbar and thoracal spine) were even more pronounced than in experienced runners, despite the lower running speed (Möhler, Fadillioglu, et al., 2021) and are a sign of compensatory movements of the trunk (Hinrichs, 1987) which could be due to an insufficient core musculature. The RoM of the CoM trajectory in novice runners was increased in the horizontal plane in the POST state. However, the RoM of their vertical displacement was not affected. This is in line with the nonexistent changes in the stiffness parameters.

7.5.3 Time Series Analyses of Joint and CoM Movements

To not limit our analysis to discrete parameters, we performed a time series analysis by means of SPM. Several joint angles showed significant effects of fatigue.

The ankle joint showed an increased plantarflexion and pronation throughout the swing phase, which may be and indicator of an unstable ankle joint due to fatigued lower leg muscles, especially the tibialis anterior (Mizrahi et al., 2000).

Even though the novice runners may lack strategies to keep up a certain running speed when fatigued, they may instinctively try to reduce the energy expenditure by adapting their running style accordingly. The lower plantarflexion around toe-off can be interpreted as an effort for saving energy since running economy was reported to be strongly related to a less extended leg at toe-off, which can be achieved through less plantarflexion (Moore, 2016). Similarly, higher flexion of hip and knee also indicated that the leg was less extended in the POST, potentially aiming at maximizing force production (Moore, 2016) to keep the speed constant under fatigue. According to Moore et al. (2012), less leg extension would allow the leg extensor muscles to produce a higher level of propulsive force by operating at a more favorable position on the force-length curve. Furthermore, a less extended leg may reduce the amount of energy needed for flexing the leg in the swing phase, which ultimately would result in a decreased level of energy cost (Moore, 2016).

The increased abduction in the hip might compensate for the pronation in order to ensure the horizontal orientation of the upper body. In addition to the changes in the lower limbs, the upper body showed pronounced reactions to fatigue. The changes in the lumbar and thoracic spine showed that runners rounded their spine more. These changes in upper body posture together with the increased flexion of the leg could explain the lower CoM in the POST. The strong increases in upper body inclination and rotation (in both the lumbar and the thoracic spine) indicate that the runners are not able to stabilize their trunk in order to counteract the torques induced by the running motion (Hinrichs, 1987).

7.5.4 Limitations

A fixed fatigue speed was chosen for all participants. Even though this speed was possibly not equally demanding for all participants, the time to exhaustion showed not too much dispersion (standard deviation: 02:27 min). So, all participants underwent a high intensity run. Since all participants were novice runners, the question rises if they really ran to exhaustion. Their Borg scale rating however showed a homogenous and high level of perceived exertion (18.7 ± 1.0 min). Even though running on a treadmill and running overground show differences (Strohrmann et al., 2012), treadmill running was preferred in this study, to avoid the mixing of effects between fatigue and running speed (Schütte et al., 2018). Furthermore, treadmill running is used as a standard exercise equipment in fitness studios.

7.6 Conclusion

To the best of our knowledge, this was the first study investigating the effects of fatigue induced by a high intensity running protocol in novice runners. The results revealed that novice runners showed pronounced adaptations in joint kinematics. However, there were no changes in their spatiotemporal and stiffness parameters, which might be a hint that novice runners do not have adequate strategies to keep up a fixed running speed in an exhausted state. The changes observed in the joint kinematics, especially in foot pronation and in hip stabilization, showed patterns which have been associated with RRI (Ferber et al., 2009; Schmitz et al., 2014). From an injury prevention point of view, training programs designed for running novices should therefore involve strengthening of the ankle joint in order to prevent excessive pronation as well as of core musculature to establish a more stable hip during running. From a performance point of view, novice runners should train at high intensities to develop strategies for the maintenance of a high speed even in a fatigued state.

8. General Discussion

8.1 Aims and Main Findings

The aim of this thesis was to study the effects of expertise and fatigue on running kinematics and SSV in experienced and in novice runners. This was done by combining analyses from biomechanics, e.g. joint angles, and motor control, e.g. UCM and TNC. The combination of analyses of these two fields of research is a promising approach in advancing the field of sports science (Glazier et al., 2005). Thereby, the applicability of these approaches to problems from applied sports science was tested.

The multitude of DoF within the human body causes redundancy of the musculoskeletal system, which provides an abundance of equivalent movement solutions (Latash et al., 2002). One might assume that throughout the great number of training hours (Ericsson et al., 1993), athletes might be able to control these DoF. However, even at a very high level there is still a certain amount of trial-to-trial variability (Bartlett et al., 2007). The flexible use of these equivalent movement solutions might allow us to compensate for perturbations. One possible disturbance frequently occurring during sports is fatigue. By observing the differences in reaction to fatigue between experts and novices, we might be able to gain further insight into the functioning of these compensatory mechanisms and thus into motor control. Although both the UCM and TNC are promising approaches to study movement variability, they have rarely been applied to whole-body sports movements. Therefore, the applicability of these approaches in the sports science context was confirmed within the framework of this thesis. For the first time, the UCM and TNC approaches were applied to running. Likewise, the geometric forward model needed for these approaches consisted of a subject-specific whole body 3D model for the first time (Möhler et al., 2019).

In summary, this thesis yielded the following findings:

- Topic A – Expertise (chapter 3). It was shown that the CoM is constantly stabilized during running, since $\mathrm{UCM_{Ratio}}$ was always above zero. Contrarily to our hypothesis, the stability of the CoM did not differ between experts and novices, neither at 10 km/h nor at 15 km/h. However, variability (both $\mathrm{UCM_{\parallel}}$ and $\mathrm{UCM_{\perp}}$) was greater in the novices compared to experts in the 15 km/h condition.

- Topic B – Fatigue in Experts (chapters 4, 5 and 6). It was revealed that experienced runners increase their stance time in a fatigued state, together with lower leg and vertical stiffness and a lower CoM trajectory. Only minor changes were found using the UCM approach to study whether the variability and stability of the CoM trajectory are affected by the fatiguing run. The TNC approach allowed the effects of fatigue to be analyzed separately in the three directions. Thereby, it was shown that the CoM trajectory was more variable in a medio-lateral direction in a fatigued state. Additionally, the CoM trajectory was found to be lower and more variable in the absorption phase.
- Topic C – Fatigue in Novices (chapter 7). Against our hypothesis, neither spatiotemporal nor stiffness parameters were altered by fatigue. However, the joint angles and the CoM motion were clearly affected.

In the following paragraph, our results will be put into the context of the existing literature.

8.2 Effects of Expertise on Movement Variability in Running

As outlined in chapter 2.3, differences in running kinematics depending on the degree of running experience were shown. Both the spatiotemporal parameters and the joint kinematics were shown to be different. A consensus exists that novices perform shorter strides with a higher frequency (Cavanagh et al., 1977; Gómez-Molina et al., 2017; Nelson & Gregor, 1976; Slawinski & Billat, 2004). The development of SSV with expertise is not well understood, due to the sparsity of studies. The scaling exponent obtained from a detrended fluctuation analysis was used as a measure of SSV in existing studies (Mo & Chow, 2018a; Nakayama et al., 2010). Results in these studies are conflicting as well as in studies quantifying coordination variability (Floría et al., 2018; Mo & Chow, 2018b). These studies focused either on the variability of one parameter (Mo & Chow, 2018a; Nakayama et al., 2010) or on a combination of two joint angles (Floría et al., 2018; Mo & Chow, 2018b). However, none of these studies analyzed SSV using an approach which incorporated the multitude of DoF and their interplay. Thus, our study (see chapter 3) is the first to analyze the differences between experts and novices in SSV with respect to the CoM in a highly standardized study using the UCM approach, which enabled us to incorporate multiple DoF. We found an increase in variability in the novices, compared to the experts, when running at 15 km/h. Experts have thus adopted a more consistent running style. The stability of the CoM was not different between experts and novices, despite a higher amount of variability in the novices. This is in contrast to the existing studies using the UCM approach to study the effects of expertise. Whereas Nisky et al. (2014) and Iino et al. (2017) studied arm movements of experienced surgeons and experienced table tennis players, respectively, Koh et al. (2020) studied the response to a mechanical perturbation of experienced dancers. Koh et al. (2020) found higher amounts of $\mathrm{UCM}_{\parallel}$ and $\mathrm{UCM}_{\mathrm{Ratio}}$, thus indicating stronger synergies in the more experienced participants. In contrast to the discrete used in these studies, we studied a highly automatic, rhythmic whole-body movement (Wolpert et al., 2013), which might explain the differences.

8.3 Effects of Fatigue in Middle-Distance Running

Due to the practical relevance of fatigue effects on running kinematics, there is a large number of studies on this topic. Concerning long distance running, there are two recent reviews looking at the effects of fatigue on running kinetics, kinematics and spatiotemporal parameters (Kim et al., 2018; Winter et al., 2017). Even though the reviewed studies agree that fatigue affects the observed parameters, there is no consensus on the effects of fatigue on running biomechanics. One possible reason is the numerous methodological choices, which must be controlled for in the study design. Among others, speed, experience, age and sex have been shown to influence running biomechanics and should thus be controlled when studying the effects of fatigue (Boyer et al., 2014, 2017; Brughelli et al., 2011; Maas et al., 2018; Maurer et al., 2012; Padulo et al., 2012; van Oeveren et al., 2021). Therefore, we chose homogenous samples of young male experienced (Topic B) and novice (Topic C) runners and performed our measurements on a treadmill to ensure a fixed speed.

As studies into the effects of fatigue in middle-distance running are rare (see section 2.4), the results of our studies should be considered as databases on which targeted hypothesis can be built. Concerning the experienced runners, we found changes in spatiotemporal and stiffness parameters as well as increases in RoM, which were interpreted as a strategy to compensate for possible lower torques due to muscle fatigue. The increased upper body movements might indicate the need for functional core training, since apparently runners were not able to counteract the angular moments induced by the lower body running motion (Hinrichs, 1987). This increase in upper body motion could also be interpreted as a compensation strategy to create the needed propulsive power. Although experts showed changes in spatiotemporal and stiffness parameters, these effects were not observed among novices, although fatigue had a clear impact on the trajectories of the joint angles and the CoM. These results might be interpreted as a lack of strategies to keep up with a certain running speed in a fatigued condition. Concerning the expert runners (see chapter 4), the decreases in stiffness and increases in ground contact time found with fatigue fit well with previous results (Fourchet et al., 2015; Hayes & Caplan, 2014). Unfortunately, no previous research was available for comparison to the lack of fatigue effects on the spatiotemporal and stiffness parameters in novice runners. Due to the sparse research base in studies dealing with high-intensity fatigue protocols, the effects found in joint kinematics are not truly comparable, neither for experts nor for novices.

On a muscular level, several studies found no effect of fatigue on EMG signals (Avogadro et al., 2003; Mizrahi et al., 1997). Mizrahi et al. (1997) concluded that the effects of fatigue might be more visible in the coordination rather than in single muscles. Recently, Bergstrom et al. (2020) found a pronounced inter-individual variability in EMG signals after intensive fatiguing treadmill runs, and argued towards an analysis on a subject-by-subject basis. Despite the effects of fatigue on specific muscles, the redundancy at the muscular level could enable the CNS to compensate up to a certain degree for these fatigue effects (Nielsen et al., 2018). This underlines the importance of applying complex models of motor control in sports science to capture the extensive effects of fatigue on the musculoskeletal system. The existing studies investigating the effects on SSV mostly focused on single parameters, e.g. stride time, (Meardon et al. 2011) or on combinations of two DoF (Hafer et al., 2017). Even though these studies provided valuable results, they did not adequately reflect the complex interplay of the multitude of DoF within the human body. By applying the UCM and TNC approaches (see chapters 5 and 6), the influence of fatigue on the CoM as a function of the multitude of DoF within the human body could be analyzed.

The SSV of the CoM rose slightly with fatigue. This increase in variability is somewhat in accordance with previous research (Chen et al., 2020; Meardon et al., 2011). $\mathrm{UCM}_{\mathrm{Ratio}}$ did not change with fatigue, which indicates that experienced runners maintained stability of the CoM trajectory throughout the fatigued state. The dimensionality of the applied model, however, was assumed to have an influence on the outcome. Relating to the effects of fatigue on the upper body kinematics, this underlines the importance of the use of a 3D model when studying the effects of fatigue in running. The fact that, despite small increases in variability, the CoM trajectory was stabilized throughout the running stride to the same degree in a fatigued as in a rested state underlines the importance of the CoM as a result variable during running (van Oeveren et al., 2021). Using the TNC approach, the effects of fatigue could be further broken down in each direction. Thereby, it could be shown that changes take place particularly in the frontal plane.

However, the question remains whether specific conclusions concerning injury risk can be deduced from the results of these approaches, since risk factors have mainly been identified for single joints or couplings of two DoF (Ceyssens et al., 2019; Vannatta et al., 2020). Besides the effects of fatigue at a muscular level, one has to keep in mind that the CNS is also affected by fatigue (Millet & Lepers, 2004) which could possibly influence the coordination of the DoF. The phenomenon “fatigue” is multi-faceted. In addition to the topics addressed here, there are also psychological aspects (Marcora, 2019; Staiano et al., 2018), but the consideration of these aspects would be beyond the scope of this thesis.

8.4 Variability Analyses in Sports Movements

As discussed above, the study of the interplay or coordination of the multiple DoF in the human body is a promising approach to contribute new insights into the functioning of motor control. Additionally, the UCM and the TNC approaches offer the possibility to analyze SSV while incorporating a multitude of DoF. To apply these variability analyses, e.g. as a diagnostic tool, one has to understand how training affects the observed variability or how perturbations, like the occurrence of fatigue, interact or counteract. A subgoal of this thesis was thus to test the applicability of the UCM and TNC approaches to problems originating from applied sports science. The analysis of the same dataset and research topic with both analyses (see chapters 5 and 6) could therefore lead to a more comprehensive picture of how running-induced fatigue affects the SSV.

There are some studies applying the UCM in a sports context (Iino et al., 2017; Scholz et al., 2000; Yang & Scholz, 2005). The UCM tries to detect specific directions of variance over several movement repetitions (Latash et al., 2010). However, this structure has to be analyzed with respect to a hypothesis and thus is linked to a task-relevant RV. Hereby, a decrease in variability of the RV is interpreted as a tighter control. With respect to this RV, variability affecting it is seen as bad and variability not affecting it as good. This good variability might provide a multitude of movement executions, which are equivalent with respect to this RV (Freitas et al., 2006). By comparing the good and bad variability, a hypothesis about the stability and control of the RV is tested (Scholz & Schöner, 1999). This has proven to be a valuable tool, e.g. in gait analysis (Rosenblatt et al., 2015) or in the study of postural control (Hsu et al., 2007).

Within this thesis, a subject-specific 3D model was used for the first time in an UCM analysis. This was necessary to adequately study the effects of fatigue on SSV, since fatigue was shown to affect joint kinematics in all three planes (see chapters 4 and 7) and due to the specific anthropometrics of the athletes (Virmavirta & Isolehto, 2014). The UCM was able to detect a higher SSV in novices compared to experts when running at 15 km/h (see chapter 3). Expert runners thus have a more consistent running style, which could indicate a higher efficiency (Moore, 2016). Only minor fatigue effects were found (see chapter 5).

The TNC approach has to date only been applied to throwing movements (Cohen & Sternad, 2009; Müller & Sternad, 2009). In contrast to the UCM, good variability is not analyzed, since only variability affecting the RV is taken into account (Müller & Sternad, 2004). The bad variability is further decomposed into the three components: T, N and C. Thereby, improvements in achieving a constant RV can be linked to one of the components. As in the UCM approach, the TNC approach requires an a priori hypothesis of an RV and a forward model. However, due to the fact that the TNC is performed in the task space, it can deal with both nonlinearities and different units among the EV (Sternad et al., 2010). Therefore, it has fewer constraints limiting its applicability.

The analysis in the task space also allows for the separation of fatigue effects into the three spatial directions and the definition of an alternative RV, namely the definitions of the vector from the right foot to the CoM (see chapter 6). By doing so, it could be shown that the SSV in the medio-lateral direction was affected by fatigue. Effects concerning the CoM with respect to the right foot were more pronounced than effects concerning the CoM with respect to the fixed reference, which underlines the advantages of a task-space analysis.

In the context of movement variability, it was proposed to distinguish between end-point variability and coordinative variability (Hamill et al., 2012). According to these authors, end-point variability occurs in a variable which can be seen as the outcome of a movement, e.g. stride frequency or CoM position. Coordinative variability occurs in the interplay between the different body segments. Low end-point variability is usually desired, whereas a certain level of coordinative variability is needed to flexibly react to unforeseen perturbations and to avoid RRI. Also, a certain level of coordinative variability is needed to ensure a low end-point variability (Hamill et al., 2012). A higher coordinative variability is linked with a healthier state, although it cannot be said if this relation is causative (Hamill et al., 2012). For a functional movement analysis, both types of variability should be considered since fatigue was shown to lead to either an increase or a decrease of variability, depending on the chosen variable (Cortes et al., 2014). The parallel component of variability, $\mathrm{UCM}_{\parallel}$, comprises the variability of the interplay between the joint angles, whereas the orthogonal component, $\mathrm{UCM}_{\perp}$, comprises the end-point variability. Within the TNC approach, only end-point variability is specified. The approaches presented here could be usefully complemented by an analysis of SSV with the use of principal component analysis, e.g. as done by Maurer et al. (2013). This could be seen as an analysis of coordinative variability while incorporating the interplay between the various DoF.

As a next step, the hypothesis stated in chapter 7 - that novice runners are missing strategies to be able to keep up with a fixed running speed under fatigue - can be tested with the UCM or TNC analysis by looking at the SSV of the CoM. Further experiments should be designed which test the applicability of the conceptual assumptions, e.g. that $\mathrm{UCM}_{\parallel}$ is “good” variability. As an initial idea, one could measure two groups with different amounts of $\mathrm{UCM}_{\parallel}$, e.g. experts and novices at an elevated speed, as outlined in chapter 3. Theoretically, the group with the higher $\mathrm{UCM}_{\parallel}$ should have more options to react to e.g. perturbations. To test the conceptual assumptions of the TNC, one could reproduce the skittle-task learning studies by Müller and Sternad (2004)with a more complex sports movement. Then one should either try to improve the three components separately or form several groups with each group individually aiming at one goal at a time. One group would therefore train to have a lower dispersion in the EV, one group would train to have a more error-tolerant configuration and one group would train to make more use of covariation procedures.

To draw specific conclusions about RRI risk, a refined level of analysis might be preferable compared to the holistic approach employed here. Even though the incorporation of multiple DoF is necessary to adequately describe the complexity of the musculoskeletal system, more specific hypotheses and analyses are needed to understand the mechanisms of the specific RRI.

8.5 Limitations

All five studies included in this thesis share a similar experimental design, whose limitations will be mentioned. Since we wanted to capture consecutive strides using a 3D motion capture system, the experiments were conducted on a treadmill. Therefore, some variability was certainly abolished and there might be differences compared to overground running (Van Hooren et al., 2020). We tried to minimize this limitation by establishing a standardized treadmill familiarization period (6 min of walking and 6 min of running, Lavcanska et al., 2005; Matsas et al., 2000). Besides, the fact that the running speed is prescribed by the treadmill also prevents an overlap between the effects of changes in running speed and changes due to fatigue or expertise (Schütte et al., 2018; van Oeveren et al., 2021).

One can critically question the determination of the individual FS in experiment 2. It might have been preferable to base this speed directly on a characteristic lactate value rather than on the critical power concept (Monod & Scherrer, 1965). Similarly, in experiment 3, a subject-specific FS could have been chosen instead of setting a fixed value for all participants. Even though the participants were considerably fatigued (Borg scale rating of 19.6 ± 0.7 in topic B and 18.7 ± 1 in topic C), complete exhaustion could have been ensured by letting the runners run until falling into the safety harness, instead of letting them indicate imminent exhaustion.

Recording the whole run would also have allowed us to take more than 20 strides into account. However, other studies have found a similar number of strides was sufficient (Latash et al., 2010). Too many strides would bear the risk that the fatigue effects are visible within the sample.

To ensure the generalizability of the results, the sample size should have been larger. Due to the dependency of the running kinematics on the study sample, the results obtained in the studies presented here are restricted to young male healthy runners who were novices or experienced. Thus, the results of the presented studies should be replicated with a bigger sample and extended to other groups of participants such as female or older runners. Since the focus of experiment 2 was on middle-distance running, it would have been favorable to choose participants based on their 1500 or 3000 m performance rather than on their 10 km performance.

Within the framework of the UCM and the TNC, a RV has to be chosen. This choice is subjective. Even though there might be several important variables during human locomotion, the CoM is one of the most meaningful since it reflects the motion of the whole body (van Oeveren et al., 2021). When using geometrical forward models, the choices of possible RV are limited. To expand the range of choices for the TNC and UCM approaches, multiple regression techniques can be used (Tuitert et al., 2018). While doing so, it would be feasible to link changes in running kinematics as EV with a physiological variable as RV to better characterize the effects of fatigue on performance. Similarly, the coordinates chosen as EV can influence the results (Schöner & Scholz, 2007; Sternad et al., 2010). Therefore, our results are only valid for the chosen EV. Through the time normalization process done to prepare the data for the UCM and TNC approaches, variability in timing is abolished. The time-normalization is however essential for the application of these analyses.

Methods analyzing movement variability can be classified into different categories: linear methods as the classical measure of standard deviation, non-linear measures to sample entropy and equifinality methods such as the UCM or related methods (Sedighi & Nussbaum, 2019). When thinking of the high non-linearities inherent in our musculoskeletal system, the linearity of the UCM approach might limit its applicability. Non-linear methods could therefore be favorable if a linearization is not reasonable (Stergiou et al., 2006). Since the TNC is performed in the task space, a non-linear forward model can be employed here.

8.6 Conclusions

The results of this thesis extend the knowledge base concerning the effects of expertise and fatigue on running kinematics and SSV in experienced and novice runners. For the first time, the UCM and TNC approaches have been applied to the running movement and have proven to be applicable to problems from the field of applied sport science. In this context, a subject-specific whole-body 3D forward model was developed. The UCM and TNC approaches have been compared and discussed. They have been shown to provide valuable insights in addition to a more traditionally biomechanical approach in studying the effects of fatigue on kinematics. In sports science, as a problem- and practice-oriented field of research, these approaches now have to further prove their usefulness in the application to concrete hypotheses and in the development of recommendations for performance enhancement or injury prevention.

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Eidesstattliche Erklärung

Hiermit erkläre ich, dass ich die vorliegende Dissertation mit dem Titel

’Unraveling the Effects of Expertise and Fatigue on Kinematics and Stride-to-Stride Variability in Running’

selbständig angefertigt habe und keine anderen als die angegebenen Hilfsmittel benutzt sowie die wörtlich oder inhaltlich übernommenen Stellen als solche kenntlich gemacht und die Satzung des Karlsruher Instituts für Technologie (KIT) zur Sicherung guter wissenschaftlicher Praxis beachtet habe. Diese Arbeit wurde nicht bereits anderweitig als Prüfungsarbeit verwendet.

Felix Möhler

Karlsruhe, 25.04.2022

9. Appendix

9.1 Marker set

The marker set is depicted in Figure 11 and described in Table 14. The graphics were taken and adapted from Marahrens (2018) with permission.

Table 14: Overview of the marker set used to measure the 3D kinematics.

Location (number)	Description	Name
Head (4)	Headband, front left on the temple	LFHD
	Headband, front right on the temple	RFHD
	Headband, rear left	LBHD
	Headband, rear right	RBHD
Shoulder (6)	C7 – most prominent cervical vertebra	C7
	Acromioclavicular joint left, not on protruding tip but on plateau	LACR
	Shoulder left, center of rotation, outside at the shoulder at the level of the humerus head	LHUM
	Acromion right	RACR
	Shoulder right	RHUM
	Clavicle, throttle pit where the clavicle meets the sternum.	CLAV
Trunk (5)	Sternum, sternal septum appendix	STRN
	Left posterior hip (PSIS), directly above the posterior superior iliac spine ("dimples")	LPSI
	Left front hip (ASIS), directly above the anterior superior iliac spine	LASI
	Rear right hip (PSIS)	RPSI
	Front right hip (ASIS)	RASI
Upper arm (4)	Left elbow, on lateral epicondylus	LELB_lat
	Left elbow, on medial epicondylus	LELB_med
	Right elbow, lateral	RELB_lat

	Left elbow, medial	RELB_med
Lower arm (4)	Wrist left lateral, from outside to wrist (joint gap, on the forearm), small finger side	LWRI_lat
	Wrist left medial, from inside to wrist (joint gap, on the forearm), thumb side	LWRI_med
	Wrist right lateral	RWRI_lat
	Wrist right medial	RWRI_med
Hand (2)	Knuckle middle finger left	LFIN
	Knuckle middle finger right	RFIN
Leg (4)	Knee left lateral, at the epicondylus lateralis femoris (best to be determined with one-legged knee flexion: center of rotation); on the thigh as close as possible to the joint gap	LKNE_lat
	Knee left medial, at the epicondylus medialis femoris (best to be determined with one-legged knee flexion: center of rotation); on the thigh as close as possible to the joint space	LKNE_med
	Knee right lateral	RKNE_lat
	Knee right medial	RKNE_med
Ankle (6)	Ankle left lateral, directly on the ankle	LMAL_lat
	Ankle left medial, directly on the ankle	LMAL_med
	Ankle right lateral	RMAL_lat
	Ankle right medial	RMAL_med
	Left heel, bone appendix of heel bone located furthest dorsally (behind)	LHEEL
	Right heel	RHEEL
Foot (6)	Forefoot left lateral, height of the toe base joint from lateral, not to be glued from above	LFOOT_lat
	Forefoot left medial, height of the toe base joint from medial, not to be glued from above	LFOOT_med
	Forefoot right lateral	RFOOT_lat
	Forefoot right medial	RFOOT_med
	Big toe left, on top of the shoe (over the toe nail at the front)	LTOE
	Big toe right	RTOE

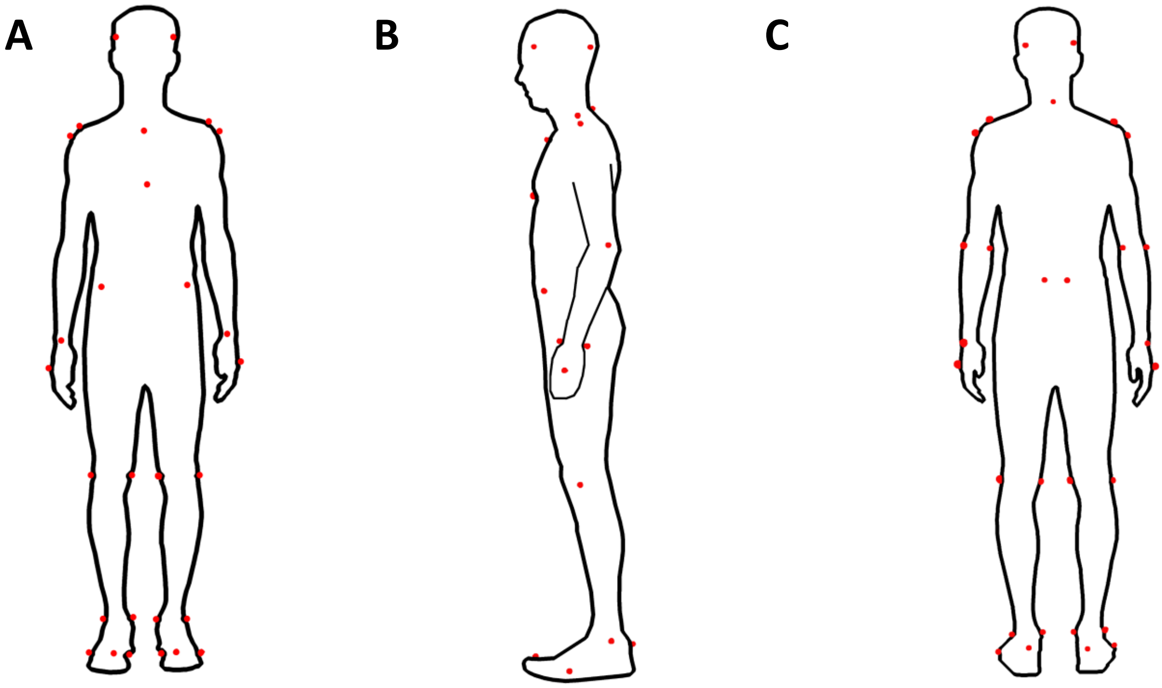

Figure 11: Depiction of the marker set. (**A**) view from the front, (**B**) view from the left side, (**C**) view from the back.

9.2 Anthropometric Model

Figure 12, Figure 13 and Figure 14 show the measures needed to calculate the volume of the single segments. The graphics are taken from Marahrens (2018) with permission. Each body segment was modeled as a geometric form. The variables determining this form are given in small letters. The segment volumes and CoMs were calculated using anthropometric measures either taken manually or calculated from marker data. These variables are given in capital letters. The vector from the segment coordinate system (shown in red) to the joint connection segment with the next one is defined as $\boldsymbol{q}_{\mathrm{rel,i}}$. The modelled geometries are the external envelope of the body segments. Therefore, the volume is corrected using the factor $\gamma = 0.63$ to achieve an average density comparable to literature values (Katch & McArdle, 1973; Wilmore & Behnke, 1969).

- Pate segment:

$$a_{\text{Pate}} = \frac{1}{2}\gamma L_{\text{Pate}},\ b_{\text{Pate}} = \frac{1}{2}\gamma(W_{\text{PateF}} + W_{\text{PateB}}),\ c_{\text{Pate}} = \frac{1}{2}\gamma(D_{\text{PateR}} + D_{\text{PateL}}),$$
$$\boldsymbol{q}_{\text{rel,Pate}} = (0 \quad 0 \quad -2a_{\text{Pate}}) \tag{9.1}$$

- Neck segment:

$$r_{\text{Neck}} = \frac{1}{2\pi}\gamma C_{\text{Cervical}},\ h_{\text{Neck}} = H_{\text{Atlas}} - H_{\text{cervical}},\ \boldsymbol{q}_{\text{rel,Neck}} = (0 \quad 0 \quad h_{\text{Neck}}) \tag{9.2}$$

- Segment breast: D_{Breast} is not shown in Figure 12. It is the measured depth of the chest:

$$a_{\text{Breast}} = \frac{1}{2}\gamma W_{\text{Breast}},\ b_{\text{Breast}} = \frac{1}{2}\gamma D_{\text{Breast}},\ h_{\text{Breast}} = H_{\text{Suprasternale}} + H_{\text{Xiphoid}}),$$
$$\boldsymbol{q}_{\text{rel,Waist}} = (0 \quad 0 \quad -2h_{\text{Breast}})\ ,\ \boldsymbol{q}_{\text{rel,UpperArm}} = (\pm a_{\text{Breast}} \quad 0 \quad -0{,}1h_{\text{Breast}}) \tag{9.3}$$

- Waist segment: the depth of the waist was not measured. We therefore iteratively adapted b_{waist} until the circumference calculated from a_{waist} and b_{waist} matched the circumference C_{waist}:

$$a_{\text{waist}} = \frac{1}{2}\gamma W_{\text{Waist}},\ h_{\text{Waist}} = H_{\text{Xiphoid}} - H_{\text{OriginHip}},$$
$$\boldsymbol{q}_{\text{rel,Neck}} = (0 \quad b_{\text{waist}} \quad -h_{\text{Waist}}) \tag{9.4}$$

- Hip segment: the functional leg length H_{Leg} was not measured up to the hip joint center. Therefore, 63% of the difference $(H_{\text{OriginHip}} - H_{\text{Leg}})$ is assigned to the hip segment. The remaining 37% is assigned to the two thigh segments:

$$r_{\text{Hip}} = \frac{1}{4}\gamma(D_{\text{HipR}} + D_{\text{HipL}}),\ a_{\text{Hip}} = \gamma(W_{\text{Hip}} - 2r_{\text{Hip}}),\ h_{\text{Hip}} = 0.63(H_{\text{OriginHip}} -$$
$$H_{\text{Leg}}),\ \boldsymbol{q}_{\text{rel,Hip}} = (\pm a_{\text{Hip}} \quad -r_{\text{Hip}} \quad -h_{\text{Hip}}) \tag{9.5}$$

- Thigh segment: 37% of the difference $(H_{\text{OriginHip}} - H_{\text{Leg}})$ is assigned to the thigh segment, as the functional leg length was not measured up to the hip joint center:

$$r_{\text{Thigh},1} = \frac{1}{2\pi}\gamma C_{\text{Thigh}}, r_{\text{Thigh},2} = \frac{1}{2\pi}\gamma W_{\text{Knee}}, l_{\text{Thigh}} = H_{\text{Leg}} - H_{\text{Knee}} + 0.37(H_{\text{OriginHip}} - H_{\text{Leg}}), \boldsymbol{q}_{\text{rel,Thigh}} = (0 \quad 0 \quad -l_{\text{Thigh}}) \tag{9.6}$$

- Lower leg segment:

$$r_{\text{LowerLeg},1} = \frac{1}{2}\gamma W_{\text{Knee}}, r_{\text{LowerLeg,max}} = \frac{1}{2\pi}\gamma C_{\text{Calf}}, r_{\text{LowerLeg},2} = \frac{1}{2\pi}\gamma C_{\text{lowerLegS}} \quad l_{\text{LowerLeg}} = H_{\text{Knee}} - H_{\text{Foot}}, \boldsymbol{q}_{\text{rel,Hip}} = (0 \quad 0 \quad -l_{\text{LowerLeg}}) \tag{9.7}$$

- Foot segment: the constant offset of 0.02m reflects the shoe height:

$$r_{\text{Foot},1} = \frac{1}{2}\gamma(H_{\text{Foot}} - 0{,}02m), r_{\text{Foot},2} = \frac{1}{2}\gamma(H_{\text{Toe}} - 0.02m), l_{\text{Foot}} = L_{\text{Foot}} \tag{9.8}$$

- Upper arm segment:

$$r_{\text{UpperArm},1} = \frac{1}{2\pi}\gamma C_{\text{UpperArmL}}, r_{\text{UpperArm},2} = \frac{1}{2\pi}\gamma C_{\text{ForeArmL}}, l_{\text{UpperArm}} = L_{\text{UpperArm}}, \boldsymbol{q}_{\text{rel,UpperArm}} = (0 \quad 0 \quad -l_{\text{UpperArm}}) \tag{9.9}$$

- Forearm segment:

$$r_{\text{ForeArm},1} = \frac{1}{2\pi}\gamma C_{\text{ForeArmL}}, r_{\text{ForeArm},2} = \frac{1}{2\pi}\gamma C_{\text{ForeArmS}}, l_{\text{ForeArm}} = L_{\text{ForeArm}}, \boldsymbol{q}_{\text{rel,UpperArm}} = (0 \quad 0 \quad -l_{\text{ForeArm}}) \tag{9.10}$$

- Hand segment: not shown in the figures. The hand is measured as a sphere. The length of the hand, L_{Hand}, was measured from the wrist to the finger tips:

$$r_{\text{Hand}} = \frac{1}{4}\gamma L_{\text{Hand}} \tag{9.11}$$

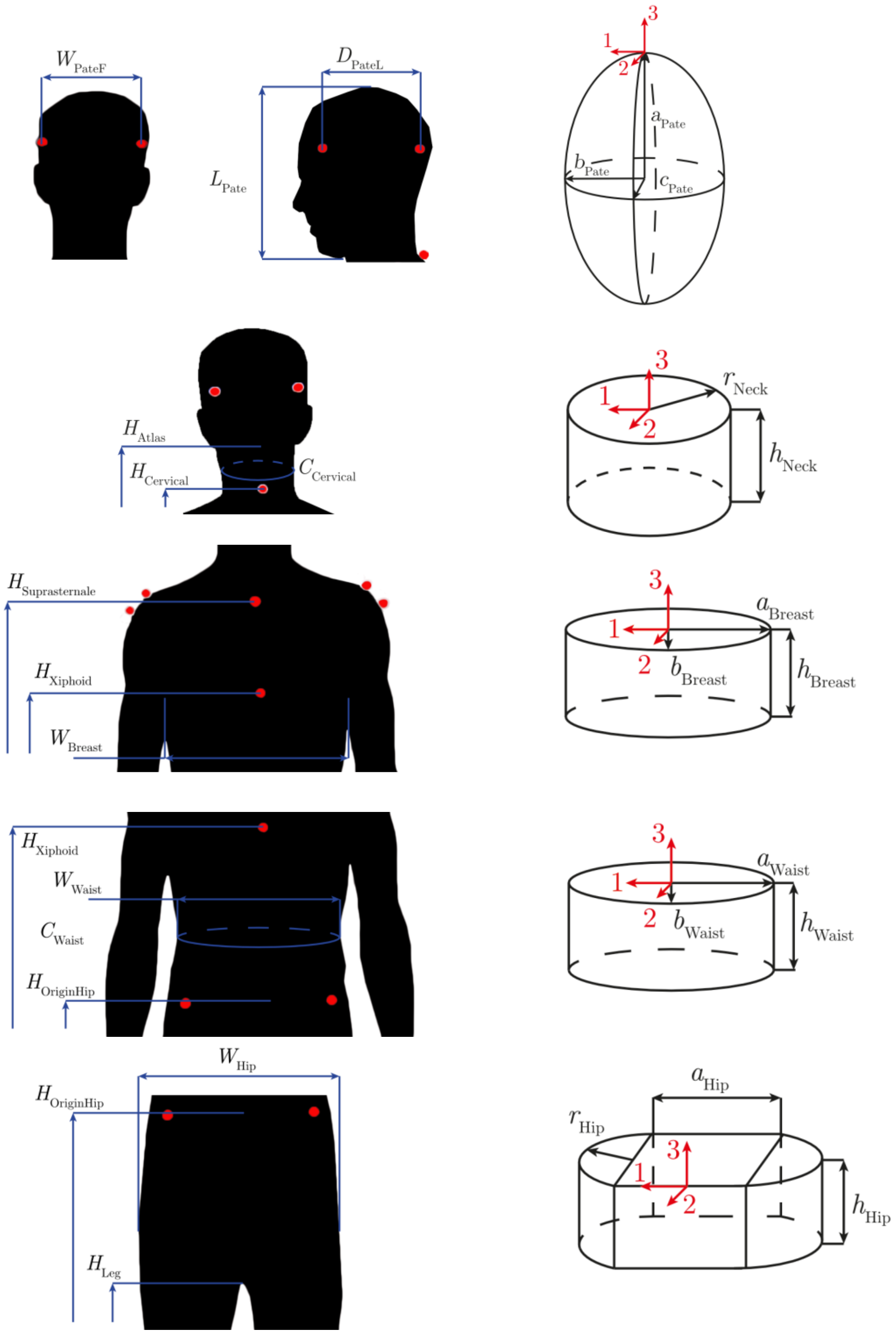

Figure 12: Model segments of the upper body. The geometric modeling of the segments, the location of the segment CoM and the measures needed to calculate the volume are shown.

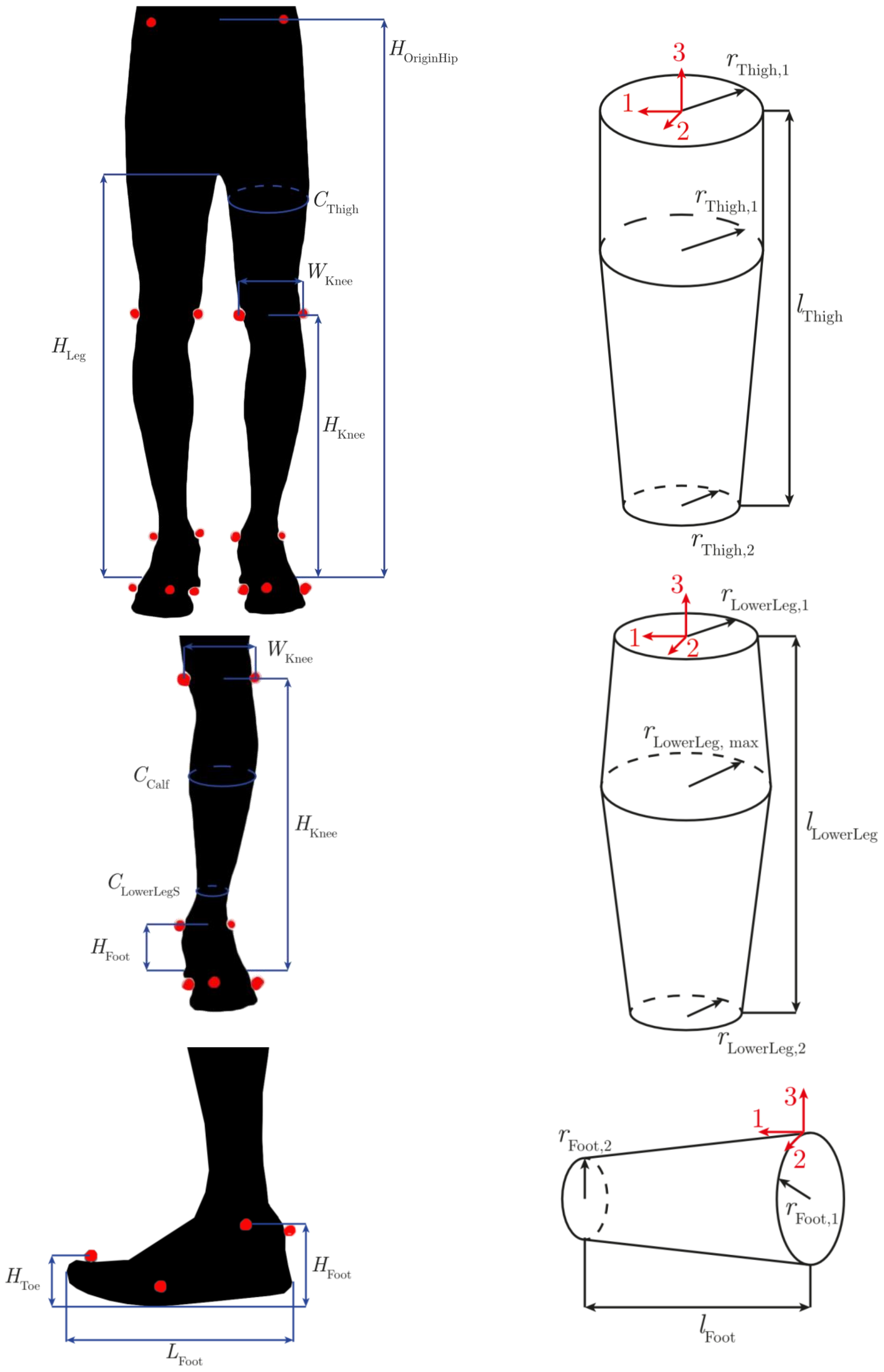

Figure 13: Model segments of the lower limbs. The geometric modeling of the segments, the location of the segment CoM and the measures needed to calculate the volume are shown.

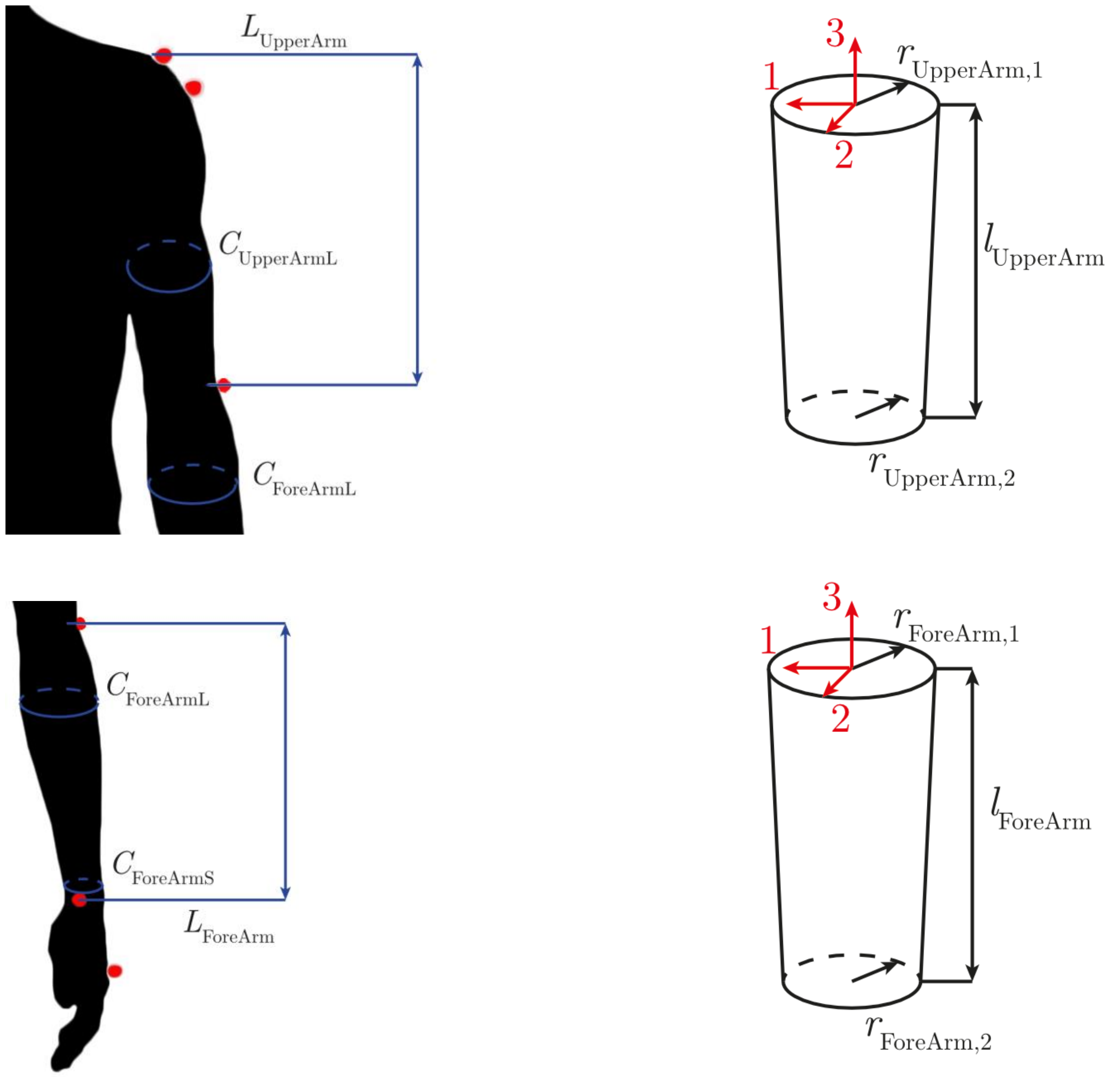

Figure 14: Model segments of the upper limbs. The geometric modeling of the segments, the location of the segment CoM and the measures needed to calculate the volume are shown.